Cawangan Melaka

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Progress in Computing and Mathematics Journal

volume 1

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Progress in Computing and Mathematics Journal
College of Computing, Informatics, and Mathematics
Universiti Teknologi MARA Cawangan Melaka, Kampus Jasin
77300, Merlimau, Melaka Bandaraya Bersejarah

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EDITORS

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PREFACE

Welcome to the inaugural volume of the **Progress in Computing and Mathematics Journal (PCMJ)**, a publication proudly presented by the College of Computing, Informatics, and Mathematics at UiTM Cawangan Melaka.

This journal represents a significant step in our commitment to fostering a vibrant research culture, initially providing a crucial platform for our undergraduate students to showcase their intellectual curiosity, dedication to scholarly pursuit, and potential to contribute to the broader academic discourse in the fields of computing and mathematics. However, we envision PCMJ evolving into a beacon for researchers both nationally and internationally. We aspire to cultivate a space where groundbreaking research and innovative ideas converge, fostering collaboration and intellectual exchange among established scholars and emerging talents alike.

The manuscripts featured in this first volume, predominantly authored by our undergraduate students, are a testament to the hard work and dedication of these budding researchers, as well as the guidance and support provided by their faculty mentors. They cover a diverse range of topics, reflecting the breadth and depth of research interests within our college, and set the stage for the high-quality scholarship we aim to attract in future volumes.

As editors, we are honored to have played a role in bringing this journal to fruition. We extend our sincere gratitude to all the authors, reviewers, and members of the editorial board for their invaluable contributions. We also acknowledge the unwavering support of the college administration in making this initiative possible.

We hope that PCMJ will inspire future generations of students and researchers to embrace research and innovation, to push the boundaries of knowledge, and to make their mark on the world of computing and mathematics.

Editors
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TABLE OF CONTENTS

PCMJ

Progress in Computer and Mathematics Journal (PCMJ)
volume 1 [October, 2024]
e-ISSN: 3030-6728
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GOLD PRICE PREDICTION USING LONG SHORT-TERM MEMORY APPROACH

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Article Info

Abstract

Gold price prediction is crucial for investors and traders to make informed decisions and mitigate financial risks. This research project focuses on developing a robust gold price prediction system using the Long Short-Term Memory (LSTM) approach. The need for accurate and reliable gold price predictions is emphasized, considering the dynamic nature of the gold market and its significant impact on the global economy and financial markets. The proposed LSTM model aims to capture both short-term and long-term dependencies in time-series data, providing valuable insights for stakeholders in the gold market. The study addresses the complexity of gold price prediction and the limitations of traditional forecasting methods. By leveraging LSTM, the model is designed to effectively capture historical price data and relevant variables, offering a promising solution to the challenges faced in predicting gold prices. The methodology involves training and evaluating the LSTM model using historical data from reputable sources, ensuring the optimization of standard hyperparameters to achieve the best possible results. The results of the LSTM model demonstrate its superior performance, surpassing other machine learning models in terms of accuracy and reliability. The model exhibits a high level of accuracy of 96.9% With an impressive MAPE value of 0.031, showcasing its potential for practical application in the gold market. The findings highlight the effectiveness of LSTM in gold price prediction and underscore the significance of leveraging advanced machine learning techniques for commodity price forecasting. In future work, the system will undergo further enhancements, potentially incorporating adversarial learning to evaluate the robustness of the model. This ongoing development aims to continually improve the performance and reliability of the LSTM-based gold price prediction system, ensuring its relevance and effectiveness in real-world scenarios.

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Keywords: Gold; Prediction; LSTM; Machine Learning; MAPE

INTRODUCTION

The Britannica Dictionary (2023) defined gold as a soft yellow metal that is very valuable and that is used especially in jewellery. Gold is a chemical element in nature as well as a currency in the global market (Yuan, 2023). In the world of financial markets, the gold market is important and gets a lot of interest from regular people, big investors, and governments. (Yurtsever, 2021). By investing their money in gold, investors can prevent potential issues in the economy, such as being eroded by inflation, while avoiding the potential collapse risk of stock investment and real estate investment.

