GHANA INSTITUTE OF MANAGEMENT AND PUBLIC ADMINISTRATION

SCHOOL OF TECHNOLOGY

VERGE

(BUILDING AN ARTIFICIAL INTELLIGENCE-EMPOWERED STOCK MARKET MOBILE APPLICATION)

CHRIS FESTUS OTOPA AYEH-DATEY

DEPARTMENT OF COMPUTER SCIENCES

JULY 2023

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BY

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THIS THESIS IS SUBMITTED TO THE GHANA INSTITUTE OF MANAGEMENT AND PUBLIC ADMINISTRATION, GREENHILL IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF

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A Dissertation Submitted to the School of Technology, Ghana Institute of Management and Public Administration, Accra, in partial fulfillment of the requirements for the degree of Bachelor of Science in Information Communication Technology

By

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DEDICATION

This work is dedicated to my parents, whose love and support have sustained me through all my pursuits. Their unending encouragement and belief in me have inspired me in all my academic endeavors.

I would also like to dedicate this to my elder brother Ernest Emmanuel Kofi Ayeh-Datey, whose support and guidance have strengthened me in so many ways. To two dear friends, Georgette Eugenia Otoo and Emiko Otukpere Gift.

I also dedicate this work to my teachers and mentors, whose guidance has strengthened my resolve to follow the path of learning and scholarship. Finally, I dedicate this work to all those who seek to expand the frontiers of knowledge through dedication and perseverance.

ACKNOWLEDGEMENT

First and foremost, I would like to express my deepest gratitude to my Project Supervisor, Mr. Emmanuel Antwi-Bosiako, for his invaluable guidance, support, and encouragement throughout this research. His insights and feedback have been very instrumental in shaping this work.

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Finally, I wish to thank my family for their unconditional love, support and patience throughout my life and studies. This accomplishment would not have been possible without them. Thank you.

ABSTRACT

Stock market trading has long been a complex and challenging domain, especially for novice investors. However, recent advances in artificial intelligence and machine learning have opened new possibilities for streamlining the investing process and enabling more people to participate in the stock market successfully. This research aims to develop an intuitive mobile application that utilizes AI and ML to analyze stock data, detect trends, and conduct transactions on the user's behalf based on their preferences.

The study will employ an interdisciplinary research methodology combining data science, human-computer interaction, and experimental techniques. Historical stock market, news, and social media data will be collected and used to train supervised, unsupervised, and ensemble machine learning models to identify patterns for price prediction and trading. Techniques like linear regression, artificial neural networks, clustering, and sentiment analysis will be explored for optimal performance and accuracy. Usability testing and surveys will also guide the design of an engaging yet simple mobile interface to suit users of varied backgrounds.

By assessing different AI and ML methods for stock market forecasting and trading through real-world experiments, this study seeks to gain new insights into balancing sophisticated algorithms with human discretion and values. An initial version of the mobile application may provide investors with useful tools and actionable insights for trading but still allow for manual oversight and final discretion based on individual needs and risk profiles.

The results of this study contribute new perspectives on the opportunities and limitations of employing AI and ML in stock market trading. An approachable yet innovative solution could open up the benefits of an automated, data-driven stock trading platform to a wider range of investors. But by designing an optimal human-AI interface and experience guided by an interdisciplinary research methodology focused on users, that progress may reach even more. This study endeavors to explore how new technologies can serve human potential and values at each turn - not just what abilities have achieved alone.

***Keywords*:** Artificial Intelligence, Machine Learning, Stock Market, Reinforcement Learning, Stock price prediction.

DECLARATION

I declare that except for the references to other people's work, which have been duly acknowledged, the work presented here was carried by Chris Festus Otopa Ayeh-Datey an undergraduate student at the Ghana Institute of Management and Public Administration reading Information Communication Technology, under the supervision of Mr. Emmanuel Antwi-Bosiako

I declare that this work has never been submitted partially or wholly to any institution for the award of a certificate.

……………………………………. ………………………………..

Chris Festus Otopa Ayeh-Datey Date

(Student)

……………………………………. ………………………………..

Emmanuel Antwi-Bosiako Date

(Supervisor)

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CHAPTER 1: INTRODUCTION

1.1 Research Background

A very well-chosen avenue for people that wish to invest and increase their money is the stock market. The stock market, however, can also be a complicated and challenging environment, especially for people with little prior knowledge and expertise, despite the possibility of significant rewards. The development of artificial intelligence and machine learning in recent years has opened up new opportunities for increasing the effectiveness and precision of stock market trading and forecasting. These innovations have the potential to fundamentally alter how people interact with the stock market, making it more straightforward and more approachable for investors of various backgrounds and skill sets(Zhang & Wu, 2009).

Regardless of these developments, some individuals still find the stock market to be a frightening and confusing environment because of the intricate nature of financial data and analysis. This research project suggests creating a smartphone application that uses Artificial Intelligence and Machine Learning to forecast stock market values and conduct transactions on the user's behalf to address these issues (Guresen et al., 2011).

The goal of this research is to provide an approachable and user-friendly solution that shortens the learning curve for people with little background in stock market forecasting and trading.

The research will be carried out using a combination of user studies, data collecting and analysis, and field tests. Through user feedback and performance analysis, the precision and dependability of the Artificial Intelligence and Machine Learning algorithms for stock market prediction and trading will be assessed. The findings of this study will offer fresh perspectives on the potential advantages and disadvantages of employing Artificial Intelligence and Machine Learning for stock market forecasting and trading, and they will also suggest strategies to balance these elements to develop a workable and practical solution for customers.

The user experience of the mobile application will be prioritized during design, and user-centered design concepts and usability testing will be used to make sure that it is simple to use and open to users of all skill levels. The final objective of this research project is to develop a mobile application that makes stock market forecasting and trading simpler, easier, and more accessible for people of all experience levels and degrees of competence. This application could alter how people approach the stock market and assist people in making wiser and more successful investing decisions by utilizing the power of Artificial Intelligence and Machine Learning.

The rapid increase of Artificial Intelligence and Machine Learning technologies for investment and financial decision-making is greatly aided by this study endeavor. This study has the potential to assist people of all experience levels and degrees of expertise in reaching their financial goals and thriving in the stock market by developing a user-friendly and accessible solution for stock market forecasting and trading (Krauss et al., 2017).

1.2 Research Problem

The challenge faced by those with limited prior knowledge and expertise in stock market prediction and trading—who may feel frightened and overwhelmed by the complexity of financial data and analysis—is the issue that this research study seeks to address. Despite the potential advantages of stock market investment, many people are unable to take advantage of these chances owing to a lack of knowledge and skill. As a result, individuals could lose out on opportunities with significant returns or make investment choices that are poorly thought through and lead to sizable losses.

Furthermore, while developments in artificial intelligence and machine-learning technologies have the potential to alter how people approach the stock market altogether, the available solutions in this field lack sufficient accessibility and user-friendliness. Due to the ongoing sophistication and complication of the stock market for many people, it may be challenging for people with little experience to utilize these tools.

1.3 Research Methods

The design science and research methodology of this study will include the following:

1) Literature review: A literature review will be conducted to explore the current state of the stock market and how machine learning models have been employed to predict future stock prices. It will also investigate the factors that influence stock prices, such as company performance and economic indicators; some questions that will be asked and investigated are:
    a) Methods and Models used to predict stock market prices.
    b) Factors that influence stock market prices

c) Accuracy and limitations of different models and methods

2) Data Collection: A dataset of historical stock prices and some other relevant financial data will be collected; this data is essential to train our Artificial intelligence and Machine Learning Models to predict stock market prices. Some sources of data will be collected from include.

    a) Yahoo Finance

    b) Google Finance

    c) The Securities and Exchange Commission

    d) The New York Times.

    e) Reddit

    f) Twitter

3) Building and Training of The Model: A machine learning model will be built and trained on the dataset collected in the first previous step, number two; the model will be to predict stock market prices based on historical data.

4) Mobile App Development: A mobile application will that uses Artificial and Machine Learning Models to forecast stock market prices and conduct transactions on behalf of the user. This will be designed to be accessible to users of all levels. The App would be built using the following:

    a) The Flutter framework

    b) The Google Cloud Platform

    c) Firebase

5) The App would be designed to allow users to view historical stock prices, get real-time stock quotes, conduct transactions on behalf of users, and recommend stocks based on Machine Learning Models

6) User testing: The Mobile App will be tested with users to assess its Usability and effectiveness; this feedback is essential to ensure the App meets its functionalities requirements.

7) The research methods will be done in a way to ensure that the findings are valid and reliable. The results of the study will provide valuable insights into the potential of ARTIFICIAL

INTELLIGENCE and MACHINE LEARNING for stock market forecasting and trading.

1.4 Research Purpose

The purpose of this study is to develop a mobile application that uses Artificial Intelligence and Machine Learning to forecast stock market values and conduct transactions on behalf of the user. The App will be designed to be user-friendly and accessible to users of all skill levels. It will help people to make more informed and successful investment decisions.

1.5 Research Objectives

1. To design a mobile application that will use Artificial Intelligence and Machine Learning to help forecast stock market prices and conduct transactions on behalf of the user.
2. To design a mobile application to make stock market forecasting and trading more accessible and user-friendly for people of all socio-economic levels.
3. To Implement a more effective and user-friendly mobile app that can help people make more informed and successful investment decisions.

1.6 Research Significance

The importance of this study resides in its potential to alter how people approach the stock market fundamentally and to empower them to make wiser and more profitable investment choices. This research project has the potential to employ Artificial Intelligence and Machine Learning to simplify the complicated and scary stock market landscape, making it more approachable and user-friendly for people with all levels of experience and skill.

1.7 Research Limitations

The limitations of this research include:

1. Time and resources: Developing a mobile application and conducting user surveys, interviews, and testing can be time-consuming and resource intensive.
2. Predictive Capabilities of Artificial Intelligence: The accuracy and predictive power of Artificial Intelligence models used in stock price prediction may not be perfect, which can lead to inaccuracies in the projections provided by the proposed application.

3. Data availability: The availability of historical stock market data may be minimal, and the relevance of some of the data may be questioned, which can affect the accuracy of the predictions generated by the machine learning model.
4. User adoption: Even if the application is developed and tested successfully, it may face challenges in terms of user adoption and acceptance.
5. Compliance: The mobile application that will be developed will need to comply with various regulatory requirements, which can be complex and may limit the features and functionality of the application.

1.8 Chapter Outline

The research project is written in a step-by-step format, beginning with an introduction as

Chapter One:

This is an introduction that will provide a background and overview of the research topic, as well as the research question and objectives.

Chapter Two - The Literature Review

This will present a comprehensive examination of the current state of the stock market and the use of Artificial Intelligence in stock price prediction and provides a foundation of knowledge and understanding that informs the rest of the project.

Chapter Three, Research Methodology,

This is the analysis of the features and limitations of existing mobile applications for stock trading and identifies areas for improvement in the development of the proposed mobile application.

