alamSYS: Development of Stock Market Price Trend Forecasting System Using Dynamic Mode Decomposition, Long Short-Term Memory, and Auto Regression Integrated Arnaud Legoux Moving Average

A Special Problem
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Introduction

1.1 Background and Rationale

The stock market is a type of market that allows companies to raise capital by issuing shares of stock to investors. These shares represent a share of ownership in the company and entitle the holder to a share of the company's profits and voting rights. The stock market also provides a platform for investors to buy and sell these shares, allowing for the efficient trading of company ownership. By allowing companies to raise capital and investors to buy and sell shares, the stock market plays a crucial role in the growth and development of the economy (Chen, 2022; The Economic Times, n.d.).

Contrary to popular belief, the stock market is not a form of gambling. It involves a significant amount of analytical thinking and risk management, and the returns are based on the supply and demand for a given stock, rather than on false promises or assurances. In other words, the stock market is a legitimate platform for investing and generating returns, rather than a scam or gamble (Schwab-Pomerantz, 2021; Adams, 2022; Summers, 2022).

1.1.1 The Philippine Stock Exchange (PSE)

The Philippine Stock Exchange (PSE), Inc. is the official stock exchange market in the Philippines. It is a non-stock company that was incorporated in 1992 and manages and operates the stock market in the country. Registered individuals can participate in market exchanges on the PSE. (The Philippine Stock Exchange, Inc., n.d.-a).

Moreover, the main index of the Philippine Stock Exchange (PSE) is the Philippine Stock Exchange Index (PSEI). The PSEI is a market capitalization-weighted price index that is based on the 30 largest and most actively traded companies on the PSE. These companies are pre-determined based on strict criteria, such as liquidity and market capitalization. The PSEI is often used as a benchmark for the performance of the overall stock market in the Philippines. (Bangko Sentral ng Pilipinas, n.d.) The companies that make up the PSEI are often referred to as blue-chip companies, as they are typically large, well-established companies with a history of strong financial performance. As of October 2022, there are 286 companies listed on the PSE, providing a diverse range of investment opportunities for investors. (Fayed, 2022; The Philippine Stock Exchange, Inc., n.d.-b).

1.1.2 Economic Relevance and Benefits of Stock Market Investment

It is commonly accepted that the stock market plays a crucial role in economic growth, as it allocates and provides capital to businesses, which in turn drives economic activity and growth. This is evident from the fact that stock market performance is often correlated with a country's Gross Domestic Product (GDP) (Trade Brains, 2022; Hall, 2022; Bae & Kang, 2017) Additionally, historical trends in stock prices can provide insight into broader economic movements (Campbell, 2021).

Moreover, a study by Balaba (2017) found that the stock market has a positive effect on the economy of the Philippines. The data from the study showed that as the stock market grew, the country's unemployment rate declined. This is because the stock market's performance leads to job creation, which in turn drives economic growth. This relationship has been evident in the Philippines for the past 10 years.

1.1.3 Benefits of Investing for the Individual

The Philippine Stock Exchange allows individuals in the Philippines to trade shares of listed companies. Investing in the stock market can provide several benefits for an individual, such as:

(a) Protects the value of an individual's money from inflation: Inflation in the Philippines was at 6.9% as of September 2022 (Trading Economics, n.d.), while savings account deposit interest rates are only between 1-3% annually (Bureau of the Treasury Bangko Sentral ng Pilipinas, n.d.). This means that savings in deposit banks may not keep pace with inflation, potentially reducing the purchasing power of an individual's money (Royal Bank of Canada Direct Investing Inc., n.d.; EdwardJones, n.d.).

(b) Provides opportunities for capital growth: Investing in the stock market can provide individuals with the potential for significant capital growth, without the need for direct involvement in business operations. This can be beneficial for individuals such as students or working professionals, who can grow their capital while focusing on their studies or careers (U.S. Securities and Exchange Commission, n.d.).

1.1.4 Utilization of Machine Learning in Stock Market Trading

In recent years, there has been a growing interest in applying machine learning techniques to predict the movement of the stock market, both in the short and long term. This has led to numerous studies and practical applications exploring the use of machine learning in stock market prediction. These efforts aim to improve the accuracy of predictions and help investors make informed decisions. (Kumbure, Lohrmann, Luukka, & Porras, 2022; Strader, Rozycki, Root, & Huang, 2020; Soni, Tewari, & Krishnan, 2022; Rea, 2020; Guo, 2022). Wherein, one of the common techniques used in machine learning for stock market prediction is Long Short-Term Memory (LSTM). A study by Budiharto (2021) found that LSTM was effective in predicting the Indonesian stock market by 95% using short-term data. This indicates that LSTM can be a valuable tool for making short-term stock market predictions.

Recently, the use of Dynamic Mode Decomposition (DMD) for predicting stock market price trends has gained momentum in the financial and scientific communities. DMD is a mathematical method that can be used to identify patterns and trends in complex data sets, such as stock market data. By applying DMD to stock market data, it is possible to make more accurate predictions about future stock price movements. This can help investors make informed decisions about their investments and potentially generate better returns. In connection to this, a study by Lu and Tartakovsky (2020) found that DMD can be a faster predictor than Proper Orthogonal Decomposition (POD), but it is less accurate.

Furthermore, other studies have shown that DMD can be effectively applied to the Turkish and Indian stock markets to predict market price trends (Savaș, 2017; Kuttichira, Gopalakrishnan, Menon, & Soman, 2017). These studies indicate that DMD is easy to implement and can be a useful tool for making stock market predictions.

Aside from LSTM and DMD, another model is also being used in stock market predictions, which is the Auto Regression Integrated Moving Average (ARIMA). In a study conducted by Ayodele Ariyo Adebiyi (2014), ARIMA model shows satisfactory results for predicting stock prices on the short-term period. Moreover, in this special problem the author will also explore the feasibility of using Arnaud Legoux Moving Average (ALMA) in combination with ARIMA. This will be done since compared to the traditional Moving Average (MA), ALMA produces a more reliable signal (Sarkar, 2019).

1.2 Statement of the Problem

The Philippines' economic growth is expected to decline in the coming years due to the global pandemic, high inflation, and low employment rates. (Alegado, Lopez, & Calonzo, 2022; Canto & Romano, 2022; Reuters, 2022).

Currently, the lack of free and publicly available stock market predictive systems or tools creates a gap in the information available to the public compared to large private individuals or institutions. These large institutions have the resources to spend a significant amount of money on stock market research, giving them a significant advantage in the investing market. This lack of access to the same information puts the public at a disadvantage (Kim, 2022).

Furthermore, the lack of publicly available stock market prediction tools can lead to unwise investment decisions by individuals, particularly first-time investors, resulting in significant losses and discouragement from investing in the stock market. This is a significant problem, as the number of local investors in the Philippine Stock Market is already quite low, comprising only around 1% of the total population. Not to mention, there also has been a massive decline in foreign investment in the Philippines in recent years (Business World, 2022), leading to a corresponding decline in investment volume. As suggested by the study of Balaba (2017), this is expected to have a negative multiplier effect on the country's economic development in the future.

Hence, the development of a publicly available, easy-to-use, and accurate stock market price trend prediction system could help to reduce the information gap and level the playing field for individual investors. By providing the public with fast and reliable information, this system could help to increase transparency and fairness in the stock market, leading to a more informed and confident investing decisions, and ultimately a more stable and prosperous market. Additionally, such a system could help to increase the participation of individual investors in the market, leading to a more diverse and stable market overall. (Statista Research Department, 2022; Commission on Population and Development, 2021).

Despite the clear and functional benefits of investing in the stock market, many Filipinos remain hesitant to do so for the following reasons:

(a) The complexities associated with learning the fundamentals of effective stock investing.

(b) The time-consuming nature of technical and fundamental analysis, particularly for students and working individuals with limited time; and

(c) The higher financial risk due to the volatility of the stock market, as well as the potential for emotional decision-making to compromise investments

These factors *(along with other external factors not listed above)* contribute to a lack of confidence and understanding among potential investors, making it difficult for them to take advantage of the opportunities offered by the stock market.

As such the development of the proposed system, shall help to address the following:

(a) The lack of free and publicly available stock market prediction systems or tools.

(b) The time and resources required to study complex traditional market analysis tools, such as fundamental and technical analysis.

(c) The potential for inaccurate market decisions leading to significant investment losses; and

(d) The hesitancy of the Filipino public to begin investing in the Philippine stock market.

1.3 Significance of the Study

The significance of this special problem lies in its potential to develop a system that will greatly benefit the stock market, individual investors, and the overall economy. The system's contributions to data-driven investing, financial protection and management, and economic development will provide a valuable resource for investors and help to promote financial stability and growth. Additionally, the development of publicly accessible data-driven investing tools will enable more Filipinos to participate in the market and take control of their own financial future. Overall, this study has the potential to make a meaningful impact on the stock market and the economy in the Philippines.

Specifically, this study is significant for the following reasons:

(a) The development of the alamAPI will provide the following benefits to the Filipino people:

1. Access to simplified yet accurate information – The proposed system will provide Filipino investors with fast, accurate, and relevant information necessary for effective decision making in the stock market. Using advance machine learning regression models, the system will provide users with the two most important pieces of information: which stocks to buy, and which stocks to sell. This simplified investing model will help investors to make informed decisions and navigate the stock market with confidence.
2. Provide an application interface to facilitate data-driven and wise market decisions – The proposed system will provide users with an intuitive and user-friendly application interface to facilitate data-driven investment decisions, particularly during times when the market is unpredictable or experiencing a downturn. Whereas traditional market analysis tools may not be sufficient to navigate these challenging conditions, the system's advanced machine learning algorithms will provide investors with the insights and guidance they need to make informed and wise decisions. This will help to promote confidence and stability in the market, even during times of uncertainty.

3. A platform for accessible stock market investment – The proposed system will provide all investors, regardless of their investment knowledge, educational attainment, and societal status, with a platform for participating in the stock market. By offering a simplified yet accurate model for investment decision making, the system will empower users to make informed decisions and invest with confidence. This will help to democratize access to the stock market and promote financial inclusion for all Filipinos.