A prediction is a statement about what will happen or might happen in the future (The Britannica Dictionary, 2023). Prediction systems are becoming an essential ingredient in many modern products and services (Robnik-Šikonja, 2018). Nowadays, it is widely used in various fields, such as finance, weather forecasting, sports, marketing, and healthcare. With the help of this technology, it gives a lot of benefits to many people, especially for the gold price prediction system that can help investors to make informed decisions about when to buy or sell gold. Predicting the gold rate can help investors to protect money as its value fluctuates dramatically (Radhamani et al., 2022).

However, there are several problems that should be considered when developing this gold price prediction model. First, the price of gold is influenced by a wide range of factors that are difficult to quantify, such as geopolitical events, economic indicators, and global market trends. Yurtsever (2021) pointed out that the gold price is affected by many external factors, such as the market environment, economic crises, oil price increases, tax advantages and interest rates. Consequently, the causes of gold price fluctuations are very complex (Livieris et al., 2020). As evidence, The price of gold achieved a record high and increased to USD 1,011 per ounce due to the mortgage crisis and subsequently spread globally (Bayram & Abdullah, 2022). Second, traditional statistical models and forecasting methods often fail to capture the long-term dependencies and complex patterns present in gold price data. As a result, investors face difficulties in determining the optimal timing for buying, selling, or holding gold, leading to potential financial losses or missed investment opportunities.

The aim of this project is to develop a system that can accurately predict the future price of gold based on historical price data and other relevant variables. To achieve this aim, several specific objectives have been outlined. First, to design a web application system that can effectively capture the patterns in the gold price data. Second, to develop a system that can accurately predict future gold prices using the LSTM approach. Lastly, to test the functionality and accuracy of the developed system.

LITERATURE REVIEW

This chapter discussed the literature review, which will include descriptions of the research conducted on the issue of the project. This chapter also includes comparisons of existing apps and approaches that can be implemented.

Prediction Methods

Prediction methods, also known as forecasting methods, are techniques used to estimate or project future outcomes based on existing data or patterns. These methods play a crucial role in numerous fields such as economics, finance, weather forecasting, and data science. There are several types of prediction methods available for making forecasts. The first one is time series analysis, which focuses on analyzing patterns and trends in data collected over time. The second type is rule-based systems, which primarily focus on capturing and applying expert knowledge and domain-specific rules to make predictions or decisions. The third type is machine learning, where it learns patterns from existing data and makes predictions based on that knowledge.

Machine Learning

Machine learning (ML) methods and especially prediction models are becoming an essential ingredient of many modern products and services (Robnik-sikonja, 2018). Machine learning is a subfield of AI that focuses on developing algorithms and models that enable computers to learn and make predictions or decisions without being explicitly programmed. The main goal of machine learning is to empower computers to autonomously acquire knowledge and adapt their actions without relying on human intervention (Kumar & Sonia, 2023). Empirical research has consistently shown that machine learning algorithms used for time series prediction consistently deliver highly competitive results, often surpassing the performance of statistical models (Rafael & Parmezan, 2019).

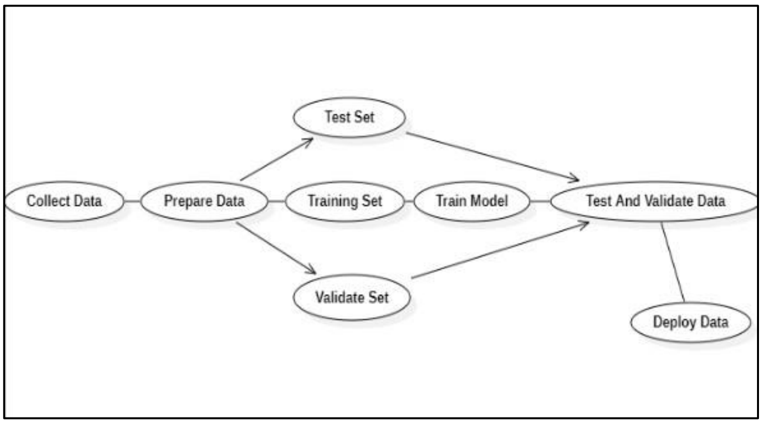

Figure 1: Machine Learning Methodology
(Source: Tripurana et al., 2021)

Figure 1 shows the methodology of machine learning. It involves the development of mathematical and statistical models that can learn patterns and relationships from data and then use that knowledge to make informed predictions or take actions. In machine learning, the learning process starts with a dataset, which consists of input data and corresponding output or target values. The dataset is typically divided into training data and testing data, where the training data is used to train the model and the testing data is used to evaluate its performance. Several machine learning algorithms exist, encompassing various types such as supervised learning, unsupervised learning, and reinforcement learning (Kumar & Sonia, 2023).

