FOREX MARKET PRICE PREDICTION USING MULTI-TIME SERIES ANALYSIS WITH DEEP LEARNING

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ABSTRACT

The foreign exchange market is a medium for the transaction of currencies. It can provide lavish profits but also incur massive losses. Predicting the future market prices is challenging due to the multitude of factors that may affect price movements. Various studies are conducted by using machine learning to predict the future Forex prices, where the prediction models typically utilize the daily historical prices as the predictors. However, historical prices can exist in multiple timeframes such as in 30-minute intervals, 1-hour interval, etc. This study investigates the prediction performance when using a combination of multiple timeframes of the historical price data to predict the closing price of next trading day. The proposed method utilized prediction models that are developed using the long short-term memory (LSTM) algorithm and gated recurrent unit (GRU) algorithm. The dataset comprised of four features representing the open, high, low, and close prices. Where the dataset is preprocessed into a supervised learning problem using the sliding window method and transformed into seven different timeframes. Each algorithm predicted the closing price of the next trading day for every timeframe based on a timestep of 20 trading days. The predicted outputs are aggregated based on a specific combination of timeframes and fed to a feedforward neural network that produces the final prediction. The findings from this study show that using multiple timeframes as input data produced a prediction model of improved performance. In addition, it is identified that the GRU models performed better than the LSTM models in general. However, the results showed that the performance of the GRU models is better when using a smaller dataset while the performance of the LSTM models is better when using a larger dataset. Furthermore, it is identified that the selection of timeframes to be combined would greatly influence the prediction outputs, where not every timeframe combination can produce an improved prediction output.

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LIST OF ABBREVIATIONS

AdaGrad............ Adaptive Gradient Algorithm
Adam .... Adaptive Movement Estimation
AdaMax .... Adaptive Movement Estimation Extension
ANN.................. Artificial Neural Networks
CNN.................. Convolutional Neural Networks
ARIMA............. Autoregressive Integrated Moving Average
BPTT .... Backpropagation Through Time
DER .... Debt-to-Equity Ratio
EPS .... Earnings Per Share
EU..................... European Union
Forex................. Foreign Exchange
GRU.................. Gated Recurrent Unit
KNN.................. K-Nearest Neighbor
LSTM................ Long Short-Term Memory
MACD .... Moving Average Convergence Divergence
MA.................... Moving Average
MAE .... Mean Absolute Error
MSE.................. Mean Squared Error
Nadam............... Nesterov-accelerated Adaptive Moment Estimation
PCA .... Principal Component Analysis
PER................... Price to Earnings Ratio
ReLu .... Rectified Linear Unit
RF .... Random Forest
RMSE .... Root Mean Squared Error
RMSprop .... Root Mean Square Propagation
RNN.................. Recurrent Neural Networks
ROA.................. Return on Assets
RSI.................... Relative Strength Index
SGD .... Stochastic Gradient Descent
SLP .... Single Layer Perceptron
SVM.................. Support Vector Machine

TanH .... Hyperbolic Tangent

US .... United States

CHAPTER 1

INTRODUCTION

1.1 Background

The financial market provides a system that facilitates the trade of various financial securities between buyers and sellers. One of the financial markets, specifically for trading of currencies named foreign exchange (Forex) market, dominated the financial market in terms of volume as it holds the largest daily trading volume and the highest liquidity as compared to other types of financial markets. The Forex market involves participants from a broad spectrum of backgrounds. However, most of the market volume is generated from financial institutions and multinational corporations.

Predicting the future prices of the forex market typically involves two methods, which are widely utilized and well known by every market participant. The first method is called fundamental analysis, which refers to the discovery of the intrinsic value of a security through the analysis of macroeconomic and microeconomic factors. While the second method is called technical analysis, which involves the study of historical market prices to forecast future market trends. In practice, a financial analyst would combine the use of both fundamental and technical analysis to identify potential market opportunities. However, information derived from both the analysis can be excessive and resource intensive, which the analysts are not capable of completing the analysis and deriving an informed decision promptly which may result in missed opportunities.

With the continuous advancement of computing architecture, the application of machine learning in various domains has become more feasible and accessible, leading to the revolutionary change in how things used to work. Similarly in the financial market, the use of machine learning has been widely adopted in assisting the prediction of future prices. Example, in the works of Cohen et al. (2020), an image recognition model has been developed to automatically label potential market opportunities on the price chart to assist the financial analyst in the market analysis process. This has led to increased efficiency and accuracy in identifying hidden opportunities in the market, which resulted in an increased profit and minimized losses.

The ability to accurately predict the future market prices is highly in demand. This is due to the potential profits that can be generated from the correctly predicted market opportunities. However, a wrong prediction made can result in huge losses. To be able to accurately predict the future financial market price remains a profound challenge, as the market exhibit irrational behavior where the price movements are affected by a multitude of factors. Therefore, this has driven the studies conducted in predicting the financial market prices to utilize machine learning techniques which are capable of learning non-linearities to identify hidden patterns which a normal analyst may not. Various machine learning algorithms have been utilized in developing prediction models for predicting the financial market prices, such as Support Vector Machines (SVM) by Tao et al. (2020), K-Nearest Neighbor (KNN) by Khattak et al. (2019), Convolutional Neural Networks (CNN) by Kusuma et al. (2019), Artificial Neural Networks (ANN) by Vijh et al. (2020), Recurrent Neural Networks (RNN) by Ranjit et al. (2018), Gated Recurrent Unit (GRU) by Islam and Hossain (2021), Long Short-Term Memory (LSTM) by Srivastava et al. (2021), etc.

Generally, the machine learning models would utilize the historical prices as the predictors. However, there exists other types of predictors being used, such as the use of public sentiments by Khan et al. (2020), the use of technical indicators by de Souza et al. (2018), the use of chart patterns by Jarusek et al. (2022), etc. The data format of the historical prices is typically a time series, which represents a sequence of price information recorded over an equally spaced points in time. The historical price data contains valuable information which can be used to predict future prices which Qu and Zhao (2021) has validated this claim. In addition, the author mentioned that historical market trends will often repeat and show up in future prices. Moreover, the historical prices are often used in the formulation of technical indicators which provides additional information for analysis. Therefore, historical prices are one of the crucial data available for use in predicting the future prices in the financial market.

Due to the nature of the historical price data, the RNN-based algorithms are frequently utilized by researchers in developing prediction models to forecast future prices. In simple terms, this is due to the present of a memory storing capability in RNN-based algorithms where it can remember historical inputs and utilize it to influence the future inputs and outputs. Especially the LSTM model, which is an enhanced variant of RNN, has been widely applied and achieved substantial results in predicting the future financial market prices (Islam & Hossain, 2021; Yıldırım et al., 2021). However, the majority of studies utilized only the historical price data based on the daily timeframe, where the data points are recorded once every 24 hours interval.

This has caused the missing out of valuable information that can be found in between the smaller timeframes. In practice, financial analysts would typically utilize multiple timeframes to conduct their market analysis to observe the short-term market trend up to the long-term market trend to identify confluence of signals before validating the identified market opportunities.

Therefore, this study proposes the use of deep learning algorithms and a combination of historical Forex market prices from multiple timeframes to predict the future prices. The use of multiple timeframes facilitates the extraction of potential hidden information from different timeframes and aggregating such information to produce a more reliable prediction, which ultimately leads to a prediction model of better accuracy.

1.2 Problem Statement

There has been much research into developing prediction models to predict the future prices in the Forex market. Generally, the historical price data, which is a time series data is used as the predictor to forecast the future prices. The time series data can be represented in various timeframes such as 1-hour, 4-hour, 12-hour, etc. Which represents the snapshot of the market at the specified intervals. However, majority of the studies utilized only one timeframe which is the daily timeframe (24-hour) as the predictor (Dautel et al., 2020; Dobrovolný et al., 2020; Escudero et al., 2021). This has likely caused the missing out of valuable information that can be derived from the smaller timeframe of the time series price data. As mentioned by Wei and Li (2019), different timeframes from a time series price data may contain different information about the market conditions. This is due to the price movement details that are presented differently in different timeframes. Where a smaller timeframe would present a low-level overview of the price movement while the bigger timeframe presents a high-level overview of the price movement.

In practice, a financial analyst would observe the price chart with a combination of multiple timeframes to detect trends, cycles, and confluence of signals to identify market opportunities (Cohen et al., 2020). By analyzing the price chart from different timeframes, a better understanding of the market conditions can be identified. Where, a bigger timeframe would define the primary trend of the longer-term market movement while a smaller timeframe defines the trend of the shorter-term market movement.

Therefore, there exists a need to study the combination usage of price data from multiple timeframes as predictors which may lead to the benefit of improving the accuracy of the price prediction outcomes. This study adopts the concept introduced by Wei and Li (2019) of using historical Forex price data from two different timeframes and developing separate LSTM models for each of the dataset. The outputs from the two models are combined to produce the market price prediction. The author utilized the 5-minute and 30-minute timeframes to develop the prediction models, which are suitable to predict short-term prices but are insufficient to predict the market prices of the longer-term duration. Therefore, this study extends the concept introduced, by studying various predictor combinations of different timeframes ranging from the 30-minute up to the 24-hours timeframe to allow better representation of the market in the longer term. In addition, the author developed the concept using only the LSTM algorithm which lacked the applicability of the concept in other prediction algorithms. Thus, this study also extends the inadequacy, by developing the prediction models using multiple prediction algorithms as a means to compare the effect and performance when different prediction algorithms are used.

1.3 Research Questions

To study the effect of using multiple timeframes from a time series data in forecasting the future Forex prices with deep learning techniques, the following questions are to be addressed:

1. What are the data preprocessing tasks required to prepare the time series data to be used as predictors?
2. How is the information from different timeframes of a time series data to be converged and used as predictors for the next daily closing price?
3. How is the information from different timeframes able to facilitate a better prediction outcome?
4. How is the price prediction model tested and evaluated?

1.4 Objectives of The Study

The aim of this study is to design and develop a Forex price prediction model using deep learning techniques and multiple time series to produce highly accurate prediction of the closing price of the next trading day. The following outlines the objectives to be achieved from this study:

1. To identify and implement suitable data preprocessing to prepare the time series data in a format usable for deep learning algorithms.
2. To design and develop price prediction models with the use of deep learning algorithms and combination of data from different timeframes as input features.
3. To investigate and compare the predicted outputs from this study with a baseline model to determine the feasibility.
4. To evaluate performance of the developed prediction models using evaluation metrics to identify the best performing model and timeframes combination.

1.5 Significance of The Study

According to the Bank for International Settlements (2019), the Forex market has achieved a daily trading volume of 6.6 trillion USD in the year 2019, which is considered the largest among the entire financial market. The volume is proportional to the number of market participants, with the major players being the financial institutions such as reserve banks, commercial banks, and hedge funds. These institutions conduct Forex transactions in large volume for means of speculative trades and for client requests. The next major participant in the Forex market is the multinational corporations, which rely on Forex transactions to pay for goods and services as they are engaged in international trade.

The currency prices in the Forex market can experience high fluctuations within a short period of time. This would introduce currency exchange risks to the market participants which would significantly impact on those who transact in large volume. Therefore, these participants typically perform forecasting to identify the best time to enter the market for conducting the transactions to minimize currency exchange risks. The consequence of inaccurate forecasting would lead to a decrease in the value exchanged and even incurring losses for the intended transactions. However, accurately forecasting the prices in the Forex market is an extremely difficult task.

Therefore, the prediction models developed from this study would facilitate a high accuracy of future price prediction for the Forex market. This would provide a better indicator for the market participants as a supplement to their decision-making process before conducting the final transactions, which results in minimizing the currency exchange risks. In addition, the proposed method can be extended to other financial markets, as the market prices generally follow the classic rule of supply and demand.

1.6 Scope of The Study

1. The currency pair used for the prediction task will be limited to only the EUR/USD pair. This is due to the EUR/USD pair having the highest trading volume (80%) as compared to other currency pairs in the Forex market (Yıldırım et al., 2021). This feature indicates high liquidity in the EUR/USD pair which provides a smoother and lower noise in the historical price data. This would facilitate the development of the prediction models and to achieve higher prediction accuracy.
2. The EUR/USD historical price data will be extracted from HistData.com. It is a publicly available repository of various historical price data of different Forex currency pairs, dating back to the year 2000. This source is chosen as it provides historical price data in the 1-minute timeframe which can be easily transformed into the required timeframe in line with this study.
3. The time horizon of the time series data will be confined between the year 2015 to year 2021, which is a total of seven full years of complete historical price data. This is due to the market trend existing over these years has remained relatively consistent and in similar price ranges.
4. The features used for developing the prediction models will only comprise of five features, namely date and time, open price, high price, low price, and close price. This is to ensure the model complexity remains relatively low for feasible computational time.

1.7 Structure of The Report

Chapter 1: Introduction

This chapter introduces the Forex market and how machine learning techniques are benefiting the financial market in facilitating the price prediction. In addition, a brief mentioned of the proposed methodology on how it aligns with the identified research gap is discussed. Moreover, the research questions, aim, significance, and scope of the study are outlined.

Chapter 2: Literature Review

This chapter provides an overview of the literature which includes a brief of the financial market and price prediction methods used in predicting the financial market. The literature review would include methods ranging from the classical of fundamental and technical analysis to the modern approaches of utilizing machine learning techniques in forecasting the market prices.

Chapter 3: Research Methodology

This chapter discusses the proposed methodology of this study which predicts the future prices of the Forex market utilizing various deep learning algorithms and multiple time series. In addition, a research plan detailing the schedule of the tasks and milestones of this study will be displayed.

Chapter 4: Implementation

This chapter discusses the implementation process of the proposed methodology in this study. Which includes outlining the best performing models along with their hyperparameters. In addition, the data exploration and data transformation procedure are discussed.

Chapter 5: Results and Discussion

This chapter discusses the evaluation of the prediction models and the interpretation of the computed results. In addition, visualizations of the model predictions are displayed along with the interpretation of the predicted outcomes. Finally, a discussion section is provided to interpret the performance of the model and results in detail.

Chapter 6: Conclusion

This chapter concludes the study by providing a summarization of the report and addressing the established research questions. In addition, a section outlining the research contribution and future recommendations is provided.

CHAPTER 2

LITERATURE REVIEW

2.1 Financial Market

The financial market exists as a medium for buyers and sellers to transact the sales and purchases of financial assets. Various types of financial assets are available to trade in the financial market, including but not limited to stocks, bonds, Forex, derivatives, commodities, and cryptocurrencies. This results in the establishment of different types of financial market, each catering for a specific type of financial asset such as the stock market, bond market, Forex market, etc.

The high accessibility and variety of financial products in the financial market has promoted the volume of trading activities in financial assets. This has allowed the efficient allocation of capital and assets which can stimulate the flow of capital, resulting in growth of the economy. An example where a company can utilize the stock market to raise funds for growth, which promotes employment and innovation thus providing a positive impact to the overall economy. Which, the earnings from the company can be reinvested into the financial market to promote growth of other sectors. This results in a cycle of economic growth which enables the development of the overall nation. In addition, a developing nation attracts foreign investment which further contributes to the development (Parray et al., 2020).

In addition to raising funds, the financial market facilitates the price discovery of financial assets, which is identifying the equilibrium price point based on supply and demand of the asset. The price equilibrium is achieved through the interactions between buyers and sellers of an asset. Factors such as market sentiment and publicly available information, plays a significant role in influencing the price discovery process (Zhao, 2021). Market sentiment concerns the risk appetite of investors, which affects the amount of allocation of investment capital into higher risk or lower risk assets. Publicly available information such as the release of earnings report can contain information about the financial status and prospects of the company, which can significantly increase or reduce the demand for the shares of a company.

Participants in the financial market can be grouped into several categories, namely retail investors, corporates, governments, regulators, and market intermediaries. Retail investors are typically net purchase of securities issued by companies, with the expectation to gain profits from the investment. In contrast, corporates are net borrowers who offer securities in exchange for funds, which are used to expand the company or invest in other assets to generate a higher revenue. Government entities may purchase or sell securities in the financial market as a measure to control market liquidity or to control the budget deficit. Regulators in the financial market exist to monitor, manage, and control the trading mechanism and flow of funds. The primary objective is to maintain the liquidity in the market by executing the buying and selling of treasury bills. Market intermediaries are the investment managers or investment bankers who facilitate the process of capital investment between the investors and users of funds.

Furthermore, market participants can be categorized based on different purposes in the financial market, namely investors, speculators, hedgers, and arbitrageurs. Investors invest money into different financial assets hoping to make a profit over the long term. Speculators make directional bets on various financial assets by taking advantage of the market price volatility by executing multiple trades in the short term. Hedgers utilize the financial market to mitigate risks by investing in an opposite position in a relative asset to offset risks. Similar to speculators, the arbitrageurs make directional bets in the financial market, but by identifying and taking advantage of mispricing or price anomalies in the market.

2.1.1 Forex Market

The main purpose of the Forex market is to facilitate the trade of currencies. The Forex market is like any other financial market which is built upon the fundamental concept of economics which is the rule of supply and demand (Ranjit et al., 2018). Where a high demand for one currency would drive the value of such currency higher, while a low demand for one currency would drive the value of such currency lower.

Several characteristics of the Forex market have been identified which differentiate it from other financial markets. Such characteristics would include high liquidity, 24-hour operations daily except weekends, low transaction costs, no middlemen, access to leverage, rapid transaction executions, and no commissions (Yıldırım et al., 2021). In addition, the issue of insider trading is not present in the Forex market. As moving the market prices would require a huge volume of money which can be hard to attain and sustain thus the Forex market is not prone to price manipulation (Islam & Hossain, 2021).

There are various factors that would influence the value of a currency. Where each factor would have a different influential capacity on the rise and drop of a currency value. Patel et al. (2014) conducted a study to identify the factors that would influence the prediction of currency value using statistical modelling. Eleven factors were identified which would have a significant impact on the rise and drop of a currency value. These factors are inflation, rate of interest, capital account balance, role of speculators, cost of manufacture, debt of the country, gross domestic product, political stability and economic performance, employment data, relative strength of other currencies, and macroeconomic and geopolitical events.

With the multitude of factors that may influence the market prices, predicting the Forex market remains a challenging task. These factors contributed to the non-stationary and noisy nature of the currency value (Khattak et al., 2019; Ranjit et al., 2018). However, this does not stop the researchers and analysts from trying to develop different techniques in understanding and predicting the market behavior and prices.

2.2 Traditional Prediction Methods

The classical approach to analyzing and predicting the financial market involves two main methods. The methods are fundamental analysis and technical analysis. The methods can be utilized in isolation or in combination to understand the market condition and to identify potential market opportunities.

2.2.1 Fundamental Analysis

The goal of performing fundamental analysis is to identify the intrinsic value of a security in the financial market. It is gauged using publicly available information derived from the economic, social, and political factors (Yıldırım et al., 2021). Commonly used fundamental indicators from the macroeconomic standpoint includes interest rate, unemployment rate, monetary policy, etc. While from the microeconomic standpoint, this would include Price to Earnings Ratio (PER), net profit margin, book value per share, etc. There are a vast number of fundamental indicators available for use. With proper evaluation and implementation of the fundamental indicators, valuable information can be derived to attain profitability from the market.

Luckieta et al. (2020) studied the influential effect of four fundamental indicators in affecting the stock market prices using linear regression analysis. The four fundamental indicators used are Return on Assets (ROA), Earnings Per Share (EPS), PER, and Debt-to-Equity Ratio (DER).

It was identified that EPS, PER, and DER provided a positive and significant impact on the prediction of the stock prices. Where an increase of the EPS, PER, and DER values would likely result in an increase in the stock prices. However, ROA is identified to be negatively impacting stock prices, where an increase in ROA would result in a decrease in the stock prices. Therefore, fundamental indicators have the potential to be used in predicting the financial market. However, an understanding of how each indicator would affect the prices is critical. In a similar work where Shaharudin et al. (2018) performed a comparison of using fundamental analysis and technical analysis in predicting the stock market specifically in food industry. The fundamental indicators used included net profit margin, PER, and total asset turnover. The author identified that net profit margin and PER did not provide a positive and significant return on the stock prices which is contrasting to the former author. Only the total asset turnover is providing a positive and significant impact to the stock prices. This may be due to the different countries and sectors analyzed by both authors thus resulting in contradicting claims. However, the results showed that both fundamental and technical analysis can produce a positive return when used in isolation. In addition, both authors claimed the use of fundamental analysis in predicting the stock market can outperform the use of technical analysis.

Khan et al. (2020) studied the applicability of public sentiments in the future trend prediction of stock markets using sentiment analysis based on various machine learning models. A comparison of prediction accuracies in the models with and without the public sentiment attribute was performed. It was identified that prediction models with the public sentiment attribute resulted in an improvement of prediction accuracy by one to three percentage. The task was a three-class classification of the market trend. The unexpectedly low increase in accuracy is due to the poor classification rate of the neutral trend, as the number of observations identified in the neutral trend was very low. However, the study still proves that public sentiments can provide a positive influence in the prediction of the market prices.

2.2.2 Technical Analysis

Technical analysis is the use of mathematically formulated indicators to perform market analysis to predict the future market price movement, which are widely utilized by investors and traders. The main components of technical analysis are historical market price analysis and price chart analysis (Yıldırım et al., 2021). Based on the historical market prices, different technical indicators can be computed mathematically. These technical indicators and chart patterns represent the trends, inflection points, and flow of capital in and out of the market in a summarized manner (Parray et al., 2020). This allows market participants to quickly understand the market conditions and perform quick decision making. Some examples of commonly used technical indicators would include Moving Average (MA), Relative Strength Index (RSI), and On-Balance Volume. While some examples of popular chart and candlestick patterns would include head and shoulder, double bottom, engulfing, doji, etc. Qu and Zhao (2021) utilized different similarity measures to study if historical trend in prices would provide any useful future price prediction capability. It was proven by the author that price patterns are often repeated in the past and concluded that the future market prices would likely exhibit a similar price pattern as the historical prices. Therefore, historical prices can contribute and be utilized for future price predictions.

de Souza et al. (2018) studied the profitability of using different periods of the MA indicator as the trading strategy in stock markets of five developing countries. It was identified that the trading strategy worked well only in several stock exchanges but overall, the profits from the trading strategy were able to surpass the losses by a small margin. Therefore, the author concluded that MA trading strategy is viable, provided with better fine tuning of the periods used in setting the MA indicators. In addition, the author mentioned that a combination usage of technical and fundamental analysis would yield a better result in predicting the stock market.

Lee et al. (2020) attempts to explore the use of different technical indicators with deep learning to predict the Taiwan stock prices. Five commonly used technical indicators namely Stochastic Indicator, RSI, Bias Ratio, William's Oscillator, and Moving Average Convergence Divergence (MACD) were tested individually with the LSTM algorithm. The LSTM model with MACD indicator returned the highest prediction accuracy. However, the performance among the five indicators does not significantly differ much. This was explained due to the technical indicators used are highly correlated to the MA thus producing similar results.

2.2.3 Combined Analysis

In practice, both technical and fundamental analysis are typically utilized in parallel when conducting market analysis. The benefit of combining both analyses is that it provides a better overall understanding of the market condition and improves the confidence and reliability of the identified market opportunities. However, it is much more time-consuming and resource intensive as an analyst would have to compile and associate the news and reports with the current market prices. This increases the number of variables to be analyzed which can be overwhelming and causes confusion that can lead to worse decision making. Therefore, it requires an experienced analyst to properly blend and decipher the information derived from the combined method. Successfully deriving the information would provide an advantage to identify high value market opportunities. de Souza et al. (2018) supported this type of combined analysis, which mentioned that this yields better results in the stock market as compared to using fundamental or technical analysis in isolation.

Ezzeddine and Achkar (2021) attempted to utilize machine learning to aggregate the financial news data and technical indicators to be used as predictors for the future trend of stock prices. The financial news data were processed using a natural language processing model, while the technical indicators were processed via ANN. The outcomes from both models were aggregated and the future trend was classified by a Logistic Regression model. The model was able to produce a 92% accuracy which indicates the feasibility of combining different types of data to be used in predicting the stock prices.

2.3 Machine Learning Prediction Methods

Various machine learning techniques have been adopted in trying to predict the financial market. However, a vast majority of the studies focused on predicting the stock market. Machine learning techniques applied in the stock market can be adapted to apply in the Forex market.

2.3.1 Machine Learning in Financial Market

Wang (2020) studied the application of Logistic Regression and SVM in predicting the Chinese stock market. The regularization L1 (Lasso Regression) and L2 (Ridge Regression) is used to develop the logistic regression models. While for the SVM, a linear kernel is used. It was identified that Ridge Regression and SVM have similar performance while Lasso Regression has the lowest performance. This is due to Lasso Regression producing a sparse solution which increases complexity of the model leading to lower performance as the model fitness reduces. This is in line with the study from Khattak et al. (2019), which mentioned that data sparseness would lead to the degradation of prediction results. The author aimed to solve the data sparsity problem present in stock market data by applying Z-score normalization onto the dataset and removing any identified outliers. The KNN algorithm was used to classify the future trend of the market and has outperformed baseline models. In addition, the author mentioned that KNN is suitable to evaluate financial terms and is less prone to overfitting. Thus, data normalization has proved beneficial for improving the accuracy of the prediction.

Altan and Karasu (2019) studied the effect of using different kernel scale values for SVM on the price prediction of different Forex currency pairs. It was identified that with proper tuning of the kernel scale values, a highly accurate SVM prediction model can be developed. In addition, mentioned by the author, one of the benefits of SVM is that it can be effectively applied to both linear and nonlinear data. Tao et al. (2020) utilized the whale optimization algorithm for optimizing the kernel parameters and penalty factors of SVM in prediction of the stock market trend. The author achieved a higher efficiency in optimizing the hyperparameters for SVM, resulting in higher prediction accuracy. Thus, the whale optimization algorithm provides a satisfactory result in identifying the best hyperparameters combination for SVM model more efficiently. Both authors mentioned the importance of performing hyperparameter tuning when using SVM which can result in improved model predictions.

Parray et al. (2020) set out to study the effect of using different validation techniques, namely k-fold cross-validation and train-test split to compare the performance of the prediction models for the stock market prices. Three algorithms were used to develop the models namely logistic regression, SVM, and Single Layer Perceptron (SLP). It was identified that applying k-fold cross-validation provided a higher prediction accuracy for all prediction models. This is due to k-fold cross-validation iteratively utilizes the whole dataset for training and testing the model. However, among the three prediction algorithms, SLP performed the worst. As mentioned by the author, this may be due to the ineffectiveness of SLP in handling the complexity of time series data.

