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Comparative Analysis of AI Language Models for Stock Trend Prediction -Based on ARIMA, GARCH, ARIMA-GARCH

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Declaration

This dissertation is submitted to Newcastle University in accordance with the requirements of the degree of MSc Computer Science. I declare that this dissertation represents my own work, except where otherwise stated.

Abstract
This dissertation investigates the application of AI models for stock price prediction, a critical and emerging research area given the rapid advancements in AI across various fields. Traditional statistical models like ARIMA and GARCH are widely used for time series forecasting but often fail to capture the non-linear patterns in stock market data. This study explores the potential of these models, alongside a hybrid ARIMA-GARCH model, to enhance prediction accuracy. Using historical stock data from 2018 to 2023, the models are evaluated using four key metrics: RMSE, MAPE, MAE, and R^2. The findings indicate that traditional models outperform the hybrid model in long-term forecasting, highlighting the need for further research into more effective hybrid approaches.

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1.0 Introduction

Considering the rapid development of AI tools across various fields, such as agriculture, sales and marketing, and healthcare, stock market prediction has emerged as a significant topic and a promising research trend. The inherent volatility of stock markets, driven by numerous unpredictable factors acting simultaneously (as discussed in Chapter 2.3.1), makes accurate and reliable stock price forecasting crucial for informed investment decisions. To manage future uncertainties, time series forecasting plays a vital role in effective management and precise decision-making [1] (as discussed in Chapter 2.1). For these reasons, an increasing number of investors, particularly from younger generations, are more open to embracing new technologies to mitigate the high risks associated with stock markets [2].

Traditional statistic models, such as the Autoregressive Integrated Moving Average (ARIMA) model and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)model, are widely used in data science due to their ability to model linear relationships and volatility clustering (as mentioned in Chapter 2.2.1). However, these models struggle to capture non-linear patterns present that are often present in stock market data. Therefore, to address these limitations, the hybrid models, like the ARIMA-GARCH model, are typically designed to combine the strengths and address the shortcomings of these traditional statistical approaches.

The purpose of this dissertation is to carry out the potential of these three models and to analyse and compare their performance in stock price forecasting. Additionally, this research explores whether hybrid model effectively mitigates the weaknesses of the two traditional statistical models and outperforms them.

Thorough the background research, literature review and the detailed methodology (as discussed in Chapter 3), this project aims to enhance the accuracy of model predictions. The implementation process involves feeding the three AI models with the most recent stock price data before conducting the next forecast. The dataset would be from 1st January 2018 to 31st December 2023, which are collected from Yahoo Finance. In addition, to avoid potential biases in model predictions due to different stock categories, this report will use three different types of stocks: common stock, ETFs, and cryptocurrency.

Data visualization is a crucial step in making experimental results more understandable and accessible. This project uses the Python library Seaborn to create visualizations, including line graphs to display the forecasting results of the three models and bar graphs to represent the evaluations based on four different metrics.

In this project, four metrics—RMSE, MAPE, MAE, and R^2—are used to evaluate the accuracy of model forecasting. Each metric has its own strengths in assessing different aspects of model performance. The evaluation results indicate that traditional statistical models, ARIMA and GARCH, delivered more accurate predictions compared to the hybrid ARIMA-GARCH model. Due to the limitations of the ARIMA-GARCH model in long-term forecasting, it did not effectively enhance forecasting accuracy. Instead, the ARIMA and GARCH models consistently provided higher accuracy in their predictions.

1.1 Aim

The aim of this project is to train and evaluate three different Artificial Intelligence models for forecasting the prices of three stocks. This includes two traditional statistical models—the ARIMA and GARCH models—and a hybrid model that combines the two (ARIMA-

GARCH). The project will analyse and compare the accuracy of these models using four different performance metrics.

1.2 Objectives

The Objectives chapter outlines the specific goals and methods that this project aims to address. To ensure that this dissertation meets the necessary requirements and achieves a high standard, the following key objectives have been outlined:

- Enhance model accuracy
  The accuracy of the three models will be improved by carefully setting appropriate parameter orders, preprocessing the dataset effectively, and iteratively updating the models with the latest price data.

- Address issues
  To effectively deal with challenges that may arise during the forecasting process, it is crucial to understand the definitions and limitations of each model. This involves identifying potential problems and implementing solutions to ensure the robustness and reliability of the forecasts.

- Assess model performance
  The predictive performance of the models will be thoroughly evaluated using various metrics (e.g., RMSE, MAE, MAPE, R^2). Data visualization techniques will be employed to make the models' performance more interpretable and accessible.

- Compare statistical and hybrid models
  The comparative analysis will be conducted between traditional statistical models (ARIMA, GARCH) and the hybrid ARIMA-GARCH model. The comparison will demonstrate if the hybrid model effectively mitigates the weaknesses of the traditional models.

- Suggest direction for future research
  Based on the findings and conclusions, recommendations for future research will be provided. This may include exploring additional machine learning techniques and alternative methods for addressing forecasting challenges.

1.3 Motivations

The motivation behind this dissertation stems from the critical need for accurate and reliable stock price forecasting in financial markets. Stock price trends are highly volatile and can be influenced by multiple factors simultaneously (as discussed in Chapter 2.3.1), making investment decisions riskier and more challenging.

Traditional statistical AI models, while effective to a certain extent, often fall short in capturing the complex and non-linear nature of time series data in stock markets. Therefore, this project will utilize two different statistical models: the ARIMA model and the GARCH model.

Moreover, a thorough literature review reveals that few studies have demonstrated whether hybrid models can efficiently mitigate the weaknesses of traditional statistical models. This project is also motivated by the desire to explore and validate the potential advantages of hybrid models in improving the accuracy and reliability of stock price forecasting compared to traditional approaches. Consequently, a hybrid model (the ARIMA-GARCH model) will be implemented in this project as well.

1.4 Project Scope

This dissertation explores the application of artificial intelligence models for time series forecasting, with a focus on stock price prediction. Key points to consider in the scope of this project include:

- A thorough background research and literature review in the relevant field, ensuring a comprehensive understanding of key terms and concepts.

- The methodology outlines the research process, including the setup of the appropriate environment and libraries, the methods for selecting and collecting data, and the techniques for time series forecasting using three different AI models.

- The design of this project involves using three different stocks. This allows the prediction outcomes to demonstrate whether the accuracy of the models is influenced by different stock categories.

- Different metrics have their own strengths and weaknesses. To achieve a more comprehensive evaluation of the prediction results, this project will utilize four different metrics.

- The data visualization includes both the prediction line graph and the evaluation bar graph, making this dissertation more readable and accessible to readers.

- The critical focus of the analysis and comparison is on the performance of the three models. Furthermore, the discussion will explore whether the hybrid model is more accurate than original statistical models.

1.5 Outline of Materials

This dissertation consists of seven chapters. The brief structure and content summarise as follows.

- Chapter one: This chapter introduces the dissertation in detail. It covers the project's key concepts, goals, and research approach. It also discusses the motivation behind selecting the topic, along with the research boundaries and limitations.

- Chapter two: This chapter focuses on background research, providing foundational knowledge. It includes definitions of key terms like time series forecasting and artificial intelligence models, a literature review of the models used in the project, an overview of different stock types and potential influencing factors, and an evaluation of the metric measurements.

- Chapter three: The methodology chapter outlines the main research methods used in this dissertation. It details the step-by-step process of training the models for stock price prediction, including coding explanations and the visualization of prediction outcomes for the three models using line graphs.

- Chapter four: This chapter centres on the analysis and comparison of the models' performance, based on metric evaluations. The results are presented using bar graphs for clear visualization.

- Chapter five: The summary and conclusion chapter offer an overview of the experimental results, discussing the key findings and insights gained throughout the project and suggestions for potential improvements. Additionally, it reflects on the learning and provides recommendations for future research directions.

- Chapter six: The bibliography section lists all references in numerical order, following the IEEE citation format.

- Chapter seven: The chapter seven provides links to supplementary materials, including relevant files, source code, and referenced documents.

2.0 Background research

This section covers the essential background knowledge required before starting this project. By understanding the details of the project components, the training process can be more organized and clearer. The following paragraph will introduce the major elements of this project and explain the reasons for their inclusion or exclusion.

2.1 Time Series Forecasting

Time series forecasting is a data science technology which is applied to predict future trend by utilizing historical data. The difficulty of prediction is mostly related to the application of time series data. Therefore, by providing huge time series data, this technology is widely utilized in various region, such as Astronomy, Weather forecasting, Econometrics, Earthquake prediction.

For stock market, the feature of Time Series method is suitable for prediction because of its ability to deal with complex and dynamic data. Time Series model, which would be mentioned in next section, can enhance the decision strategy by monitoring the potential risk. Time Series Forecasting starts from examining the previous data, like seasonal sale or finance report. The analysis which applies Time Series can combine different method to enhance accuracy of predication and present the result in different way [3].

In addition, Time Series Forecasting is also indicated a learning method of machine learning; for example, Neural Networks and XGBoost. For example, the combination of machine learning and Time Series Forecasting shows very high result in short-term stock prediction [4]. Compound neural network (CNNs) algorithm in Time Series Forecasting achieved exact accuracy results.

2.2 Artificial Intelligence Language Models

AI refers to the ability of computer system to deal with complicated tasks. With different AI model develop, AI language model is applied to various field and significantly help people make more precious decisions. The section would introduce three models applied in this project, ARIMA, GARCH, and ARIMA-GARCH.

2.2.1 Statistical Model

Statistical model is the use of mathematical model and statistic science to create data representation and performance algorithms. Using numerous statistical data and assumption, this model can generate sample data and prediction. The application of statistical model help data scientists preciously analysis and make predictions. Therefore, statistical model also plays a critical role in stock market.

- **ARIMA**

  The Autoregressive Integrated Moving Average (ARIMA) model, which is introduced by Box and Jenkins in the early 1970s is a general model used in Time Series Forecasting [5]. Three elements in this model are the Autoregressive (AR) model, the Differencing process (I), and the Moving Average (MA) model. The ARMIA model is a regression analysis model which can evaluate the strength between one independent variable and other unstable variables.

