T.C.

BİNGÖL ÜNİVERSİTESİ

SOSYAL BİLİMLER ENSTİTÜSÜ

İŞLETME BÖLÜMÜ

İSLAMİ FINTECH UYGULAMARI VE MAKİNE ÖĞRENMESİ YÖNTEMLERİ İLE PORTFÖY OPTİMİZASYONU

Gökmen KILIÇ

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Bu çalışma *TÜBİTAK* tarafından *2214-A Yurt Dışı Doktora Sırası Araştırma Burs* programı kapsamında desteklenmiştir.

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SCIENTIFIC ETHICS STATEMENT

In this dissertation study entitled "**Islamic Fintech Applications and Portfolio Optimization Using Machine Learning Methods**" I hereby declare that all information in this document has been obtained and presented under academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work. Finally, I hereby declare that the Bingöl University social sciences institute directorate can store and make available electronically the present dissertation.

01/08/2024

Gökmen KILIÇ

DISSERTATION ACCEPTANCE AND APPROVAL

BİNGÖL UNIVERSITY
SOCIAL SCIENCES INSTITUTE DIRECTORATE

This Ph.D. dissertation study prepared by Gökmen KILIÇ, entitled "**Islamic Fintech Applications and Portfolio Optimization Using Machine Learning Methods"** was found to be successful as a result of the dissertation defence examination held on the date of 01/08/2024 and approved with the unanimity of votes by the jury and has been accepted as a Ph.D. in the department of business administration.

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CONFIRMATION

This dissertation was accepted by the jury determined in the / /2024 session of the board of directors of the sciences institute of Bingöl University.

Director of the Institute

DEDICATIONS

"Every journey begins with a single step"[1].

I would like to dedicate this thesis to all the people who have walked me during my Ph.D. journey and who have inspired me to take that single step to start and who have supported me to finish this journey successfully.

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[1] Lao Tzu

ÖZET

Tezin Başlığı: İslami Fintech Uygulamaları ve Makine Öğrenmesi Yöntemleri ile Portföy Optimizasyonu

Tezin Yazarı: Gökmen KILIÇ

Danışman: Dr. Öğretim Üyesi Yavuz TÜRKAN

Anabilim Dalı: İşletme

Bu tez, Türkiye'de İslami bankacılık ile fintech arasındaki etkileşimi, açık bankacılık uygulamalarını esas alarak incelemeyi amaçlamıştır. İslami fintech, Şeriat ilkelerini dijital gelişmelerle birleştirerek finansal katılımı, operasyonel verimliliği ve etik normlara uyumu geliştirme kapasitesine sahiptir. Çalışma, Şeriat uyumlu dijital bankacılık, kitlesel fonlama ve açık bankacılık sistemlerinin sonuçları gibi çok çeşitli fintech seçeneklerini araştırmaktadır. Bu çalışma aynı zamanda Kapı Özyinelemeli Geçitler (GRU), Çift Yönlü LSTM (Bi-LSTM), Uzun Kısa Süreli Bellek (LSTM), XGBoost, Rastgele Orman (RF), Destek Vektör Makinesi (SVM) olmak üzere altı makine öğrenme modelinin, Borsa Istanbul Katılım Tüm Endeksi'ndeki 163 adet stoğun 2007 ilk çeyrek ile 2022 son çeyrek arasındaki verileri ile fiyat tahminlemesini ve LSTM, Bi-LSTM ve GRU modelleri ile portföy optimizasyonu uygulamalarını içermektedir. XGBoost modeli, hisse senedi fiyat tahmini açısından en yüksek doğruluk düzeyine ulaşarak üstün performansı, 0,1619 MAE, 0,0377 MSE, 0,1943 RMSE değerleri ile ulaşmıştır. Portföy optimizasyonda LSTM, modeller arasında en yüksek özsermayeye ulaşarak en iyi performansı göstermiştir. Bi-LSTM modeli, risk ve getiri arasındaki en uygun dengeyi sergileyerek 0,0719 ile en yüksek yıllıklandırılmış Sharpe Oranını elde etmiştir. Öte yandan GRU modeli, en yüksek hata metriklerine sahip olmasına rağmen değişken piyasalara yanıt verme kapasitesini en düşük yıllık değişkenlik oranına ulaşarak göstermektedir. Tez, sektörün ilerlemesini yönlendirmek için hükümetin, finansal kurumların ve teknoloji oyuncularının katılımını içeren entegre bir yaklaşımı destekleyen perspektif sunmaktadır. Bu çabaların birleştirilmesiyle Türkiye'nin dünya çapındaki İslami fintech endüstrisinde lider konumuna gelebileceğinin dinamikleri verilmektedir.

Anahtar Kelimeler: İslami fintekler, açık bankacılık, portföy optimizasyonu, İslami stok fiyat tahmini

ABSTRACT

Title of the Thesis: Islamic Fintech Applications and Portfolio Optimization Using Machine Learning Methods	
Author: Gokmen Kilic	
Supervisor: Asst. Prof. Dr. Yavuz TÜRKAN	
Department: Business Administration	

This thesis examines the advantageous relationship between Islamic banking and fıntech in Türkiye, with a focus on its capacity to impact open banking. Islamic fintech can improve financial inclusion, operational efficiency, and compliance to ethical norms by combining Shariah principles with digital advancements. The study explores widely various fintech options, such as Shariah-compliant digital banking, crowdfunding, and the consequences of open banking systems. This study also investigates the application of six machine learning models, namely Gated Recurrent Unit (GRU), Bidirectional LSTM (Bi-LSTM), Long Short-Term Memory (LSTM) and XGBoost, and Random Forest (RF) and Support Vector Machine (SVM) in the stock price prediction in the Borsa Istanbul Katılım Tum Index between Q1 2007 - Q4 2022 with 163 stocks as well as LSTM, BiLSTM and GRU models for portfolio optimisation applications. The XGBoost model demonstrated superior performance, attaining the highest levels of accuracy in terms of stock price prediction. It produced an MAE (Mean Absolute Error) of 0.1619, MSE (Mean Squared Error) of 0.0377, RMSE (Root Mean Squared Error) of 0.1943. LSTM concluded with a highest equity value among models in terms of portfolio optimisation. The Bi-LSTM model exhibited the most favourable balance between risk and return, achieving the greatest annualised Sharpe Ratio of 0.0719. On the other hand, the GRU model demonstrated its capacity to respond to volatile markets, despite having the highest error metrics. These solutions demonstrate the flexibility and innovative capability of Islamic finance in addressing existing financial requirements while maintaining ethical and moral guidelines. The thesis supports for an integrated approach that includes the participation of the government, financial institutions, and technology players to drive the sector's progress. It suggests that by combining these efforts, Türkiye can establish itself as a leader in the worldwide Islamic fintech industry.

Keywords: Islamic fintech, open banking, portfolio optimization, Islamic stock market price prediction

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ABBREVIATIONS AND SYMBOLS

Abbreviation	**Explanation**
AAOIFI	Accounting and Auditing Organization for Islamic Financial Institutions
AI	Artificial Intelligence
AML	Anti-Money Laundering
APIs	Application Programming Interfaces
AUX	Auxiliary
Bi-LSTM	Bidirectional Long Short-Term Memory
BIST	Borsa Istanbul
CAPM	Capital Asset Pricing Model
CNN	Convolutional Neural Network
DL	Deep Learning
EMA	Exponential Moving Average
GDPR	General Data Protection Regulation
GRU	Gated Recurrent Unit
HPC	High Performance Computing
IFSB	Islamic Financial Services Board
LSTM	Long Short-Term Memory
LTCM	Long-Term Capital Management
MAE	Mean Absolute Error
MENA	Middle East and North Africa
ML	Machine Learning
MPT	Modern Portfolio Theory
MSE	Mean Squared Error
MVO	Mean-Variance Optimization
OBIE	Open Banking Implementation Entity
P2P	Peer-to-Peer
PCA	Principal Component Analysis
PSD2	Payment Services Directive 2

RAPMs	Risk-Adjusted Performance Measures
RF	Random Forest
RMSE	Root Mean Squared Error
ROI	Return on Investment
SDGs	Sustainable Development Goals
SLSQP	Sequential Least Squares Programming
SMA	Simple Moving Average
SMEs	Small and Medium Enterprises
SVM	Support Vector Machine
SVR	Support Vector Regression
TPPs	Third-Party Providers
VCs	Venture Capitals
VIAs	Virtual Influencer Agents
XGBoost	Extreme Gradient Boosting
XKTUM	Borsa Istanbul Katılım Tum

INTRODUCTION

The motivation behind this thesis is the growing convergence of Islamic finance and fintech, which is seen as a vital pathway to improving financial inclusion, operational effectiveness, and Shariah compliance in Türkiye. This study aims to investigate the possibilities of Islamic fintech, specifically in relation to open banking, to improve Türkiye's standing in the international Islamic finance industry within the fast-changing financial landscape. The study explores a range of fintech developments, including crowdfunding and digital banking that complies with Shariah, and assesses the effects of open financial systems. The thesis investigates the use of several advanced machine learning (ML) models in the financial domain, evaluating their effectiveness in predicting stock prices and optimising portfolios in Borsa Istanbul Katılım Tum Index. This study aims to provide a comprehensive understanding for using fundamental and advanced financial models with high-performance computing to drive the growth of using ML and artificial intelligence (AI) technologies in the applications of Islamic fintech.

The first chapter sets the context through investigating the connections between Islamic finance and fintech in Türkiye. It's a basic overview of the topic that touches on the political and historical context that have shaped the development of Islamic banking and fintech in the nation. This section first defines and contextualises fintech before examining its growth in Türkiye. It also looks at the Islamic fintech industry's explosive growth and bright future in Türkiye's banking industry. The ethics and transparency that form the foundation of the fintech sector are also examined in this chapter, along with the tenets of Islamic finance. This chapter analyses Türkiye's position in the global Islamic fintech landscape by considering global trends, strengths, weaknesses, and a comparison with other notable Islamic fintech nations. The final section of the chapter looks ahead to possible development, expansion, and strategies for increasing innovation and competitiveness in Türkiye's Islamic fintech industry.

The development and applications of Islamic fintech are examined in the second chapter. It acts as an overview, defining the boundaries that Islamic fintech may work inside. This chapter looks at how Islamic fintech complies with Islamic law, with particular attention on how it fits within the framework of the Islamic moral economy.

Then, important uses of Islamic fintech are explored, accompanied with instances of the most recent advancements in this area. The usage of blockchain technology and Islamic cryptocurrencies, takaful and Insurtech, digital banking and payment solutions, P2P lending platforms and crowdfunding, wealth management and robo-advisory services, and digital banking are a few examples of these applications. This chapter approaches Islamic fintech from the perspective of financial computing, examining how artificial intelligence (AI), machine learning (ML), deep learning (DL), and analytics can be used in areas such as cloud-based Islamic banking and finance, investment strategies, fraud detection, compliance, algorithmic trading, and risk assessment that complies with Shariah. The chapter also covers the role of international bodies and authorities in tackling the challenges of standardisation and the regulatory environment in Islamic finance. A synopsis of the key points and findings concludes the chapter.

We investigate how open banking might impact the development of Islamic fintech in the third chapter. The concepts of open banking and open finance are examined in this chapter, along with their definitions and differences. It examines these concepts and how important APIs and data sharing are to the creation of new financial services. This chapter looks at how the open banking environment has affected Islamic finance and offers an overview of the global scene as well as the core ideas of this ecosystem. It looks at open banking and how it could allow participants in the Islamic finance ecosystem to collaborate and provide services that comply with Shariah law. This chapter investigates how open banking has affected Islamic fintech from a societal perspective, with a particular emphasis on financial inclusion, emancipation, and strengthening community-based finance. Additionally, it looks into how open banking fits into the sustainable developments goals (SDGs) and Islamic finance principles, and it showcases ideas and solutions for sustainable finance that are powered by open banking. The major ideas and their implications are summed up in the chapter's conclusion.

In the chapter four, we take an extensive look into a wide range of algorithms intended to improve investing strategies via risk analysis and predictive analytics. In order to visualise the Efficient Frontier, we first go over the fundamental ideas of Markowitz Portfolio Theory, including portfolio return, variance, and the covariance matrix of a multi-asset portfolio. The explanation of risk-adjusted performance indicators follows, offering a framework for assessing assets in relation to their risk. We also look at ensemble techniques like random forest (RF), support vector machines (SVM), and extreme gradient boosting (XGBoost), as well as more sophisticated machine learning models like long short-term memory (LSTM), its bidirectional counterpart (Bi-LSTM), and gated recurrent unit (GRU). These methods are evaluated for how well they handle sequential versus non-sequential data, which is an important distinction in the context of stock price prediction. Each model's advantages and potential applications are highlighted.

We use a structured approach to examine the data analysis and findings of our investigation in chapter five of the thesis. We first go over the study framework that directs our analysis, and then we go into great detail into the techniques used for data collecting and preprocessing. The chapter then moves on to feature engineering, emphasising its role in improving model performance, and presents Principal Component Analysis as a means of dimensionality reduction for our datasets. Next, in order to improve model efficiency, we optimise training operations by implementing dropout and early stopping approaches. Later analyses concentrate on different machine learning models, such as RF, SVM, XGBoost, GRU, LSTM, and Bi-LSTM, paying particular attention to how well each model performs. At the end of the chapter, these models are compared in the context of stock price prediction, and their relative efficacy in portfolio optimisation strategies is discussed. GRU, LSTM, and Bi-LSTM models are also used for portfolio optimisation in context of Markowitz portfolio theory. This thorough review highlights the useful applications of sophisticated analytical approaches in the field of financial modelling in addition to clarifying the methodologies used.

A summary of the results, a discussion of the implications for Islamic fintech practitioners and policymakers, and recommendations for future study areas are included in the dissertation's conclusion. The goal of this study is to further the scholarly sympathetic of fintech’s role in expanding Islamic finance's reach and functioning while offering useful advice for putting it into practice, especially in the Türkiye landscape.

CHAPTER ONE

FINTECH AND ITS TÜRKİYE LANDSCAPE WITHIN THE ISLAMIC FINANCE PERSPECTIVE

1.1. Introduction

The nexus of technology and finance, or "fintech," has become a major player in the reorganisation of the financial industry, changing the ways in which financial services are provided. The objectives of this convergence are to promote inclusivity, democratise access to financial services, and improve the efficiency of banking operations. Fintech offers a distinct set of potential and problems in the field of Islamic banking, which follows the precepts of Shariah law. This comparison highlights how fintech can improve accessibility, expedite Islamic banking procedures, and guarantee adherence to Islamic legal and ethical norms. It also draws attention to the challenges of coordinating technology developments with the strict guidelines of Shariah law, which calls for a careful analysis of fintech's place in the Islamic financial sector.

This argument is based on the first chapter, looks at the Türkiye fintech scene from the point of view of Islamic banking. The first part of the chapter gives an outline of the relationship between Islamic finance and fintech in Türkiye. This shows how important this relationship is to the country's financial system. It tells a lot about the past and events that have affected the growth of Islamic finance and fintech in Türkiye.

The next part of the chapter outlines and builds a framework for fintech by describing its main features and possible uses. The history of Islamic finance is looked into, including its beginnings and how it has changed over time. This is necessary to understand how fintech have changed in Türkiye. It also looks at how fintech has grown in the Turkish financial sector, showing how it came about and how it has changed traditional financial services.

It is very important that this part looks into the rise of Islamic fintech in Türkiye. This part looks at how Islamic finance-aligned fintech solutions have grown and changed over time. It does this to show what makes this industry unique and how it can grow in the Turkish market.

Islamic finance is based on a set of rules that are explained in more depth in the first chapter. This chapter looks into whether Shariah-compliant goods can be used in the fintech market. It stresses how important it is to follow Islamic rules when making and using fintech solutions.

In the banking field, honesty and ethics are very important things to think about. The chapter puts a lot of weight on how important honesty and ethics are in fintech, especially when it comes to Islamic banking. In it, the ethical problems and the need for openness in financial dealings are discussed, showing how important these issues are for building trust among stakeholders.

This part looks at Türkiye's role in the global Islamic fintech scene, pointing out the pros and cons of the country compared to others. Global Islamic fintech trends and changes are looked at in order to understand how the industry works as a whole and find places where people can work together and grow. This part also compares Türkiye to other top Islamic fintech markets so that you can get a better idea of Türkiye's situation and its chances of getting better.

At the end of the chapter, possible growth and development paths for Islamic fintech in Türkiye are laid out. It gives ideas on how to encourage new ideas and competition in the Türkiye Islamic fintech sector. It also talks about how to use the country's strengths and handle its weaknesses to ensure long-term success and growth.

As a result, chapter one gives a complete look at the Türkiye fintech scene from the point of view of Islamic banking. It sets the stage for appreciative the uses, possible impacts, and growth and innovation prospects in the area of Islamic fintech in Türkiye. It also lays the groundwork for further research in later parts.

1.1.1. Background and Context

In recent years, financial technology, often known as fintech, has emerged as an essential component of the financial sector all over the world. Also, Islamic Finance, which is characterized by compliance with Shariah law, has attracted significant attention as a substantial and viable alternative to conventional finance (Iqbal & Mirakhor, 2011). This can be explained by the fact that Islamic Finance is characterized by compliance with Shariah law. There is a rare and interesting crossing of these two financial models in Türkiye, which is a country that is predominately Muslim. According to Hasan (2023), the Türkiye financial system is seeing an exciting mix of contemporary financial services powered by new technology and the traditional ethical precepts that form the basis of Islamic banking. The financial system in Türkiye combines cutting-edge technology with the fundamentals of Islamic banking in a way that is not seen in other nations, resulting in a unique fusion of ethical and innovative practices.

Although Islamic finance has been a part of the financial landscape in Türkiye since the early 1980s, the development of the technology has drastically impacted how financial transactions are performed (Ayub, 2009). Ethical investment practises have been present in Türkiye since the early 1980s. Islamic banking institutions and other financial service providers in Türkiye are utilizing new technology to offer a variety of Shariah-compliant goods and services (Hasan & Lewis, 2009). This is due to the growing prevalence of Fintech. This is developing a financial industry that is more inclusive and offering new options for clients as well as investors in the country.

1.2. Definition and Framework of Fintech

According to Arner, Barberis, and Buckley (2016, p. 1271-1319), the application of technology in the delivery of financial services is referred to as "fintech." This term is derived from the phrase "financial technology." It includes a wide variety of applications and platforms, such as mobile banking, online trading, cryptocurrencies, and peer-to-peer lending (Schueffel, 2016). However, it is not restricted to only these areas of financial technology. According to Zavolokina, Dolata, & Schwabe (2016), fintech attempts to improve and automate the supply of financial services and has been at the center of the change of the financial industry by boosting efficiency, decreasing costs, and improving the quality of the client experience.

The foundation of fintech is comprised of a wide variety of stakeholders, including established financial institutions, new businesses in the technology sector, and regulators. These organizations are actively involved in the conceptualisation, development, and deployment of various financial technologies. The framework is also characterized by regulatory and legal elements, which are critical for ensuring that the operations and services supplied by fintech companies are in accordance with the existing financial regulations (Zetzsche, Buckley, Arner, & Barberis, 2017, p. 393-431). The regulatory and legal components of the framework are essential for ensuring that the framework is characterized by regulatory and legal aspects.

Using the work of global standard-setting bodies and other foreign groups as a starting point, we present the "fintech tree" in Figure 1.1 As a way to think about how policies should respond to fintech. The fintech tree divides things into three groups: fintech actions, policies, technologies that make them possible. Fintech activities, like digital banking or robo-advice, can look different and happen in different parts of the financial business. Enabling technologies, like cloud computing or artificial intelligence, make it possible for new financial services to be offered. They are what hold fintech activities together. Policy drivers are actions and programmes taken by the government, like digital ID systems, that help fintech activities grow and make use of enabling technologies.

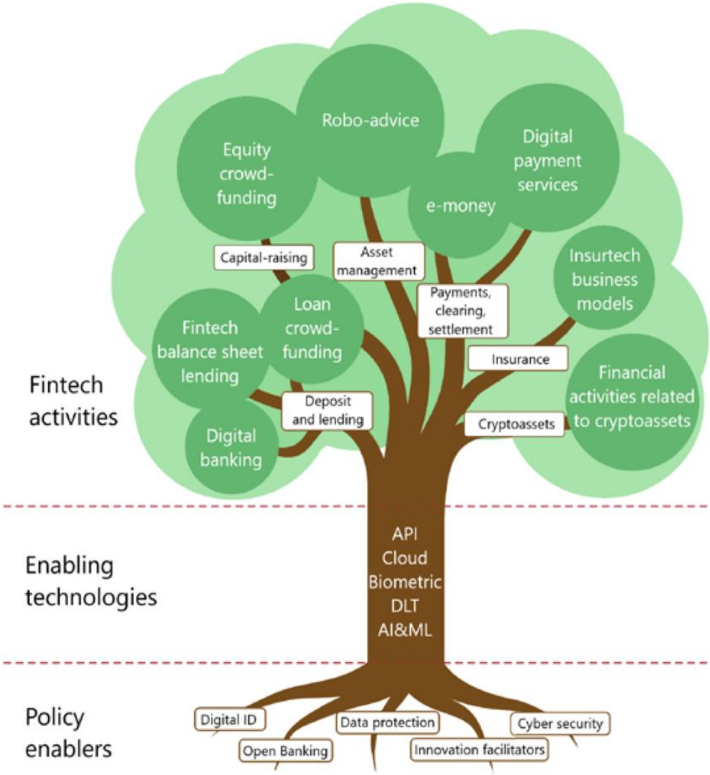

Figure 1.1: Fintech Tree: A Classification of the Fintech World

Source: (Bank for International Settlements, 2020)

According to the fintech tree, fintech activities fall into the following financial services groups; deposits and loans; capital-raising and other ways to accumulate money; asset management, trading, and related services; payments, clearing, and settlement services; insurance; and crypto assets. We agree that most crypto assets could be put into one of the other types of financial services, based on how they work economically, what rights they come with, and how they are used in business. But for the goals of this chapter, we chose to keep them separate because crypto-related services use a lot of different approaches, and their uses change quickly.

In the context of Islamic finance and fintech can also involve the inclusion of Shariah principles into technology solutions, which is where the term 'Islamic Fintech' comes from. This involves financial technologies that are compliant with Islamic law and includes technologies that permit the provision of sharia-compliant lending, Islamic crowdfunding, and other Shariah-compliant financial products and services (Wijayanti & Yandra, 2021).

1.3. How Fintech and Islamic Finance Have Changed Over Time in Türkiye

1.3.1. How Islamic Finance Has Changed Over Time

Islamic banking has its roots in the 7th century, when profit-sharing and partnership-based business practices were first put in place. But the modern era of Islamic finance started around the middle of the 20th century, when the first Islamic banks were founded with the goal of offering Islamic-based financial services. In the first phase, small, community-based institutions were set up to meet the needs of Muslims looking for financial services that were in line with Shariah.

The 1970s were a big turning point because they were when petrodollar wealth in Muslim-majority countries led to the creation of Islamic banks. In this time, the first other Islamic banks opened their doors. These banks offered a variety of financial products that were in line with Shariah law, such as Murabaha, Mudarabah, and Ijara. These goods offered moral alternatives to common financial tools, drawing people who follow religion as well as those who want to invest in a moral and socially responsible way.

In the 1990s, the opening up of economies and making financial markets more global made it easier for Islamic banking to grow across borders. During this time, Islamic financial principles became more integrated with global finance. This led to traditional banks opening Islamic subsidiaries and Islamic financial goods being sold in Western markets. A big part of this growth was the work of groups like the Accounting and Auditing Organisation for Islamic Financial Institutions (AAOIFI) and the Islamic Financial Services Board (IFSB) to make Islamic banking more in line with international rules.

At the start of the 21st century, Islamic banking became more popular, and the market for Sukuk grew a lot. Sovereign and corporate Sukuk issues became popular ways to raise money because they were a Shariah-compliant option to regular bonds. The Sukuk market grew with the help of Islamic equity funds, takaful and other financial tools. These added to the sector's appeal to a wider range of investors.

In the past few years, Islamic banking has embraced new technologies, and fintech solutions have sprung up to meet the needs of consumers who are concerned with Shariah. Digital platforms have changed the way Islamic banking services are provided, making them easier to get and more effective. Blockchain and smart contracts are two new technologies that could make Islamic financial deals even more open and legal.

The practice of Islamic finance in Türkiye has a long and illustrious history. Islamic banking in Türkiye may be traced back to the early 1980s, with the founding of Albaraka Turk in 1984, followed by Family Finans in 1988 (Demirguc-Kunt, Klapper, & Randall, 2013). Albaraka Turk was the first financial institution in Türkiye to practice Islamic principles. These banks intended to provide an alternative to traditional banking services while holding to the tenets of Shariah law. In comparison to conventional banking, Islamic banking is generally regarded as having a higher moral standing, which has contributed to its growing popularity over the years can be seen in Table 1.1.

Table 1.1: Timeline of Critical Points Islamic Banking in Türkiye

Year	**Occasion**
1984	Establishment of Albaraka Turk
2005	Changing Special Finance House to Participation Banks
2010	First Sukuk issuance from Kuveyt Turk
2010-2013	Growth in the number of Shariah-compliant products
2018	Türkiye's sovereign Sukuk issuance reached $6.6bn

Source: Created by Author

The Islamic finance market in Türkiye had steady expansion during the 1990s, albeit slow and steady. Regulations for "Participation Banks," which is the term used in Türkiye to describe Islamic banks were first adopted by the government at the beginning of the twenty-first century. This opened the door for a wider variety of services and products, such as Sukuk, which are also known as Islamic bonds and were first issued in the year 1999.

1.3.2. Fintech's Rise in Türkiye's Financial Sector

Following the year 2010, the Turkish banking sector went through a period of fast digital transformation. According to Yazici, (2019, p. 188-197), high rates of internet and smartphone penetration, a huge population of young people, and favourable policies all contributed to the rapid growth of the fintech industry. The use of technology-based financial services such as mobile banking, online trading platforms, digital wallets, and other services has completely changed the landscape of the financial industry.

Türkiye's fintech ecosystem was less influenced by the global recession in 2022. In the near future, there will be more mergers, which means that the ecosystem will be busier. This is because there are more financial startups operating around the world now than in the past, and these startups are likely to be more open to merging and becoming a part of a bigger picture as shown at Figure 1.2.

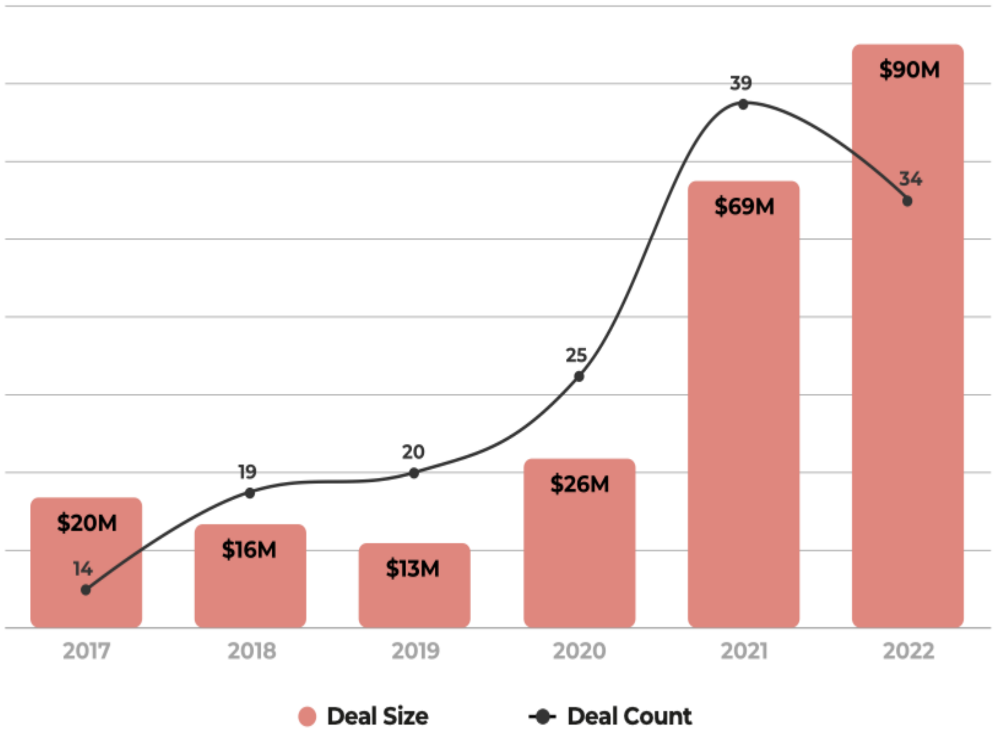

Figure 1.2: Fintech Deals in Türkiye

Source: (Presidency of the Republic of Türkiye, Digital Transformation Office, 2022)

Since its founding in 2013, Fintech Istanbul has been an instrumental player in the creation of a hub that serves as a meeting place for startups, investors, and financial institutions (Fintech Istanbul, 2016). According to Arslanian and Fischer (2019), the Turkish government made it possible for innovative financial products to be tested in a safe setting after establishing the regulatory sandbox in 2015. Those developments explained in Table1.2.

Table 1.2: Key Developments in Fintech in Türkiye

Year	**Event**
2013	Establishment of Fintech Istanbul
2015	Introduction of Regulatory Sandbox
2016	Launch of first Turkish digital wallet (BKM Express)
2017	The Banking Regulation and Supervision Agency (BRSA) started to regulate payment services
2019	The Central Bank of the Republic of Türkiye (CBRT) announces its intention to launch a digital currency
2023	First Digital Bank (Hayat Finans)

Source: Created by Author

There has been a huge amount of progress in the startup ecosystem across the whole country. For example, there were 65 accelerator courses in the country in 2020, up from only six in 2010. As of June 2021, the country also has 82 incubation centres and 38 co-working places. There are nine angel investment networks in the country as of November of last year. They are ARYA, EGIAD, Erban, Galata Business Angels, GAP BAN, Keiretsu Forum, Mavi Ocean, Şirket Ortağım, and TR Angels. As of September, of last year 674 angel investors were part of the government-backed angel accreditation scheme, which began in 2013 (Fintechtime, 2022) shown at Figure 1.3.

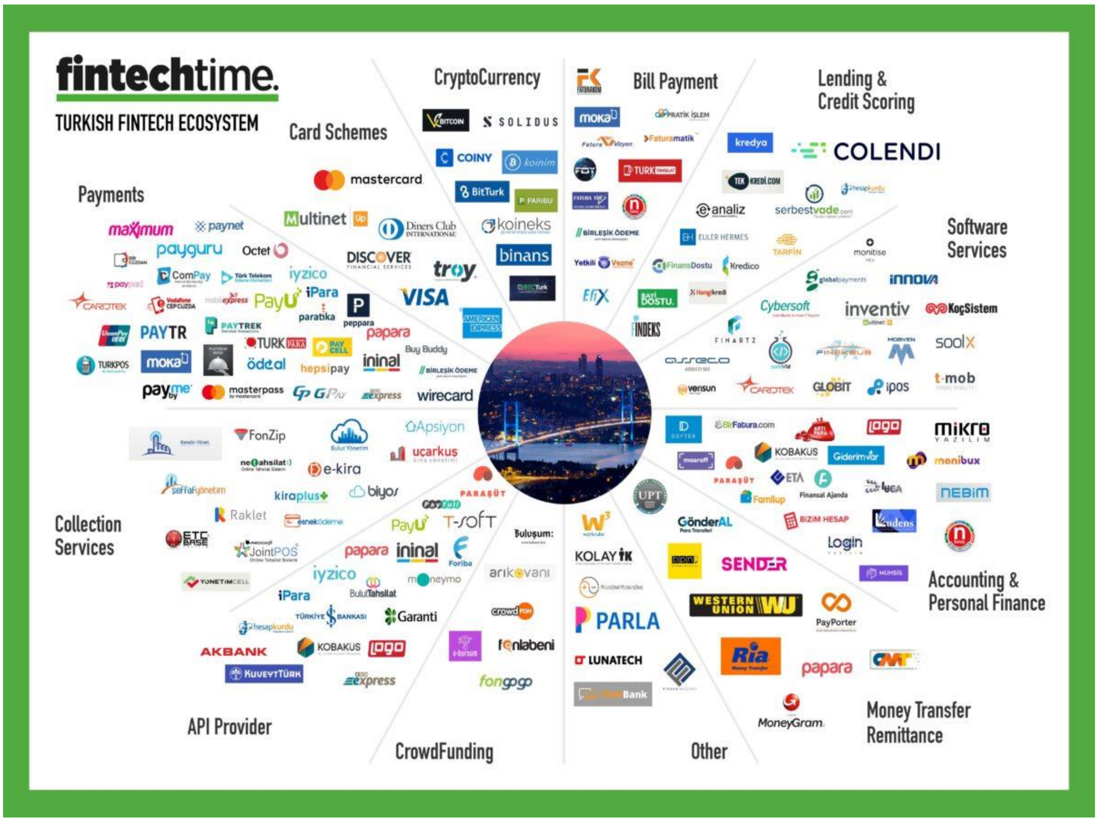

Figure 1.3: Türkiye Fintech Landscape

Source: (Fintechtime, 2022)

The fintech ecosystem in Turkey is made up of a wide variety of businesses in industries such as payments, card schemes, cryptocurrency, lending, and credit scoring. This entails providing equitable and transparent financial services, like asset-backed cryptocurrencies, Shariah-compliant payment gateways, and profit-sharing lending products.

1.3.3. Emergence of Islamic Fintech in Türkiye

Thomson Reuters says that by 2022, the Islamic banking sector will have $3.8trn in assets and 1,400 Islamic banks will be operating in over 80 countries. Muslims make up almost a quarter of the world's population, and that number is likely to rise in the years to come. However, the share of Islamic assets in total global financial assets is much lower than the share of the world's people that it serves (TheCityUK, 2022).