Tang et al. (2018) developed a KNN model with the implementation of Principal Component Analysis (PCA) to achieve dimensionality reduction. The proposed method provided the benefit of speeding up the KNN algorithm calculation and improving the overall prediction performance. The model outperformed the baseline which is a KNN model without the application of PCA. In addition, mentioned by the author, the benefits of PCA include increasing effectiveness of extracting information from the dataset and reducing variables that exhibit multicollinearity.

Kusuma et al. (2019) performed stock market prediction using CNN model with candlestick chart images as input. The model provided promising prediction accuracy of greater than 90% for different stocks investigated. In addition, different trading periods were utilized to study the effect it has on the result. It was mentioned that using a longer trading period as input has improved the prediction performance, specifically in this study the 20-day trading period, which is the highest period used in the study, provided the best prediction accuracy. Thus, this study shows the potential use of images as input data as a viable option to predict the financial market.

Vijh et al. (2020) performed a comparison between ANN and Random Forest (RF) model in predicting the stock market prices of companies from different sectors. It was identified that the ANN model outperformed the RF model in all the stocks chosen from different sectors. Thus, proving that ANN is a better model to be used in predicting the stock market as compared to RF model. However, a claim by Torralba (2019) which mentioned that ANN is ineffective for stock market data which is sequential data type. This is due to the incapability of ANN in storing and utilizing previous inputs for future inferences, which temporal dependence is an essential characteristic of time series data.

2.3.2 Machine Learning Challenges in Price Prediction

One of the data that is readily and widely available for the Forex market is the historical price data. As mentioned by Torralba (2019), historical price data may contain hidden patterns that exhibit behaviors of the market participants and effects from the market sentiments and political conditions. However, the historical price data exists in the form of time series. Which is a sequence of data points indexed by the date and time, which means the current data is dependent on the previous data values to produce a meaningful insight (Srivastava et al., 2021). Due to the properties of the time series data, not all machine learning algorithms are capable of effectively extracting information from such data.

Time series data are generally non-stationary data which means the data have means, variances, and covariances that vary over time. The classical approach of predicting the market prices using regression model such as Autoregressive Integrated Moving Average (ARIMA) are not able to receive non-stationary data. However, data transformation can be applied to convert the non-stationary data into a stationary data format to facilitate the use of ARIMA algorithm and other models that work only with non-stationary data. Example in the works of Srivastava et al. (2021), which applied log transformation to convert the time series data into a stationary data to be used as predictors for predicting the market prices using machine learning techniques. In addition, mentioned by the author that stationary data may provide an improved model performance as compared to using the non-stationary time series data.

The problem of prediction algorithms not able to directly receive non-stationary data can be overcome by using RNN-based models, which can directly receive time series data without the need to apply any data transformation. In addition, RNN-based models are proven to be effective in learning non-linearities and sequential data. However, the simple RNN model suffers from the problem of vanishing and exploding gradients. Simple RNN model would typically encounter such problems when working with long sequential data. Vanishing gradient refers to the loss of gradient information over long sequential data. While exploding gradient refers to the rapidly increase in gradient information during the model training phase resulting in an unstable network. Therefore, resulting in simple RNN ineffective for capturing correlation between temporally distant events of long sequences. However, RNN is effective and efficient for tasks that use data of shorter sequences, which can produce a lower time and memory complexity model as compared to the more advanced variants of RNN namely GRU and LSTM.

LSTM is an enhanced version of RNN which is developed to overcome the exploding and vanishing gradients problems faced by simple RNN when dealing with long sequential data. However, training and tuning LSTM models can be a very computationally intensive task. Therefore, properly preprocessing the data must be performed to enhance the efficiency of the model training process. Escudero et al. (2021) mentioned that data scaling is an important process especially for deep neural networks. As the different range in values in the observations would affect the performance and efficiency of the activation functions, especially the sigmoidal and Hyperbolic Tangent (TanH). Similarly mentioned by Srivastava et al. (2021) which uses LSTM as the prediction algorithm, has utilized MinMax scaler to confined the range of value for the observations between zero and one to mitigate the problem mentioned earlier.

2.4 Related Works

Wei and Li (2019) proposed a method of predicting the Forex market trend by combining two different LSTM models. Each model receives a different historical price dataset of different timeframes, specifically the 5-minute timeframe and the 30-minute timeframe. The rational of using multiple timeframes is that the dataset of the bigger timeframe can signify the information from the long-term trend of the market while the dataset from the smaller timeframe can signify the information from the short-term trend of the market. The outputs from the two LSTM models were concatenated using a dense neural network which predicts the trend of the market. The proposed model was compared to other RNN-based models using only the 30-minute timeframe dataset. It was identified that the proposed model outperforms all benchmark models. The study shows that the use of multiple timeframes in prediction model can perform better than models that use only a single timeframe.

Ranjit et al. (2018) attempts to compare the prediction performance between four algorithms namely ANN, RNN, GRU, and LSTM for several Nepalese Rupees currency pairs from the Forex market. The dataset was normalized between zero and one to improve computation efficiency. The models were developed with one hidden layer but with varying hidden neurons between one to ten. It was identified that LSTM outperformed all other models in every currency pair studied. It was mentioned by the author, the models for different currency pairs would have a different optimal number of hidden neurons. Thus, the study showed that LSTM model can predict the Forex market well and performed better than other models.

However, in the works of Dautel et al. (2020), which compared the performance of the same set of deep learning algorithms but using a sliding window evaluation technique for several Forex major currency pairs. This is different from the sliding window training approach, where in this study, the model is tuned in each sliding window. The results showed that the performance between the four models did not significantly differ much. In some cases, the ANN and simple RNN model outperformed the GRU and LSTM model. Concluded by the author, that using LSTM and GRU may not always yield better results than a simple RNN or ANN model. In addition, the author mentioned that the window-based evaluation approach requires immensely high computation resources as each study period is represented by one model, which requires isolated hyperparameter tuning. The study consists of 144 study periods where each study period requires isolated model training and hyperparameter tuning. Thus, the author utilized the random search strategy to identify the optimal hyperparameter combinations for each model. The prediction models may not be properly optimized which led to the results contradicting the former author.

Qu and Zhao (2019) compared the performance between RNN and LSTM algorithms in predicting the Forex market prices. Hyperparameters were set to be the same for both models, but various combinations of hyperparameters were used. It was identified that LSTM outperformed RNN in all different combinations of hyperparameter settings. This proves that LSTM is better than RNN in identifying relationships in historical time series data. In addition, it was mentioned that the number of hidden layers and number of neurons in each layer plays a significant role in determining the prediction performance of the model.

Srivastava et al. (2021) performed a comparison in stock price prediction of Dell Technologies Incorporated between the use of ARIMA and LSTM model. Log-transformed has been applied to convert non-stationary data into stationary data for the ARIMA model. While feature scaling using Min-Max Scaler was performed for the time series data for the LSTM model. It was found that ARIMA outperformed LSTM in the short-term forecasting, while LSTM outperformed ARIMA in the long-term forecasting. However, mentioned by the author, LSTM is favorable as it facilitates the long-term dependency problem, and it is useful to predict the long-term and short-term market reliably.

Yıldırım et al. (2021) proposed the use of separate LSTM models to forecast the Forex market trend based on different dataset. One of the LSTM models is handling the macroeconomic indicator dataset while another LSTM model is handling the technical indicator dataset. Each model generates an entry signal which is classified into buy, sell, or take no action. Signals generated from both models were combined using a rule-based metric. The proposed method yielded a prediction accuracy of around 73%. It was identified that using separate LSTM models for separate dataset can generate a better prediction accuracy, as compared to combining the dataset as one and fed into a single LSTM model. In addition, it was mentioned that a higher number of iterations used for the LSTM models would result in an increase of prediction accuracy, but it would also lead to increasing computational time.

Islam and Hossain (2021) proposed a method of combining the GRU and LSTM into a single model to predict the Forex market prices. The model contains three hidden layers of which the first layer is a GRU layer, followed by the LSTM layer, and finally a dense layer. The proposed method was compared to standalone GRU and LSTM models and outperformed the standalone models. In addition, it was mentioned that MSE and RMSE evaluation metric is suitable for the Forex prediction task, as the error obtained in the study was low in value. This is due to the MSE and RMSE metric would penalize larger error value. The MSE obtained in this study ranged from 0.00001 to 0.00084 while the RMSE ranged from 0.00301 to 0.02895. Several major currency pairs were investigated, but the EUR/USD pair obtained the best performance.

Torralba (2019) studied how the number of hidden layers in LSTM would affect the prediction accuracy for stock market trends. All other hyperparameters were held constant except for a varying number of hidden layers from one to five. Three banking company stock data were used to develop the prediction models. Each model for a different company stock data returns a different optimal number of hidden layers. However, the error computed from different number of hidden layers does not differ much. It was identified that a continuous uptrend or downtrend or a sudden spike in the historical price data within the specified time step would result in the model overestimating the prices. Therefore, time steps selected for the LSTM model are encouraged to include market prices that exhibit both uptrend and downtrend for a better predicted outcome. However, it can be difficult to determine the optimal time step based on the mentioned requirement, as the market behavior is not consistent throughout the period. In addition, mentioned by the author, LSTM is robust to outliers and captures temporal patterns well.

Dobrovolný et al. (2020) investigated the optimal time step to be used with a LSTM model to predict the Forex market. It was identified that a time step of 30 days and 100 epochs of training yielded the best performance. However, using the same time step of 30 days but different number of epochs yielded worse results. Therefore, identifying the optimal time step for LSTM is highly dependent on other hyperparameter settings. It is encouraged to experiment with various hyperparameter settings to determine the optimal prediction model.

Rana et al. (2019) studied the effects of different combination of activation functions and optimizers on stock price prediction using LSTM models. Four activation functions namely linear, Rectified Linear Unit (ReLU), Sigmoid, and TanH were used. While seven optimizers namely Adaptive Movement Estimation (Adam), Adaptive Gradient Algorithm (AdaGrad), Nesterov-accelerated Adaptive Moment Estimation (Nadam), Root Mean Square Propagation (RMSprop), Adadelta, Stochastic Gradient Descent (SGD), and Adaptive Movement Estimation Extension (AdaMax) were used. 28 LSTM models were developed based on different combinations of activation function and optimizer. It was identified that a combination of linear activation function and AdaMax optimizer produced the best performing model. Followed by the combination of tanh activation function and Adam optimizer which produced relatively similar result.

Table 2.1: Summary of related works

Author	Objectives	Dataset	Prediction Model	Model Evaluation	Outcome	Limitation
Islam and Hossain (2021)	- Development of a novel hybrid model that consists of GRU and LSTM as hidden layers in a single neural network model in Forex market price prediction. - Predicts prices of 10 minutes and 30 minutes into the future.	- EUR/USD, GBP/USD, USD/CAD, USD/CHF. - Dataset in 10 minutes timeframe from January 2017 to December 2018 - Dataset in 30 minutes timeframe from January 2019 to June 2020 - Features: Momentum, average price, price range, open, high, low, close price	A hybrid neural network model consisting of GRU in the first layer followed by LSTM in the second layer followed by a layer of dense neurons	- MSE - RMSE - MAE	- Best performance observed in GBP/USD and USD/CAD. - Using 10 minutes timeframe dataset for GBP/USD model: MSE: 0.00001 RMSE: 0.00357 MAE: 0.00253 - Using 10 minutes timeframe dataset for USD/CAD model: MSE: 0.00004 RMSE: 0.00597 MAE: 0.00387 - Using 30 minutes timeframe dataset for GBP/USD model: MSE: 0.00084 RMSE: 0.02895 MAE: 0.01448 - Using 30 minutes timeframe dataset for USD/CAD model: MSE: 0.00018 RMSE: 0.01358 MAE: 0.00998 - The proposed method outperformed ordinary LSTM and GRU models.	- Different currency pairs require different tuning of the GRU and LSTM layer for optimal performance. - The use of different timeframes can be explored.
Yıldırım et al. (2021)	- Development of a novel hybrid model that combines outputs from two LSTM models in Forex	- EUR/USD - Dataset period from January 2013 to January 2018 - Features: Open, high, low, close price,	- Hybrid LSTM that combines the outputs using a rule-based decision mechanism	- Accuracy	- One day ahead: 73.09% - Three days ahead: 68.31% - Five days ahead: 79.42% - The proposed method provides an improved prediction accuracy as compared to standalone LSTM	- Considers only the EUR/USD pair, other currency pairs may yield different results. - Only the iteration hyperparameter was

	market trend prediction. - Predicts daily prices of various days ahead.	inflation rate, interest rate, Fed funds rate, S&P500 index, DAX index, MA, MACD, Rate of Change, Momentum, RSI, Commodity channel index, Bollinger bands	- One LSTM model receives input of macroeconomic data - Second LSTM model receives input of technical indicator data.		model that receives all inputs in one model.	varied in the LSTM models while other hyperparameters were fixed when identifying the best performing model.
Srivastava et al. (2021)	- Performance comparison between LSTM and ARIMA model in Stock market price prediction. - Predicts daily prices of one day ahead.	- New York Stock Exchange company Dell - Dataset period from 17th August 2016 to 21st May 2021 - Features: Volume, open, high, low, close price, adjusted close price	- ARIMA - LSTM	- RMSE - MAE - MSE	- ARIMA performs better overall. However, the author mentioned that ARIMA model performs better in short-term forecasting while LSTM model performs better in long-term forecasting. - ARIMA model: RMSE: 1.46585 MAE: 1.05855 MSE: 2.14872 - LSTM model: RMSE: 2.12477 MAE: 1.58560 MSE: 4.51465	- Only one stock company was considered in the experimentation - No extensive hyperparameter optimization was performed for the LSTM model
Dobrovolný et al. (2020)	- Studies the effect of different time steps used in LSTM model in Forex market price prediction. - Predicts daily prices of one day ahead.	- EUR/USD - Dataset period from April 1971 to May 2019 - Features: open, high, low, close daily prices	- LSTM	- MAE - MSE	- Best combination of time step and epoch identified is 30 days and 100 epochs for LSTM MSE: 0.003052 MAE: 0.002390 - However, when time step of 30 days and 300 epochs were used, worse results were obtained.	- Number of epochs used were fixed to either 100 or 300 for the models. - Different combination of hyperparameters should be explored to further achieve better model performance.

Dautel et al. (2020)	- Performance comparison between LSTM, GRU, RNN and ANN in Forex market trend prediction. - Predicts daily prices of one day ahead.	- EUR/USD, GBP/USD, USD/JPY, USD/CHF - Dataset period from January 1971 to August 2017 - Feature: One-day percentage return	- LSTM - GRU - RNN - ANN	- Log loss - Accuracy	- LSTM and GRU outperformed RNN and ANN. - LSTM Log loss: 0.6993 Accuracy: 0.5076 - GRU Log loss: 0.6992 Accuracy: 0.5107 - RNN Log loss: 0.7115 Accuracy: 0.5103 - ANN Log loss: 0.7026 Accuracy: 0.5062	- Hyperparameter tuning for the sliding window-based evaluation approach is not feasible due to the requirement of huge computational resources as compared to conventional evaluation method.
Torralba (2019)	- Studies the effect of different number of hidden layers used in LSTM model in Stock market price prediction. - Predicts daily prices of one day ahead.	- 3 companies from banking sector in Philippine Stock Exchange - Dataset period from 1999 to 2017 - Features: Open price, volume, average daily price, price variation	- LSTM	- RMSE	- Different stock studied have a different optimal number of hidden layers: Stock 1: 4 hidden layers Stock 2: 2 hidden layers Stock 3: 1 hidden layer - It is identified that time step used for the model is to be selected carefully since data exhibiting only single trend within the time step would cause model to perform poorly.	- Other hyperparameters were fixed and not optimized. - Stocks selected were only from the banking sector.
Qu and Zhao (2019)	- Performance comparison between LSTM and RNN in Forex market price prediction. - Studies the combination of various	- EUR/USD - Dataset period from June 1993 to March 2018 - Features: Open, high, low, close price, MA3, MA20, MA73, MACD,	- LSTM - RNN	- RMSE - MAE	- Different types of hyperparameter are compared in pairs in each experiment setup - In every experimentation, the LSTM outperforms the RNN	- Each set of experiments compares two types of hyperparameters to identify the best performing model.

	hyperparameters to achieve optimal model - Predicts daily prices of one day ahead.	Bollinger Band, Bias, RSI, etc. (18 features)				- No experimentation on combination of every hyperparameters.
Rana et al. (2019)	- Studies the effect of different combination of activation functions and optimizers used in LSTM model in Stock market price prediction. - Predicts daily prices of one day ahead.	- Spanish Stock Exchange company Acciona - Dataset period from 2008 to 2018 - Features: open, high, low, close price, volume	- LSTM	- RMSE	- Best performance of LSTM model observed when using Linear and AdaMax or TanH and Adam combination - Both achieved the best performance with RMSE of 0.0151	- Only the LSTM algorithm is considered. - All models used the same hyperparameter settings except varying the activation functions and optimizers.
Wei and Li (2019)	- Development of a novel hybrid model that combines multiple timeframes of dataset in Forex market trend prediction. - Predicts prices of 30 minutes into the future.	- EUR/USD, EUR/AUD - Dataset period from January 2009 to October 2018 - Dataset transformed into 5-minute timeframe - Dataset transformed into 30-minute timeframe - Features: open, high, low, close price	- Two LSTM and combining results using a feedforward neural network	- Accuracy - F1 - Precision - Recall	- The proposed model outperforms conventional single channel models - EUR/USD: Accuracy: 53.32% F1: 52.80% Precision: 60.00% Recall: 53.40% - EUR/AUD Accuracy: 53.69% F1: 52.60% Precision: 59.00% Recall: 53.60%	- Model considers only two channels of LSTM of dataset from small timeframes which can limit the perspective of the model. - Uses only the LSTM algorithm.

Ranjit et al. (2018)	- Performance comparison between LSTM, GRU, RNN, and ANN in Forex market price prediction. - Studies the effect of different number of hidden neurons influencing prediction accuracy. - Predicts daily prices of one day ahead.	- USD/NPR, EUR/NPR, GBP/NPR - Dataset period of 10 months but no details mentioned - Features: open, high, low, close price	- LSTM - GRU - RNN - ANN	- MAE	- LSTM outperformed all other models with the use of five hidden neurons. - The optimal number of hidden neurons for different algorithms do not necessarily have to be the same.	- Uses only one hidden layer in all models but varying the hidden neurons. - The time step hyperparameter for all models is using only the previous one day, which can limit the perspective of the models.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Framework

The SEMMA methodology will be utilized in this study to guide the data mining process. Initially developed by SAS Institute, it is a sequence of five stages that facilitate the data mining project. The stages consist of Sample, Explore, Modify, Model, and Assess. The proposed method in this study will be outlined in the following section based on the stages outlined in the SEMMA methodology.

3.1.1 Sample

The sample stage consists of portioning the dataset into different subsets for different usage during the model development phase. The historical price data of the EUR/USD currency pair will be extracted from the website www.histdata.com. The source is chosen as it provides free access to the data usage and has a complete set of data. The features present from the dataset would include open, high, low, and close price of the currency pair EUR/USD. The dataset would cover a period of seven years from January-2015 to December-2021. The data points exist in the form of time series in the 1-minute interval recorded throughout 24 hours daily on every available trading day. Considering the 1-minute time interval, the dataset provides about 2.6 million data points within the specified seven years.

The dataset would be split into three subsets namely training set, validation set, and testing set. Which will be used for model fitting, training validation, and overall model performance evaluation. The training set will be having five years of data within the period from January-2015 to December-2019. The validation set will be having one year of data from January-2020 to December-2020. While the testing set would have one year of data within the period from January-2021 to December-2021.

3.1.2 Explore

The explore stage consists of data exploration tasks which are aimed to identify trends and anomalies in the dataset and gaining a deeper understanding of the dataset. This is performed using exploratory data analysis which consists of statistical and graphical methods to provide an understanding and to identify potential outliers in the dataset. The use of line chart for the time series data would provide an overview of the market trend and allow the identification of anomalies.

3.1.3 Modify

The modify stage consists of data modification by means of transformation. The dataset does not contain any missing values thus no missing value imputation will be performed in this study. However, the dataset containing the time series data in a 1-minute timeframe is to be converted into specified timeframes mentioned below. This is to facilitate the study of different combinations of timeframes influencing the predicted outcome. Several combinations of timeframes are identified based on the rule of thumb used by financial analysts when selecting timeframes for market analysis. Generally, two or three number of timeframes are used concurrently to identify market opportunities, which the different timeframes would represent the market trends in different terms. Example, an analyst would typically use the 30-minute timeframe and the 4-hour time frame which would represent the short-term trend and the medium-term trend to analyze the market.

The rule of thumb in selecting timeframes would typically follow the ratio of 1:4 or 1:6. Table 3.1 shows the combination of timeframes to be used in the models which consist of a combination of two or three number of timeframes following the ratio mentioned which are typically used by an analyst. In addition, a single 24-hour timeframe model will be developed and used as the benchmark for comparison, as it is typically used by researchers in conducting market price prediction.

Table 3.1: Combination of timeframes to be studied

Number of Timeframe	Ratio	Short-Term	Medium-Term	Long-Term
1	1:1	-	-	H24
2	1:4	H1	H4	-
2	1:6	H1	H6	-
3	1:4	M30	H2	H8
3	1:6	M30	H4	H24

Data Conversion

To understand the conversion of the time series data from 1-minute timeframe into the specified timeframe in the table above, the 30-minute timeframe will be used as an example for the conversion illustration. A similar procedure will be applied to convert into other required timeframes. The following outlines the procedure for the conversion:

- For the time and date attribute, an interval between 30 instances is identified and grouped to form a single instance which will represent a single 30-minute interval time series data.
- The opening price for the single 30-minute interval data will be determined using the opening price of first instance within the identified 30 instances.
- The high price for the single 30-minute interval data will be determined using the highest price value among the identified 30 instances.
- The low price for the single 30-minute interval data will be determined using the lowest price value among the identified 30 instances.
- The closing price for the single 30-minute interval data will be determined using the closing price of the last instance within the identified 30 instances.

Figure 3.1 illustrates the mentioned data conversion procedure from using 30 of the 1-minute timeframe instances into a single 30-minute timeframe instance. The procedure is repeated for the entire dataset resulting in a sequence of data in the required timeframe format.

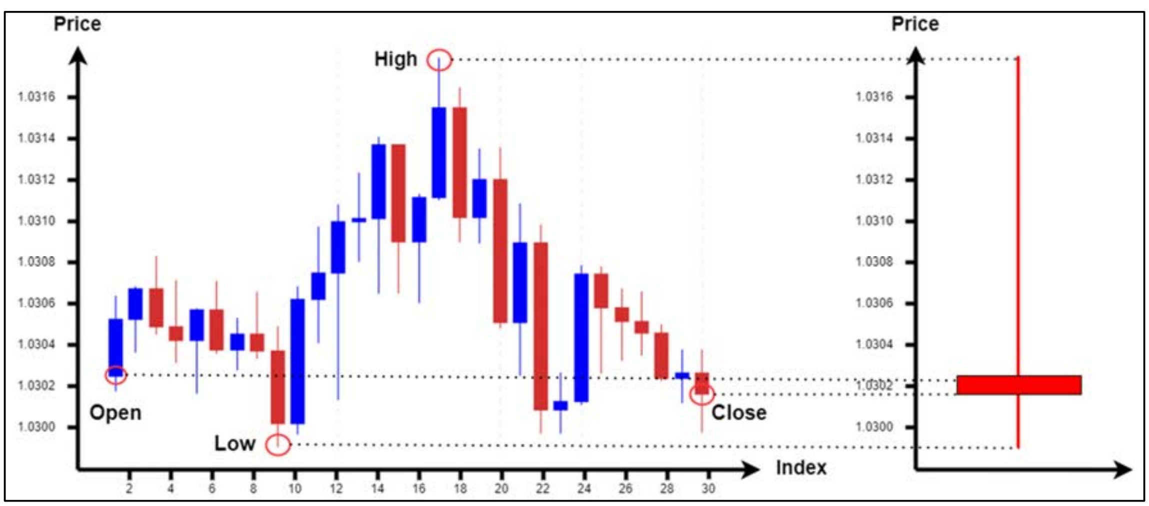


Figure 3.1: Data conversion illustration from 1-minute timeframe to 30-minute timeframe

3.1.4 Model

The model stage consists of the development of prediction models. In addition, this section outlines a brief introduction on simple RNN followed by the two prediction algorithms utilized in this study. The prediction algorithms would include GRU and LSTM, which are enhanced variants of the simple RNN. These algorithms are chosen due to the capability and proven application in handling time series data and predicting the financial market.

Recurrent Neural Network

The RNN is a type of neural network algorithm which contains feedback loops to retain and reuse historical information. It is designed to work with sequential data and is typically seen in the application of time series forecasting and natural language processing. It is well suited for sequential data due to the ability to utilize prior inputs to influence the current inputs and outputs. Which can be seen as having a memory that can remember historical input and using such memory to influence the future outcomes. Such a feature is not present in other types of neural network algorithms, which makes the RNN algorithm favorable for tasks that uses sequential data and or with temporal dynamics.

Using Figure 3.2 to understand the architecture of RNN. On the left of the figure shows a typical example of the compressed RNN with a feedback loop. While on the right shows the RNN unrolled into several time steps which have the resemblance of a sequence of same copies of neural networks. At each time step, information from the previous network will be passed onto the next network which will be used to influence the output.