  The parameter of the ARIMA(p,d,q)[6]:
  - p: the order of lag observations
  - d: the degree of times the raw different observations
  - q: the order of moving average

  $$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \quad [6]$$

  In the above equation, parameter c is a constant, $\phi k(1 \leq k \leq p)$ are the coefficients of the autoregressive, $\theta i(1 \leq i \leq q)$ are moving average models, and εt is a white noise series. Through “d” difference, the ARIMA model can convert non-stationary sequence into stationary sequence, after that “p” and “q” (the Autoregressive and the Moving Average) is based on stationary sequence[7].

  The strength and weakness order of the ARIMA model:
  - Strength

    The strength of the ARIMA model is straightforward and easy to implement and supported by abundant research and software. Moreover, the ARIMA model is suitable for stable dataset; therefore, it is usually applied to time series forecasting.
  - Weakness

    The assumption of the ARIMA model is linear relationships. As the result, the assumption would limit the performance when the dataset is complex and non-linear. In other words, The ARIMA model is hard to deal with the complexity of time series data.

- **GARCH**

  The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was developed by Dr. Tim Bollerslev in 1986 [5]. The GARCH is a method, which is imported into Autoregressive Conditional Heteroskedasticity (ARCH) by economist Robert Engle in 1982, to deal with issues in asset price volatility. Based on the ARCH model; by adding pth-order term, the GRACH model can significantly present heteroskedastic[8] function in the long-term memory The GARCH model is a statistical model used in analyse time series data. The assumption is that the variance of the error term is governed by an autoregressive moving average process. The GARCH model can exactly simulate the changeable violability in time series data[5], then further evaluate the risk of investment.

  The parameter of GARCH(p,q)[8]:

- p: the number of lagged variance terms (the order of the GARCH model)
- q: the number of lagged error terms (the order of the ARCH model)

$$y_t = x_t^T \gamma + \varepsilon_t \quad , \quad \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad [7]$$

In the above equation, xt represents the vector of explanatory variables, γ is the vector of coefficients, ϵt is the disturbance term, ω is the constant term and coefficient in the ARCH and GARCH models. σ2 t−1 is the variance of predicting previous period.

The weakness and strength of the GRACH model:

- Strength
  The GRACH model is commonly used in econometrics and finance filed. The feature is more flexible to model the complicated and volatile time series data. Therefore, the GARCH model is good at evaluating risk and forecasting the conditional variance.

- Weakness
  For precious prediction, the GARCH model need larger and fit dataset owing to the sensitive and complicated nature of estimate process. In addition, the GARCH model assume the error terms is regular and normal, which would cause inaccurately forecasting in the variable finance dataset.

2.2.2 Hybrid Models

Hybrid model is a combination of multiple techniques to enhance accuracy of prediction and mitigate the weakness. The common illusion of the hybrid model, such as the CNN-LSTM model, demonstrate the efficiency and accuracy of the hybrid model in volatile stock forecasting [9]. The research pointed out the performance of the CNN-LSTM model has high forecasting accuracy after evaluating by multiple metrics [10], which would discuss in Chapter 2.4. The next section would introduce the hybrid model used in this project: the ARIMA-GARCH model.

- **ARIMA-GARCH**
  The ARIMA-GARCH model is the combination of linear time series ARIMA model with non-linear GARCH model, which aims to mitigate the insufficiency of two statistical model (mention in Chapter 2.2.1). The article [11]shows that non-liner time series model is better at forecasting and modelling than liner time series model. The ARIMA-GARCH model, as a non-linear time series model, is particularly effective in capturing time-varying variance, making it a powerful tool in statistical forecasting.

2.3 Stock

Stock represents a portion of ownership in an issuing company, with individual units referred to as shares. The stock market primarily operates through third-party intermediaries known as collective exchange markets [12]. To safeguard investors, companies listed on stock exchanges must be publicly traded and comply with relevant regulations. The movement of stock prices is influenced by various factors (as discussed in Chapter 2.3.1), such as company performance, global economic conditions, and more. To address uncertainties and enhance the accuracy of stock investments, this project aims to compare the performance of three models across different types of stocks. The model prediction results will demonstrate whether the accuracy of forecasting varies based on different stock types. The following section introduces the three investment types used in this project: Common Stock, ETFs, and Cryptocurrency.

- **Common Stock**
  Common stock represents a share of ownership in a company. Stockholders who hold common stock are considered partial owners of the corporation. The primary advantage of common stock is the potential for higher returns over the long term. However, the downside is that investors are exposed to significant price volatility.

  Unilever PLC (ULVR.L), used in this project, is a British multinational company specializing in fast-moving consumer goods, headquartered in London, UK, and Rotterdam, Netherlands. It is one of the world's leading suppliers of food, beverages, cleaning agents, and personal care products. Unilever's stock is primarily listed on the London Stock Exchange under the ticker symbol "ULVR".

- **ETF**
  An Exchange-Traded Fund (ETF) is an investment fund that pools together various assets and trades on the stock market like a regular stock. ETFs are particularly popular among novice investors due to their structure, which allows them to track specific investment targets easily. Additionally, ETFs offer investors access to a wide range of global markets, often at a low cost. Most ETFs are passive investments, designed to replicate the performance of a specific group of assets.

  The FTSE 100, or Financial Times Stock Exchange 100 Index, is a stock market index comprising the 100 largest companies listed on the London Stock Exchange (LSE). It is one of the most widely recognized indicators of the performance of the UK stock market.

- **Cryptocurrency**
  Cryptocurrency is a form of virtual currency that uses cryptography to secure transactions [13]. It operates on decentralized networks that leverage blockchain technology—a distributed ledger maintained by a diverse network of computers. Unlike traditional currencies issued by governments or financial institutions, cryptocurrencies are independent of any nation or centralized authority.

  Bitcoin created in 2008 and launched in 2009, is the first and most widely traded cryptocurrency, and it is utilized in this project. The ticker symbol BTC-USD represents the trading pair of Bitcoin against the US Dollar.

2.3.1 Potential factors

In stock market, various factors can influence price trends, often leading to unpredictability and potential missteps by investors. One of the primary factors is a company's operational performance. Quarterly and annual financial reports reveal crucial data such as revenue growth and profit margins, which reflect the company's performance during specific periods. This performance significantly impacts investor sentiment, which in turn influences stock prices.

Beyond company-specific factors, broader elements also play a role in shaping both company operations and stock performance. These include global events like pandemics, economic indicators such as currency fluctuations and inflation rates, and political developments like the Russia-Ukraine War. For example, during the initial phase of the COVID-19 pandemic, there were sharp declines in stock markets across all industries. However, as the pandemic progressed, changes in consumer behaviour led to the success of sectors such as healthcare and e-commerce, driving up stock prices in these areas. Research indicates that COVID-19 had a profound negative impact on major stock markets, causing unprecedented increases in conditional volatilities and a higher likelihood of adverse market conditions [14].

2.4 Metric Measure

Metric measure is a quantifiable method to carefully and comparably assess the whole process [1], [15]. Metrics provide a quantifiable method to carefully and comparably assess the entire forecasting process, which offer valuable insights into how well a model performs in relation to others. In this project, metric measure would be an important step to comprehensively evaluate the performance of three forecasting models: ARIMA, GARCH, and ARIMA-GARCH. Moreover, each metric measure offers a unique perspective on model performance and also capturing different aspects of prediction accuracy and error. This project would adapt four metrics to provide more comprehensive evaluation. This section would describe the four metrics: RMSE, MAPE, MAE, R^2.

- **RMSE**

  The formula of RMSE[1], [16]:

  $$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

  The Root Mean Squared Error (RMSE) is a standard performance metric for measuring regression models, estimating the ability of the model which predict quantitative data [16]. The RMSE metric indicate the average difference between predicted and actual values. When RMES shows lower number, the accuracy of forecasting models is more precise.

- **MAPE**

  The formula of MAPE[15], [17]:

  $$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100$$

  The Mean Absolute Percentage Error (MAPE) is a relative error metric for regression models [17]. The MAPE uses absolute values to avoid positive and negative errors from cancelling each other out. This approach ensures that the whole measurement accurately reflects and provide a clearer picture of model performance. However, given the definition, the main disadvantage is that the MAPE is unsuitable for predictive model with expected large error value.

- **MAE**

  The formula of MAE[17]:

  $$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

  The Mean absolute error (MAE) is a liner score to measure the error average between predicted value and actual value [1], [17]. From math aspect, the MAE metric presents the average of absolute errors and value the magnitude between predicted and actual value without considering direction.

- **R^2**

The formula of R^2[17]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

R-squared (R^2), also known as the coefficient of determination, is applied to assess the quality of a regression model[17]. The metric range is from 0 to 1. Value 1 means the forecasting models perfectly match with dataset. Although R^2 is a useful tool to evaluate the accuracy of machine learning models

2.5 Reflection of literature review

There is a wealth of research dedicated to time series forecasting, employing various models to predict future values based on historical data. This chapter focuses on key areas within existing literature to identify existing research topics and gaps in knowledge.

2.5.1 Comparison and analysis of models

The aim of this dissertation is to conduct a comparative analysis of the performance of traditional statistical models and hybrid models in time series forecasting. Therefore, the first key area of focus involves reviewing existing literature that compares these models.

- Statistical model
  Statistical model, used in this project, is a representation of observed data that aims to capture the relationships between different variables[18].

- Machine learning model
  Machine learning models is a mathematical model that consider that variables are either dependent variables or independent variables. Machine learning model is designed to identify patterns and relationships in data, enabling them to perform tasks such as classification, regression, clustering, etc[18].

- Deep learning model
  A deep learning model is a subset of machine learning that focuses on the use of neural networks. These models are particularly effective for tasks involving large, complex datasets due to their ability to automatically learn and extract from complex datasets[18].