There are a number of reasons that may be credited for the expansion of Islamic financial technology in Türkiye. Firstly, the growing demand for financial products that are in accordance with Sharia law among Türkiye's largely Muslim population has produced an environment that is conducive to the development of Islamic financial technology. Second, the supportive policies of the Turkish government, which include regulatory reforms and incentives, have encouraged the development of an environment that is favourable to the expansion of Islamic fintech. The last point to consider is that the development of novel financial services that follow to the principles of Islamic finance has been made possible by the advent of technology. Those factors demonstrated in Table 1.3.

Table 1.3: Factors Influencing the Expansion of Islamic Fintech in Türkiye

Factors	**Description**
Cultural Alignment	A substantial segment of the populace demands financial services that are in accordance with Islamic values.
Government Support	Initiatives and regulations that encourage the development of Islamic fintech.
Technological Improvement	Utilising artificial intelligence, blockchain, and mobile technology to provide cutting-edge financial services that adhere to Sharia principles.

Source: Created by Author

The Turkish people's ever-changing requirements are being met by a combination of Islamic principles and contemporary financial technologies, which allows them to remain true to their religious beliefs while yet meeting their modern needs.

1.4. Principles of Islamic Finance

1.4.1. Core Islamic Finance Principles

The Shariah, which is the Islamic legal system, provides the foundation for the guiding principles that are used in Islamic banking. It ensures that all financial transactions are carried out in an ethical manner and in a way that is fair and equitable for all parties engaged in the transaction. The following are some fundamental ideas:

The practice of charging or receiving interest is forbidden in Islamic finance since it is regarded as an unjust method of enrichment (El-Gamal, 2006).

Profit and Loss Sharing: It places an emphasis on mutual risk-sharing through contracts such as Mudarabah and Musharakah, in which both profits and losses are shared among the parties concerned (Hassan & Lewis, 2007).

Contracts ought to be free from excessive doubt and ambiguity in terms of the subject matter and terms of the contract. This is referred to as the prohibition of gharar, which translates to "uncertainty" or "ambiguity."

Asset Backing: According to Chong and Liu (2009), speculative financial transactions can be avoided by ensuring that a financial transaction is backed by a tangible asset or service.

Islamic finance does not allow investments in firms that deal with alcohol, gambling, and other activities considered Haram (unlawful) in Islam. All over core Islamic principles tried to describe in Table 1.4.

Table 1.4: Core Islamic Finance Principles

Principle	**Explanation**
Prohibition of Riba	No charging or paying of interest
Profit and Loss Sharing	Mutual risk-sharing in contracts
Prohibition of Gharar	No excessive uncertainty or ambiguity in contracts
Asset Backing	Transactions must have underlying tangible assets
Prohibition of Haram Activities	No investment in unlawful businesses

Source: Created by Author

The table summarises the fundamental ideas of Islamic finance and points out five important points: the prohibition on riba (interest), which guarantees that no interest is charged or paid; profit and loss sharing, which entails sharing contractual risks between parties; the ban on gharar, which means that there should be no overpowering uncertainty or ambiguity in contracts; asset backing, which mandates that transactions have tangible assets as their foundation; and the ban on haram activities, which forbids investing in illegal ventures. (Türkan, 2019, p. 79). By guaranteeing that financial procedures comply with Shariah law, these guidelines encourage moral and just financial dealings.

1.4.2. The Importance of Shariah-compliant Products in the Fintech Industry

Banking online in accordance with Islamic standards many financial institutions now offer online banking services that are compliant with Islamic standards. According to Gheeraert (2014, p. 4-20), these products include interest-free savings accounts, personal finance and investment products backed by assets.

As a result of the ongoing development of fintech, there is a growing demand for financial goods and services that are in compliance with Shariah law. there is particularly fundamental in countries where the majority of the population is Muslim, like as Türkiye, because there is where there is a substantial market for Islamic financial services.

Islamic crowdfunding refers to a practice in which online platforms that offer crowdfunding services take measures to ensure that the money raised is put toward endeavours that are in accordance with Shariah law. According to Aysan, Disli, Ozturk, and Turhan (2016), these platforms do not levy interest fees or charges of any kind on the funding that is delivered.

Islamic Robo-Advisors: There are robo-advisory platforms that offer automated investment advice and ensure that the investments are made in Shariah-compliant financial instruments. Islamic robo-advisors are also known as virtual investment advisors (VIAs).

In terms of product delivery, fintech firms utilise technology that have the potential to improve Islamic finance by improving efficiency and decreasing expenses. The worldwide head of Islamic finance at ratings firm S&P worldwide Ratings, suggests that this might potentially reduce expenses related to payment services and transactions. Artificial intelligence technologies may also improve compliance. The widespread implementation of blockchain technology has the capacity to mitigate the risk of fraudulent transactions. Emirates Islamic Bank is now employing the technology to verify the authenticity of paper checks in the United Arab Emirates (The Economist Intelligence Unit, 2020).

1.4.3. The Importance of Ethics and Transparency in Fintech

In Islamic banking, ethics and being open are two very important ideas. This is also true for uses of fintech; it is important to make sure that new technologies don't lower ethical standards and that businesses are honest in their dealings and operations. Zetzsche, Buckley, Arner, and Barberis (2017, p. 393-431) say that following ethical standards in the financial technology industry means not only keeping your clients' data safe, but also being open about how your services work and making sure that your services don't take advantage of customers by using unfair or unseen pricing or other dishonest business practices. These moral standards are in line with the principles of Islamic finance, which is more proof that fintech and Islamic finance can work together.

The traditional core principles of finance ethics are based on seven basic principles found in the codes of conduct of 11 professional financial services associations. These are honesty, objectivity, competence, fairness, privacy, professionalism, and hard work as shown in Table 1.5.

Table 1.5: List of Financial Ethics Concepts and Definitions

Principle	**Definition**
Integrity	Self-government based on morals, independence, loyalty, and honesty. Thoughts and actions that are consistent, a clean mind, and responsible behaviour
Objectivity	It is important to protect and improve the client's interests. Making sure that trust and beliefs are correct. Not letting bias and conflicts of interest happen
Competence	Giving customers professional financial services. Keeping up to date on skills needed at work by continuing schooling and work experience
Fairness	Customers should be treated fairly, the "Golden Rule" should be followed, fair returns should be guaranteed for everyone, interests should be balanced, and unfair treatment should be avoided.
Confidentiality	Managing client relationships in a discreet way, keeping private data safe and not sharing it, and establishing and keeping trust by giving information
Professionalism	Professionals must treat their clients with politeness and respect, build trust with them, and keep that trust with both clients and the public.

Source: (Prastyanti, R. A., Rezi, & Rahayu, I, 2023, s. 255-260)

In conclusion, it is very important for the fintech business to incorporate Islamic financial ideas. This is especially true in countries where most of the people are Muslim. Together, these two areas make sure that financial services are not only up to date with technology, but also morally sound and in line with most people's views and values. Islamic finance is based on the basic principles of ethics, justice, and openness. As fintech grows, it is very important that it stays true to these values.

1.5. Where Türkiye Stands in the World of Islamic Fintech?

1.5.1. Trends and Changes in Islamic Fintech Around the World

The panorama of Islamic financial technology around the world has been quickly emerging. Islamic financial technology is gradually gaining a footing in an increasingly competitive market. Examples of Islamic financial technology includes peer-to-peer lending platforms, crowdfunding, digital wallets, and robo-advisory. Countries such as Malaysia, the United Arab Emirates, Indonesia, and Bahrain are at the forefront of this business.

Table 1.6: Islamic Fintech Hubs Around the World

Country	**Developments**
Malaysia	Established itself as a global Islamic fintech Hub with regulatory support and a strong base of Islamic financial institutions.
UAE	Focused on Dubai as a hub for Islamic fintech startups and innovations.
Indonesia	Rapid growth in the adoption of Islamic financial products supported by technology.
Bahrain	Encouraging fintech startups through regulatory sandbox environments and supporting Islamic finance innovation.

Source: Created by Author

Table 1.6 demonstrates major developments in Islamic fintech hubs globally, concentrating on four nations: Indonesia, which is seeing a rapid increase in the adoption of technologically enabled Islamic financial products; Malaysia, which has established itself as a global Islamic fintech hub with regulatory support and a strong base of Islamic financial institutions; the UAE, especially Dubai, which acts as a hub for Islamic fintech startups and innovations; and Bahrain, which supports Islamic finance innovation and encourages fintech startups through regulatory sandbox environments. These nations provide as excellent examples of notable developments in the growth and promotion of the Islamic fintech industry.

There is change from one year to the next in the Top 20, with Bangladesh, Türkiye, and Brunei making the biggest jumps. In 2022, Türkiye, Nigeria, and Brunei all make it into the top 20 shown as Figure 1.4.

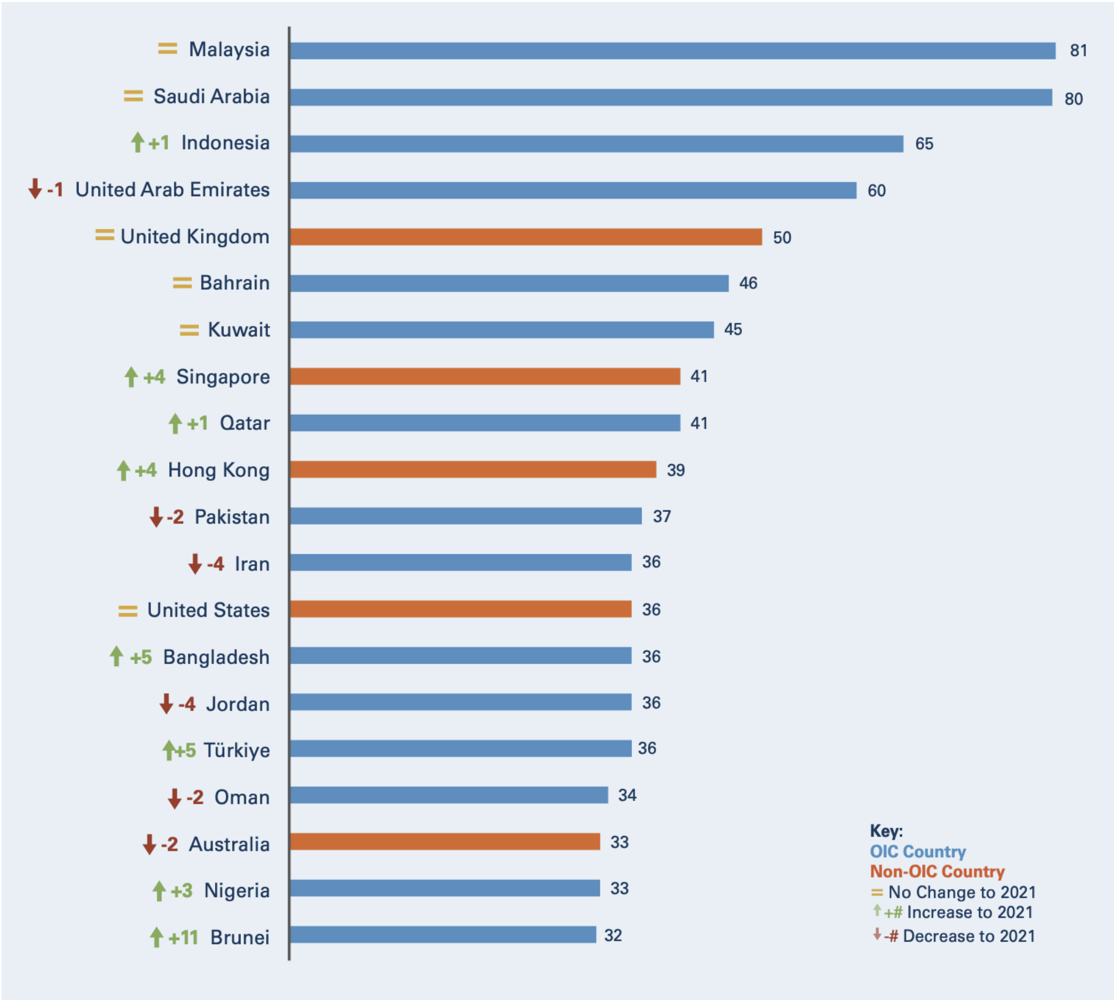

Figure 1.4: Top 20 Countries by Global Islamic Fintech Index Scores

Source: (Qatar Financial Centre, 2022)

The Organisation of Islamic Cooperation (OIC) and non-OIC nations are shown in the Figure 1.4 along with a ranking of the nation's according to their standing in the Islamic fintech ecosystem. The salient features comprise:

- With a score of 81, Malaysia tops the list, closely followed by Saudi Arabia (80).
- With a score of 61, Indonesia has moved up one spot to third place.

- With a score of 60, the United Arab Emirates (UAE) sits in fourth place, down one spot from the previous year.
- Notable non-OIC nations include Bahrain and the United Kingdom, with scores of 46 and 50, respectively.
- Among the other prominent OIC nations in the top rankings are Hong Kong (38), Singapore (41), Kuwait (45), and Qatar (41).
- Bangladesh (36) and Jordan (36) are two nations that have significantly improved, rising five and four spots, respectively.
- With a score of 34, Türkiye comes in at number sixteen, indicating a significant presence in the Islamic fintech market.
- The graph also shows how nations like Nigeria (33) and Australia (34) are significantly improving the ecosystem.

Using the earlier definition as a starting point, the following framework shows the general fintech landscape, which is made up of nine key technologies that provide important financial services to end users and help with back-office operations can see at Figure 1.5.

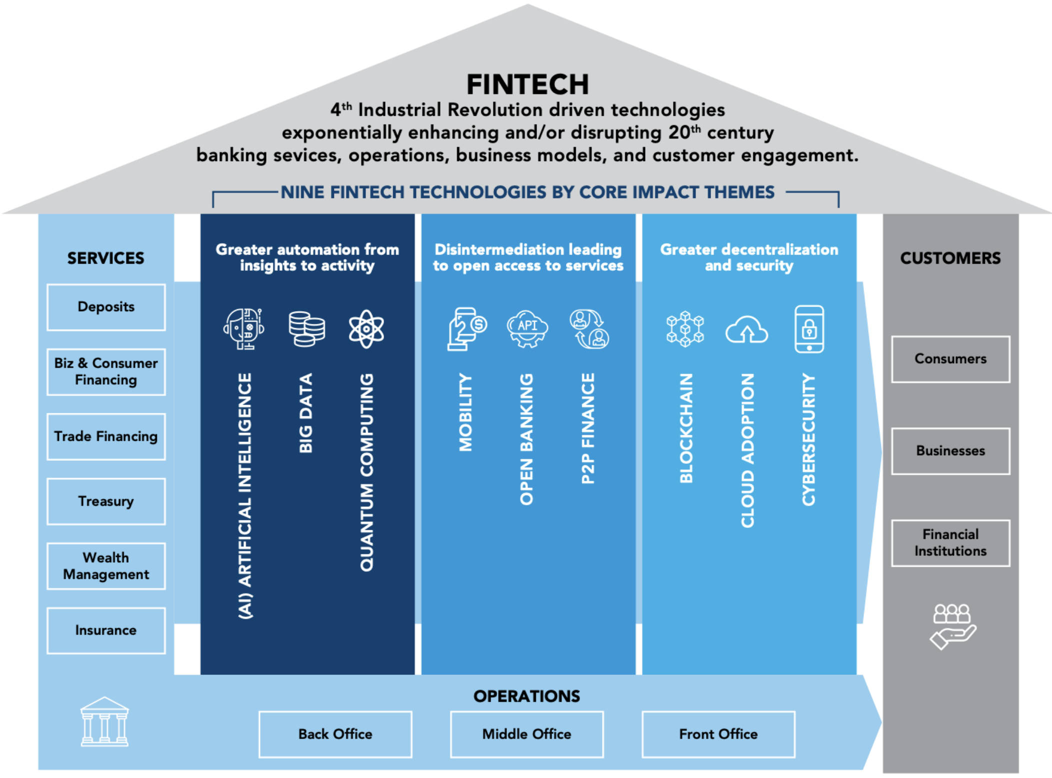

Figure 1.5: Global Fintech Framework

Source: (Qatar Financial Centre, 2018)

The figure shows how traditional banking services and operations are changing due to fintech innovations, which are being driven by the Fourth Industrial Revolution. It divides these technologies into three main areas of impact: decentralization/security (blockchain, cloud adoption, cybersecurity), open access (mobility, open banking, P2P finance), and automation (AI, big data, quantum computing). By changing client engagement, business models, and operational procedures in the financial sector, these innovations improve efficiency, democratise financial services, and boost security, which benefits businesses, financial institutions, and consumers alike.

1.5.2. Evaluating Türkiye's Advantages and Disadvantages in the Worldwide Islamic Fintech Industry

Support from legislation: Türkiye has been making progress in developing legislation that will foster an atmosphere that is favourable to Islamic finance. The Participation Banks Law, the establishment of the Istanbul Finance Centre, regulatory sandbox projects, directives from the Turkish Presidency of Religious Affairs, and lobbying by the Participation Banks Association of Türkiye are examples of the country's laws that favour Islamic fintech.

Growing Market Potential: According to Gheeraert (2014, p. 4-20), a population that is mostly Muslim and has a demand for items that are compliant with Sharia law presents a substantial opportunity for market growth. Competence in technology a young population combined with high smartphone penetration rates gives an opportunity for technology advancements in Islamic finance.

Restricted product diversity: When compared to global players, Türkiye has a comparatively restricted variety of Islamic financial technology products (Ayub, 2009).

The market is fragmented due to the presence of many small companies, which has the potential to restrict both scale and expansion (Aysan et al., 2016, p. 388–398).

Türkiye's strategic geographical location at the intersection of Asia and Europe has positioned it as a noteworthy player in the financial industry, allowing it to play an essential role in financial and digital advancements. At the onset of the 2000s, the proportion of the Turkish population utilising credit cards stood at 9%. However, this figure experienced a significant increase to 40% due to the advancement of fintech and the implementation of digital payment systems (Cengiz & Özkan, 2023, p. 1-14).

1.5.3. Comparative Breakdown of Türkiye and Other Islamic Fintech Markets

Malaysia's regulatory environment is more advanced than that of its counterparts and provides an ecosystem that is favourable for Islamic fintech businesses. In the meanwhile, the United Arab Emirates is concentrating on high-profile investments and international collaborations. Indonesia makes the most of its enormous population as well as its rapidly expanding middle class. While, Türkiye has a considerable market potential, in order to effectively compete with these countries, it needs to increase the variety of its products and develop the regulatory frameworks that govern them. Comparative market breakdown of analysis given at Table 1.7.

Table 1.7: Comparative Market Breakdown

Aspect	**Türkiye**	**Malaysia**	**UAE**	**Indonesia**
Regulatory Support	Moderate	Strong	Strong	Moderate
Market Size	Medium	Medium	Small	Large
Product Diversity	Limited	Diverse	Diverse	Growing Diversity
Technological Base	Strong	Strong	Strong	Moderate

Source: Created by Author

Although, Türkiye occupies a prominent place in the global Islamic fintech landscape, there is potential for improvement in the country's efforts. Türkiye has the ability to reach its full potential in the Islamic fintech area if it draws inspiration from the successes of other leading countries and places an emphasis on improving regulatory support and product diversification.

In 2022, Türkiye got a $1.6bn start-up investment and was put in the Super League, which is for countries that have gotten investments of $1bn to 10bn. The figures show that Türkiye is ranked 10th in Europe and 3rd in the MENA as shown in Figure 1.6 (Startups.watch, 2023).

Europe ($B)

UNITED KINGDOM	24.3	(1790)
FRANCE	11.7	(591)
GERMANY	11	(910)
SWEDEN	3.5	(205)
SWITZERLAND	3.4	(325)
SPAIN	3.4	(356)
NETHERLANDS	2.3	(330)
IRELAND	2.2	(132)
ITALY	1.7	(155)
TÜRKİYE	**1.6**	**(300)**
ESTONIA	1.5	(100)
FINLAND	1.3	(124)
BELGIUM	1.2	(96)
NORWAY	1.2	(84)
AUSTRIA	1.1	(94)
DENMARK	1.1	(102)

Figure 1.6: Global Position of Türkiye in Europe

Source: (Startups.watch, 2023)

The above figure illustrates Türkiye's 12nd-place standing among European nations in terms of fintech investments $1.6 billion with 300 startups. This indicates Türkiye's increasing significance in the startup scene, especially in the field of Islamic finance. Türkiye is an emerging participant with growing investment, indicating its ability to leverage its strategic location and strong economic infrastructure to become a major hub for Islamic financial technology. This development demonstrates the nation's dedication to promoting innovation and growing its clout in the international Islamic fintech scene.

1.6. Potential Outlook for Islamic Fintech in Türkiye

1.6.1. Possible Roads for Development and Enlargement

The Türkiye fintech scene has been slowly growing and getting attention from around the world. For the first time ever, startup watch says that 165 startups raised a total of 139M USD from angels and VCs in 2020. There are 12 traditional Insurtech startups around the world that have raised US$ 2.1 million between 2016 and 2018. These startups act as risk management, data and risk analysis, and brokers. Even though the Takaful sector has had a lot of promise and prospects in recent years, it hasn't seen nearly as much fintech activity as its Insurtech counterparts in Türkiye. But this shows that there is a chance to get into the Takaful market, which is a new area of Islamic fintech. The third Global Islamic Fintech Summit will be held in Istanbul in March 2022 to show what financial innovation can do (Katılım Finans, 2022).

Türkiye offers various potential areas where growth and expansion can be achieved, and these areas are continuing to evolve as the global Islamic fintech landscape does so as well.

Banking on the Internet: Türkiye is able to meet the needs of its younger and more technologically savvy population by concentrating on growing the breadth of digital banking services that are compliant with Shariah law.

Crowdfunding and Peer-to-Peer financing: According to Ahmed (2016), Türkiye has the potential to broaden its Islamic fintech ecosystem by creating and supporting platforms for crowdfunding and peer-to-peer financing that adhere to Shariah standards.

InsurTech: The implementation of InsurTech has the potential to change Takaful, also known as Islamic Insurance, making it possible to provide insurance services that are more effective, transparent, and approachable.

One important way for Islamic fintech to grow in Türkiye is for the government to make it easier for new ideas to be implemented while still following Sharia law. According to Ahmad (2023, p. 91-114), the Turkish government and financial regulatory officials could learn from Malaysia and the United Arab Emirates, which have set up complete legal and regulatory environments that help Islamic fintech grow.

Given that agriculture is Türkiye's primary industry, investing in agricultural technology platforms that centre on the production of halal food and agriculture in accordance with Shariah principles could be a lucrative niche market for Türkiye can be seen in Table 1.8.

Table 1.8: Potential Areas for Growth

Area	**Description**
Digital Banking	Expanding Shariah-compliant digital banking services
Crowdfunding & P2P	Supporting Islamic crowdfunding and peer-to-peer lending platforms
InsurTech	Integrating technology with Takaful for better insurance services
Agritech	Focusing on Halal food production and Shariah-based agricultural tech

Source: Created by Author

Four important areas for Islamic fintech growth are outlined in the table: Agritech, by emphasising Halal food production and Shariah-based agricultural technology; Crowdfunding & P2P, by supporting Islamic crowdfunding and peer-to-peer lending platforms; InsurTech, by integrating technology with Takaful for better insurance services; and Digital Banking, by expanding Shariah-compliant digital banking services. These domains provide noteworthy prospects for novelty and growth in the Islamic banking industry.

1.6.2. Approaches to Promoting Innovation and Enhancing Competitiveness in the Turkish Islamic Fintech Industry

In February 2023, a total of 34 financial technology companies received a combined investment of $89 million. The year 2022 marked the highest level of investment in this sector. Despite the decline in global risk appetite due to the Covid-19 pandemic, fintech investments in Türkiye have continued to show an upward trend as shown on Figure 1.7.

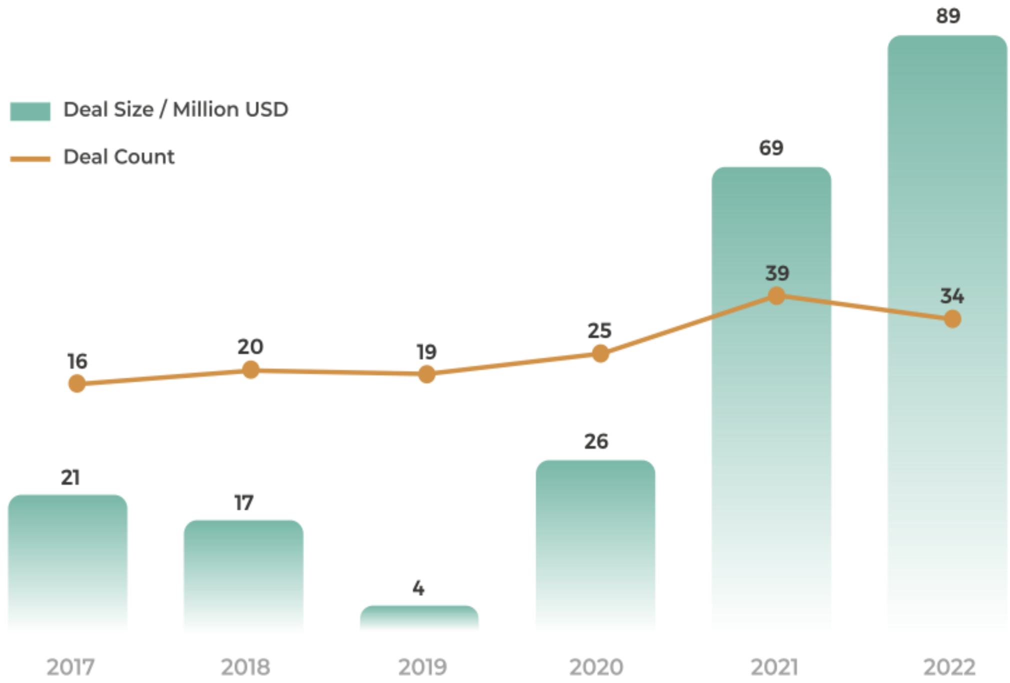

Figure 1.7: Fintech Investments by Years in Türkiye

Source: (CBFO & Startups.watch, 2022)

Regulatory Sandbox refers to a controlled environment where innovative ideas and technologies can be tested and developed under the supervision of regulatory authorities. Buckley et al. (2020) found that establishing a regulatory sandbox specifically for Islamic fintech companies can promote innovation by allowing these firms to experiment with their products under supervision.

Wilson (2017, p. 255-271) suggests that offering education and training in Islamic finance and technology can lead to the development of a skilled workforce, hence adopting innovation in terms of academic and instructional preparation.

Establishing connections with well-known Islamic fintech centres on a global scale can facilitate the exchange of knowhow and cooperation. These collaborations can be established on a worldwide level. Promoting and facilitating investments in research and development can lead to revolutionary advancements in Islamic fintech. These strategies for development innovation and competitiveness shown in Table 1.9.

Table 1.9: Strategies for Development Innovation and Competitiveness

Strategy	**Description**
Regulatory Sandbox	Create a controlled environment for testing new fintech services
Education - Training	Develop a skilled workforce in Islamic finance and technology
International Partnerships	Collaborate with global Islamic fintech hubs for knowledge Exchange
R&D Investment	Encourage investments in research and development

Source: Created by Author

The above table lists tactics for promoting growth, creativity, and competitiveness in Islamic fintech: Regulatory Sandbox, which is establishing a supervised setting for the examination of novel fintech offerings; The objectives of education and training are to create a workforce with the necessary skills in Islamic finance and technology. International partnerships are to engage with international Islamic fintech hubs to exchange information, and R&D investment is to encourage research and development expenditures.

In conclusion, there is reason for optimism regarding the future of Islamic financial technology in Türkiye. Türkiye has the ability to position itself as a prominent participant in the global Islamic fintech landscape if it places a primary emphasis on areas that have substantial potential for growth and implements initiatives to stimulate innovation and competitiveness in the country.

CHAPTER TWO

EMERGENCE OF ISLAMIC FINTECH AND ITS APPLICATIONS

2.1. Introduction

The term "Islamic fintech," which refers to Islamic financial technology, has become more and more popular in the global financial ecosystem. The rising popularity of this industry is due to a desire to align financial services with Shariah principles, which are Islamic regulations drawn from the Holy Qur'an and the Sunnah (Prophet Muhammad's (s.a.w) example). The advent of Islamic fintech, its uses, and the regulatory systems that oversee it are all critically examined in this study.

Since the development of the internet and the spread of digital advances in the financial sector, the term "Fintech," a portmanteau of "financial technology," has been popular (Arner et al., 2015, p. 393-431). Islamic fintech is a highly specialized area that has recently gained popularity. Islamic fintech, as opposed to conventional fintech, is founded on Islamic financial principles, which forbid usury, speculation, and investing in things that are considered sinful (Iqbal & Mirakhor, 2011).

The concept of the Islamic moral economy is directly tied to the development of Islamic fintech. Accepting that Shariah law includes a comprehensive moral and ethical framework that regulates economic activity is fundamental (Asutay, 2007, p. 167-195). We explain how Islamic fintech fits with the Islamic moral economy approach, illuminating its fundamental principles and ethical ramifications.

The variety of emerging front-line applications and use cases is one of Islamic fintech's most fascinating features. We look at important applications such as Islamic finance-compliant payment methods and digital banking (Qudah et al., 2023, p. 76). Businesses and entrepreneurs can now access funds in a Shariah-compliant manner thanks to the adaptation of crowdfunding and P2P lending platforms for Islamic financing (Dawood et al, 2022, p. 329). Another industry where technology is essential is wealth management, particularly with robo-advisory services that guarantee investments adhere to Islamic standards (Saad et al, 2020). Technology and Takaful (Islamic insurance) have been combined to create Insurtech, which streamlines the distribution of insurance products that adhere to Shariah (Rammal & Zurbruegg, 2010,

p. 209-221). Finally, the emergence of cryptocurrencies and blockchain technology has had substantial effects on Islamic finance, leading to the creation of Islamic cryptocurrencies (Gomber et al., 2018, p. 220-265).

The use of computing methods is a fascinating component of Islamic fintech that is also covered in this study. Islamic finance has undergone a revolution thanks to the incorporation of Artificial Intelligence (AI) for risk assessment that complies with Shariah, machine learning for investment strategies, and deep learning for fraud detection. In addition, big data analytics, cloud-based Islamic banking, high-frequency trading, and algorithmic trading methods have become essential elements for Shariah-compliant financial services (Gheeraert, 2014, p. 4-20).

Regulatory Technology, or RegTech, is another notable component of Islamic fintech. RegTech in the world of Islamic finance refers to the utilisation of trailblazing technology to ensure that financial operations are both efficient and in accordance with the evolving Shariah rules. As fintech solutions continue to improve, it is more essential than ever to monitor them and ensure they adhere to the norms of Islamic finance. RegTech tools that employ AI and blockchain enable real-time regulatory reporting and compliance reviews. They also facilitate the automation of complex Shariah audit processes. As the standards for Islamic financial operations become more complex, RegTech can play an even larger role in ensuring that innovation and compliance do not conflict (Syamlan & Antonio, 2023, p. 67-97).

As a result of fusing technology with Islam's deep moral and ethical precepts, Islamic fintech is a disruptive force in the financial sector. This industry can increase financial inclusion, promote economic growth, and offer a variety of effective and transparent financial solutions compliant with Shariah. Islamic fintech can overcome obstacles and keep thriving as a powerful force in the global financial scene with constant innovation and cooperation among stakeholders.

2.2. Definition and Framework of Islamic Fintech

Islamic fintech is a new area that has attracted a lot of interest lately. Islamic fintech is fundamentally the fusion of Islamic financial concepts with financial technology. Shariah law, which derives from the Qur'an and the Sunnah and attempts to ensure fairness, openness, and moral financial transactions, is the cornerstone of Islamic finance (Ahmed, 2011).

It is important to outline the ideas that set Islamic finance apart from traditional finance in order to comprehend Islamic fintech. The prohibition of Riba (interest), Gharar (uncertainty), and Maysir (gambling) are among the fundamental precepts. Islamic finance also prioritizes risk-sharing, asset-backing, and the ban on investment in sectors that are deemed Haram, such as those that involve alcohol, gambling, and pork (Hassan & Lewis, 2007).

Islamic fintech aims to offer financial services that are innovative, effective, and compliant with Shariah principles through the use of contemporary technologies. An overview of the main elements and guiding principles of Islamic fintech is given in Table 2.1.

Table 2.1: Components and Principles of Islamic Fintech

Components	**Principles**	**Description**
Shariah Compliance	Riba (Interest)	Prohibition of fixed or floating payments or interests
	Gharar (Uncertainty)	Prohibition of excessive uncertainty and ambiguity
	Maysir (Gambling)	Prohibition of gambling and speculation
Risk Sharing	Profit and Loss Sharing	Both parties must share profits and losses in transactions
Asset Backing	Tangible Assets	Financial transactions must have an underlying asset
Ethical Investments	Haram Screening	Avoidance of investments in alcohol, gambling, etc.

Source: (Hassan & Lewis, 2007; Ahmed, 2011)

Islamic fintech covers a wide range of services and applications in terms of its framework. These assistances are made to cater to the demands of Muslims and anyone else looking for an ethical substitute for traditional financial services. Shariah-compliant digital banking, peer-to-peer lending, crowdfunding, payments and money transfer services, and wealth management are a few of the services offered (Hasan et al., 2020, p. 752-771).

The potential effect of Islamic fintech on global financial inclusion is likewise considerable. According to the World Bank, there are more than 1.7 billion unbanked adults worldwide, with a sizable fraction living in countries with a majority of Muslims (Demirgüç-Kunt et al., 2018, p. 177-218). These people may be able to receive financial services that are in line with their religious convictions thanks to Islamic fintech.

Islamic fintech is also a component of the larger Islamic economy, which also includes modest clothing, halal food, Islamic tourism, and Islamic media and entertainment. These industries frequently need certain financial services and goods that adhere to Islamic values. As a result, Islamic fintech can expressively contribute to the development of these industries (Wilson, 2014, p. 255-271).