(b) The development of the alamAPI, specifically the Stock Market Price Trend Forecasting System (SMPTF Sys), will provide the following benefits to the future developers or researchers:

1. Extension of functionality to other financial markets – The proposed system can be easily adapted or expanded to address related problems in other financial markets, such as investing in government bonds or personal finance management. This flexibility and versatility will make the system a valuable tool for a wide range of investment and financial management scenarios.
2. Testing of new trading algorithms and machine learning models – The system provides a platform for introducing and testing new data-driven trading algorithms and machine learning models. This will allow researchers and developers to continually improve the system and keep it at the forefront of data-driven investing technology.
3. Development of a graphical user interface – To further improve the public accessibility of the system, a user-friendly graphical user interface can be developed as a web or mobile application. This will make the system easy to use and intuitive for all users, regardless of their technical expertise.

(c) The development of the alamAPI will help to stimulate economic recovery and development in the country by increasing the number of local investors. As discussed in previous sections, the benefits of the system will encourage more people to invest in the stock market, leading to a multiplier effect that will benefit the economy in several ways. For example, the increased participation in the market will lead to the creation of jobs and a lowering of unemployment rates. Additionally, the influx of capital into the market will drive fast developments and innovations in various industries, and the increased consumer spending that results from successful investing will stimulate economic growth. Overall, the development of the alamAPI will have a positive and far-reaching impact on the economy of the Philippines.

1.4 Objectives

The main objective of this special problem is to develop a system that will make investing easier, more publicly available, data-driven, and more approachable to the public by minimizing both the time required for stock price trend analysis, and potential financial risk by using DMD-LSTM and ARIALMA *Modified ARIMA*. Specifically, it aims to do following:

(a) Develop a RESTful API, which will be referred to as alamAPI, using the combination of Python libraries and MongoDB for the backend services and database, respectively.

Whereas this backend service will be using Python's FastAPI that will enable different user to connect to the database and collect the information provided by the Stock Market Price Trend Forecasting Model.

Specifically, this will be done by doing the following:

1. Develop a Data Collector Module (DCM), which will get the historical data every day for the past 200 days every after market close from Mondays to Fridays. The data collected will be eventually processed by the Pre-Database Processor (PDP) with the help of the Preprocessor Utilities Module (PUM). Wherein, DCM, PDP, and PUM will be part of the Preprocessor Module (PPM) of alamAPI.
2. Develop a database that will store the results provided by the PPD, and other essential data about the stock market that is needed to be provided in the backend service.

3. Develop the necessary API endpoints that will provide recommendation on which stocks to buy or sell. Additionally, it provides the general information about these stocks.

(b) Develop the following Stock Market Price Trend Forecasting Machine Learning Models:

1. Model A (DMD-LSTM) – Utilize the dynamic modes in DMD as a parameter to the LSTM model.
2. Model B (ARIALMA) – Modify ARIMA by using the optimized parameters for ALMA instead of the traditional MAs.

(c) Finally, develop a mobile-based test application to showcase the main functionalities of the developed RESTful API.

1.5 Scope and Limitations

This study is limited only within the companies listed in the Philippine Stock Exchange, including the PSE Index itself. Wherein, only 20 selected high volume trade stocks from the year 2021 to 2022 which are has following stock symbols: (1) MEG, (2) JGS, (3) BDO, (4) FGEN, (5) ICT, (6) ALI, (7) SMC, (8) TEL, (9) GLO, (10) BLOOM, (11) RLC, (12) MER, (13) AC, (14) PGOLD, (15) LTG, (16) MPI, (17) AP, (18) RRHI, (19) URC, and (20) PSE Index will be included in the system, instead of the total 286 listed under the Philippine Stock Exchange, this is because the data directly from the Philippine Stock Exchange Inc., is not free, and the free data provided by a third-party only allows for 20 requests per day. Also, using data scraping tools may prove to be illegal, as it is considered as data theft because data provided in those websites are for public viewing purposes only and are also paid by the companies hosting them.

1.6 Definition of Terms

(a) alamAPI - xxx

(b) alamSys - xxx

(c) Auto Regression Integrated Moving Average (ARIMA) – xxx

(d) Arnaud Legoux Moving Average (ALMA) – xxx

(e) Data Collector Module (DCM) - xxx

(f) Dynamic Mode Decomposition (DMD) – xxx

(g) Machine Learning - xxx

(h) Pre-Database Processor (PDP) – xxx

(i) Preprocessor Module (PPM) - xxx

(j) Preprocessor Utilities Module (PUM) - xxx

(k) Stock Market - xxx

(l) Long Short-Term Memory (LSTM) – xxx

Chapter 2

Review of Related Works and Literature

One of the challenges facing investors in the Philippine Stock Market is the limited availability of resources and tools for making market decisions. In contrast, other countries have begun implementing machine learning techniques for stock market prediction and analysis, which allows for more accurate decision-making and reduces the risk of poor investment outcomes. As a result, these countries are likely to experience better returns on their investments.

In this literature review, the following general topics are reviewed, discussed, and synthesized: (a) Integration of Machine Learning based Trading Algorithms; and (b) Utilization of Dynamic Mode Decomposition on the Financial markets.

2.1 Integration of Machine Learning based Trading Algorithms

Stock market analysis is crucial for effective risk management. This involves using various methods, such as technical and fundamental analysis, to make informed decisions for investors and traders. In recent years, the growth of computing power and resources has led to the increasing use of machine learning techniques for stock market prediction and analysis. These advances help companies better predict upcoming market trends and make more informed decisions.

The integration of machine learning algorithms in the stock market is growing, as investors and traders increasingly rely on fast and accurate market information to reduce potential risks and make better decisions. These algorithms allow for more efficient analysis of market data, leading to more informed decisions and improved investment outcomes (Obthong, Tantisantiwong, Jeamwatthanachai, & Wills, 2020).

2.1.1 Comparison of Machine Learning and Deep Learning Models in Stock Market Predictions

To have a better grasp in the accuracy of the different models used in algorithmic trading it is essential that different models are compared against each other.

T

ODO: ADD ADDITIONAL SUBSECTIONS FOR ARIMA

Combination of Computational Efficient Functional Link Artificial Neural Network (CEFLANN) and Traditional Technical Analysis

This hybrid model combines a classification-based model: CEFLANN and the traditional technical analysis to create a stock trading framework Dash and Dash (2016), which the results show a profit of 24.29%.

Deep Long Short-Term Neural Network (LSTM) with Embedded Layer

In one of the models developed by Pang, Zhou, Wang, Lin, and Chang (2020), it shows that by adding an embedded layer to the LSTM it yields to a stock market price prediction accuracy of 57.2%. However, its accuracy dips to 52.4% when the model is applied to individual stocks.

LSTM with Automatic Encoder

As part of the second model developed by Pang et al. (2020), this model shows a slightly inaccurate stock market prediction, by only having a measured accuracy of 56.9%. However, compared to the first model developed by the group this is 0.1% more effective for individual stocks.

Optimal Deep Learning (ODL)

In the study conducted by sManish Agrawal, Khan, and Shukla (2019) they have created a stock price prediction model using an Optimal Deep Learning (ODL) which combine the concepts of Correlation-Tensor and an Optimal LSTM algorithm. Whereas their results show a mean and highest accuracy of the model as 59.24% and 65.64%.

NMC-BERT-LSTM-DQN-X Algorithm

More recently, a team have applied a combination of three models for forecasting the market trends. Namely, (1) Non-stationary Markov Chain (NMC), (2) Bidirectional Encoder Representations from Transformers (BERT), (3) Long Short-Term Memory (LSTM). Wherein their model shows an accuracy of 61.77%. Furthermore, the team also mentioned that the model produces 29.25% annual return on investment, with a maximum losses rating of -8.29% (Liu, Yan, Guo, & Guo, 2022).

2.2 Utilization of Dynamic Mode Decomposition (DMD) on the Financial Markets

Dynamic Mode Decomposition (DMD) as an emerging data-driven technique which allows spatial-temporal pattern recognition from a complex set of data and was first introduced in the field of fluid mechanics by (SCHMID, 2010).

2.2.1 Chronological Utilization of DMD in the Financial Markets

In (2015) Mann and Kutz proved that DMD can be used as data-driven analytics on the financial market data. Wherein, DMD allows a predictive assessment of the market dynamics, which helps in the capitalization of stock market strategies and decisions to be applied.

Utilization of DMD for Determining the Cyclic Behavior in the Stock Market (2016)

By utilizing the reproducible Koopman modes it made it possible to have extracted four cyclic variations (also reproducible modes) in the stock market, which were previously unknown and have persisted since the 1870s' global economic crisis (Hua, Roy, McCauley, & Gunaratne, 2016; Williamson, 2015).

Utilization of DMD as part of an Algorithmic Trading Strategies for the Turkish Stock Market (2015 and 2017)

The study of Mann and Kutz (2015) in the utilization of DMD for financial stock market prediction has become the foundation of the study by Savaş (2017) on the algorithmic trading strategies with Dynamic Mode Decomposition for the Turkish Stock Market. Wherein, based on their results they found out that the timing of DMD analysis was not significantly accurate, as such they have used a simple moving average with genetic algorithm to improve the market timing of

DMD, which prevents 80% of the false trade signals.

Furthermore, this also shows that DMD is an effective alpha model that is easy to implement and use for any algorithmic trading strategy, and the addition of technical analysis tools can further improve its capabilities, especially on the predictive temporal side of the data.

Utilization of DMD-based Trading Strategy in the Chinese Stock Market (2016)

In the study by Cui and Long (2016), they have found that DMD was able to capture the dynamic patterns of the Chinese Stock Market, especially in a sideway trending market.

Their study also shows that the predictive ability of DMD can effectively model the behavior of the Chinese Stock Market, even if there are no clear trends that can be observed.

Utilization of Adaptive Elastic DMD to Improve Momentum Strategies (2021)

A study by Uchiyama and Nakagawa (2021), using Adaptive Elastic Dynamic Mode Decomposition (AEDMD) shows that they were able to estimate the market trend, and were able to demonstrate that the approach is better than existing momentum strategy which are only based on simple past trends.