A research paper presented a comprehensive comparison of time series forecasting algorithms, including Vanilla Long Short-Term Memory (V-LSTM), Gated Recurrent Unit (GRU), Bidirectional LSTM (BD-LSTM), Autoencoder LSTM (AE-LSTM), Convolutional Neural Network LSTM (CNN-LSTM), LSTM with Convolutional Encoder (ConvLSTM), Attention Mechanism Networks, and the Transformer network [19]. Among these algorithms, the Transformer model outperformed the others.

Another study highlights that Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) outperform other models in time series forecasting[20]. The models compared in the study include Multilayer Perceptron (MLP), Elman Recurrent Neural Network (ERNN), Gated Recurrent Unit (GRU), Echo State Network (ESN), and Temporal Convolutional Network (TCN).

To effectively manage healthcare and address issues related to blood shortages and wastage, a 2019 study conducted time series forecasting using five years of blood supply data. The study concluded that the Seasonal Exponential Smoothing Method (ESM) and the ARIMA model produced the most accurate forecasts, with minimal error.

One research includes extensive review of ARIMA, and various machine learning algorithms applied to time series forecasting across multiple fields, involving energy, weather, finance, and noise prediction[21]. The study gathered papers that compared the ARIMA model with other techniques like Support Vector Machines (SVM) and Artificial Neural Networks (ANN), as well as ARIMA versus XGBoost. However, it did not include the hybrid ARIMA-GARCH model. Therefore, this dissertation focuses on filling this gap by comparing the ARIMA, GARCH, and ARIMA-GARCH models to evaluate their performance in stock price forecasting.

3.0 Methodology

The project adopted a comprehensive methodology to develop stock price forecasting models using various AI models techniques [3]. The approach involved assessing the performance of statistical models (the ARIMA model and the GARCH model) and hybrid model (the ARIMA-GARCH) through different evaluation metrics (RMSE, MAPE, MAE, and R^2). Additionally, the performance and evaluation results were visualized using two types of graphs. In the end, based on the outcome of forecasting experiment, the comparison and conclusion would be presented in next two chapters.

The figure below present flowchart that briefly illustrates the steps of this project [22]. The following paragraph further discussed each method step by step.

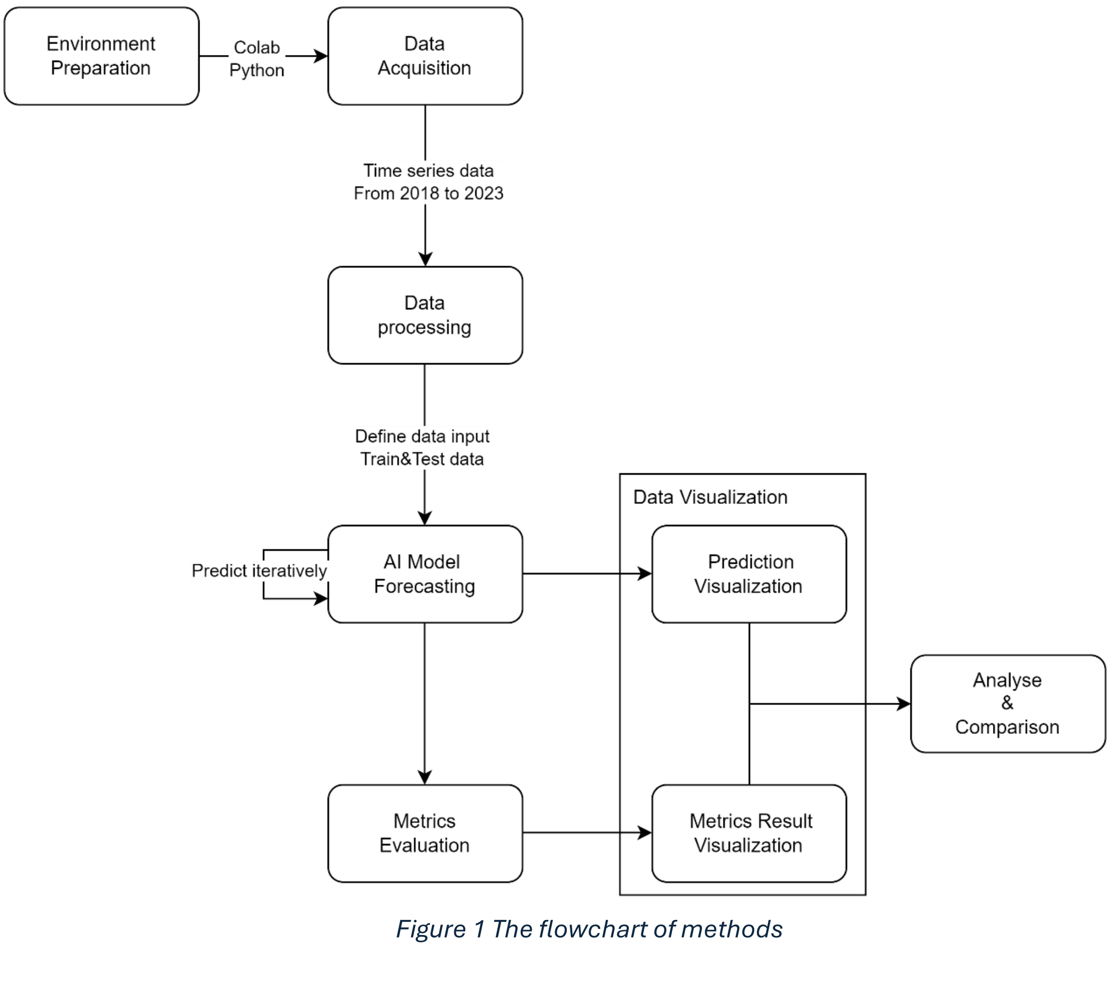

Figure 1 The flowchart of methods

3.1 Outline of methodology

These online of methodology provide a clear framework for systematically addressing each component of the study, ensuring thoroughness and accuracy in the research process. To ensure the successful completion of this dissertation, the following list outline the key aspects of preparation and the research methodology.

- Background research and literature review
  This initial step of the dissertation involves conducting thorough background research to gather all the necessary knowledge for the project. Additionally, a comprehensive review of relevant literature will be carried out to identify existing research, avoid redundancy, and sharpen the focus on the primary research objectives.

- Setup the implementation environment
  1. Implementation Platform: Google Colab
  2. Programming Language: Python
  3. Install and import relevant libraries: yfinance, arch, and seaborn, etc.

- Dataset preparation and processing
  1. Data resource: Yahoo Finance
  2. Data processing: Load historical stock prices within a specified time range, split the dataset, and define inputs for model fitting.

- Select and Train AI Language Model
  1. AI language models: Statistical models (ARIMA and GARCH) and a hybrid model (ARIMA-GARCH)
  2. The forecasting process – Initialise the AI models with appropriate parameter settings and iteratively conduct the time series forecasting process.

- Comparative Analysis:
  Evaluate and compare the performance: Assess the accuracy and effectiveness of the trained AI models using four different metrics.

- The visualisation of prediction and evaluation
  1. Line graph: Illustrates the stock price trends and model predictions.
  2. Bar graph: Displays the evaluated results of the metrics.

- Documentation and Reporting:
  1. Documentation: Record the training process, data handling, and evaluation methods.
  2. Reference support: Gather research papers from university libraries and academic databases such as Google Scholar, ACM Digital Library, IEEE Xplore, and Science Direct. Use Mendeley to manage citations and organize references.
  3. Comments: Include clear and relevant comments in the programming code to enhance readability and accessibility of the project.

3.2 Environment preparation

Environment preparation is the first step in software program development to ensure that all necessary tools, libraries, and configurations are in place for the future efficient coding and testing. Proper environment preparation contributes to a smooth development process and reduces potential errors. The next section introduced the program platform and coding language.

- Implement environment-Colab
  Google Colaboratory, known as Colab, is cloud-based platform provided by Google. Developer can execute Python code in a Jupyter notebook service environment, which are interactive and support live code, equations, visualisations, and narrative text. Therefore, users can implement project without setup. Colab also provides free access to computing resources, including GPUs and TPUs. In addition, Colab integrate with Google Drive, letting users easily organise and store projects.

- Code language-Python
  Python is a popular language for time series forecasting due to its extensive libraries and frameworks, which enable efficient development. These tools provide powerful capabilities for data manipulation, statistical modelling, evaluation, machine learning, and deep learning. The following table is the library used in this project:

Table 1 The list of libraries in this project

Name	Definition
pandas_datareader.data	This library is used to pull financial data from various online sources.
datetime	This library is for working with dates and times.
pandas	It’s a data manipulation and analysis library that provides data structures.
yfinance	A Python library from Yahoo Finance to fetch financial data.
matplotlib.pyplot	A plotting library is used to create data visualizations in Python
seaborn	It’s a statistical data visualization library to generate graphics.
numpy	It’s a scientific computing package providing function like arrays, matrices, and mathematical functions
math	This library provides math operation, such as square roots.
statsmodels	From this library, we can import the ARIMA model.
arch	A Python package for estimating the ARCH and GARCH models
sklearn.metrics	We can import metrics, MAPE, MAE, R^2 form this machine learning library

3.3 Data Acquisition

The datasets imported in the project are from yfinance, which is an open-source Python library. Yfinance, allows users to download historical market data from Yahoo Finance’s API. Yahoo Finance offers a wide range of stock market data and information, including stock, ETFs, bonds, currencies, and market news [23]. In this project, the time series datasets are from 1st January 2018 to 31st December 2023, consists of common stock: Unilever PLC (ULVR.L), ETF: FTSE 100 (^FTSE), and Cryptocurrency: Bitcoin (BTC-USD). These background knowledge of stock type introduced in Chapter 2.3.

3.4 Data processing

Data processing is an essential step to deal with raw data before extracting useful information [24]. These series of actions involve transforming, organizing, sorting, and analysing data. The author will explain how to process data for this project.