Nevertheless, there are obstacles to the growth of Islamic fintech, such as the requirement for regulatory frameworks that uphold both technology innovation and Shariah standards. Additionally, it is key to inform consumers and investors about Islamic fintech and make sure that technology is used in a way that strictly supports Islamic financial principles.

In conclusion, Islamic fintech is a fast-developing industry that has the potential to advance economic growth, financial inclusion, and moral financial conduct in conformity with Shariah law. It is an inventive marriage of modern technology with conventional Islamic financial concepts that have the power to change the way in which finance is conducted.

2.3. The Emergence of Islamic Fintech: Aligning with The Islamic Moral Economy Perspective

The intricacies of the Islamic fintech framework, it becomes evident that it is not an isolated entity, but rather intertwined with the ethical framework rooted in Islamic values. The fundamental objective of Islamic fintech is to offer financial solutions that align with the ethical principles of Islam, hence being fundamentally linked to the moral economy of the Islamic faith.

The intersection of technology and Islamic moral economy presents an opportunity for Islamic fintech to emerge as a substantial domain. This field enables the provision of financial transactions and services that adhere to Sharia law while also aligning with the raised moral principles advocated by Islamic teachings. The aforementioned concept can be interpreted as a manifestation of Islamic moral economy facilitated by technology, with the aim of ensuring that contemporary financial solutions adhere to the moral and ethical principles mandated by Islamic philosophy.

The notion of the Islamic moral economy, which includes the ethical, social, and economic pillars supporting Islamic financial principles, and the development of Islamic fintech are closely related (Asutay, 2012, p. 93-113). With an emphasis on justice, equity, and welfare in economic operations, the Islamic moral economy framework offers an alternative to traditional economic theories (Chapra, 2000).

The Islamic moral economy's ban of Riba (interest), Gharar (uncertainty), and Maysir (gambling) serves as one of its guiding principles. According to El-Gamal (2006), these factors are thought to contribute to unfairness and inequality in economic interactions. By adhering to these criteria, Islamic fintech can seek to harmonize financial innovation with the morals and ideals of the Islamic moral economy.

The emphasis on financial inclusion is another indication of how Islamic fintech is in line with the Islamic moral economy. Particularly in emerging nations, a sizable percentage of the population is frequently excluded from traditional financial services. According to the World Bank (2022), approximately 29% of people worldwide do not have access to banking services. By providing digital financial services that adhere to Shariah, Islamic fintech can increase financial inclusion for people who were previously excluded from the banking system for ethical reasons. Therefore, we examined comparison of Islamic moral economy and Conventional economy in Table 2.2.

Table 2.2: Comparison of Islamic Moral Economy and Conventional Economy

Aspect	**Islamic Moral Economy**	**Conventional Economy**
Basis of Transactions	Asset-backed, Profit and Loss Sharing	Interest-based
Ethical Considerations	High (Shariah Compliance)	Generally Low
Risk Sharing	Emphasized	Not emphasized
Financial Inclusion	Strong Focus	Weak Focus
Social Welfare	Integral	Often secondary

Source: (Chapra, 2000; El-Gamal, 2006)

Additionally, Islamic fintech projects like P2P financing platforms and crowdfunding can be using at the forefront of advancing social welfare and entrepreneurship development. The emphasis on social welfare and economic justice in the Islamic moral economy is congruent with these platforms' provision of alternative funding sources for small- and medium-sized enterprises (SMEs) and social projects.

Islamic fintech wealth management is uniquely different from other conventional wealth management tools since it adheres to Shariah rules. Islamic ethical factors, which include the impact on society and the environment, are taken into account when evaluating investments in addition to their financial returns.

Islamic fintech must continually analyse and reevaluate its methods to ensure that technological advancements do not deviate from the core values and tenets of the Islamic moral economy. Industry stakeholders, including regulators, academics, and practitioners, must collaborate to ensure that Islamic fintech adheres to its ethical foundations while utilizing the benefits of financial technology (Raza Rabbani et al., 2021).

Islamic fintech cultivates a financial ecosystem that can prioritizes moral economy, hence can boosting inclusion and enhancing financial stability. The concept envisions a societal framework in which financial institutions can serve not only as instruments for economic advancement, but also as channels for promoting ethical values and communal welfare.

As we investigate deeper into the realm of Islamic fintech, it becomes clear to uphold a strong ethical framework and recognize that the rise of Islamic fintech serves as a promising indication of the potential to harmonize contemporary technologies with ethical economic principles. This convergence has the potential to cultivate a society that not only achieves economic prosperity but also upholds moral integrity.

In conclusion, by merging moral, social, and economic factors into financial innovation, Islamic fintech represents an alignment with the Islamic moral economy. This alignment has the potential to improve social welfare, economic justice, and financial inclusion.

2.4. Key Applications of Islamic Fintech: Innovations and Use Cases

Islamic fintech is quickly developing as it combines modern technology with Islamic financial principles as we can see in the Global Islamic Fintech Report 2022 (GIFT, 2022). This union has the opportunity to produce a wide range of apps that cater to numerous industries while upholding Shariah standards.

This section explores the exciting and diverse ways in which Islamic fintech has been orchestrating a new era of financial solutions that are not just innovative but also ethically grounded. Herein, we examine the pivotal realms of digital banking and payment solutions, crowdfunding and P2P lending platforms, Takaful Insurtech, wealth management and robo-advisory services, and the integration of blockchain technology and cryptocurrencies into the Islamic financial sector. Through this exploration, we seek to uncover the unique functionalities and use cases that stand as a testament to the rich potential of Islamic fintech in promoting a financial ecosystem that is robust, modern, and morally grounded.

2.4.1. Digital Banking and Payment Solutions

The Digital banking and payment solutions in Islamic fintech enable safe, fast and convenient transactions while preserving the fundamental principles of Islamic finance, which emphasize transparency.

Contemporary Islamic financial institutions provide mobile banking services. These mobile platforms include services like as transferring funds, making bill payments, and accessing account statements, all in accordance with Sharia-compliant financial products and services.

The Islamic fintech sector is also currently experiencing adoption of contactless payment methods. These payment methods prioritise ethical transactions and utilise technology to offer improved convenience and safety. We also can see that QR code payments involve the scanning of a QR code Islamic fintech companies have successfully included QR code payment solutions into their platforms. This integration has enabled the provision of efficient and secure payment choices, resulting in reduced transaction durations and enriched convenience in sharing payment details.

Digital payment systems, which enable customers to execute transactions via mobile devices, are another important component. "Zilzar Life," which facilitates Halal transactions and has attracted users from all around the world, is one such application (Zilzar Life, 2021).

Digital wallets guarantee conformity to ethical principles and compliance with Islamic law during the execution of transactions and provision of services. These wallets provide a transaction experience while connect to Halal principles by refraining from engaging in businesses such as gambling, alcohol, or arms.

The digitalization of banking services is a component of digital banking. In terms of Islamic finance, this entails the development of websites that provide services like financing, investing, and savings in accordance with Shariah. One such is Maybank Islamic in Malaysia, which provides numerous online services that adhere to Shariah (Maybank, 2021).

These digital alternatives to traditional banking offer accessibility, effectiveness, and convenience while also having ability to address the Shariah concerns of a sizable Muslim population.

2.4.2. Crowdfunding and P2P Lending Platforms

In the dynamic and ever-changing field of Islamic fintech, crowdfunding and peer-to-peer (P2P) lending platforms emerge as effective mechanisms for investments and financial transactions. These platforms promote inclusiveness, transparency and socioeconomic empowerment by combining Islamic principles with contemporary financial technology. We can categorize crowdfunding in three types as Table 2.3.

Table 2.3: Types of Crowdfunding

Type	Features
Donation-Based	Platforms where people can give money to campaigns without expecting any money back. This is in line with the Islamic concept of charity.
Reward-Based	Backers get a good or service in exchange for their money, making the deal halal and moral.
Equity-Based	Investors get shares in an enterprise or venture, which encourages equity participation that is in line with the law of the Sharia.

Source: Created by Author

EthisCrowd, a platform for financing Islamic real estate, serves as an illustration. It enables people to pool their money and participate in profitable social housing projects that also benefit society (EthisCrowd, 2021).

Peer-to-peer lending and Islamic crowdfunding are financial intermediation approaches that match lenders and borrowers in a way that complies with Shariah. They are designed to adhere to Islamic finance's fundamental concepts of profit and loss sharing and asset-backed financing (Muryanto et al., 2021, p. 239–252). P2P lending can be put into three groups, as shown in Table 2.4.

Table 2.4: Types of P2P Lending and Their Principles

Type	Principles
Qard Hassan	Loans with no interest that emphasise kindness and where the lender only wants the capital amount back.
Mudarabah	Profit-sharing agreements in which the gains are split in a way that has already been decided.
Musharakah	There are joint venture deals in which the profits and losses are shared.

Source: Created by Author

Blossom Finance (2023) is an Islamic peer-to-peer (P2P) microfinance platform that aims to facilitate Sharia-compliant microfinancing options. The site is designed to promote ethical financing practices and contribute to economic growth.

Platforms for Islamic crowdfunding and peer-to-peer financing can have opened up a new frontier in the Islamic financial ecosystem. These platforms point to an encouraging future for Islamic financial technology, as they create potential for halal and inclusive investments that are founded on the Islamic principles of economic justice and welfare.

Islamic fintech envisions a future in which finance is not just a tool for promoting economic progress, but also a way of development social harmony, transparency, and economic justice. This future can be envisioned by cultivating a financial landscape that places an emphasis on ethical investments and collaborative financial engagements.

2.4.3. Takatech

The Islamic equivalent of traditional insurance, takaful is founded on the concepts of risk sharing and collaboration. Applications like automated underwriting, claim management systems, and customer support chatbots are examples of Insurtech in Takaful.

The Islamic financial ecosystem has experienced the emergence and expansion of Takaful, a Sharia-compliant alternative to conventional insurance. Takaful operates based on the concepts of mutual help and risk-sharing. In recent times, there has been a notable potential in the adoption of technology in the Takaful industry, commonly referred to as Insurtech. This integration can result in the advancement and improved effectiveness of Takaful services. This section examines the phenomenon of Takaful Insurtech, its global competitive landscape, and its significance in catering to the financially underserved community.

Takaful is based on Islamic concepts that advocate for the practise of cooperative risk-sharing and the prohibition of uncertainty (gharar) and gambling (maysir). Participants make financial contributions to a collective fund that is utilised to compensate for any losses experienced by any member of the group. We can state takaful’s model in four models as Table 2.5.

Table 2.5: Takaful Models

Models	**Description**
Mudarabah (Profit-Sharing Model)	The participants and owners have reached a consensus to jointly distribute both financial gains and losses.
Wakalah (Agency Model)	In a pure agency contract, the operator receives compensation in the form of a fee.
Wakalah - Waqf Model	Taking the wakalah plan for funding and adding an endowment fund (waqf) to hold takaful donations. Extra money isn't given back to the players; it's kept for future use or to help good causes.
Hybrid (Wakalah & Mudarabah)	Contains parts of both the Wakalah and Mudarabah types. For underwriting and running costs, a wakalah fee is charged, and investments are handled on a mudarabah basis.

Source: Created by Author

The incorporation of technology into the Takaful industry has facilitated the development of inventive solutions, including the use of digital platforms for policy management, the implementation of blockchain technology for claim processing, and the adoption of artificial intelligence-driven risk assessment tools. These advancements have contributed to superior operational efficiency and improved user comfort.

Noor Takaful in the UAE is one such; it has adopted Insurtech to provide customers with a streamlined online experience for Takaful products, including automating the claims process (Noor Takaful, 2021).

Takaful faces strong competition from well-established insurance companies in a global context. We can examine the comparison of Takaful and global insurance in Table 2.6.

Table 2.6: Takaful vs Conventional Insurance

Aspects	**Takaful**	**Conventional Insurance**
Foundation	Cooperative risk-sharing	Commercial risk transfer
Investments	Sharia-compliant	Can be non-compliant
Revenue Model	Based on helping each other and giving back to the community	Based on premiums

Source: Created by Author

Takaful Insurtech is a keyway to reaching people who don't have bank accounts because it provides easy-to-use, digitalized, and affordable insurance options that follow Islamic principles. Two main strategies can be suggested to reach the Unbanked population in Table 2.7.

Table 2.7: Strategies to Reach Unbanked Population

Strategy	**Description**
Micro-Takaful	Designed for low-income individuals, it provides inexpensive payments while covering essential risks.
Mobile Applications	Providing easy access to Takaful services via smartphones, hence reaching a larger clientele.

Source: Created by Author

An Insurtech company in Malaysia can be given as an example of digital Takaful services through an intuitive mobile app, ensuring accessibility for the unbanked population (Salam Takaful, 2023).

Takaful Insurtech is a harmonic blend of tradition and modernity, creating a system based on mutual aid, risk-sharing, and ethical considerations and a beacon of hope in promoting financial inclusion and providing security to the weakest sectors of society, with a focus on binding technology to reach the unbanked people. It can envision a future in which insurance is more than just a financial tool, but also a medium for promotion community well-being, based on the rich principles of Islamic finance.

2.4.4. Wealth Management and Robo-Advisory Services

Islamic wealth management involves Shariah-compliant financial planning, portfolio management, and investment guidance. Robo-advisory services, which use algorithms to provide investment advice, have had a disruptive impact.

Robo-advisors refer to digital platforms that employ algorithms and artificial intelligence to deliver automated financial advising and investment management services. The mentioned platforms have been designed in accordance with Islamic principles in order to provide robo-advisory services that are compliant with Sharia law. We can categorize its components as Table 2.8.

Table 2.8: Components of Robo-Advisory Services

Components	**Descriptions**
Algorithm-Based Advice	Using algorithms to analyse market data and give financial advice that is in line with Sharia.
Automated Portfolio Management	Using automated tools to keep an eye on portfolios and make sure purchases follow Sharia rules.

Source: Created by Author

Wahed Invest is an example of a Robo-advisor, using algorithms to build and manage diversified portfolios of Shariah-compliant assets. It ensures that the investments are in line with Islamic ethical concerns while taking into account the individual's risk tolerance and investment goals (Wahed Invest, 2021).

The integration of technology with Islamic principles in the form of Islamic wealth management and robo-advisory services can significantly transform the financial industry. Furthermore, it can promote inclusivity by expanding its reach to a wider range of individuals, such as the technologically proficient younger demographic and those residing in geographically isolated areas. This enables them to conveniently participate in halal investments, therefore providing them with a chance to be involved in this financial activity.

It can present a comprehensive analysis of select Islamic fintech enterprises specialising in robo-advisory and wealth management in Table 2.9. The table highlights the distinctive areas of knowledge of each company and provides a concise overview of their respective service contributions.

Table 2.9: Islamic Fintech Enterprises Specialising in Robo-advisory and Wealth Management

Company Name	Specialty	Brief Description
Wahed Invest	Robo-Advisory Services	A global halal robo-advisor that gives people access to halal investment possibilities through an automated platform and a diversified portfolio.
Sarwa	Robo-Advisory Services	It is the first robo-advisory tool in the Middle East. Its goal is to make investing in globally diversified portfolios of low-cost index funds easier and more accessible.
Qardus	Wealth Management	Even though Qardus is mostly a P2P lender, it also has investment chances where people can invest in asset-backed halal products.
Yielders	Wealth Management	A UK-based Islamic financial company that follows ethical and Sharia-compliant principles and makes it easier for people to invest in real estate. It gives people a chance to take part in real estate projects that are funded by crowdsourcing.
Elipsa	Wealth Management	A platform that helps ensure Sharia compliance in the wealth management field by giving personalised financial advice and investment solutions that are powered by AI.
Simply Ethical	Robo-Advisory Services	Offers a wide range of financial goods and services that are in line with Sharia, including an automated advisory platform that helps investors make smart halal investments.
Islamicly	Wealth Management & Advisory	An app that helps find and track Shariah-compliant securities around the world. This helps investors keep a halal portfolio and make sure their investment plans are in line with Islamic law.
ShariaPortfolio	Wealth Management	Offers wealth management services that are in line with Sharia, as well as personalised financial advice.
Habib Bank AG Zurich (HBZ)	Robo-Advisory Services	Offers a range of Sharia-compliant products and has recently gotten into robo-advisory, using technology to make halal investments easier through investment strategies that are driven by algorithms.

Source: Created by Author

Wealth management and robo-advisory services are being provided by the mentioned firms using innovative technological tools. These marketplaces can play a critical role in promoting ethical investing options that are in line with Islamic beliefs, as well as boosting financial inclusion. It's important to keep in mind that certain firms' service presents may extend beyond wealth management and robo-advisory to include other forms of financial guidance as well.

2.4.5. Islamic Cryptocurrencies and Blockchain Technology

The emergence of cryptocurrencies and blockchain technology can transform the worldwide financial environment, yielding noteworthy ramifications for the field of Islamic banking. The advent of cryptocurrencies poses both obstacles and opportunities in Islamic banking. The inherent characteristics of cryptocurrencies, such as decentralisation and digitization, can fit with the principles of Islamic finance, hence facilitating financial inclusion. The ongoing discourse revolves around how the suitability of cryptocurrencies can use a financial tool within the framework of Islamic fintech.

In light of the inherent volatility observed in cryptocurrencies, the adoption of stable coins, which are supported by actual assets such as gold or fiat currency, could potentially present a more congruent solution with the principles of Islamic finance.

Islamic fintech has incorporated blockchain and cryptocurrency technology. For instance, Stellar is a cryptocurrency platform that may be used by Islamic financial institutions because it has received certification as Shariah-compliant (Stellar, 2021). We can see some other Islamic cryptocurrencies in Table 2.10.

Table 2.10: Examples of Islamic Cryptocurrencies

Name	Description	Unique Function/Application
HB Token (HalalChain)	Built on the Ethereum platform and geared towards the supply chain of the Halal food business.	Ensures the authenticity and traceability of Halal foods.
ADAB Solutions	Only Shariah-compliant initiatives are listed on the First Islamic Crypto Exchange (FICE).	A Shariah-compliant cryptocurrency trading facility.
Noorcoin	Halal-centric cryptocurrency based on Islamic principles.	Integrates blockchain technology for Halal sector transparency and traceability.

Source: Created by Author

Additionally, blockchain technology is being investigated for uses in Islamic finance. Integrating Blockchain into Islamic fintech has great potential, as it aligns perfectly with the emphasis on transparency, dependability, and equity in Islamic finance principles. Its immutable record-keeping can streamline the zakat collection and distribution processes, thereby nurturing donor confidence. Moreover, the technology facilitates the automation of Shariah-compliant contracts, efficient cross-border remittances, and the tokenization of tangible assets, which is essential for fields such as Islamic real estate investments and sukuk (Selcuk & Kaya, 2021, p. 137-152). Some of examples about blockchain-based Islamic fintech projects given in Table 2.11.

Table 2.11: Examples of Blockchain-based Islamic Fintech Projects

Financial Institution	**Country**	**Blockchain Initiative/Use-case**
Al Rajhi Bank	Saudi Arabia	Services for international money transfers utilising blockchain technology.
Abu Dhabi Islamic Bank (ADIB)	UAE	Utilise blockchain for trade finance and intelligent contracts.
Islamic Development Bank (IsDB)	Multinational	Partnered with entrepreneurs to investigate the potential of blockchain for Islamic finance solutions.
Kuwait Finance House (KFH)	Kuwait	Ripple's blockchain-based solution for international transactions was evaluated.
Emirates Islamic Bank	UAE	Using blockchain technology to improve finance services and security.
Finterra	Singapore	Provides a blockchain-based platform for administering end-to-end Islamic financial services, including waqf (charitable trust) and crowdfunding.

Source: Created by Author

In summary, Islamic Fintech is a developing industry that combines financial technology advances with the moral and ethical tenets of Islamic banking. These technologies, which range from blockchain to digital banking, aim to offer effective, open, and moral financial services to a large worldwide audience.

2.5. Applications of Islamic Fintech: Financial Computing Perspective

Numerous applications that develop efficiency, security, and customer experience have emerged as a result of the integration of computing technologies with Islamic fintech. In the context of Islamic finance, this section examines a number of such applications and their ramifications.

The field of Islamic finance currently has a significant capacity for change as it incorporates fintech developments that comply with Sharia law. This integration can reach incredible levels, involving the use of three powerful technologies: Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL). Artificial intelligence (AI) can help achieve this by automating the tracking of Islamic investments and transactions and providing predictive assessments to help make real-time decisions. In contrast, machine learning (ML) can serve as a powerful tool for formulating Islamic investment strategies as it has the capacity to analyze comprehensive datasets, adapt and improve its methods, and distinguish investment opportunities that comply with ethical principles mandated by Islamic law.

Deep Learning has the ability to solve critical problems in maintaining the integrity of Islamic finance using fraud detection and compliance measures. It rigorously examines transaction data to identify anomalies and ensure compliance with regulatory standards. Automating compliance monitoring through the interpretation of complex Shariah laws and regulations can contribute to establishing a transparent and secure ecosystem. The integrated use of artificial intelligence (AI), machine learning (ML) and deep learning (DL) in the Islamic fintech space not only guarantees adherence to Sharia principles and ethical standards in financial operations, but also marks a unique, notable era.

2.5.1. AI for Shariah-Compliant Risk Assessment

Artificial Intelligence (AI) plays a central role in risk assessment in the financial industry, enabling financial institutions to create knowledgeable decisions through the analysis of enormous datasets and the provision of accurate risk forecasts (Gai, Qiu, & Sun, 2018, p. 262-273). In the context of Islamic finance, artificial intelligence has been effectively integrated to ensure Shariah-compliant risk assessment, thereby contributing to the efficiency, transparency, and resiliency of Islamic financial system.

Due to its adherence to Islamic laws that prohibit interest (riba), uncertainty (gharar), and wagering (maysir), risk assessment in Islamic finance differs from that of conventional finance (Hassan, Antoniou, & Paudyal, 2005). Therefore, AI in Islamic finance must take these prohibitions into consideration when assessing risk.

Risk assessment using artificial intelligence (AI) has been done in Shariah-compliant frameworks. Islamic financial institutions may make sure that investments and products are compliant with Shariah law and risk appetites by utilizing AI. For example, banks can automate the process of stock screening for Shariah compliance by employing AI.

2.5.2. Machine Learning for Islamic Investment Strategies

Machine Learning (ML), a subset of Artificial Intelligence, is essential to the development of optimal investment strategies. ML algorithms can predict future trends and create knowledgeable investment decisions by learning from historical data and patterns.

ML algorithms can be used to filter Shariah-compliant equities based on business activities and financial ratios of the companies analyzed according to Shariah-screening rules. On the basis of these factors, support vector machines and decision tree algorithms can categorize equities as Shariah-compliant or non-compliant.

Machine learning can optimize portfolio selection in Islamic finance. ML algorithms can recommend optimal portfolio compositions that maximize returns while maintaining Shariah compliance by analyzing past performance, market trends, and risk factors (Gai, Qiu, and Sun, 2018, p. 262-273).

Robo-advisors are a notable application of machine learning in Islamic investment strategies. Robo-advisors are digital platforms that offer algorithm-driven, automated financial planning services with minimal human oversight. In the context of Islamic finance, robo-advisors analyse large datasets to provide Shariah-compliant personalized investment advice to clients.

The implementation of machine learning in Islamic investment strategies is not, however, without obstacles. It calls for high-quality, pertinent, and clean data, interpretability of machine learning models, and privacy and security considerations.

In conclusion, the use of machine learning for Islamic investment strategies has the potential to increase efficiency and personalization in the Islamic finance industry, but its effective application requires addressing certain challenges and assuring the alignment of ML applications with Shariah principles.

2.5.3. Deep Learning in Fraud Detection and Compliance

Deep learning, a sophisticated subset of machine learning, has been increasingly utilised in the financial industry for fraud detection and compliance. These algorithms are capable of learning from large datasets and recognizing complex patterns, allowing for more effective and efficient fraud detection.

The implementation of deep learning is indispensable for ensuring Shariah compliance and detecting fraudulent activities. First, deep learning algorithms can detect anomalies or discrepancies in financial transactions that may indicate fraudulent activity. They can learn and adapt from each transaction, making them extraordinarily effective at detecting fraudulent patterns and preventing potential hazards (Hodge & Austin, 2004, p. 85-126).

Given the ethical and moral principles that govern the operations of Islamic financial institutions, compliance is an essential component of Islamic finance. Deep learning algorithms can be used to monitor and verify compliance, ensuring that all transactions and operations adhere to the Islamic law principles. This may entail analysing complex financial structures, analysing complex contractual agreements, and confirming that these entities adhere to Shariah principles.

Anti-Money Laundering (AML) is one area where deep learning has been utilised in Islamic finance. Deep learning algorithms can shift through immense quantities of transactional data to identify suspicious patterns and flag possible instances of money laundering.

There are challenges associated with the application of deep learning to fraud detection and compliance. It requires vast quantities of high-quality data, sophisticated technical capability, and robust computational resources. It is also essential to ensure the interpretability and transparency of deep learning models.

Finally, the implementation of deep learning for fraud detection and compliance in Islamic finance can enhance the integrity, dependability, and robustness of Islamic financial systems. However, to assure successful integration, the obstacles must be carefully addressed, and the applications must be in accordance with the principles of Islamic law.

The aforementioned technologies, including artificial intelligence (AI), machine learning (ML), deep learning, algorithmic trading, cloud computing, and big data analytics, are not exclusive to the domain of Islamic fintech. The computational techniques are widely applicable and have been utilised in many industries and for a multitude of objectives. The notable aspect of these entities is in their implementation within the framework of Shariah-compliant financing. We can compare the computing technologies in Islamic fintech in Table 2.12.

Table 2.12: Comparison of Computing Technologies in Islamic Fintech

Technology	Application in Islamic Fintech	Example	Reference
Artificial Intelligence (AI)	Shariah-compliant risk assessment	Automating stock screening for Shariah compliance	(Gai, Qiu, & Sun, 2018, p. 262-273)
Machine Learning (ML)	Islamic Investment Strategies	Developing portfolios of Shariah-compliant stocks	(Adeyemi & Nakhooda, 2018, p.752-771)
Deep Learning	Fraud Detection and Compliance	Neural networks identifying patterns indicating fraud	(Hodge & Austin, 2004, p. 85-126)
Algorithmic Trading	Shariah-Compliant Trading Strategies	Customized algorithms for trading halal stocks	(Wahed Invest, 2021)
Cloud Computing	Islamic Banking and Financial Services	iMAL by Path Solutions	(Path Solutions, 2021)
Big Data Analytics	Shariah-Compliant Investment Decisions	Analysis of Shariah-compliant stocks performance	(Sultan & Bechter, 2019, p. 21–31)

Source: Created by Author

The above applications indicate a clear demand for start-ups to engage in innovative practices and offer solutions within the domain of Islamic fintech. Companies that possess the ability to harmonise technology inventions with the principles of Shariah have the potential to capture a substantial market share, given the considerable size of the global Muslim community.

In brief, the broad applicability of these technologies, along with their distinct utilisation within the framework of Shariah-compliant financial practises, renders them a subject of significance within the domain of Islamic fintech.

2.5.4. RegTech in Islamic Fintech

Regulatory Technology (RegTech) is an important asset in this space as it influences technological advances to facilitate organizations to achieve regulatory compliance with increased efficiency and reduced spending. It is important to understand the role and possibilities of RegTech in the Islamic fintech space, focusing on its capacity to ensure regulatory compliance, increase operational efficiency and substitute innovation. RegTech's potential in helping Islamic fintech businesses navigate the regulatory environment effectively should not be overlooked.

RegTech is a relatively new industry that emerged in the wake of the 2008 financial crisis. It employs progressive technology such as artificial intelligence (AI), machine learning (ML), and big data in order to assist businesses in more effectively complying with laws. In the context of Islamic fintech, RegTech can be of assistance in ensuring that all financial goods and transactions comply with Sharia law, thereby cultivating a system that is founded on compliance and trust. Its applications can be found in a variety of fields, including as transaction monitoring, identity management and control, regulatory reporting, and risk management.

RegTech solutions play a important role in enabling the continuous monitoring of financial transactions in real-time. This capability is particularly important in the context of Islamic finance, where adherence to Sharia standards is necessary at every stage of the transaction process. We can see the applications of RegTech in Islamic fintech as shown Table 2.13.

Table 2.13: RegTech Applications in Islamic Fintech

Application Field	**Description**	**Application in Islamic Fintech**
Risk Management	Using technology to assess and handle risks.	**Syfe:** A robo-advisor that offers investment portfolios with risk management based on Islamic principles.
Identity Management and Control	Establishing digital identity solutions that are compliant with regulatory standards and are secure.	**HelloGold:** A gold trading platform with identity management security.
Regulatory Reporting	Automating the regulatory reporting procedure to ensure transparency and compliance.	**RegAlytics:** Providing solutions for automated regulatory reporting according to the Sharia law.
Transaction Monitoring	Real-time monitoring of transactions to identify immediately any non-compliant activities.	**OneGram:** A digital currency secured by gold that ensures compliance through real-time monitoring.

Source: Created by Author

Upon contemplation of the development of RegTech within the Islamic fintech domain, it can become apparent that it serves as more than simply a supplementary instrument, but rather an imperative foundation that guarantees the longevity and advancement of the industry. Through the utilisation of technology, the facilitation of Shariah-compliant financial transactions establishes a foundation for a financial ecosystem that is more inclusive and ethical. This ecosystem is organically congruent with the Islamic ideals of equity, transparency, and shared wealth.

Furthermore, RegTech serves as a fundamental element in mitigating the complexities associated with regulatory compliance. Consequently, the accuracy and efficiency of these operations are improved. In addition, the analytical functionalities of RegTech can contribute to the real-time surveillance and documentation, promoting a flexible framework that can promptly address any instances of non-compliance, thereby safeguarding the integrity of Islamic financial activities.

CHAPTER THREE
POTENTIAL IMPACT OF OPEN BANKING ON THE DEVELOPMENT OF ISLAMIC FINTECH

3.1. Introduction

Over the past few decades, there has been a dramatic shift in the financial sector. Technological progress and the proliferation of digital innovations have been instrumental in dramatically altering the global financial system. Consumer and business use of financial services have been profoundly altered by two of the most revolutionary innovations: open banking and fintech (Quddus, 2020). This chapter explores how open banking could affect the growth of Islamic financial technology.

Open banking is a type of financial service that provides APIs for third-party access to customer banking, transaction, and other financial data. This paves the way for the development of novel applications and services that provide individuals and organizations more freedom and agency over their financial information (Ghosh, 2016, p. 70–82). Services like budgeting, bill paying, and alternative credit scoring could all benefit from open banking.

Islamic fintech, on the other hand, is the implementation of technological advances in the provision of financial services in accordance with Shariah. These programs are designed to help the Islamic community achieve its economic and social goals, such as greater economic and social equality and more access to banking services (Firmansyah & Ramdani, 2018). So, it's worth considering how open banking, as a facilitator, may help Islamic fintech flourish.

The convergence of open banking and Islamic fintech, at the crossroads of these two philosophies, has the potential to produce a more democratic and accessible financial system. For example, Islamic fintech can use the information made available by open banking to develop individualized, Shariah-compliant presents for the unbanked or underserved (Zetzsche, Buckley, Arner, & Barberis, 2017, p. 393-431). This is especially important in areas where Muslims have historically been underbanked due to discrimination.

Open banking also has the potential to facilitate more cooperation and interoperability among participants in the Islamic financial sector. Using application programming interfaces (APIs), Islamic financial institutions can easily link and share data with fintech firms, flooring the way for the creation of novel products and services that can meet the needs of a wide range of customers without compromising on adherence to Shariah principles (Omarova, 2019, p. 1041).

The role that open banking could play in bringing Islamic finance in line with SDGs is another important angle to investigate. Given Islamic finance's focus on societal good and ethical financing, adopting open banking could spur the development of novel approaches to sustainability (Ullah, 2014, 182–199). Environmental, social, and governance (ESG) challenges may be addressed by these strategies without compromising the tenets of Islamic finance.

In this chapter, we will examine the function of application programming interfaces (APIs) and data sharing in the context of open banking and open finance. It will cover the state of open banking around the world and examine how it may be used in Islamic banking. There will also be a focus on financial inclusion, emancipation, and community-based finance as we talk about the societal effects of open banking on Islamic technology. At the chapter's end, we'll take a look at sustainable finance and the role open banking may play in bringing Islamic finance in line with the SDGs.

In conclusion, a new era of financial services that are not only innovative and efficient but also socially responsible and inclusive stands to be ushered in with the convergence of open banking and Islamic fintech. Financial institutions, fintech firms, regulators, and consumers can all work together to create a more sustainable and fair financial environment if they have a shared considerate of the synergies between these two sectors.

3.2. Definition and Differences Between Open Banking and Open Finance

Application programming interfaces (APIs) let third-party financial service providers get to customer banking, transaction, and other financial data from banks and non-bank financial institutions. This is known as "open banking." It is a set of rules meant to encourage new ideas, competition, and financial equality in the banking sector. Because of open banking, new apps and services can be made that give people more ways to handle their money, make payments, and get credit. Regulations, like the European Union's Payment Services Directive 2 (PSD2), often make Open Banking possible. PSD2 says that banks must share their customers' data with authorised providers in a safe and standard way, as long as the customers agree.

APIs are a great shift in the financial industry that allow external suppliers to retrieve consumer banking, transaction, and other financial information. This access enables the development of novel applications and services, authorising users and enterprises with increased options and increased authority over their financial data (Eccles, Grout, Siciliani, & Zalewska, 2024). For instance, using open banking, users can manage several bank accounts, start transactions, or even apply for loans based on a more thorough credit evaluation using third-party applications.

Open Finance takes the ideas behind Open Banking and applies them to a bigger range of financial products and services, such as insurance, savings accounts, pension plans, and more. By giving a full picture of a person's finances, it aims to make personalised financial advice, better credit scoring, and more suitable financial goods possible. Open Finance is based on the same technology as Open Banking. It uses APIs to let more financial companies and third-party providers safely share financial information with each other. This easier access to more data encourages new ideas, makes competition stronger, and helps more people get access to money across the whole financial environment. People think that Open Finance will be the next step forward after Open Banking. It has the ability to change the financial services industry even more by using data in a wider range of financial activities.