2.3 Synthesis

Fast and accurate market information is an essential tool for stock market participants. In recent years, the development of machine learning models for the financial markets, such as stocks, has proven to be increasingly effective in predicting future stock prices and trends. The use of Dynamic Mode Decomposition (DMD) in the stock market has also been shown to be effective in predicting stock price trends. The simplicity and elegance of the Koopman Decomposition Operator make it an ideal basis for the development of a Stock Market Price Trend Forecasting System (SMPTF System).

These studies are crucial for the development of the alamAPI to provide investors with fast and accurate information about which stocks are likely to go up or down, allowing them to make more informed decisions about buying or selling those stocks.

In addition to the potential benefits for investors and traders, the implementation of machine learning techniques in the stock market can also help improve market efficiency and reduce the risk of market manipulation. By providing a more accurate and comprehensive view of market trends, these techniques can help ensure that prices reflect the true value of stocks and other assets, leading to more stable and fair market conditions.

Chapter 3

Materials and Methods

This chapter will discuss the materials and methods that will be used for the development of the proposed system: alamAPI. Specifically, the following will be discussed in this chapter:

(a) Development Tools and Software Requirements

(b) System Diagrams

(c) Hardware Requirements

(d) Methodology

(e) Gantt Chart

3.1 Development Tools and Software Requirements

The development of the alamAPI will use the following development tools and software requirements:

3.1.1 Development Tools

(a) Visual Studio (VS) Code – This is a highly functional code editor, which will be used as the main development interface for the project.

(b) MongoDB Compass – This is a graphical user interface used for the development and management of different MongoDB databases.

(c) GitHub – This will serve as the code repository and version control system (using git) for the project.

3.1.2 Software Requirements

(a) Python (version 3.11.x) – this will serve as the main programming language for the development of the different components of alamAPI, more specifically the following libraries will be used:

- For the development of the API and Database ODM
    - FastAPI (version 0.85.0) – This is a library primarily used for building modern, fast, and high-performing web framework APIs (Tiangolo, n.d.). This will be utilized in the development of the project because of its (1) ease of utilization; (2) fast implementation; (3) high-performance; (4) built-in robust API documentation; and (5) high scalability.
    - mongoengine (version 0.24.2) – This is a library developed as an Object-Document Mapper, which lets Python connect and work with MongoDB (MongoEngine, n.d.) This will be used in the alamAPI to connect the API endpoints to the MongoDB database.
    - json (pre-installed) – This is a python library that can transform Python dictionary into json object, and vice versa. This will be used in the development of alamAPI for parsing and conversion of the data from the API and to the MongoDB database through an ODM.
    - datetime (pre-installed) – This python library is used for creating a datatime object, which as the name suggests is an object that

contains the date and time information. This will be used in the development to keep track with all the processes that is happening in the system through a date and time logs.

- os (pre-installed) – This is a python library that enables the user to do operations in the operating system such as creating directories, files, accessing operating system information, etc. This will be used to access the operating system's environment variables, and to help in other OS-based functions.

- For the pre-processor (data collector)
  - requests (version 2.28.1) – This library allows the user to create web requests to an external or internal servers. This will be used to connect and collect the current EOD market data from the third-party market historical data provider: EODHD.
    EODHD – A third-party market fundamental and historical data APIs provider (EODHD, n.d.).
- For the pre-processor (machine learning processor):
  Note that these libraries will also be used in the development of the machine learning model.
  - pickle (pre- installed) – This allows an object to be saved and reloaded as a variable in Python, as such this will be used to save the machine learning developed and be utilized to process the new and updated data provided by the data collector.
  - joblib (pre-installed) – xxx
  - numpy - xxx
  - pandas - xxx
  - sklearn - xxx
  - tensorflow - xxx
  - matplotlib - xxx
  - seaborn - xxx

(b) MongoDB – This will be used as the non-relational (document-based) database, that will hold the stock information, stocks to buy, and stocks to sell.

(c) Jupyter Notebook – This will be used during the training and testing of the machine learning model that will be developed as part of the alamAPI.

(d) CRON – A Linux-based scheduler. This will be used in the system to set a schedule for the historical data collection and processing for each market end-of-day (EOD) every 5 PM from Mondays to Fridays. Moreover, the scheduler is part of the pre-processor module of the system.

(e) Docker – This is a very useful tool to creating containers, whereas a container contains a code and all its dependencies in one standard unit of software, which can be run in different machines regardless of its difference from the development machine used (Docker, n.d.). As such this will be used to create containers for each of the component of alamAPI, to enable it to run in different deployment machines.

(f) Docker-compose – In order to run multiple containers at once, docker-compose will be used. This will be further discussed in the Container Diagram section of this chapter.

(g) Dart and Flutter - xxx

(h) Git - xxx

3.2 System Diagrams

In this chapter, the appropriate system diagrams will be shown and discussed. This shall help in the understanding of the system's features, data flow, and processes. Whereas all the diagrams can be viewed in full resolution, using the GitHub repository, provided in the author's note at the title page.

3.2.1 Top-Level Overview Diagram of the alamAPI and Its Interactions to External Systems

Figure 3.1 shows the top-level overview of the alamAPI and its interactions to any third-party or external applications.

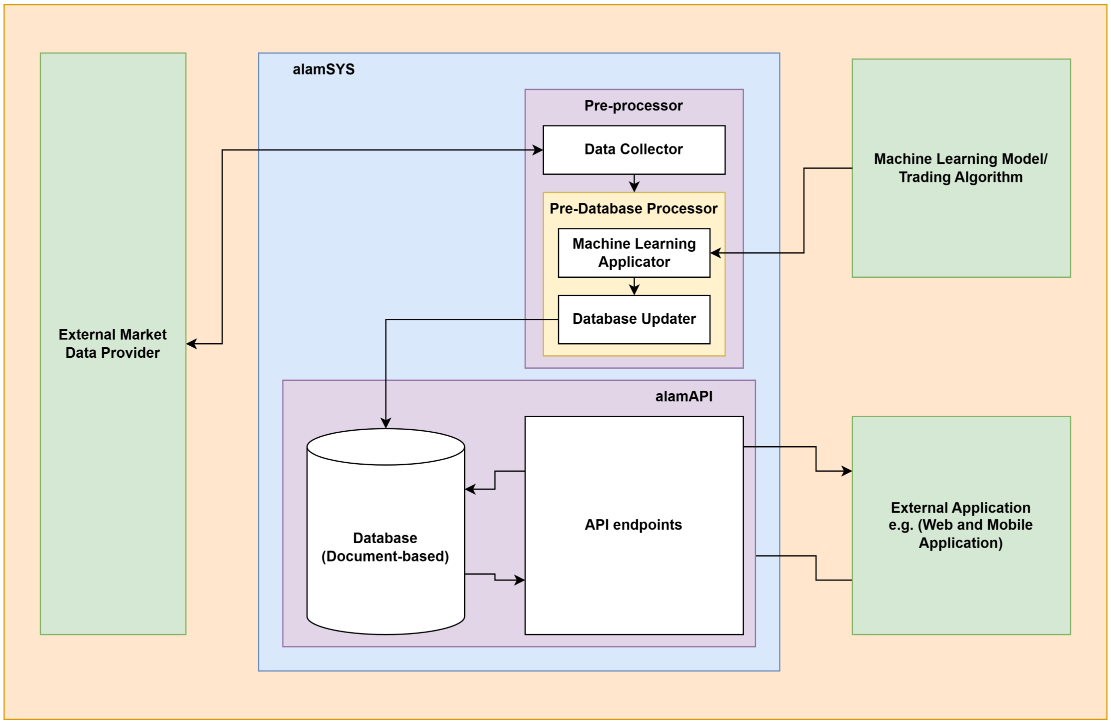

Figure 3.1: Top-Level Overview of the alamAPI and Interactions with External Applications/Systems

As shown from the figure above, the alamAPI is connected to three external entities: (1) External Market Data Provider, which provides the system with the needed historical market data; (2) Machine Learning Model or Trading Algorithm, in the case of this special problem, a machine learning model will be developed and will be utilized by the system, however as previously discussed the system is created to accept any other machine learning model or proprietary trading algorithms that other developers may or want to develop in the future; and (3) External Application, which can be a web-based or mobile-based application.

On the middle of the diagram the alamAPI is observed to have three main components, namely, (1) Pre-processor, which is further divided into sub-components: (a) Data Collector, which collects the data from the external market data provider; (b) Pre-Database Processor, which processes the historical market data collected by applying the developed machine learning model and sending it to the database updater module; (2) Database, which is running on MongoDB a document-based and non-relational database; finally, the database is connected to the (3) API end-points which processes the request and responses of the system to any external application connected to the API via a network.

3.2.2 Process Flow Diagram

The diagram shown in Figure 3.2 the different processes that the system will undergo once it has been deployed in the server.

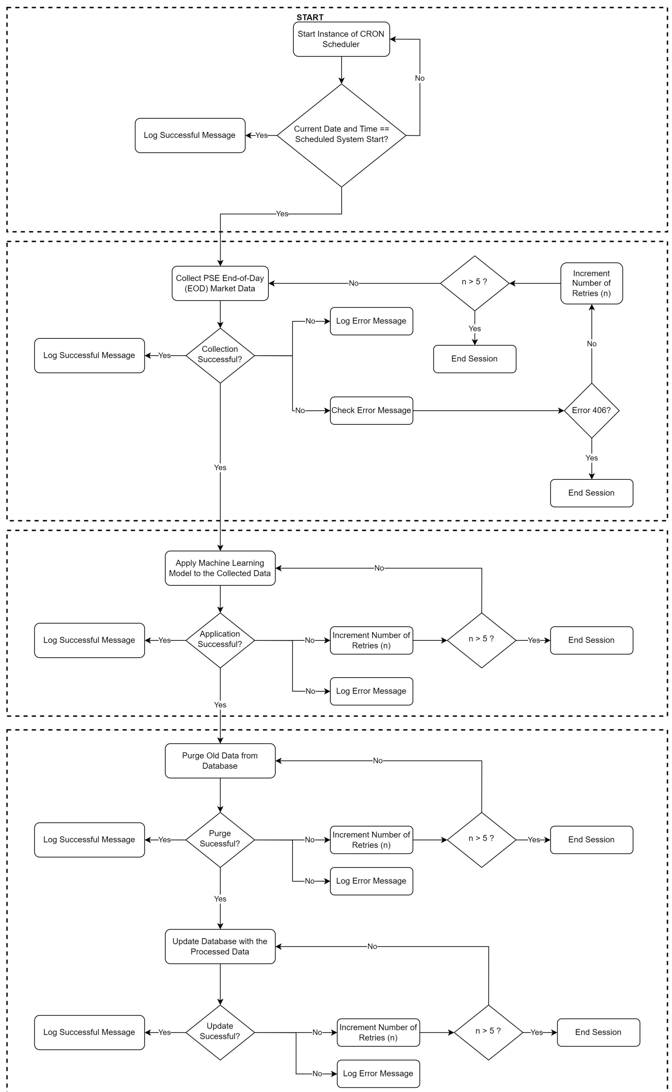

Figure 3.2: Full Overview of the Process Flow Diagram for the alamAPI

To better view and understand the flow of the processes, we can divide the discussions per components in the diagram.