First of all, ‘yf.download’ is used to fetched the target stock data form Yahoo Finance. Then the code defines the date range of data be retrieved, setting the start_date as 1st January 2018 and end_date as 31st December 2023.Save fetched data to a CSV file and format the date as “year- month-date”.

Secondly, the author splits the data into training and testing sets, with the training set comprising 80% of the entire dataset and the testing set making up the remaining 20%. The next step is to convert the column: ‘Close’, which represents the daily closing price of the stock, into list for further processing.

Thirdly, before feeding data to AI model, we need to convert the data into graphical format for data visualization, as introduced in Chapter 3.5.

Figure 2 The visualised figure of Unilever price trend

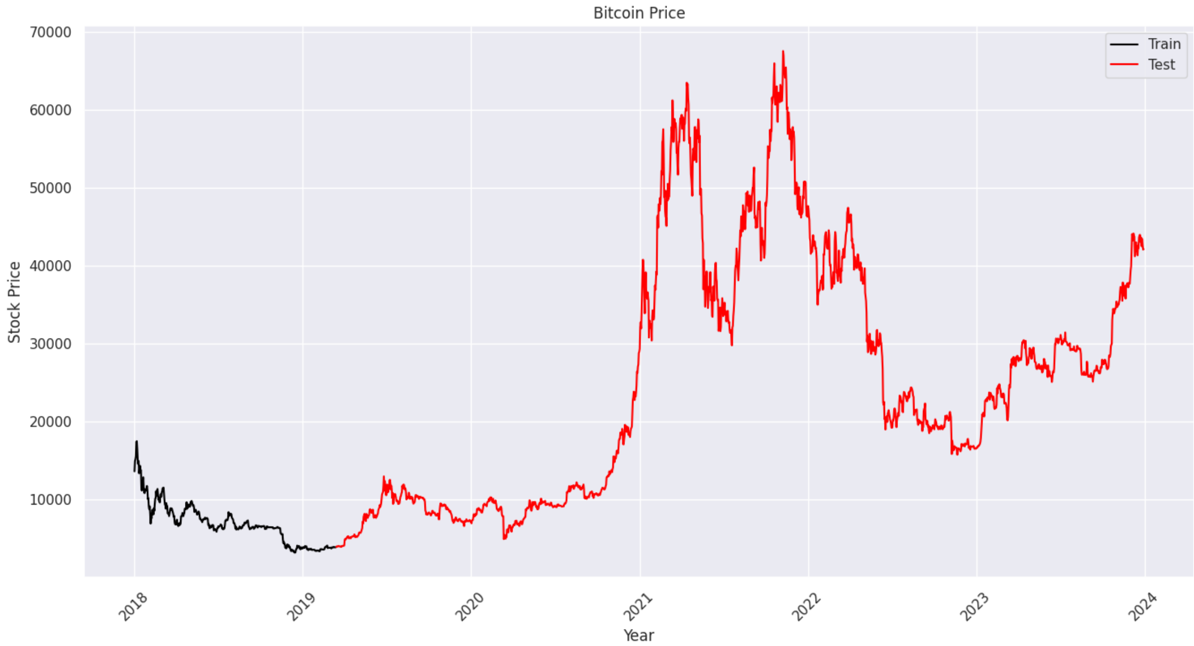

Figure 3 The visualised figure of Bitcoin price trend

3.5 AI Model Forecasting

The AI model will be trained using historical stock price data (from 1st January 2018 to 31st December 2023) with specific parameter order to capture the underlying patterns. To update the model with each new observation, this project will implement a rolling approach, using a "for loop" to iteratively update the model and generate predictions.

- **ARIMA**

  Firstly, the author initializes the AutoRegressive Integrated Moving Average (ARIMA) model with the “train_data” (as mentioned in Chapter 3.3), which comprises 20% of the data from the “start_date” to the “end_date” (approximately one year). The parameters of the ARIMA model are set to (1,1,0).

  Secondly, The author make the initial prediction and set up an empty list to store the predictions generated by the ARIMA model.

  The final step in the prediction process involves forecasting iteratively. At each iteration, the ARIMA model is initialized and fitted to the updated price list. A forecast is then generated and added to the predictions list. The actual price from the test data is appended to the historical price list, updating the data used for subsequent model fitting and predictions.

  The following figures represent the visualised predictions of the ARIMA model for three different stocks.

Figure 4 The ARIMA Prediction of Unilever price

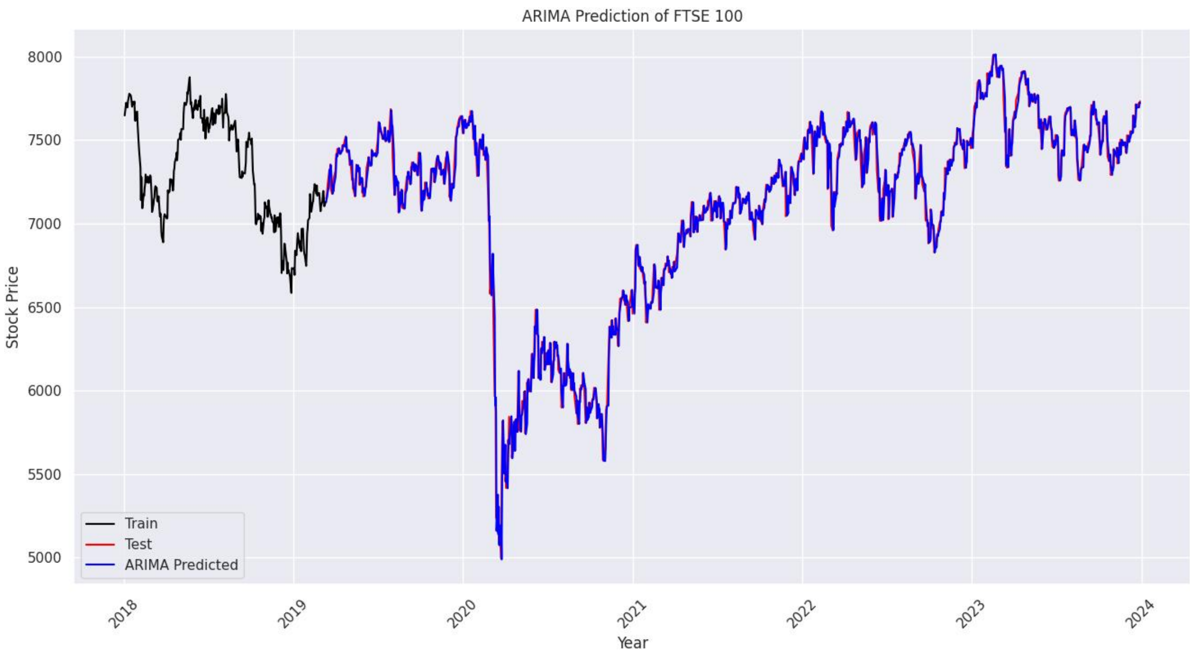

Figure 5 The ARIMA Prediction of FTSE100 price

Figure 6 The ARIMA Prediction of Bitcoin price

- **GARCH**

  To train an AI model for stock price prediction, the process of using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is similar to that of the ARIMA model.

  First, the historical stock prices are fitted to the GARCH model with parameters (1,1). Use the .forecast() method, setting the horizon parameter to 1, which instructs the model to forecast only the next value. Additionally, the standard deviation is calculated by taking the square root of the forecasted variance.

  Secondly, the first prediction result generated by the GARCH model is stored into the initialised list.

  Thirdly, perform iterative forecasting by adding the latest observations to the historical price list. The author uses the GARCH model to make each subsequent prediction. By refitting the model at each step, the forecasted standard deviations are stored in the list of GARCH model predictions.

  However, as shown in the figure, the GARCH model did not perform as expected across the three stocks. Not only was there a discrepancy between the predicted and actual prices, but in one specific period, the price trend was completely opposite to the real trend.

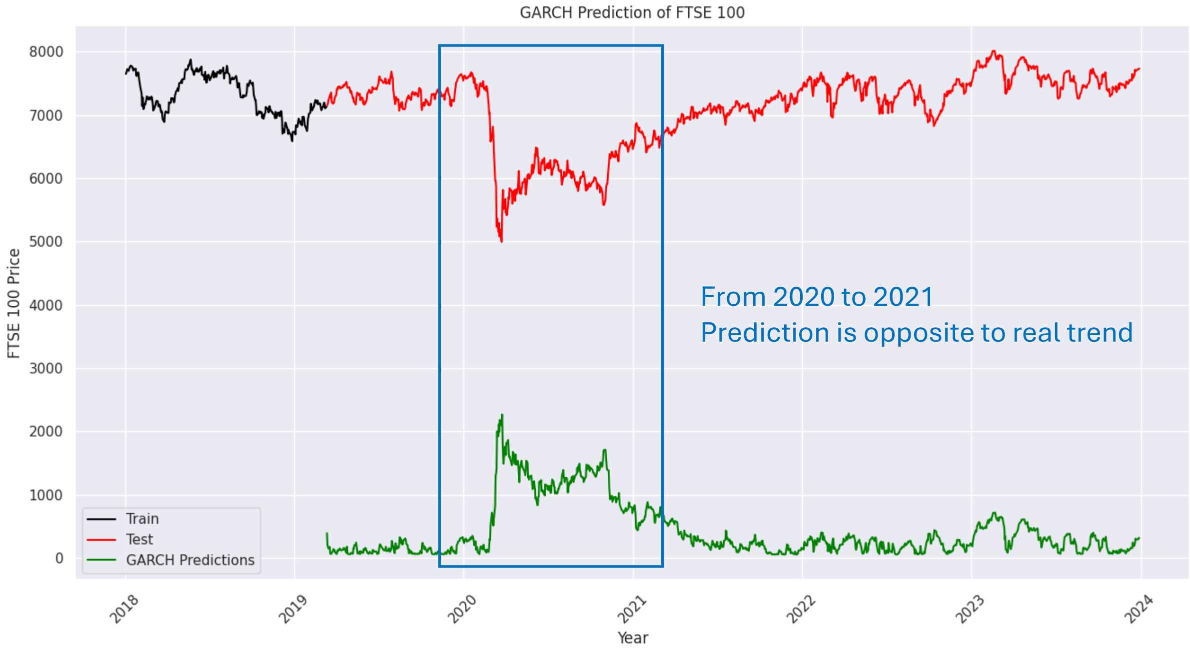

Figure 7 Failed GARCH Prediction

An error message was returned:
"warnings. warn(/usr/local/lib/python3.10/dist-packages/arch/univariate/base.py:311: DataScaleWarning: y is poorly scaled, which may affect convergence of the optimizer when estimating the model parameters. The scale of y is 1.696e+04. Parameter estimation work better when this value is between 1 and 1000. The recommended rescaling is 0.1 * y."