Open Banking and Open Finance provide client ownership over their financial data via data security, customer permission, and privacy. These frameworks provide a more open, linked, and creative financial services ecosystem that gives customers more options, better services, and greater financial control.

As opposed to open banking, open finance applies the same concepts to a wider range of financial products and services. (Vezzoso, 2022) lists investment accounts, insurance plans, pensions, and other non-banking financial products as examples of this. With the help of an integrated financial ecosystem, open finance strives to make it possible to securely and effectively share data from multiple sources. We can see the differences between open banking and open finance in Table 3.1.

Table 3.1: Differences Between Open Banking and Open Finance

Aspect	Open Banking	Open Finance
Scope	Primarily focused on bank accounts and payment services	Covers a broader range of financial products and services
Data Access	Through APIs, primarily for banking data	Through APIs, for a variety of financial data
Goal	Greater competition and innovation in banking services	Integrated financial ecosystem with seamless data sharing
Primary Benefit	More options and better control over banking data for users	Holistic financial management across different products

Source: (Vezzoso, 2020)

Open finance expands upon the ideas of open banking, allowing third-party access to a broader range of financial products including mortgages, loans, investments, and pensions. This initiative aligns with the worldwide movement towards open data and data portability. It will facilitate greater integration across other industries beyond finance, such as healthcare, retail, and government. Additionally, it will expand the pool of third-party entities that can compete or facilitate financial transactions as shown in Figure 3.1.

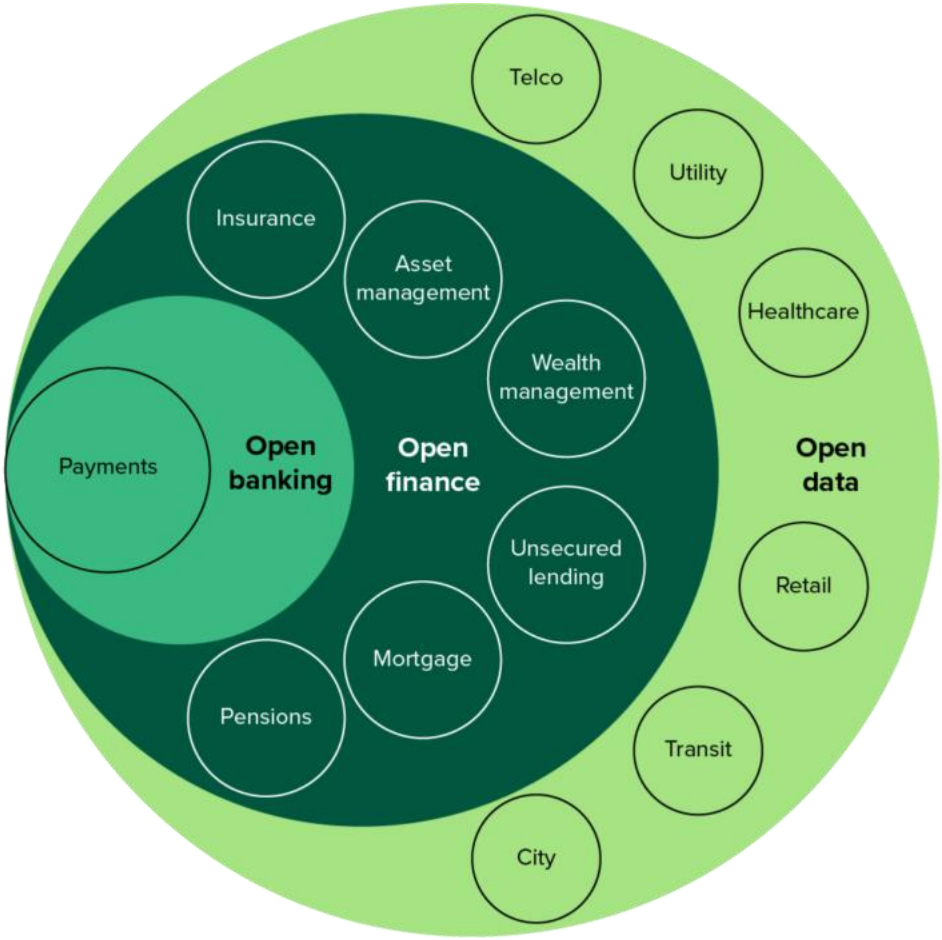

Figure 3.1: Crossroads Between Open Banking and Open Finance

Source: (Forrester, 2021)

The graphic depicts how open banking and open finance are changing the financial services industry and how open data is enabling these changes to spread into new industries. Open finance which includes insurance, asset management, wealth management, unsecured lending, mortgages, and pensions integrates with open banking, which is mostly concerned with payments. Open data projects have an impact on a wide range of businesses, including telecommunications, utilities, healthcare, retail, transit, and city services, in addition to the financial sector. This integrated ecosystem highlights how open data may improve transparency, efficiency, and customer involvement in a variety of industries, making it more broadly applicable and potentially transformative.

3.2.1. The Role of APIs and Data Sharing in Facilitating These Concepts

The facilitation of open banking and open finance depends heavily on APIs. A set of guidelines and procedures known as an API enables various software programs to connect with one another (MuleSoft, 2021). If the customer has given permission, open banking APIs allow third-party providers to securely access the banking information of the customer. RESTful APIs, which are typically thought to be more flexible and effective than conventional SOAP APIs, are frequently used to do this (Tarkar & Parker, 2018, p. 319–322).

Similar to this, open finance makes use of APIs to gain access to a wider variety of financial data. This includes information from banks as well as information from insurance companies, investment accounts, pension funds, and other providers of financial services. A use case of a person who is retirement planning can be used to demonstrate the data sharing provided by APIs in open finance. A financial planning tool that uses open finance may compile information from a person's bank accounts, investment portfolios, and pension funds to provide them a complete picture of their financial state and suggest ways to reach their retirement goals.

Open APIs provide upselling and cross-selling possibilities by permitting data exchange and interoperability with third parties. This promotes the growth of digital marketplace environments in the long run. Additionally, APIs provide a scalable framework for platform administration and governance, guaranteeing platform owner control and profitability. API monetization potential differ greatly based on the business strategy implemented by the provider; this is not even to mention the issue of API copyrightability, which might further fortify the owners' property rights. Because of all these benefits, the use of APIs results in higher sales, market capitalization, intangible assets, and net income together with lower operational expenses. It follows that the fact that some of the most respected firms in the world today, including Apple, Microsoft, and Google, all share a platform ecosystem model centred on developer communities on the outside is not unexpected (Borgogno, O., & Colangelo, G., 2019, p. 105-114).

Data security and privacy issues are raised by data exchange via APIs, though. The Gramm-Leach-Bliley Act (GLBA) and the General Data Protection Regulation (GDPR) of the European Union and the United States, respectively, both set standards for data processing and mandate that organizations obtain consumer consent before sharing data in order to protect consumer information (European Commission, 2016; Federal Trade Commission, 1999).

Additionally, API standardization is essential for interoperability. For instance, all participating banks and financial institutions must use the API standards created by the UK's Open Banking Implementation Entity (OBIE) (OBIE, 2019). This guarantees a uniform approach to data access and sharing, making it easier to integrate services from various sources.

By integrating financial services, both banks and the companies that use them can learn useful details about their customers. This makes loans and insurance more efficient and lets service providers provide more personalised services. In this case, the process works better when there is more data. Because of this, the way stores deal with customers is likely to change in the future. For example, they might offer personalised banking (like savings) and more accurate loans. Each party benefits: banks gain by white labelling their services; customers gain by finding it easier and more streamlined to buy things; and businesses gain by reaching more customers and often saving money as shown in Figure 3.2.

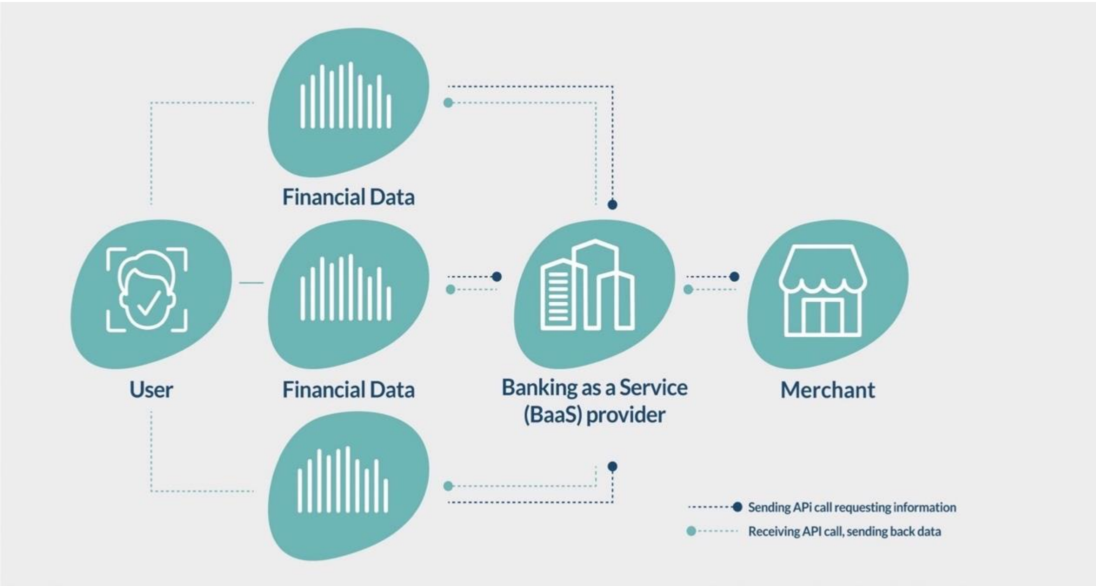

Figure 3.2: How APIs Facilitate the Exchange of Financial Data

Source: (Unnax, 2021)

For creators of APIs, an API needs to store rules about how to describe and access certain data items, while also taking into account that different users may be able to understand these rules in different ways. To put it another way, an API's affordance depends on how well it turns real-world ideas like traffic flow or the number of people using public buildings into data objects that different types of users can understand. This is called "encapsulating meaning" in the API itself (Holmboe, 2005, p. 188-192).

A third-party supplier in Europe named Yolt gathers account information from different banks using open banking APIs, enabling consumers to manage their money more effectively (Yolt, 2021).

Open banking and open finance, in summary, signal a change toward a more transparent and integrated financial sector. At the centre of this transition are APIs and data sharing, which have made it possible to create new services and applications that provide users more power and financial insight. To ensure interoperability and efficiency in this new environment, standardization is essential. However, concerns regarding data security and privacy must be addressed.

3.3. The World of Open Banking and Its Worldwide Perspective

Globally, open banking has been developing quickly due to technical developments, shifting consumer tastes, and regulatory initiatives. The major principles, adoption trends, and regulatory frameworks of the global open banking ecosystem are covered in detail in this section.

The Global Open Banking Report (2023) looks at how the global open banking sector is doing now and how it is expected to grow in the future. According to the illustration, more than 60 countries are already using it, and the market is projected to grow to $43 billion by 2026. By 2024, 132 million people will have used it. This evaluation talks about what these numbers mean for the financial business, how people act, rules and regulations, and new technologies as shown in Figure 3.3.

Figure 3.3: Open Banking Global Landscape

Source: (CBI, 2023)

According to Briones de Araluze and Cassinello Plaza (2022), bibliometric research shows that academics are becoming more interested in open banking and the difficulties of studying it from different fields. This rising interest shows that financial services around the world are becoming more open, easy to use, and focused on the customer. Open banking will change the banking business around the world by using technology to let banks and third-party providers safely share data. It makes it possible for new financial goods and services to be created, increases competition, and makes the experience of customers better.

Open banking seeks to temporary innovation and competition in the banking sector by granting third-party providers (TPPs) access to consumer financial data via APIs. (Rastogi, Goel, & Doifode, 2022, p. 432–444). As a result, new financial services and products are developed and adapted to satisfy various consumer needs. A couple of concepts in open banking shown in Table 3.2.

Table 3.2: Significant Concepts in Open Banking

Concept	Explanation
Application Programming Interface (API)	A set of rules and protocols for building and integrating application software. In open banking, APIs are used to securely transmit data between financial institutions and third-party providers (MuleSoft, 2021).
Third-Party Providers (TPPs)	Companies other than banks that provide financial services using data accessed through APIs (Rastogi, Goel, & Doifode, 2022). These services include account information services (AIS), payment initiation services (PIS), etc.
Consent Management	A system that ensures that consumer data is only shared with third-party providers once the consumer has given their explicit consent. This is a critical component in protecting consumer data privacy (Zachariadis, 2020).

Source: Created by Author

The Revised Payment Services Directive (PSD2), which went into effect in 2018, was the first regulatory framework for open banking to be established by the European Union. If the customer has granted authorization, PSD2 requires banks to allow TPPs access to customer data via APIs (European Commission, 2015). Since then, a number of European nations have seen a spike in fintech developments, including better payment methods and personal finance management apps.

Neobank Monzo, with headquarters in the UK, uses open banking to offer its customers tools like spending tracking, budgeting, and immediate payment alerts (Monzo, 2021).

Open banking adoption in the US has primarily been pushed by the market, with organizations like Plaid providing connections between fintech applications and consumer bank accounts (Plaid, 2021).

As was mentioned, regulatory frameworks have influenced how open banking has been adopted. These policies strike a balance between consumer rights, innovation, and data protection. To secure data privacy in Europe, PSD2 is supplemented by the General Data Protection Regulation (GDPR) (European Commission, 2016).

Open Banking building blocks let established banks and new banks work together and share information to create value for users. The API building blocks include the API description, the resource structure, the documents, and the versioning. This also talks about the planning, programming, testing, and upkeep of the API. The rules for how to describe and store data are in the data building block. This includes the description and framework, permits and entry rights, and the style and portrayal of the data (Premchand, A., & Choudhry, A., 2018, p. 25-29).

For all over perspective, API development is an important part of fintech innovation because it makes it possible for different financial systems to work together and talk to each other easily. Because of open banking, traditional banks have had to make their APIs public. This has made it easier for fintech apps to provide personalised financial services. Making access to financial data more open to everyone has sped up the creation and use of new fintech solutions, cutting the time it takes to get them to market by a large amount and letting startups compete with big banks. Because of this, customers are getting a wider range of services, better user experiences, and more access to money.

Numerous opportunities are presented by open banking, including more competition, innovation, and consumer choice. To reach its full potential, however, issues like data privacy, security, and interoperability must be resolved (Tachev, 2016).

Finally, open banking is transforming the world of finance by promoting innovation and competition. However, in order to reap its rewards, parties must work together and negotiate obstacles using strong regulatory frameworks.

3.4. Open Banking in Islamic Finance

3.4.1. Accelerating Shariah-compliant Financial Services via Open Banking

Shariah law, which regulates Islamic finance, prohibits activities such as charging interest (riba) and investing in ventures that are considered haram (such as the selling of alcohol or gambling). Conversely, it encourages the practice of distributing risks, funding through collateralized assets, and engaging in morally responsible investments. (Chachi, 2006). Since open banking advances innovation and competition among financial service providers, including Islamic financial institutions, it can make it easier to deliver Shariah-compliant goods and services.

Islamic banks have the opportunity to forge partnerships with fintech companies using open banking in order to develop innovative products such as robo-advisors that comply with Shariah principles, digital wallets, and platforms for alternative financing. For example, a robo-advisor could aid Muslim investors in constructing and overseeing portfolios that adhere to Shariah principles by incorporating into APIs (Lutsyshyn and Vorobiova, 2021).

Ninety percent of Islamic finance professionals surveyed by IslamicMarkets.com think that open banking will be used more by banks, governments, fintechs, and other groups by 2025. Almost half of those respondents (38%) think that use will increase dramatically (Gannage-Stewart, H., 2023). What the study also found was that better rules will likely help open banking grow in Islamic finance. Three-quarters of Islamic finance workers polled thought that regulations would get a lot stricter, while five-nine percent thought that regulations would get a little stricter.

Open banking also enables Islamic banks to provide more customized goods and services to customers, improving customer experiences. Banks can learn customers' financial preferences and behaviour by gaining access to their customer data, which allows them to modify their product assistances. For that purpose, we described examples of shariah-compliant services facilitated by open banking in Table 3.3.

Table 3.3: Examples of Shariah-Compliant Services Facilitated by Open Banking

Service Type	**Explanation**
Shariah-compliant robo-advisors	Automated investment platforms that build and manage investment portfolios in line with Shariah principles.
Digital wallets	Digital wallets allowing for Shariah-compliant transactions, encouraging cashless transactions in accordance with Islamic financial principles.
Alternative financing platforms	Platforms facilitating Shariah-compliant financing methods such as Mudarabah (profit-sharing) and Murabaha (cost-plus financing).

Source: Created by Author

The table shows how Shariah-compliant financial services can be developed and delivered more easily with open banking, offering creative solutions that follow Islamic financial principles. Robo-advisors that adhere to Shariah law provide automated investment management services, guaranteeing ethical investment portfolios. Digital wallets facilitate cashless transactions while adhering to Islamic principles, hence advancing financial inclusivity and ease.

3.4.2. Facilitating Interoperability and Collaboration in the Islamic Finance Ecosystem

In order to promote cooperation and interoperability within the Islamic finance ecosystem, open banking is essential. Islamic banks are able to easily connect their systems to those of fintech firms, payment service providers, and other stakeholders by using APIs (Unal & Aysan, 2022, p. 388-398). By encouraging the interchange of knowledge and resources, this strengthens the ecosystem as a whole.

For instance, open banking facilitates the smooth integration of platforms for Waqf (endowment) and Zakat (almsgiving) with Islamic banks. Customers can conveniently fulfill their religious duties by designating a percentage of their earnings or savings to these sites.

Additionally, partnerships made possible by open banking can aid Islamic financial institutions in extending their reach, particularly in areas with high rates of underbanked and unbanked people. Islamic financial institutions can offer financial services to people in remote locations, promoting financial inclusion, by collaborating with fintech firms and leveraging mobile technologies (Omarova, 2019). Towards enable Shariah-compliant real estate investments, the Islamic crowdfunding site Ethis has integrated open banking technologies (Ethis, 2021). Aferwards, benefits of interoperability and collaboration in Islamic Finance shown in Table 3.4.

Table 3.4: Benefits of Interoperability and Collaboration in Islamic Finance

Benefit	**Description**
Enhanced Customer Experience	Seamless integration of services leading to more personalized and efficient products for customers.
Financial Inclusion	Reaching unbanked and underbanked populations through collaborations with fintech companies and mobile technologies.
Fulfillment of Religious Obligations	Easier and more efficient methods for Muslims to fulfill obligations such as Zakat and Waqf through integrated platforms.

Source: Created by Author

The benefits of collaboration and interoperability in Islamic finance are outlined in the above table. These benefits include improved financial inclusion by reaching unbanked and underbanked populations through fintech and mobile technologies, improved customer experience through seamless service integration, and more effective fulfilment of religious obligations like Waqf and Zakat through integrated platforms.

In conclusion, open banking offers Islamic finance the chance to innovate and broaden its product contributions while still adhering to Shariah guidelines. Open banking can promote financial inclusion and better customer experiences by facilitating seamless integration and cooperation across the Islamic finance ecosystem.

3.5. The Social Impact of Open Banking on Islamic Fintech

3.5.1. Financial Inclusion and Empowerment

Development socioeconomic fairness and inclusiveness is one of Islamic finance's main goals. By promoting greater financial inclusion and enablement, open banking can considerably help with this, especially in areas with sizable Muslim unbanked communities.

Islamic financial institutions can partner with fintech firms to provide specialized financial products and services by accessing consumer data through open banking. This is especially helpful for those who might not have had access to financial services in the past because there weren't any options that complied with Shariah.

The growth of Islamic microfinance services can be facilitated by mobile technologies and open banking. For small business owners and microentrepreneurs in poor nations, these services can be very powerful.

3.5.2. The Role of Open Banking in Strengthening Community-Based Finance

The promotion of socioeconomic justice and inclusion is one of the primary goals of Islamic finance. Open banking can considerably contribute to this by facilitating greater financial inclusion and inspiration, especially in regions with large Muslim populations that lack bank accounts.

Open banking can play a fundamental role in bolstering community-based finance, which is fundamental to Islamic financial principles. Open banking enables the incorporation of community-based Islamic financial services such as Zakat, Waqf, and Sadaqah with traditional banking services by encouragement collaboration via APIs.

Through automated platforms and mobile applications, this integration makes it simpler for individuals to fulfil their religious obligations and contribute to the common good. In turn, this strengthens communal ties and promotes social cohesion by facilitating the efficient distribution of funds to those in need. In addition, open banking enables the development of innovative community-based financial products, such as crowd-funded investments, which can be Shariah-compliant and support community development initiatives. Also, we can see social impacts of open banking in Islamic fintech in Table 3.5.

Table 3.5: Social Impacts of Open Banking in Islamic Fintech

Social Impact	Description
Financial Inclusion	Enables greater access to Shariah-compliant financial products and services, promoting economic empowerment among previously unbanked populations.
Strengthening Community-Based Finance	Facilitates efficient and automated methods for fulfilling religious obligations and contributing to community welfare through services like Zakat, Waqf, and Sadaqah.
Encouraging Ethical Investment	Enables access to investment platforms that align with Shariah principles, advance ethical investment and community development.

Source: Created by Author

Islamic social finance has the right tools and cash services for this kind of situation. We need to make sure that Islamic social finance tools like Zakat, Qardh-Al-hasan, Awqaf, Islamic financing, takāful ta'awuni, and others work with the government's fiscal and monetary policies to help the poor and vulnerable people in society. In order to reach a social and economic goal, Islamic social finance means giving poor and defenceless people useful financial services. Figure 3.4 below shows the tools that are used in Islamic social economics.

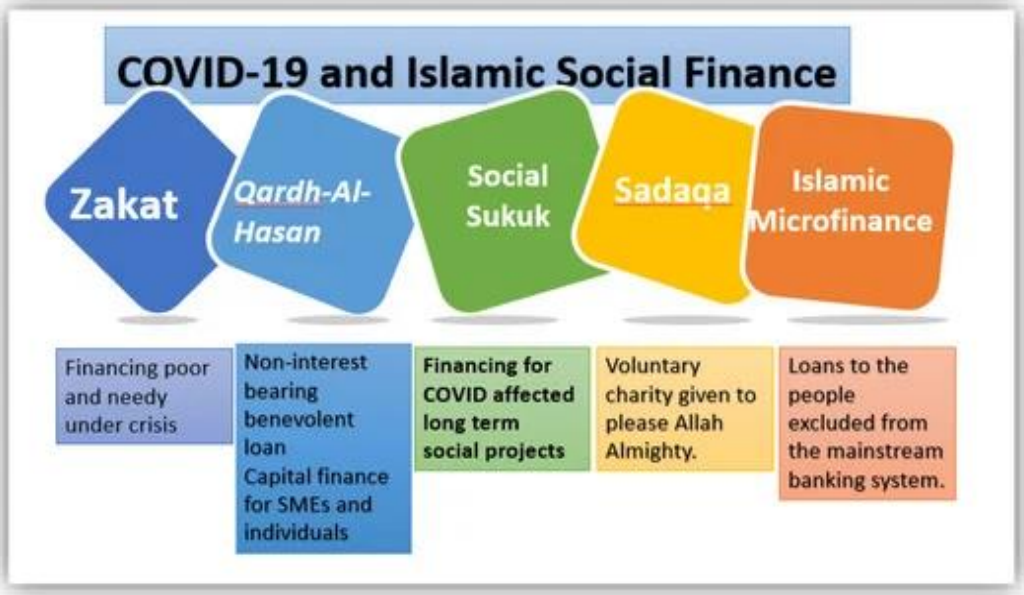

Figure 3.4: COVID 19 and Islamic Social Finance Tools

Source: (Rabbani et al., 2021, s. 136)

In conclusion, open banking has the potential to be a significant enabler for achieving Islamic finance's social goals. Open banking can support socio-economic justice and authorisation in line with Shariah principles by promoting financial inclusion, bolstering community-based financing, and encouraging ethical investing.

3.6. Sustainable Finance and the Role of Open Banking in Islamic Fintech

3.6.1. Associating Islamic Finance Principles with Sustainable Development Goals

Islamic finance's emphasis on social justice, risk-sharing, and asset-backed transactions makes it basically compatible with sustainability principles (Chachi, 2006, p. 39-41). The United Nations' Sustainable Development Goals (SDGs) include goals like eradicating poverty, minimizing inequality, and guaranteeing environmental sustainability, all of which are consistent with the moral and ethical foundations of Islamic banking.

By encouraging the creation of revolutionary, Shariah-compliant financial products and services that also advance sustainability, open banking can serve as a catalyst in bringing Islamic finance principles and the SDGs together. Islamic financial institutions can produce specialized solutions aimed at socioeconomic growth and environmental sustainability by making use of the client data made available through open banking.

3.6.2. Open Banking-Driven Sustainable Finance Solutions and Innovations

Through a variety of channels, open banking can promote sustainable financial solutions in the Islamic fintech industry. It makes it easier for Islamic banks, fintech firms, and sustainability-oriented groups to work together, which results in the creation of creative solutions can be seen in Table 3.6.

a) Green Sukuk: Islamic bonds called Sukuk can be set up to support environmentally friendly initiatives. Open banking can make it easier for investors to acquire Green Sukuk, directing money toward environmentally friendly projects.

b) Impact Investing: Open banking can help platforms for Shariah-compliant impact investing develop. Impact investing entails making investments with the goal of producing a beneficial, quantifiable social and environmental impact in addition to a financial return.

c) Microfinance for Sustainable Projects: Islamic microfinance organizations may be able to provide products designed to finance modest-scale sustainable projects, such as renewable energy efforts, thanks to open banking.

Table 3.6: Open Banking-Driven Sustainable Finance Solutions

Solution	**Description**
Green Sukuk	Islamic bonds structured to finance environmentally sustainable projects.
Shariah-compliant Impact Investing	Investments made with the intention of generating positive, measurable social and environmental impact in line with Shariah principles.
Microfinance for Sustainable Projects	Islamic microfinance products geared towards financing small-scale sustainable projects such as renewable energy initiatives.

Source: Created by Author

As a conclusion, the arrival of open banking is a huge chance for Islamic finance to change things for the better and make the sector's social and moral goals a reality. Islamic technology can make a big difference in promoting economic justice and women's freedom by using the features of open banking. This is in line with Shariah principles. This combination not only helps people who don't normally have access to financial services, but it also makes community-based finance systems stronger. Open banking helps create shared data ecosystems that make it possible for new financial goods to be made that meet the needs of these groups. This makes them more economically active and improves their health.

CHAPTER FOUR

PORTFOLIO OPTIMIZATION WITH MACHINE LEARNING

4.1. Introduction

Ever since Harry Markowitz came up with the basic idea for it in 1952, modern financial engineering has placed a substantial emphasis on portfolio optimization as one of its primary areas of concentration. It focuses mostly on the concept of allotting funds to various investments in such a way as to either maximize return on investment (ROI) for an established level of risk or limit risk for an established level of ROI. Both of these outcomes are desirable. Against the backdrop of a dynamic and uncertain financial market landscape, the quest of optimal returns has led to the development and implementation of more sophisticated approaches and methodologies.

The application of machine learning, a subfield of artificial intelligence, has recently emerged as a potentially fruitful strategy in this area. Portfolio optimization has been given a new dimension as a result of the ability of machine learning algorithms to learn from vast volumes of data and adapt to new knowledge without being explicitly programmed (Mitchell, 1997). Machine learning, in contrast to traditional rule-based programming, makes use of data-driven models that adaptively improve their forecasts over time. This makes it possible to have a more sophisticated grasp of and ability to forecast complicated financial markets. This fundamental shift in the paradigm has motivated an entire generation of financial analysts and engineers to make use of machine learning in the process of forecasting asset values, evaluating investment strategies, and controlling risk.

Throughout the years, the business of finance has witnessed a wide variety of machine learning strategies being implemented for the purpose of portfolio optimization. Support vector machines (SVM), random forests, long short-term memory (LSTM) are some of the methods that can be used, but this list is not exhaustive (Mnih et al., 2015). For this reason, a more in-depth considerate is required before any of these strategies can be utilized successfully in the process of portfolio optimization. Each of these methods possesses its own distinct set of traits and applicable scenarios.

For example, Markowitz's Portfolio Theory continues to be an important theory in the field of portfolio optimization. This theory laid the groundwork for mean-variance analysis (Markowitz, 1952). On the other hand, as the complexity of the financial markets continues to grow, more advanced and adaptable technologies, such as machine learning algorithms, have grown increasingly popular. Methods such as the Moving Average technique have been used to generate trading signals based on historical price trends. Meanwhile, LSTM, a type of recurrent neural network, is adept at processing sequential data, making it ideal for time-series forecasting tasks commonly found in financial applications (Hochreiter & Schmidhuber, 1997, p. 1272-1280). Methods such as these have been used to generate trading signals in the past.

The Random Forest algorithm is a flexible approach to machine learning that can deal with a wide variety of data formats and relationship configurations. According to Breiman (2001), people have used it to anticipate future returns, grasp the value of features, and obtain insightful interpretations of complex investment methods. SVM, a sophisticated classification algorithm, has also been utilized in financial markets to anticipate price direction by grouping data into two categories: rise and fall (Sain & Vapnik 1996, p. 273-297). This was accomplished by classifying prices as either rising or falling. Convolutional Neural Networks, or CNNs, are well-known for their aptitudes in image processing; nevertheless, they have also been ingeniously used to the task of analyzing patterns in financial time-series data (LeCun et al., 1998).

Last but not least, techniques of reinforcement learning such as Deep Q-Networks have found applications in portfolio management. This is especially true in contexts where the objective is to learn an optimal policy over the course of time. They are particularly well-suited to the dynamic and highly stochastic character of financial markets as a result of their ability to learn from trial and error and maximize reward (Mnih et al., 2015).

Each of these machine learning models and techniques comes with its own distinct collection of advantages and disadvantages, and as a result, some of them are more suited to specific circumstances than others. If financial engineers and analysts have a better sympathetic of these characteristics, they will be able to implement them more effectively, which will result in better investment strategies and higher returns.

This chapter will provide a full analysis of the machine learning approaches that were mentioned, expanding on ideas, features, and portfolio optimization applications as we go. In addition, it will go into the discussion on how machine learning as an overarching field is altering the financial industry and shaping the future of investment and asset management. Specifically, it will focus on how this is happening.

It is vital, in order to be able to harness the full potential of machine learning in portfolio optimization, to not only have a profound perspective of the various algorithms, but also to be conscious of the changing market dynamics and regulatory landscapes. This is because machine learning is a relatively new field, and there is still a lot of room for growth in this field. This chapter will go into the mechanics of portfolio optimization algorithms in the following sections, as well as elaborate on the machine learning models and approaches that are currently being utilized to promote innovation and performance in the field of financial investing.

4.2. Portfolio Optimization Algorithms

4.2.1. Markowitz Portfolio Theory

In order the perform Markowitz portfolio selection, we need to estimate the vector of expected returns and the covariance matrix of returns. Historically, finance literature mostly emphasised estimating expected returns rather than covariance estimates. In mean-variance optimisation, the covariance is considered more stable and less problematic than anticipated returns, making accurate predictions less critical. Prior studies have demonstrated that estimating the projected returns vector is more challenging than estimating the covariances of asset returns. Errors in estimating predictable returns have a greater influence on portfolio weights than errors in estimating covariances. Recent academic research has emphasised minimum-variance portfolios, which are based on covariance estimations and are less affected by estimation errors compared to mean-variance portfolios.

The primary goal of portfolio optimisation is to continuously achieve higher returns than a benchmark index while maintaining a specific level of risk. The benchmark being referred to may be a conventional market index, such the BIST 100 Index. We can have a look deeply at Markowitz analysing return, variance and covariance, covariance matrix of an example portfolio and variance of a portfolio to see how the portfolio optimization works and what mathematical logic behind it. Hence, we can see at Figure 4.1 to describe how MPT works.

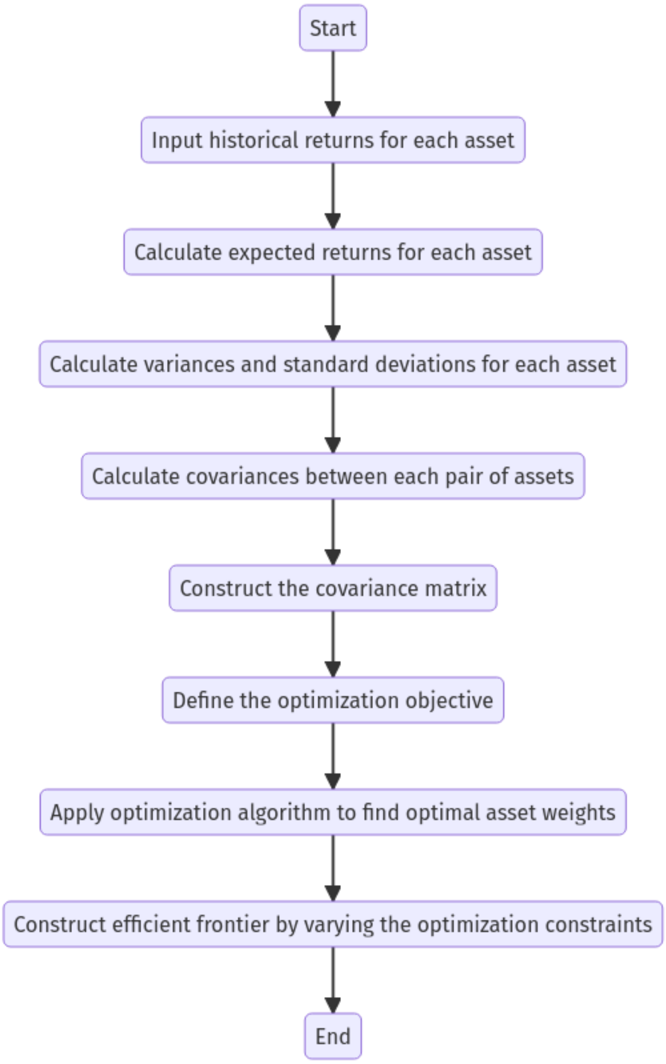

Figure 4.1: Flowchart of Markowitz Portfolio Theory

Source: Created by Author

The steps involved in portfolio optimisation are shown in this flowchart:

- Start: Initiate the procedure.
- Put each asset's historical returns in: For every asset, compile and enter historical performance data.
- Determine the anticipated returns for every asset: Using historical data, calculate each asset's expected return.
- Determine the standard deviations and variances for every asset: Calculate the return variability and volatility of each asset.