Scheduler

Using CRON, a Linux-based scheduler, a scheduled task is provided to the server running the system. Since, the system will be containerized in a Linux System, the scheduler will run once the instance of the Docker Engine is running on the server system, which can be of any operating system. Then, if the current date and time of the contained system matches the scheduled date and time from CRON, it will log that the scheduled task has started, otherwise, it will not do anything and will check again for the current date and time.

The consequent processes in this process flow diagram will run after the scheduled task is initiated. Wherein the schedule task will run everyday from Mondays to Fridays, every 5:00 P.M. And the whole process can be seen in the Figure 3.3.

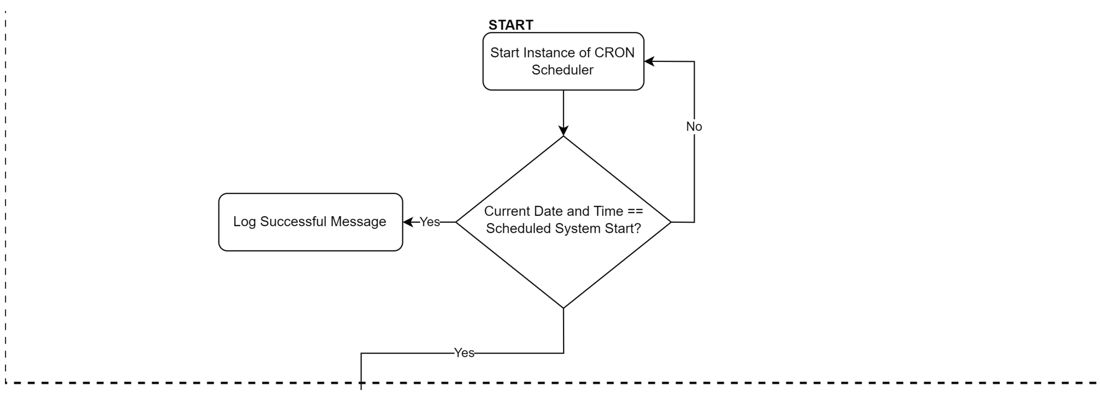

Figure 3.3: Overview of the Process Flow Diagram for the Scheduler

Data Collector

This is the first task that the scheduled activity will do, which is simply to connect to the historical market data provider and collect the historical market data that is updated for the current date.

Wherein, if the collection is successful, it will log that the system has successfully connected and collected the updated historical market data for that day and will proceed to use the collected data to the Machine Learning Model.

Otherwise, it will log the error, and it will check the error message. Wherein, if the error message shows "Error 406" of "Payment Needed", then the scheduled task will end in this section. This is also the reason why the end of each process ends in logging the activities of the system, so that the maintainers of the system can easily pin-point the problem to be fixed during the actual deployment of the alamAPI. Moreover, if the error is anything else, then the system will retry to collect the data for a maximum of five tries, and if it still encounters an error during the retry window, the session will also end.

The flow of processes discussed above can be observed in Figure 3.4.

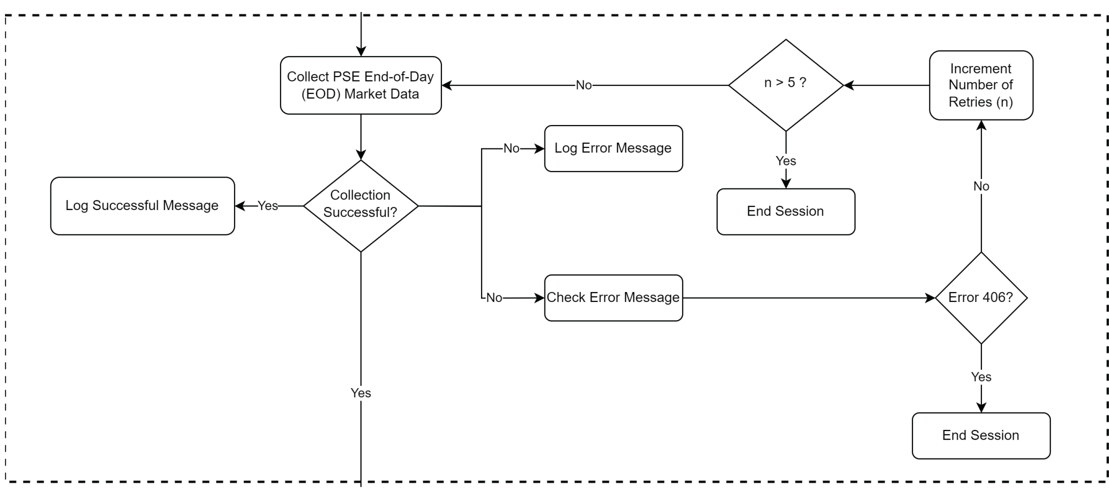

Figure 3.4: Overview of the Process Flow Diagram for the Data Collector

Machine Learning Model Application

In this process the developed machine learning model/algorithm will use the current historical market data collected to predict the future trend of the stock market and decide whether that stock should be bought or sold for the next market day.

Wherein if the application of the machine learning model is successful, then the system will log the success of the operation and proceeds into updating the database.

Otherwise, it will log the error, and will retry the operation for a maximum of five times. Once after the five retries is unsuccessful, then the system will end the session at this stage.

The flow of processes discussed above can be observed in Figure 3.5.

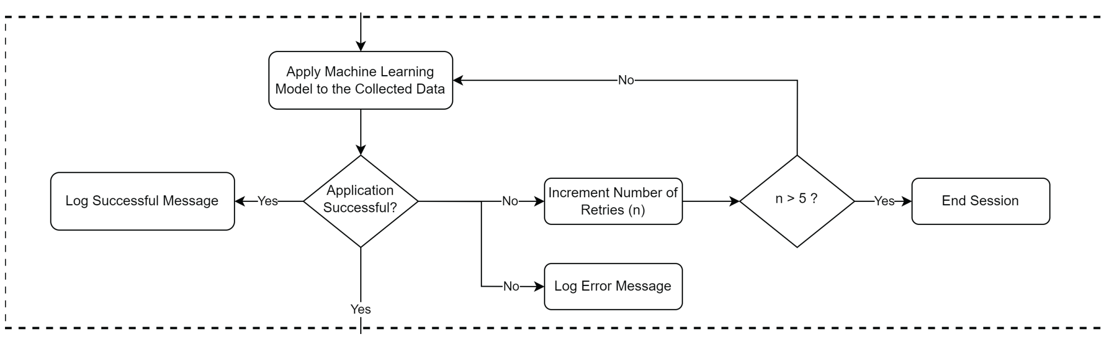

Figure 3.5: Overview of the Process Flow Diagram for the Machine Learning Model Application

Database Updater

This process flow will purge the old content of the database, and once successful it will update the database with the new documents created from the previous process.

The flow of processes discussed above can be observed in Figure 3.6.

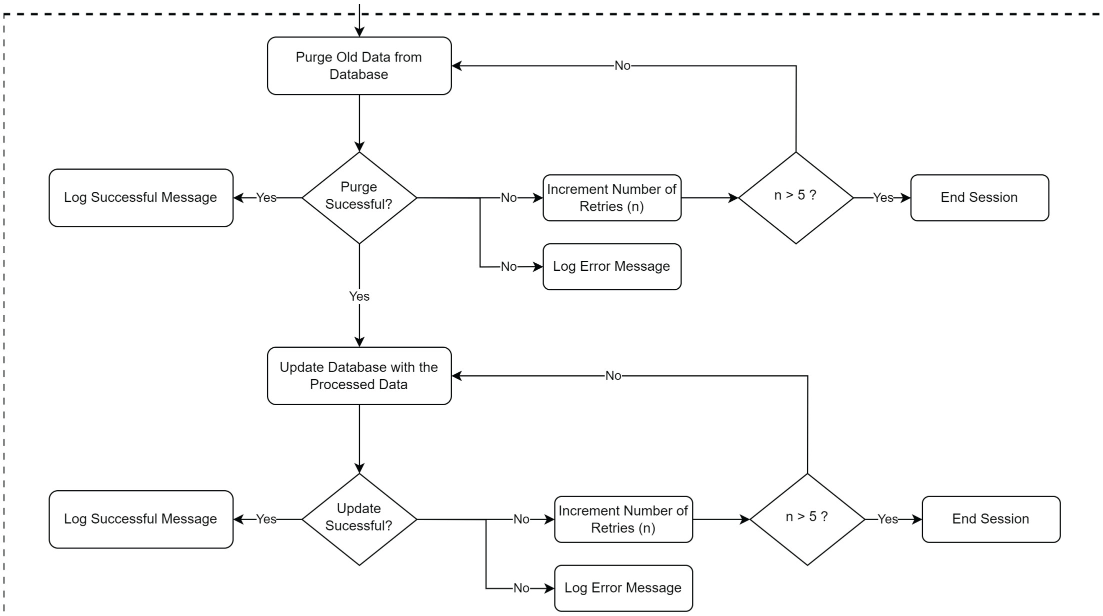

Figure 3.6: Overview of the Process Flow Diagram for the Database Updater

3.2.3 Data-Flow Diagram (DFD)

In this section the DFD of the alamAPI, specifically the Stock Market Price Trend Forecasting System will be presented and discussed. A data-flow diagram will help to better understand how the processes works, and how data flows from one process to another. This is specifically important as it shows the overview of the security of the data by showing how it can be accessed. In the case of alamAPI, the data that can only be accessed publicly is the listed stock to buy and sell, as well as the stock information as provided in its database, and as allowed by the API endpoints.