Given this error, the code will be adjusted by modifying two parameters: rescale and mean. Setting rescale=True will automatically scale the input data to a range more suitable for numerical optimization. Set mean=0, as the focus is primarily on modelling volatility (variance) rather than the level of the time series.

The following figures represent the visualised predictions of the GARCH model for three different stocks.

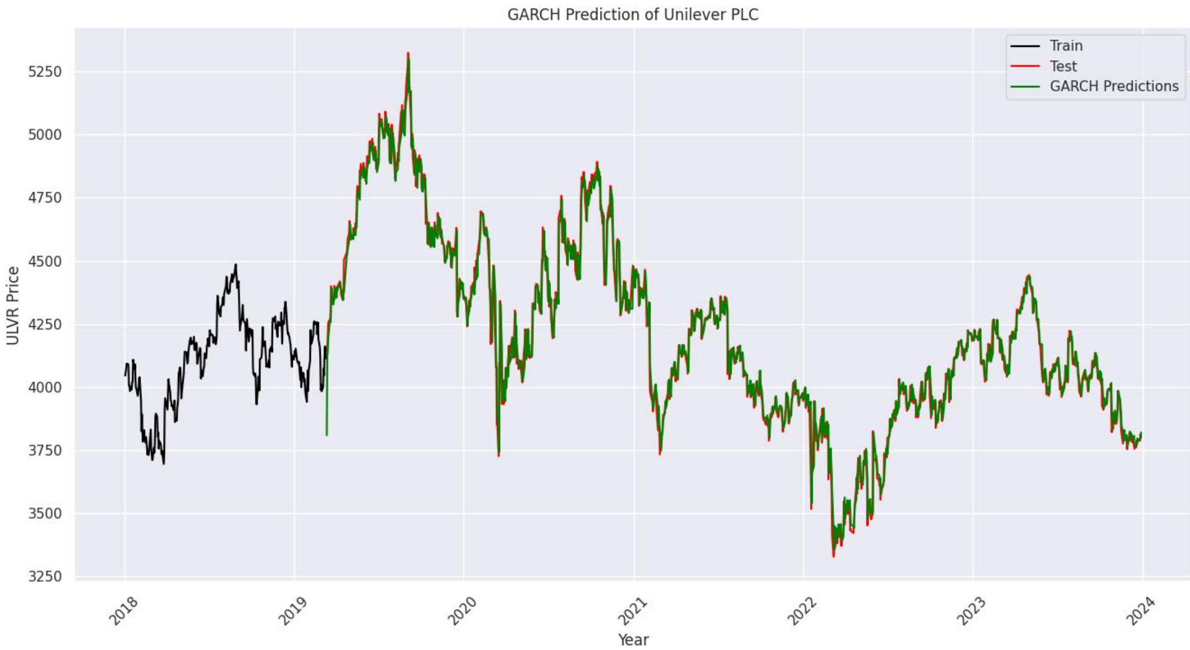

Figure 8 The GARCH Prediction of Unilever price

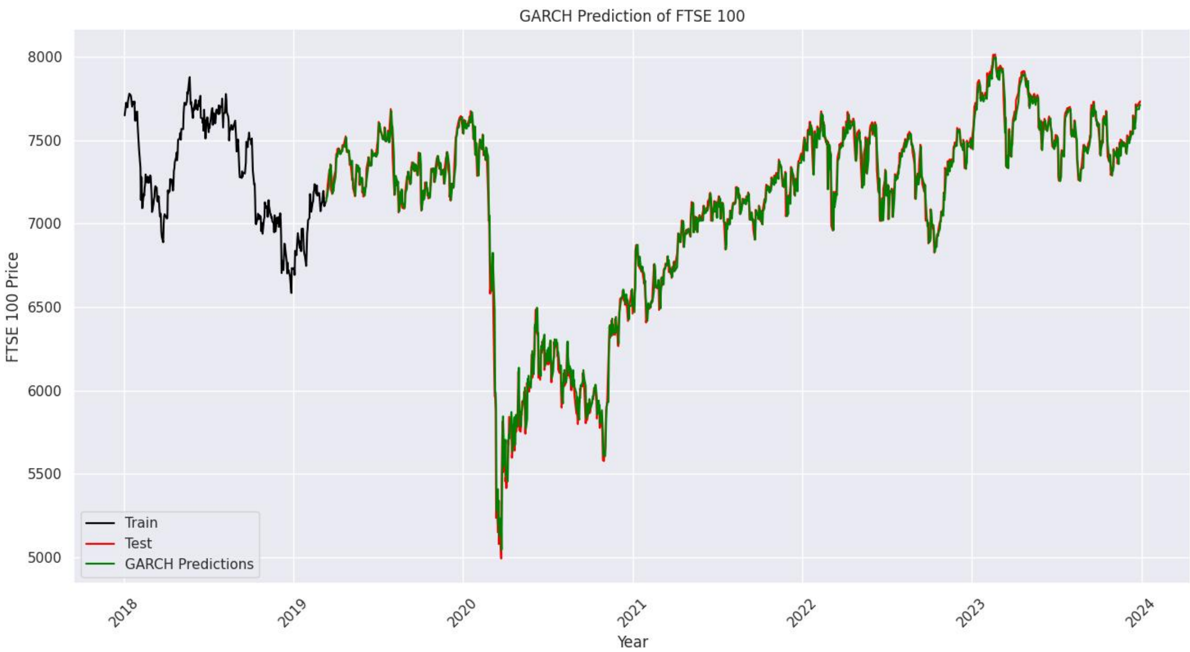

Figure 9 The GARCH Prediction of FTSE 100 price

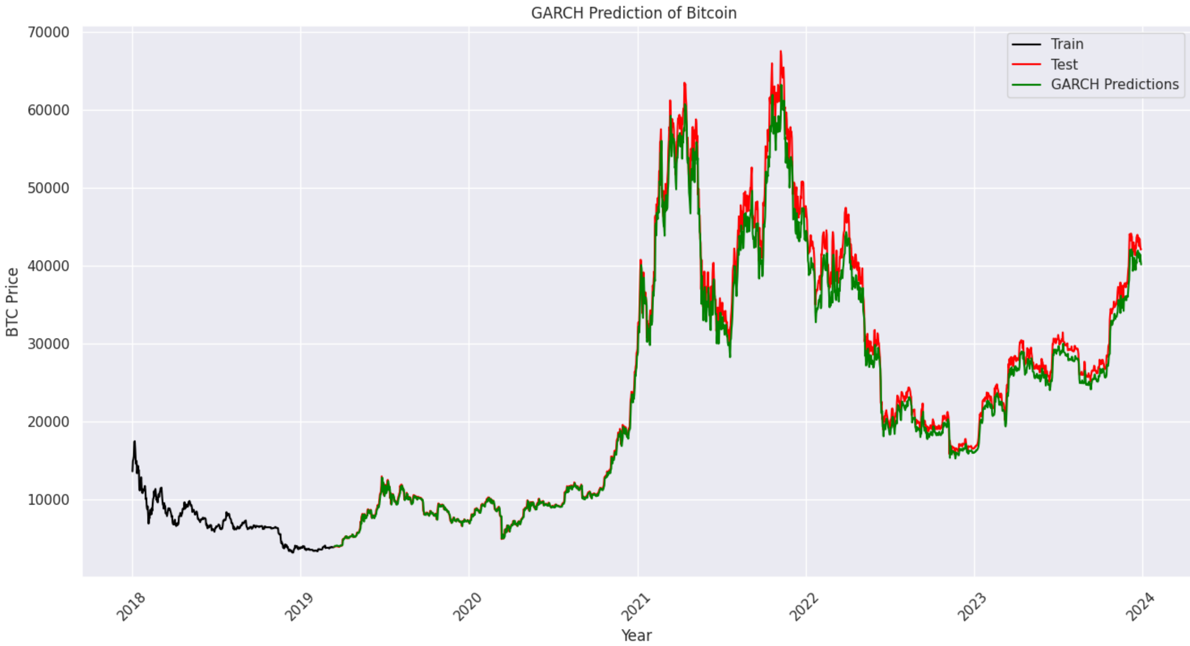

Figure 10 The GARCH Prediction of Bitcoin price

- **ARIMA-GARCH**

  In the process of training the hybrid model, we combine the forecasting methods of both the ARIMA and GARCH models. Specifically, the ARIMA model is used first to generate the forecasted mean. This forecasted mean is then combined with the standard deviation (obtained by taking the square root of the variance) from the GARCH model to enhance the accuracy of the predictions.

  Use a for-loop to iteratively forecast the mean from the ARIMA model with the order (1, 1, 0). After each prediction, update the historical price list and refit the ARIMA model to the updated data. Next, fit the residuals (the differences between the actual values and the ARIMA model's predicted values) to the GARCH (1,1) model. Combine the mean forecast from the ARIMA model with the standard deviation (derived from the GARCH model). Store the combined result in the ARIMA-GARCH prediction list. This result represents a comprehensive prediction that accounts for both the expected mean and the associated volatility. This step-by-step approach enhances the accuracy of the forecasts by considering both the trend and the volatility of the time series data.

  The following figures represent the visualised predictions of the ARIMA-GARCH model for three different stocks.