Evaluation Approach

Among the approaches of Random Forest, RNN (Recurrent Neural Network), and LSTM (Long Short-Term Memory) for a gold price prediction system, the LSTM approach stands out as the most suitable choice. This is because gold price prediction involves analysing time series data, where the sequential nature and temporal dependencies play a crucial role. LSTM, being a specialized type of RNN, is specifically designed to capture long-term dependencies in time series data, making it highly appropriate for gold price forecasting.

LSTM models can effectively handle the complexities and patterns inherent in gold price data, such as short-term fluctuations and long-term trends. The architecture of LSTM enables it to retain and learn from past information, allowing it to capture and remember relevant patterns and dependencies over time. Compared to Random Forest, LSTM offers several advantages for gold price prediction. LSTM excels at modelling nonlinear relationships in sequential data, which is valuable when dealing with the intricate dynamics and complexities

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often observed in financial time series. While Random Forest, may struggle to capture these nonlinear dependencies effectively. Table 1 shows the comparison between models.

Table 1: Models Comparison

Model	Complexity	Advantage	Disadvantages
Random Forest	Influenced by tree and feature count	- No need to normalizing the data - reduces overfitting in decision trees - Handles missing values automatically - Versatile for classification and regression tasks - Effective with categorical and continuous values - No need to normalizing the data	- Challenging to assess individual variable significance - high computational and resource demands - Lengthy training time
Recurrent Neural Networks	Depends on the number of hidden units	- Non-Linear Mapping - Ability to capture temporal dependencies in sequential data. - Memory Of Past Inputs - The occurrence of vanishing or exploding gradients - Parameter Sharing	- Lack of parallelism - The occurrence of vanishing or exploding gradients - Difficulty in capturing Long-Term dependencies - Computational complexity
Long Short-Term Memory	Depends on the number of LSTM units.	- Retaining long-term dependencies - Memory blocks with gated access - exceptional performance of data over a long period of time. - Continuous prediction -Preventing prediction biases	- More complex architecture compared to traditional neural networks. - Fixed network topology - Limited memory - Ambiguity in achieving modularization

Related Works

Each prediction model must undergo assessment to determine its accuracy, and the commonly employed metrics for accuracy evaluation include the root mean squared error (RMSE), mean absolute percentage error (MAPE), mean square error (MSE), mean absolute error (MAE), and coefficient of determination (R2) (Nti et al., 2019). Table 2 shows the comparison of related article about prediction system. These studies demonstrate a range of techniques and their corresponding results in gold price prediction. The methods employed include ARIMA, SVM, RBFNN, LSTM, GRU-NN, KNN, XGBoost, LightGBM, ANN, and hybrid models combining ANN with GA. The reported performance metrics such as RMSE and R2, were used to highlight the effectiveness of these approaches in predicting gold prices over various time periods and datasets.

Table 2: Models Comparison

Title (Citation)	Dataset	Technique	Result RMSE	Result R^2 (%)
Prediction of gold price with ARIMA and SVM (Pratiwi & Hadijati, 2021)	The data used in this study research are daily gold prices, that can be retrieve from the World Gold Council. The prices from the World Gold Council are indicated as per troy ounce. The dataset consists of the daily prices from the January 1979 to December 2019, thus makes the total number of years of observation be 41.	ARIMA	36.18	86.2
		SVM	2.49	99.8
A novel hybrid model on the prediction of time series and its application for the gold price analysis and forecasting (Jianwei E et al., 2019)	The experimental data is gathered from the World Gold Council. The gold prices data (opening price and closing price) collected from January 1979 to December 2017 (public resource: https://www.gold.org/data/gold-price).	ARIMA	40.77	96.0
		RBFNN	37.50	97.0
		LSTM	36.80	98.0
		GRU-NN	36.31	99.0
A Novel Bitcoin and Gold Prices Prediction Method Using an LSTM-P Neural Network Model (Zhang et al., 2022)	The data employed in this model for the empirical application consist only of historical price series for gold, which were collected between September 2016 and September 2021. Gold daily prices are sourced from the London Bullion Market Association.	LSTM	1.169	79.7
Gold and Bitcoin Price Prediction based on KNN , XGBoost and LightGBM Model (Yuan, 2023)	The study is based on the daily data (closing prices) for CME and XAU ranging from October. 2017 to October 2022 collected from the investing.com, which is a stock website provided with all the information globally.	KNN	14.32	99.4
		XGBoost	3.611	99.6
		LightGBM	3.323	99.7
A Hybrid Model of Artificial Neural Network and Genetic Algorithm in Forecasting Gold Price (Khamis & Yee, 2018)	The gold price per troy ounce data in USD starting from January 1987 to December 2016 was obtained from the official website of World Gold Council. The data was separated by using 80-20 proportions.	ANN	22.291	85.9
		GA-NN	18.544	87.2