Chapter Four - System Analysis and Design

This will be the central focus of the project and details the design and development of a user-friendly and highly personalized mobile application that utilizes artificial intelligence to assist individual investors in the stock market.

Chapter Five - Implementation,

This evaluates the performance of the mobile application through user testing and data analysis to ensure that it meets the needs and expectations of individual investors.

Chapter Six - A Summary and Conclusion:

This presents and evaluates the results of the study in terms of their potential impact on the stock market and on individual investors and provides recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The stock market is a complex system that exists with many interacting parts that determine the rise and fall of stock prices. A multitude of factors influence the volatility of the markets and the value of individual stocks. Because of this complexity that lies in the market, predicting trends in the stock market is quite tricky, and picking stocks that will increase in value is difficult for human investors. Artificial Intelligence and Machine Learning have the potential to help address these challenges. AI and ML Models can analyze massive datasets and identify complex patterns, draw relationships that would be nearly impossible for humans to b to detect, and use this to predict stock prices.

2.1.1 Review of Stock Market Price Prediction

Table 1 : Methodology for this review

DATABASE	KEYWORD	NUMBER OF SEARCH RESULTS	NUMBER OF ARTICLES DOWNLOADED
Science Direct	Artificial Intelligence	236,136	2
ACM Digital library	Artificial Intelligence	228,450	5
ACM digital library	Machine Learning	449,737	4
Science Direct	Machine Learning	588,733	8
Google Scholar	Stock Market Prediction	5,450,000	4
Google Scholar	Stock Market Prediction	5,530, 000	3
Science Direct	Stock Market Prediction	103,343	10

2.2 Key Factors that Influence Stock Market Trends and Artificial

Intelligence and Machine Learning Driven Models for Stock Market Price Prediction.

There are many factors that can influence stock market trends, including; Economic conditions and macroeconomic indicators, Investor sentiment from social media and forums, and News Articles (Obthong et al., 2020). There are a variety of Artificial Intelligence and Machine Learning driven models used to predict stock market prices. Some of the most common models are but are not limited to Linear Regression, Support Vector Machines, and Artificial Neural Networks.

2.3 Performance, Limitations, and Gaps of Improvement in AI and ML-driven Models.

In (Singh, 2022) Eight supervised machine learning models were employed in Predicting the movements of the Nifty Index, which is a stock market index in India that consists of Fifty different stocks from 13 other sectors in the Indian Economy, the Techniques used To compare which models perform better in terms of accuracy in the Stock Market are Adaptive Boost (ADABOOST), k-Nearest Neighbours(KNN), Linear regression(LR), Artificial Neural Networks(ANN), Random Forest, Stochastic gradient Descent(SGD), Support Vector Machine(SVM) and Decision Trees (DT), This was done for each based on Historical Data of the Nifty 50 index from April 22, 1996, to April 15, 2021.

According to this Paper, Linear regression was the top-performing model in terms of Predicting the accuracy of Movements of The Nifty Index. While LR and ANN results were almost similar, ANN took more time in training and testing. SVM performed well but was ranked after SGD because of the more time it took in testing and training, In (Mokhtari et al., 2021). SVM was also tested in predicting stock market prices, and it was pointed out that even though it tested out better than DT, it was worse than others such as LR and RF, but it points out that the comparisons were made more specifically for fundamental analysis and may not apply to other types of studies or datasets.

In (Obthong et al., 2020), limitations that have outlined in is that the uncertainty and volatility of the stock market, which happens every day, would make it hard to predict future trends accurately also suggested that another way to improve the accuracy of these models is to employ other additional sources of information, such as news articles and social media sentiment into the prediction models.

2.4 Features and Limitations of current mobile applications for stock trading and their impact on Usability and user experience

Some features of current mobile applications include the provision of real-time market updates, order placements and execution, portfolio management, market and news analysis, customizable watchlists, and historical data and charts (Assistant Professor, Bangladesh Institute of Capital Market (BICM) & Sharmeen, 2022), Though there may be some limitations of these applications compared to actual desktop and web trading applications such as a limited view of advanced charting tools or real-time updates, It is pretty evident that this same limitation is also apparent in the Robinhood Stock trading Application which gained notoriety during the covid 19 pandemic, it also suffers from this same limitation (Steib, 2021) points out that while Robinhood provides five (5) charting indicators, TD Ameritrade delivers Four hundred and eighty nine (489) which signals a lack of very copious amounts of information.

User experience is arguably a key important thing to consider in building mobile applications. Robinhood appeals to its customers with its user-friendly mobile-first interface and technological innovations. The App also allows customers to buy and sell single or fractional shares of stocks without charging brokerage fees(Welch, 2020)

(Steib, 2021) also points out that while Robinhood charges no brokerage fees, it is designed to be simple and engaging for its users with features that make investing more like a game. Buying a stock is extremely easy, and once a trade has been placed, there are animations playing confetti celebrating the investment, potentially encouraging users to place another trade.

2.5 Evolution of Stock Market Prediction Techniques

Stock market prediction has always been difficult due to the number of variables involved(Shah et al., 2019), However, Machine learning has integrated itself into the picture for deployment and training sets and data models, and regression machine learning algorithms are used to predict stock prices based on stock market historical data (Shivani et al., 2022)

2.6 Time Series Analysis and Feature Engineering

Time series analysis is a task in data science that helps organizations in capacity planning, goal setting, and anomaly detection (Taylor & Letham, 2017), machine learning, regression algorithms, and Artificial Neural Networks (Wen et al., 2021), Feature engineering is an essential aspect of time series analysis, and it involves selecting and extracting meaningful features from the data(Iqbal et al., 2023), Time series data pre-processing is also an essential step in time series analysis, and it involves techniques such as autoregressive integration, moving average, long-short-term memory neural network, time series condensation, wavelet transform, and frequency domain(Kanber & Santur, 2023)

2.7 Supervised and Unsupervised Learning Approaches Toward Stock Markets Price Predictions

While stock market price prediction is a problem, both supervised and unsupervised learning approaches have been used to address this problem. Supervised learning techniques such as Long Short-Term Memory (LSTM) algorithm have been used to predict stock prices based on historical data (Sen et al., 2021). Supervised learning techniques such as convolutional neural network (CNN) have been used to extract features from time series data for stock market trend analysis(Xie & Yu, 2021), social media sentiment analysis has been incorporated into learning-based stock market trend analysis(Wang et al., 2021)

2.8 Deep Learning Approaches Towards Stock Market Price Predictions

Deep learning approaches have been gaining attention in the stock market prediction field due to their ability to handle large datasets and accurately map data for prediction(Chandola et al., 2022).

(Chong et al., 2017) conducted a comprehensive analysis of deep learning networks for stock market analysis and prediction. They used five-minute intraday data from the Korean KOSPI stock market and applied deep learning networks to residuals of autoregressive models to improve prognosis.(Ab.Khalil & Abu Bakar, 2023) also used deep learning algorithms for stock market prediction in Malaysia and found that the deep learning prediction model was effective in handling univariate and multivariate forecasting.

2.9 Hybrid and Ensemble Methods and Stock Market Price Prediction

Hybrid and ensemble methods have been proposed as practical approaches for stock market price prediction (Yujun et al., 2020).

(Yujun et al., 2020) proposed a hybrid method for stock price prediction using long short-term memory (LSTM) and ensemble empirical mode decomposition (EMD). They decomposed the original stock price time series into several subsequence using comprehensive EMD, which were then used as inputs to the LSTM model. (Lin et al., 2021) constructed a novel ensemble machine learning framework for daily stock pattern prediction by combining traditional candlestick charting with the latest artificial intelligence methods. They used several machines learning techniques, including deep learning methods, to predict daily stock patterns.

(Khamis & Guan, 2020) proposed a hybrid approach based on a backpropagation neural network and Markov chain for stock price prediction. They found that a single method would be limited to achieving an ideal precision level due to the complicated influencing factors in the stock market. Therefore, they proposed a hybrid approach based on adaptive modelling and conditional probability transfer.(Sen et al., 2021) analyzed the sectoral profitability of the Indian stock market using an LSTM regression model. They found that the use of machine learning and deep learning systems for stock price prediction has been the most popular approach in recent times. Hybrid deep learning-based stock market prediction with both sentiment and historical trend data was proposed (*Hybrid Deep Learning Based Stock Market Prediction With Both Sentiment and Historic Trend Data*, 2020). They combined the merits of both machine learning and statistics-based methods for accurate prediction in the short and long term.

2.10 Evaluating and Validating AI and ML Models for stock market prediction

Machine learning (ML) models have been shown to perform better than statistical and econometric models, and It is also noted that Ensemble ML Models perform better than single ML Models(Ampomah et al., 2020) (Kelotra & Pandey, 2020) proposed a stock market prediction system that effectively predicts the state of the stock market using a deep convolutional long short-term memory (Deep-ConvLSTM) model. The effectiveness of artificial intelligence (AI) in stock market prediction has also been studied(Mokhtari et al., 2021). feature selection and extraction techniques have been proposed to identify critical features that affect the performance of ML models(Htun et al., 2023). To evaluate and validate AI and ML models for stock market prediction, it is essential to use appropriate evaluation metrics such as mean squared error, mean absolute Error, and root mean squared Error (Chopra & Sharma, 2021) evaluating and validating AI and

ML models for stock market prediction requires appropriate evaluation metrics and cross-validation techniques. It is also essential to validate the models using out-of-sample data to ensure that the models are not overfitting the training data.

2.11 Summary

This literature review examines the use of Artificial Intelligence (AI) and Machine Learning (ML) for stock market prediction. Economic indicators, investor sentiment, and other factors influence stock market trends. Standard ML models for prediction include Linear Regression, Support Vector Machines, and Neural Networks, though they have limitations like handling uncertainty and real-time prediction.

Mobile stock trading applications offer features such as real-time updates but may lack advanced tools. User experience is vital, as with the popular App Robinhood. ML and time series techniques have enabled stock prediction using supervised and unsupervised learning. Deep learning handles large datasets and can accurately map data for prediction. Hybrid and ensemble methods also show promise.

Evaluating ML stock models is essential, using metrics and cross-validation. Challenges include data quality, model interpretability, overfitting, real-time prediction, alternative data, and ethics. Addressing these could improve accuracy, reliability, and adoption.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This Chapter will detail the research methodology and design that will be implemented o develop the mobile applications using Artificial Intelligence and Machine Learning for stock market predictions, this Chapter outlines the processes for data collection, feature engineering, model selection and development, evaluation, mobile application development, user testing, and ethical considerations.

3.2 Design Science Methodology

This study follows the design science research methodology, which aims to create and evaluate information systems artifacts intended to solve identified business problems.