Figure 11 The ARIMA-GARCH Prediction of Unilever price

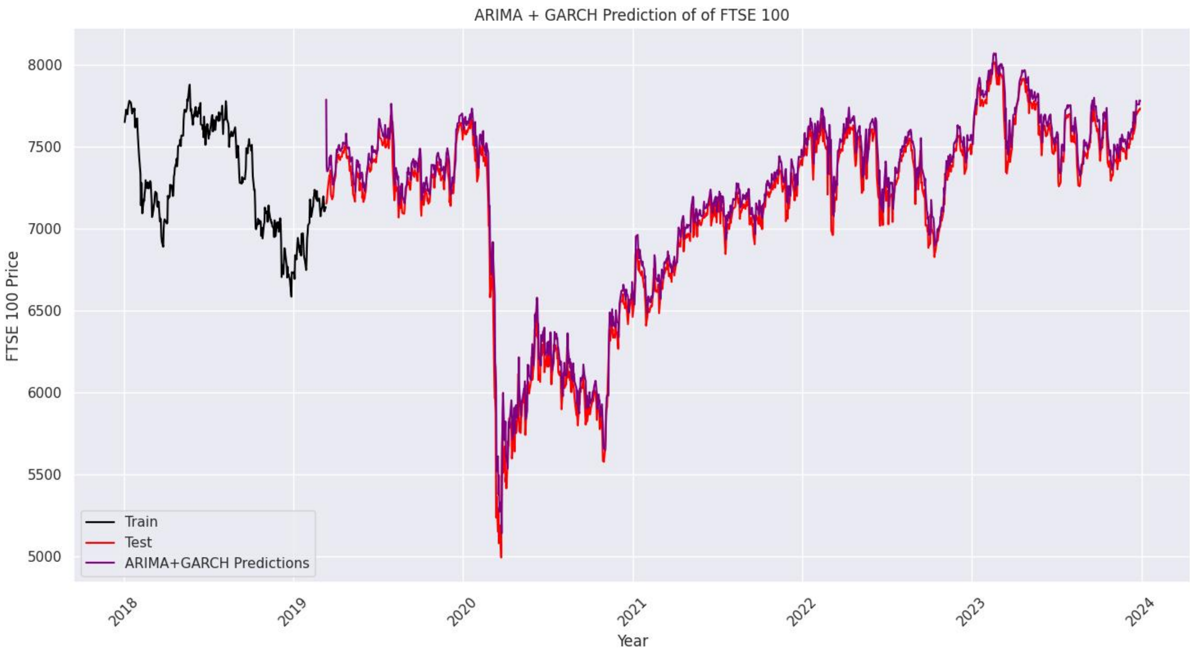

Figure 12 The ARIMA-GARCH Prediction of FTSE price

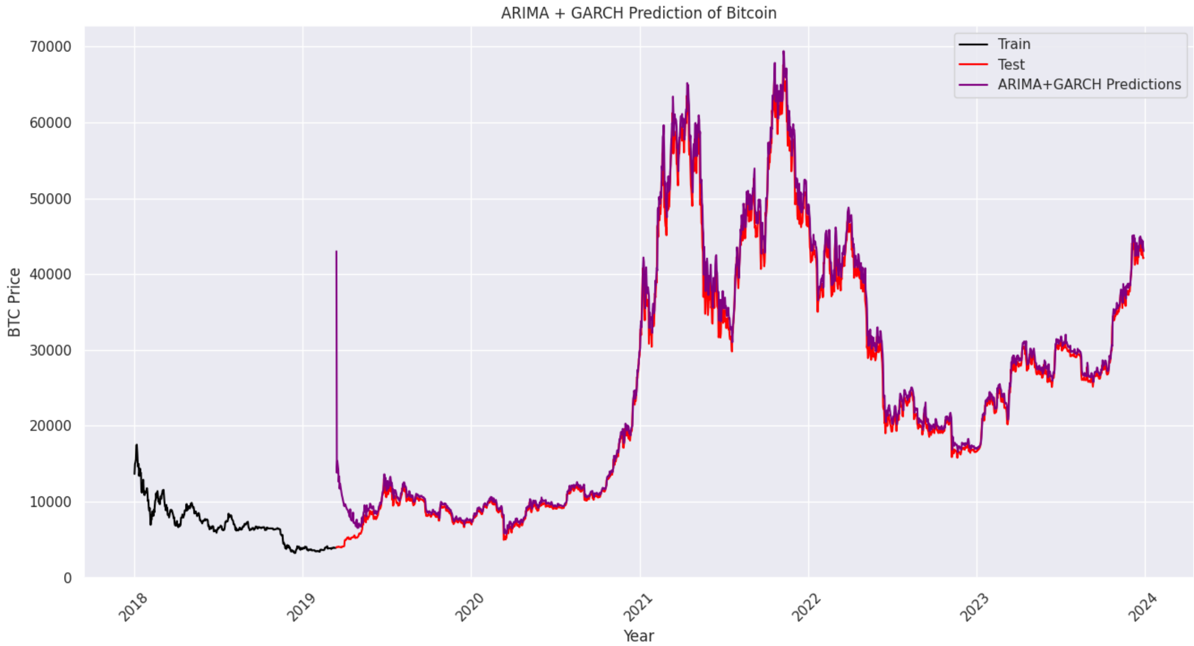

Figure 13 The ARIMA-GARCH Prediction of Bitcoin price

3.6 Data visualization

Data visualization is the scientific process of transforming data and information into graphical representations, such as charts, graphs, maps, and other visual tools [25]. The primary objective of data visualization is to simplify complex data, making it easier for readers to comprehend and analyse. This approach allows users to quickly grasp patterns, trends, and insights that might be difficult to detect in raw data.

In this project, data visualization is utilized to display both the forecast results of the three models and the evaluation outcomes of the four metrics (demonstrated in Chapter 4.0). The comprehensive graphs make it easier to present and compare the performance of the three models.

Seaborn is a Python data visualization library built on top of Matplotlib [26]. Its high-level interface allows developers to easily transform complex data into informative statistical graphics with just a few lines of code.

- Line Graph: Used for visualizing stock price predictions.
  First, initialize a new figure with a size of 16 inches by 8 inches. Next, separately plot the training data, test data, ARIMA model predictions, GARCH model predictions, and ARIMA-GARCH model predictions. Add a title, and labels for both the x-axis and y-axis. Additionally, rotate the x-axis labels (years) by 45 degrees to enhance the appearance of the graph.

The following figures illustrate the combined performance of the three models across three different stocks, making the data easier to compare and more understandable.