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METHODOLOGY

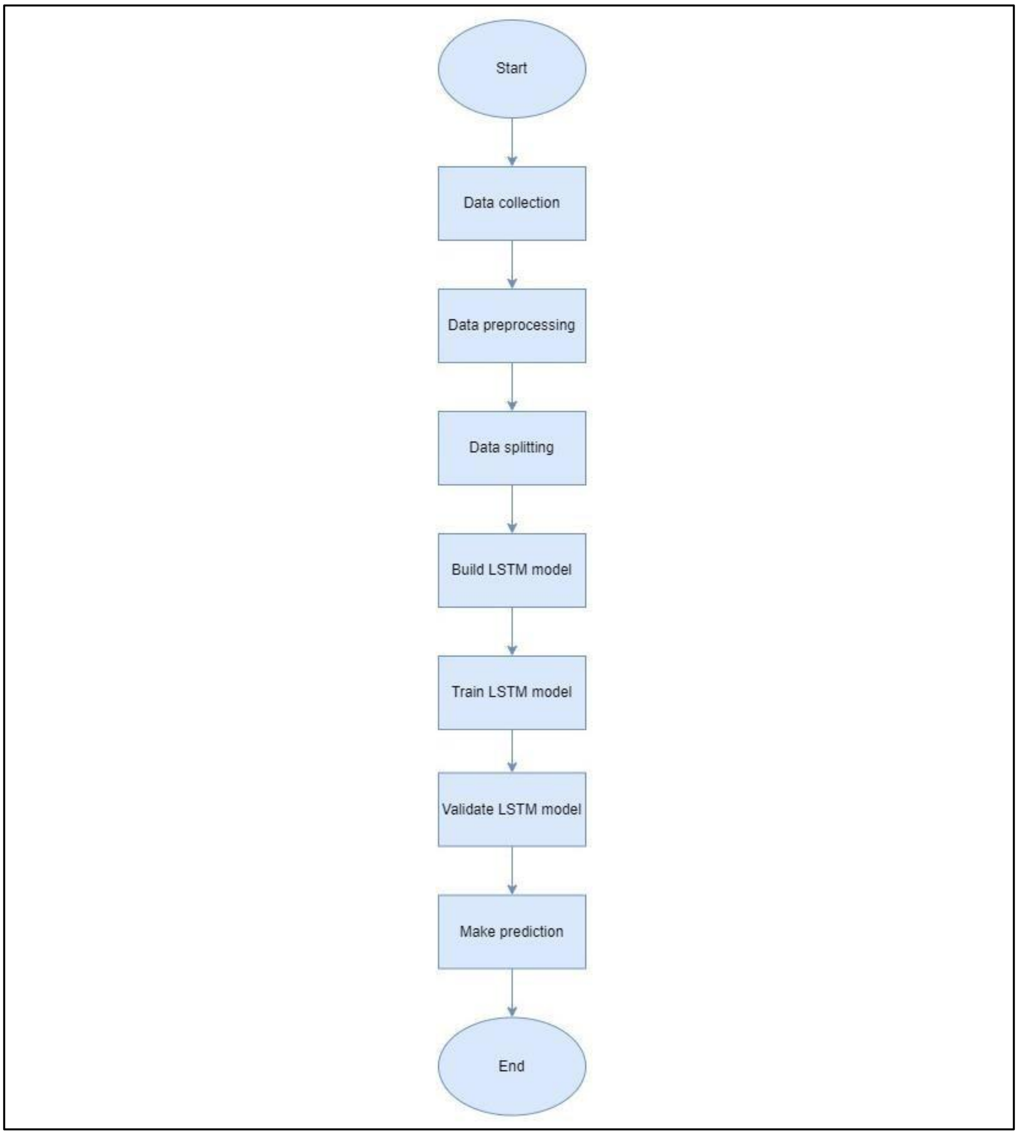

Figure 2: System Flowchart

Figure 2 shows the flowchart for the gold price prediction system. It begins with data collection, where historical gold price data is gathered from trustworthy sources. This data is then preprocessed to handle missing values and to scale the values if necessary. Following preprocessing, the data is split into training and testing sets. An LSTM model is then built and configured, setting parameters such as the number of layers, units per layer, and activation functions. The training data is used to train this LSTM model. Once trained, the performance of the model is validated using the testing data to ensure it can generalize well to new data. Finally, the trained and validated LSTM model is used to make predictions about gold prices.

PCMJ

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Figure 3: Use Case Diagram

Figure 3 shows the use case diagram of the system. In this use case diagram, the gold price prediction system consists of two actors which are the general users and the administrators. The general users have five primary actions. First, they can view the predicted prices of gold, which provides insights into future trends and assists in making informed decisions about gold investments. Second, users can check the performance of the prediction model. This feature allows users to understand how well the model has performed in the past, providing an indication of its reliability. Third, users can read articles related to gold prices. These articles can provide additional information and context about the gold market