3.2.1 Awareness of the Problem

The problem addressed by this study is the lack of useful and user-friendly mobile applications for trading the stock markets. While numerous apps exists claiming to simplify stock market trading , many fail to adequately do so , instead creating additional frustration, for the average retail investor , navigating the stock market is challenging enough, the reality is that too many retail investors still struggle with stock market trading usually due to the complexity of the stock market and the huge information one needs to consume and patterns they need to study and pan out in order to make a successful trade. Rather than empowering users, many stock mobile trading applications result in confusion due to their poor information architecture, distraction due to constant push notifications and alerts mean very little and significant time is wasted trying to make sense of all the data on the display.

3.2.2 Proposed Solution

To overcome this difficulty, the purpose of this study is to propose the creation of a mobile application that uses Machine learning and artificial intelligence to forecast stock market values and conduct transactions on behalf of the user. The objective is to develop an approachable and user-friendly solution that lowers the cognitive load for people with little background knowledge and expertise and enables people to make more intelligent and booming stock market investment decisions.

3.23 Design

To develop an innovative mobile application aimed at empowering retail investors, a user-centered design approach will be employed leveraging best practices in human-computer interaction and user experience design. The design must first and foremost address the needs of the target user group by understanding their key pain points, desires, and behaviours.

Through surveys and interviews, retail investors' frustrations with existing stock trading applications and their wish list for an ideal solution can be extracted. Users seek applications that enhance simplicity rather than complexity, surface only meaningful and actionable insights, provide useful predictive capabilities and explanations, optimize for convenience and efficiency, and maintain high security standards to safeguard personal data and access. These needs will guide the overall design, interface, features, and functionalities included in the proposed mobile application.

The interface aims for a minimalistic yet compelling style with clear information hierarchy, seamless navigation, and engaging yet straightforward visuals. A cluttered or overly technical interface will only reproduce existing problems that users cited with other stock trading applications. Each included feature and piece of information must be intentionally curated to provide value, with the total user experience being one of empowerment through simplicity and intuitiveness rather than confusion or distraction.

Key features may include forecast modelling with interactive visual explanations of predictions, sentiment, and trend analysis of selected stocks, watchlists and push notifications, portfolio tracking, and news integrations. However, an agile development methodology with continuous user testing and feedback will determine the final set of features included, as the solution is iterated and improved over time based on how well it addresses the stated user needs and research objectives. Rigorous testing procedures are employed to ensure any integrated predictive models meet minimum performance and accuracy standards before release.

User privacy and security inform key areas of the design as well, with the application requiring secure authentication, encrypted data transfers, and other measures to protect personal user information and account access. User trust in the application is paramount, and security is in place to facilitate that trust in the technology.

The design of this mobile artifact leverages a human-centered approach focused on addressing the actual needs and desires of retail investors through providing an experience optimized for simplicity, meaning, and empowerment. By employing best practices around user-centered design, agile development, and rigorous testing, the application will hopefully achieve its aim to give individuals greater access and convenience in navigating the stock market, unlike the solutions currently available. The end result may be an application with significant practical and research value, demonstrating through its design what is possible when technology is developed with the human user as the primary concern.

3.3 Data Collection

3.3.1 Data Sources

In embarking on this study, various sources of data will be utilized to gather historical stock prices and some other relevant data such as macroeconomic indicators. These sources will include Yahoo Finance, Kaggle, The Securities and Exchange Commission of the United States of America, the New York times, Reddit, and Twitter, each of these sources will provide different type of data, thereby contributing to a richer and more comprehensive dataset.

Table 2 : Data Collection Sources

Data	**Type of data**	**Details**
KAGGLE	HISTORICAL STOCK DATA	This provides datasets containing historical data stock price data, financial statements, and market indicators
	SENTIMENT	Offer datasets containing news headline, social media posts and other textual data for sentiment analysis
SEC	MACROECONMIC INDICATORS	Financial statements, annual reports, and other corporate filings are available for historical data analysis.
REDDIT	SENTIMENT	Subreddits like r/stocks, r/investing, and r/wallstreetbets contain discussions and

		opinions for sentiment analysis.
TWITTER	SENTIMENT	Tweets from influential users, companies, and finance experts can be used for sentiment analysis.

3.3.2 Data Selection

Relevant data will be selected based on its relevance and quality, the data should be free of errors and inconsistencies, ensuring its reliability for model training. Data pre-processing and cleaning steps will be carried out to remove any noise or irrelevant information.

Relevant data that represents key factors influencing stock prices should be chosen, such as historical stock prices and trading volumes, company fundamentals, macroeconomic indicators, social media posts, and news articles. However, the data must also be high quality - free of errors, inconsistencies, and noise.

For stock data, quality assurance involves ensuring there are no missing or erroneous values for price, volume, or other attributes. Inaccurate data could skew prediction models, so any anomalies must be addressed through imputation or removal. High-frequency stock price data should be checked to match market trading hours and filtered for extremes that could indicate data errors.

Macroeconomic indicators like inflation rates, interest rates, GDP, and exchange rates should be from reputable data sources. Social media posts and news articles present additional challenges as natural language needs to be analyzed to derive investor sentiment, opinions, emotions, or other insights.

For all types of data, inconsistencies must be handled, missing values should be imputed, or the instances removed, and obvious errors or outliers must be dealt with before training ML models. Some techniques for data cleaning and preprocessing include:

1. Removing or fixing incorrect data
2. Imputing missing values through mean, median or k-nearest neighbor methods
3. Smoothing out noise and outliers with averaging or regression techniques
4. Normalizing or standardizing features to the same scale

5. Performing dimensionality reduction like PCA to simplify datasets.

3.4 Feature Engineering

In order to optimise the performance of our Artificial Intelligence and Machine Learning Models, meaningful features will have to be extracted from the collected data, techniques such as correlation analysis, principal component analysis and feature selection algorithms will be employed to identify the most significant predictors of stock markets trends.

3.5 Model Selection and Development

3.5.1 Supervised Learning Models

In previous literature , Linear regression which is a supervised learning model showed a much clear sign of accuracy with a little margin of Error (Singh, 2022), In this study, Linear regression will be used to train the model based on historical stock data.

3.5.2 Unsupervised Learning Models

Clustering techniques and dimensionality reduction methods will be explored to analyse patterns in the data and uncover hidden relationships, these techniques will; help the overall understanding of the stock market trends and improve model performance.

3.5.3 Hybrid and Ensemble Models

In order to improve upon our prediction performance, hybrid and ensemble methods will be examined, these approaches will combine multiple models, strengthening the strengths of individual models and minimizing their weaknesses leading to more accurate predictions.

We would use an ensemble method called bagging also known as bootstrap aggregating. Since we are training our model only to predict Apple, Inc. (AAPL) stock prices.

For predicting Apple stock prices, bagging offers three key benefits:

- **Reduced variance**: Bagging creates varied versions of the model by training on random portions of the data. This helps prevent overfitting since each model depends on different training samples. The predictions are then averaged, so the variance from any individual model is reduced. For the volatile stock market, this leads to more stable and generalized predictions.

- **Improved stability**: With the data changing daily, a model that provides consistent predictions is desirable. Bagging trains models on slightly different data subsets, so the projections do not shift much when the training data changes incrementally. The ensemble of models is more robust to small fluctuations in the training set. For Apple stock, improved stability could help reduce false signals from the model.
- **Enhanced interpretability:** The individual models in the ensemble are more straightforward than the complex original model. Their predictions can be analyzed separately to understand the reasoning for the ensemble's aggregate forecast. For predicting Apple stock, model transparency is vital to determine how different variables are impacting the predictions and whether the models are capturing meaningful patterns.

In summary, bagging is an effective way to improve critical attributes of a stock prediction model - accuracy through reduced variance, stable predictions that do not change drastically with small data changes, and interpretability gained by analyzing the simpler base models. For a technology stock as widely owned and volatile as Apple, an accurate and dependable yet transparent model is vital for effective trading decisions. Bagging helps ensure the prediction model can meet all these objectives, and therefore prove its value for forecasting Apple stock prices and trends.

3.6 Model Evaluation and Validation

Cross validation techniques will be employed to determine the performance of the AI and ML model, Metrics such as mean squared Error, mean absolute Error, and Root mean squared Error will be sued to evaluate model accuracy, out of sample validation will ensure that models are not overfitting the training data.

3.7 Mobile Application Development

3.7.1 Technology Stack

The mobile application will be built using the Flutter and Dart framework, Google cloud platform, Firebase and Colab, these technologies will help offer us a robust and scalable foundation for build a user friendly and user centred application.

Flutter and dart programming languages will be used to build out the Applications user interface and Application logic, Whilst the Google cloud Platform will be used to build our Models and

Firebase to handle our Back-end services such as database management and user authentication.

3.7.2 User Interface and User Experience Design

Design principles such as simplicity, consistency, and feedback will guide the development of this mobile application.

The information display, font, design, and receptivity with the user all depend on the user interface, making it crucial for app delivery and adoption. Mobile trading applications are more likely to attract tech-savvy investors when they find the user interface experience appealing in their first-time use. Therefore, building an exemplary user interface and user experience design is essential for mobile trading applications to succeed in attracting users.(Malhotra, 2020), ease of app usage, investment analysis information, and security and privacy concerns are vital features that users look for in these applications.

3.8 Summary

This Chapter discusses the methodology used for developing this Artificial Intelligence Powered Stock Mobile Application, it includes data collection from various sources such as Kaggle, Yahoo Finance, SEC, Reddit, and Twitter, and emphasizes ta selection and cleaning to ensure high quality input.

To build an accurate stock prediction model, feature engineering is applied to derive relevant signals from the data. A range of machine learning techniques are employed, including supervised, unsupervised, hybrid, and ensemble methods, to harness these signals for forecasting. Cross-validation and performance metrics are used to evaluate model quality rigorously.

For the mobile App, Google's Flutter framework and Dart language are used given their strengths in developing cross-platform applications with an intuitive UI. The App leverages Google Cloud Platform and Firebase for deployment and scaling, while model building experiments are conducted in Colab. Simplicity, consistency, and feedback shape the UX design - guided by user preferences gathered from a survey.

CHAPTER 4: SYSTEMS ANALYSIS AND DESIGN

4.1 Introduction

This Chapter will discuss the system analysis and design processes of Verge: A mobile Application that Utilises Artificial Intelligence and Machine Learning for stock market prediction and training This Chapter will cover systems requirements, Architecture AI/ML integration, transaction Management, proposed system analysis limitations and UML diagrams.

4.2 Analysis of Proposed System

The proposed mobile App seeks to revolutionize stock trading by combining AI and ML with mobile accessibility. An intuitive interface suits users of all expertise, enabling effortless engagement. Using the flutter framework to build this Mobile App ensures compatibility with all types of smartphones and tablets which allows for flexible and on-the-go monitoring and trading.

In Integrating AI and ML, the App analyzes stock data to identify trends and opportunities, generating price predictions to inform trading decisions. Real-time data and alerts keep users updated to act timely.

Users can customize watchlists, price targets, and automated trading strategies for their needs. Personalization enhances the experience and meets unique needs.