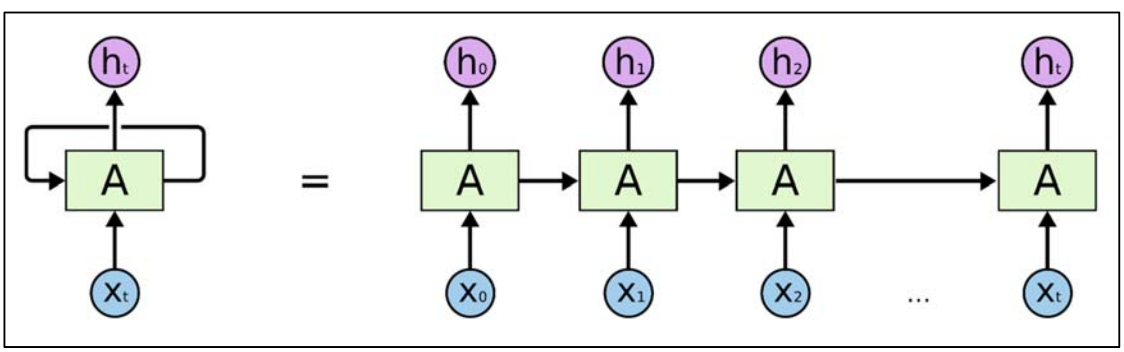


Figure 3.2: RNN unrolled into a series of same network (Olah, 2015)

To minimize the loss function, RNN utilizes both gradient descent and backpropagation through time (BPTT). Backpropagation is typically used for feedforward neural networks. It is the calculation of the gradients of an error function with respect to the weights of a neural network.

However, it is slightly different in RNN, due to the use of sequential data, the backpropagation is performed through the time attribute as well, meaning the errors at each time step will be summed during the backpropagation.

There are two problems typically faced by simple RNN when working with large networks, namely exploding gradients and vanishing gradients. Exploding gradient refers to the recursive multiplication of a gradient, causing the gradient to have an extremely large value which will result in an unstable model. While vanishing gradient refers to the diminishing of the gradient to the point where the value becomes too small and close to zero which will inhibit the network from learning new weights. Therefore, the GRU and LSTM algorithms are typically applied to overcome the mentioned issue when working with longer sequences.

Long Short-Term Memory

The LSTM is a variant of the simple RNN, capable of learning long-term dependencies. It is developed to overcome some of the shortcomings of simple RNN which is the exploding and vanishing gradients. Such capabilities are achieved through the use of gates, which regulate information to the cell state. Figure 3.3 shows the internal architecture of an LSTM network which comprises of three step processes in regulating the information.

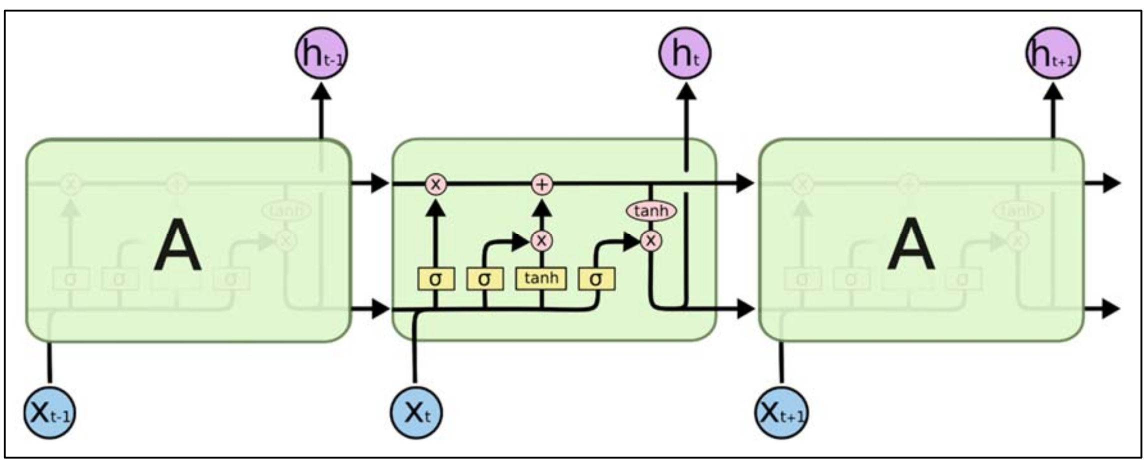


Figure 3.3: Architecture of LSTM in a sequence (Olah, 2015)

The first step involves deciding what information is to be neglected from the cell state. It uses a sigmoid layer which outputs between zero and one in deciding to keep or eliminate the information from the cell state. This step is referred to as the forget gate.

The second step involves deciding what information is to be added to the cell state. Two components are present in this layer. The first component uses a sigmoid layer to decide what values are to be updated. The second component uses a TanH layer to create a new vector consisting of the values from the previous sigmoid layer where it will be added to the cell state. This step is referred to as the input gate.

The third step involves deciding what information should the cell state output. Two components are present in this layer. The first component uses a sigmoid layer to decide what units of the cell state to output. The second component uses a TanH layer to scale the output between negative one and one. This step is referred to as the output gate.

Gated Recurrent Unit

Another variant from the simple RNN is the GRU algorithm. It has a simpler internal architecture as compared to the LSTM algorithm, which contains only two gates namely the update gate and the reset gate. These gates are used to regulate the information passing through the hidden state in GRU. Figure 3.4 shows the internal architecture of a GRU unit which is less complex as compared to the LSTM. Due to the simpler architecture, GRU typically computes faster than LSTM while producing comparable results.

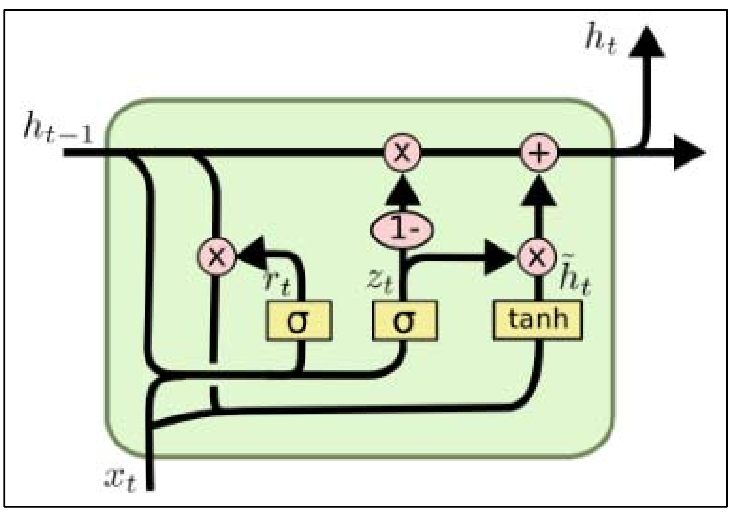


Figure 3.4: Internal architecture of GRU (Olah, 2015)

As compared to the LSTM architecture, the operation in GRU is made simpler by combining the forget gate and input gate, producing a single gate coined the update gate in GRU. The function of the update gate in the GRU architecture is to determine the amount of past information to be carried forward to the next state. This provides the benefit of carrying historical information in addition to eliminating the risk of encountering vanishing gradient problem. While the reset gate in GRU functions as a filter to determine the amount of historical information to be discarded or retained.

3.1.4.1 Model Development Procedure

The prediction models will be developed using two different RNN-based algorithms namely GRU and LSTM. Using the combination of timeframes from 30-minute, 4-hour, and 24-hour for illustration, the following describes the procedures of the proposed methodology in this study to predict the closing price of EUR/USD for the next trading day:

1. Based on the number of combination of timeframes mentioned, three separate prediction models will be developed using different datasets where each one is transformed into the specified timeframe.
2. Each model will receive four features as inputs namely the open, high, low, and close prices.
3. The time step used for each model will be fixed at 20 trading days. Depending on the timeframe used, the number of samples would differ for each passing. Example, for the 24-hour timeframe model, it would have 20 samples, while the 4-hour timeframe model would have 120 samples, and the 30-minute timeframe would have 288 samples. The samples represent a single observation that the model would use for fitting.
4. The entire dataset would be represented using the rolling window format, containing the different number of samples for the different timeframes used.
5. Each separate model will go through a set of hyperparameters and predict the closing price of the next trading day.
6. The hyperparameter optimization will be performed using various combinations of hyperparameter settings and finally evaluated to determine the best performing model for each timeframe.
7. Once the optimal model is determined, the training set is passed through the optimal model once again to allow the model to predict the closing price of the next trading day. Where, the prediction outputs from the run will be saved in an array.
8. The array consisting of prediction outputs from all three models will be combined and used as inputs for the feedforward neural network.
9. Similarly, hyperparameter optimization will be performed for the feedforward neural network using various combinations of hyperparameters.

10. Once the feedforward neural network model has achieved optimal performance, the testing dataset will be passed through the entire network for overall model performance evaluation.
11. The evaluation metrics will be computed for each experiment based on the optimized model for comparison and analysis.
12. The entire procedure will be repeated using both GRU and LSTM algorithm, thus two sets of results will be obtained for comparison.

Figure 3.5 illustrates the process flow of the proposed method using GRU algorithm and the combination timeframes of 30-minute, 4-hour, and 24-hour data for explanation purpose.

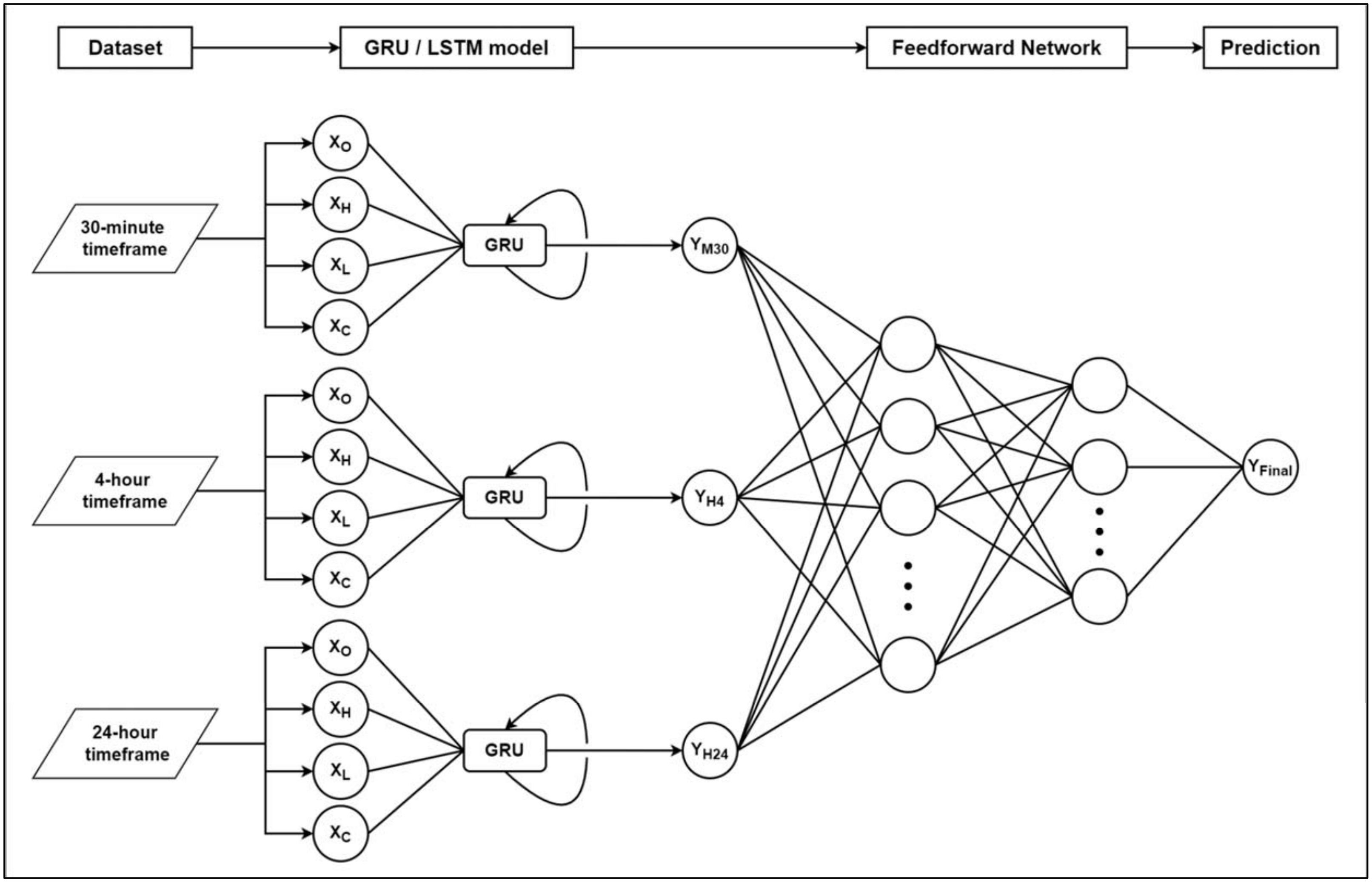


Figure 3.5: Model process flow illustration

3.1.4.2 Model Hyperparameters

This section discusses the hyperparameters to be utilized for both GRU and LSTM models in this study. Hyperparameter optimization ensures the best performance is achieved by the prediction models. Seven hyperparameters will be studied to identify the best combination to produce the best performing model. The hyperparameters are time steps, activation function, optimizer, number of hidden layers, number of hidden neurons, batch size, and number of epochs.

Time Step

The time step parameter is a crucial hyperparameter for the RNN-based model. It refers to the number of past data in each observation that the model would use for fitting. The time step in this study would be fixed to 20 trading days, which is equivalent to one month of trading activities. It is chosen based on literature, which the studies have experimented with different number of time steps and yielded best results when a time step between 20 to 30 trading days is utilized (Dobrovolný et al., 2020; Kusuma et al., 2019; Qu & Zhao, 2019). A time step that is too long would produce a highly complex model which would result in high computational cost, while a time step that is too short would inhibit the model from learning the market trend resulting in an inaccurate model.

Activation Functions & Optimizers

Although various activation functions and optimizers are available for use. The activation function and optimizer used in this study will be confined to TanH and Adam. It is chosen as per study from Rana et al. (2019), which investigates the optimal combination of activation functions and optimizers when using LSTM for forecasting financial market. This combination can provide efficient performance to the neural network while achieving optimal results.

Hidden Layers

Based on the study conducted by Torralba (2019), the optimal number of hidden layers for each model would vary according to different hyperparameter settings. Thus, it is advisable to experiment by developing various models with different numbers of hidden layers. This study would experiment with one to four number of hidden layers for each model which followed the experiment conducted by Torralba (2019), as the results showed that most models performed well in this range of number of hidden layers.

Hidden Neurons

The number of hidden neurons in each hidden layer plays a major role in affecting the prediction accuracy of the model (Qu & Zhao, 2019). If the number of hidden neurons is too high, the model may overfit. While if the number of hidden neurons is too low, the model may not effectively learn from the data. Thus, the number of hidden neurons to be used in this study would be experimented over a range of values. The number of hidden neurons in the hidden layers to be experimented with in this study would range from 50 to 150 with a step of 50.

Batch Size

Batch size refers to the number of samples for each passing through the network. The dataset will be partitioned based on the batch size and each batch will be used for updating the weights of the model. This study utilizes mini-batch gradient descent with the typical batch size of 32, 64, and 128 samples. The use of batch size less than the number of observations would improve the model training efficiency leading to faster computation and lower memory consumption. However, a smaller batch size would introduce more fluctuation during the gradient descent. An optimal batch size would ensure the model training process is efficient while obtaining improved prediction accuracy.

Epoch

Epoch refers to the number of complete passing of the entire dataset through the network. An optimal epoch number would result in a model with good fit. Since the number of epochs directly affects the computational time, experimenting the number of epochs will be limited to three selections. The number of epochs will be experimented using 50, 100, and 150 for each model.

Table 3.2 shows the summary of the hyperparameters that will be experimented with in this study as part of the model optimization process.

Table 3.2: Hyperparameters for GRU and LSTM network

Hyperparameter	Value Ranges
Time Step	20 trading days
Activation Function	TanH and Adam
Hidden Layer	1 to 4 with step 1
Hidden Neuron	50 to 150 with step 50
Batch Size	- 32 - 64 - 128
Epoch	50 to 150 with step 50

3.1.4.2 Hyperparameter for Feedforward Neural Network

This section outlines the hyperparameters to be optimized for the feedforward neural network. A similar range of hyperparameters used for the RNN-based models will be experimented with for the feedforward neural network for network optimization. The hyperparameters included are activation function, optimizer, number of hidden layers, number of hidden neurons, batch size, and number of epochs. Table 3.3 shows the summary of hyperparameters that will be experimented in this study for the feedforward neural network.

Table 3.3: Hyperparameters for feedforward neural network

Hyperparameter	Value Ranges
Activation Function	ReLu and Adam
Hidden Layer	1 to 4 with step 1
Hidden Neuron	50 to 150 with step 50
Batch Size	- 32 - 64 - 128
Epoch	50 to 150 with step 50

3.1.5 Assess

The model predicts the closing price of the next trading day which is a numerical value. Thus, evaluation metrics for continuous value outputs will be utilized. In this study, two evaluation metrics will be utilized to evaluate the performance of the model, namely Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

Root Mean Squared Error

The RMSE is an extension of the Mean Squared Error (MSE). The RMSE is calculated during the evaluation phase to evaluate the model performance. The benefits of RMSE are that the units of RMSE are the same as the target value which provides a better comprehension of the error value. The RMSE can be calculated based on the following equation:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \quad (3.1)$$

From the equation, the y_i represents the expected value, while the $\hat{y}$ represents the predicted value, and the N represents number of samples. A point to note when using RMSE, due to the quadratic nature, larger errors will be inflated. This is not favorable for prediction models which will return high error values. A lower RMSE value is better, which indicates a higher accuracy where the predicted values are very close to the expected values.

Mean Absolute Error

Like the RMSE, the MAE has units that are same as the target value which provides a better comprehension of the error value. In contrast to RMSE, the MAE increases linearly with increasing error thus does not inflate the bigger error values. In addition, interpreting the MAE would be more straightforward as it has a linear nature. The MAE can be calculated based on the following equation:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \quad (3.2)$$

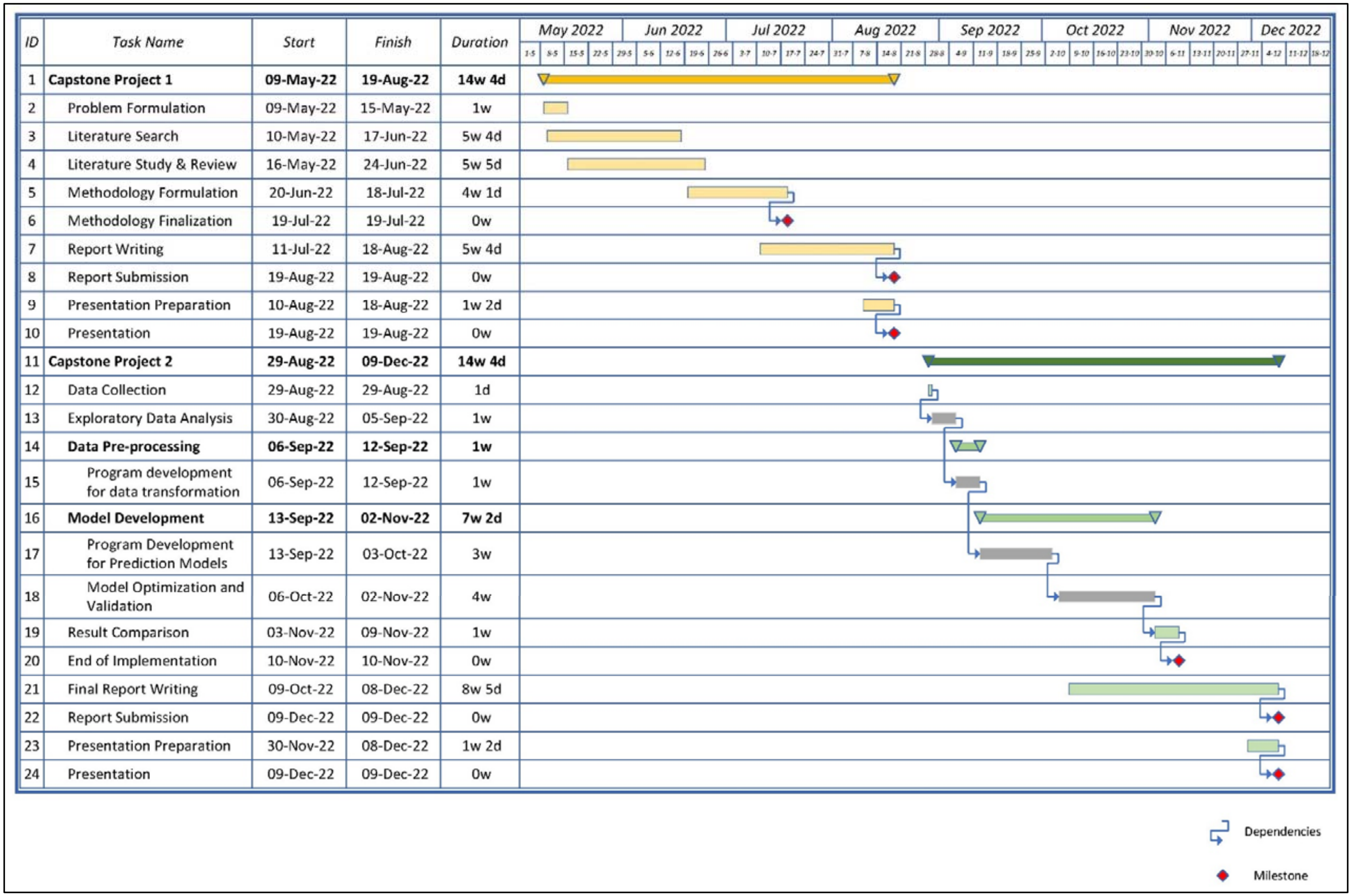
A lower MAE value is better, which indicates a higher accuracy where the predicted values are very close to the expected values.

3.2 Research Plan

Figure 3.6 shows the Gantt chart illustrating the schedule and tasks to be performed throughout the study. The study is partition into two major components namely the research phase and the implementation phase. Each major component is performed within the duration of one semester thus the entire project is spanned across two semesters.

The research phase would include deliverables of problem formulation, literature review, and methodology formulation. This phase would begin on 9th May 2022 and expected to be completed on 19th August 2022. Two milestones are targeted in this phase, the first milestone is the finalization of the proposed methodology falling on 19th July 2022. The second milestone is the completion and submission of the proposal report which falls on 19th August 2022. Following the submission, a presentation of the proposed methodology will be conducted.

The implementation phase would include deliverables of development of prediction models, discussions on findings, and write up of the final report. This phase would begin on 29th August 2022 and expected to be completed on 9th December 2022. Two milestones are targeted in this phase, the first milestone is the completion of the implementation stage which consists of the prediction models development and this falls on 10th November 2022. The second milestone is the completion and submission of the final report which falls on 9th December 202. Following the submission, a presentation of the final report will be conducted.



ID	Task Name	Start	Finish	Duration
1	**Capstone Project 1**	**09-May-22**	**19-Aug-22**	**14w 4d**
2	Problem Formulation	09-May-22	15-May-22	1w
3	Literature Search	10-May-22	17-Jun-22	5w 4d
4	Literature Study & Review	16-May-22	24-Jun-22	5w 5d
5	Methodology Formulation	20-Jun-22	18-Jul-22	4w 1d
6	Methodology Finalization	19-Jul-22	19-Jul-22	0w
7	Report Writing	11-Jul-22	18-Aug-22	5w 4d
8	Report Submission	19-Aug-22	19-Aug-22	0w
9	Presentation Preparation	10-Aug-22	18-Aug-22	1w 2d
10	Presentation	19-Aug-22	19-Aug-22	0w
11	**Capstone Project 2**	**29-Aug-22**	**09-Dec-22**	**14w 4d**
12	Data Collection	29-Aug-22	29-Aug-22	1d
13	Exploratory Data Analysis	30-Aug-22	05-Sep-22	1w
14	**Data Pre-processing**	**06-Sep-22**	**12-Sep-22**	**1w**
15	Program development for data transformation	06-Sep-22	12-Sep-22	1w
16	**Model Development**	**13-Sep-22**	**02-Nov-22**	**7w 2d**
17	Program Development for Prediction Models	13-Sep-22	03-Oct-22	3w
18	Model Optimization and Validation	06-Oct-22	02-Nov-22	4w
19	Result Comparison	03-Nov-22	09-Nov-22	1w
20	End of Implementation	10-Nov-22	10-Nov-22	0w
21	Final Report Writing	09-Oct-22	08-Dec-22	8w 5d
22	Report Submission	09-Dec-22	09-Dec-22	0w
23	Presentation Preparation	30-Nov-22	08-Dec-22	1w 2d
24	Presentation	09-Dec-22	09-Dec-22	0w

Figure 3.6: Gantt chart for the research project

CHAPTER 4

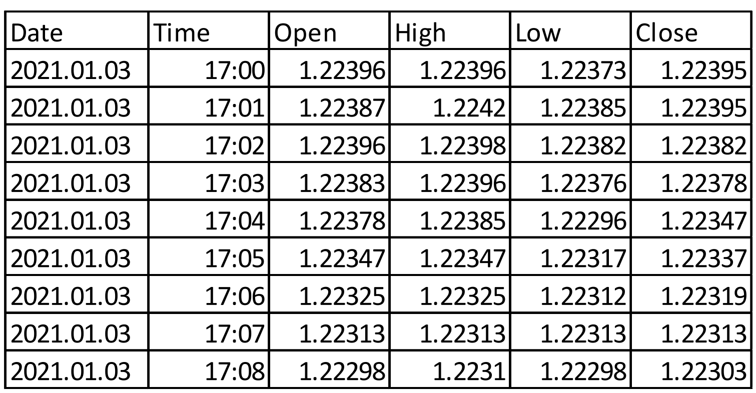
IMPLEMENTATION

4.1 Exploratory Data Analysis

The initial data exploratory task provides a glimpse into the dataset to generate useful insights that may assist the analysis process. In addition, a comprehensive understanding of the dataset is essential to determine the suitable and necessary data pre-processing steps to be applied.

4.1.1 Dataset

The currency pair used in this study is limited to only one pair, specifically the EUR/USD currency pair. As mentioned, the EUR/USD pair exhibits several characteristics which are favorable and likely result in better prediction accuracies. The historical price data is obtained from the year 2015 to year 2021, which contains seven years of complete data. In addition, the data exist in the 1-minute timeframe format, where the market prices are recorded at every one-minute interval. The source of the data can be retrieved from the following link: http://www.histdata.com/download-free-forex-data.