Moreover, the DFD paradigm used in the diagrams presented in this section follows the Gane-Sarson DFD symbols, which utilizes four basic symbols: (1) Entity / External Entity; (2) Data Flow; (3) Process; and (4) Data Store

(VisualParadigm, n.d.)

Context Diagram

First, let us start by showing the overview of the whole process by showing the context diagram of the system itself as process 0, which can be seen in the provided in Figure 3.7.

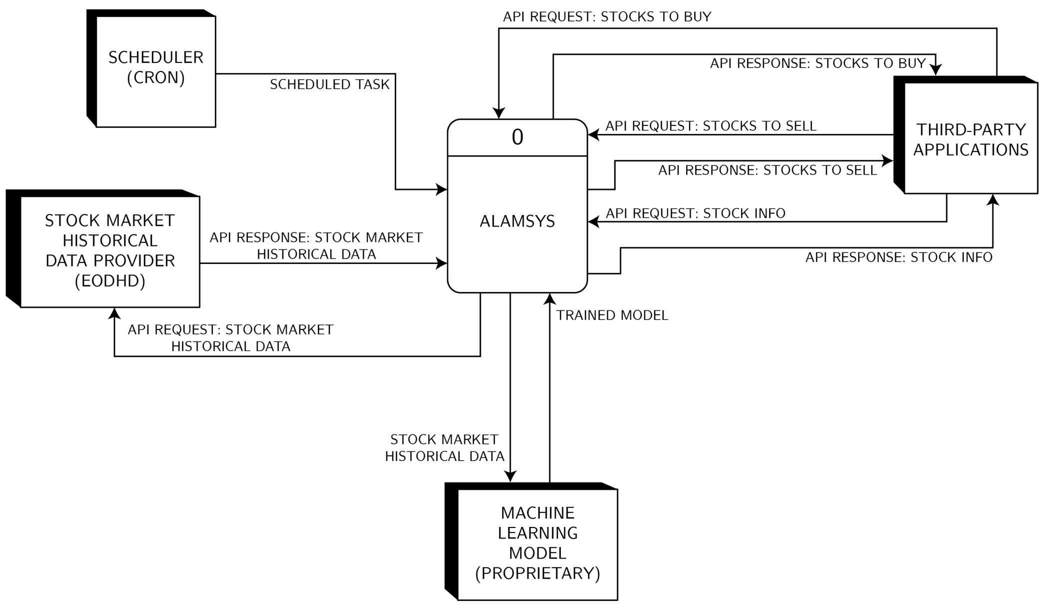

Figure 3.7: Context Diagram of the Stock Market Price Trend Forecasting System

The above figure shows the root process (process 0), which is the underlying system of the alamAPI itself: Stock Market Price Trend Forecasting (SMPTF) System which is connected to four external entities: (1) Scheduler, which will be provided by CRON; (2) Stock Market Historical Data Provider, which will be EODHD; (3) Machine Learning Model, which will be developed along side the development of the system; and (4) Third-Party Application, which will also be developed in the conduct of this special problem as the test application for accessing, testing, and showcase of the features of alamAPI.

Moreover, all the necessary data flow lines can also be observed: (1) Scheduled task, which is the committed task on schedule as indicated in the CRON application; (2) API Request: Stock Market Historical Data, which is the request information passed by the root process to the historical market data provider; (3) API Response: Stock Market Historical Data, which is the data passed by the historical market data provider to the process after accepting its request; (4) Trained Model, this is the object class from the Machine Learning model that will be developed and used by the system; (5) Stock Market Historical Data, as the name suggests this is the historical market data which will also be used to train and improve the machine learning model; (6) API Request: Stocks to Buy, which is the data passed from the third-party application to the root process to request for which stocks are in the Buy document of the database; (7) API Response: Stocks to Buy, upon the request of the third-party application, the root process will process the request to the API and sends back the list of stocks to buy to the requester; (8) API Request: Stocks to Sell, which is the data passed from the third-party application to the root process to request for which stocks are in the Sell document of the database; (9) API Response: Stocks to Sell, upon the request of the third-party application, the root process will process the request to the API and sends back the list of stocks to sell to the requester; (10) API Request: Stock Info, which is the data passed from the third-party application to the root process to request for the general information about a particular stock, this will be further discussed in the Object-Document Mapped (ODM) diagram; and (11) API Response: Stock Info, upon the request of the third-party application, the root process will process the request to the API and sends back the information of the stock based on what was requested.

DFD of Diagram 0

To better understand how each data going in-and-out of the root process, is being processed, it is essential that we look inside the inner workings of the root process, which is shown in the DFD of Diagram 0, as provided in Figure 3.8.

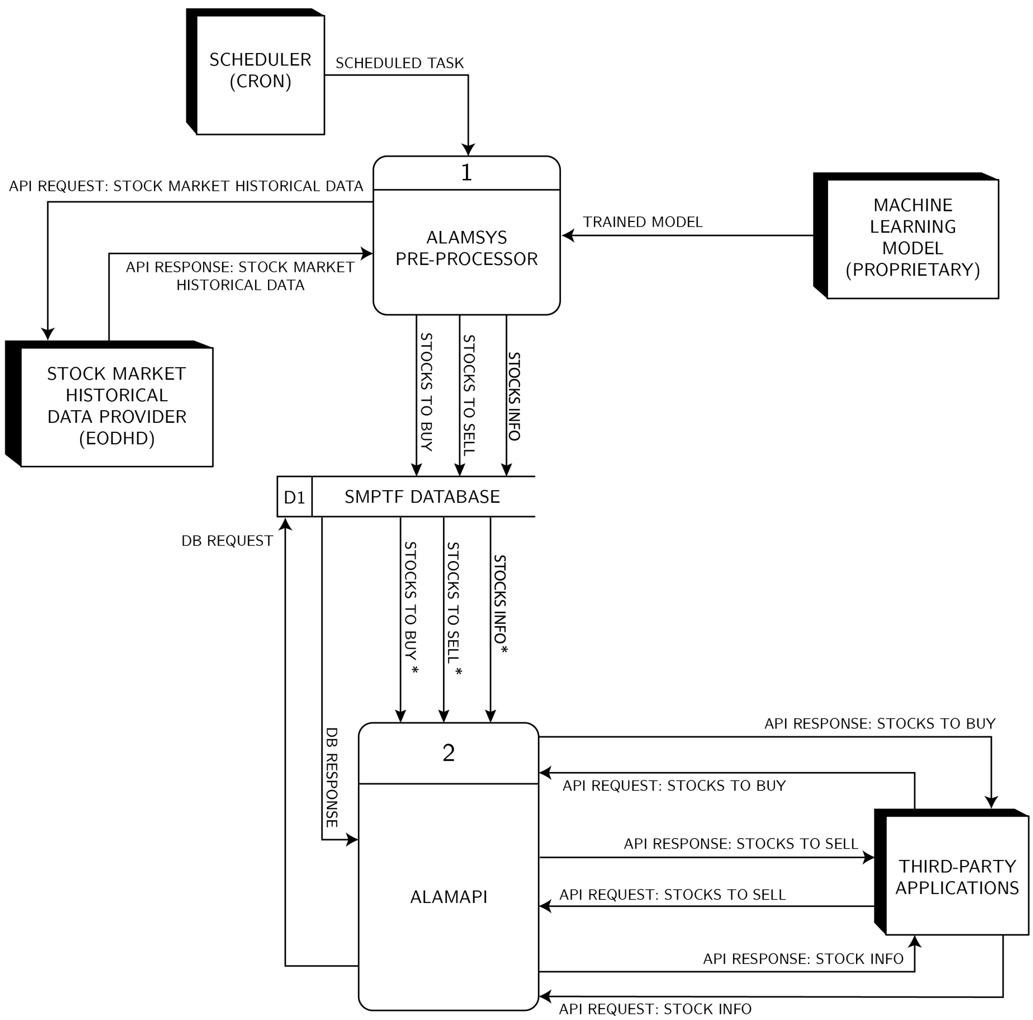

Figure 3.8: DFD of Diagram 0

From the figure above, the root process, has two main processes: (1) SMPFT System Pre-Processor, which is the system's data processing unit; and (2) SMPFT System API and DB Model Module, which processes the API requests and responses, as well as the database of the system.

DFD of Diagram 1

To better understand the internal workings of the Process 1, it will be useful to check the DFD of that process, which is provided in Figure 3.9

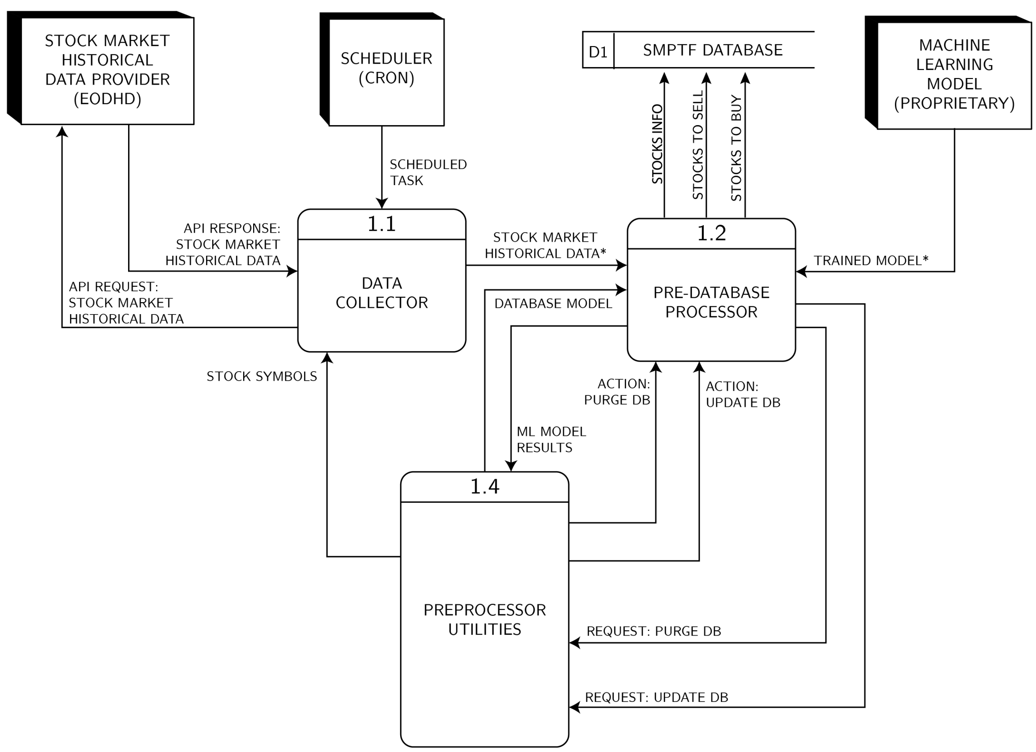

Figure 3.9: DFD of Diagram 1

From the figure shown above, it can be observed that Process 1 is composed of 4 internal processes, namely, (1) Data Collector, which is the main process responsible for collecting the historical market data; (2) Pre-Database Processor, which is the processes that the collected data goes into before being sent to the system's database, the internal processes of this process will be further discuss in the succeeding part of this section; (3) Machine Learning Model Processor, which is the training module or process for the machine learning model that is used to externally train the machine learning model that will be used by the system in the pre-database processor; and (4) Preprocessor Utilities, this will be the processes the process any system utilities such as the database actions, database models, and stores temporary data and system variables.