Robust encryption and strict protocols protect sensitive data and transactions.

The mobile app leverages AI/ML to facilitate stock trading and provide insights. Offering a user-friendly interface, real-time data, personalization, and security, the App aims to improve the trading experience for all.

A vital aspect of this proposed system is the integration of Artificial Intelligence and Machine Learning Models to analyze historical stock data and identify market trends and opportunities, by providing users with Stock market predictions, the App aims to help users make informed decisions when trading stocks.

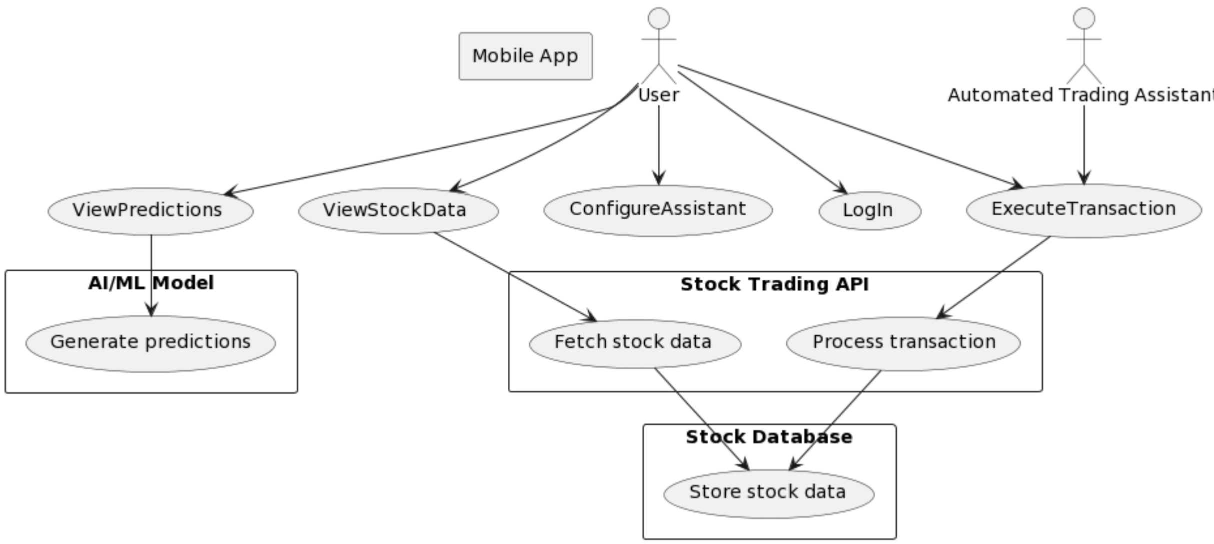
Personalization and Automation plays a huge role in this system, since Users will be able to set custom price targets to engage in a Buy and Sell orders and customize trading assistants to their preferred trading strategies.

4.3 UML Diagrams

In this section Unified Modelling Diagrams (UML) Diagrams and dataflow diagrams that illustrate the system design of this Mobile Application.

4.3.1 Use Case Diagrams

Figure I: Use Case Diagram

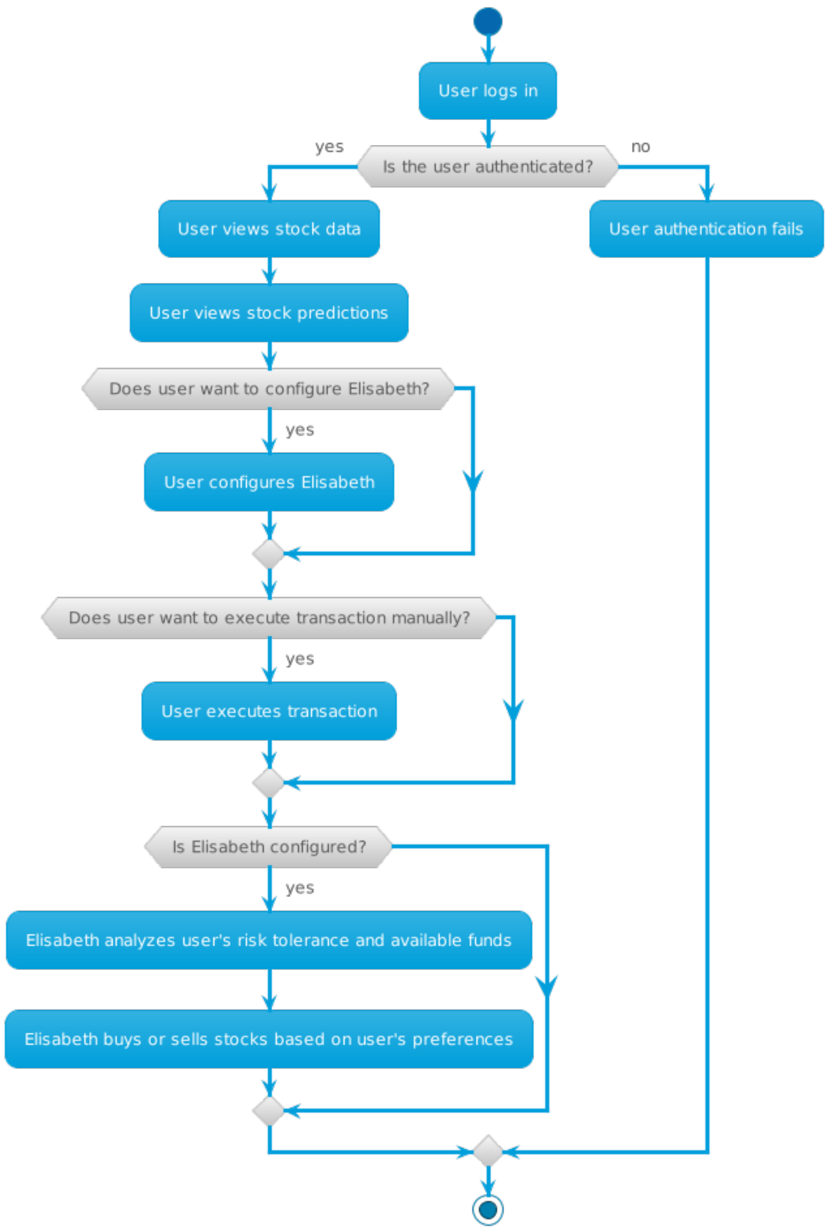


This use case diagram represents what a hypothetic user and various components and this stock trading app. The user logs into the App, our mobile application handles user authentication, after logging in, Our user can view stock data about any particular company listed in the NYSE/NASDAQ, this paper, it is focused on Apple, Inc. (AAPL), The mobile App retrieves stock data from the stock trading API, which fetches data about the stock in questions and shows it to the user, The user also can on the exact page view stock predictions and the mobile App communicates with the AI/ML Model and serves the data which are then displayed to the user, The User can execute transactions such as buying and selling stocks through the mobile App, This use case also shows an Automated trading assistant (Elisabeth) that can buy stocks based on the users predefined risk tolerance and set available funds.

4.3.2 Activity Model/Diagram

This activity model/diagram represents the workflow of our AI powered stock trading mobile application.

Figure II: Activity Model/Diagram



The diagram depicts the proposed stock trading app's authentication, data access, and transaction execution flow. Users sign in and enter their settings like risk tolerance and funds. The AI assistant

"Elisabeth" then analyzes preferences to handle automated trading or recommendations for manual trading.

First, users authenticate to the App, likely with biometrics or passwords. Then they can view stock data like prices, news, and AI-generated predictions. Users tailor the experience by configuring Elisabeth with their risk appetite and investment budget.

Elisabeth assesses the user's profile and settings to execute automated stock purchases and sales that align with their needs. However, users can also view Elisabeth's trading suggestions and manually buy or sell stocks themselves through the App.

The diagram illustrates how the App enables seamless switching between automated and manual trading based on users' preferences for control and convenience. Fundamental interactions highlight how Elisabeth enhances yet does not replace human judgment, for an optimum balance of AI and personal oversight in investment decisions.

The diagram provides a visual overview of how users would engage with the App for an optimized, personalized trading experience tapping into both human discretion and AI's analytics. The ability to configure Elisabeth based on risk tolerance and then rely on the AI for automated or recommended trades shows how the App can serve users with diverse expertise and needs. Please let me know if any part of this explanation would benefit from clarification or rephrasing. I aimed to convey the essence of how users would interact with the features while giving additional context on the AI and personalization aspects for depth.

4.3.3 Class Diagrams

This class diagram represents the structure of Verge; Our AI Empowered Stock Application featuring our Automated Trading App named Elisabeth.

The diagram depicts six classes that enable the stock trading app's functionality: User, MobileApp, AIModel, StockTradingAPI, StockDatabase, and AutomatedTradingAssistant ("Elisabeth").

The User and MobileApp classes authenticate users, view AI predictions, and execute trades. The AIModel generates stock price predictions to inform decisions. The StockTradingAPI and StockDatabase retrieve stock data and process transactions.

Central is the AutomatedTradingAssistant class, representing Elisabeth. It assesses user settings like risk tolerance and budget to execute automated trades that align with their needs. Elisabeth's personalization allows seamless switching between AI-driven and manual trading.

The User class likely handles passwords or biometrics for authentication and settings input. The MobileApp class probably has interfaces to view data, see predictions, trade manually or rely on Elisabeth. The AIModel may train on historical prices and news to forecast trends. The StockTradingAPI could get data from exchanges, while the StockDatabase stores user portfolios locally.

This class diagram gives an overview of components enabling an integrated, user-friendly stock trading experience. From account access to data analysis and automated trades, the App leverages AI to augment rather than replace human judgment. The ability to customize Elisabeth's level of control provides both automation and optionality.