Date	Time	Open	High	Low	Close
2021.01.03	17:00	1.22396	1.22396	1.22373	1.22395
2021.01.03	17:01	1.22387	1.2242	1.22385	1.22395
2021.01.03	17:02	1.22396	1.22398	1.22382	1.22382
2021.01.03	17:03	1.22383	1.22396	1.22376	1.22378
2021.01.03	17:04	1.22378	1.22385	1.22296	1.22347
2021.01.03	17:05	1.22347	1.22347	1.22317	1.22337
2021.01.03	17:06	1.22325	1.22325	1.22312	1.22319
2021.01.03	17:07	1.22313	1.22313	1.22313	1.22313
2021.01.03	17:08	1.22298	1.2231	1.22298	1.22303

Figure 4.1: Dataset sample view

Figure 4.1 shows a sample from the dataset which contains six features. As seen from the figure, the market prices are recorded at every minute interval. Therefore, the total combined number of observations from the seven years of historical prices is 2,603,498 observations. Table 4.1 shows the data quantity details in each year of the dataset.

Table 4.1: Dataset observation quantity details

Year	Number of Trading Days Recorded	Quantity of Observations
2015	312	372,210
2016	312	372,679
2017	310	371,635
2018	313	372,607
2019	313	372,530
2020	314	372,335
2021	312	369,502

Based on Table 4.1, the Forex market on average in a year has approximately 313 trading days. The number of trading days is more than the usual working days in a year due to the global presence of the Forex market. Where countries are situated in different time zones causing the starting and ending of a particular trading session to be different. Thus, resulting in the additional trading days as compared to a regular stock exchange market which has approximately 252 trading days. Although some years may have the same or a greater number of trading days, the quantity of observations recorded is different. The variation is due to the alignment of holidays with weekends causing earlier and longer market closure. Thus, each year would have a slightly different number of observations.

Table 4.2 shows the data dictionary for the dataset used. It has six features, of which the date exists as an ordinal data type, while the time, open, high, low, and close exist as ratio values. The features to be used as predictors will be limited to the open, high, low, and close prices. The date and time features will be dropped from the analysis as it merely represents the index for the observations.

Table 4.2: Data dictionary

Feature Name	Description	Data Type
Date	Date of price recorded	Ordinal
Time	Time of price recorded	Ratio
Open	Opening price	Ratio
High	Highest price reached in 1-minute interval	Ratio
Low	Lowest price reached in 1-minute interval	Ratio
Close	Closing price	Ratio

	Open	High	Low	Close
count	2.603498e+06	2.603498e+06	2.603498e+06	2.603498e+06
mean	1.138713e+00	1.138794e+00	1.138631e+00	1.138712e+00
std	4.532009e-02	4.531588e-02	4.532393e-02	4.532008e-02
min	1.034430e+00	1.034560e+00	1.034060e+00	1.034350e+00
25%	1.107190e+00	1.107260e+00	1.107120e+00	1.107190e+00
50%	1.131240e+00	1.131330e+00	1.131160e+00	1.131240e+00
75%	1.175740e+00	1.175810e+00	1.175660e+00	1.175740e+00
max	1.255400e+00	1.255500e+00	1.255270e+00	1.255410e+00

Figure 4.2: Full dataset descriptive statistics

Figure 4.2 shows the descriptive statistics of the full dataset. Each feature contains 2,603,498 observations. It is observed that the four features have an almost identical dispersion and range of values. This can be explained by the similar values observed in the mean, standard deviations, minimum, and maximum values generated from each feature.

Feature scaling is an essential data pre-processing step when utilizing the neural network algorithm. It is typically performed when the value ranges among the features are different. It transforms the features into a same scale which facilitates the model training efficiency. In addition, it ensures the fitted model is not biased towards the feature with the bigger magnitude. However, due to the similar value ranges among the features in this dataset, feature scaling will not be performed in this study.

Figure 4.3: Candlestick chart for EUR/USD year 2015 to year 2021

Figure 4.3 shows the full dataset of the EUR/USD prices plotted in the candlestick format. It is observed that from year 2015 to end of year 2016, the EUR/USD prices have remained relatively stable within the range from about 1.05 to about 1.15. However, starting from the year 2017, the EUR/USD experiences an uptrend until the first quarter of year 2018. Where the prices observed a continuous uptrend from about 1.04 to about 1.25. The rise was attributed by three main reasons (Kottasová, 2017). Firstly, strong economic growth is observed in the European Union (EU), causing the Euro dollar to strengthen. Secondly, the weakening of the dollar and pound due to slower economic growth and geopolitical pressures. And lastly, the anticipated election outcome in France which is won by centrist leader Emmanuel Macron.

After the peak from quarter one 2018, the EUR/USD experiences a continuous downtrend until approximately first quarter of 2020. Where the prices fell from the peak of about 1.25 towards a low of 1.07. The downturn was attributed mainly to geopolitical tension. Where the United States (US) and China trade war has impacted the overall economy of the EU, causing the Euro dollar to slip. The US urges EU to impose tariffs on goods exporting to China. However, due to the strong trading relations between EU and China, putting EU in a difficult position to balance the economy and political relationships. Which resulted in political and economic uncertainty within the EU.

The EUR/USD price begins to rise again from the first quarter of the year 2020 to the end of the year 2020. It is observed that the prices rose from about 1.07 towards 1.23. The rise is mainly attributed by the weakening of the US dollar, due to the tension from the trade war and the emergence of Covid-19 which significantly impacted and slowed down the economy in US (Clayton, 2021). In addition, the political uncertainty in the US with the upcoming election in 2020 causes further downturn in the US dollar. Moreover, the decisions from the Federal Reserve to maintain lower interest rates for US in year 2020 causes an unfavorable hold of the US dollar. Therefore, due to the mentioned events which put the US at a disadvantage, the EUR/USD prices rose.

However, the rise is short lived as the EU was also greatly impacted by the surge of Covid-19 cases causing economic slowdown. From the year 2021 onwards, the EUR/USD experiences a continuous downtrend from the previous peak of 1.23. This is mainly attributed to the increase in political stability and recovery of the economy in the US. In addition, there is an expectation of shifting of the monetary policy favoring a hawkish approach in the US, while the EU maintains a dovish approach. This has caused the strengthening of the US dollar causing the EUR/USD prices to drop.

4.1.2 Missing Data

The dataset was checked for missing values using the isnull() function from the pandas library. The results returned false for every year and every feature of the dataset. Thus, the dataset does not contain any missing value.

4.2 Data Transformation

This section documents the data transformation procedure performed in this study to prepare the dataset in a suitable format aligning with the methodology in this study. Several procedures are performed which ultimately present the dataset in a sliding window format to facilitate the closing price prediction of EUR/USD in the next trading day.

4.2.1 Dataset Split

The dataset is split into three portions namely training set, validation set, and testing set. The training set contains five years of data from year 2015 to year 2019. The validation set and the testing set each contain one year of data which derives from the year 2020 and year 2021 respectively. Since the data from the source is provided in comma separated values file in individual years. The three subsets of data are formed by simply concatenating the files based on required years. Table 4.3 tabulates the number of observations identified in each subset after the data split.

Table 4.3: Number of observations in each data subsets

Data subsets	Year	Number of Observations
Training set	2015, 2016, 2017, 2018, 2019	1,861,661
Validation set	2020	372,335
Testing set	2021	369,502

4.2.2 Data Segmentation

This study performs EUR/USD price prediction based on historical prices represented in several timeframes. There are seven timeframes to be used in this study namely 30-minute, 1-hour, 2-hour, 4-hour, 6-hour, 8-hour, and 24-hour. The data segmentation procedure divides the data into batches based on the specified timeframe to prepare the dataset to be used for further processing. Since the original dataset exists in the 1-minute timeframe, an assumption is made to divide the dataset into batches using a fixed number of observations based on the timeframe of interest in this study. Table 4.4 shows the number of generated batches for each timeframe based on the number of samples in each batch. While Figure 4.4 shows an example of two batches of data generated using the 24-hour timeframe.

Table 4.4: Data batches generated for each timeframe

Timeframe	**Samples in Each Batch**	**Total Number of Batches**		
		Training	**Validation**	**Testing**
M30	30	62,056	12,412	12,317
H1	60	31,028	6,206	6,159
H2	120	15,514	3,103	3,080
H4	240	7,757	1,552	1,540
H6	360	5,172	1,035	1,027
H8	480	3,879	776	770
H24	1440	1,293	259	257

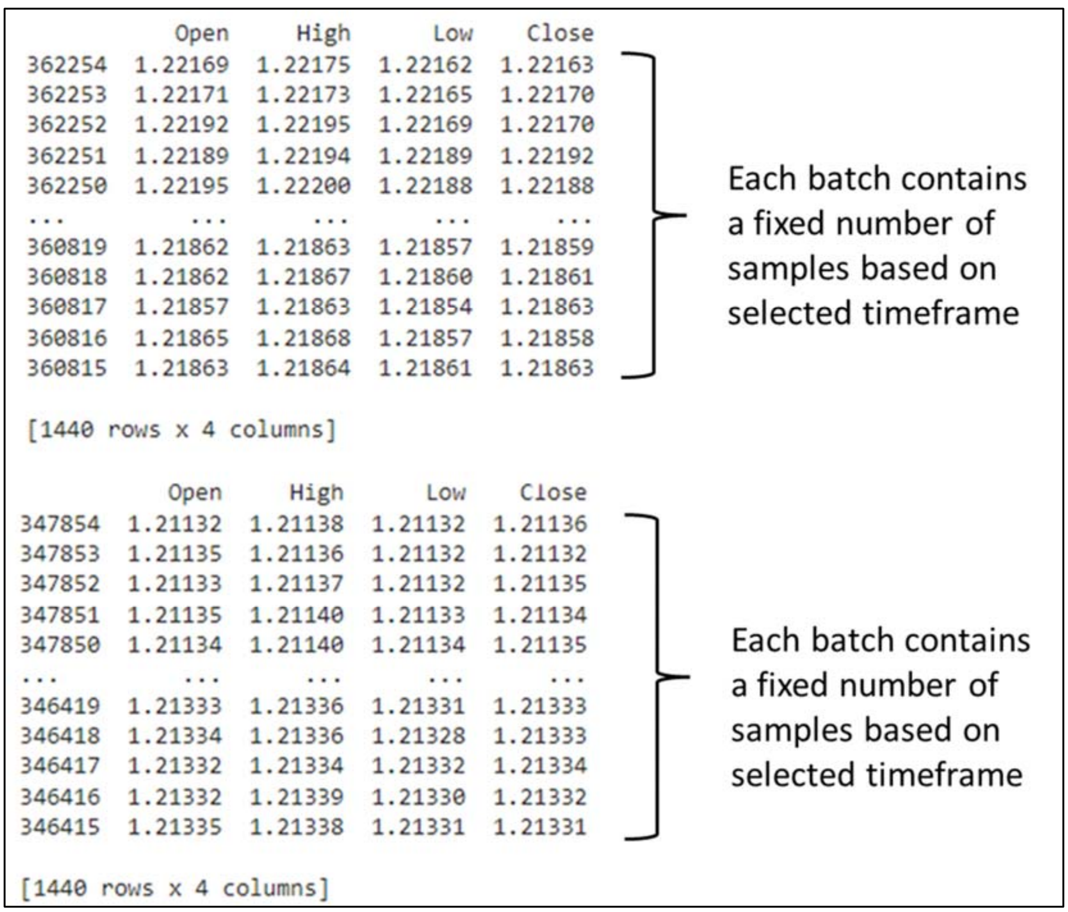


Figure 4.4: Example segmented data for H24 timeframe

4.2.3 Timeframe Conversion

Data segmented in the previous section are still in the 1-minute timeframe. A conversion is required to transform the dataset into a specific timeframe representation. Where the samples in each batch will be represented by a single observation. The detailed procedure of the conversion is outlined in Chapter 3. Table 4.5 shows the total number of observations generated for each timeframe. While Figure 4.5 shows an example of the converted dataset from the original 1-minute timeframe into the 24-hour timeframe.

Table 4.5: Observations generated for each timeframe

Timeframe	Total Number of Observations		
	Training	Validation	Testing
M30	62,056	12,412	12,317
H1	31,028	6,206	6,159
H2	15,514	3,103	3,080
H4	7,757	1,552	1,540
H6	5,172	1,035	1,027
H8	3,879	776	770
H24	1,293	259	257

	Open	High	Low	Close
0	1.12099	1.12391	1.11974	1.11985
1	1.11989	1.12207	1.11712	1.11759
2	1.11759	1.11883	1.10960	1.10963
3	1.10963	1.11088	1.10794	1.10829
4	1.10830	1.10934	1.10690	1.10883
...	...	...	...	...
1288	1.18057	1.18586	1.17541	1.18211
1289	1.18218	1.19588	1.18021	1.19384
1290	1.19350	1.19687	1.18841	1.19128
1291	1.19148	1.20155	1.18664	1.20104
1292	1.20117	1.21072	1.20074	1.20962

1293 rows × 4 columns

Each row represents an observation in the 24-hour timeframe

Figure 4.5: Example of converted data for H24 timeframe

4.2.4 Sliding Window Representation

The time series dataset can be converted into a supervised learning problem. The dataset will be represented using a sliding window method where a selected number of previous inputs will be used as the independent variable while a single output is selected for used as the dependent variable. The timestep used in this study will be fixed at 20 trading days. Therefore, due to the various timeframes utilized, each timeframe will have a different number of timestep where the sum of the timesteps will be equivalent to 20 trading days. Table 4.6 shows the number of timesteps to be used for each timeframe during model development.

Table 4.6: Timesteps for each timeframe

Timeframe	Timestep
M30	960
H1	480
H2	240
H4	120
H6	80
H8	60
H24	20

Figure 4.6 illustrates the sliding window representation of the data using the 24-hour and 8-hour timeframes as examples. The main objective of this study is to predict the closing price of the next trading day. Therefore, to represent the 24-hour timeframe data into a sliding window method, the closing price of the first observation is taken as the target label. While the consecutive 20 prior observations will be taken as the predictors. Illustrated in Figure 4.7, shows the first two batches from the 24-hour timeframe data represented in the sliding window method. The procedure will be repeated for the entire chain of the 24-hour timeframe dataset.

However, for other timeframes, an additional note is to be taken when representing the dataset in the sliding window method. Due to the prediction target used is to be taken as the closing price of the next trading day. The procedure for identifying the target label for dataset of timeframes other than the H24 timeframes will be slightly different. As shown in Figure 4.6, using H8 timeframe as an example. The target label will be taken from the closing price of the next trading day of H24 timeframe. While the sequence of observations in the next window will have a step size equivalent to one trading day which is three observations for the example using H8 timeframe. Illustrated in Figure 4.8, shows the first batch from the 8-hour timeframe data represented in the sliding window method. The procedure will be repeated for the entire chain and all other timeframes mentioned in this study.

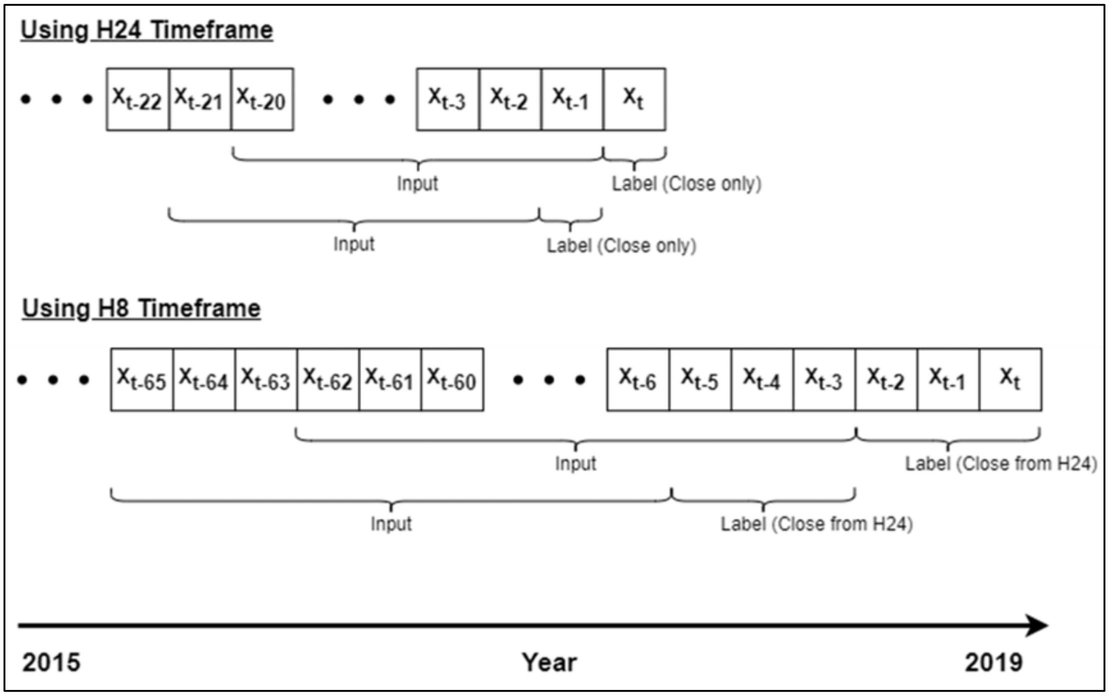
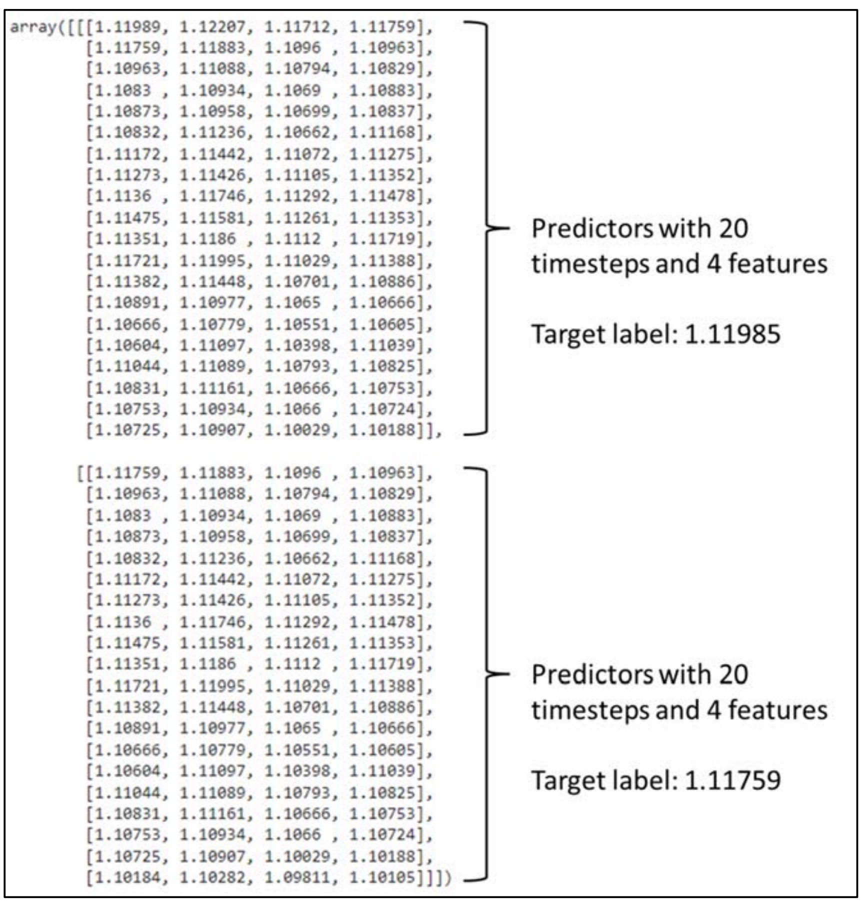


Figure 4.6: Sliding window representation illustration



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        [1.10753, 1.10934, 1.1066 , 1.10724],
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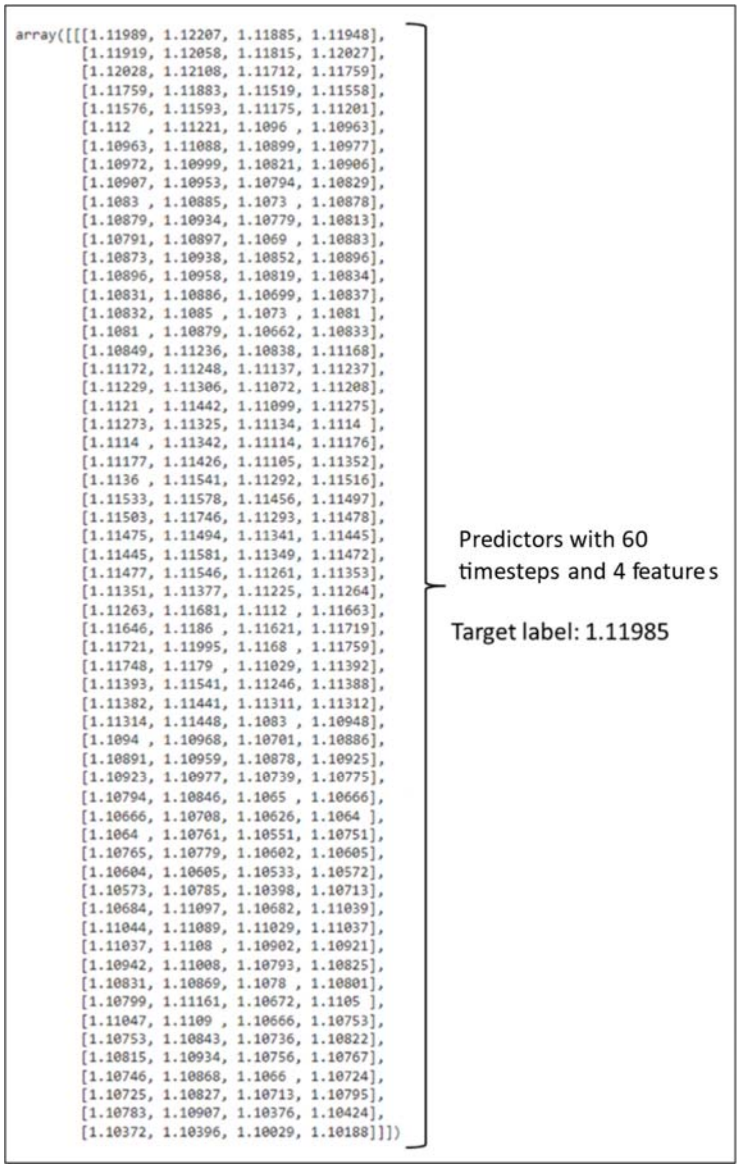
Figure 4.7: Example H24 timeframe sliding window representation of first and second batch