DFD of Diagram 1.2

This shows the processes inside the process 1.2: Pre-database Processor.

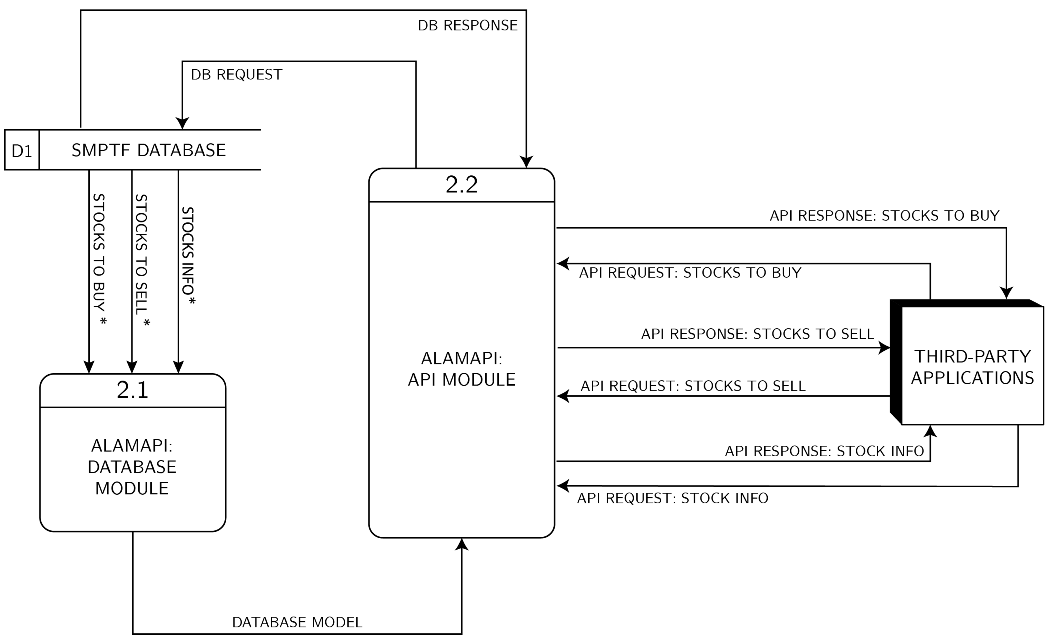

Figure 3.10: DFD of Diagram 1.2

As previously discussed, the pre-database processor consists of processes inside that processes the data before it will be eventually sent to the database of the system. Wherein the process and data flow is shown in the figure above. Namely: (1) Machine Learning Applicator, which applies the trained machine learning model to the collected data; and (2) Database Updater, which processes the document outputs from the Machine Learning Applicator process, to be used in the database of the system.

DFD of Diagram 2

The final diagram will show the inner processes of the Process 2: SMPFT System API and DB Model Module.

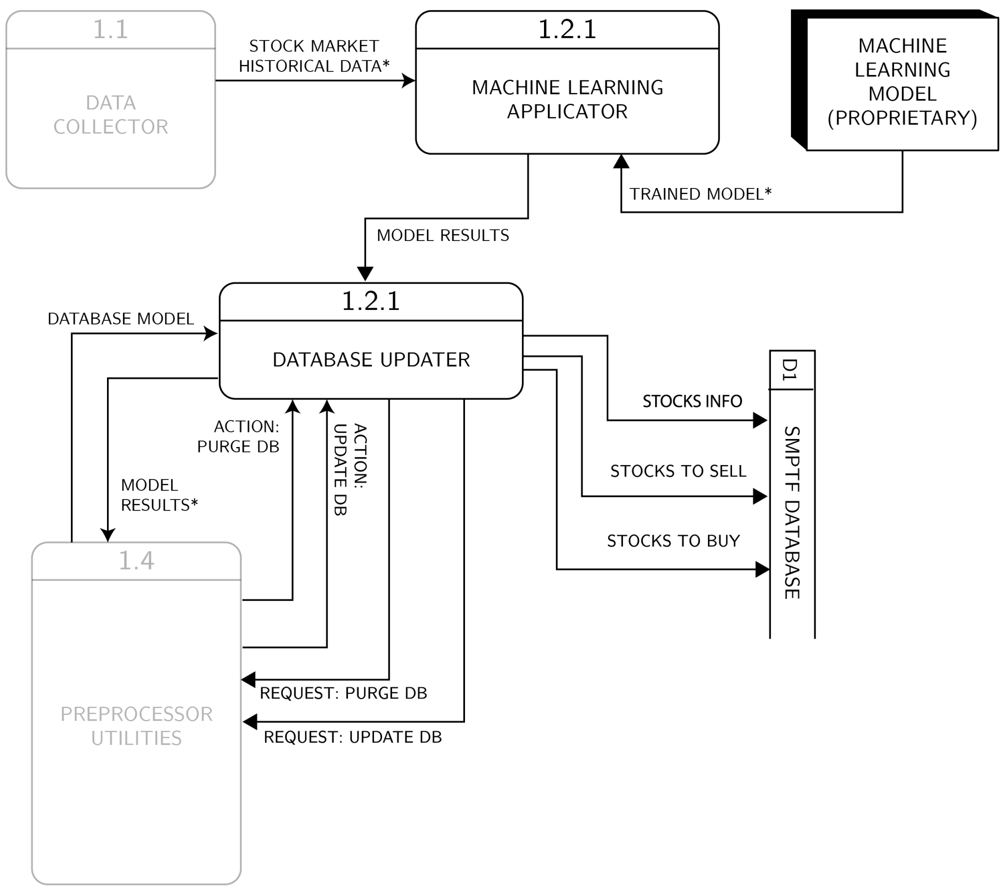

Figure 3.11: DFD 2: Data-Flow Diagram for the alamAPI

The figure above shows two internal processes of the Process 2, namely, (1) SMPFT DB Model, which the database model that is used to process and connect

MongoDB to the Python program; and (2) SMPFT API, which is composed of the API endpoints that processes the requests and response to and from the system, respectively.

3.2.4 Object Document Mapper (ODM) Diagram

Since the database that will be developed for the system will be a non-relational, hence an Object Document Mapper (ODM) diagram is shown in this section rather than an Entity Relationship Diagram (ERD).

The ODM diagram is shown in Figure 3.12:

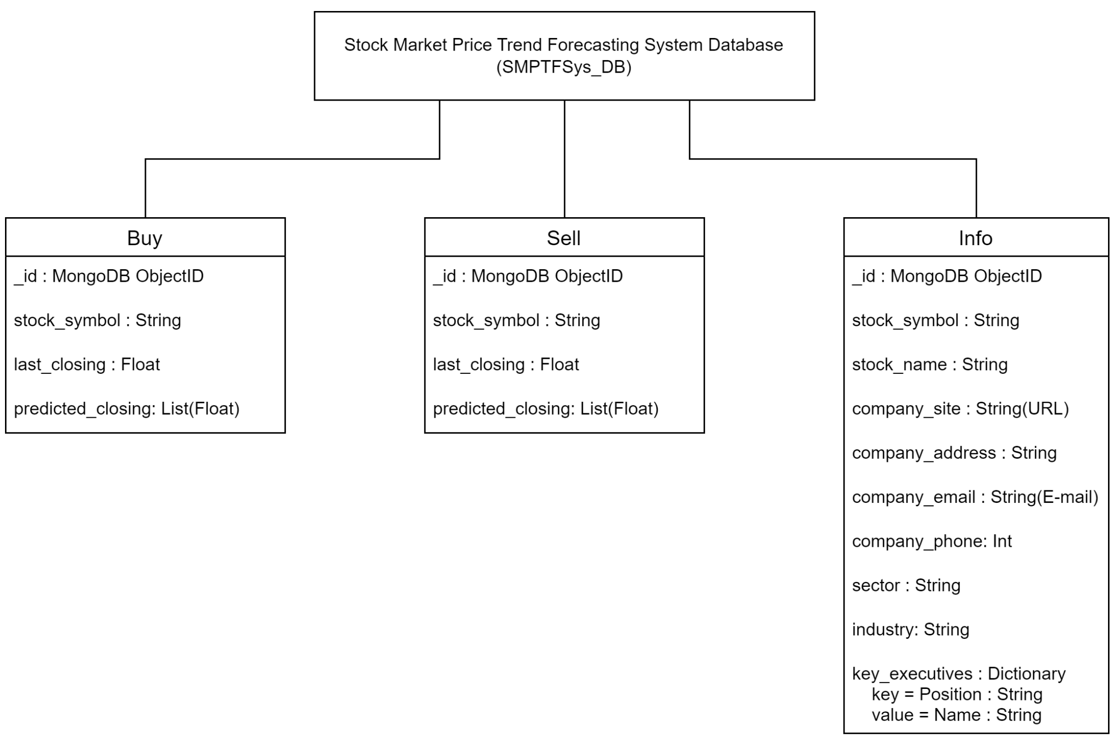

Figure 3.12: Object-Data-Model for the alamAPI

As shown from the Figure 3.12, the SMPTFSys_DB will be the collection name of the non-relational database of the system. Wherein it will be composed of three documents with the list items following this convention: "item name":

"item type". Note that each document are their own separate entities, hence the database is called non-relational, as the documents are not in any way related to each other.