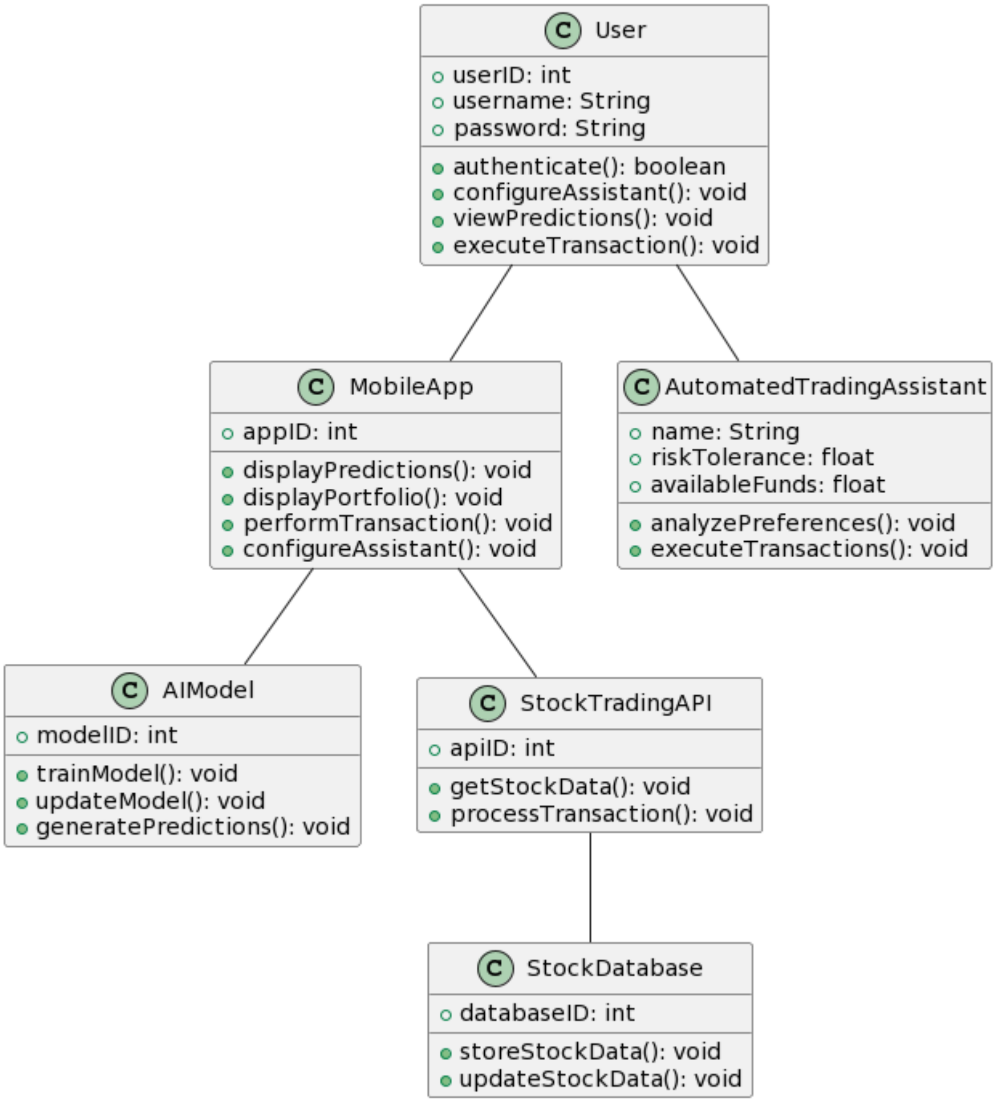


Figure III: Class Diagram

4.3.4 Transition (State) Diagram

The diagram depicts states and actions for users of the stock trading mobile app with the AI assistant Elisabeth. It highlights how users can access the system, tap into AI insights or manual features, personalize the experience, and navigate in a seamless flow.

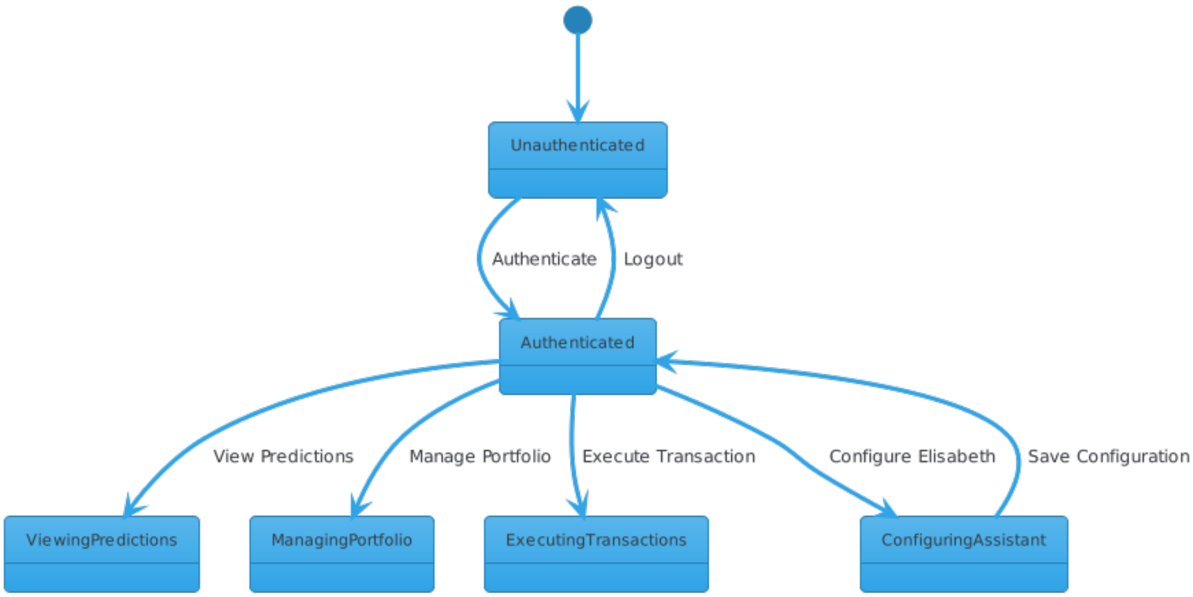


Figure IV: Transition diagram

Initially, users are unauthenticated outside the App. By signing in, they reach an authenticated state to view stock data, news, predictions, and portfolios. Users can buy or sell stocks manually or rely on Elisabeth for automated trades based on their preferences.

The configured Elisabeth state allows tailoring the AI to users' risk appetite and budget. Then Elisabeth handles automated stock transactions that align with their needs while also providing recommendations for manual review. Users remain in control and can adjust or turn off Elisabeth's automation at any time based on their evolving needs and market changes.

Other actions like viewing predictions or portfolio details do not change the overall state but allow interaction with certain app features. At any point, users can log out and return to an unauthenticated state outside the system.

This Transition diagram highlights the dynamic experience enabled by balancing AI automation with human judgment and optionality. The ability to configure Elisabeth's level of control provides a personalized experience for users with diverse expertise and needs. The clearly visualized states and transitions give an overview of how users can navigate the App, relying on machine or human direction.

This transition (state) diagram outlines an intuitive flow from accessing the App to leveraging its AI, data, and manual features for an integrated trading experience. The transitions between states are designed for optimal switching between automation and oversight in a seamless manner. Please let me know if any part of this explanation can be improved or expanded on in my own words. I aimed for a high-level sense of the user journey and experience while speculating on the balance of control and personalization the App provides.

4.3.5 Entity Relationship Diagram

Our Entity relationship diagram consists of four (4) entities, User, Stock, Transaction and AssistantConfiguration.

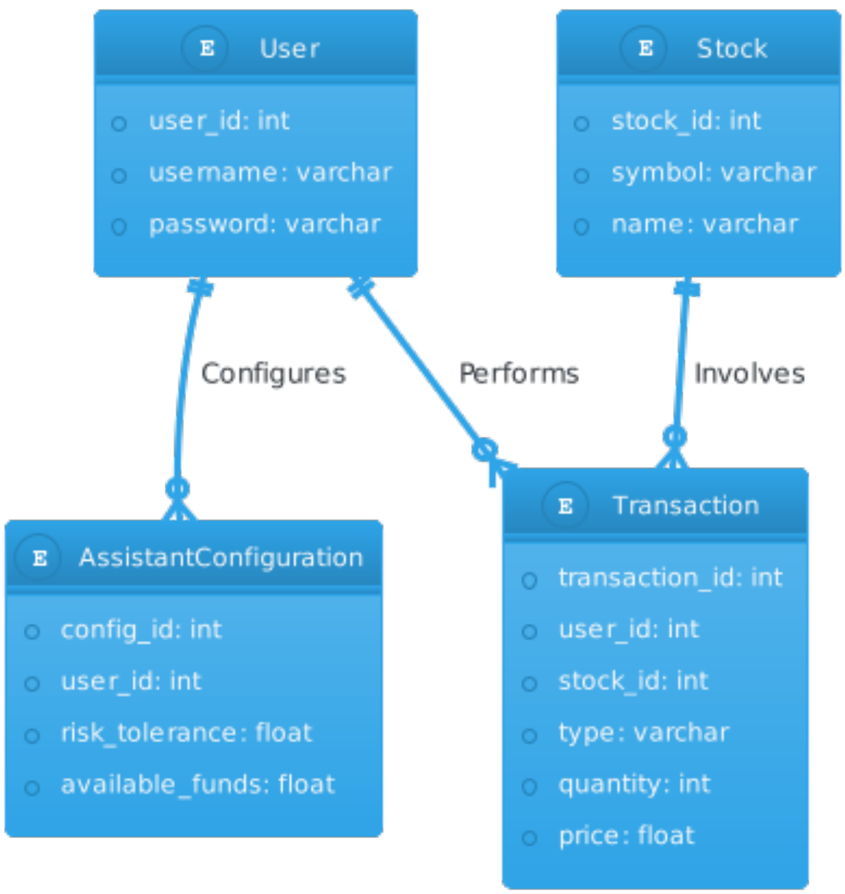


Figure V: Entity relationship Diagram

The Entity relationship diagram shows four key entities for the stock trading app: User, Stock, Transaction, and AssistantConfiguration.

The User entity represents app users. The Stock entity denotes the actual stocks that users can trade. The Transaction entity links users to the stocks they buy or sell, enabling the core functionality.

Central is the AssistantConfiguration entity, which stores each user's settings for customizing Elisabeth, the AI assistant. By inputting details like risk tolerance, investment budget, or trading frequency, users can tailor Elisabeth's level of automation to their needs. Elisabeth then handles stock transactions on users' behalf or provides recommendations for their review based on these personalized configurations.

The entities and relationships in this diagram reflect an integrated experience that balances machine automation with human control. Users ultimately remain in charge but can adjust how much discretion they delegate to Elisabeth based on a spectrum of expertise and changing needs. The ability to customize the AI provides for dynamic personalization over time.

The User and Stock entities likely have a many-to-many relationship since users can trade in multiple stocks. Each Transaction probably links one user to one stock for a buy or sell action. The AssistantConfiguration settings may have a one-to-one relationship with the User entity as users customize Elisabeth independently based on their unique profiles.

In order to summarize this, Our Entity relationship diagram outlines how the key data entities - user, stock, transaction, and AI configuration - relate to enable a personalized stock trading experience. The relationships between entities illustrate how the App allows seamless switching between automated AI trades and manual transactions based on user preferences. Please let me know if any part of this summary would benefit from clarification or revision in my own words. I aimed for a high-level overview of the entities, relationships, and functionality while providing some additional details on the balance of human and AI control for context.