- Determine the covariances between every asset pair. Examine the movements of the returns on various assets in connection to one another.
- Create the matrix of covariance: Compile the covariances between each pair of assets into a matrix.
- Describe the goal of the optimisation: Decide on the optimization's objective, such as risk reduction or return maximisation.
- Utilise an optimisation technique to determine the ideal asset weights: To get the ideal asset allocation for investments, apply an algorithm.
- Create an effective border by changing the optimisation parameters: Plot the range of ideal portfolios, with the limitations changed, that strike a balance between return and risk.
- Close out: Complete the procedure.

This procedure aids in the construction of an investment portfolio with the goal of obtaining the highest return for a particular degree of risk.

4.2.1.1. Portfolio Return

Investment returns show how much money and investment made or lost over a certain time period. They are one of the most important ideas in finance. They are very important for figuring out how well investments are doing, comparing different types of money, and making smart investment choices. Returns can be shown either in terms of the amount invested or as a percentage of that amount. This gives us a standard way to judge how profitable and efficient an investment is (Bodie, Kane, & Marcus, 2014).

Both private and institutional investors need to be able to evaluate financial results. It helps buyers figure out how well their investment plans are working, understand the trade-off between risk and return, and make changes to their portfolios based on their risk tolerance and financial goals. Also, investment yields are used as a starting point for financial theories and models, like the Capital Asset Pricing Model (CAPM) and the Efficient Market Hypothesis (EMH), which try to explain how markets work and how prices are set for assets (Sharpe, 1964, p. 425).

For financial research to work, it's important to get the returns right. The simple return formula is an easy way to figure out how much a property has gained or lost over time:

$$\mathbf{R} = \frac{\mathbf{P_{end} - P_{begin} + D}}{\mathbf{P_{begin}}} \times \mathbf{100}\% \tag{4.1}$$

Bodie, Kane, and Marcus (2014) use this equation to show how changes in prices and income (e.g., dividends or interest) affect the total gain.

When an investment is kept for more than one year, the annualised return is often used to normalise the return on an annual basis. This makes it easier to compare returns over different time periods and types of investments:

$$\mathbf{R_{annualized}} = \left(\frac{\mathbf{P_{end}}}{\mathbf{P_{begin}}}\right)^{\frac{1}{n}} - \mathbf{1} \times \mathbf{100}\% \tag{4.2}$$

This math assumes compounding, which shows how getting returns affects returns earned in the past (Sick, Ross, & Westerfield, 1988).

The logarithmic return, also known as continuously compounded return, is used for theoretical and statistical investigations because of its mathematical qualities, including symmetry and additivity over time:

$$\mathbf{R_{log}} = \mathbf{l\,n}\left(\frac{\mathbf{P_{end}}}{\mathbf{P_{begin}}}\right) \tag{4.3}$$

Logarithmic returns are appreciated in financial modelling and risk management for aggregating returns across time and analysing assets with fluctuating values (Lo, 1988).

Comprehending and precisely computing returns is essential for risk management, portfolio optimisation, and strategic investment planning. Investment performance, in terms of returns, impacts judgements on asset allocation, choice of investment strategies, and assessment of fund managers (Elton, Gruber, Brown, & Goetzmann, 2009). Studying past returns is important for predicting future returns, but it has limitations because of market volatility and unexpected economic developments.

Investment returns are fundamental in financial analysis since they allow investors to evaluate the success of their assets and make well-informed decisions. Various techniques, ranging from basic formulae to advanced annualised and logarithmic computations, offer the means to gain a detailed comprehension of investment profitability and risk. Accurate analysis of returns is key for making sound financial decisions, developing effective investment strategies, and achieving financial goals.

4.2.1.2. Portfolio Variance

Variance is a key element in Modern Portfolio Theory (MPT), which was created by Harry Markowitz. It quantifies the variability of a financial asset's returns and serves as a critical gauge of investment risk. Variance in Modern Portfolio Theory (MPT) measures the spread of returns for an individual asset or a portfolio, offering information on the possible risk that investors might encounter.

The amount that an asset's returns depart from its mean (average) return during a given time period is measured by its variance. It is computed as the mean of the squared deviations between each return and the mean return for a specific asset. We can describe the n is the number of observations, R_i is the return in period i, $\bar{\boldsymbol{R}}$ is the average return. The following formula may be used to find an asset's variance ($\boldsymbol{\sigma^2}$):

$$\boldsymbol{\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(R_i - \bar{R})^2} \tag{4.4}$$

Accepting how the mix of various assets impacts total portfolio risk is another area of attention for portfolio theory. In addition to the weighted average of the variances of the individual assets that make up the portfolio, the variance of a portfolio also takes into account the covariance between each pair of assets, which represents the way that asset returns move together: $\boldsymbol{\sigma_p^2}$ is the portfolio variance, $\boldsymbol{w_i}$ and $\boldsymbol{w_j}$ are the weights of assets $\boldsymbol{i}$ and $\boldsymbol{j}$ in the portfolio, $\boldsymbol{\sigma_{ij}}$ is the covariance between the returns of assets $\boldsymbol{i}$ and $\boldsymbol{j}$, $\boldsymbol{n}$ is the number of assets in the portfolio. The portfolio variance formula is:

$$\boldsymbol{\sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}} \tag{4.5}$$

According to Modern Portfolio Theory investors can lower the total risk in their portfolio without necessarily compromising projected returns by diversifying their holdings or choosing a combination of assets with different correlation levels. Building the efficient frontier, a graphical depiction of the most efficient portfolios based on risk-return profiles, requires a considerate of portfolio variation. For a given amount of risk, portfolios that are on the efficient frontier offer the maximum projected return.

Variance is a key component of Modern Portfolio Theory and a basic indicator of risk. Investors may strategically allocate their assets to minimise risk and maximise profits by knowing and calculating the variance and covariance of each asset. Investment strategy and portfolio management have been significantly impacted by MPT's insights on the dynamics of portfolio variance, highlighting the need of diversity in reaching financial objectives.

4.2.1.3. Covariance Matrix of a N-asset Porfolio

In Modern Portfolio Theory (MPT), covariance is an important statistical term that quantifies the degree to which the returns of two assets fluctuate in relation to one another. Harry Markowitz created MPT and emphasised the significance of diversity in portfolio creation. By assessing the co-movement of assets, covariance aids investors in comprehending the advantages of diversity and facilitates the construction of a portfolio that may lower risk without sacrificing projected profits.

The degree to which two assets tend to move in opposing directions (negative covariance) or in the same direction (positive covariance) is indicated by their covariance. The returns on the two assets are presumably independent of one another if there is zero correlation. The method by which the covariance of two assets is computed $\boldsymbol{X}$ and $\boldsymbol{Y}$, is:

$$\boldsymbol{\sigma}_{\mathbf{XY}} = \frac{\mathbf{1}}{\mathbf{n-1}} \sum_{\mathbf{i=1}}^{\mathbf{n}} (\mathbf{X_i} - \overline{\mathbf{X}})(\mathbf{Y_i} - \overline{\mathbf{Y}}) \tag{4.6}$$

In an n-asset portfolio, the covariance matrix, represented by the symbol $\boldsymbol{\Sigma}$, is a symmetric matrix that captures all covariances between asset pairings. Considerate the interrelationships between asset returns and the creation of $\boldsymbol{\Sigma}$ are essential for accepting portfolio optimisation techniques.

For an n-asset portfolio, a covariance matrix typically has the following form:

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\sigma}_{\mathbf{11}} & \boldsymbol{\sigma}_{\mathbf{12}} & \cdots & \boldsymbol{\sigma}_{\mathbf{1n}} \\ \boldsymbol{\sigma}_{\mathbf{21}} & \boldsymbol{\sigma}_{\mathbf{22}} & \cdots & \boldsymbol{\sigma}_{\mathbf{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{\sigma}_{\mathbf{n1}} & \boldsymbol{\sigma}_{\mathbf{n2}} & \cdots & \boldsymbol{\sigma}_{\mathbf{nn}} \end{bmatrix} \tag{4.7}$$

$\boldsymbol{\sigma_{ij}}$ symbolises the correlation between asset returns, the asset variance is represented by (the diagonal elements) $\boldsymbol{\sigma_{ii}}$.

Calculating the covariance between two assets, $\boldsymbol{i}$ and $\boldsymbol{j}$, is as follows:

$$\boldsymbol{\sigma}_{\mathbf{ij}} = \mathbf{E}\left[(\mathbf{R_i} - \boldsymbol{\mu}_{\mathbf{i}})\left(\mathbf{R_j} - \boldsymbol{\mu}_{\mathbf{j}}\right)\right] \tag{4.8}$$

$\boldsymbol{E}$ is the expectation operator, $\boldsymbol{R_i}$ and $\boldsymbol{R_j}$ are the random variables representing the returns of assets $\boldsymbol{i}$ and $\boldsymbol{j}$, $\boldsymbol{\mu_i}$ and $\boldsymbol{\mu_j}$ are the expected returns of assets for $\boldsymbol{i}$ and $\boldsymbol{j}$.

One way to think about asset $\boldsymbol{i}$ variance is as a particular instance of covariance where $\boldsymbol{i = j}$,

$$\boldsymbol{\sigma_{ii} = \mathbf{E}[(\mathbf{R_i} - \mu_i)^2]} \tag{4.9}$$

This is the anticipated value of the squared deviations of asset i returns from its mean return.

Taking a look at a portfolio that consists of three assets (A, B, and C). The computed covariances and predicted returns μ might be as follows:

$$\Sigma = \begin{bmatrix} \sigma_{AA} & \sigma_{AB} & \sigma_{AC} \\ \sigma_{AB} & \sigma_{BB} & \sigma_{BC} \\ \sigma_{AC} & \sigma_{BC} & \sigma_{CC} \end{bmatrix} \tag{4.10}$$

If we calculate the standard deviation of a portfolio consisting of three assets (A, B, and C):

$$\sigma_p = \sqrt{w_A^2 \cdot \sigma_{AA}^2 + w_B^2 \cdot \sigma_{BB}^2 + w_C^2 \cdot \sigma_{CC}^2 + 2 \cdot w_A \cdot w_B \cdot \sigma_{AB} + 2 \cdot w_A \cdot w_C \cdot \sigma_{AC} + 2 \cdot w_B \cdot w_C \cdot \sigma_{BC}} \tag{4.11}$$

The standard deviation of a portfolio's returns is utilised in Modern Portfolio Theory to determine the total risk of the portfolio. Finding an asset mix that minimises risk for a given level of projected return, or maximises return for a given level of risk, is the aim of portfolio optimisation.

Converting a covariance matrix into standard deviations and a correlation matrix is imperative for portfolio optimisation in Modern Portfolio Theory. Standard deviation quantifies individual asset risk, whereas the correlation matrix reveals the relationship between assets and is essential for diversification schemes. Building a portfolio with assets that have low or negative correlations can decrease total portfolio risk without significantly decreasing projected returns, reflecting the core premise of Modern Portfolio Theory diversification.

4.2.1.4. Efficient Frontier

The efficient frontier, a technique that enables investors to build portfolios to maximise projected returns based on a specific amount of market risk, is central to the MPT idea. The purpose of this work is to present a thorough analysis of the efficient frontier, looking at its theoretical foundations, historical development, and portfolio management implications.

The idea behind the efficient frontier is that a portfolio's total risk may be decreased by diversification. The concept that a portfolio's risk might be reduced for a given level of projected return by carefully balancing the proportions of different assets was first presented by Markowitz (1952). The projected return of the portfolio is optimised mathematically against its variance, or standard deviation, which is regarded as a stand-in for risk.

Although the efficient border and MPT have been widely used, they have not been without criticism. The normal distribution of returns and static risk preferences, two tenets of MPT, are criticised for not properly reflecting actual market realities. The rationality assumption of MPT is called into question by behavioural finance theories, which contend that psychological variables play a role in investors' decisions.

Consider graphing every feasible portfolio with the anticipated return on the y-axis and risk (as determined by standard deviation) on the x-axis. The upper portion of this region's border, which runs from the portfolio with the least variation (risk) to the portfolio with the highest return, is known as the Efficient Frontier. Because it is impossible to find a lower-risk portfolio without surrendering some returns, and because it is impossible to obtain larger returns without taking on more risk, portfolios on the Efficient Frontier are thought to be optimum.

The optimisation of portfolios to identify those that either maximise returns for a given level of risk or minimise risk for a given level of return is the mathematical basis of the Efficient Frontier. In order to minimise the portfolio variance, one must solve an optimisation problem to find the efficient frontier $\boldsymbol{\sigma_p^2}$ for an assumed expected return $\boldsymbol{R_p}$ for a assumed $\boldsymbol{\sigma_p^2}$ with the restriction that the total of the weights equals 1:

$$\boldsymbol{\sum_{i=1}^{n} w_i = 1} \tag{4.12}$$

Usually, LaGrange multipliers or numerical optimisation methods are used to overcome this issue. If we visualise the Efficient Frontier by graphing a theoretical group of portfolios:

- Sub-optimal portfolios are those that give lower returns for the same risk or more risk for the same returns, and they are not on the Efficient Frontier.
- The trade-off between risk and return is reflected in the Efficient Frontier's concave curve towards the origin.

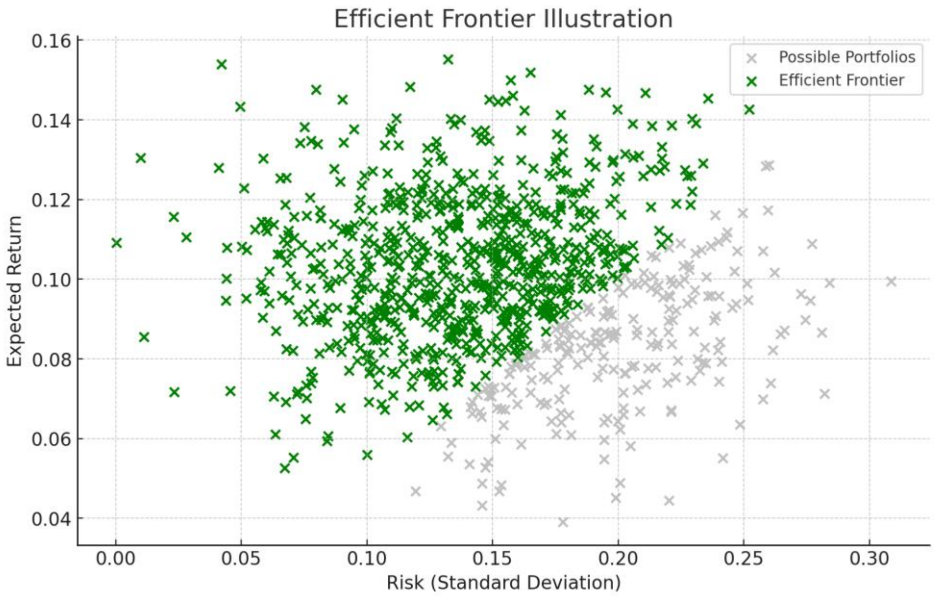

Figure 4.2: Efficient Frontier

Source: Created by Author

The Efficient Frontier notion is shown in the Figure 4.2 in relation to Modern Portfolio Theory. A potential portfolio with a certain degree of risk (standard deviation) and predicted return is represented by each silver dot. The portfolios that make up the Efficient Frontier are shown by the green dots. Because these portfolios provide the highest expected return for a given level of risk or the lowest risk for a given level of expected return, they are regarded as optimum.

Reasonable investors favour portfolios on the Efficient Frontier since any deviation from it will either raise risk without raising anticipated return or lower expected return without lowering risk sufficiently.

4.2.2. Equal Weight Portfolio Optimisation

Regardless of the risk, return, or other attributes of each asset in the portfolio, an investor using the equal weight portfolio optimisation technique allots the same proportion of capital to each asset. This strategy's primary goal is to increase diversity by minimising bias and over-concentration on any one asset or class of assets (Taljaard & Mare, 2020).

This strategy might be interpreted as a critique of Harry Markowitz's mean-variance optimisation (MVO) approach, which looks for the efficient frontier where the best expected return for a particular degree of risk is attained. Equal weighting is easier to apply since it does not take variations or expected returns into account. But this ease of use could mean that it's not 'optimal' in the Markowitz sense.

A strong and frequently false assumption behind equal weighting is that all assets have the same predicted return, risk, and correlation with other assets. More complicated solutions are frequently evaluated against the equal weight strategy (Prakash, 2020, p. 28-31).

The equal weight portfolio strategy avoids the need for asset return prediction analytics by implementing a diversification paradigm. An investor uses this schema to uniformly distribute funds over a range of $\boldsymbol{N}$ assets, thereby assigning an identical weight, $\boldsymbol{w_i}$, to each asset $\boldsymbol{i}$. The essence of this strategy is articulated through its allocation rule:

$$\boldsymbol{w_i = \frac{1}{N} \forall i \in 1, 2, \dots, N} \tag{4.13}$$

In this instance, $\boldsymbol{w_i}$ represents the portion of the total capital allocated to the asset $\boldsymbol{i}$.

The return of the equal weight portfolio, $\boldsymbol{R_P}$ the total of each individual asset's returns, each given equal weight, within a predetermined time range. The portfolio return is expressed mathematically as follows:

$$\boldsymbol{R_P = \sum_{i=1}^{N} w_i R_i} \tag{4.14}$$

The total of the asset returns can be reduced to the mean due to the uniformity of asset weights in an equal weight construct:

$$\boldsymbol{R_P = \frac{1}{N} \sum_{i=1}^{N} R_i} \tag{4.15}$$

This formulation provides a simple but efficient method for calculating portfolio returns without the need for predictive financial data.

An observable indicator of risk is the equal weight portfolio's variance, or $\boldsymbol{\sigma_P^2}$. It combines the correlations between the returns of several assets as well as the volatility of each asset alone. The following is an estimate of the portfolio risk:

$$\boldsymbol{\sigma_P^2 \approx \frac{1}{N^2} \sum_{i=1}^{N} \sigma_i^2 + \frac{1}{N^2} \sum_{i \neq j} \rho_{ij} \sigma_i \sigma_j} \tag{4.16}$$

Here $\boldsymbol{\sigma_i^2}$ symbolises the variation in the return on the $\boldsymbol{i^{th}}$ asset, while $\boldsymbol{\rho_{ij}}$ captures the relationship coefficient between asset returns $\boldsymbol{i}$ and $\boldsymbol{j}$**,** with $\boldsymbol{\sigma_i \sigma_j}$ as the product of the standard deviations of each of them.

The equal weight portfolio avoids the complexities of Mean-Variance Optimisation (MVO) and other advanced allocation strategies that call for covariance matrix computation and return forecasting. Its ability to withstand estimating errors makes it a desirable characteristic since it eliminates the requirement for accuracy when forecasting future asset performances. It may accept a higher empirical risk in comparison to a portfolio designed on the lowest variance frontier, but it provides protection from estimate errors and market capitalization biases (Sen & Sen, 2023). Comparison of portfolio techniques shown in Table 4.1.

Table 4.1: Comparison of Portfolio Techniques

Feature	**Equal Weight Portfolio**	**Markowitz Portfolio Theory (MPT)**
Objective	Ensure that there is unbiased diversity and streamline the allocation process.	Make the best possible trade-off between risk and expected reward.
Complexity	Low; easy to comprehend and apply.	High; calls for covariance, variance, and estimated return calculations.
Assumptions	Every asset has the same risk and expected return.	Investors are risk averse, and returns are distributed normally.
Risk Management	Managing risk mostly involves diversification.	A portfolio is built on the efficient frontier in order to reduce risk relative to a certain level of projected return.
Data Requirement	Minimal; doesn't need covariance matrices or return forecasts.	Extensive; necessitates accurate projections of risks and returns in the future.
Error Estimation	Minimal; independent of anticipated returns.	Higher; estimate errors may cause considerable departures from the ideal portfolio.

Source: Created by Author

The Equal Weight Portfolio and Markowitz Portfolio Theory (MPT) approaches are contrasted in the above table. By giving each asset, the same weight and assuming equal risk and return, the Equal Weight Portfolio approach emphasises simplicity and is simple to apply with low data needs and error estimation. MPT, in comparison, requires more intricate computations of covariances, variances, and predicted returns in order to optimise the trade-off between risk and return. MPT relies on the assumption of risk-averse investors and a normal distribution of returns; hence, it necessitates detailed data and accurate predictions, yet imprecise projections could result in large estimation errors.

4.2.3. Risk-Adjusted Performance Measures

Throughout the field of investment management, a portfolio's effectiveness is not only determined by the absolute returns it generates, but also by how well it performs when adjusted for risk. A risk-adjusted statistic like this one provides a more comprehensive picture by comparing the investment's return to the risk taken to get it. The important point of this research is risk-adjusted performance measures (RAPMs), which provide a baseline for comparing investment portfolios with varying risk profiles (Plantinga & de Groot, 2001). We are tried to gather different risk-adjusted performance measures for portfolio optimization in Table 4.2.

Table 4.2: Different Risk-adjusted Performance Measures for Portfolio Optimization

Performance Measure	Formula	Focus	Advantage	Reference
Sharpe Ratio	$\frac{R_p - R_f}{\sigma_p}$	Total risk	Balances reward with total risk	(Sharpe, 1966, p. 425)
Sortino Ratio	$\frac{R_p - R_f}{\sigma_d}$	Downside risk	Underlines returns in relation to downside volatility	(Sortino & Price, 1994, p. 59-64)
Treynor Ratio	$\frac{R_p - R_f}{\beta_p}$	Market risk	Reflects systematic risk instead of total risk	(Treynor, 1965, p. 63-75)
Alpha	$R_p - [R_f + \beta_p(R_b - R_f)]$	Excess return	Specifies performance on a risk-adjusted basis beyond the benchmark	(Jensen, 1968, p. 389-416)
Omega Ratio	$\frac{\int_{\mathrm{MAR}}^{\infty}(1 - F(x))\ dx}{\int_{-\infty}^{\mathrm{MAR}} F(x)\ dx}$	Gain to loss probability	Compares the probability of gains versus losses relative to a minimum suitable return	(Shadwick & Keating, 2002, p. 59-84)

Source: Created by Author

In comparing risk-adjusted performance measures, a variety of metrics that are customised for distinct aspects of risk and return are seen. The fundamental metric is the Sharpe Ratio, which was developed by Sharpe (1966, p. 425). It gives investors an idea of the excess return per unit of overall volatility and accounts for both upward and downward changes in the value of the portfolio. Its simplicity and wide applicability are its strongest points, even though it cannot distinguish between beneficial negative risk and acceptable upward volatility.

By focusing only on the downside deviation, the Sortino Ratio (created by Sortino and Price, 1994) improves on this strategy and provides a more focused evaluation of risk that penalises negative volatility, which is the main worry of most investors. Developed by Treynor (1965), the Treynor Ratio turns the focus to market risk by using beta to explain how a portfolio moves with the market. This makes it more accessible to investors who are more interested in systematic risk than in the overall volatility of their portfolio.

Extending the perspective even further, the Omega Ratio (Shadwick and Keating, 2002, p. 59-84) compares the probability and size of gains to losses in relation to a selected threshold, so capturing a more comprehensive perspective by taking into account the complete range of returns. Last but not least, Young (1991) introduced the Calmar Ratio, a metric that is highly valued in the assessment of hedge funds and other comparable investment vehicles. It focuses specifically on drawdown risk and provides insight into the return of a portfolio in the context of the maximum observed loss over a given period.

Overall, every ratio offers a different perspective; some evaluate performance in relation to overall risk, while others give more weight to downside risks or systemic risks associated with fluctuations in the market. The appropriate implementation of these safeguards relies on the investment horizon, the investor's risk tolerance, and the particular goals of the portfolio under consideration. These risk-adjusted performance metrics are essential tools in the portfolio optimisation toolbox, helping to maximise absolute returns, minimise losses, or monitor performance in comparison to a benchmark.

4.2.4. Long Short-Term Memory (LSTM)

The use of Long Short-Term Memory (LSTM) networks in portfolio optimisation is examined in this section. Portfolio optimisation is an essential field of finance that aims to distribute assets throughout a portfolio to maximise return and minimise risk. Because of its special ability to handle sequential data, LSTM networks are a priceless tool for financial time series analysis. LSTM may greatly increase the accuracy of asset price forecasts by capturing the temporal relationships in market data. This improves the executive process in portfolio management (Lu, 2023).

Through their distinct architecture, LSTM networks can process and predict data sequences more efficiently than typical neural networks. They are especially well-suited for jobs like speech recognition, time-series analysis, and natural language processing because of this aptitude. The input gate, forget gate, and output gate are the three primary gates that make up the LSTM model. The memory cell, which stores the internal state of the network, and the information flowing into and out of it are both controlled by these gates. A simplest LSTM architecture can be seen in Table 4.3.

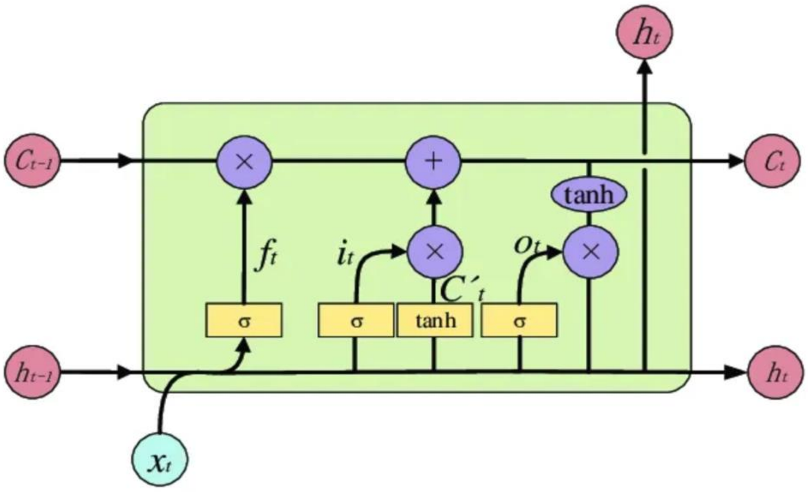

Figure 4.3: LSTM Architecture

Source: (J. Doe, 2023)

The following is a description of the mathematical processes that occur inside an LSTM cell:

1. **The Forget Gate:** Selects which data from the cell state should be removed.
2. **The Input Gate:** Adds fresh data to the cell state.
3. **The Output Gate:** Decides the next hidden state, based on the cell state and the output of the input and forget gates.

The operations within an LSTM cell can be mathematically represented as follows:

Forget Gate: $\boldsymbol{f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)}$ (4.17)

Input Gate: $\boldsymbol{i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)}$ (4.18)

Cell State Update: $\boldsymbol{\widetilde{C}_t = \tan\mathrm{h}(W_C \cdot [h_{t-1}, x_t] + b_C)}$ (4.19)

Final Cell State: $\boldsymbol{C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t}$ (4.20)

Output Gate: $\boldsymbol{o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)}$ (4.21)

Hidden State: $\boldsymbol{h_t = o_t * \tan\mathrm{h}(C_t)}$ (4.22)

As a result of their exceptional capacity to identify long-term dependencies in sequential data, LSTM (Long Short-Term Memory) networks are particularly well-suited for a number of applications in the financial industry. Time-series data, which is widely available in finance and includes stock prices, market indices, and economic indicators, is frequently the focus of these applications (Zhang, 2023, p. 335-342). We go into further detail on LSTM network applications in finance below, focusing on more extensive and specialised applications:

1. **Stock Price Prediciton:** Using historical data, LSTM networks can forecast future stock prices. Because of their ability to simulate complicated patterns in time-series data, they are perfect for identifying trends and seasonality in stock price movements. To increase forecast accuracy, LSTM models can additionally include extra data like trade volume, open interest, and economic indices.

2. **Market Sentiment Analysis:** Market sentiment, a significant factor in determining market movement, can be measured by LSTM networks through the analysis of textual data from news articles, social media, and financial reports. Sentiment research models are able to forecast the effects of news events and public opinion on market indexes and stock prices.

3. **Portfolio Optimization:** An asset portfolio's expected future returns can be forecast using LSTM networks. Long-term capitalization rate (LTCM) models are useful for building portfolios that optimize returns while minimizing risk, responding over time to shifts in market conditions by analyzing the correlations and temporal patterns among various assets.

4. **Algorithmic Trading:** LSTMs can be used in algorithmic trading to forecast short-term changes in stock prices, allowing traders to enter winning trades in response to anticipated changes in price. To help them make quick trading decisions, these models can be trained on high-frequency trading data and can incorporate a variety of market indications.

5. **Risk Management:** LSTM networks may analyze sequential data on payment histories, economic conditions, and other pertinent financial variables to model the probability of default on loans or credit products. This can be very helpful in determining and controlling credit risk.

6. **Fraud Detection:** Unusual patterns in transaction data that can point to fraud can be found by LSTM models. The model is able to identify transactions that considerably depart from the regular patterns of legitimate transactions.

4.2.5. Bidirectional Long Short-Term Memory (Bi-LSTM)

The conventional LSTM architecture is extended with bidirectional long short-term memory (Bi-LSTM) networks, which enable data processing in both forward and backward orientations. This method is especially helpful in the financial industry, where forecasts can be improved by knowing the data sequence from both historical and prospective viewpoints (Graves & Schmidhuber, 2005, p. 1272-1280). For example, by capturing dependencies in both directions of time, Bi-LSTMs can use this bidirectional processing to create more accurate forecasts in stock price prediction.

Two LSTM layers make up a Bi-LSTM; these layers process the input sequence both forward and backward, concatenating their outputs at each time step. As a result, the model is able to incorporate data from the sequence's past and future settings (Graves & Schmidhuber, 2005).

Regarding a series of inputs $\mathbf{X} = (\mathbf{x_1}, \mathbf{x_2}, \dots, \mathbf{x_T})$**,** the B-LSTM produces forward hidden states $\left(\overrightarrow{\mathbf{h_1}}, \overrightarrow{\mathbf{h_2}}, \dots, \overrightarrow{\mathbf{h_T}}\right)$ and backward hidden states $\left(\overleftarrow{\mathbf{h_1}}, \overleftarrow{\mathbf{h_2}}, \dots, \overleftarrow{\mathbf{h_T}}\right)$**,** combining these at each time step to form $\mathbf{h_t} = \left[\overrightarrow{\mathbf{h_t}}; \overleftarrow{\mathbf{h_t}}\right]$**.**

To be able to use Bi-LSTM models for stock pirce prediction, sequences of past stock prices and maybe other pertinent financial data must be included. This way, the model can learn from the extensive temporal context and forecast future prices like the illustrated in Figure 4.4. This methodology offers a considerable edge in stock price prediction by identifying patterns and relationships that unidirectional models could miss (Murugesan, Mishra, & Krishnan, 2022).

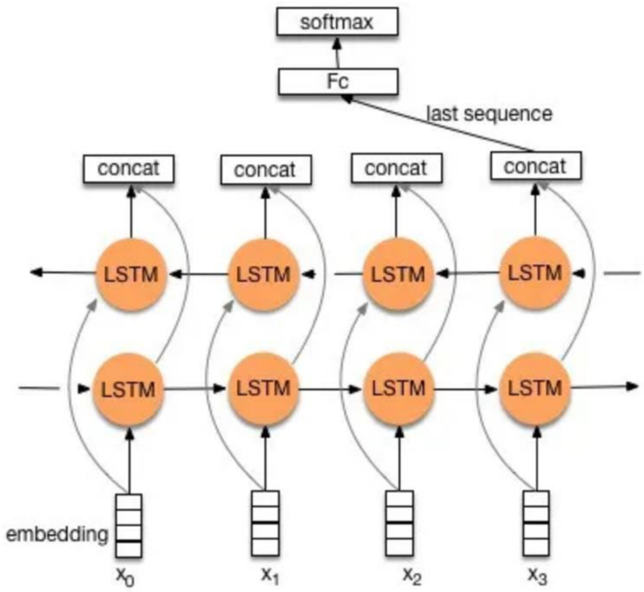

Figure 4.4: Bi-LSTM Architecture

Source: (J. Doe, 2023)

Bi-LSTM networks are a major development in financial prediction modelling. Their capacity to handle data sequences from both historical and prospective perspectives enables a more thorough comprehension of the variables affecting stock prices. These models have the ability to improve forecast accuracy, which makes them a desirable tool in financial analysis despite their increased complexity and processing demands.

In the context of literature, Long Short-Term Memory (LSTM) and Bidirectional Long Short-Term Memory (Bi-LSTM) networks are mainly differentiated by their ability to process directions and the intricacy of their architecture, which in turn affects how well-suited they are for different types of predictive modelling applications. In time-series data, where historical context is necessary, LSTMs are skilled at capturing long-term dependencies because they progressively analyse data from the past to the future. Because of this unidirectional flow, LSTMs are especially useful for applications like stock price prediction and time-series forecasting, which reduce the complexity of the design and computational requirements. On the other hand, by processing data in both forward and backward directions, Bi-LSTMs improve the LSTM framework by combining the past and future contexts for each given point in the sequence. This bidirectional analysis makes it easier to comprehend data sequences more thoroughly, particularly in domains like natural language processing and some complicated financial studies where the context of the future can greatly influence how previous occurrences are interpreted. Nevertheless, higher computational and architectural requirements accompany this superior experiences. As a result, the particular requirements of the task determine which of the LSTM and Bi-LSTM models to use, weighing model complexity and computational efficiency against the requirement for contextual completeness.