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        [1.10372, 1.10396, 1.10029, 1.10188]]])
```


Figure 4.8: Example H8 timeframe sliding window representation of first batch

After the transformation of the dataset in the sliding window method. The dataset is ready to be used by neural network algorithms for price predictions. The total number of data batches generated from the data transformation into the sliding window method is tabulated in Table 4.7 for the different data subsets.

Table 4.7: Number of data batches in sliding window method

Dataset	**Total number of batches**
Training	1272
Validation	238
Testing	236

4.3 Prediction Model Development

This section documents the development of prediction models. The development process can be split into two phases. The first phase involves the training and identifying of the best performing model which uses the RNN-based algorithms namely GRU and LSTM. While the second phase involves the concatenation of the predicted outputs from the first phase using a feedforward neural network to produce the final prediction outcome.

4.3.1 Phase 1 - GRU and LSTM

The GRU and LSTM algorithms were chosen as the prediction algorithms due to the use of sequential data and their proven applicability in time series forecasting. In addition, the performance between the models developed using GRU and LSTM can be compared. The models will receive a timestep of 20 trading days to predict the closing price of the next trading day. Therefore, in phase 1, each available timeframe will be used to generate a set of predicted outcomes for the next trading day as illustrated in Figure 4.9.

The predictions generated by the 24-hour timeframe dataset from each algorithm will also function as the benchmark for comparison. Which simulates the price predictions of using data from a single source. Using the 24-hour timeframe dataset for price prediction is widely used by other researchers. Therefore, this study utilizes it to compare the model performance between using multi-timeframe data and single sourced data.

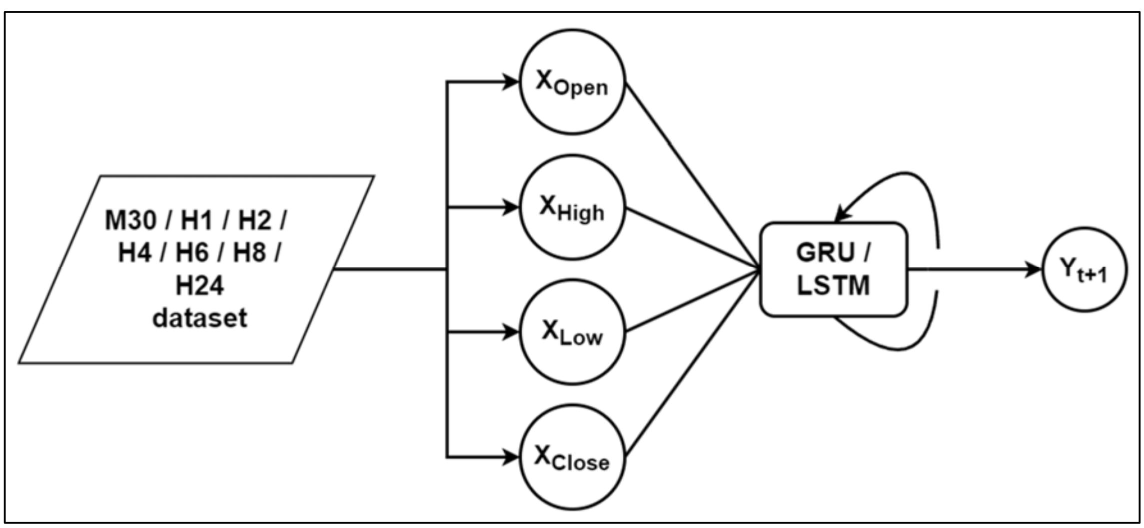

Figure 4.9: RNN-based model prediction

In Figure 4.10 shows an example of the first five predictions made by the best performing GRU models for every timeframe along with the last column showing the actual value. Following in Figure 4.11 is the sample predictions made using LSTM models. Based on the figures, the GRU models seemed to perform better than the LSTM models. Based on overall observation of the predicted values, the GRU models seem to have a smaller deviation of the predicted values from the actual values as compared to LSTM models.

	M30	H1	H2	H4	H6	H8	H24	Actual
0	1.116308	1.120412	1.120557	1.120145	1.118438	1.118039	1.117535	1.11985
1	1.111919	1.117010	1.116794	1.115613	1.113680	1.113278	1.114114	1.11759
2	1.106673	1.110617	1.110988	1.110143	1.108831	1.108985	1.109892	1.10963
3	1.105942	1.109235	1.109748	1.109051	1.107954	1.108239	1.109290	1.10829
4	1.106139	1.109684	1.110179	1.109497	1.108510	1.108676	1.110084	1.10883

Figure 4.10: First five prediction outputs for GRU models

	M30	H1	H2	H4	H6	H8	H24	Actual
0	1.111810	1.112943	1.116154	1.116260	1.112741	1.118323	1.117368	1.11985
1	1.109004	1.110106	1.113350	1.111571	1.108469	1.115322	1.115898	1.11759
2	1.108979	1.109391	1.112303	1.108754	1.106429	1.113754	1.114548	1.10963
3	1.108721	1.108955	1.112595	1.108267	1.106364	1.113931	1.114802	1.10829
4	1.109591	1.109490	1.113396	1.108638	1.107073	1.114769	1.115507	1.10883

Figure 4.11: First five prediction outputs for LSTM models

Hyperparameter Tuning

Based on the iterating hyperparameters mentioned in Chapter 3, by using the GRU and LSTM algorithms, a total number of 15,120 iterations of model training is performed using various hyperparameter combinations. The best performing model will be chosen based on the lowest validation loss at the end of each model training phase. Table 4.8 shows the hyperparameter combination for the best performing model for each timeframe using the GRU algorithm while tabulated in Table 4.9 is for using the LSTM algorithm.

Table 4.8: Best performing model in phase 1 using GRU algorithm

Timeframe	Hidden Units in each layer				Epoch	Batch Size	Loss ($x10^{-5}$)	Validation Loss ($x10^{-5}$)
	Layer 1	Layer 2	Layer 3	Layer 4				
M30	50	150	50	50	150	32	3.60468	1.78436
H1	100	50	50	100	150	32	3.34713	**0.63531**
H2	150	50	50	50	150	32	3.34537	0.78511
H4	100	-	-	-	150	32	**1.39282**	0.85315
H6	150	50	50	-	150	32	2.47169	1.05491
H8	50	50	50	-	150	32	4.03467	1.21087
H24	50	100	150	50	150	32	6.81610	1.09180

Table 4.9: Best performing model in phase 1 using LSTM algorithm

Timeframe	Hidden Units in each layer				Epoch	Batch Size	Loss ($x10^{-5}$)	Validation Loss ($x10^{-5}$)
	Layer 1	Layer 2	Layer 3	Layer 4				
M30	150	150	50	50	50	32	52.21299	52.10558
H1	50	50	150	50	150	128	45.87160	40.11743
H2	100	150	50	50	150	32	23.17782	4.97807
H4	50	100	50	50	150	32	**3.85486**	**2.77719**
H6	150	150	50	50	150	32	11.51744	3.95538
H8	50	50	100	50	150	32	8.36327	5.03497
H24	50	100	150	150	150	32	13.67744	5.30009

Based on Table 4.8 and Table 4.9, the overall training loss and validation loss observed in the LSTM models are higher than the GRU models. Which indicates that the GRU models overall have a better prediction performance as compared to the LSTM models. In addition, the model training losses observed among the GRU models are more consistent and confined within a smaller range of values. Which for training loss, the range is between $1.39282x10^{-5}$ to $6.81710x10^{-5}$ and the range for validation loss is between $0.63531x10^{-5}$ to $1.78436x10^{-5}$. While for the LSTM models, the model training losses are observed to have higher range and dispersion. Which for training loss, the range is between $3.85486x10^{-5}$ to $52.21299x10^{-5}$ and the range for validation loss is between $2.77719x10^{-5}$ to $52.10558x10^{-5}$.

The higher training and validation loss can be due to the internal architecture of the LSTM algorithm being more complex than the GRU algorithm, resulting in a higher number of trainable parameters which causes greater volatility during gradient descent. In addition, a higher utilization of computational resources is observed when training the LSTM models as compared to the GRU models in this study. Which aligned with the fact that LSTM algorithms are more complex than the GRU algorithms, where more computation operations are to be completed when using a LSTM model as compared to a GRU model.

In addition, it is observed that the LSTM models in general are using more hidden units and hidden layers to achieve optimal performance when comparing the same timeframes with GRU models. Which indicates that LSTM models have higher model complexity than the GRU models. However, the higher model complexity did not result in better performance.

With the completion of development of the GRU and LSTM models, the prediction outputs from the best performing models will be utilized in the next phase. Which involves the concatenation of predicted outputs.

4.3.2 Phase 2 – Feedforward Neural Network

Based on the best performing GRU and LSTM models, the predicted outputs from each algorithm in different timeframes will be combined to be used as predictors based on the specified combination of timeframes as tabulated in Table 3.1. Thus, a total of eight models will be developed by combining the predicted outputs from the GRU and LSTM models. In addition, a model using the 24-hour timeframe from each algorithm will be used as benchmark for comparison. The predicted outputs from the GRU and LSTM models will be combined using a feedforward artificial neural network. As illustrated in Figure 4.12, shows an example of combining the predicted outputs from the 1-hour and 4-hour timeframe of the GRU models in a feedforward neural network.

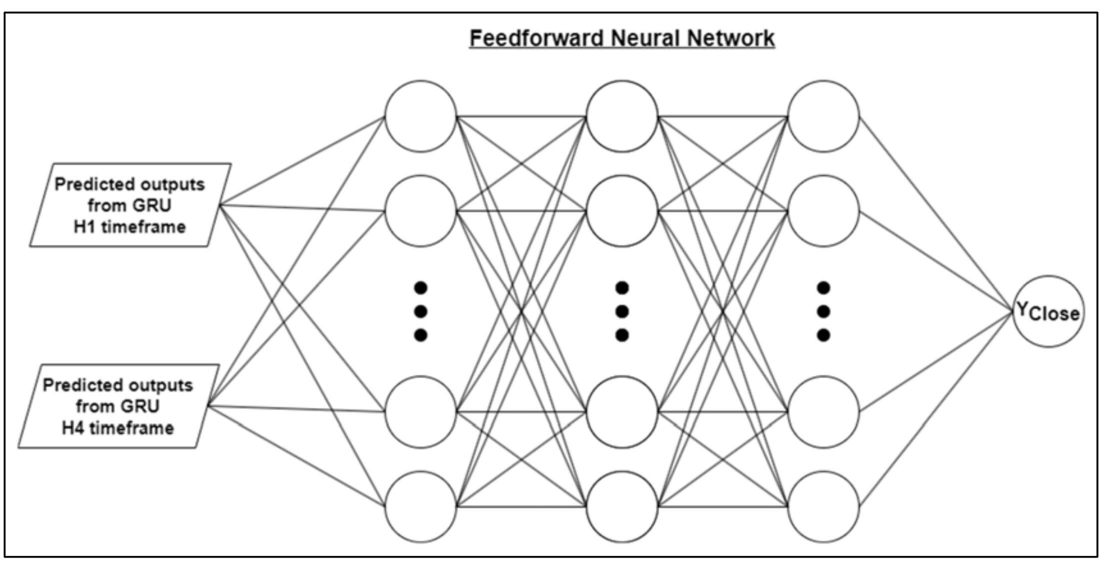

Figure 4.12: Feedforward neural network example using 1-hour and 4-hour timeframe

Figure 4.13 shows an example of the first five predictions made by combining specific timeframes using the outputs from the best performing GRU models along with the last column showing the actual values. Following in Figure 4.14 are the sample predictions made using outputs from the LSTM models.

	M30+H4+H24	M30+H2+H8	H1+H6	H1+H4	Actual
0	1.132527	1.132799	1.132407	1.132480	1.13247
1	1.132594	1.133055	1.133182	1.133127	1.13479
2	1.131866	1.131964	1.131574	1.131800	1.13132
3	1.132418	1.132635	1.132413	1.132610	1.13270
4	1.132021	1.132669	1.132207	1.132346	1.13085

Figure 4.13: First five prediction outputs for combined GRU models

	M30+H4+H24	M30+H2+H8	H1+H6	H1+H4	Actual
0	1.132653	1.132936	1.132438	1.133119	1.13247
1	1.131873	1.132448	1.131696	1.132262	1.13479
2	1.132345	1.132600	1.132099	1.133017	1.13132
3	1.132272	1.132442	1.132132	1.132874	1.13270
4	1.132341	1.132111	1.132011	1.133130	1.13085

Figure 4.14: First five prediction outputs for combined LSTM models

Hyperparameter Tuning

Hyperparameter optimization for the feedforward neural network will be performed based on the selected hyperparameters as shown in Table 3.3. A total number of 8,640 iterations of model training using various combinations of hyperparameters were performed for the mentioned combination of timeframes. The best performing model will be chosen based on the lowest validation loss at the end of each model training. Table 4.10 shows the hyperparameter combination for the best performing dense model for each timeframe combination using the prior outputs from GRU model while tabulated in Table 4.11 uses prior outputs from LSTM model.

Table 4.10: Best performing model in phase 2 using prior GRU outputs

Timeframe	Hidden Units in each layer				Epoch	Batch Size	Loss ($x10^{-5}$)	Validation Loss ($x10^{-5}$)
	Layer 1	Layer 2	Layer 3	Layer 4				
H1 + H4	50	150	150	100	100	32	0.93614	**0.61290**
H1 + H6	150	150	150	-	150	32	1.84273	0.62121
M30 + H2 + H8	50	50	-	-	150	32	**0.88243**	0.92719
M30 + H4 + H24	50	-	-	-	150	32	1.00574	0.84943

Table 4.11: Best performing model in phase 2 using prior LSTM outputs

Timeframe	Hidden Units in each layer				Epoch	Batch Size	Loss ($x10^{-5}$)	Validation Loss ($x10^{-5}$)
	Layer 1	Layer 2	Layer 3	Layer 4				
H1 + H4	50	150	150	-	150	64	**2.70240**	**2.15647**
H1 + H6	50	150	150	-	150	64	3.06237	2.67925
M30 + H2 + H8	100	150	100	50	150	32	6.20408	3.97186
M30 + H4 + H24	50	50	100	100	150	64	2.52928	2.27324

Based on Table 4.10 and Table 4.11, the overall training loss and validation loss observed in the models using prior LSTM outputs are higher than the models using prior GRU outputs. This can be due to the better prediction performance from the GRU models in phase 1. Which leads to better performance models in phase 2.

Based on Table 4.10, the model with the lowest validation loss is observed when using a combination of GRU outputs from the 1-hour and 4-hour timeframe. While based on Table 4.11, the same result is observed when using the LSTM outputs. This may indicate that the combination usage of the 1-hour and 4-hour timeframe is potentially optimal provided that the timestep of 20 trading days is used. Which aligns with the fact that the 1-hour and 4-hour timeframe is one of the most used timeframes for market analysis among the traders. However, the results are likely to differ if a different timestep is used in the study.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Model Evaluation

The best performing models identified from the implementation stage will be evaluated using the RMSE and MAE metrics. The metrics are computed by passing the models through the predefined testing dataset. Using the computed evaluation metrics, the models are compared with the baseline to determine the feasibility of the proposed method in this study. Table 5.1 shows the evaluation metrics computed using the GRU-based models while the evaluation metrics for LSTM-based models are tabulated in Table 5.2.

Table 5.1: Evaluation metrics of GRU-based models

Model	Root Mean Squared Error		Mean Absolute Error	
	Training Set	Testing Set	Training Set	Testing Set
Baseline (H24)	0.0034256	0.0022927	0.0026017	0.0017871
H1 + H4	**0.0023737**	0.0019269	**0.0016600**	0.0014619
H1 + H6	0.0024056	**0.0019182**	0.0016749	**0.0014392**
M30 + H2 + H8	0.0030018	0.0023715	0.0021614	0.0018446
M30 + H4 + H24	0.0029596	0.0021395	0.0021588	0.0016516

Table 5.2: Evaluation metrics of LSTM-based models

Model	Root Mean Squared Error		Mean Absolute Error	
	Training Set	Testing Set	Training Set	Testing Set
Baseline (H24)	0.0076351	0.0049065	0.0060145	0.0039551
H1 + H4	**0.0049057**	**0.0036188**	**0.0036833**	**0.0027898**
H1 + H6	0.0053790	0.0037245	0.0039820	0.0028455
M30 + H2 + H8	0.0064191	0.0042493	0.0048494	0.0033935
M30 + H4 + H24	0.0049467	0.0036621	0.0036931	0.0028353

Based on Table 5.1 and 5.2, it is observed that the overall values of RMSE and MAE of the testing set are higher in the LSTM-based models as compared to the GRU-based models. Which indicates that the GRU-based models are performing better than the LSTM-based models. In addition, it is observed that the RMSE values are greater than the MAE values for all models. This is expected due to the quadratic nature in RMSE as compared to the linear nature in MAE.

The best performing GRU-based model is identified when using the 1-hour and 6-hour timeframe data as inputs. Which received the lowest RMSE and MAE value with the testing set of 0.0019182 and 0.0014392 respectively. A slightly different result is observed with the LSTM-based model, where the best performing LSTM-based model is identified when using the 1-hour and 4-hour timeframe data as inputs. Which received the lowest RMSE and MAE value with the testing set of 0.0036188 and 0.0027898 respectively. However, when comparing between the algorithms, the GRU-based model still performs better with lower errors.

It is observed that in the GRU-based models, the models using three timeframe inputs yielded a higher RMSE and MAE value as compared to models using two timeframe inputs. This may be because GRU performs better when using a smaller dataset as compared to LSTM which can maintain performance even with a larger dataset (Yang et al., 2020). Both LSTM-based and GRU-based models observed the least performance when using the three timeframe inputs of 30-minute, 2-hour, and 8-hour timeframe combination. When excluding the least performance model, the LSTM-based model using three timeframe inputs yielded a relatively similar performance as the two timeframe inputs. Which potentially indicates that the LSTM-based models can perform better than GRU-based models when utilizing a larger dataset.

When comparing model performances with the baseline, it is observed that three out of four GRU-based models outperformed the baseline while every LSTM-based model outperformed the baseline. This indicates that the proposed method in this study is practical, and the idea of extracting features from the different levels of data granularity existing in different timeframes can contribute to the price prediction performance.