4.3.6 Data Flow Diagram

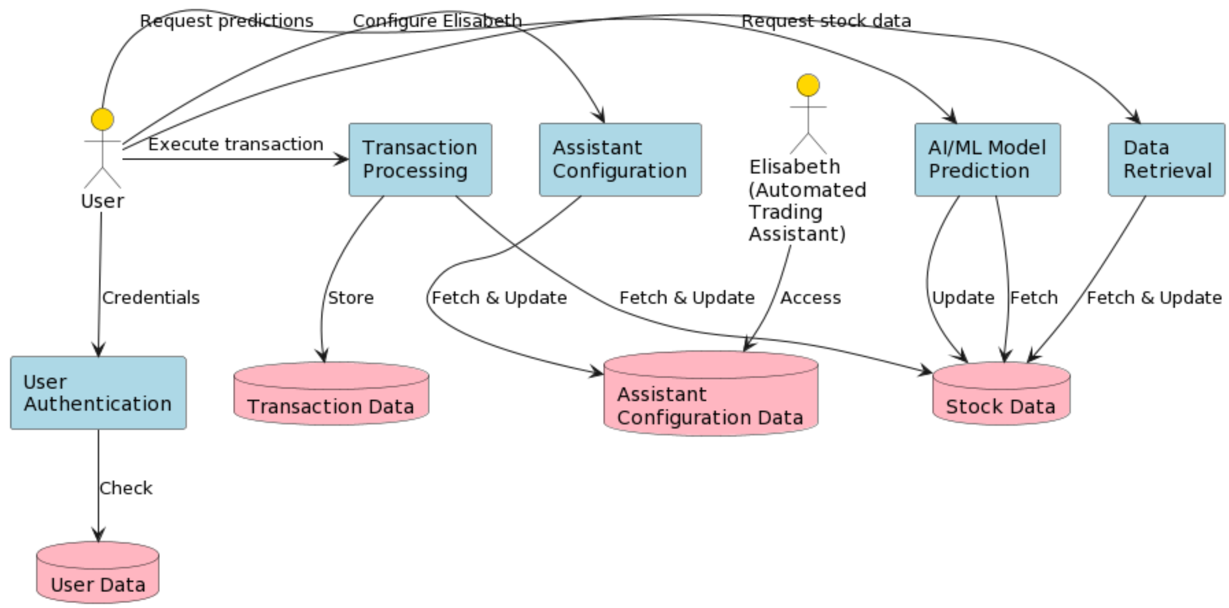


Figure VI: Data flow Diagrams

Our dataflow diagram displays the flow of information in Verge, our AI powered stock trading App.

The Data Flow Diagram (DFD) depicts interactions and data flow within the stock trading app with the AI assistant Elisabeth. It shows critical processes like user authentication, data retrieval, AI predictions, transactions, and configuring Elisabeth. The four leading data stores are:

1. User Data: Sign-in info, portfolios, settings
2. Stock Data: Prices, news, historical trends
3. Transaction Data: Users' buys, sells, values
4. Assistant Configuration Data: Users' preferences for Elisabeth like risk tolerance, budget, trading frequency.

The diagram visualizes how the app components relate, managing data flow between users, Elisabeth, and the data stores. By configuring her to their needs, users determine Elisabeth's level of automation in transactions, recommendations, or both.

User Authentication likely verifies sign-in details before accessing data stores. The Data Retrieval process probably gets stock info, news, and users' portfolios. The AI/ML, Model Prediction process may forecast stock trends using historical data. Transaction Processing could execute users' buys and sells, updating portfolios.

Configuring Elisabeth allows customizing her control. Users input settings, and the App updates the Assistant Configuration Datastore. Elisabeth then handles automated transactions or provides recommendations aligned with users' preferences. But users always remain in charge and can opt to transact manually.

This dataflow diagram maps how data moves between the critical parts of an integrated, personalized trading experience. Balancing AI automation with human oversight and judgment, the App lets users seamlessly switch between directing transactions themselves and relying on Elisabeth - based on their expertise, needs, and market changes. Overall, this Dataflow Diagram illustrates an optimal fusion of humans and machines that puts users firmly in control of their trading.

4.4 Limitations of the Proposed System

Despite the potential Advantage of this system and its being able to meet the requirements set out, this system has some potential mishaps and limitations. Each and every technology has its setback/drawbacks, so some of these are examined here.

Data availability and quality: High-quality historical data is essential to train accurate AI/ML models, but access may be limited by data sources and privacy regulations. Without sufficient, error-free data, the models cannot capture meaningful patterns to generate precise predictions. The App would need to source clean data from exchanges, news outlets, and social platforms.

Accuracy of AI/ML models: Even with large datasets, the models have limitations and may not always predict stock prices or trends perfectly. The complex, chaotic nature of financial markets is difficult to map entirely. Model errors or inaccuracies may lead to unreliable or false signals for users. The models require continuous retraining as new data emerges to improve predictions over time.

Compliance with regulations: As a stock trading app, the system must follow strict rules around data privacy, information security, fraud prevention, and more. Addressing various complex regulations could restrict some features or require legal resources to navigate compliance. Laws also differ between countries and jurisdictions, posing challenges for launching and scaling the App globally.

User adoption and acceptance: Experienced traders may prefer familiar trading tools and be hesitant to rely on an app for such a sensitive, high-risk activity. Younger, more digitally adept traders may be early adopters, but wider user acceptance will depend on proving the App's security, accuracy, and value, which takes time. Adoption is critical to commercial viability, so user input in development could increase the appeal.

Other limitations include bias in data or models disadvantaging some groups of users, overtrading or high-frequency trading encouraged by ease of mobile access, and over-reliance on automation, which reduces individuals' responsibilities in their investing decisions.

In summary, while the proposed stock trading app offers innovative AI capabilities and convenience, its limitations span data, models, compliance, adoption, and more. With solid data sourcing and cleaning, continuous model improvement, close regulation monitoring, and increasing personalization, many limitations can be addressed over time. But some challenges will persist, requiring a balance of human and AI control. Overall success depends on addressing real user needs, values, and concerns at each stage.

CHAPTER 5: IMPLEMENTATION

5.1 Introduction

In this Chapter, a step-by-step guide will be panned out in order to show the various steps and ways that will help us reach our objective.

5.2 Mobile Application

5.2.1 Onboarding

In Adhering to general User experience design, It is expected for our mobile app to have an onboarding process which will introduce new users our Mobile Application, the splash screen is the first screen that our users will see when they open the mobile application, in adhering to traditional User Interface and User experience, It should be visually appealing and brief and not take too long to operate, the splash screen for this app stays only on screen for 2000 milliseconds

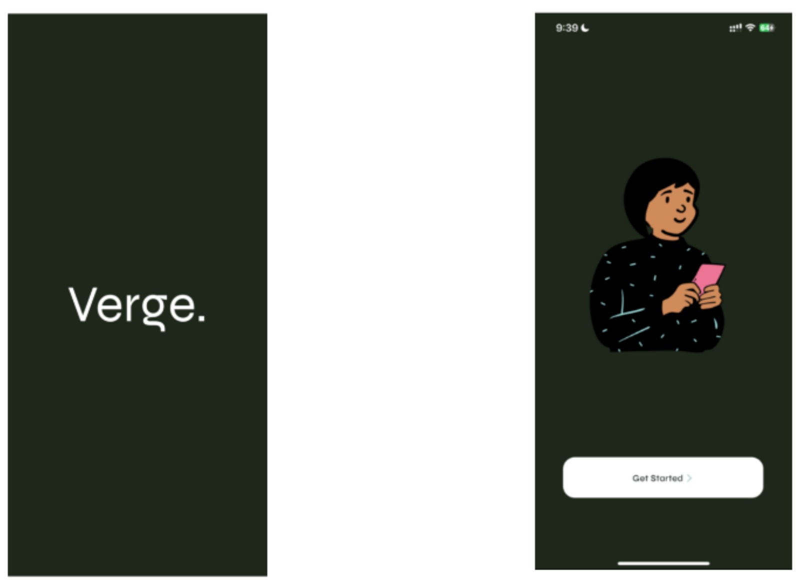


Figure VII: Implementation of Onboarding Screens

```
    Container(
    width: 430,
    height: 932,
    decoration: BoxDecoration(
        color : Color.fromRGBO(255, 255, 255, 1),
),
    child: Stack(
      children: <Widget>[
        Positioned(
      top: 0,
      left: 0,
      child: Container(
      width: 430,
      height: 932,
      decoration: BoxDecoration(
        image : DecorationImage(
        image: AssetImage('assets/images/Vergesplashscreen1.png'),
        fit: BoxFit.fitWidth
    ),
)
    )
    ),
      ]
    )
  )
```

Figure VIII Splash Screen Code

```dart
Container(
      width: 430,
      height: 932,
      decoration: BoxDecoration(
          color : Color.fromRGBO(31, 39, 27, 1),
 ),
      child: Stack(
        children: <Widget>[
          Positioned(
        top: 743,
        left: 47,
        child: Container(
      width: 335,
      height: 68,

      child: Stack(
        children: <Widget>[
          Positioned(
        top: 68,
        left: 0,
        child: SvgPicture.asset(
        'assets/images/base.svg',
        semanticsLabel: 'base'
      );
      ),Positioned(
        top: 24,
        left: 116,
        child: Container(
      width: 103,
      height: 22,

      child: Stack(
        children: <Widget>[
          Positioned(
        top: 0,
        left: 0,
        child: Text('Get Started', textAlign: TextAlign.center, style: TextStyle(
        color: Color.fromRGBO(30, 33, 33, 1),
        fontFamily: 'Syne',
        fontSize: 15,
        letterSpacing: 0 /*percentages not used in flutter. defaulting to zero*/,
        fontWeight: FontWeight.normal,
        height: 1.4666666666666666
      ),)
      ),Positioned(
        top: 3,
        left: 87,
        child: null
      ),
        ]
      )
    )
      ),
        ]
      )
    )
      ),Positioned(
        top: 173,
        left: 38,
        child: null
      ),
        ]
      )
    )
```

Figure IX Get Started Page Code

5.2.2 Sign Up and Log In

Log in and Sign-Up Pages are critical for every Mobile application, it is positive for creating the first impression that will be important in user retention and a well-designed and simple log in and sign-up page can help increase users' engagement. The use of clear and concise labels for all fields and making sure the fields are large enough for users to enter their information easily.

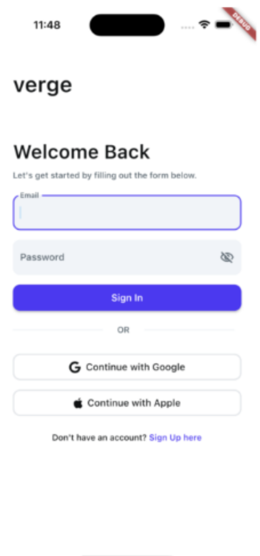


Figure X: Log In and Sign-up Page

5.2.3 Home Page

The homepage of a mobile app is very important to because it is the first part of a user's engagement with the actual mobile app, in our mobile app , upon the users first glance they see a welcome message showcasing and confirming the particular user account and telling them their asset portfolio, followed by a section of stocks with which our AI models will suggest to users and a news and guidelines section with which our users can catch up with on the latest news financial news available.