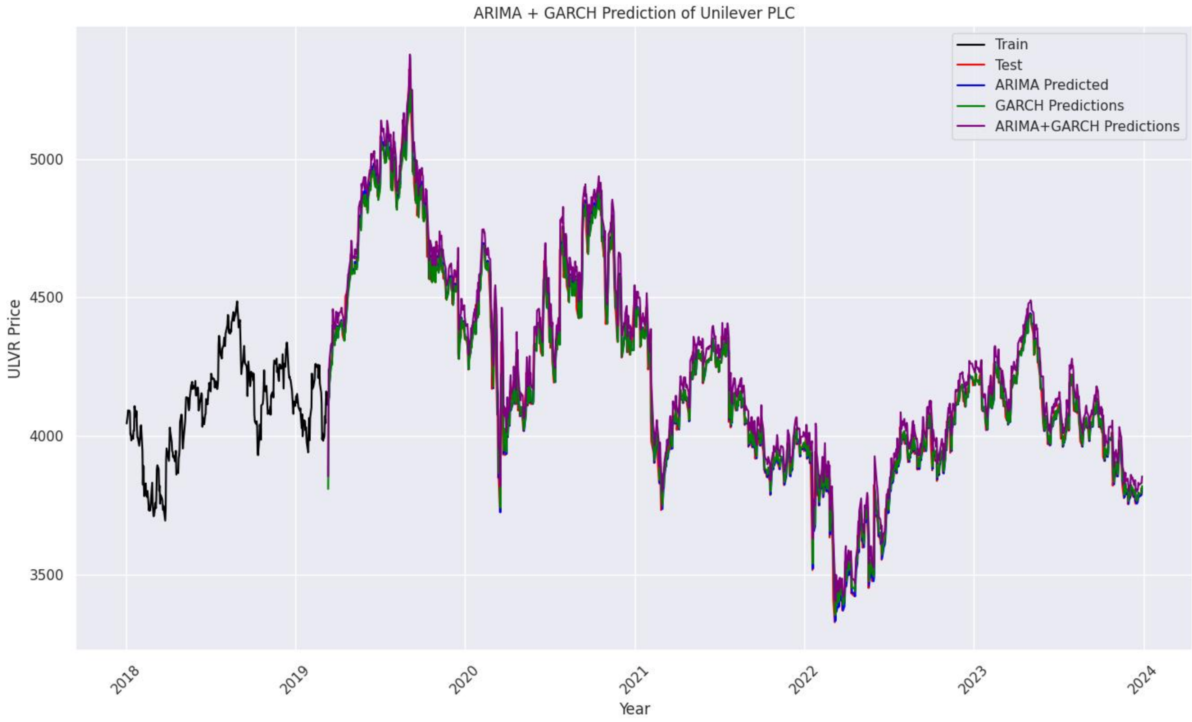

Figure 14 The three model Prediction of Unilever price

Figure 15 The three model Prediction of FTSE100 price

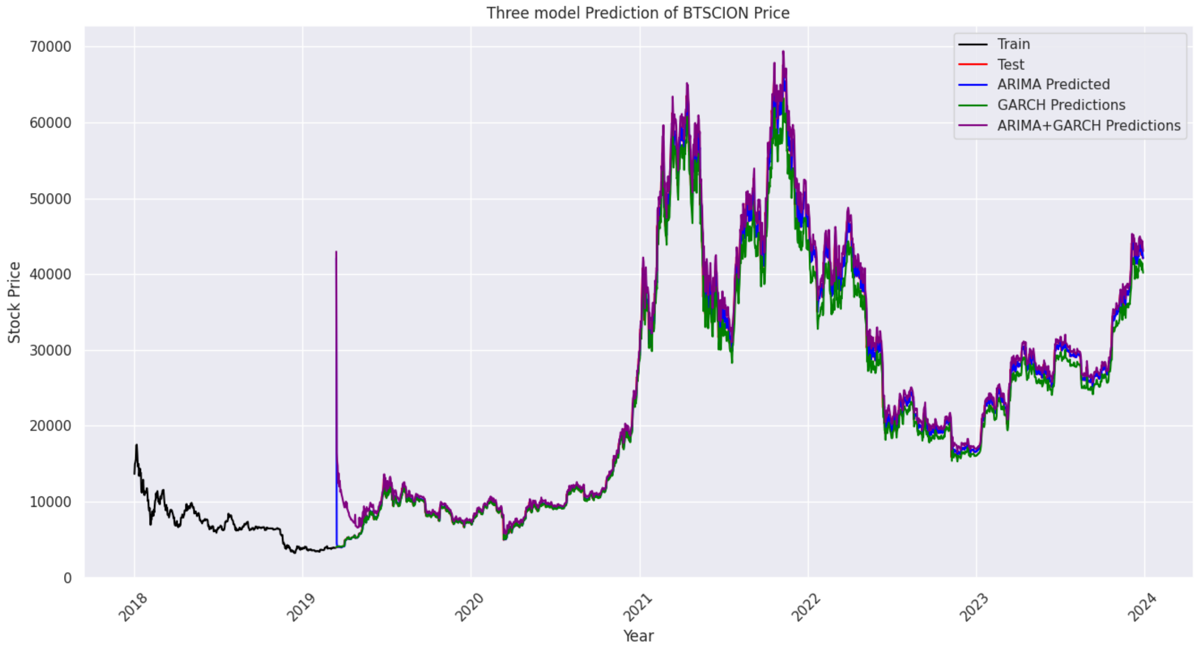

Figure 16 The three model Prediction of Bitcoin price

- Bar Graph: Used for evaluating metrics, as the figures demonstrated in Chapter 4.0. First, set the style to "whitegrid," which provides a white background with grid lines. Next, initialize a figure with a specified size of 10 inches by 6 inches. Then, use Seaborn to create a bar plot that visualizes the values of four metrics for each model. Finally, add title, x-axis and y-axis label, and annotation for each bar.

4.0 Comparison and analysis of Model Results

In this chapter, the performance of the ARIMA, GARCH, and ARIMA-GARCH models is analysed using various metrics, including RMSE, MAPE, MAE, and R^2 (as discussed in Chapter 2.4). The following four sections present the results of these metric evaluations and demonstrate them through bar graphs. The bar graph uses three colours to represent the models: blue for ARIMA, orange for GARCH, and green for ARIMA-GARCH.

- RMSE evaluations

  The Root Mean Square Error (RMSE) measures the average magnitude of the errors between predicted and actual values. A lower RMSE value indicates higher prediction accuracy, as it reflects smaller differences between the predicted and actual values.

  As shown in the graph below, the ARIMA model outperforms the other two models for both Unilever PLC and Bitcoin. For the FTSE 100, the GARCH model provides better predictions. The ARIMA-GARCH model, however, performs the worst across all three cases.

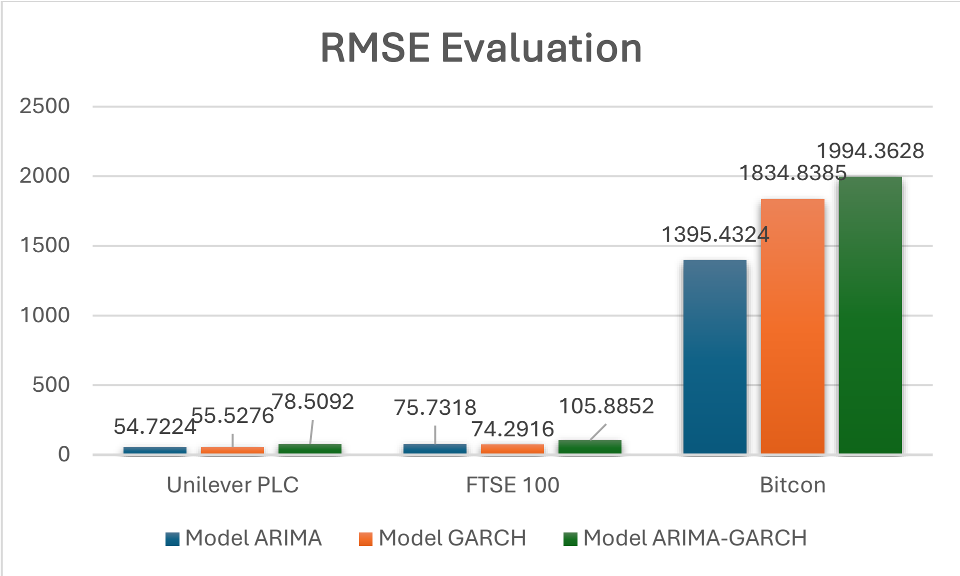

Figure 17 The bar graph of RMSE evaluation result

- MAPE evaluations
  The Mean Absolute Percentage Error (MAPE) primarily measures the average absolute percentage difference between predicted and actual values. Similar to the Root Mean Square Error (RMSE), a lower MAPE value indicates that the prediction results are closer to the actual values.

  For forecasting the stock prices of Unilever PLC and Bitcoin, the ARIMA model consistently shows the lowest error values, indicating better accuracy. For the FTSE 100 index, the ARIMA model and the GARCH model perform equally well, with similar error values. The hybrid model, ARIMA-GARCH, consistently ranks third across all cases.

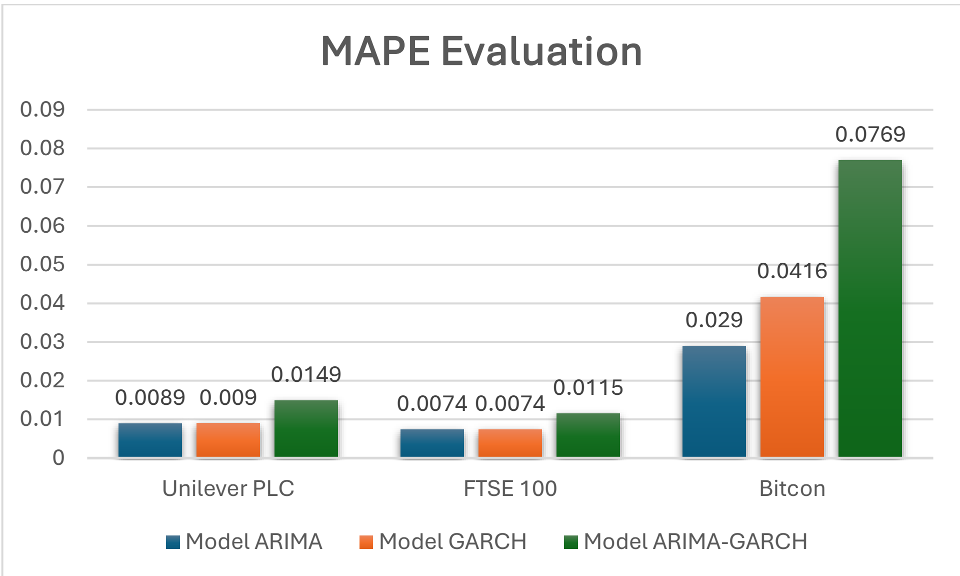

Figure 18 The bar graph of MAPE evaluation result

- MAE evaluations

The Mean Absolute Error (MAE) measures the average magnitude of the errors without considering their direction. As a result, the lower value indicates the higher accuracy.

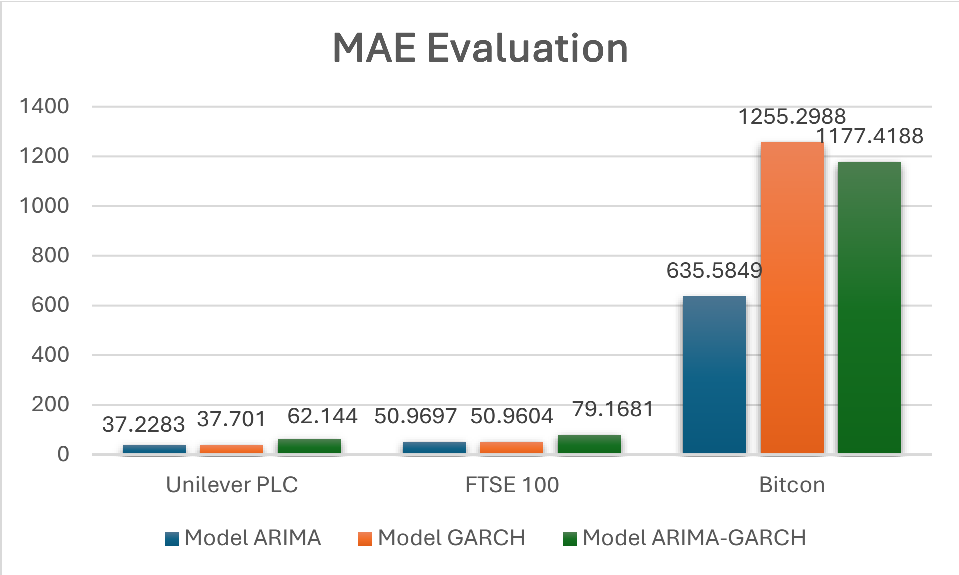

Figure 19 The bar graph of MAE evaluation result

- R^2 evaluations
  R-squared (R^2) is a statistical measure that shows how well the independent variables (the factors you're using to make predictions) explain the variation in the dependent variable (the thing you're trying to predict). The R-squared (R^2) value ranges from 0 to 1, with values closer to 1 indicating a more accurate prediction by the model.