5.2 Model Prediction Plots

This section provides the visualizations of the predicted closing prices versus the actual closing prices from the developed models. The line graphs presented are shown in a combined format as a means to compare the performance between the LSTM-based and GRU-based models. Graphs for individual models showing the predicted prices versus the actual prices or baseline are attached under Appendix C, which can show a clearer picture of the individual model performance. Figure 5.1 shows the predicted prices from the baseline model which uses only a single set of data input as predictors. While Figure 5.2 to Figure 5.5 shows the predicted prices of models using two or three sets of timeframe data inputs as predictors.

5.2.1 Baseline Model

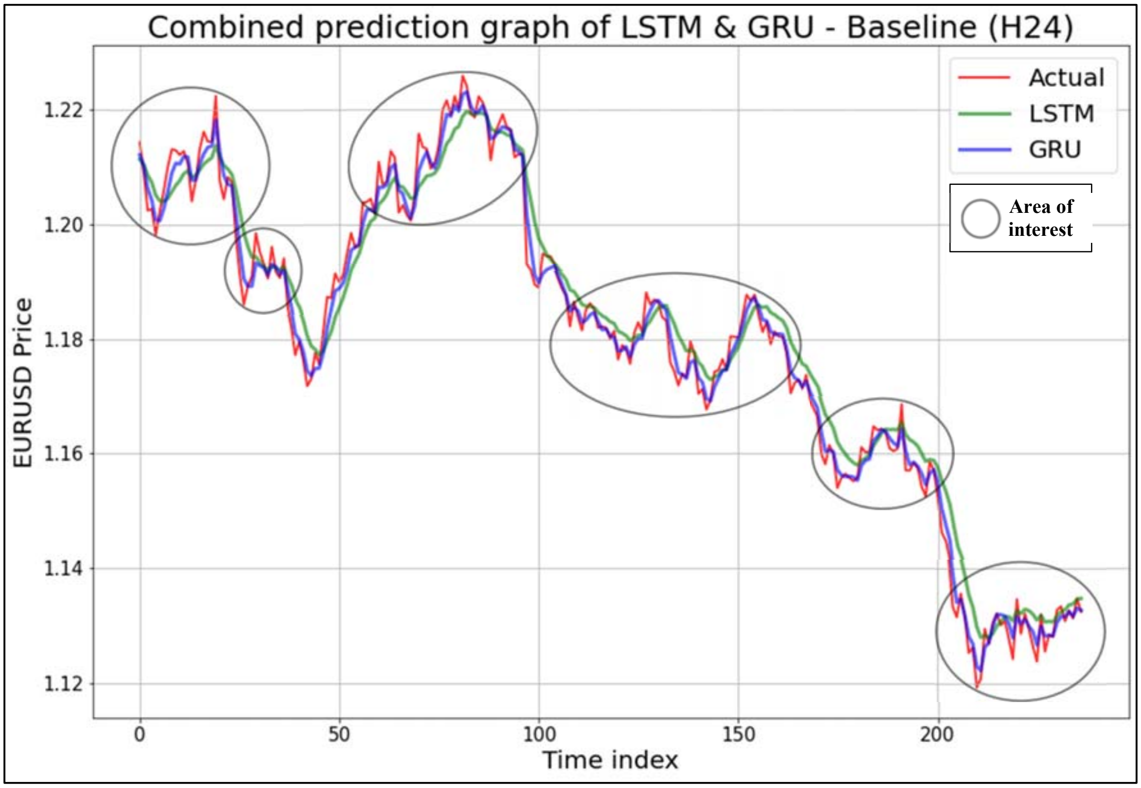

Figure 5.1: Baseline model predictions

Based on Figure 5.1, it is observed that using a single dataset input which in this case the 24-hour timeframe, resulted in very poor prediction performance. Price predictions from both the LSTM and GRU models highly deviated from the actual prices, with the LSTM model evidently performing worse than the GRU model.

It is observed that the LSTM model performs very poorly when prices are highly volatile. Indicated in the figure by the black circles, shows several zones where the predicted prices from the LSTM model resembling a smoothed line instead of an oscillating line following the market price fluctuations, which indicates poor performance from the model to follow market volatility. In addition, the predicted prices of the LSTM model are further away from the actual prices when compared with the GRU model.

The performance of the GRU model is just slightly better than the LSTM model. It was able to predict some of the price fluctuations in high volatility markets. However, the predicted prices are still far away from the actual prices.

5.2.2 Models with Two Dataset Input

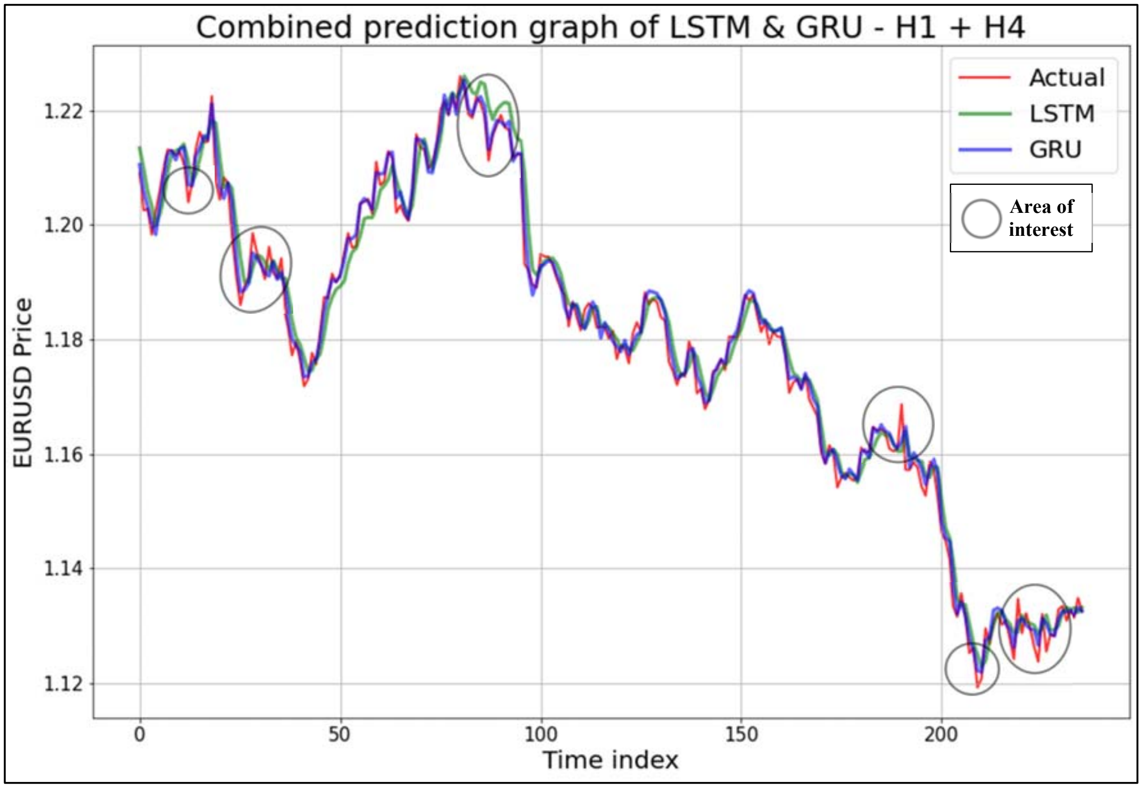

Figure 5.2: Model predictions using H1 and H4 inputs

Based on Figure 5.2, it is observed that the prediction performance from both the LSTM-based and GRU-based models are significantly better than the baseline plot when two timeframe dataset is used as inputs. However, the GRU-based model still performs better than the LSTM-based model. This is due to the fact that the predicted prices from the GRU-based model are much closer to the actual prices observed from the plot.

In addition, the models were significantly better at predicting prices that are oscillating when compared to the baseline models. However, when prices suddenly surged or dropped followed by a quick rebound, the models were not able to track the movement and predicted a shorter peak or trough. As indicated on the figure by the black circles, it shows that the predicted prices are not able to follow the sudden movements of the market, resulting in poorer performance when such market conditions occurred. However, the predicted prices from both models were able to follow the general trend of the market prices.

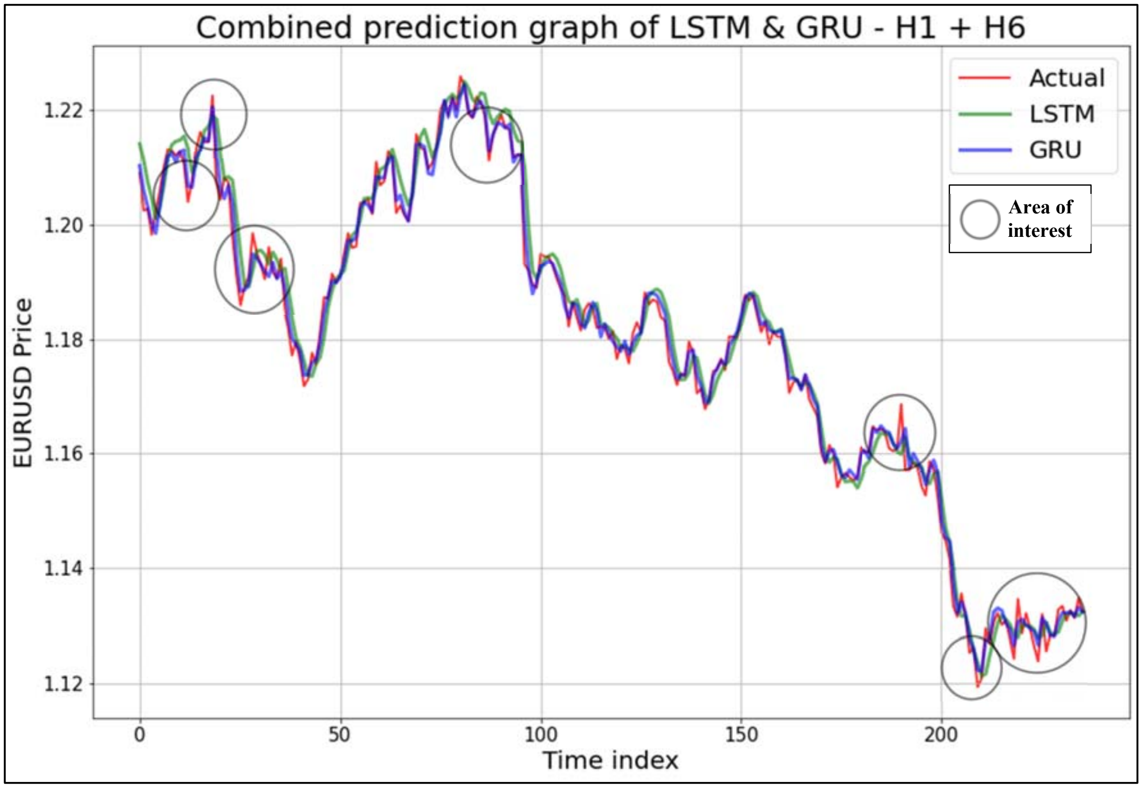

Figure 5.3: Model predictions using H1 and H6 inputs

Based on Figure 5.3, the prediction performance for models using the 1-hour and 6-hour inputs exhibits a similar observation as models using the 1-hour and 4-hour inputs. Where during high volatile and price reversal market conditions, the models are unable to follow the sudden market movements, and this results in poor prediction performance. In addition, the same result is observed where the GRU-based model performs better than the LSTM-based model. Moreover, both models were able to predict prices that follow the general market trend.

5.2.3 Models with Three Dataset Input

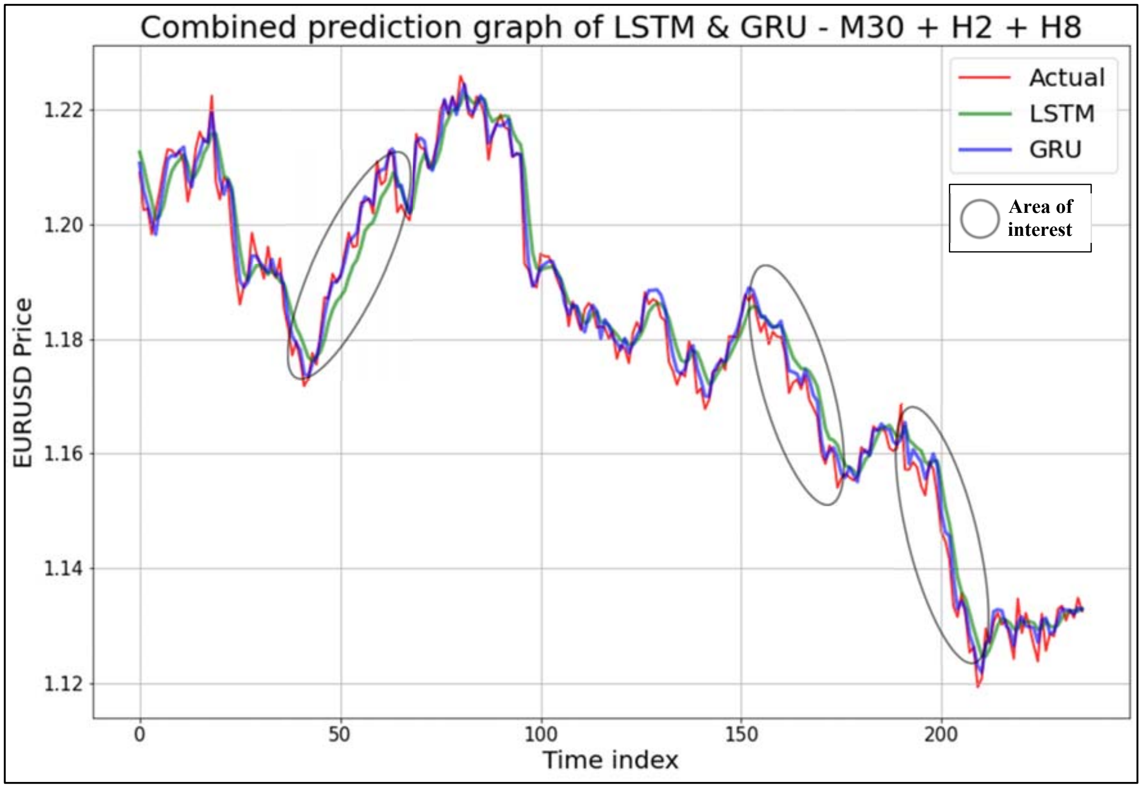

Figure 5.4: Model predictions using M30, H2, and H8 inputs

Based on Figure 5.4, the predicted prices seemed to deviate slightly more than the actual prices, when three input dataset is used as compared to when two input dataset is used. However, it is evident that the LSTM-based model is having a poorer performance as compared to the GRU-based model. Which indicated on the figure by the black circles, shows that the LSTM-based model performed poorly during the trending market. A trending market is when the prices are continuously going up or going down over a period with slight retracement and consolidation in between. During the trending market, the predicted prices from the LSTM-based model deviated further from the actual prices as compared with the GRU-based model.

In addition, the LSTM-based model was not able to predict the short-term consolidation and retracement of prices within the trending market. However, the GRU-based model showed some capacity in predicting the consolidation and retracement within trending market. Moreover, the same problem faced by the previous two input dataset models are still apparent in this model, where the models are unable to follow sudden market movement and result in poor prediction performance when such market conditions occurred. However, both models were able to predict prices that follow the general trend.

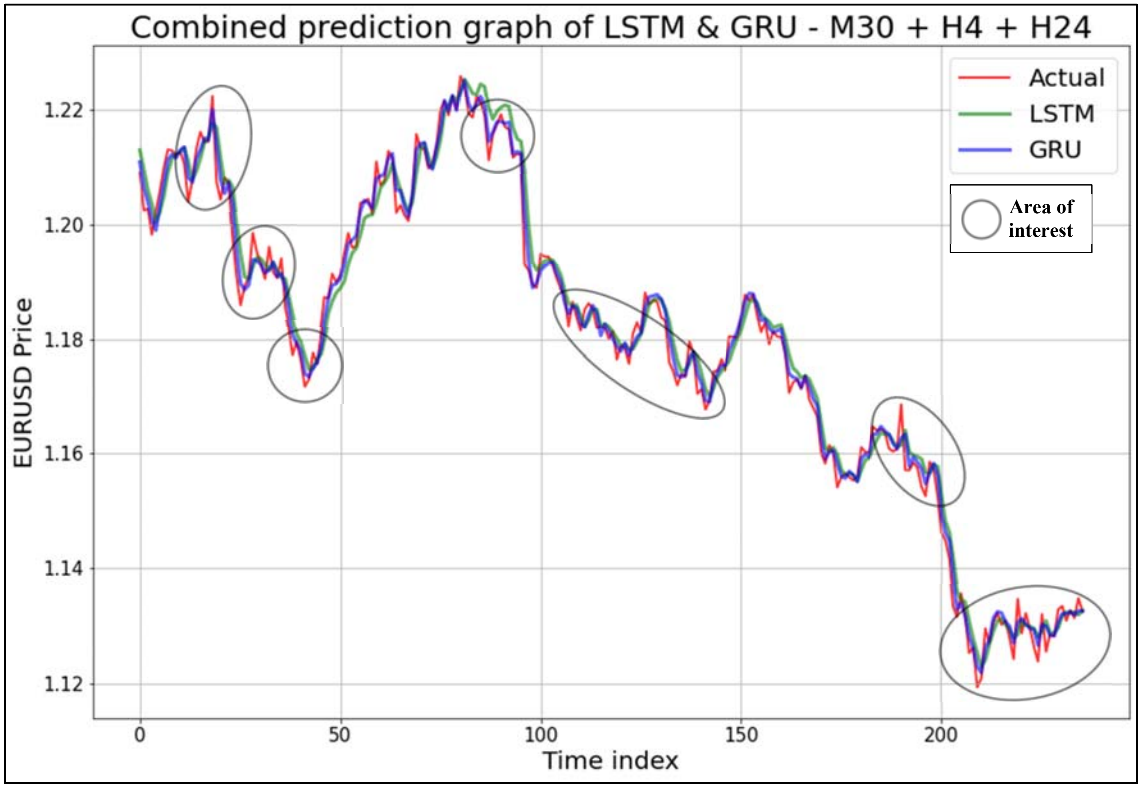

Figure 5.5: Model predictions using M30, H4, and H24 inputs

Based on Figure 5.5, the prediction performance is better than the previous model that uses 30-minute, 2-hour, and 8-hour as data input, but still worse than the models that use two dataset inputs. However, the same problem persists, where the models are unable to follow sudden market movement and result in poor prediction performance when such market conditions occur. In addition, the prediction model is not effective when prices suddenly surged or dropped followed by a quick rebound. Where the predicted prices are shorter than the actual peak or trough. However, both models were able to predict prices that follow the general market trend.

5.3 Discussion

Based on the findings, it is concluded that the GRU-based models and the LSTM-based models were able to outperform the baseline model. In addition, it is also identified that the GRU-based models performed better than the LSTM-based models. It is part of the expectation that the GRU-based models will outperform the LSTM-based models which coincide with the results from Dautel et al. (2020). Moreover, comparing between using two datasets as inputs and three datasets as inputs, models that used two datasets as inputs typically performed better than models that used three datasets as inputs. While for the general performance of the models, it is identified that the models can predict the general market price trend very well, however the performance dropped when encountering a market period of high volatility. Therefore, it can be concluded that the proposed method in this study is feasible and beneficial in providing higher accuracies in Forex market price prediction under certain market conditions. This is in line with the concept proposed by Wei and Li (2019), where the use of multiple timeframe datasets as predictors would result in an improved performance as compared to using a single timeframe dataset as predictors.

The models performed poorly during a market period of high volatility as compared to a market period of stable and consistent rise or drop of prices. The high volatility market period can be caused by government intervention or the reactions of the market to certain critical news releases such as announcements of changes in monetary policy, interest rate decisions, inflation rate, etc. These types of news create a huge inflow or outflow of money to and from the market, causing an instantaneous rise or drop in prices in a very short period of time. Example, in the recent case of the Japanese government intervention in the Forex market. Starting from late September 2022, the Bank of Japan intervened in the Forex market to uphold the Yen from falling further, where the Yen suddenly spike in value from 151.94 Yen per Dollar to 144.50 Yen per Dollar in a matter two hours (Leika Kihara et al., 2022). Shown in Figure 5.6 the recent price chart for the Dollar Yen, where extreme movement of prices are observed during the government intervention. Such price movements are extremely difficult to predict even for an experienced trader. Therefore, the prediction models performing poorly during such events are expected, as the outcomes from such events are unpredictable and unannounced.

In addition, it is likely that the timestep of 20-trading days utilized to develop the models is insufficient to include variation of market conditions. Thus, leading to ineffectiveness in predicting the market prices during a slightly volatile market. It is mentioned by Torralba (2019) that prediction models developed with timesteps that lack in variation of market conditions often failed to perform. However, identifying an optimal timestep for model development is difficult due to the inconsistent market conditions that are affected by a multitude of factors throughout the year.

Figure 5.6: Example of extreme price volatility

The model performance dropped when three timeframe datasets were used as inputs. This issue is more apparent in the GRU-based models as compared to the LSTM-based models. It is with the expectation that when a larger number combination of timeframe datasets is used, the model will perform better. This is due to the expectation that the additional information provided would facilitate better decision making. However, the models performed poorly when the specific combination of 30-minute, 2-hour, and 8-hour timeframe dataset is used as predictors. Models that used another combination which is the 30-minute, 4-hour, and 24-hour timeframe datasets, performed relatively better and comparable to models using two timeframe datasets as inputs. It is a point to note that the 2-hour and the 8-hour timeframes are not the typical timeframes that the market participants would use for market analysis. Typical timeframes used by majority traders would include the 15-minute, 30-minute, 1-hour, 4-hour, and 24-hour timeframe. Therefore, it is likely to be concluded that the 30-minute, 2-hour, and 8-hour timeframe combination is not as effective when compared to the frequently used timeframes to be used as predictors. Which leads to the point where the selection of timeframes for analysis is an important factor to be considered.

It is observed in the GRU-based models, when a larger dataset is used, both the RMSE and MAE values tend to be higher as compared to when a smaller dataset is used. As shown in Table 4.5, when a smaller timeframe is used, the number of observations increases. Therefore, based on Table 5.1, it can be observed in the two timeframe inputs that the smaller dataset (H1 + H6) performs better than the larger dataset (H1 + H4). While using three timeframe inputs, the smaller dataset (M30 + H4 + H24) performs better than the larger dataset (M30 + H2 + H8). And overall, using two timeframe inputs performed better than using three timeframe inputs.

The situation is the opposite for the LSTM-based models, where the use of larger dataset (H1 + H4) resulted in better performance as compared to the use of smaller dataset (H1 + H6). While the use of three timeframe inputs resulted in slightly better performance as compared to the use of two timeframe inputs. It was mentioned by Srivastava et al. (2021) and Yang et al. (2020) that the performance of the GRU algorithm may degrade when used with a larger dataset as compared to LSTM algorithm which can maintain or improve performance when using a larger dataset. Therefore, the computed results shown in this study align with the claim that the GRU algorithm performs better when used with smaller dataset while the LSTM algorithm performs better when used with larger dataset.

5.3.1 Insights

Based on the result analysis from the previous section, several points can be concluded which can be beneficial in the real word application of Forex price prediction. A point to note that this study predicts the closing price of EUR/USD for the next trading day based on the price action of the previous 20 trading days. Therefore, the findings may not be fully applicable if other conditions are present.

The selection of trading timeframes for conducting market analysis is critical. This study identified that certain timeframes produced better model performance, specifically the 1-hour and 4-hour combination. This can be due to the specific combination having a better representation of the short-term and medium-term market behavior thus a more accurate information extraction can be achieved. In addition, this study shows that the use of multiple timeframes in conjunction is better than using a single isolated timeframe. This is due to the confluence of information that can exist between different timeframes which improves confidence of the identified market opportunities. Therefore, the selection and number of timeframes utilized when conducting market analysis is crucial, which can lead to better judgement of market opportunities.

Any trading activities should be avoided temporarily prior to any anticipated major news releases such as the announcement of unemployment rate, gross domestic product growth rate, interest rate, etc. These news releases typically induce a high inflow or outflow of money to and from the market, which causes the price movement to be highly volatile momentarily. This study shows that the price prediction models often failed to predict the market prices during high volatility periods. Therefore, it is suggested to halt any market entries prior to any major news releases. In addition, any market analysis should be complemented with the use of fundamental analysis to gain a more comprehensive view of the market condition and to anticipate any impactful news releases which can cause market volatility to increase.

5.3.2 Limitations

There are several limitations of the proposed method in this study. The following outlines the limitations identified:

1. The predictors utilized considered only the market prices, which may not provide sufficient representation of the market conditions where prices are typically influenced by a multitude of factors.
2. The predictors utilized considered only the EUR/USD currency pair, where a different currency pair may exhibit a different behavior. Thus, causing the model developed in this study to be unable to generalize if the price prediction is to be performed on a different currency pair.
3. The predictors utilized considered only a time horizon of seven years, where the market behavior can be different if a longer time horizon is used which resulted in the model having a partial representation of the actual market.