The three documents are as follows:

(a) Buy – this document will contain all the stocks that the machine learning model predicted and classified as a stock to buy. The diagram shown in Figure 3.12 also tells the path in which this document can be accessed, that is:

$$MongoDBInstance \rightarrow SMPTFSys_DB \rightarrow Buy$$

Wherein, information regarding the stocks can be accessed using the stock_symbol, since the _id is a private id.

[b) Sell – this document will contain all the stock that the machine learning model predicted and classifies as a stock to sell. The diagram shown in 3.12 also tells the path in which this document can be accessed, that is:

$$MongoDBInstance \rightarrow SMPTFSys_DB \rightarrow Sell$$

Wherein, information regarding the stocks can be accessed using the stock_symbol, since the _id is a private id.

(c) Info – this document will contain the general and relevant information about a stock, or the general company information. The diagram shown in 3.12 also tells the path in which this document can be accessed, that is:

$$MongoDBInstance \rightarrow SMPTFSys_DB \rightarrow Info$$

Wherein, information regarding the stocks can be accessed using the stock_symbol, since the _id is a private id.

3.2.5 Machine Learning Model Diagram

In this section, the process on how the machine learning model will be developed is shown in Figure 3.13. Wherein, the process overview is based on the

Fine-Tuned Support Vector Regression Model for Stock Predictions by Dash and Dash (2016).

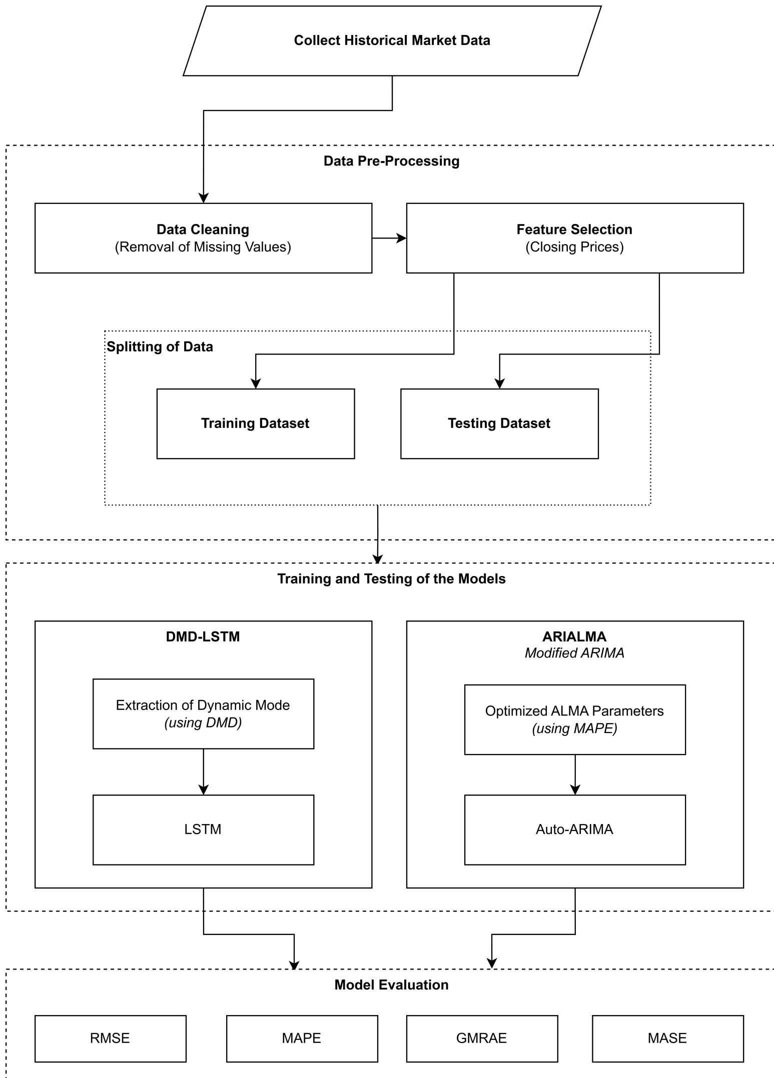

Figure 3.13: Machine Learning Model for the alamAPI

3.2.6 Docker-Compose Layer Diagram

In this section, the different layers of the docker-compose containers are shown based on the way it will be used in the deployment of the system. Moreover, Figure 3.14 based on the provided diagram in the Docker documentation, regarding containers. Note that in the diagram shown below, the lowest level is the "Server Infrastructure" and the highest level are the three Docker instances.

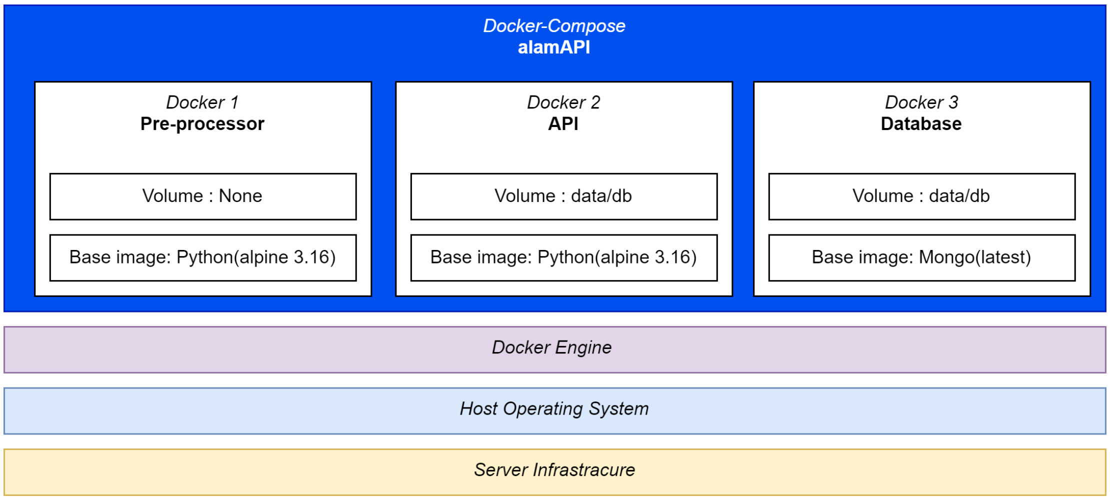

Figure 3.14: Docker-Compose Layer Diagram for the alamAPI

3.3 Hardware Requirements

In this section, the hardware requirements will be discussed.

3.3.1 For the Development of the alamAPI, and Training and Testing of the Machine Learning Model

To develop the alamAPI and the underlying system that it utilizes, the project developer would be needing a laptop with at least the following minimum requirements:

(a) A desktop class 4-core CPU running on 2GHz (minimum).

(b) 16 GB of Random Access Memory (RAM). This is to ensure that multiple instances of programs can run efficiently in the system.

(c) An up-to-date GPU with CUDA cores, this will be used specifically for faster training and testing of the machine learning model. Although if this is not available then a more powerful CPU maybe required.

3.3.2 For the Development of the Test Application and System Testing

(a) A device that can connect to a network such as a smartphone (preferably an Android smartphone: as the test application that will be developed will run on Android devices). Moreover, the device specifications does not matter, as long as it can run a browser or the developed Android test application.

3.4 Methodology

This section of the Chapter 3 will be divided into two sections:

(a) Software Development Process, wherein an Agile development will be discussed; and

(b) Procedures, wherein the general procedures of development will be tackled.

3.4.1 Software Development Process

Due to the expected heavy time constraints of the development of the system, the author of this paper decided to follow an Agile Software Development Process, primarily it will be using Agile Sprints for an efficient time management during the whole software development process. Wherein the following are the list of Sprints and sub-activities that will be followed are shown in the Table below:

Table 3.1: Summary of Sprints and Target Activities

Sprint Number	**Target Activities**	**Allotted Time**[1]
1	**Main Activity:** System Planning and Evaluation **Sub-Activities:** • Topic Proposal • Drafting of Chapters 1 to 3 for the Special Problem Proposal • System Architecture and User Requirement Analysis	**12 Weeks** Start: September 15, 2022 End: December 9, 2022

Table 3.1 continued from previous page

Sprint Number	Target Activities	Allotted Time[1]
2	**Main Activity:** System Prototyping **Sub-Activities:** • Build the different component of the alamAPI as indicated in the top-level overview diagram of the system, the following prototype will be developed: [1.] API endpoints [2.] Database [3.] Preprocessor • Testing of the build prototype. This also include creating unit test cases for each component. • Initial Documentations, this will be done inside the GitHub repository.	**12 Weeks** Start: September 30, 2022 End: April 3, 2023

Table 3.1 continued from previous page

Sprint Number	Target Activities	Allotted Time[1]
3	**Main Activity:** Machine Learning Model Training, Testing, and Evaluation **Sub-Activities:** • Collection of Historical Data, outside the Data Collector module of the system. As the full data will be needed for each stock for the training, rather the 200-day only historical data. Whereas the last date on the market data should be January 13, 2023. • Development of the Machine Learning Model. This includes data standardization, data splitting, and data training. • Machine Learning model testing and evaluation. • Revision of Chapter 1-3, in preparation for the final paper submission.	**10 Weeks** Start: January 15, 2023 End: March 30, 2023

Table 3.1 continued from previous page

Sprint Number	Target Activities	Allotted Time[1]
4	**Main Activity:** Integration of Machine Learning Model to the alamAPI and Additional Data Collection **Sub-Activities:** • Testing and Evaluation of alamAPI with the integration of the Machine Learning Model. • System Testing, this will be done to verify the functionality of the whole system, given a test deployment environment. Moreover, this will be done in a span of 4 weeks • Drafting of Chapter 4 and 5	**6 Weeks** Start: March 31, 2023 End: May 12, 2023

Table 3.1 continued from previous page

Sprint Number	Target Activities	Allotted Time[1]
5[2]	**Main Activity:** System Documentation **Sub-Activities:** • Updating and Finalization of Documentations included in the GitHub Repository. • Writing of the results, discussions, conclusions, and recommendations for Chapter 4 – 5 • Special problem paper revisions • Start the development of the test application (for showcasing of the system features)	**6 Weeks** Start: April 14, 2023 End: May 26, 2023

Table 3.1 continued from previous page

Sprint Number	Target Activities	Allotted Time[1]
6[2]	**Main Activity:** Preparation for Final Defense and System Presentation **Sub-Activities:** • Finalization of the mobile-based test application • Revisions and Finalization of the special problem paper. • Creation of presentation slide deck for the presentation of the special problem.	**3 Weeks** Start: May 27, 2023 End: June 17, 2023

1. Start and End Dates are based on the University's Academic Calendar and the Schedule provided by the Special Problem Adviser.
2. Sprints 5 and 6 are no longer part of the actual system development but is still included as a basis for the Gantt chart. Moreover, these activities can still be considered as part of the documentation process.