4.2.6. Gated Recurrent Unit (GRU)

Cho et al. (2014, p. 1724-1734) introduced Gated Recurrent Units (GRUs) as a kind of recurrent neural network (RNN) architecture as a simplified version of Long Short-Term Memory (LSTM) networks as illustrated in Figure 4.5. Like LSTMs, GRUs can also detect long-term dependencies within sequential data, but they do so with a simpler structure and fewer parameters. Because of this, GRUs provide an effective substitute without appreciably sacrificing the model's performance, particularly in applications with constrained computational resources.

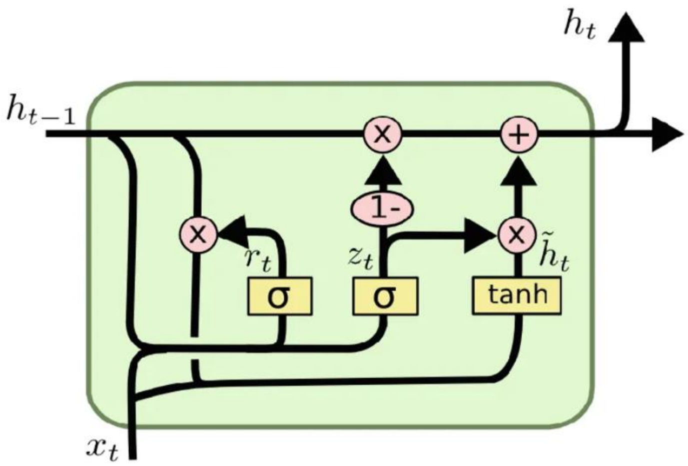

Figure 4.5: GRU Architecture

Source: (J. Doe, 2023)

The reset gate and the update gate are the two gates that make up the GRU architecture. By deciding how much of the previous data should be carried over into the future, these gates solve the vanishing gradient issue that plagues conventional RNNs.

- **Reset Gate:** Decides how much of the past information to forget.
- **Update Gate:** Determines how much of the past information to pass to the future.

The GRU operations can be described as follows:

1. **Update Gate:** $\mathbf{z_t} = \boldsymbol{\sigma}(\mathbf{W_z} \cdot [\mathbf{h_{t-1}}, \mathbf{x_t}])$ (4.23)
2. **Reset Gate:** $\mathbf{r_t} = \boldsymbol{\sigma}(\mathbf{W_r} \cdot [\mathbf{h_{t-1}}, \mathbf{x_t}])$ (4.24)
3. **Candidate Activation:** $\tilde{\mathbf{h}}_\mathbf{t} = \mathbf{tan\,h}(\mathbf{W} \cdot [\mathbf{r_t} * \mathbf{h_{t-1}}, \mathbf{x_t}])$ (4.25)
4. **Final Output:** $\mathbf{h_t} = (\mathbf{1} - \mathbf{z_t}) * \mathbf{h_{t-1}} + \mathbf{z_t} * \tilde{\mathbf{h}}_\mathbf{t}$ (4.26)

Where:

- $\boldsymbol{x_t}$ is the input at time step $\boldsymbol{t}$,
- $\boldsymbol{h_t}$ is the output at time step $\boldsymbol{t}$,
- $\boldsymbol{\sigma}$ denotes the sigmoid function, and
- $*$ denotes an element-wise multiplication.

GRUs have been effectively used in the financial realms, especially in the prediction of stock prices, where their capacity to handle time-series data and identify temporal connections is essential. GRUs are able to forecast future stock prices with a level of accuracy that rivals that of more sophisticated models, like LSTMs, by using historical stock price data as well as possibly other pertinent financial factors.

In the field of sequence modelling, Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTMs) networks—as well as its bidirectional variant, Bi-LSTMs—each have particular benefits that are mainly attributed to their computational efficiency and architectural complexity. Since they require more computing power to capture long-term dependencies, LSTMs with their three-gate mechanism are well suited for a wide range of challenging jobs where deep temporal connection modelling is essential. By combining gates and states, GRUs streamline the LSTM architecture and produce a more computationally efficient model that can still handle long-term dependencies well. This makes them a good option in situations where speed is fundamental or computational resources are limited. While B-LSTMs double the computational requirements, they offer a comprehensive view of the sequence data and are especially useful for tasks where understanding the full context significantly improves model performance. B-LSTMs extend the LSTM framework to analyse data from both past and future contexts. The application's unique requirements, such as the degree of temporal dependencies, the requirement for bidirectional context processing, and the available computational resources, will determine which of these designs is best (Hamayel & Owda, 2021, p. 477-496). We described comprehensive analysis of LSTM, GRU and Bi-LSTM in Table 4.3.

Table 4.3: Comprehensive of LSTM, GRU and Bi-LSTM

Characteristic	LSTM	GRU	Bi-LSTM
Gates	3 (input, output, forget)	2 (update, reset)	3 (input, output, forget) for each direction
Parameters	More, due to separate gates and states	Fewer, due to merged gates and states	Double that of LSTM, due to bidirectional processing
Computational Efficiency	Lower, due to complexity	Higher, due to simplification	Lower, because of processing data in both directions
Training Time	Longer, due to more parameters	Shorter, compared to LSTM	Longer, because of increased computational demand
Ability to Capture Long-term Dependencies	High	Slightly lower than LSTM	High, with added advantage of capturing dependencies from both past and future
Suitability for Bidirectional Context	Unidirectional	Unidirectional	Fundamentally bidirectional, captures context from both directions
Common Applications	Complex sequence modeling tasks (e.g., machine translation, text production)	Tasks involving efficient computation without significant loss in performance (e.g., language modeling, speech recognition)	Tasks where context from both past and future is analytical (e.g., sentiment analysis, text classification)

Source: Created by Author

When it comes to computational efforts on high-performance computing (HPC) systems, GRUs are more appropriate for speed and resource optimisation because of their higher efficiency and faster training times than LSTMs, which are more complex and demand a lot of resources. Because of its bidirectional processing and doubled parameters, bi-LSTMs require the highest computational power and training time, which makes them perfect for jobs requiring thorough dependency capture and bidirectional context.

4.2.7. Random Forest (RF)

Regarding classification, regression, and other tasks, Random Forest is an ensemble learning technique that builds a large number of decision trees during training and outputs the class that represents the mean regression or the mode of the classification of the individual trees. By compensating for decision trees' propensity to overfit to their training set, Random Forests offer a more broadly applicable solution. This method, which was first presented by Breiman (2001), creates a potent predictive modelling strategy by fusing the flexibility of decision trees with their simplicity.

Random Forest is a useful tool in finance that may be used to solve a variety of issues, including stock market prediction and credit scoring. Random Forest forecasts future stock prices by utilising historical data as its input. The approach is especially helpful for analysing complicated financial markets where many variables can effect stock prices since it can handle multidimensional data and find the most influential aspects.

So as to divide nodes, the Random Forest algorithm first randomly chooses a subset of features for every single tree. For regression problems, the final forecast is determined through averaging the forecasts of all trees, while for classification, it is determined by a majority vote. This process is repeated for a predetermined number of trees (Hota & Dash, 2021, p. 1-9).

Assuming a collection of training vectors $X = x_1, x_2, \dots, x_n$ with matching goals set $Y = y_1, y_2, \dots, y_n$, a Random Forest regressor employs averaging to boost prediction accuracy and manage over-fitting by fitting multiple classification decision trees on different subsamples of the dataset like in Figure 4.6.

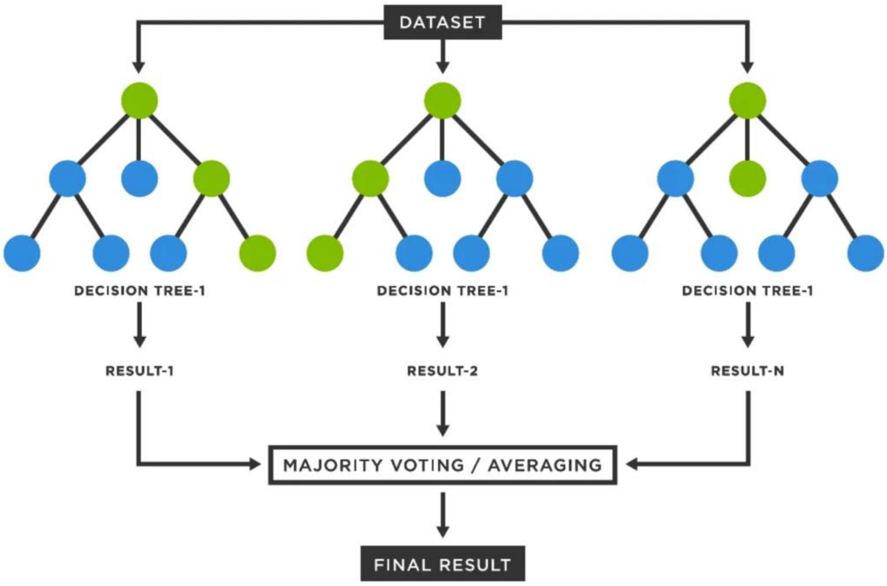

Figure 4.6.: Random Forest Decision Tree

Source: (Gunay, D., 2023)

Random subspace and bagging are essentially the two fundamental ideas on which random forest is based.

- **Bagging (Boostrap Aggregating):** It involves combining random sampling with replacement to create several subsets of the training data, which are then used to train a number of decision trees. The model is less prone to overfitting and more accurate as a result of the combination of these trees' predictions.
- **Random Subspace:** Each every decision tree in the ensemble, it describes the process of arbitrarily choosing a subset of features (variables or attributes) from the initial feature set. More precise and reliable predictions are produced by the Random Forest, particularly when working with high-dimensional datasets or datasets with a large number of irrelevant features, because each tree is able to concentrate on a distinct collection of features, allowing the Random Forest to identify various patterns and relationships within the data (Gunay, D., 2023).

4.2.8. Support Vector Machines (SVM)

A strong and adaptable supervised machine learning approach for regression, outlier identification, and classification is called Support Vector Machine (SVM). SVM was first introduced by Cortes and Vapnik in 1995. It is especially well-known for its efficacy in high-dimensional spaces and situations where there are more dimensions than samples. The basic idea behind it is to maximise the distance between the nearest points in each class by identifying the hyperplane in the feature space that best divides the various classes.

Stock price prediction is one of the many predictive tasks in finance that SVM may be used for. Through the classification of stock price fluctuations, such as an increase or decrease in price, SVM can be trained on past financial data to forecast future trends. The technique can be modified to employ Support Vector Regression (SVR), which focuses on minimising the error within a specific threshold, for regression tasks (e.g., forecasting the actual stock price) (Ji,2022, p. 267-272). A simplest example for SVM stock price prediction illustrated in Figure 4.7.

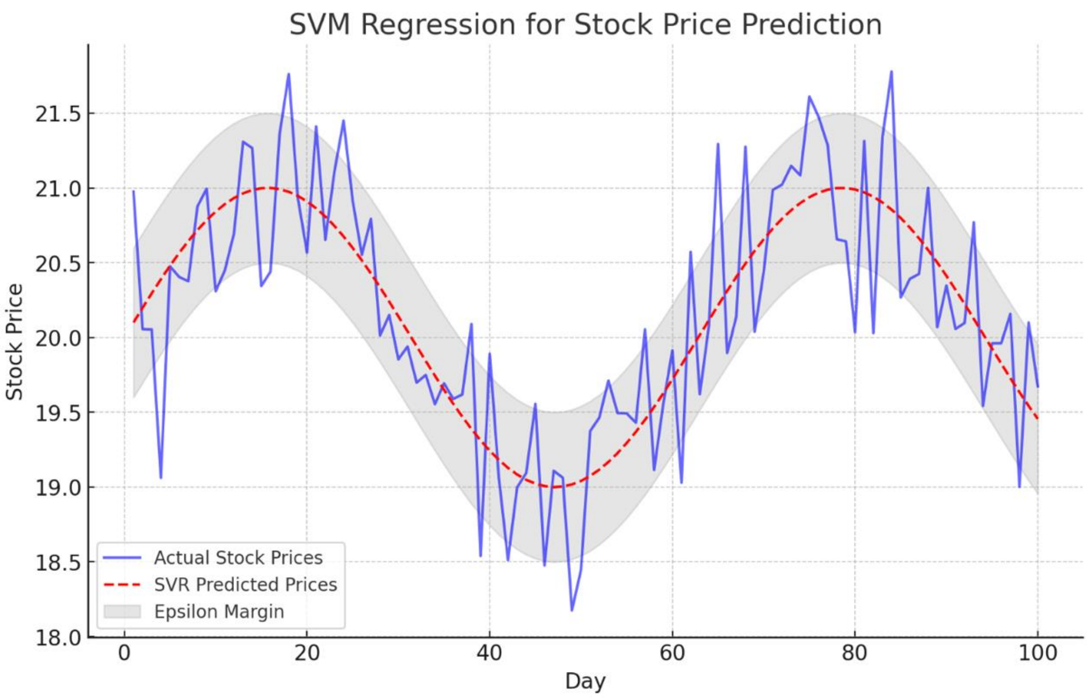

Figure 4.7: Stock Price Prediction with SVM Regression

Source: Created by Author

The idea of Support Vector Regression (SVR) in relation to stock price prediction is demonstrated in the graphic above. The actual stock prices over a 100-day period are represented by the blue line, which exhibits some swings around a sinusoidal trend. The SVR's projected stock values are shown by the red dashed line, which closely tracks the real prices' underlying pattern.

The ϵ-margin is shown as the dark grey region surrounding the SVR prediction line. The SVR model considers predictions within this margin to be acceptable, and errors within this zone are not penalised. This SVR feature acknowledges the noise and volatility that are inherent in stock price fluctuations and permits some variations between the expected and actual values.

In order to solve problems with regression, Support Vector Regression (SVR) modifies the ideas of Support Vector Machines (SVM). SVR seeks to fit the optimal hyperplane within a predetermined margin of tolerance (ϵ) that captures as many data points as feasible, as opposed to SVM classification, which finds a hyperplane to distinguish various classes while maximising the margin between classes. This method works well for continuous outcome prediction tasks like stock price forecasting since it tolerates some prediction errors as long as they stay within a predetermined range (Shi, Li, & Li, 2011, p. 468-471).

Finding a function $\boldsymbol{f(x)}$that is as flat as possible and deviates from the actual observed targets $\boldsymbol{y_i}$ by a value no larger than $\boldsymbol{\epsilon}$ for each training data point $\boldsymbol{x_i}$ is the aim of support vector rewriting (SVR). Because of its flatness, the model appears to be attempting to minimise the weights, which lowers the model's complexity and helps prevent overfitting.

Regarding linear SVR, the function $\boldsymbol{f(x)}$can be represented as:

$$\mathbf{f(x) = w \cdot x + b} \tag{4.27}$$

Where:

- $\mathbf{w}$ is a vector,
- $\mathbf{x}$ **represents** the input features,
- $\boldsymbol{b\ is\ bias}$,

The objective is to reduce the following:

$$\boldsymbol{\frac{1}{2}|w|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)} \tag{4.28}$$

Subject to:

$$\mathbf{y_i - (w \cdot x_i + b) \leq \epsilon + \xi_i} \tag{4.29}$$

$$\mathbf{(w \cdot x_i + b) - y_i \leq \epsilon + \xi_i^*} \tag{4.30}$$

$$\mathbf{\xi_i, \xi_i^* \geq 0} \tag{4.31}$$

Here, $\boldsymbol{\xi_i}$ $\boldsymbol{and}$ $\boldsymbol{\xi_i^*}$ are slack variables that quantify the extent to which the $\boldsymbol{\epsilon}$ – insentive zone by the predictions (when these values are outside of the ϵ-margin, the separation from the real values). $\boldsymbol{C}$ is a regularization parameter that balances the transaction between the flatness of $\boldsymbol{f}(\boldsymbol{x})$ and the amount up to which abnormalities larger than $\boldsymbol{\epsilon}$ are accepted. In other words, SVR attempts to fit the error within a certain threshold (ϵ), ensuring that errors do not exceed this margin, while also keeping the model as simple or "flat" as possible to escape overfitting. This creates SVR particularly useful for predicting constant variables, such as stock prices, where an edge of prediction error is acceptable and even predictable.

SVR's versatility and efficacy in capturing the complicated, nonlinear correlations present in market data are demonstrated by its application in financial fields like stock price prediction, which provides insightful information for financial analysis and investment strategies (Papadimitriou, Gogas, & Athanasiou, 2020, p. 241-258).

4.2.9. Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting, or XGBoost, is a sophisticated gradient boosting method that excels in speed and functionality. Since its introduction by Chen and Guestrin (2016, p. 785-794), XGBoost has gained significant popularity as a machine learning competition tool due to its accuracy, scalability, and efficiency. In order to minimise the loss function, it adds predictors (trees) one after the other, correcting the errors created by the preceding ones through the use of gradient descent.

XGBoost can be used for a number of applications in the finance industry, such as fraud detection, credit scoring, and stock price prediction, among others. For stock price predition, we illustred XGBoost in Figure 4.8. In order to anticipate future stock prices, XGBoost can examine past stock data in addition to other financial factors. Complex patterns in financial time series data can be captured with exceptional effectiveness thanks to its capacity to handle nonlinear correlations and interactions between feature (Wu, 2023, p. 3383-3388).

Under a combination of various improvements, including a new tree learning algorithm that manages sparse data, a more regularised model formalisation that prevents over-fitting, and more effective computation of the gradient statistics, XGBoost outperforms the gradient boosting framework. XGBoost seeks to optimise the objective function denoted by:

$$\mathrm{Obj}(\boldsymbol{\theta}) = \sum_{i=1}^{n} l\left(y_i, \widehat{y_i^{(t)}}\right) + \sum_{k=1}^{t} \Omega(f_k) \qquad (4.32)$$

Where:

- n is the number of instances,
- t indexes the trees,
- l is a convex loss function that is differentiable and calculates the difference between the expected value $\hat{y}_i^{(t)}$ and the actual target y_i,
- f_k represents the kth tree,
- Ω penalizes the complexity of the model to avoid overfitting, defined as penalises the model's complexity in order to prevent overfitting, which is described as $\Omega(\mathbf{f}) = \gamma \mathbf{T} + \frac{1}{2}\lambda \parallel \mathbf{w} \parallel^2$, where T is the number of leaves, w is the leaf weights, and γ and λ are regularization parameters.

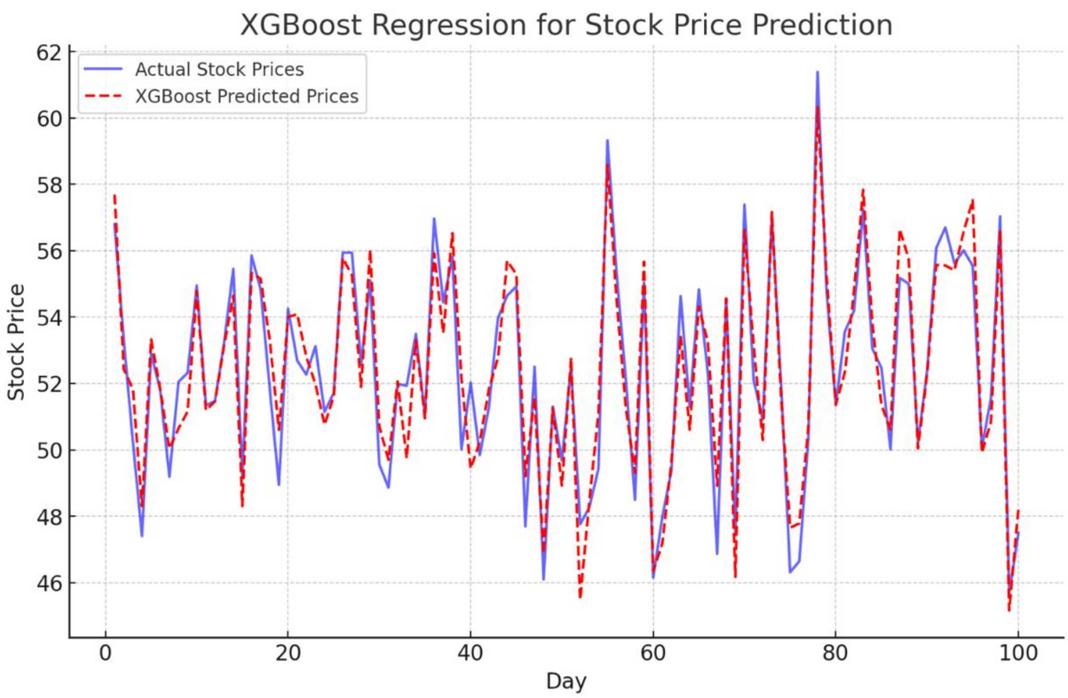

Figure 4.8: Stock Price Prediction with XGBoost Regression

Source: Created by Author

A conceptual example of employing XGBoost for regression in the context of stock price prediction is shown in the Figure 4.8. The blue line shows the real stock prices over a period of 100 days, including oscillations and trends driven by the factors that were synthesised, namely trading volume, price change from the previous day, and sentiment in the market. The stock prices predicted by an XGBoost regression model are displayed as a red dashed line; this line closely tracks the actual values and captures the underlying trend.

A potent hybrid method, the LSTM-XGBoost combo can be especially useful in fields like stock price prediction where accurate modelling of both temporal dynamics and complicated feature interactions is required. This method combines the special powers of LSTM with XGBoost to provide a powerful toolkit for addressing difficult forecasting jobs in finance and other domains (Zhu, 2023, p. 94-109). We compered RF, SVM and XGBoost in Table 4.4.

Table 4.4: Comprehensive of RF, SVM and XGBoost

Characteristic	RF	SVM	XGBoost
Model Type	Ensemble of decision trees	Supervised learning algorithm	Gradient boosting framework
Strengths	Suitable for high-dimensional data; handles overfitting; feature importance	Effective in high-dimensional spaces; works well with clear margin of separation; kernel trick	Fast performance; handles missing data; regularized model to prevent overfitting
Weakness	Slow with large numbers of trees; less explainable with more trees	Can be slow with large datasets; sensitive to feature scaling; difficult parameter tuning	Prone to overfitting; complex hyperparameters
Parameters	Number of trees; max depth; min samples split	Kernel type; regularization (C); kernel coefficient (gamma)	Learning rate; max depth; subsample rates; colsample rates
Training Time	Reasonable (can be parallelized)	Can be long because of computational cost	Fast (especially with GPU acceleration)
Interpretability	Suitable (individual trees can be visualized)	Low (decision function is not easily explainable)	Reasonable (model provides feature importance)
Computational Efficiency	Efficient (with fewer trees)	Less efficient (especially with non-linear kernels)	Very efficient (with parallel computing and tree pruning)
Classification Acceptability	Suitable (via majority voting)	Highly suitable (original design for classification)	Suitable (optimized for both classification and regression)
Typical Applications	Classification and regression tasks in varied fields; feature selection	Image recognition; text classification; bioinformatics	Structured data prediction; competitive machine learning

Source: Created by Author

The table outlines the advantages and disadvantages of the Random Forest (RF), Support Vector Machine (SVM), and XGBoost algorithms in the context of high-performance computing (HPC) systems. RF is a decision tree ensemble that performs well with high-dimensional data and can be parallelized effectively, which makes it appropriate for HPC environments. However, when a large number of trees are used, RF may become slow. Since SVM requires considerable tweaking for factors like the kernel type and regularisation coefficients, it can be less efficient and computationally expensive on high-performance computing (HPC) systems, especially when using non-linear kernels. SVM is effective in high-dimensional spaces with distinct margins of separation. The gradient boosting framework XGBoost is well suited for HPC systems due to its quick speed and computational efficiency, especially when using parallel computing and GPU acceleration. Its suitability for intricate, large-scale machine learning tasks common in HPC environments is further enhanced by its capacity to manage missing data and prevent overfitting with regularised models.

4.3. Sequence vs. Non-Sequence Data in Stock Price Prediction

The way that modelling and forecasting are approached in the field of stock price prediction is essentially shaped by the difference between sequence and non-sequence data. Sequence data pertains to datasets where the sequence in which observations are made is of utmost importance, such as time series data such as stock prices. On the other hand, non-sequence data refers to datasets in which the order of observations has no inherent significance for making predictions (Broby, 2022, p. 145-161).

The chronological order of sequence data is a defining characteristic in stock price prediction. This hierarchy is essential since a stock's value at any given moment is probably impacted by its past values. These temporal dependencies are captured by models specifically made for sequence data, such GRU (Gated Recurrent Unit), Bi-LSTM (Bidirectional Long Short-Term Memory), and LSTM (Long Short-Term Memory).

In the context of stock price prediction, non-sequence data may comprise collections of independent variables that do not have an underlying time-based ordering that affects their predictive ability. These could be outside variables that affect stock prices, technical indicators, or measures from fundamental analysis. This kind of data is more suited for machine learning models like XGBoost (eXtreme Gradient Boosting), SVM (Support Vector Machine), and RF (Random Forest).

Sequence versus non-sequence data models are chosen based on the type of data and the particular prediction task at hand:

- Sequence models provide a sophisticated method that can capture complicated time-dependent linkages for forecasts that primarily rely on past price movements and temporal patterns.
- Non-sequence models can effectively find patterns and correlations within the data when predictions are to be made based on a set of features where the chronological order is not a major factor.

In actuality, a hybrid strategy or ensemble approaches that incorporate both non-sequence and sequence models may offer a thorough approach, utilising the advantages of both data sources for improved stock price forecast accuracy. We can see those differences between sequence and non-sequence models in Table 4.5.

Table 4.5: Comprehensive of Sequence Models and Non-Sequence Models

Type	**Sequence Models**	**Non-Sequence Models**
Definition	Models that consider the data's order are best suited for datasets in which historical data can be used to forecast future events.	Models that concentrate on the relationship between attributes and the target at a specific time, analysing data without taking the sequence into account.
Examples	LSTM (Long Short-Term Memory) GRU (Gated Recurrent Unit) Bi-LSTM (Bidirectional Long Short-Term Memory)	RF (Random Forest) SVM (Support Vector Machine) XGBoost (eXtreme Gradient Boosting)
Dependency	High	Low
Memory	Yes	No
Complexity	High	Moderate to High (depends on the model and implementation)

Source: Created by Author

Financial modelling requires a considerate of the differences between sequence and non-sequence models, particularly for predicting stock prices. While non-sequence models make strong predictions based on the examination of cross-sectional data, sequence models offer profound insights into time-dependent patterns. The optimum option is determined on the particulars of the dataset and the prediction goals; a combination of models frequently produces the best outcomes.

CHAPTER FIVE

DATA ANALYSIS AND RESULTS

5.1. Introduction

The application of machine learning (ML) techniques has transformed the way that stock price prediction and portfolio optimisation are approached in the quickly developing field of finance. Conventional financial models sometimes fail to capture the nonlinear complexities and dynamic changes present in financial markets since they are primarily based on linear assumptions and historical averages. More advanced analytical techniques that can anticipate and adjust to turbulent market behaviours are thus desperately needed. This chapter outlines the study methodology and methods used to optimise equity portfolios and improve stock price projections by utilising machine learning, with the goal of bridging the gap between conventional financial theories and contemporary computer intelligence.

To address the shortcomings of traditional financial models which frequently struggle to manage big datasets or accurately represent the shades of market dynamics machine learning was first applied in the financial domain. With algorithms that can learn from data and generate predictions or judgements without needing to be specifically programmed to carry out particular tasks, machine learning presents a viable substitute. Because of its flexibility, machine learning (ML) is especially useful in the finance industry, where market circumstances are often shifting.

The assurance of machine learning models to greatly improve portfolio management efficiency and stock price forecast accuracy is what drives this research. The conventional models employed in these fields, such the Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM), mostly rely on the assumptions of market efficiency and a normal distribution of returns, which frequently do not hold true in practical situations. In contrast, machine learning models have the ability to draw conclusions and patterns from massive amounts of data that contain concealed variables and non-linear correlations.

Portfolio optimisation is the process of constructing an assortment that maximises gains while reducing loss (Markowitz, 1952). This is achieved through the meticulous selection of asset allocations for the portfolio. Portfolio optimisation within the framework of Islamic finance must adhere to the principles of Shariah, which proscribe investments in particular sectors such as wagering and alcohol, in addition to interest-bearing financial instruments (Elgari, 2008).

An indicator utilised to assess the performance of Shariah-compliant stocks listed on the Borsa Istanbul (BIST) stock exchange, the BIST-XKTUM Islamic Index is a benchmark in Türkiye. Alternatively stated, the index assesses the relative performance of Shariah-compliant equities regarding other stocks listed on the BIST stock exchange. Investors have the potential to align their investment strategies with their ethical and religious convictions through the utilisation of this index to specifically optimise their portfolios with Islamic equities and the subsequent optimisation process.

The optimisation process involves determining the optimal asset allocation by considering various parameters such as risk measures, anticipated returns, and correlations among the Islamic equities comprising the BIST-XKTUM Islamic Index.

Investors have the ability to effectively distribute their capital among the Islamic equities that are included in the BIST-XKTUM Islamic Index through the implementation of these portfolio optimisation techniques, all the while accounting for risk mitigation and diversification strategies. The primary aim is to construct investment portfolios that maximise returns while remaining compliant with the principles of Islamic finance.

5.2. Research Framework

The research framework diagram represents a methodical procedure for creating and assessing machine learning models with the objective of predicting stock performance and optimising investment portfolios as shown in Figure 5.1 below.

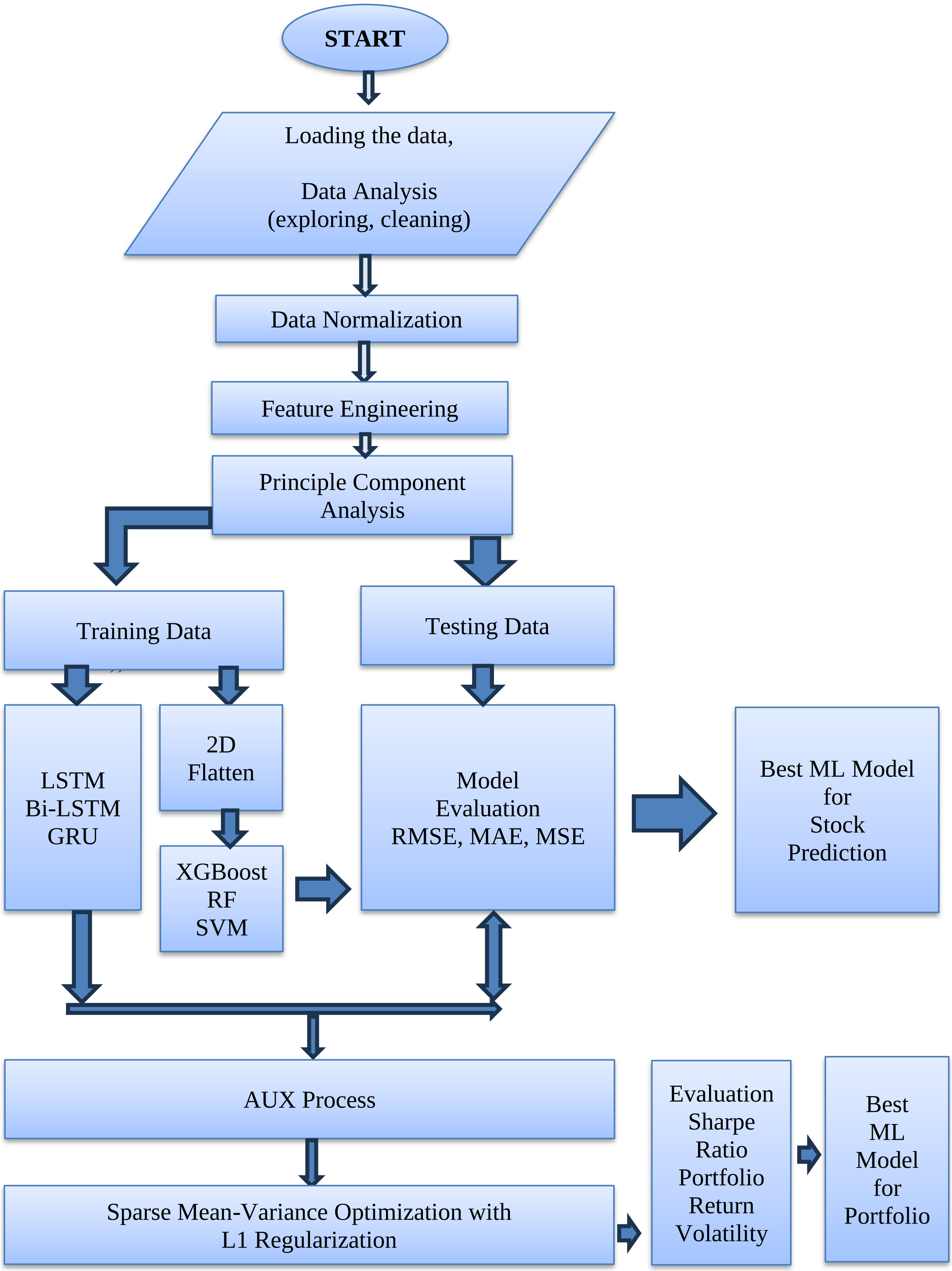

Figure 5.1.: Research Framework

Source: Created by Author

The first step is to load the data, which will then go through a full data analysis. The main goal of this analysis is to look at the dataset and understand its qualities. It also looks for and deals with abnormalities, outliers, and missing values, all of which are necessary to make sure the next analysis is valid.

The next step after cleaning the data is normalisation. The values in the dataset are brought into line with a similar scale using this method, but the ranges of values are kept as varied as possible. Normalisation is very important because it lets you compare data that was recorded on different scales at first and gets the dataset ready for machine learning algorithms to use.

Once the data has been normalised, feature engineering can be done. At this stage, new features are made from the existing data in order to improve the performance of the predictive models. It's a necessary step that can improve the model's predictions and give us more information.