4. Due to the limited computational resources and time constraint, the hyperparameter tuning process for the deep learning models may not be optimal. Where only several types of hyperparameters are considered for tuning and only one cycle of model training for each hyperparameter combination is performed. Where the random initialization of weights in neural networks can be a factor that may lead to a different outcome.
5. The evaluation metrics for the prediction models utilized in this study considered only the basic RMSE and MAE values from the prediction results. The computed error values may not represent the true error rate when application in the live market is considered. There are transactional costs and other factors to be considered when deciding market entries. Therefore, the actual error may be higher when such factors are considered in the calculation.

CHAPTER 6

CONCLUSION

6.1 Conclusion

This study aimed to develop a Forex price prediction model with the adoption of multiple timeframe analysis and deep learning techniques. The claim is that the prediction model using dataset with multiple timeframes as inputs, would yield a better prediction result as compared to using a dataset with only a single timeframe as input. This is due to the different information that can exist in different granularity levels that are contained in the different timeframes. By utilizing the capability of deep learning techniques, such information can be extracted to produce an improved prediction outcome. Based on the findings, it can be concluded that using datasets of multiple timeframes as inputs resulted in improved prediction accuracy. The experiments were conducted with prediction models using datasets of two or three timeframes as inputs. The models were able to outperform the baseline which uses dataset that included only single timeframe.

The dataset acquired for the EUR/USD currency pair from the year 2015 to year 2021 is transformed into different timeframes of 30-minute, 1-hour, 2-hour, 4-hour, 6-hour, 8-hour, and 24-hour. This is done by formulating batches of data and consolidating it into rows of observations. These observations are then segmented by a sliding window approach into a dependent variable which consists of the closing price of the next trading day and independent variables which consist of the open, high, low, and close prices of the prior 20 trading days. This formulates the dataset into a supervised learning approach which is then partitioned into three subsets for utilization of model training, validation, and testing.

The price prediction models were developed using deep learning algorithms namely LSTM or GRU. For each timeframe, a prediction model was developed to predict the closing price of the next trading day based on instances of the prior 20 trading days. These predicted outcomes are then concatenated to be used in a feed forward neural network to produce the final prediction output. The concatenation of outcomes consists of timeframes which are combined from either two or three number of timeframes. Extensive hyperparameter tuning was performed for the LSTM, GRU, and feed forward neural network models, particularly for the number of hidden layers, number of hidden neurons in each layer, epochs, and batch size.

The proposed method in this study where the prediction models utilize two or three combinations of timeframes as predictors is compared to a baseline model which uses only instances from a single 24-hour timeframe as predictor. Four different combinations of timeframes that are formulated based on a rule of thumb ratio are experimented with each deep learning algorithm. Seven of the eight models were able to outperform the baseline model. The models with two timeframes as predictors, specifically the 1-hour and 4-hour combination and the 1-hour and 6-hour combination produced relatively similar performance and outperformed the models using three timeframes as predictors. Thus, the use of multiple timeframes as predictors benefited the prediction performance.

The developed models are evaluated using a holdout testing dataset. The predicted prices are compared with the actual prices to determine the RMSE and MAE metric. The model with the lowest RMSE and MAE value is deemed the best performing model for each timeframe combination. In addition, these optimal models are compared among each other to determine the best performing deep learning algorithm and timeframe combination.

In overall, it was identified that the GRU-based models performed much better than the LSTM-based models. However, it is also identified that the GRU-based models performed better when used with a smaller dataset. In contrast to the LSTM-based models, a bigger dataset yielded a better performance. Moreover, all the models suffered from the same problem of failure to identify peaks and troughs accurately during highly volatile market conditions. In addition, using combination of timeframes that are uncommon among the traders would result in an ineffective prediction model that produces poorer results as compared to using combination of timeframes that are typical. Therefore, proper selection of timeframe combination is an essential task to be considered to ensure high prediction accuracy.

6.2 Contribution

The trading of currencies in the Forex market can provide considerable profit with the proper execution of trades at the right prices along with a well-managed risk plan. On the other hand, huge losses can be incurred if trade executions are done without sufficient information analysis. A multitude of factors ranging from macroeconomics to microeconomics are to be considered when planning for a trade execution. Such information easily overwhelmed any financial analysts, as the quantity of information to be analyzed has increased due to the technological advancement which promoted the flow of information faster than ever before. Therefore, the adoption of machine learning is required to assist the decision-making process when identifying market opportunities.

Various price prediction studies conducted are utilizing only the single timeframe as inputs, where valuable information from other timeframes is neglected. This study tries to identify the feasibility of extracting hidden information that is available from different timeframes to improve prediction performance. Based on the findings, the method in this study where the use of multiple timeframes as inputs facilitated a better prediction output. Which proved the feasibility and effectiveness of the method. Therefore, the method in this study can be utilized by market participants to assist in identifying market opportunities more efficiently and accurately. In addition, this study provides the validation of using multivariate inputs can facilitate a better price prediction outcome.

Moreover, the findings where the GRU algorithm outperformed the LSTM algorithm can be used as a reference where the use of a more complex algorithm does not equate to better performance. Finally, the result from this study validates the claim that GRU algorithm performs better with smaller dataset while LSTM algorithm performs better with bigger dataset.

6.3 Future Recommendations

There are several recommendations that can be proposed for the improvement of this study. The following outlines the recommendations proposed:

1. The predictors utilized for model training can be extended to include fundamental and technical indicators such as market sentiment, news releases, moving averages, etc. The inclusion of the additional data types may facilitate a better feature representation that is likely to result in an improvement in model performance.
2. The predictors utilized for model training can be extended to include different currency pairs and even other financial instruments. The price movement of certain currencies is highly correlated to some of the financial instruments available. Example, the Canadian Dollar is positively correlated to the prices of oil. Therefore, this concept of correlation between financial instruments can be explored and adopted which may facilitate the prediction performance.
3. The prediction algorithms utilized in this study considered only the simple GRU and LSTM. Where newer and more advanced algorithms such as transformers can be explored which may provide improvement in terms of computation efficiency and model prediction accuracy.

4. The hyperparameter tuning for the deep learning models can be more comprehensive to include other timeframes and different combinations that may lead to better prediction models and the realization of better timeframes to be used in analysis. In addition, it is advised to perform multiple runs of the same model to obtain an average result, since the weights in deep learning models are subjected to random initialization.
5. Explainable machine learning can be incorporated to provide better understanding and interpretation of the prediction process. Where the influential factor of the features can be identified to facilitate better enhancement of the model efficiency and accuracy.
6. The model evaluation metrics can be enhanced by incorporating factors such as transaction costs or slippage which better represent the live market trading environment. This is to attain a better representation of the performance from the prediction models.

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APPENDIX A

LOG SHEET

(APU: Serial Number)

PLS V1.0

Project Log Sheet – Supervisory Session

Notes on use of the project log sheet:

1. This log sheet is designed for meetings of more than 15 minutes duration, of which there must be at minimum SIX (6) during the course of the project (SIX mandatory supervisory sessions).
2. The student should prepare for the supervisory sessions by deciding which question(s) he or she needs to ask the supervisor and what progress has been made (if any) since the last session and noting these in the relevant sections of the form, effectively forming an agenda for the session.
3. A log sheet is to be brought by the STUDENT to each supervisory session.
4. The actions by the student (and, perhaps the supervisor), which should be carried out before the next session should be noted briefly in the relevant section of the form.
5. The student should leave a copy (after the session) of the Project Log Sheet with the supervisor and to the administrator at the academic counter. A copy is retained by the student to be filed in the project file.
6. It is recommended that students bring along log sheets of previous meetings together with the project file during each supervisory session.
7. The log sheet is an important deliverable for the project and an important record of a student's organisation and learning experience. The student **must** hand in the log sheets as an appendix of the final year documentation, with sheets dated and numbered consecutively.

Student's name: LEE KEAN LIM **Date: 5-July-2022** **Meeting No: 1**

Project title: Forex market price prediction using multi-time series analysis with deep learning.

Supervisor's name: Dr. Dewi Octaviani **Supervisor's signature:** Dewi ……..……………..

Items for discussion (noted by student before mandatory supervisory meeting):
- Overview of the introduction chapter.
- Overview of the literature review chapter.
- Overview of the methodology chapter.

Record of discussion (noted by student during mandatory supervisory meeting):
- Insufficient justification for research gap in problem statement.
- Lacking summary table for literature review on similar works.
- Insufficient discussion performed in the research methodology.

Action List (to be attempted or completed by student by the next mandatory supervisory meeting):
- To include more discussion on justifying the research gap in problem statement.
- To include discussion on how the proposed study is different with other similar works.
- To produce a summary table based on literature review of similar works.
- To provide a detailed discussion outlining every detail of the proposed methodology.

Note: A student should make an appointment to meet his or her supervisor (via the consultation system) at least ONE (1) week prior to a mandatory supervisor session – please see document on project timelines. In the event a supervisor could not be booked for consultation, the project manager should be informed ONE (1) week prior to the session so that a meeting can be subsequently arranged.

(APU: Serial Number)

PLS V1.0

Project Log Sheet – Supervisory Session

Notes on use of the project log sheet:

1. This log sheet is designed for meetings of more than 15 minutes duration, of which there must be at minimum SIX (6) during the course of the project (SIX mandatory supervisory sessions).
2. The student should prepare for the supervisory sessions by deciding which question(s) he or she needs to ask the supervisor and what progress has been made (if any) since the last session and noting these in the relevant sections of the form, effectively forming an agenda for the session.
3. A log sheet is to be brought by the STUDENT to each supervisory session.
4. The actions by the student (and, perhaps the supervisor), which should be carried out before the next session should be noted briefly in the relevant section of the form.
5. The student should leave a copy (after the session) of the Project Log Sheet with the supervisor and to the administrator at the academic counter. A copy is retained by the student to be filed in the project file.
6. It is recommended that students bring along log sheets of previous meetings together with the project file during each supervisory session.
7. The log sheet is an important deliverable for the project and an important record of a student's organisation and learning experience. The student **must** hand in the log sheets as an appendix of the final year documentation, with sheets dated and numbered consecutively.

Student's name: LEE KEAN LIM **Date: 19-Aug-2022** **Meeting No: 2**

Project title: Forex market price prediction using multi-time series analysis with deep learning.

Supervisor's name: Dr. Dewi Octaviani **Supervisor's signature:** Dewi ……..……………..

Items for discussion (noted by student before mandatory supervisory meeting):
- Review of presentation slides for capstone project 1 presentation.

Record of discussion (noted by student during mandatory supervisory meeting):
- Insufficient elements provided in the slides.

Action List (to be attempted or completed by student by the next mandatory supervisory meeting):
- To include a summary section at the end of the presentation slides.
- To include a future works section indicating tasks to be performed in capstone project 2.
- To include details of dataset and data dictionary.

Note: A student should make an appointment to meet his or her supervisor (via the consultation system) at least ONE (1) week prior to a mandatory supervisor session – please see document on project timelines. In the event a supervisor could not be booked for consultation, the project manager should be informed ONE (1) week prior to the session so that a meeting can be subsequently arranged.