From Table 3.1, it is shown that there is a total of 39 weeks; from September 15, 2022, to June 17, 2023, however it must be noted that an additional 1 week was added to each sprint's allotted time to compensate for any unforeseen events during each sprint.

It should also be noted that Sprint 1 and Sprint 2 overlaps as the development of the prototype will start at Week 3, this will be possible as there will already be an initial system design to be followed, and any changes made during Sprint 1 can easily be adjusted to the creation of the prototype of the system in Sprint 2. This is also the case for Sprints 4 and 5, since their activities overlaps with each other, such that there are things in Sprint 4 that are unsupervised, hence, to better manage the time it is reasonable to start the activities of Sprint 5 along side the later parts of Sprint 4.

Moreover, the full details about the scheduling will be further discussed in the Gantt Chart of this chapter.

3.4.2 Procedures

In this section, the step-by-step procedures that will be followed in line with the development and testing of the system; alamAPI. Whereas the following are the procedures:

(a) Designing of the System Architecture for alamAPI

(b) Designing of Machine Learning Model

(c) Development of System Prototype

(d) Training, Testing, and Evaluation of the Machine Learning Model

(e) Integration of the Machine Learning Model to the alamAPI

(f) Initial testing for alamAPI, this shall also include any debugging, bug fixing, and code refactoring.

(g) Pre-deployment testing, this testing phase includes the following tests that will be done for a one-month continuous system operation:

  – Functional Testing, by monitoring the functionality of the alamAPI over 30 days and checking the success and error logs at the end of the given timeframe.

- Stress Testing, by creating ten-million artificial requests to the API everyday for 30 days.

(h) Logging and summarization of results from all the prior tests conducted

(i) Analysis and discussion of test data results.

(j) Code Documentation

(k) Maintenance, which will span beyond the time scope of the special problem.

3.5 Gantt Chart

Based on Table refsummary-sprints, the following figures for the Gantt Chart (created using TeamGantt) shows the software development schedule for the development of alamAPI. The Gantt Chart is divided into the different sprint to present the project scheduling. Moreover, a zoomed-out view of the whole Gantt Chart, will also be provided at the end of this section.

3.5.1 Gantt Chart for Sprint 1

Figure 3.15 shows the schedule of activities for Sprint 1. Wherein, it will start on September 15, 2022, and end on December 9, 2022.

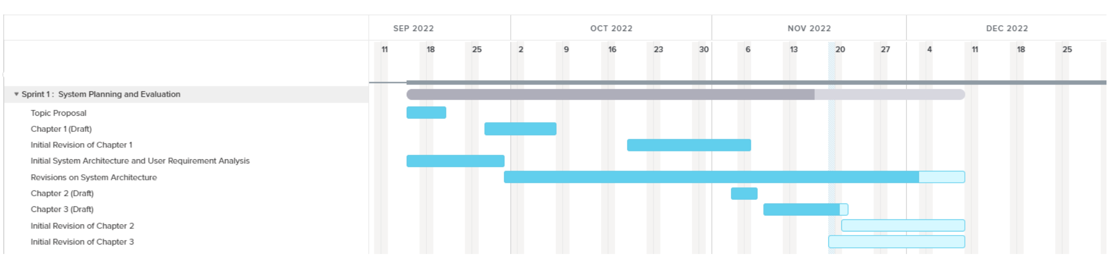

Figure 3.15: Gantt Chart for Sprint 1

3.5.2 Gantt Chart for Sprint 2

Figure 3.16 shows the schedule of activities for Sprint 2. Which will start on September 30, 2022, and end on January 5, 2023.

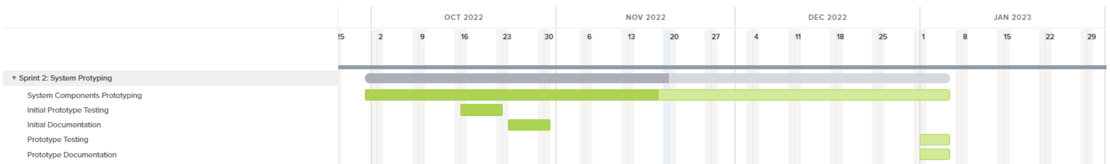

Figure 3.16: Gantt Chart for Sprint 2

3.5.3 Gantt Chart for Sprint 3

Figure 3.17 shows the schedule of activities for Sprint 3. Wherein, it will start on January 15, 2023, and end on March 30, 2023.

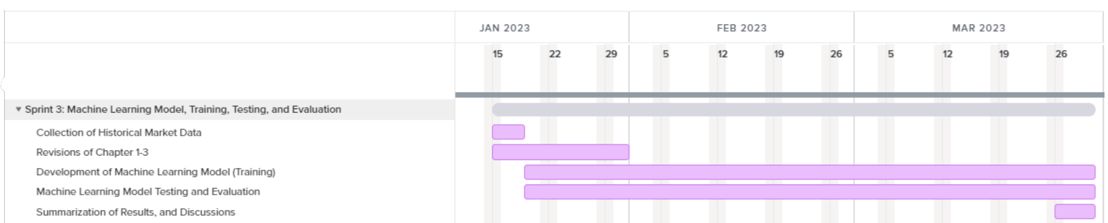

Figure 3.17: Gantt Chart for Sprint 3

3.5.4 Gantt Chart for Sprint 4

Figure 3.18 shows the schedule of activities for Sprint 4. Which will run from March 31, 2023, until May 12, 2023.

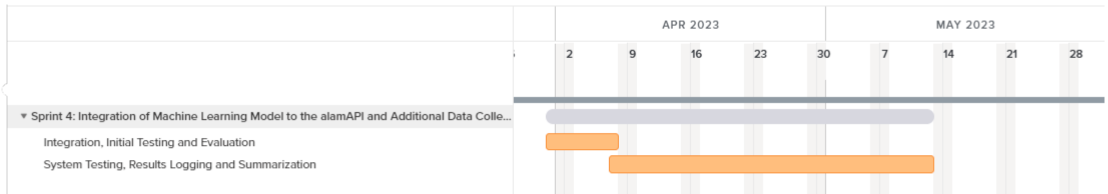

Figure 3.18: Gantt Chart for Sprint 4

3.5.5 Gantt Chart for Sprint 5

Figure 3.19 shows the schedule of activities for Sprint 5. Which will be from April 14, 2023, to May 12, 2023.

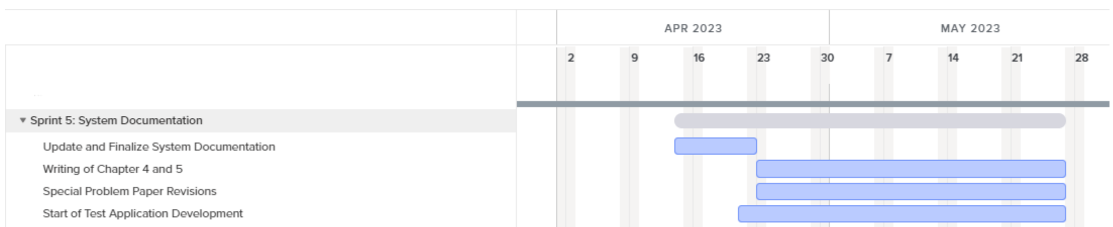

Figure 3.19: Gantt Chart for Sprint 5

3.5.6 Gantt Chart for Sprint 6

Figure 3.20 shows the schedule of activities for the final sprint for the development of alamAPI. Which will be done from May 27, 2023, until June 17, 2023. However, it should be noted that the end day may change, depending on the scheduled final defense.

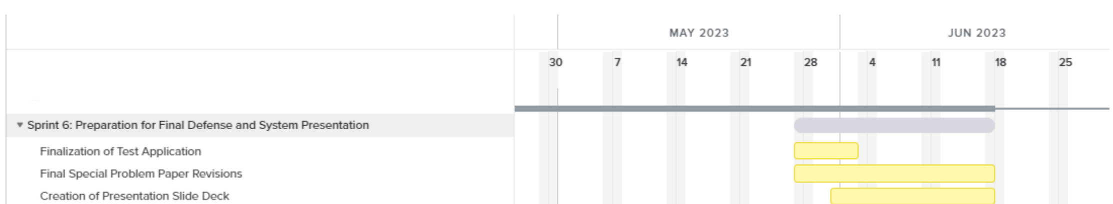

Figure 3.20: Gantt Chart for Sprint 6

3.5.7 Full Gantt Chart

To have an overview of the whole schedule of each Sprints, the full Gantt chart is shown in Figure 3.21.

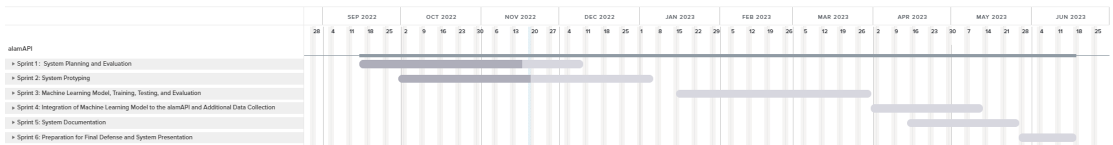

Figure 3.21: Full Gantt Chart

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