After the feature engineering is done, Principal Component Analysis is used. PCA is a way to reduce the number of variables in a set of data by selecting the most important ones from a larger group. This makes the dataset easier to understand without giving up any important data.

The prepared data is then divided into two sets: training data and testing data with 80/20 rule. The training data is used to build and train various machine learning models, including:

- Long Short-Term Memory networks (LSTM)
- Bidirectional LSTM (Bi-LSTM)
- Gated Recurrent Unit networks (GRU)
- eXtreme Gradient Boosting (XGBoost)
- Random Forest (RF)
- Support Vector Machine (SVM)

After training, the models are tested to see how well they did use the testing data. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE) are some of the measures used for evaluation. The accuracy and dependability of the models' predictions can be judged by these measures.

Two main results come out of the evaluation part that are very important to the investment strategy's success:

- **Best Model Stock Prediciton:** It is decided that the best model for predicting stock prices is the one with the lowest error metrics (RMSE, MAE, MSE). The ability of this model to correctly predict stock market trends is very important for making investment decisions in the future.

- **Best Model for Portfolio Optimisation:** In the auxiliary (AUX) process, which is similar to stock forecast, the portfolio is optimised. This process is very important for allocating assets, and the following measures are used to judge it: sharpe ratio, annualized return and annualized volatility.

The model that selects the best combination of these metrics maximizing the Sharpe Ratio while taking into account the required levels of annualised return and managing annualised volatility is chosen for portfolio optimisation. This methodology allows investors to align their return targets with their risk tolerance, so optimising their investment strategy for sustained financial gain in the long run.

The research approach ultimately identifies and verifies the most appropriate models for both stock prediction and portfolio optimisation. The chosen stock prediction model has exceptional accuracy in predicting, while the portfolio optimisation model stands out for its capacity to provide the most favourable risk-adjusted returns. These models work together to support strong and well-planned management in the field of stock market investment, by considering both short-term predictive accuracy and long-term investment goals.

5.3. Data Collection and Preprocessing

5.3.1. Data Collection

Within the domain of financial economics, the establishment of an ideal investment portfolio is an objective of the utmost importance. The efficacy and inclusiveness of the underlying dataset are of the utmost importance to the process (Markowitz, 1952). The objective of this research undertaking was to amass a comprehensive dataset specifically designed to enable a nuanced investigation of portfolio optimisation in the stock market by utilising historical stock price data.

The BIST XKTUM index between first quarter 2007 to fourth quarter of 2022 consists of 203 stocks that meet the Sharia screening criteria. However, due to the time range limitations, we had to exclude the 47 most recently listed stocks from our sample, they have not data since 2007. It is very significant that the time uniformity of points of data throughout the chosen stocks is maintained to ensure the accuracy of statistical studies and the study's results (Lo, 2017). Adding stocks with shorter history records could make the analysis much more biassed. This is especially true for time-series models, where the length and consistency of data have a big effect on how well the model can detect and predict trends.

The statistical power of the study goes up with a bigger sample number. This lets researchers get more accurate predictions of the parameters of the whole community. In terms of optimising a portfolio, this means getting more accurate estimates of the returns, volatility, and relationships between the stocks in the BIST XKTUM index. In the financial markets, where small changes can have big effects, the stability that comes from a large dataset is especially critical (Rao, 2010, p. 64).

The fundamental dataset was obtained from Yahoo Finance, a reputable repository of historical financial data that provides comprehensive coverage of stock market information (including adjusted closing prices, daily trading volumes, opening, closing, high, and low prices). The rationale for choosing Yahoo Finance was its extensive collection of data and regular application in both academic and practical financial analyses (Bodie, Kane, & Marcus, 2014).

The historical range lasted for 15 years, starting from 2007 to 2022. It provided a thorough historical view that encompassed several economic cycles, market booms, and recessions. Temporal depth is central for comprehending the extended performance and volatility trends of stocks, which are necessary factors for enhancing portfolio optimization.

Large datasets are often needed for portfolio optimization methods that use complicated machine learning and statistical models because they are so complicated. There are 468,261 samples available, which lets advanced analysis methods be used to guess stock prices and make portfolios work better within the BIST XKTUM index's Sharia-compliant structure. Because the dataset is so big, it's possible to look into complicated connections and patterns that would be impossible to see in smaller datasets (Heaton, 2017, p. 305-307).

The scope of the dataset was carefully delineated to encompass a wide range of equities, thereby guaranteeing a presence in multiple sectors and market capitalizations. The inclusion of a wide range of market behaviours and the strengthening of the portfolio optimization process are both dependent on this diversity (Van Home, 1977, p. 84). The selection of equities was predicated on their pertinence to the overarching research objectives, with particular emphasis on companies that exhibited significant market activity and had accessible data throughout the designated timeframe.

The **quantmod** package in R, a potent tool for developing trading strategies and quantitative financial modelling, was used to automate the data retrieval process. The function **getSymbols** made it easier to obtain the stock data within the chosen temporal range in an effective manner. The value of this function is found in its immediate retrieval and organization of stock data in a structured manner, allowing for subsequent analysis. Verifying the completeness and quality of the retrieved data was necessary to ensure data integrity. Considering the dependence on outside data sources this step was essential. The purpose of the data integrity assessment was to verify that the data was consistent amongst stocks and time periods and that it could be used for further analytical projects.

Even though financial data is typically regarded as public information, ethical issues were carefully explored when gathering this information. The study acknowledged the privacy and proprietary concerns related to financial data and closely followed Yahoo Finance's standards for data utilization.

5.3.2. Data Preprocessing

A key stage in financial research is data preparation, which improves the quality of the data and makes sure it is suitable for modelling and interpretation. This sets the stage for further analysis. This approach is critical to handling the subtleties and inherent complexity of data from financial time series in the framework of portfolio optimization inside the BIST XKTUM index. Preprocessing consists of a number of stages; each designed to improve the dataset's analytical usefulness and address certain issues.

In financial datasets, missing data is a common problem that might result from data entry mistakes, market closures, or non-trading days. Missing data can cause major distortions in predictive modelling and statistical studies, therefore finding and imputation of missing values requires careful consideration. Through a methodical analysis of the information, missing values were painstakingly found in this study. Python packages were utilized to identify missing data points for a variety of financial indicators, such as opening, closing, high, low, and trading volumes.

It was decided to use imputation techniques, giving priority to those that keep the data's core patterns and relationships. For numerical variables, mean estimation was used to fill in missing values with the variable's mean. This method was chosen because it is easy to use and keeps the overall distribution of the dataset (Zuccolotto, 2011, p. 171-183). This method is in line with what Schafer and Graham (2002, p. 147-177) say should be done, which is to keep the original format of the data as intact as possible.

Data cleaning entailed correcting errors and removing discrepancies in the dataset. The method involved verifying stock symbols, correcting data input mistakes, and standardizing financial measures to maintain uniformity throughout the dataset. Thorough cleaning is essential to avoid mistakes from spreading in research, which might jeopardize the accuracy of the results (Azuaje, 2006).

Data preparation is a important aspect of this study, preparing the information for sophisticated analytics focused on enhancing portfolios inside the BIST XKTUM index. The study has created a strong foundation for investigating Sharia-compliant portfolio optimization by carefully cleaning, imputing, engineering features, transforming data, and splitting datasets. This paves the way for in-depth analyses and esteemed contributions to the Islamic finance sector.

The dataset contained daily financial information for 163 distinct stocks spanning 15 years, such as open, high, low, close, and adjusted closing prices, as well as trading volumes. Upon first assessment, missing values were found in many columns such as open, high, low, close, volume, and adjusted prices, requiring a comprehensive cleaning procedure.

Due to the essential significance of correct data for time-series analysis in financial datasets, our main strategy was to detect and eliminate rows with missing values. The technique was used to preserve the historical integrity of the information, which is essential for future time-series analysis and forecasting models. The dataset was reduced to 467,682 full records by this procedure, providing a strong basis for additional investigation.

The dataset for THYAO.IS, obtained from Yahoo Finance, comprises daily price measures spanning from 2007 to 2022. Figure 1 displays a time series graph illustrating the daily closing prices of THYAO.IS stock, along with a 30-day rolling average as shown in Figure 5.2. This graph effectively highlights significant patterns and variations in the stock's performance over time.

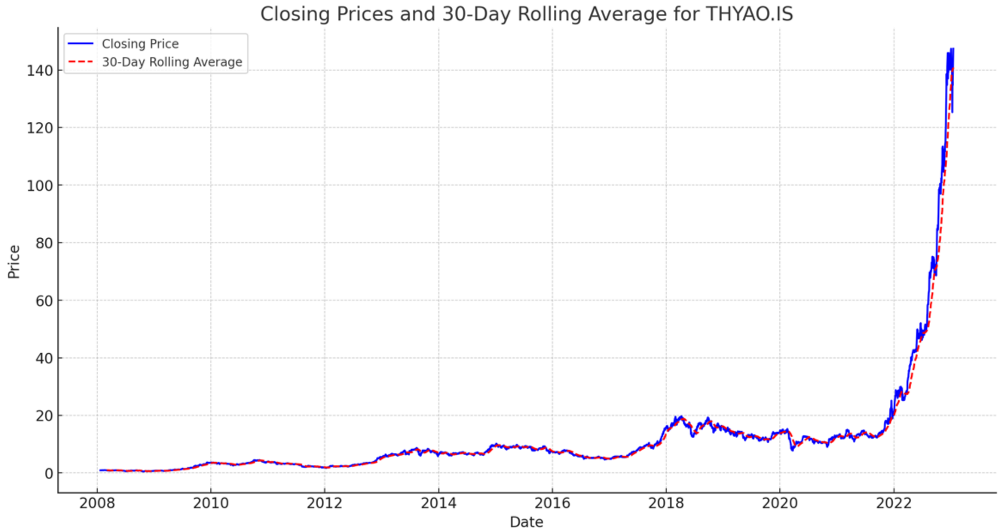

Figure 5.2: Closing Prices and 30-Day Rolling Average for THYAO.IS

Source: Created by Author

Each stock is characterised by its daily 'Open', 'High', 'Low', 'Close' prices, as well as the 'Volume' of shares traded. The information also includes 'Adjusted' closing prices, which take into consideration business events such as dividends and stock splits. Figure 5.3 below is a good example of the closing prices and trading volumes for 'ALBRK.IS'. It showcases typical daily trading patterns and highlights major market actions.

Figure 5.3: Closing Prices and Volume for ALBRK.IS

Source: Created by Author

The following table presents a detailed statistics summary for 'YATAS.IS', which is one of the stocks included in the dataset obtained from Yahoo Finance. This summary provides fundamental information, including the mean, standard deviation, minimum, maximum, and quartiles, for the open, high, low, close prices, and trading volume as shown Table 5.1.

Table 5.1: Statistical Summary for YATAS.IS

	Open	High	Low	Close	Volume
count	3862.0	3862.0	3862.0	3862.0	3862.0
mean	3.9966444396685654	4.075850285603315	3.912487162610047	3.9954605075090623	2678022.7879337133
std	5.745163757806534	5.876282286972842	5.619035760374221	5.75366371687507	4691656.433279352
min	0.141389	0.150225	0.139179	0.143598	0.0
25%	0.342857	0.351428	0.34	0.342857	717881.5
50%	0.6642855000000001	0.671428	0.652676	0.662857	1510977.5
75%	6.08	6.1875	5.95	6.055	2980618.25
max	36.380001	37.68	35.259998	36.5	134955800.0

Source: Created by Author

This serves as an exemplary illustration of the meticulous study made possible by our dataset, showcasing the diversity and trading patterns of stocks within the BIST XKTUM index.

5.4. Future Engineering

The creation of predictive models in finance is heavily dependent on feature engineering, which also has a major influence on the models' accuracy and performance. Researchers can improve model resilience and predictive capacity by uncovering hidden patterns that are not obvious right away by the careful selection, modification, or creation of new features from raw data (Franklin, 2005, p. 83-85).

Financial models may be further improved by adding technical indicators as features, which go beyond simple financial measures. Technical indicators offer further insights into market patterns and investor behaviour through mathematical computations based on stock price and volume. As demonstrations, consider:

- **Moving Averages:** For identifying trends, price data is smoothed out using the Simple Moving Average (SMA) and Exponential Moving Average (EMA). Plotting SMAs and EMAs above stock price charts may be useful in identifying trend directions and crossing points, which indicate possible times to purchase or sell.
- **Relative Strength Index (RSI):** This indicator evaluates whether the market is overbought or oversold by calculating the size of recent price fluctuations. Models are able to take momentum effects into account when RSI is included as a feature in the dataset. This is important for short-term trading strategies. Plotting price data alongside an RSI time series graph might show divergences that might occur before price reversals.
- **Bollinger Bands:** These bands expand during times of higher market volatility and shrink during times of lower volatility. They self-adjust depending on this information. By adding Bollinger Bands to the information, one may obtain a more nuanced accepting of market circumstances by measuring price volatility in relation to moving averages.

We computed a number of new financial measures in order to improve the quality of our dataset and the prediction ability of our models. These measures were selected in order to accurately reflect each stock's return and volatility characteristics, which are key markers of risk and financial success. Among the newly designed features are:

1. **Daily Returns:** Determined by summing the percentage changes in closing prices over the course of a day.
2. **20-Day Returns:** Determined by calculating the closing price's percentage change over a 20-day rolling timeframe.

3. **Rolling 20-Day Volatility:** This indicator of price volatility and risk is calculated as the standard deviation of daily returns over an extended 20-day span.
4. **Normalized 20-Day Returns and Volatility:** In order to make model comparison and incorporation easier, the min-max scaling approach was used to normalize both the 20-day returns and the rolling 20-day volatility.

Our manufactured features are anticipated to provide a substantial contribution to our financial models' prediction accuracy, allowing for a more sophisticated comprehension of volatility patterns and trends in stock performance.

Our dataset is reliable because of the thorough feature engineering and data cleaning procedures that were carried out, and they also add insightful information on stock performance and volatility. These improvements are essential for lowering bias and raising our financial models' overall predictive power, providing a strong basis for further studies.

Figure 5.4 illustrates the daily returns and 20-day rolling volatility of specific equities, obtained from our dataset.

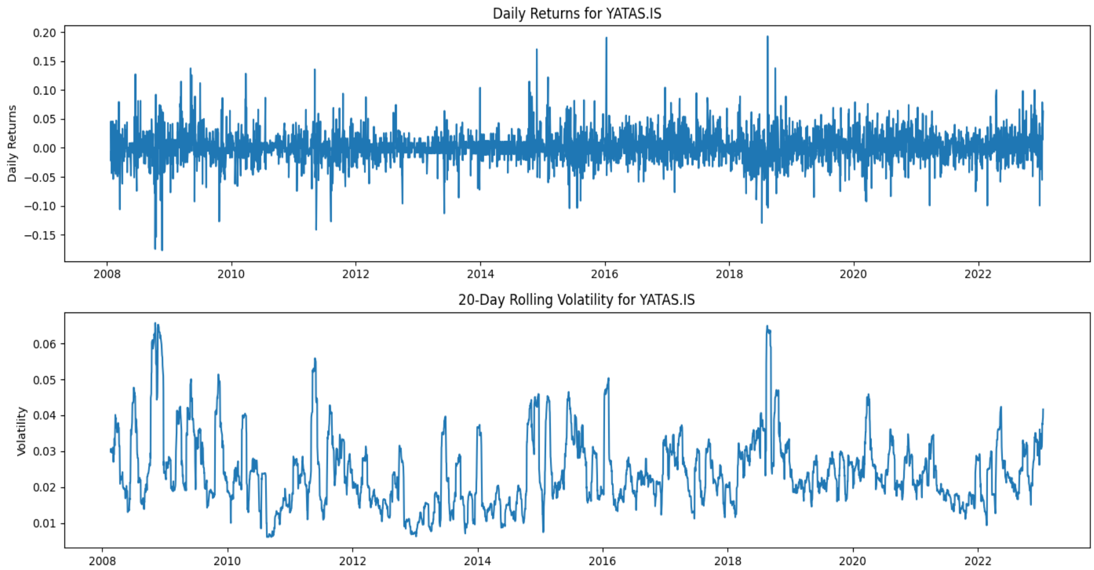

Figure 5.4: Daily Returns and 20-Day Rolling Volatility for YATAS.IS

Source: Created by Author

The upper panel exhibits the daily returns, emphasising the brief swings in stock values. The lower panel displays the 20-day rolling volatility, offering insights into the stability and risk associated with each company for a set period.

5.5. Dimensionality Reduction via Principal Component Analysis

Handling and examining several stocks in financial analytics and portfolio optimization is challenging because of the dataset's high dimensionality. Traditional analytic methods may not effectively capture the underlying patterns and relationships in a dataset of 163 stocks, each representing a dimension. Principal Component Analysis (PCA) is a critical approach for reducing dimensionality, allowing for better executive in portfolio development by capturing the core aspects of the data (Jolliffe & Cadima, 2016).

PCA is a statistics method that uses an orthogonal transformation to turn a set of data of variables that might be related into a set of values for variables that are not related in any way. These values are called principal components. Because of how the change is set up, the first principal component has the most variance possible. After that, each component has the most variance possible as long as it is orthogonal to the ones that came before it. This makes an orthogonal basis set of vectors that are not related to each other (Pearson, 1901).

There are several processes involved in applying PCA to stock market data, namely the dataset that is being studied. To address the issue of scale disparity among various stocks, the daily returns of the 163 stocks are first standardized to have a mean of zero and a standard deviation of one. The covariance matrix of the standardized returns, which shows how much stock pairings move together, is then calculated.

The primary components, which each indicate a pattern in the data that contributes to the overall variance explanation, are revealed via eigen decomposition of the covariance matrix. A determination of how many primary components to keep is achieved by looking at the explained variance ratio and the eigenvalues. Usually, the decision centres on capturing a sizable fraction of the overall variation while drastically decreasing the complexity of the dataset (Gebre Teklezgi L, 2023).

The normalisation of the dataset is an essential first step in the process of developing a model. In order to do this, the training and test datasets' characteristics of closing prices within the bound were scaled evenly using the MinMaxScaler [0, 1]. By guaranteeing that each feature contributes equally, this normalisation reduces the excessive impact of outliers and makes it possible to create a more balanced analytical framework.

After the closing prices data are scaled, the research applies the normalisation procedure to the entire features dataset. To standardise the features before Principal Component Analysis (PCA) is applied, the MinMaxScaler is utilised. The two-phase normalisation process emphasises how carefully data preparation is done, guaranteeing that the dataset is in the best possible condition for principal component extraction.

In order to get ready for the time series forecasting phase, a key function called processData has been carefully designed to divide the dataset into a set of input-output pairs that meet the needs of supervised learning models. This function cleverly changes the temporal data into a format where each input vector, X, includes a certain amount of observations from the past, which is called the lookback period, and each output vector, Y, includes observations from the future, which is called the forecast horizon.

- **Lookback Period (252 Days):** This parameter tells the model how many days of past data it can use to make each forecast. The use of a 252-day lookback time is a good way to give the model a full year's worth of trading data, which gives it the temporal dynamics that come with a fiscal year.
- **Forecast Horizon (22 Days):** On contrary, the forecast horizon shows how far into the future the estimate is. It is set at 22 days to match the number of trading days in a normal month. This horizon shows the range of what the model can project.

The function goes through the dataset repeatedly, pulling out segments that correspond to the lookback period as input features and the next interval that corresponds to the forecast horizon as the goal output. The jump parameter controls how slowly the dataset is moved through. This makes sure that all of the temporal data is sampled, and the dataset is then filled with many input-output pairs that can be used to train the model.

5.6. Implementing Early Stopping and Dropout for Optimal Training

A significant problem in deep learning model training is determining the right number of epochs. If you set this parameter too high, the model can be overfit to the training set and end up capturing noise instead of the underlying pattern, which would make it perform poorly on untried data. On the other hand, insufficient epochs could lead to underfitting, a situation in which the model is unable to identify pertinent patterns in the data, resulting in less-than-ideal performance.

We used the Early Stopping strategy to solve this problem and evade the laborious process of testing every conceivable configuration for the era. Early Stopping is a regularisation technique that prevents overfitting by stopping the training process before the model's performance on a validation set starts to decline. This eliminates the requirement for manual epoch selection. It keeps an eye on the learning curve and steps in when it determines that more training won't improve generalisation.

The model's propensity to enter a local minimum in the error surface is a frequent problem during training. If learning is dependent only on quick performance gains, this could prematurely end the process. The 'patience' parameter in the Early Stopping technique gets around this by allowing the training to go on for a predefined amount of epochs even in the event that there is no improvement. This method gives the model a chance to break out of local minima and possibly perform better. The patience parameter for our training was set to 15 epochs, which provided the model with a healthy margin of error to bounce back from temporary drops in performance without jeopardising training efficiency.

In order to prevent overfitting, we additionally incorporated Dropout regularisation into our model architecture. Dropout works by arbitrarily removing a set of neurons after each training stage to protect the network from becoming overly reliant on any single neuron. This encourages further strong, generalised learning. According to published research, dropout rates normally fall between 0.2 and 0.8, depending on the particular network architecture and issue domain. We started our training with a 0.4 dropout rate, with the intention of changing this value in later tuning stages after the ideal model setup was found.

In conclusion, a key component of our plan to improve model performance is the joint application of Early Stopping and Dropout approaches. Dropout is a useful way to reduce overfitting, resulting in a robust and adaptable model, while Early Stopping guarantees that our models stay efficient and generalizable by ending training at the right time. We will investigate additional changes to these parameters in order to improve the performance of our model after determining which model architecture is the most promising.

5.7. Evaluation of Models

5.7.1. LSTM Results

A range of batch sizes and neuron counts were tested in order to determine the best configuration for the LSTM model to forecast stock prices. Three primary error measures were used to evaluate each configuration's performance: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These measures are essential because they offer various viewpoints on the distribution and magnitude of errors, which aid in comprehending the prediction accuracy and consistency of the model.

The Mean Absolute Error (MAE) for different batch size and neuron configurations is shown in Table 5.2. Without taking into account the direction of the errors, the MAE calculates the average size of the forecasts in a collection (i.e., over- or under-predictions are considered equally). A model with higher prediction accuracy is shown by a lower MAE number. The table illustrates how bigger batch sizes typically result in fewer MAE values, especially when 4 neurons are used at a batch size of 256. This highlights how effective this arrangement is at lowering prediction error.

Table 5.2: Prediction MAE for Single-layered LSTM

Batch Size - Neurons	4	8	16	32	64
8	0.2058	0.2122	0.2057	0.2090	0.2123
16	0.2151	0.2097	0.2071	0.2143	0.2074
32	0.2076	0.2078	0.2055	0.2067	0.2109
64	0.2091	0.2083	0.2075	0.2117	0.2068
128	0.1995	0.2086	0.2068	0.2110	0.2059
256	0.1989	0.2041	0.2075	0.2062	0.2098

Source: Created by Author

The Mean Squared Error (MSE) for various settings is shown in Table 5.3. The mean square error (MSE) is a risk indicator that significantly penalises greater errors by squaring them. Because of this, MSE is sensitive to outliers and is particularly useful in situations when excessive errors are especially undesirable. One of the lowest

MSE values is shown by the setup with four neurons and a batch size of 256, indicating a dependable model with fewer significant errors.

Table 5.3: Prediction MSE for Single-layered LSTM

Batch Size - Neurons	4	8	16	32	64
8	0.0688	0.0740	0.0689	0.0724	0.0737
16	0.0747	0.0720	0.0670	0.0750	0.0695
32	0.0702	0.0719	0.0702	0.0691	0.0723
64	0.0713	0.0703	0.0714	0.0736	0.0706
128	0.0639	0.0673	0.0707	0.0739	0.0699
256	0.0644	0.0676	0.0709	0.0699	0.0727

Source: Created by Author

Table 5.4 displays the Root Mean Squared Error (RMSE) results. The square root of the mean square error (RMSE) makes comprehension easier by providing error measurements in the same units as the predicted values. Larger errors are given more weight by the RMSE, just like by the MSE. According to the table, larger batch sizes and fewer neurons are often linked to lower RMSE values; the batch size of 4 and 256 neurons perform very well.

Table 5.4: Prediction RMSE for Single-layered LSTM

Batch Size - Neurons	4	8	16	32	64
8	0.2624	0.2721	0.2625	0.2691	0.2716
16	0.2734	0.2684	0.2588	0.2739	0.2637
32	0.2650	0.2682	0.2650	0.2629	0.2689
64	0.2670	0.2652	0.2673	0.2713	0.2657
128	0.2527	0.2595	0.2659	0.2719	0.2644
256	0.2538	0.2601	0.2662	0.2644	0.2697

Source: Created by Author

The results of the studies showed that the setup with 4 neurons and a batch size of 256 produced the best results, with the lowest MAE of 0.1989. Additionally, this arrangement performed admirably in terms of MSE and RMSE, with scores of 0.0644 and 0.2538, respectively. These findings point to a model that is robust and dependable since it not only predicts with minimum error on average (MAE), but also exhibits reduced volatility in errors across predictions (MSE and RMSE).

The model's capacity to generalise across various data sets is improved by the use of a bigger batch size and fewer neurons, which help handle larger datasets effectively and avoid overfitting. Without overfitting to the noise in the training set, this arrangement shows to be especially good at collecting the underlying patterns in the stock price data.

In order to find out if adding a second layer could improve our system's predicted accuracy, we investigated the performance of two-layered LSTM models in addition to single-layered LSTM models. By reducing the possibility of overfitting, the two-layered models were evaluated with different neuronal topologies and dropout rates in an effort to increase model robustness. In the second layer, the investigated topologies had 256 and 512 neurons with dropout rates varying between 0.1 and 0.4.

The two-layered LSTM models' Mean Absolute Error (MAE) shows that raising the dropout rate has no discernible positive impact on the MAE for various neuron configurations as shown in Table 5.5. The lowest MAE recorded was 0.2191, for dropout rates of 0.2 and 0.3 with 256 neurons. This indicates that one can reduce average prediction errors with a moderate degree of regularisation (via dropout) without having to significantly increase the number of neurons.

Table 5.5: Prediction MAE for Two-layered LSTM

L2_ Neurons - Dropout	256	512
0.1	0.2195	0.2198
0.2	0.2191	0.2224
0.3	0.2191	0.2211
0.4	0.2228	0.2419

Source: Created by Author

Models with 256 neurons often outperform those with 512 neurons, according to the Mean Squared Error (MSE) data in Table 5.6; this is especially true for dropout rates of 0.2 and 0.3, when the MSEs are 0.0782. Based on this trend, models with 256 neurons and modest dropout rates are able to better restrict the variance of error magnitudes than configurations with a higher number of neurons.

Table 5.6: Prediction MSE for Two-layered LSTM

L2_ Neurons - Dropout	256	512
0.1	0.0794	0.0796
0.2	0.0782	0.0801
0.3	0.0782	0.0799
0.4	0.0794	0.0888

Source: Created by Author

Based on Root Mean Squared Error (RMSE), the findings are in line with the MSE analysis in Table 5.7. Models with 256 neurons and 0.2 and 0.3 dropout rates have the lowest RMSE, which is 0.2797. This indicates that for reducing the effect of significant prediction mistakes, these parameters within the two-layer design are ideal.

Table 5.7: Prediction RMSE for Two-layered LSTM

L2_ Neurons - Dropout	256	512
0.1	0.2818	0.2821
0.2	0.2797	0.2830
0.3	0.2797	0.2827
0.4	0.2818	0.2980

Source: Created by Author

The best single-layered LSTM model configurations beat the two-layered models in terms of error metrics, despite the two-layered models having more complexity and the capacity to capture patterns in the data. In particular, when compared to all configurations examined in the two-layer models, the optimal configuration for the single-layer model (with a batch size of 256 and 4 neurons) produced reduced error scores across MAE, MSE, and RMSE. This suggests that increasing dropout combined with more layers and neurons may not always result in improved predictive performance for this dataset; rather, it may raise computing costs without improving accuracy.

5.7.2. Bi-LSTM Results

We desire to investigate the possible advantages of using a Bi-directional LSTM (Bi-LSTM) architecture for our stock price prediction model after comparing single-layered and two-layered LSTM models. By processing the data in both forward and backward directions, the Bi-LSTM model was created to improve learning capacities and perhaps capture new patterns and relationships that a normal LSTM could miss**.**

The Bi-LSTM model was configured with 256 neurons in the layer, chosen based on the optimal neuron count identified in the single-layer LSTM experiments. The model was trained over 50 epochs with early stopping set at 15 epochs to prevent overfitting. The input to the model included data shaped by the previously defined **lookback** and **num_companies** parameters, with the output dimension determined by the horizon.

After the Bi-LSTM layer, a dropout rate of 0.4 was used to add regularisation and diminish the chance of overfitting by randomly excluding some of the feature detectors during training. The purpose of this configuration is to improve the model's ability to generalise to new, untested data.

The Bi-LSTM model achieved the following performance metrics:

- Mean Absolute Error (MAE): 0.2035
- Mean Squared Error (MSE): 0.0663
- Root Mean Squared Error (RMSE): 0.2575

These indicators point to a strong model with consistent error control and forecast accuracy. Specifically, the MAE and RMSE figures indicate that the model performs better than some previously evaluated setups at handling high errors and successfully minimises average prediction errors.

The superior ability of the BiLSTM model to handle sequential data from both temporal directions, so offering a more comprehensive comprehension of the data's underlying patterns, led to the selection of the model based on the obtained results. The performance measurements showed that, particularly in complicated time-series forecasting tasks like stock price prediction, the BiLSTM model, with its unique configuration, offers a viable substitute to conventional single-directional LSTM models.

The goal of using a BiLSTM model was to take advantage of its sophisticated pattern recognition abilities, which are especially useful for financial time series analysis. Based on empirical data from prior studies, the chosen model configuration was optimised to effectively balance model complexity and predictive accuracy.

5.7.3. GRU Results

We developed a Gated Recurrent Unit (GRU) model, which is well-known for its effectiveness and efficacy in handling sequential data as compared to more sophisticated models like LSTMs, in order to investigate alternative recurrent neural network designs. GRUs are especially appreciated for their less complex structure, which can result in quicker training periods without noticeably sacrificing performance.

Robust prediction skills were maintained while optimising computing efficiency in the architecture of the GRU model. In the GRU layer, we used 256 neurons, which reflects the best possible trade-off between model complexity and performance, as determined by previous LSTM research. In order to reduce the possibility of overfitting, the model was programmed to train over 50 epochs with an early stopping mechanism at 15 epochs.

After the GRU layer, a dropout rate of 0.4 was used to add regularisation. By limiting the model's dependence on any one feature in the training set, this technique helps improve the model's capacity to generalise to new data.

The performance of the GRU model was assessed using the following metrics:

- Mean Absolute Error (MAE): 0.2089
- Mean Squared Error (MSE): 0.0721
- Root Mean Squared Error (RMSE): 0.2685

For assessing the effectiveness of a more straightforward but effective substitute for LSTM architectures, the GRU model was chosen. The findings imply that GRUs can be a useful stand-in, particularly in situations where training time and model complexity are important limitations. The GRU model is a strong option for tasks needing quick model deployment and iteration due to its performance.

5.7.4. XGBoost Results

We used the eXtreme Gradient Boosting (XGBoost) model as part of our investigation into machine learning approaches for financial time series prediction. When it comes to performance and speed in regression and classification issues, XGBoost is well-known. To determine whether this model was effective in capturing complex nonlinear patterns in the data, it was evaluated with different configurations of maximum depth and number of estimators.

The XGBoost models were assessed using various combinations of **n_estimators** (50, 100, 150) and **max_depth** (3, 5, 7). These parameters set the maximum depth at which a tree can grow during a boosting round and the maximum number of trees that can be built before a run ends. Together, they control the model's complexity.

The Mean Absolute Error (MAE) measures the average magnitude of the errors in predictions, without considering their direction as shown in Table 5.8. The results showed that a max_depth of 5 and 7 and n_estimators of 50 provided the lowest MAE of 0.1629, suggesting that less complex models with fewer trees can achieve highly accurate predictions. Increasing both max_depth and n_estimators generally led to higher errors, particularly noticeable at max_depth of 7 with 150 trees.

Table 5.8: Prediction MAE for XGBoost

Estimator - Max_depth	50	100	150
3	0.1629	0.1827	0.1938
5	0.1619	0.2027	0.2277
7	0.1619	0.2023	0.2272

Source: Created by Author

The results of the Mean Squared Error (MSE) study corroborated the findings from the MAE analysis as in Table 5.9; MSE values of 0.0377 at max_depth 5 and 50 trees indicated that more favourable outcomes were obtained at lower max_depth and fewer trees. Greater variance in prediction errors was indicated by a significant increase in the MSE for these parameters.

Table 5.9: Prediction MSE for XGBoost

Estimator - Max_depth	50	100	150
3	0.0384	0.0478	0.0587
5	0.0377	0.0541	0.0713
7	0.0378	0.0543	0.0713

Source: Created by Author

Lower values of the Root Mean Squared Error (RMSE), which indicates greater performance, provide insight into the size of mistakes generated by the model. In Table 5.10 with an RMSE of 0.1943, the max_depth 5 and 50 estimator setup produced the lowest RMSE, demonstrating the effectiveness of the model at this level of complexity.

Table 5.10: Prediction RMSE for XGBoost

Estimator - Max_depth	50	100	150
3	0.1959	0.2186	0.2423
5	0.1943	0.2326	0.2671
7	0.1944	0.2330	0.2670

Source: Created by Author

According to the XGBoost model's best results at lower complexity settings (max_depth 5, n_estimators 50), simpler models should be adequate for this dataset in order to capture the important predictive dynamics without overfitting. This demonstrates how well XGBoost handles various data distribution types and how successful it is in lowering the possibility of discovering bogus patterns.

5.7.5. RF Results

The Random Forest algorithm, a well-known ensemble learning technique for regression tasks, was employed in this study. Using GridSearchCV, we systematically investigated and fine-tuned the Random Forest model's hyperparameters with the goal of improving the model's predicting accuracy for financial time series.