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Project Log Sheet – Supervisory Session

Notes on use of the project log sheet:

1. This log sheet is designed for meetings of more than 15 minutes duration, of which there must be at minimum SIX (6) during the course of the project (SIX mandatory supervisory sessions).
2. The student should prepare for the supervisory sessions by deciding which question(s) he or she needs to ask the supervisor and what progress has been made (if any) since the last session and noting these in the relevant sections of the form, effectively forming an agenda for the session.
3. A log sheet is to be brought by the STUDENT to each supervisory session.
4. The actions by the student (and, perhaps the supervisor), which should be carried out before the next session should be noted briefly in the relevant section of the form.
5. The student should leave a copy (after the session) of the Project Log Sheet with the supervisor and to the administrator at the academic counter. A copy is retained by the student to be filed in the project file.
6. It is recommended that students bring along log sheets of previous meetings together with the project file during each supervisory session.
7. The log sheet is an important deliverable for the project and an important record of a student's organisation and learning experience. The student **must** hand in the log sheets as an appendix of the final year documentation, with sheets dated and numbered consecutively.

Student's name: LEE KEAN LIM **Date: 25-Oct-2022** **Meeting No: 3**

Project title: Forex market price prediction using multi-time series analysis with deep learning.

Supervisor's name: Dr. Dewi Octaviani **Supervisor's signature:** Dewi ……………………..

Items for discussion (noted by student before mandatory supervisory meeting):
- Review of the implementation chapter.
- Review of the results and discussion chapter.
- Review of the conclusion chapter.

Record of discussion (noted by student during mandatory supervisory meeting):
- How the analysis results from the study can benefit the people in the domain?
- Insufficient components in the conclusion chapter.

Action List (to be attempted or completed by student by the next mandatory supervisory meeting):
- To include further discussion on how the analysis results can be applied in real world application and benefits the users of the domain.
- To include explanations on how the research objectives are achieved.

Note: A student should make an appointment to meet his or her supervisor (via the consultation system) at least ONE (1) week prior to a mandatory supervisor session – please see document on project timelines. In the event a supervisor could not be booked for consultation, the project manager should be informed ONE (1) week prior to the session so that a meeting can be subsequently arranged.

APPENDIX B

FAST TRACK FORM

Office Record	Receipt – APU Fast-Track Ethical Approval
Date Received: Received by:	Student name: Student number: Received by: Date:

APU/APIIT FAST-TRACK ETHICAL APPROVAL FORM (STUDENTS)

Tick one box (level of study):

- ☑ POSTGRADUATE (~~PhD / MPhil~~ / Masters)
- ☐ UNDERGRADUATE (Bachelors degree)
- ☐ FOUNDATION / DIPLOMA / Other categories

Tick one box (purpose of approval):

- ☐ Thesis / Dissertation / FYP project
- ☐ Module assignment
- ☑ Other: Capstone Project

Title of Programme on which enrolled Msc in Data Science and Business Analytics

Tick one box: ☑ Full-Time Study or ☐ Part-Time Study

Title of project / assignment Multi-time series analysis on Forex market price prediction using deep learning

Name of student researcher Lee Kean Lim

Name of supervisor / lecturer Dr. Dewi Octaviani

Student Researchers- please note that certain professional organisations have ethical guidelines that you may need to consult when completing this form.

Supervisors/Module Lecturers - please seek guidance from the Chair of the School Research Ethics Committee if you are uncertain about any ethical issue arising from this application.

		YES	NO	N/A
1	Will you describe the main procedures to participants in advance, so that they are informed about what to expect?			✓
2	Will you tell participants that their participation is voluntary?			✓
3	Will you obtain written consent for participation?			✓
4	If the research is observational, will you ask participants for their consent to being observed?			✓
5	Will you tell participants that they may withdraw from the research at any time and for any reason?			✓
6	With questionnaires and interviews will you give participants the option of omitting questions they do not want to answer?			✓
7	Will you tell participants that their data will be treated with full confidentiality and that, if published, it will not be identifiable as theirs?			✓
8	Will you give participants the opportunity to be debriefed i.e. to find out more about the study and its results?			✓

If you have ticked No to any of Q1-8, you should complete the full Ethics Approval Form.

		YES	NO	N/A
9	Will your project/assignment deliberately mislead participants in any way?			✓
10	Is there any realistic risk of any participants experiencing either physical or psychological distress or discomfort?			✓
11	Is the nature of the research such that contentious or sensitive issues might be involved? This includes research which could induce psychological stress, anxiety or humiliation, or cause more than minimal pain.			✓
12	Does your research involve the use of sensitive materials? Eg, records of personal or sensitive confidential information,			✓

13	Does your research require external agency approval?			✓
14	Does your research use hazardous or controlled substance?			✓
15	Does your research require you to visit participants in their home or non-public space?			✓
16	Does your research use genetically modified organisms?			✓
17	Does your research investigate illegal activities or behaviours?			✓
18	Does your research involve discussion or collection of information on potentially sensitive, embarrassing or distressing topics, administrative or secure data? This includes research involving respondents through internet where visual images are used, and where sensitive issues are discussed			✓
19	Does your research involve invasive or potentially intrusive procedures?			✓
20	Does your research involve administration of substances?			✓
21	Will your research be involved in the collection/ processing of human tissue samples			✓
22	Will your participants be receiving financial compensation for participating in your research?			✓
23	Will your research data be used in the future after the conclusion of your project?			✓
24	Will your research involve in processing sensitive data belonging to an organisation/persons?			✓
25	Will your research be collecting photographs, videos, and audio recordings of the participants?			✓
26	Will the participants' personal particulars be known to any third party?			✓
27	Will the participants' data confidentiality be made known to the public?			✓
28	Will the research be conducted where the safety of the researchers maybe in question?			✓
29	Will be the research be conducted outside of the UK and/or Malaysia?		✓	
30	Will your research involve human participants at premises other than those of the University?			✓

If you have ticked Yes to any of Q9 – 30, you should complete the full Ethics Approval Form. In relation to question 10 this should include details of what you will tell participants to do if they should experience any problems (e.g. who they can contact for help). You may also need to consider risk assessment issues.

			YES	NO	N/A
31	Does your project/assignment involve work with animals?				✓
32	Do participants fall into any of the following special groups? **Note that you may also need to obtain satisfactory clearance from the**	Children (under 18 years of age)			
		People with communication or learning difficulties			
		Patients			
		People in custody			
		People who could be regarded as vulnerable or lack capacity to make decision for themselves			✓
		People engaged in illegal activities (eg drug taking)			
		Groups of people whose relationship among each other allow one to have influence over the other such as: Carers and patients with chronic conditions; teachers and their students; prison authorities and prisoners;			

	relevant authorities	employers and employees			
		Deceased person's body parts or other human tissues including bodily fluids (e.g. blood, saliva).			
		groups where permission of a gatekeeper is normally required for initial access to members.			
		Human participants who are off-campus APU staff or students who wish to carry out investigations involving human participants at premises other than those of the University			
33	Does the project/assignment involve external funding or external collaboration where the funding body or external collaborative partner requires the University to provide evidence that the project/assignment had been subject to ethical scrutiny?				✓

If you have ticked Yes to any Q31-33**,** you should complete the full Ethics Approval Form. There is an obligation on student and supervisor to bring to the attention of the APU School Research Ethics Committee any issues with ethical implications not clearly covered by the above checklist.

STUDENT RESEARCHER

Provide in the boxes below (plus any other appended details) information required in support of your application. THEN SIGN THE FORM.

Please Tick Boxes

I consider that this project/assignment has no significant ethical implications requiring a full ethics submission to the APU School Research Ethics Committee.	✓
I am aware of APU liability policy and will make the necessary arrangement for insurance coverage of all researchers and participants of the project/assignment.	N/A
Give a brief description of participants, procedure of recruitment and procedure of data collection (methods, tests used etc) in up to 150 words. No participants will be involved in this research project. The project involves the development of a price prediction model in the foreign exchange market using deep learning algorithms and time series analysis. Evaluation of the model would be performed against existing related works. Historical price data is obtained from HistData.com which provides free access and usage to the data.	
I also confirm that: i) All key documents e.g. consent form, information sheet, questionnaire/interview, and all material such as emails and posters for the purpose of recruitment of participants are appended to this application.	N/A
Or ii) Any key documents e.g. consent form, information sheet, questionnaire/interview schedules which need to be finalised following initial investigations will be submitted for approval by the project/assignment supervisor/module lecturer before they are used in primary data collection.	N/A

Signed… … … Kean … … … … … … … Print Name… Lee Kean Lim … … … … Date.5/4/2022
(Student Researcher)

Within this document, any variation to the items considered which affects ethical issues of the stated research will require submission of a revised research plan and research methodology details; as a consequence, new ethical consent may need to be sought.

The completed form (and any attachments) should be submitted for consideration by your Supervisor/Module Lecturer

SUPERVISOR/MODULE LECTURER
PLEASE CONFIRM THE FOLLOWING:

Please Tick Box

I consider that this project/assignment has no significant ethical implications requiring a full ethics submission to the APU School Research Ethics Committee	✓
I have checked and approved the key documents required for this proposal (e.g. consent form, information sheet, questionnaire, interview schedule)	N/A

SUPERVISOR AND SECOND ACADEMIC SIGNATORY

STATEMENT OF ETHICAL APPROVAL (please delete as appropriate)

1) **THIS PROJECT/ASSIGNMENT HAS BEEN CONSIDERED USING AGREED APU PROCEDURES AND IS NOW APPROVED**

2) **THIS PROJECT/ASSIGNMENT HAS BEEN APPROVED IN PRINCIPLE AS INVOLVING NO SIGNIFICANT ETHICAL IMPLICATIONS, BUT FINAL APPROVAL FOR DATA COLLECTION IS SUBJECT TO THE SUBMISSION OF KEY DOCUMENTS FOR APPROVAL BY SUPERVISOR (see Appendix A)**

Signed… Dr Dewi … Print Name… Dr. Dewi Octaviani … Date… 05/04/2022 …
(Supervisor/Lecturer)

Signed… SIV … Print Name… Dr. V. Sivakumar … Date… 05/04/2022 …
(Second Academic Signatory)

Office Record Date Received: Received by:	Receipt – Appendix A (APU Fast-Track Ethics Form) Student name: Student number: Received by: Date:

APPENDIX A
AUTHORISATION FOR USE OF KEY DOCUMENTS

Completion of Appendix A is required when for good reasons key documents are not available when a fast track application is approved by the supervisor/module lecturer and second academic signatory.

I have now checked and approved all the key documents associated with this proposal e.g. consent form, information sheet, questionnaire, interview schedule

Title of project/assignment… …

… ……………………….

Name of student researcher ……….

Student ID: ………………………………… Intake: … … … … … … … … … … … … … … … … ……..

Signed… … … … … … … … … … … … Print Name… … … … … … … … … … … … Date… … ………………..
(Supervisor/Lecturer)

APPENDIX C

MODEL PREDICTION PLOTS

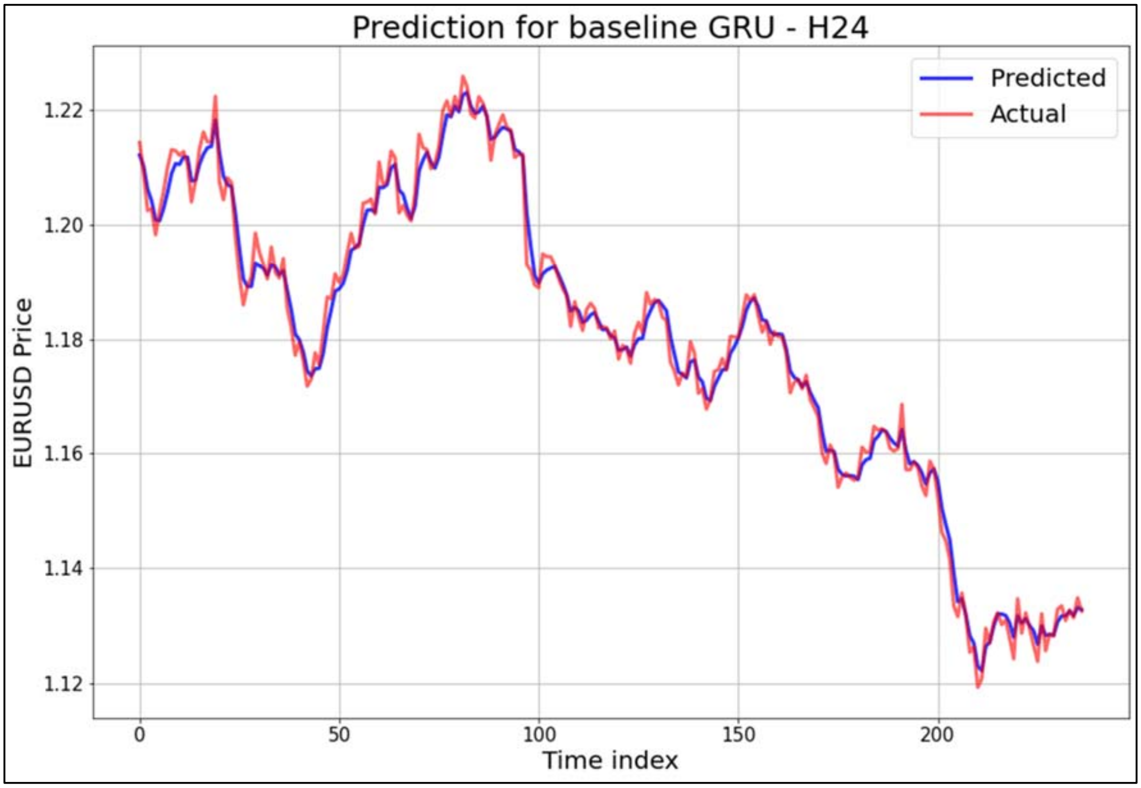

Figure C.1: GRU-based baseline model predictions

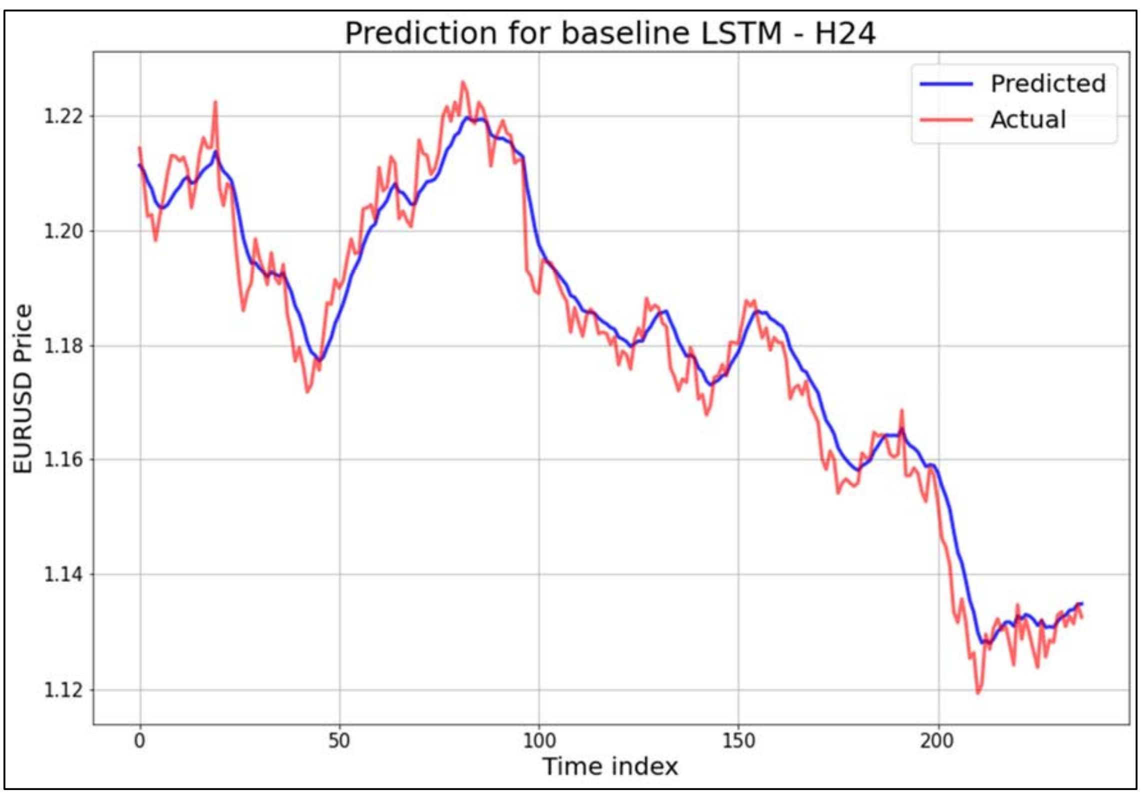

Figure C.2: LSTM-based baseline model predictions

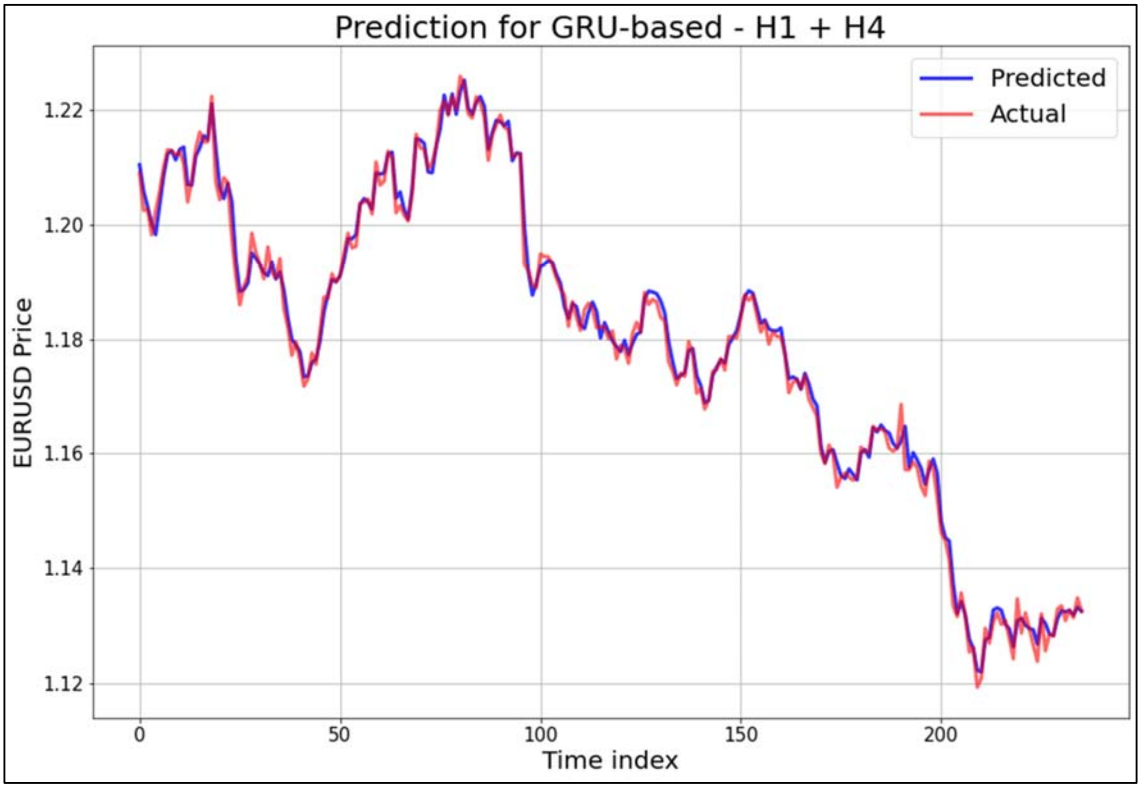

Figure C.3: GRU-based using H1 and H4 model predictions

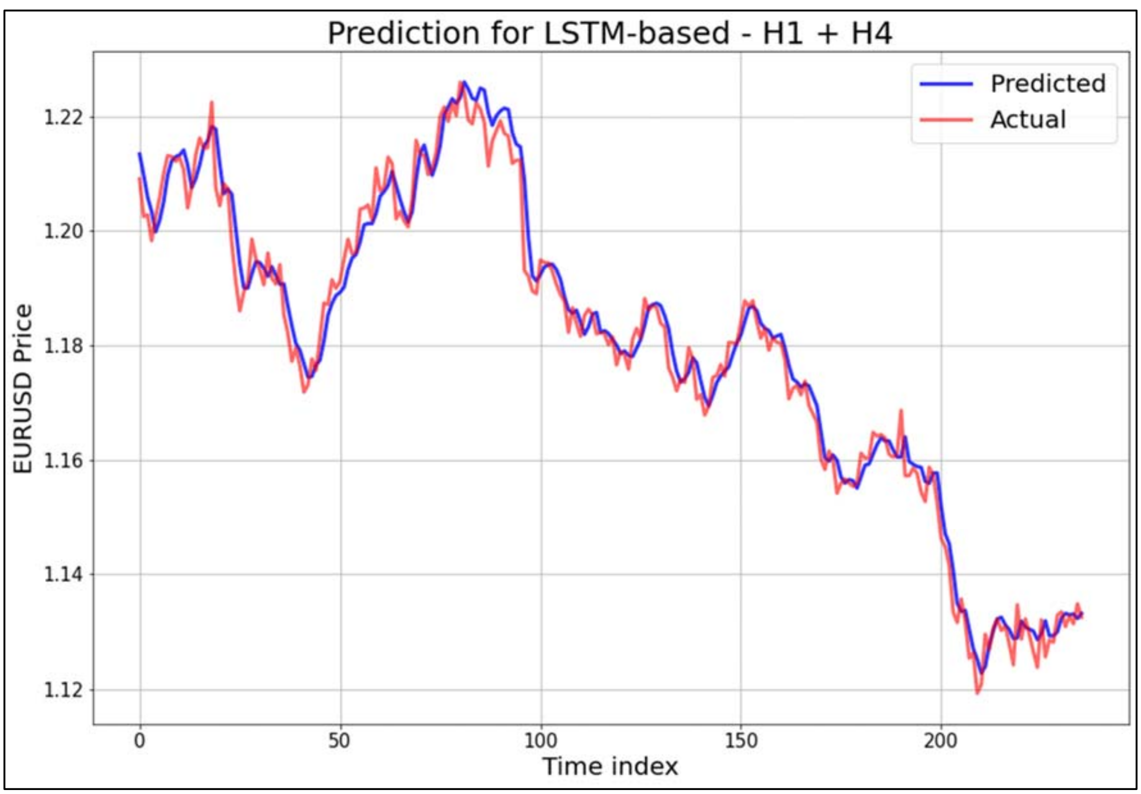

Figure C.4: LSTM-based using H1 and H4 model predictions

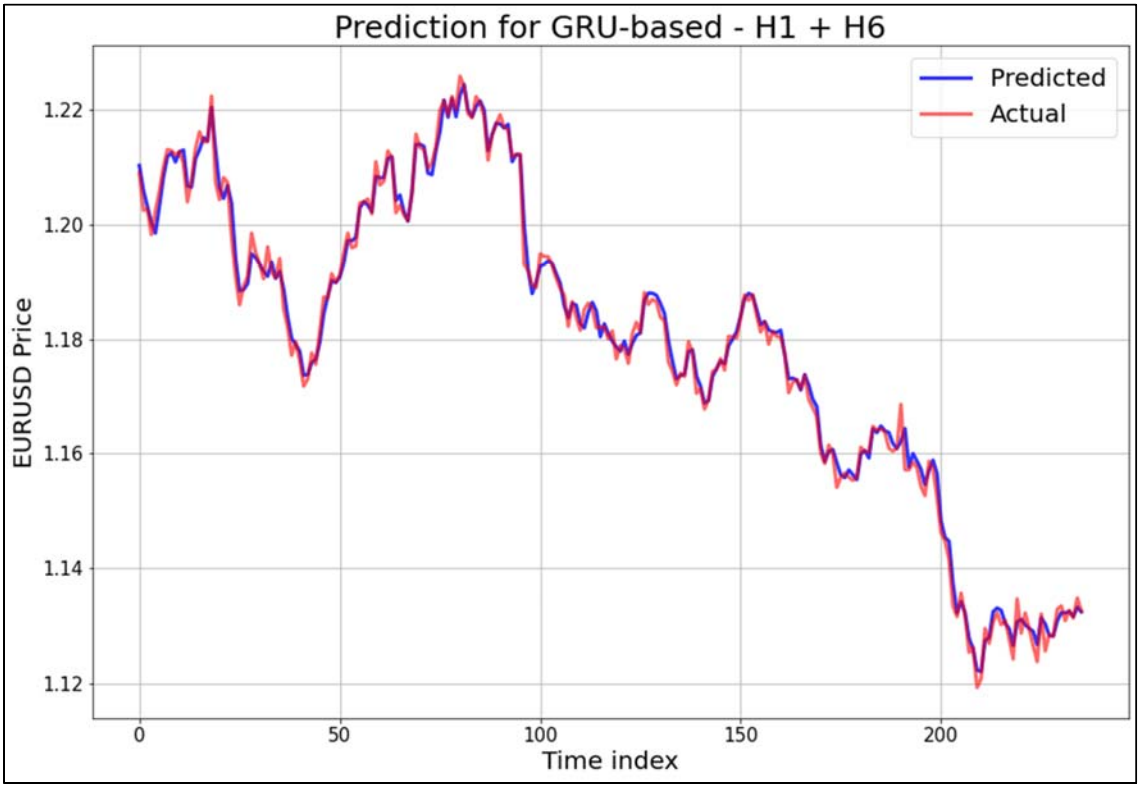

Figure C.5: GRU-based using H1 and H6 model predictions

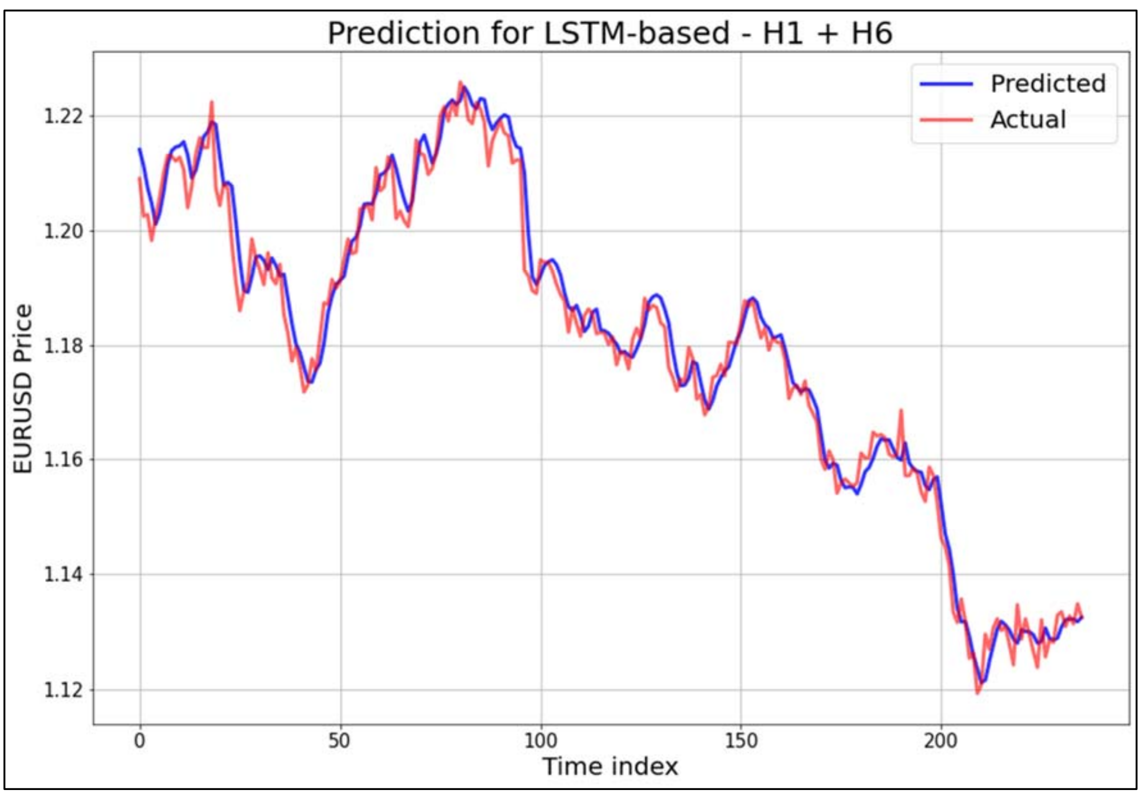

Figure C.6: LSTM-based using H1 and H6 model predictions

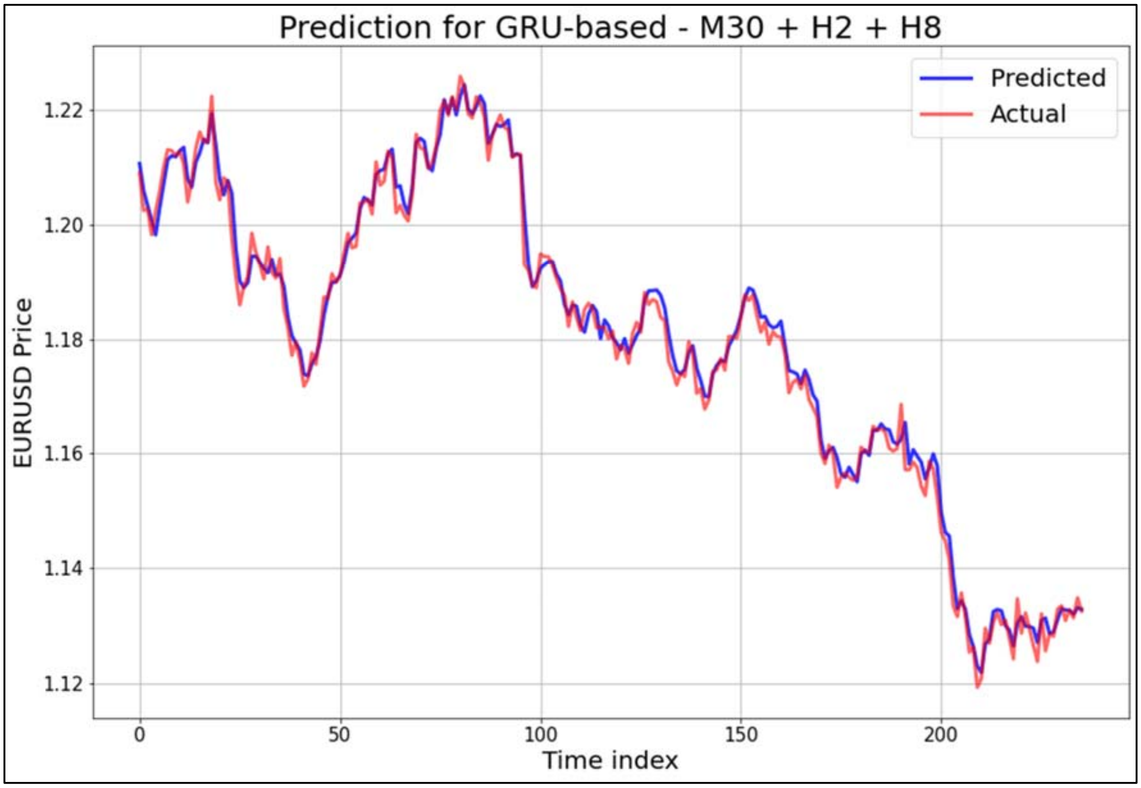

Figure C.7: GRU-based using M30, H2, and H8 model predictions

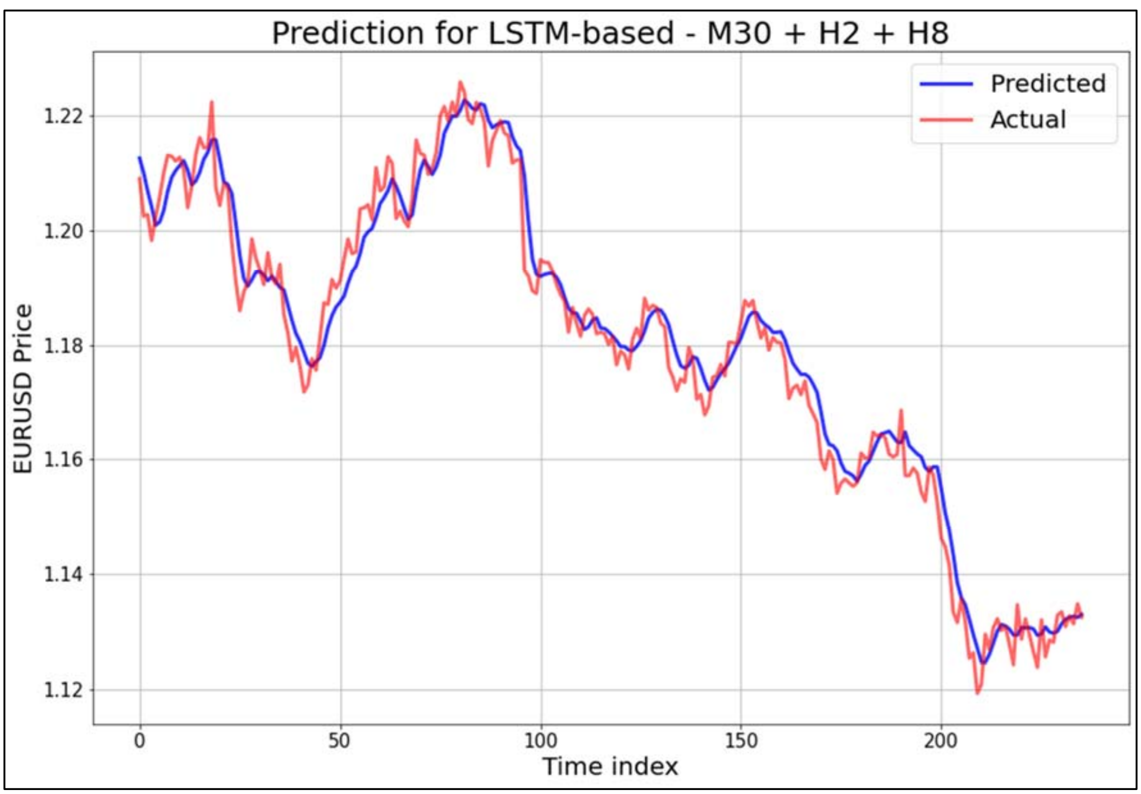

Figure C.8: LSTM-based using M30, H2, and H8 model predictions

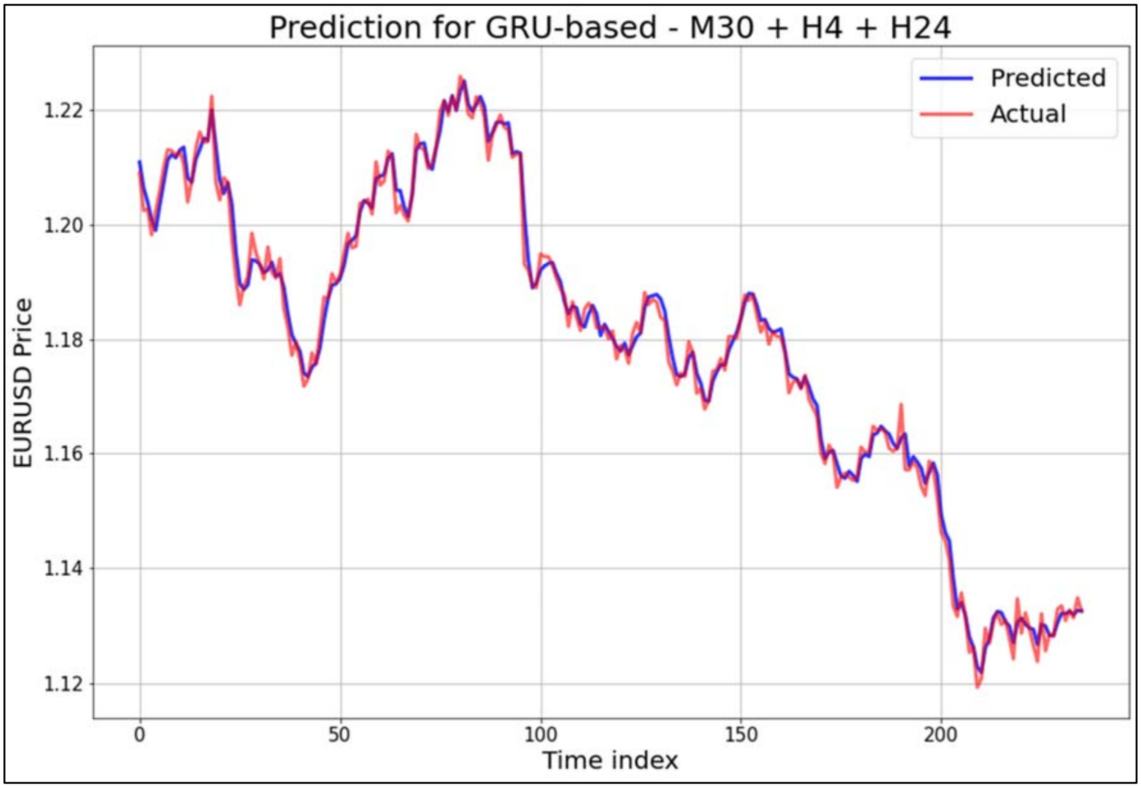

Figure C.9: GRU-based using M30, H4, and H24 model predictions

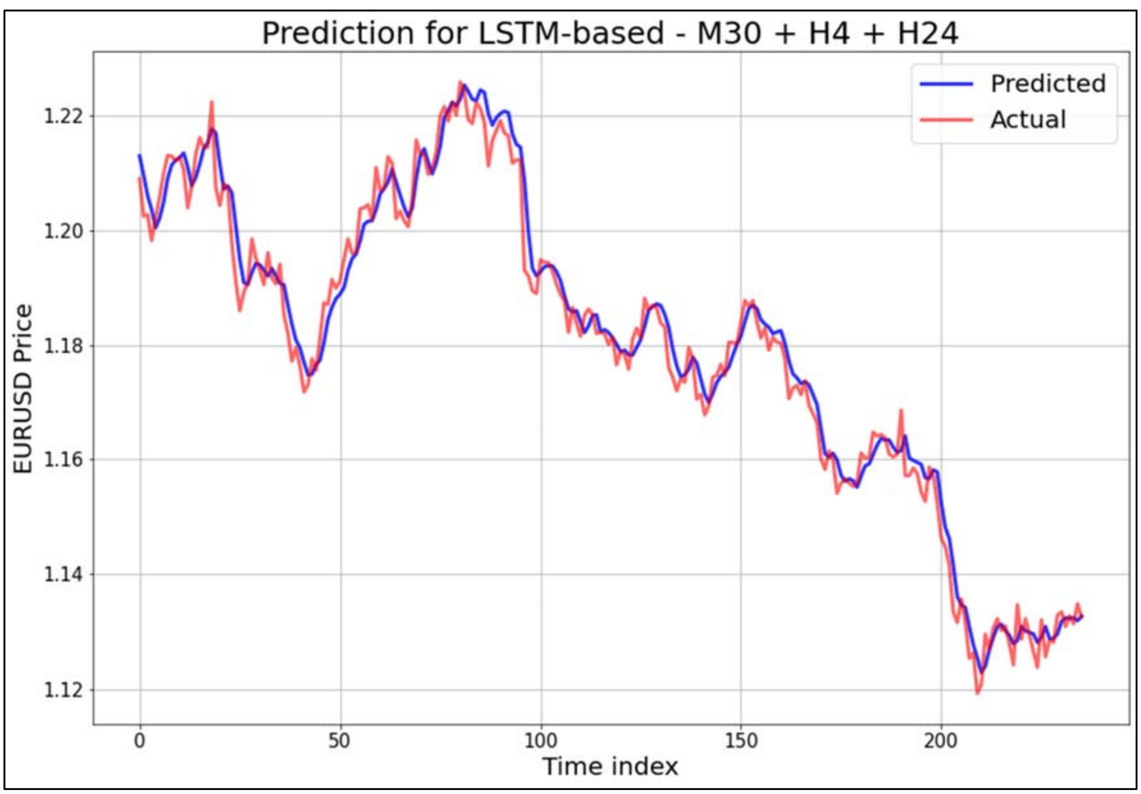

Figure C.10: LSTM-based using M30, H4, and H24 model predictions

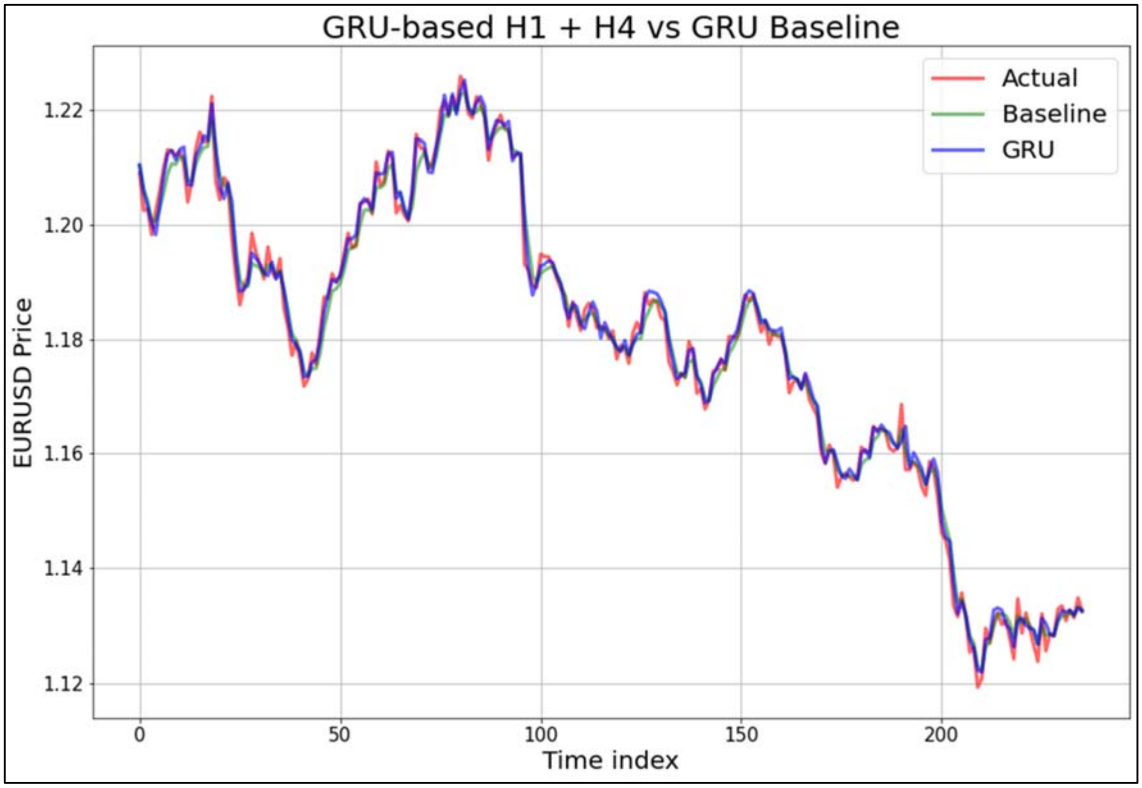

Figure C.11: GRU-based using H1 and H4 versus baseline

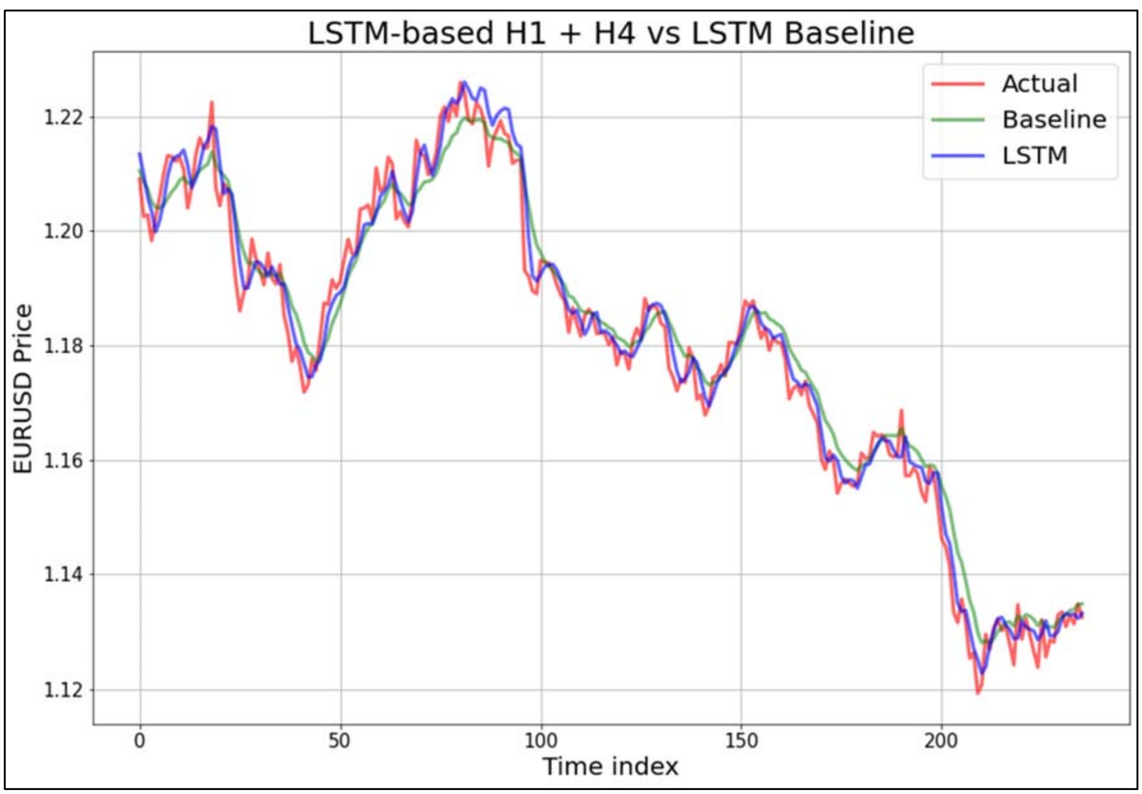

Figure C.12: LSTM-based using H1 and H4 versus baseline

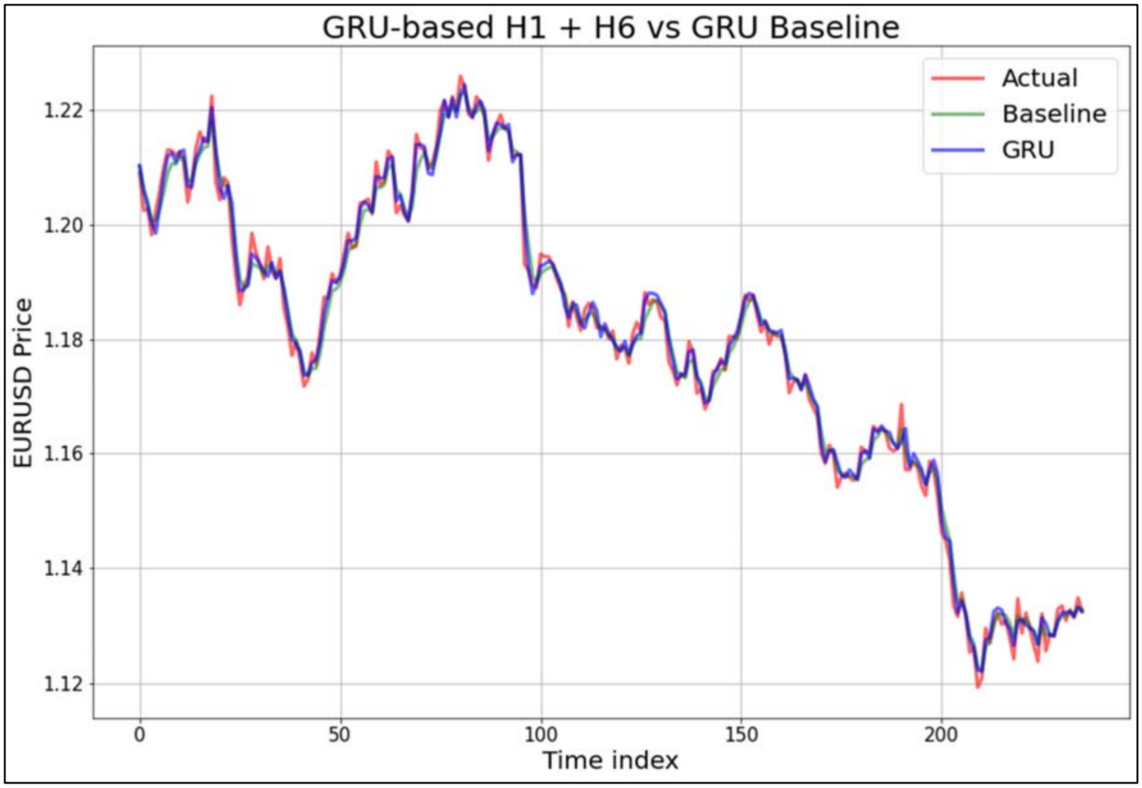

Figure C.13: GRU-based using H1 and H6 versus baseline

Figure C.14: LSTM-based using H1 and H6 versus baseline

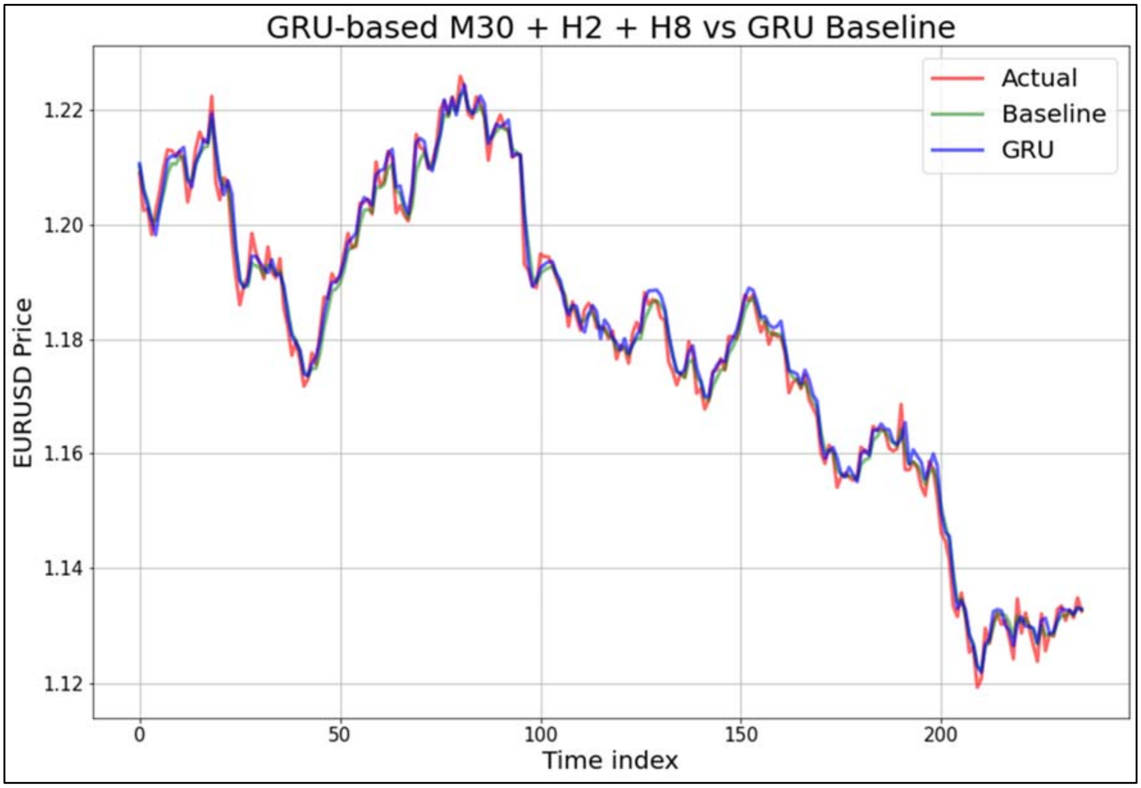

Figure C.15: GRU-based using M30, H2, and H8 versus baseline

Figure C.16: LSTM-based using M30, H2, and H8 versus baseline

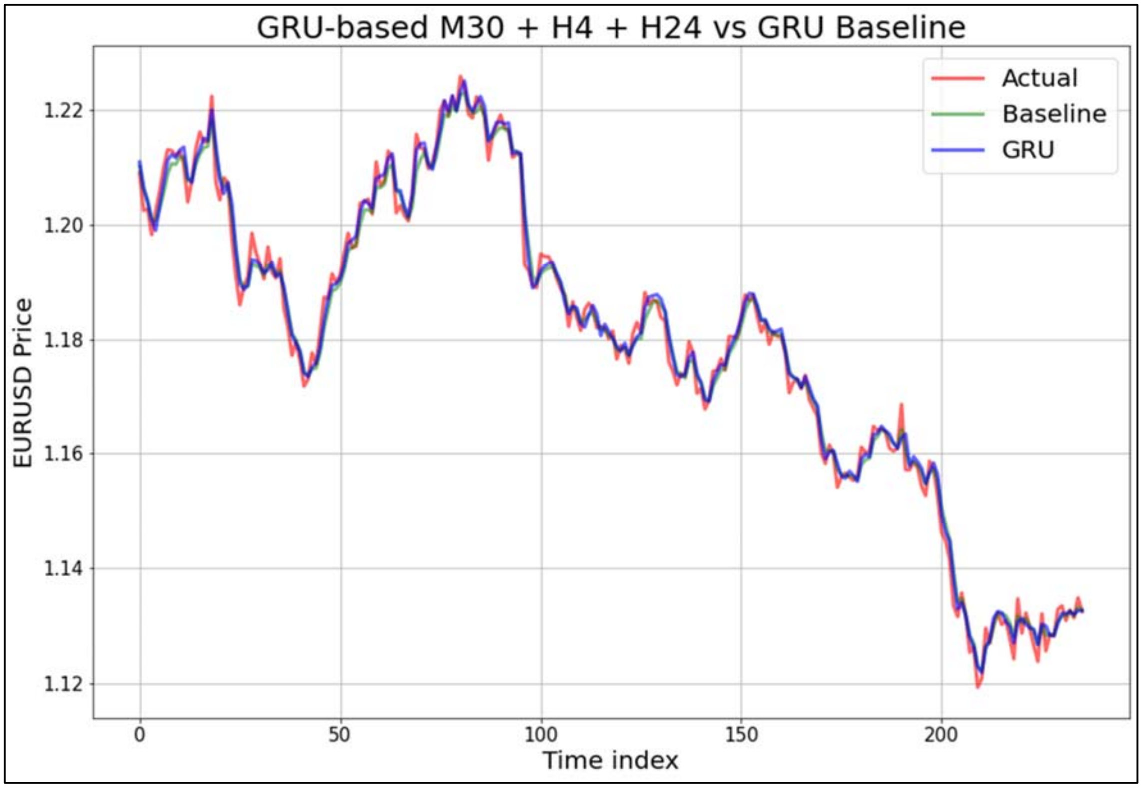

Figure C.17: GRU-based using M30, H4, and H24 versus baseline

Figure C.18: LSTM-based using M30, H4, and H24 versus baseline