  The R^2 evaluation results are consistent with the findings from the other three metrics. The ARIMA-GARCH model shows lower accuracy across the three stocks. The ARIMA model ranks first in predicting Unilever PLC and Bitcoin, while for FTSE 100, the GARCH model outperforms the other two models.

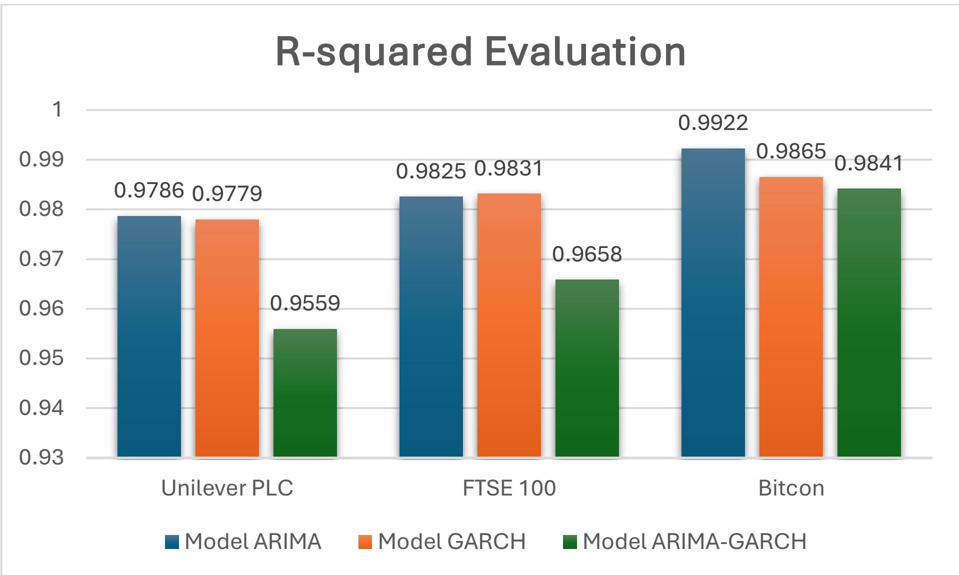

Figure 20 The bar graph of R^2 evaluation result

The above table combines the results from the four metrics evaluations. By ranking the models as first, second, and third in performance, the accuracy of the time series forecasting becomes more apparent and easier to understand. Overall, the ARIMA-GARCH model typically ranks third, indicating that it did not significantly enhance the accuracy of time series forecasting. The ARIMA model outperformed the other two models in most cases. However, in the case of ETFs, specifically the FTSE 100 index, the GARCH model performed better.

Table 2 The evaluating rank of three model performance by four metrics

RMSE				MAPE			
	ARIMA	GARCH	ARIMA-GARCH		ARIMA	GARCH	ARIMA-GARCH
Unilever PLC	1	2	3	Unilever PLC	1	2	3
FTSE 100	2	1	3	FTSE 100	1	1	3
Bitcoin	1	2	3	Bitcoin	1	2	3
MAE				**R-squared**			
	ARIMA	GARCH	ARIMA-GARCH		ARIMA	GARCH	ARIMA-GARCH
Unilever PLC	1	2	3	Unilever PLC	1	2	3
FTSE 100	2	1	3	FTSE 100	2	1	3
Bitcoin	1	3	2	Bitcoin	1	2	3

5.0 Conclusion

This study aims to predict stock prices by inputting data into three different models and forecasting iteratively. Metrics are used to estimate the accuracy of each model's time series forecasting ability. The performance of the ARIMA, GARCH, and ARIMA-GARCH models will be compared and analysed. The conclusion chapter will be divided into three parts: a summary of the entire study, an overview of the author's contributions and findings, and suggestions for future research directions.

5.1 Research summary

Artificial Intelligence (AI) language models are designed to handle complex time series data. In the stock market, using these models for forecasting helps investors make more informed decisions. This dissertation employs three models: ARIMA, GARCH, and ARIMA-GARCH. Based on the definitions provided in Chapter 2.2, the hybrid ARIMA-GARCH model is expected to combine the strengths of the two statistical models, mitigate its weakness, and provide more accurate forecasts than traditional models. However, the line graphs of model predictions (as shown in Chapter 3.0) and the evaluation of four metrics (as discussed in Chapter 4.0) indicate that the ARIMA model generally outperforms the others, with the GARCH model usually in second place. The ARIMA-GARCH hybrid model did not perform as well as expected.

The following list is review and improvement of this project. There are some potential factors that affect the performance of models:

- Overfitting
  Overfitting is a critical issue that arises when models fail to generalize well to new data [27]. This often happens because the models capture too much noise, such as small and insignificant data points, rather than focusing on the actual signal. Additionally, excessive training, including too many iterations, can cause overfitting.

- Rescaling
  In the GARCH model, an error message suggested "recommended rescaling"(as mentioned in Chapter 3.4). As a result, setting "rescale=True" for both the GARCH and ARIMA-GARCH models automatically adjusts the data to an optimal range. Misspecification of model settings, such as incorrect scaling, can significantly impact model performance [28].

- Feature of model
  The ARIMA-GARCH model is particularly well-suited for short-term forecasting due to its ability to capture both linear patterns and volatility clustering in time series data. However, the model's limitations, such as the accumulation of errors over time, make it less effective for long-term forecasting. As a result, its performance tends to degrade when applied to extended time horizons [29], [30].

5.2 Learning point

Transitioning from time series forecasting to machine learning has been an interesting but challenging journey. From a personal perspective, using AI models to predict stock prices was a new and unfamiliar research area. Over the past three months, the author has gained significant insights and knowledge through the completion of this dissertation.

- Understand the essential terms and skills
  Before implementing the code, the first step is to establish a strong foundational understanding of the essential concepts and knowledge required for this project. Through comprehensive background research, a solid foundation of knowledge was established, including key terms and concepts essential to this project. The literature review further clarified the project's scope and informed the development of the methodology.

- Learn a new programming language
  In the previous two semesters, Java was the primary programming language used. However, this dissertation relies on Python for training AI models. As a result, it became essential to develop basic coding skills in Python, which was achieved through self-learning via online resources and instructional videos.

- Train different models for time series forecasting
  This project provided a comprehensive understanding of three time series forecasting models: ARIMA, GARCH, and ARIMA-GARCH. The practical experience gained in training these models was invaluable. The process included several key steps: preprocessing data sourced from Yahoo Finance, setting appropriate model parameters, and iteratively feeding data into the models for accurate forecasting. These practical implementations greatly enhanced my knowledge of machine learning and time series forecasting techniques. Additionally, visualizing the predictions through line graphs was an essential part of the project, as it made the forecasting outcomes more interpretable and allowed for clearer comparisons between model performances.

- Handle forecasting problems
  During the model training process, several challenges arose that affected prediction accuracy, such as overfitting, model instability, and incorrect rescaling. By consulting additional materials on price forecasting models, I was able to address these issues and successfully improve forecasting accuracy.

- Assess the performance of models
  Evaluation and comparison are critical components in assessing the overall effectiveness of this project. These metrics were chosen not only for their ability to quantify errors but also for the insights they provide into the accuracy and reliability of the models. After thoroughly reviewing the definitions and implications of various metrics, we selected RMSE, MAE, MAPE, and R-squared as our primary evaluation tools. The results of these evaluations were then visually represented through bar graphs and summarized in tables, allowing for a clear comparison of the performance of the different models.

- Critical thinking throughout the dissertation
  Before analysing the results, this dissertation assumed that the hybrid model would outperform traditional statistical models. However, as the project progressed, it became evident that critical thinking was essential at every stage, particularly when the evaluation results contradicted the initial assumption. The discrepancy between the expected and actual outcomes underscores the importance of maintaining an open and analytical mindset throughout the research process. This approach ensures that conclusions are based on data-driven insights rather than preconceived notions, thereby contributing to a more robust and reliable study.

- Proper words in academic research paper
  Writing the dissertation provided an invaluable opportunity to refine academic writing skills. It required the organization of complex ideas clearly and concisely, ensuring the concepts were presented in an understandable way. Additionally, the process emphasized the importance of using appropriate term and maintaining a logical structure. These skills are essential for presenting research findings in a professional and academically rigorous manner.

5.3 Suggestion of future work
After finishing this project, we found valuable insights from the analysis and comparison of the performance of the ARIMA, GARCH, ARIMA-GARCH models in stock price forecasting. There are some suggestions for future research that can enhance the completeness of time series forecasting experiment.

- Model long term forecasting
  Due to the limitations of the ARIMA-GARCH model in long-term forecasting, future research could explore other hybrid models that incorporate machine learning techniques, such as Long Short-Term Memory (LSTM) networks.

- Avoid overfitting
  As mentioned in Chapter 5.1, overfitting negatively impacts the accuracy of model predictions. In long-term forecasting, large time series datasets can increase the risk of overfitting. Therefore, identifying strategies to prevent and address overfitting will be a critical focus for future research.

- Cross-Market Analysis
  The four bar graphs (demonstrated in Chapter 4) reveal a significant gap in the predictions for Bitcoin compared to the other two stocks, Unilever PLC and FTSE 100. This discrepancy may be attributed to the unique characteristics of cryptocurrencies, which the models struggle to predict accurately. This issue could be explored further in

future research. Additionally, this dissertation primarily focuses on stock price forecasting. Future research could expand this scope to other financial markets, such as real estate price fluctuations.

Overall, this project can be considered a success. Although the results did not align with the initial assumption that the hybrid model would outperform traditional statistical models, the project yielded valuable insights. The author identified the limitations of the models and developed solutions to improve the forecasting process. Additionally, the project opens up important avenues for future research in this area that are worth exploring further.

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7.0 Appendix

The link of supplementary material-
https://drive.google.com/drive/folders/18Mhz0thBd7coYTIPG4-5Fy936_I9WFn8?usp=drive_link

The link of code file-
https://github.com/chihhui5/Time_Series_Forecasting

The link of reference file-
Reference