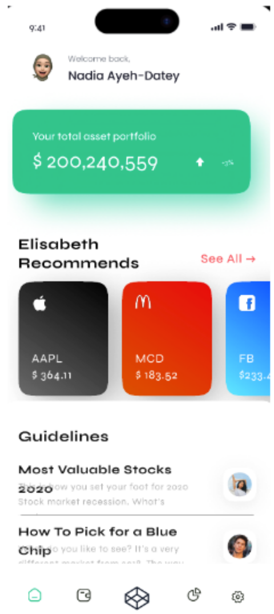


Figure XI: Implementation of Homepage in App

```
Container(
width: 430,
height: 932,
decoration: BoxDecoration(
    color : Color.fromRGBO(31, 39, 27, 1),
),
child: Stack(
  children: <Widget>[
    Positioned(
  top: 743,
  left: 47,
  child: Container(
width: 335,
height: 68,

child: Stack(
  children: <Widget>[
    Positioned(
  top: 68,
  left: 0,
  child: SvgPicture.asset(
  'assets/images/base.svg',
  semanticsLabel: 'base'
);
),Positioned(
  top: 24,
  left: 116,
  child: Container(
width: 103,
height: 22,

child: Stack(
  children: <Widget>[
    Positioned(
  top: 0,
  left: 0,
  child: Text('Get Started', textAlign: TextAlign.center, style: TextStyle(
  color: Color.fromRGBO(30, 33, 33, 1),
  fontFamily: 'Syne',
  fontSize: 15,
  letterSpacing: 0 /*percentages not used in flutter. defaulting to zero*/,
  fontWeight: FontWeight.normal,
  height: 1.4666666666666666
),)
),Positioned(
  top: 3,
  left: 87,
  child: null
),
  ]
)
)
),
  ]
)
)
),Positioned(
  top: 173,
  left: 38,
  child: null
),
  ]
)
)
```

Figure XII Homepage Code

5.2.4 User Settings and Profile

This page will allow users customise their personal information ranging from banks and card payment services and edit personal information like address and contact details and getting security options like setting password and biometric authentications.

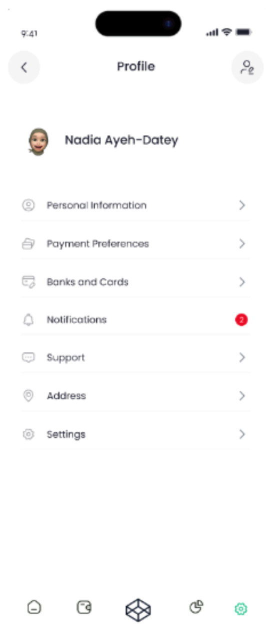


Figure XIII: User Settings and Profile Implementation

```
Container(
    width: 430,
    height: 932,
    decoration: BoxDecoration(
        color : Color.fromRGBO(255, 255, 255, 1),
),
    child: Stack(
      children: <Widget>[
        Positioned(
      top: 830,
      left: 0,
      child: Container(
    width: 430,
    height: 102,

    child: Stack(
      children: <Widget>[
        Positioned(
      top: 4.547473508864641e-13,
      left: 0.00013506412506103516,
      child: Container(
    decoration: BoxDecoration(
        boxShadow : [BoxShadow(
        color: Color.fromRGBO(237, 237, 237, 0.25),
        offset: Offset(0,-4),
        blurRadius: 16
    )],
    color : Color.fromRGBO(255, 255, 255, 1),
),
```

Figure XIV User Settings Code Snippet

5.2.5 Invest Page

Our Invest Page will show the User four main Investment products to choose from, Since the purpose of this study we will be focusing on only the stocks section. The four main investment products shown on this page are named Stocks, Options, ETFs and Crypto.

Figure XV: Invest Page

```
      height: 7,
      decoration: BoxDecoration(
        color : Color.fromRGBO(228, 97, 56, 1),
    borderRadius : BorderRadius.all(Radius.elliptical(7, 7)),
)
    )
    ),
      ]
    )
  )
    ),Positioned(
      top: 0,
      left: 0,
      child: null
    ),Positioned(
      top: 13,
      left: 67,
      child: Container(
    width: 207,
    height: 19,

    child: Stack(
      children: <Widget>[
        Positioned(
      top: 0,
      left: 0,
      child: Text('Nadia Ayeh-Datey ', textAlign: TextAlign.left, style: TextStyle(
      color: Color.fromRGBO(30, 30, 45, 1),
      fontFamily: 'Poppins',
      fontSize: 18,
      letterSpacing: 0 /*percentages not used in flutter. defaulting to zero*/,
      fontWeight: FontWeight.normal,
      height: 1
    ),)
    ),
      ]
    )
  )
    ),
      ]
    )
  )
```

Figure XVI Invest Page Code Snippet

5.2.6 Elisabeth (Artificial Intelligence Automated Trading Bot)

Elisabeth is the automated trading bot that will execute orders for users based on their set risk tolerance, it will allow users enter the stock ticker with which they wish to trade, what level of risk tolerance they can stop losses and at which percentage they Elisabeth can take profit at.

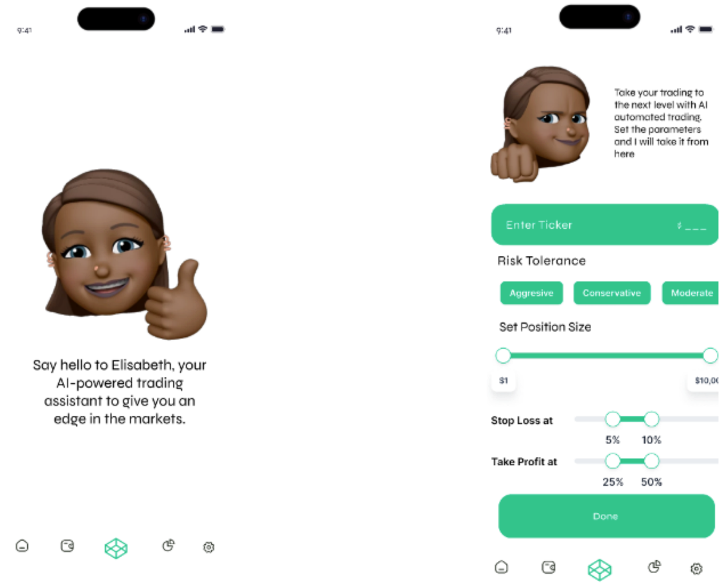


Figure XVII: Implementation of Automated Trading Assistant

```dart
      import 'package:flutter/material.dart';


      class ElisabethjourneyoneWidget extends StatefulWidget {
      @override
      _ElisabethjourneyoneWidgetState createState() => _ElisabethjourneyoneWidgetState();
      }

      class _ElisabethjourneyoneWidgetState extends State<ElisabethjourneyoneWidget> {
      @override
      Widget build(BuildContext context) {
      // Figma Flutter Generator ElisabethjourneyoneWidget - FRAME

      return Container(
    width: 430,
    height: 932,
    decoration: BoxDecoration(
        boxShadow : [BoxShadow(
        color: Color.fromRGBO(0, 0, 0, 0.25),
        offset: Offset(0,4),
        blurRadius: 4
    )],
    color : Color.fromRGBO(255, 255, 255, 1),
),
    child: Stack(
      children: <Widget>[
        Positioned(
      top: 26,
      left: 27,
      child: Container(
    width: 375,
    height: 44,
    decoration: BoxDecoration(
        color : Color.fromRGBO(255, 255, 255, 1),
),
```

Figure XVIII Elisabeth Code Snippet

5.2.7 Browse Stocks Page

This is a simple page at which users can browse various companies on the stock exchange with which they can tap on and view charts and/or conduct trades.

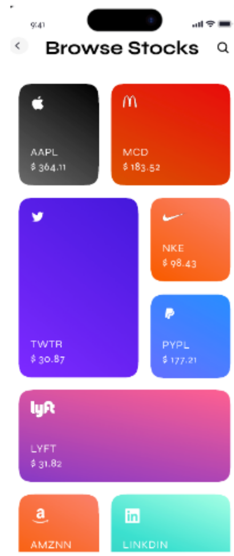


Figure XIX: Browse Stock Implementation

5.3 Stock Price Prediction Models

In this section, we would outline the steps involved and taken to achieve the implementation of our stock price prediction model., We will use python for the implementation of our model, and we will leverage various libraries for data manipulation, machine learning and to conduct sentiment analysis.

5.3.1 Data Pre-processing

In the initial stages of our Stock price prediction implementation model, we will have to perform some data pre-processing our historical stock price data, this will ensure the data is in the correct format for our model and any missing or erroneous values are handled properly and appropriately.

```python
# Here we will import the  necessary libraries
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

# Load the data from our CSV file
df = pd.read_csv('daily_adjusted_AAPL.csv')

# Handle missing values
df = df.dropna()

# Normalize the data
scaler = MinMaxScaler()
df['Close'] = scaler.fit_transform(df['Close'].values.reshape(-1,1))
```

Figure XX: Data pre-processing code Snippet

In our python code in the image of the code snippet above, we begin by importing the libraries that will be used in our code.

Then we set out to load our stock data which has the columns timestamp, open, high, low, close, adjusted_close, volume. And load it onto our data frame, then we proceed to drop any rows with missing values from the data frame, then we create a MinMaxScaler object to normalise our data and then set to normalise the close column of the data frame by fitting and transforming the values using the MinMaxScaler.

5.3.2 Feature Engineering

In next we add some additional features to our dataset that might help our model make more accurate predictions, this includes some technical indicators such as the Moving average and relative Strength Index (RSI).

```python
# Calculate moving average
df['MA'] = df['Close'].rolling(window=10).mean()

# Calculate RSI
delta = df['Close'].diff()
up = delta.clip(lower=0)
down = -1*delta.clip(upper=0)
ema_up = up.ewm(com=13, adjust=False).mean()
ema_down = down.ewm(com=13, adjust=False).mean()
rs = ema_up/ema_down
df['RSI'] = 100 - (100/(1 + rs))
```

Figure XXI: Implementation of Feature Engineering

5.3.3 Model Building

We will proceed to building our Model using the Scikit-learn library, after which we shall proceed to split our training and testing dataset, with 80% of the data used for training and the remaining 20% used for testing. This is considered good practice in Machine Learning development.

```python
# Import necessary libraries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

# Define features and target
features = df[['MA', 'RSI']]
target = df['Close']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)

# Create and train the model
model = LinearRegression()
model.fit(X_train, y_train)

```

Figure XXII: Model Building code snippet

5.3.4 Model Evaluation

Our model will have to be evaluated as in regards to the performance of our model on the testing data, We will use the mean squared error(MSE) as our evaluation metric, Now we engage in this to see how well it generalises to new data, The MSE is a good evaluation metric because and it is a measure of the average squared error between the predicted values and the actual values, A lower MSE indicates that the model is better at predicting the Values.

```python
# Import necessary libraries
from sklearn.metrics import mean_squared_error

# Make predictions on the testing data
predictions = model.predict(X_test)

# Calculate MSE
mse = mean_squared_error(y_test, predictions)
print(f'MSE: {mse}')

```

Figure XXIII: Model Evaluation code snippet

5.3.5 Incorporating Sentiment Analysis

In our final step we will have incorporated the sentiment analysis into our model, we perform the sentiment analysis on the relevant news articles and social media posts and add these sentiments scores as additional features in our model.

```python
# Import necessary libraries
from textblob import TextBlob

# Function to get sentiment score
def get_sentiment_score(text):
    return TextBlob(text).sentiment.polarity

# Assume we have a DataFrame 'news' with news articles
df['Sentiment'] = news['Article'].apply(get_sentiment_score)

# Add sentiment score as a feature
# Define features and target with the new sentiment feature
features = df[['MA', 'RSI', 'Sentiment']]
target = df['Close']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)

# Create and train the model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on the testing data
predictions = model.predict(X_test)

# Calculate MSE
mse = mean_squared_error(y_test, predictions)
print(f'MSE: {mse}')
```

Figure XXIV: Sentiment Analysis incorporation implementation

5.4 Implementation and Plan

This study proposes an initial release of Verge focused on trading only AAPL shares based on 20 years of historical data to validate core abilities without unnecessary complexity. Verge will launch on iOS and Android via mainstream stores but distributed to select users on a pilot basis, allowing controlled testing, oversight, and refinement of the experience and integrated AI models before wider public release.