The hyperparameter space was defined as follows:

- **n_estimators:** Number of trees in the forest (50, 100, 150).
- **max_depth:** Maximum depth of each tree (None, 3, 5, 7).
- **min_samples_split:** Minimum number of samples required to split an internal node (2).
- **min_samples_leaf:** Minimum number of samples required to be at a leaf node (1).

Heuristic selection was used to choose these parameters based on how they generally affected the computational efficiency and performance of the model. For each of the 12 potential parameter sets, the Random Forest model was fitted five times through the GridSearchCV procedure, for a total of sixty fits.

The best model was assessed on the test set when GridSearchCV was finished, and the following metrics were noted:

- Root Mean Squared Error (RMSE): 0.2784
- Mean Absolute Error (MAE): 0.2190
- Mean Squared Error (MSE): 0.0775

These measures show how accurate the model is at making predictions and how well it can control the amount of inaccuracy in those predictions. An indication of the error magnitude is provided by the RMSE of 0.2784, which indicates that the model, on average, deviates from the real values by roughly 0.2784 units on the RMSE scale. The average absolute error (MAE) of 0.2190 provides information about the normal error size without taking direction into account. Last but not least, the MSE of 0.0775 emphasises the prediction error average of squares, which penalises greater errors more harshly than smaller ones.

The outcomes show that the Random Forest model performs admirably on the financial time series data when its parameters are adjusted. The model may be able to identify the key trends in the data without overfitting, which is a frequent problem in financial forecasting, based on the comparatively low error metrics. By systematically optimising the model parameters through the use of GridSearchCV, it was possible to make sure that the model configuration was appropriate for the subtleties and complexity of the dataset.

5.7.6. SVM Results

A potent machine learning model, the Support Vector Machine (SVM), and its regression variation Support Vector Regression (SVR) are well-known for their efficacy in high-dimensional environments and their capacity to represent complex nonlinear relationships. Using GridSearchCV, we optimised the SVR model's hyperparameters in our study to provide the highest possible predictive performance on time series data related to finance.

The process of hyperparameter optimisation entailed experimenting with various combinations of values for the subsequent parameters:

- **C:** Regularisation parameter (0.1, 1, 10) that aids in managing the trade-off between reducing model complexity for improved generalisation and obtaining a low error on the training set of data.

- **gamma:** The 'rbf' kernel's kernel coefficient (scale, auto, 0.01, 0.1, 1) that affects the curvature of the decision border.
- **epsilon:** Defines the epsilon-tube wherein the training loss function does not impose a penalty, with the predicted points being within an epsilon of the actual number (0.01, 0.1, 1).

Featuring 225 fits spread over 5 folds for each of the 45 candidate parameter sets, the GridSearchCV procedure was extensive and made it possible to thoroughly explore the parameter space.

After the parameter tuning was finished, the test dataset was used to evaluate the optimised SVR model, producing the performance metrics listed below:

- Root Mean Squared Error (RMSE): 0.2783
- Mean Absolute Error (MAE): 0.2308
- Mean Squared Error (MSE): 0.0775

The findings show that the SVR model handles the complexity of financial time series data with competitive performance, thanks to its unique configuration of **C**, **gamma**, and **epsilon**. The model can adjust to the non-linear patterns commonly seen in financial markets thanks to the selection of an **RBF** kernel and ideal parameter choices.

All things considered, the Support Vector Regression model is a valued analytical tool for financial forecasting since it combines accuracy and robustness. In addition to improving the model's performance, the methodical approach to hyperparameter tuning using GridSearchCV also shed light on the dynamics of the model's susceptibility to various configurations. This investigation deepens our knowledge of SVM's use in finance by demonstrating how well it may be used as a forecasting tool for market trend analysis.

5.8. Comparative Performance of Machine Learning Models in Stock Price Predication

We examined the performance of six distinct models in our thorough evaluation of various predictive models applied to financial time series forecasting: LSTM, Bi-LSTM, GRU, Random Forest (RF), Support Vector Machine (SVM), and XGBoost. The three essential error metrics that were the focus of the examination were Mean

Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Table 5.11 below provides a summary of these metrics.

Table 5.11: Comparative Analysis of Machine Learning Models in Stock Price Prediction

Models / Performance Metrics	MAE	MSE	RMSE
LSTM	0.1995	0.0639	0.2527
Bi-LSTM	0.2034	0.0663	0.2575
GRU	0.2089	0.0720	0.2684
RF	0.2189	0.0775	0.2783
SVM	0.2307	0.0774	0.2783
XGBoost	0.1619	0.0377	0.1943

Source: Created by Author

Based on the comparative analysis, the XGBoost model performs better than the other models in each of the three criteria. XGBoost performs better in this situation for a number of important reasons, including:

- **Ensemble Learning:** XGBoost makes use of ensemble learning strategies, which pool predictions from several models to increase precision and better manage overfitting than single models could.
- **Handling of Non-linear Relationships:** XGBoost's capacity to represent complicated and non-linear relationships in the data is essential for identifying the complex patterns that are frequently seen in financial markets.
- **Regularisation Methods:** XGBoost has built-in regularisation that lessens overfitting and improves the model's ability to generalise.
- **Optimal Hyperparameter Tuning:** The process of optimising hyperparameters involved using GridSearchCV to make sure the model was configured as best it could be, which improved the model's predicted accuracy.

As the LSTM model can retain long-term dependencies, it performs well, particularly when processing sequential input. Given that historical patterns have a substantial impact on future prices, its resilience in modelling time series data makes it a very useful tool for stock prediction. Its capacity to precisely capture the dynamic changes in stock values is demonstrated by the comparatively low error metrics.

By processing data in both forward and backward directions, the Bi-LSTM expands the competences of the regular LSTM and provides a more thorough accepting of temporal connections. Even though it does not perform as well as the LSTM in this examination, its capacity to capture past and future contexts can be especially helpful in situations where future trends rely significantly on the combined historical data.

GRU makes LSTM's architecture simpler, which can speed up training and require less data for generalisation. GRU is still a competitive option for datasets where computational performance is important, even if it has somewhat higher error metrics than LSTM and Bi-LSTM. However, it may give up some accuracy in favour of speed.

Random Forest, an ensemble of decision trees, is well distinguished for its excellent accuracy and ability to prevent overfitting. But in this particular case, RF did not perform as well as some of the specialised sequential models. This is probably because RF is not designed to handle the temporal dependencies that are common in stock data. However, it might be helpful in situations where non-temporal predictive cues are present in the data features.

Due of its difficulties controlling noise and processing huge datasets, SVM performed the least well in this evaluation. Although SVM is widely praised for classification, its regression variant may find it difficult to handle the noise and volatility of financial time series without a great deal of parameter tweaking.

The significance of selecting a model based on the unique properties of the data and the model's inherent advantages is shown by the comparative study of different models. The superior performance of XGBoost demonstrates its resilience and flexibility in a range of situations, including financial markets. In the meanwhile, models with specialised strengths in sequential data handling, such as LSTM and Bi-LSTM, are appropriate for applications where temporal patterns are prevalent. While they might not be the best for this particular task, models like RF and SVM might be better in other situations when their special qualities can be used to their advantage.

The outcomes demonstrate how well boosting techniques—in particular, XGBoost—work in cases involving stock price prediction. Because of this model's excellent suitability for the unpredictable nature of financial markets, it can effectively handle a variety of data anomalies, including missing values, variable scales, and non-linear correlations. Furthermore, because of its regularisation competencies, the model's robustness against overfitting guarantees that it will continue to function well in the face of changes in market conditions.

Considering the intricacy and fluctuation of financial time series, XGBoost is suggested due to its improved overall efficacy. But LSTM and Bi-LSTM also provide useful features for applications that particularly need a thorough comprehension of time-dependent data. The model selected should be in line with the particular needs and limitations of the given forecasting task.

5.9. Application of Machine Learning Models for Markowitz Portfolio Optimisation

This section describes the use of sophisticated machine learning methods, namely GRU, Bi-LSTM, and LSTM models, to forecast stock prices and manage an equity portfolio. The goal is to reduce risk and maximise investment returns by utilising these models' predictive power.

First, financial data is prepared in a methodical manner. Past stock prices are then retrieved and processed. The basis for all ensuing analysis and model training is this data. A custom function called **load_and_process** is used to load and process real and forecasted stock values for each of the three models that are used: LSTM, Bi-LSTM, and GRU. This ensures data consistency and integrity between the models.

We calculate the logarithmic returns derived from the actual and anticipated prices. For a number of reasons, logarithmic returns are preferred over simple returns. Firstly, they help stabilise variance across time, which is important for the accurate performance of financial models. Secondly, they are time-additive, which makes them ideal for analyses involving multiple time periods. Finally, they are typically more normally distributed, which facilitates various statistical methods.

The **windowGenerator** function plays a critical role in our methodology by dividing the complete dataset into specific time windows, simulating a realistic trading scenario where past information is used to predict future performance. This function allows us to create overlapping or non-overlapping windows depending on the specified parameters, which include:

- **Lookback and Horizon:** These parameters specify how long past data is used for training and how long predictions are needed, respectively.
- **Step:** Manages the transition between windows, enabling non-overlapping (for separate validation) or overlapping (for continuous learning) datasets.
- **Cumulative Option:** Provides an alternate strategy in which the end point expands and the starting point stays constant, so growing the dataset with each step and possibly enhancing the robustness of the model over time.

The scipy_opt function's two-fold optimisation strategy is used to build the portfolio. This function's goal is to optimise the portfolio's predicted returns within a set of predetermined parameters and assumptions.

- **Objective Function:** A unique function that maximises the expected returns of the portfolio after adjusting for anticipated risk by integrating forecasted returns and a covariance matrix of the returns. In order to improve model generalisation and reduce overfitting, this function is additionally regularised. The L1 norm is used to promote sparsity in the portfolio weights.
- **Contraints**: provides that each weight in the portfolio is limited between 0 and 1, indicating a long-only investment strategy, and that the total weight of the portfolio equals one.
- **Solver**: Implements a Sequential Least Squares Programming (SLSQP) technique to the minimise function from SciPy's optimisation module in order to get the ideal weights that maximise the specified objective function within the specified bounds.

The performance of the portfolio is assessed by applying the established portfolio weights to the expected and actual return series:

- **Return and Variance Calculation:** We compute the expected and actual returns and variances of the portfolio using the optimised weights, yielding a quantitative assessment of risk and performance.
- **Sharpe Ratio:** For the purpose of assessing the risk-adjusted return of the portfolio and compare the performance of our techniques to rival models or benchmarks, we compute the Sharpe ratio.

In addition to improving our thoughts of the predictive power of LSTM, Bi-LSTM, and GRU models, this methodical and rigorous approach to portfolio construction using machine learning models offers a solid framework for managing real-world investment portfolios.

5.9.1. Comparative Performance of Machine Learning Models in Portfolio Optimisation

The LSTM, Bi-LSTM, and GRU models applied to equities portfolio optimisation over a given period are compared using the equity graph and related financial metrics. This analysis is essential to determining how well each model performs in leveraging market trends to optimise investor wealth.

The distribution is noticeably narrower and has a dense central peak in the histogram in Figure 1 that shows the portfolio returns for the LSTM model, indicating reduced unpredictability in portfolio performance. The returns primarily range from -1% to +3%, suggesting a cautious strategy impacted by the LSTM's capacity to recognise long-term dependencies which can be seen in Figure 5.5. The lower frequency of high returns in this model indicates that it is risk-averse, favouring steady but possibly smaller gains.

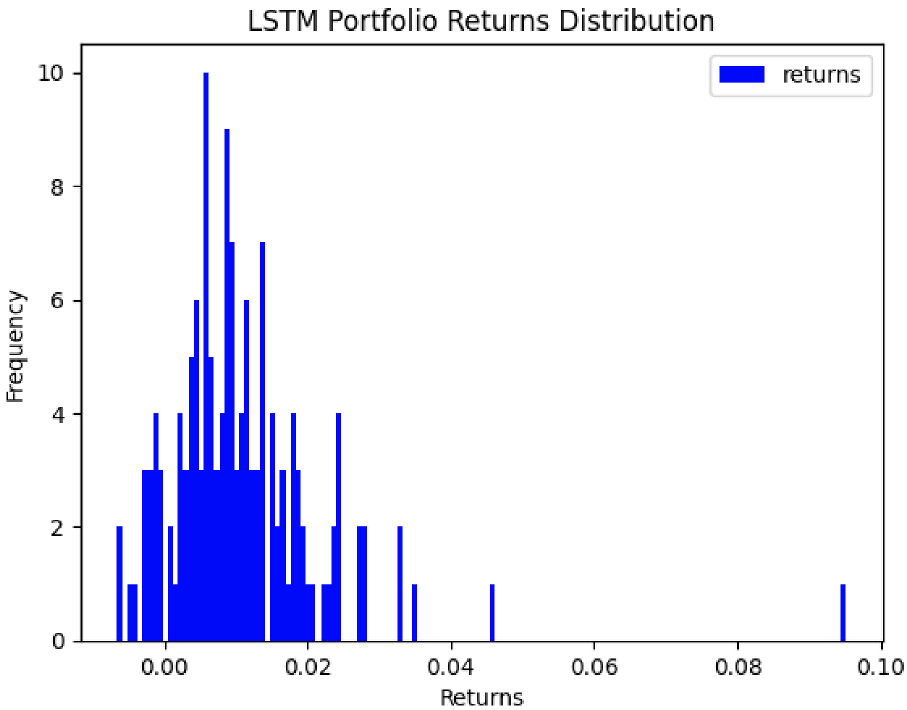

Figure 5.5: LSTM Portfolio Return Distribution

Source: Created by Author

The histogram's tighter distribution indicates that, generally speaking, the LSTM model's forecasts produced more consistent but moderate returns. This consistency may be explained by the model's ability to identify long-term relationships in the market data, which could result in a portfolio approach that is less risky.

The portfolio returns histogram as shown Figure 5.6 of the Bi-LSTM model shows a small positive skew and a concentration of results around zero. The returns are roughly between -2% and 4%, and most of the instances centre on slightly positive returns. This implies that a balanced risk-return profile, preventing excessive losses while permitting moderate gains, may be provided by the Bi-LSTM model, which is well-known for capturing bidirectional temporal relationships. Through the model's predictions, a diversified portfolio strategy aiming to lower unsystematic risk is indicated by the dispersion of returns.

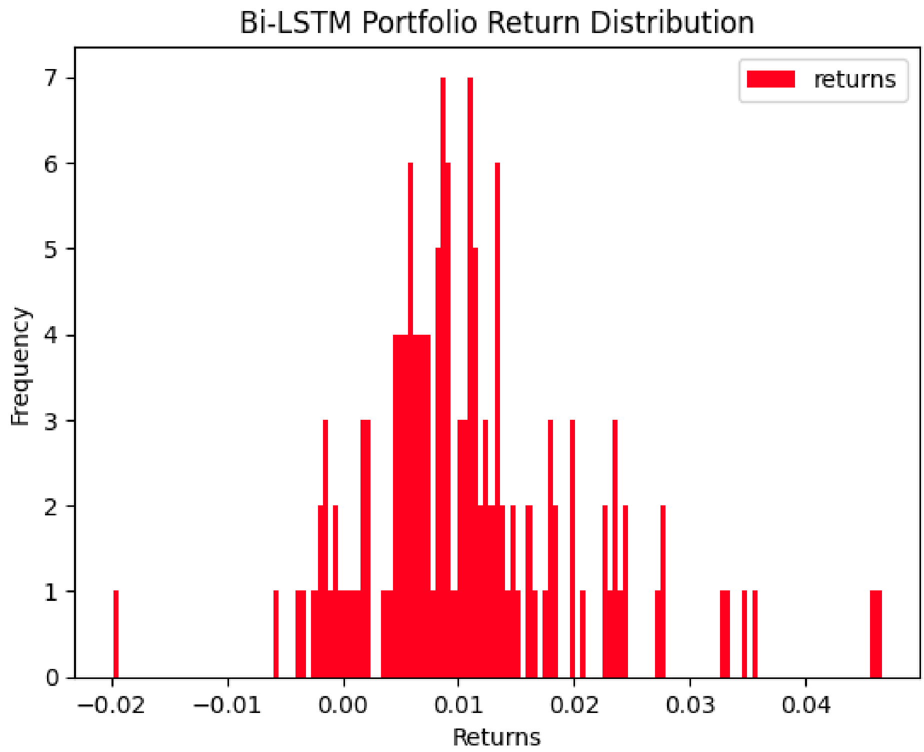

Figure 5.6: Bi-LSTM Portfolio Return Distribution

Source: Created by Author

The model's balanced approach, which captures complete temporal patterns, is indicated by the distribution's peak around a moderate positive return. This could result in a steady expansion of the portfolio with a managed exposure to risk.

Similar to the Bi-LSTM model, the GRU model's return distribution in Figure 5.7 has a broader spread, ranging from -2% to 4%. The return occurrences show a wide range of results with several peaks, which could point to both a potential rise in risk and the ability to capture a variety of market situations. This distribution may be influenced by the reduced structure of the GRU model, which represents a trade-off between prediction variance and model complexity.

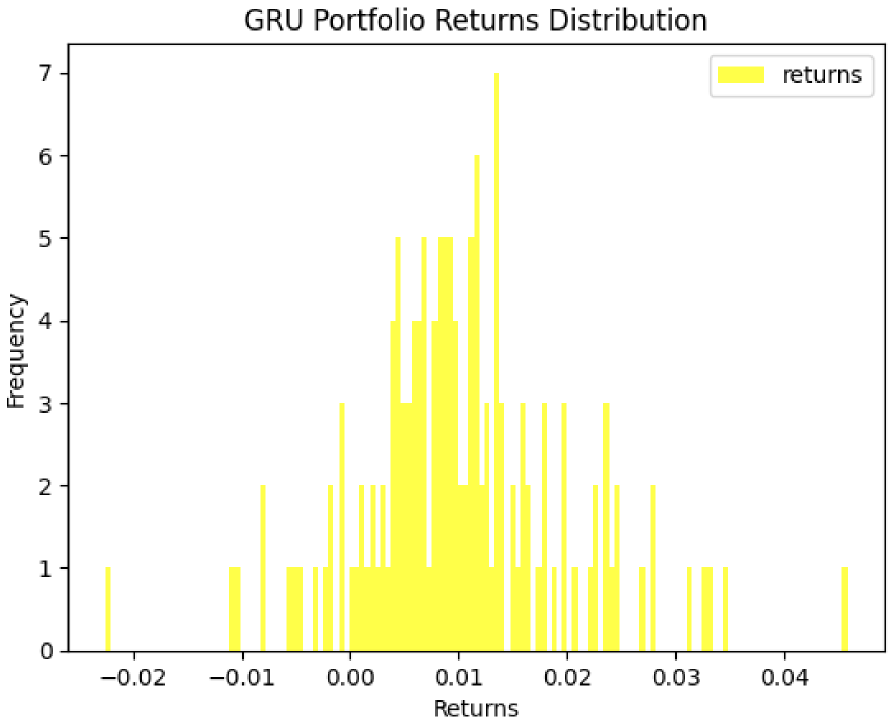

Figure 5.7: GRU Portfolio Return Distribution

Source: Created by Author

The GRU model suggests a strategy with a wider variety of outcomes and, consequently, a potential higher risk and reward because it displays a bigger distribution of returns. This is a reflection of the architecture of the GRU model, which is less complex yet still able to capture a variety of market movements with less consistency.

Comparison research indicates that compared to the LSTM model, the GRU and Bi-LSTM models seem to have more unpredictability in their predictions. The targeted distribution of the LSTM points to a model that might provide more reliable performance, which is appealing to investors who are risk averse. On the other hand, strategies with greater potential returns but higher risk levels may be represented by the Bi-LSTM and GRU models due to their wider return distributions.

Finally, the histograms offer a statistical and visual depiction of the risk profile and forecast accuracy of each model. When evaluating the model's overall fitness for portfolio optimisation, the distribution of returns plays a fundamental role in directing investment decisions that strike a balance between risk and reward.

Through the use of advanced machine learning prediction models, we were able to convert stock price projections into real portfolio growth over time. Starting with a \$100 initial investment, we evaluated the capital amplification using the LSTM, Bi-LSTM, and GRU forecasts, which are based on the following formula:

$$\mathbf{P_t} = \mathbf{P_{t-1}} \times \mathbf{e}^{\mathrm{Returns}_\mathbf{t}} \tag{5.1}$$

where $\boldsymbol{P_t}$ represents the portfolio value at time $\boldsymbol{t}$ and $\mathrm{Returns}_{\boldsymbol{t}}$ denotes the logarithmic return at time $\boldsymbol{t}$**.**

The equities graph's depiction of the portfolio value over time, given an initial investment of \$100, shows the cumulative impact of each model's forecasts on portfolio performance as shown Table 5.12 during the 12 years’ time period.

Table 5.12: Comparative Analysis of Machine Learning Models in Portfolio Optimisation

Model	Ending Equity	Annualized Sharpe Ratio	Annualized Volatility
LSTM	\$470.03	0.0604	0.000712
Bi-LSTM	\$461.38	0.0719	0.000594
GRU	\$424.55	0.0674	0.000594

Source: Created by Author

The LSTM model offered precise trading decisions with the lowest error metrics, which probably resulted in the highest final equity. Based on the aforementioned formula, the initial investment would have increased exponentially to a terminal portfolio value of \$470.03 if the LSTM had produced consistently favourable logarithmic returns as shown in Figure 5.8.

Despite having somewhat higher error measures, the Bi-LSTM model managed to produce strong portfolio growth, culminating in an ending equity of \$461.38. Even when individual predictions are less accurate than those of the LSTM, this model's bidirectionality enables it to integrate data from both past and future points in the sequence, potentially capturing a wider range of profitable trading signals that support capital growth.

The portfolio performance of the GRU model, which culminated in equity of $424.55, is indicative of its wider forecast variation. However, as the equity growth formula illustrates, the compounding impact could result in large spikes in portfolio growth due to the efficiency and quick adaption of GRUs, which can seize short-lived market opportunities.

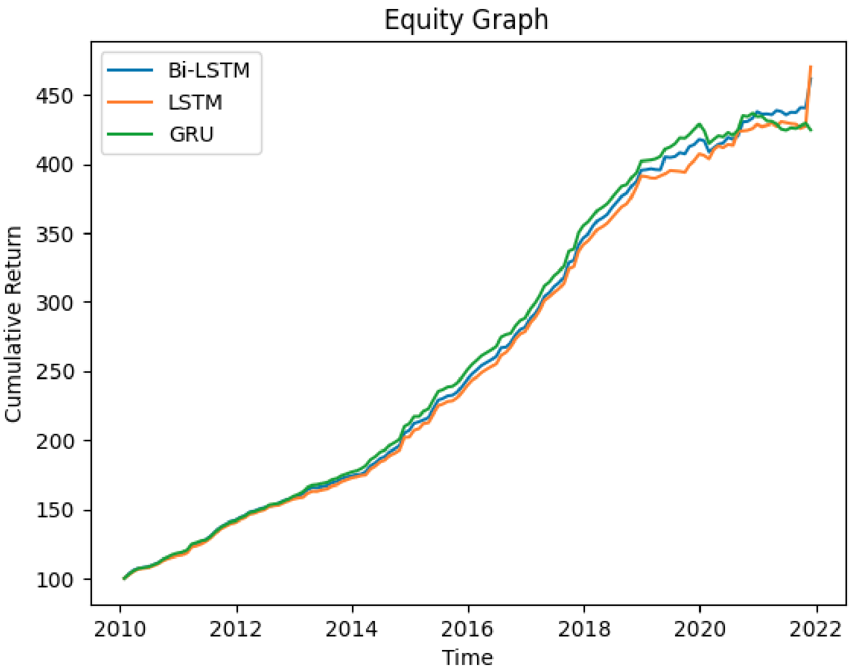

Figure 5.8: Equity Graph of Models

Source: Created by Author

An extensive picture of how successfully each predictive model translates forecast accuracy into portfolio performance may be obtained by applying the exponential growth formula to portfolio returns. A higher ending equity value is correlated with the LSTM's reduced error metrics, indicating a compounding effect of accurate predictions over time. The Bi-LSTM model achieves significant growth with moderate volatility by exhibiting a harmonic balance between risk and reward. Although successful, the GRU's portfolio indicates a potentially more volatile strategy that could result in bigger earnings at the expense of consistency. Collectively, these results clarify the complex relationship between model predictive performance and their effects on investing approaches.

CONCLUSION

This thesis concludes by showing that Islamic fintech has a great of potential to promote financial inclusion, moral and ethical financial behaviour. The path forward for Islamic Fintech requires an ongoing commitment to innovation, a focus on ethical and moral financial conduct, and an unwavering commitment to addressing the challenges of adapting latest technologies in area of finance.

The possible effects of open banking on Islamic fintech go beyond giving people more control over their money and include benefits for society. Open banking can help solve some of the most important problems communities are having right now by backing projects that put social welfare, environmental sustainability, and fair economic growth at the top of their lists. SMEs are often the backbone of developing countries but have a hard time getting access to standard banking services. This includes providing financial services that help SMEs.

Briefly, the integration of open banking into Islamic fintech represents a crossroads in the development of financial services. It offers a chance to create financial systems that are more equitable, inclusive, and consistent with ethical finance values. Islamic fintech may accomplish its social goals and establish new international benchmarks for ethical and efficient financial operations by utilising open banking. A new age in financial services is being ushered in by this intersection of technology and tradition, one that aims to make the world a better and more egalitarian place for everyone.

The respect of the handling data, reducing dimensionality is important for training the financial models. Non-linear techniques like t-Distributed Stochastic Neighbour Embedding (t-SNE), Uniform Manifold Approximation and Projection (UMAP), and Autoencoders are expected to produce more nuanced results, preserving complex relationships within the data, even though PCA yielded respected insights. Additional comprehensive data analysis would also be possible with increased computing capacity, such as adding additional stocks to the portfolio dataset and optimising over a longer time span. We presently use monthly logarithmic returns in our portfolio, but switching to daily returns would provide more analytical detail and help us better understand the strengths and weaknesses of the model.

Sequential dependencies are not considered by non-sequence models like RF, SVM, and XGBoost, which instead concentrate on the relationship between attributes and the goal variable at a particular point in time. These models can be made simpler in complexity because they usually have fewer dependencies and don't keep memory. However, the kind of model and the particular implementation might affect the level of complexity. The decision between sequence and non-sequence models ultimately comes down to the type of data and the issue at hand. While non-sequence models are adaptable to a wide range of applications that do not require sequential information, sequence models excel in applications that demand a grasp of temporal dynamics. Depending on the particular needs of a given application, each model offers a distinct set of qualities that may be utilised, balancing computing efficiency, interpretability, and predictive capacity to produce the best possible outcomes.

In summary, distinct features of both sequence and non-sequence models make them appropriate for varying data kinds and analytical goals. For datasets where the temporal order is important, sequence models like as LSTM, GRU, and Bi-LSTM work especially well. Despite their increased complexity, these models show a strong dependence on sequence and retain recollection of previous information, making them excellent at forecasting tasks that make use of prior data.

To enable the machine learning models to learn from and forecast future market behaviour, we first pre-processed historical stock data to compute logarithmic returns. The LSTM model's low error metrics and the highest ending equity in the portfolio it predicted showed that it was unusually accurate at making predictions. This implies that the structure of the LSTM is especially well-suited to capturing long-term dependencies in time series data related to finance. With its ability to analyse data in both temporal directions, the Bi-LSTM model demonstrated a strong performance and the greatest Sharpe ratio, suggesting an ideal trade-off between risk and return. The model was able to offer insights into the behaviour of the market thanks to its dual processing capacity, which produced a portfolio that consistently generated risk-adjusted returns.

The predictive power of these models was demonstrated visually and statistically by the equity graph and the comparative study of the performance measures. Each model demonstrated how neural networks may be used to improve conventional investment methods while also advancing our views of market dynamics, despite differences in their risk profiles and architectural complexity.

As the field of portfolio optimisation with machine learning changes, there are still many areas that need more study. In the future, researchers might look into how to improve the accuracy of predictions and the diversification of portfolios by adding different types of data to machine learning models, such as opinion on social media, economic indicators, or geopolitical events. It might be possible to handle both structured and unstructured data well by making hybrid models that blend the best features of sequence-based models like LSTM and GRU with more traditional financial models. Also, there is a growing need for AI that can be explained in finance. This would make AI uses clear, which would help with compliance and trust among stakeholders. Looking into systems that process data in real time and keep learning could lead to portfolio management strategies that are more flexible and quicker to adapt to changes in the market. Adding cross-market analysis and international portfolio diversification using machine learning to study could help us understand how global finance works and lower risks in different regions. It is also important to think about the legal and moral effects of using AI more in financial decisions. For example, how automated trading systems affect market security and investor fairness needs to be thought about. These improvements could make machine learning applications much more useful and complex in optimising portfolios, which would lead to more stable and flexible investment plans.

The architectures of GRU, Bi-LSTM, and LSTM exposes important trade-offs and advantages that are important for their use in different sequence modelling tasks. Because of its great ability to capture long-term dependencies, LSTM, with its three different gates (input, output, and forget), is skilled at managing complex sequence modelling jobs like machine translation and text synthesis. Longer training times and reduced computing efficiency are the outcomes of increasing complexity, though. However, GRU streamlines the architecture by combining the two gates (update and reset). This improves computational efficiency and shortens the training period, making it appropriate for tasks like speech recognition and language modelling that require efficient computation without sacrificing performance significantly.

At final analysis, there are a number of benefits and drawbacks to machine learning models such as RF, SVM, and XGBoost. An ensemble of decision trees called Random Forest performs well with high-dimensional data and reduces overfitting while providing decent interpretability through visually appealing trees. However, when there are many trees, its computational efficiency may decrease. Supervised learning algorithms such as SVM are skilled in handling high-dimensional spaces and can handle non-linear data by using the kernel method. However, it needs to have its hyperparameters carefully adjusted because it can become less efficient with huge datasets. Gradient boosting-based XGBoost is notable for its speed, particularly when using GPU acceleration, and its capacity to handle missing data; nonetheless, it contains many hyperparameters and is prone to overfitting.

Finally, a comparison of MPT and Equal Weight Portfolio reveals two distinct approaches to portfolio design, each with special advantages of its own. By giving each asset the same weight, the Equal Weight Portfolio technique prioritises impartial diversification and streamlines the allocation procedure. This strategy provides a low-complexity solution by assuming consistent risk and return across all assets and mainly using diversification to minimise risk. Because the model is simple, there aren't many data requirements or complex projections to make, and estimating errors are kept to a minimum.

On the other hand, MPT builds a portfolio that is situated on the efficient frontier in an effort to maximise the risk-return trade-off. This calls for more difficult computations of variance, covariance, and expected returns due to its increased complexity. MPT functions under the presumptions that returns are normally distributed and investors are risk averse. Due to the large amount of data required, including accurate projections of future risks and returns, the approach is prone to estimation errors that can have a major impact on portfolio optimisation. The objectives of the investor, the accessibility of data, and the required degree of portfolio management complexity all influence the decision between various approaches. Though it requires more complexity and data, MPT offers a more comprehensive framework for balancing risk and reward than the Equal Weight Portfolio.

The results of this thesis, taken together, confirm that machine learning models have the potential to surpass conventional analysis techniques when properly adjusted and utilised as effective instruments for portfolio management. They also emphasise, nevertheless, how important it is to comprehend the particular traits of each model as well as the overall economic landscape in order to properly customise investment strategies. LSTM, Bi-LSTM, and GRU models have the ability to completely transform investing strategies as algorithmic trading develops further. This potential is still very great and encouraging.

In order to improve the predicted accuracy of the models, future research could build on this idea by investigating the integration of additional data sources, such as macroeconomic indicators or news sentiment. Moreover, the investigation of hybrid models that integrate the advantages of GRU, Bi-LSTM, and LSTM architectures may provide portfolio managers and financial analysts with even more advanced instruments to pursue optimal investment performance.

Cross-validating the dataset is a notable area for improvement as it would offer a more thorough evaluation of model performance across various data subsets. This technique can reduce overfitting and improve model generalisation when combined with methodical hyperparameter optimisation. Although it produces acceptable results, our dependence on heuristic-based hyperparameter tuning has limitations when it comes to determining the ideal model configuration. A more data-driven strategy would be made possible via cross-validation, which would improve the model's forecast accuracy.

We found that the return forecasts of our LSTM model were pointedly biassed. Future work should incorporate more sophisticated feature engineering techniques to overcome this. Sentiment analysis, for example, might use natural language processing to identify useful signals from financial news and reports, potentially improving forecast accuracy. Using Fourier transforms to approximate trends could potentially highlight cyclical patterns in the data that are difficult for linear models to identify.

Enhancing the comparability of outcomes is an additional necessary factor. Standardised benchmarks could be obtained by optimising for the two core Markowitz portfolios: the Minimum Variance Portfolio and the Maximum Sharpe Ratio Portfolio. However, due to the large number of variables involved, these quadratic programming issues pose computational challenges. However, meeting these standards would offer insightful information about portfolio performance in relation to contemporary portfolio theory.

In summary, this study has indicated areas that are ready for improvement while also highlighting the potential of machine learning models in portfolio optimisation. More sophisticated feature engineering, dimensionality reduction, and portfolio optimisation methods, together with larger computing capacities, can all work together to drive future studies towards stronger and more efficient financial models.

The investigation of machine learning models for stock price prediction in this work also emphasises the potential of artificial intelligence and advanced analytics in Islamic finance. The XGBoost model's higher stock price prediction ability and the Bi-LSTM model's favourable risk-return balance highlight the importance of integrating innovative technologies into financial applications.

This study concludes by showing how fintech integration into Islamic banking not only meets current financial needs but also opens the door for creative and morally good financial solutions. Additionally, the study highlights the importance of multidisciplinary collaboration in driving these advancements. Türkiye has the ability to greatly improve its Islamic fintech scene by embracing digital innovations and encouraging cooperation among important players. This would benefit users and developers alike and establish a standard for the worldwide industry.

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