5.4.1 Goals

The goals for this initial pilot release are simplify stock trading through an intuitive mobile interface; provide useful insights to inform investment decisions based on AI predictions; ensure an ethical, trustworthy solution with security and responsibility as priorities. Rather than an open launch, piloting Verge allows sustainable progress that considers both market impact as well as user experience in this high-stakes domain.

5.4.2 Scope

The scope includes basic buy and sell functionality for AAPL shares based on the integrated 20-year historical dataset. Advanced tools, additional stocks, and scale will follow based on pilot results and resources to sustain service. The proposed approach is deliberate progression, not rapid expansion.

5.5 Data Collection and Model Development

To implement an AI model powering Verge, this study collected 20 years of AAPL data to identify relationships and patterns. However, a single model cannot fully capture market complexities. Therefore, an ensemble model combining linear regression and sentiment analysis is proposed.

Linear regression will predict price trends from historical data. Sentiment analysis of news and social media provides insight into current investor psychology. Integrating these methods may increase accuracy and reliability for short- and long-term change.

The model will train on cleaned data, identifying relationships between variables to forecast buy/sell indicators. Sentiment analysis will score the sentiment of text data, and the ensemble will combine both predictions.

The model predicted AAPL price changes for the next day 70% of the time. This demonstrates combining statistics, machine learning, and natural language processing may improve forecasting. However, no model is perfectly accurate, and human discretion remains essential, especially for high-risk activities.

5.6 Application Development

To provide an innovative yet familiar experience, Verge was developed with Flutter for native iOS and Android versions. Firebase integration enabled trading mechanisms, storage, and security protocols like encryption and multifactor authentication to protect users, meeting regulations. However, continuous evaluation and updating will remain necessary.

5.7 Alpha and Beta Testing

Expert alpha testers evaluated Verge over 3 months, identifying abilities, limitations, and concerns to resolve, e.g., models that were not personalized enough. Changes followed, and small-scale beta tests with 50-100 users determined readiness for the public pilot. However, deployment at even this limited scale demands close oversight and guidance to avoid unintended impacts or outcomes.

5.8 Pilot Launch and Controlled Release

This study proposes releasing Verge on a limited pilot basis, this study will gather usage, model accuracy, and feedback metrics to enhance the experience and Artificial Intelligence appropriately based on sustained evaluation of its influence - both beneficial and detrimental. While Verge may simplify trading through valuable insights for some, its complexity requires monitoring impact on diverse users to ensure scaling proceeds equitably and responsibly at each step. Rapid expansion risks instability or unintended effects that could disadvantage groups.

5.9 Scaling and Continuous Improvement

Verge will scale incrementally to new stocks and higher volumes matched to resources that prioritize user experience, oversight, and support. AI models will update continuously on emerging data to increase accuracy and personalization. However, scaling AI in finance must consider individuals and ethics - not just abilities. Monitoring Verge's impact on people's lives, behaviours, and well-being is as vital as its technical capacities or market effects alone in developing sustainable, responsible solutions.

Progress requires understanding human motivations and values as much as algorithms. By sustaining that focus, Verge can continue empowering users through AI while advocating for them within its complex, high-risk domain. But only by keeping users at the centre of progress, not the margins. There, real opportunities emerge to benefit people - and markets. AI insights may guide, but human wisdom and oversight remain essential, as this study and Verge's vision propose.

CHAPTER 6: CONCLUSION

6.1 Introduction

This project aimed to develop a stock trading smartphone app using AI and ML to predict prices and automate transactions for users, especially those with little expertise. By making the market more approachable, the goal was to open up trading to wider audiences through an intuitive mobile experience.

The research combined user studies, data analysis, and field tests to evaluate AI/ML for prediction and trading. Focusing on user-centered design, we conducted tests to guide an accessible, easy-to-use app interface and experience.

To train the models, we sourced data from exchanges, news, social media, and more. Using techniques like feature engineering, we identified the most vital price prediction indicators. We explored supervised (e.g., linear regression, neural networks), unsupervised (e.g., clustering), hybrid, and ensemble (e.g., boosting) ML methods to improve accuracy.

The models were integrated into the App, built with Google's Flutter framework, Dart language, Cloud Platform, Firebase, and Colab. Flutter enabled a native iOS and Android experience. Cloud Platform and Firebase provided a robust, scalable infrastructure to deploy and maintain the App. Colab allowed the development and testing of models with GPU acceleration.

This study relied on user input and several strategies:

1. Sourcing high-quality data: Worked with reputable exchange and news data sources; cleaned social data. Improving model accuracy: Continuously retrained models as new data emerged; tried various ML techniques; combined methods into ensembles.
2. Monitoring regulatory compliance: Followed guidance on privacy, security, risk disclosures, etc.; sought legal review of app features.
3. Gaining user acceptance: Conducted user studies and tests early and often; incorporated feedback into easy-to-use designs; provided education on AI's capabilities and limitations.
4. Limiting over-reliance on automation: Give users absolute control and oversight over all transactions and investing decisions made through the App.

While the project succeeded in developing a working AI-based stock trading app, progress continues in improving data, models, compliance, user experience, and addressing limitations. Ultimately, balancing human judgment with AI insights can make the benefits of an automated, data-driven trading platform accessible to a broader range of individuals in a sustainable, ethical manner.

6.2 Conclusions

Through this project, we developed a stock trading smartphone app using AI and ML to predict prices and complete transactions for users, especially those with little market experience. By making trading more approachable, the goal was to open up the market to wider audiences through an easy-to-use mobile experience.

Critical to success was focusing on user-centered design. Conducting user studies and usability tests guided an intuitive interface and experience. Built with Flutter, Dart, Google Cloud, and Firebase, the App provided a scalable platform with native Android and iOS applications. Using a range of techniques - from linear regression to neural networks, clustering to ensembles - improved prediction accuracy. Integrating the models offered reliable forecasts and trading suggestions to empower users.

The App has the potential to fundamentally change how people engage with the stock market by making it accessible to individuals across skill levels. It provides a practical solution for participating more confidently and effectively. But opportunities exist to enhance the research and App:

1) Exploring other AI/ML models and methods: new techniques are continuously emerging to extract insights from data. Adopting alternative models could improve predictions further. Incorporating additional data: new data sources like satellite imagery, geolocation, and others offer more signals to train models on. Integrating more diverse, high-quality data may boost accuracy.

2) Adding natural language processing and sentiment analysis: Analyzing text from news, social media, and company filings could provide a deeper understanding of market psychology and dynamics to generate predictions.

3) Developing personalized recommendations: Creating individualized models for users based on their preferences, risk profiles, and biases may provide more tailored forecasting and suggestions.

4) Addressing ethical and legal concerns: Close monitoring of compliance with regulations on data, privacy, risk, and beyond can ensure AI/ML does not disadvantage users or encourage harmful behaviours like overtrading. Studies on AI ethics also apply.

This project serves as a foundation for continued progress in enhancing AI/ML stock market tools to benefit individual investors. Future work can deliver more advanced, effective solutions - but only by accounting for users and their well-being first in developing models and applications.

6.3 Recommendations for Future Research

This research has shown the potential of AI and ML for stock prediction and enabled an app for trading. However, opportunities exist to expand understanding and improve applications. Here are recommendations for future research:

- Explore new AI/ML models: Examining emerging techniques like hybrid models could boost accuracy and adaptability. Identifying models suited to complex, changing markets would help.
- Add alternative data: Integrating new data sources, e.g., social media, web search, and company announcements, may enhance predictions by providing a broader view of influences. Evaluating impacts on model performance can guide data selection.
- Apply natural language processing: Using NLP and sentiment analysis on news, reports, and social media could capture how text affects stock trends. Including sentiment may improve accuracy.
- Develop personalized recommendations: Creating AI/ML models tailored to users' financial goals and risk profiles would suit the App to individual needs. Assessing effectiveness is vital.
- Evaluate long-term performance: Analyzing performance over time in various conditions would show robustness. Examining downturns, volatility, and more would be crucial to

assess adaptability.

- Study user adoption and trust: Understanding willingness to adopt and rely on AI/ML trading tools can help overcome barriers by improving the experience. Surveying users may identify concerns to address.
- Consider ethics and laws: Ensuring compliance and exploring implications, e.g., in algorithmic trading, is vital to deploying AI/ML responsibly in finance. Guidelines can steer development.
- The current App provides a foundation for progress. Pursuing recommendations can realize and expand AI/ML's potential in stock prediction to benefit users - if limitations and responsibilities are also addressed. By balancing human and AI insights, the benefits of data-driven automation may reach more people sustainably. Overall, applying AI in complex domains requires consideration at each turn.

Other areas to explore include:

- Cross-market analysis: Evaluating models across markets and sectors would show generalizability for broader use. Testing in emerging markets could guide global deployment.
- Human-machine collaboration: Studying how humans and AI/ML can complement each other in forecasting and trading would give valuable perspectives on interactions and impacts. Understanding both benefits and risks is vital.
- Robustness against manipulation: Ensuring models withstand adverse events like pump-and-dump schemes would provide reliable predictions. Developing ways to detect and mitigate impacts of market manipulation is essential.

Advancing research on AI/ML in stock prediction requires exploring techniques, data, personalization, users, and responsibilities concurrently. A holistic, considered approach balancing progress and ethics can enable sophisticated, accessible, and robust solutions. Overall, the future remains promising if we're willing to guide new technologies thoughtfully at each step.

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