that can help users understand the factors that influence gold prices. Fourth, users can convert the gold prices into different currencies. This feature is particularly useful for international users who want to understand gold prices in their local currency. Finally, Users can access frequently asked questions about the system. This feature provides quick answers to common queries that can help to improve the user experience.

On the other hand, the admin possesses several administrative functionalities. First, admins need to log in to the system using their credentials to access the administrative features. Second, admins can update the gold price predictions by uploading and training new dataset. This feature ensures that the predictions provided by the system are always up to date. Third, Admins can add new articles to provide users with the latest news and insights about the gold market. Fourth, Admins can edit existing articles to allow admins keep the content on the site current and relevant. Finally, admins can remove articles from the system. This feature helps keep the content on the site relevant and prevents outdated or incorrect information from being displayed.

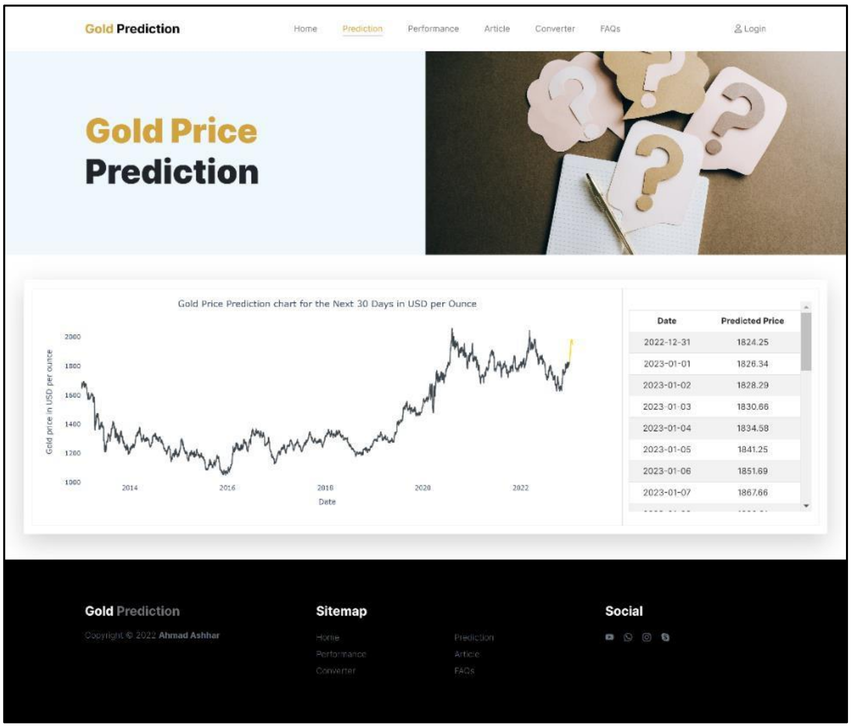

Figure 4: Prediction Page Interface

PCMJ
Progress in Computer and Mathematics Journal (PCMJ)
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Figure 4 shows the prediction page that consists of a gold price prediction chart and table for the next 30 days in USD per ounce. There are many features that users can try, such as when the cursor is on the graph, the system will display various buttons with specific features. The download feature allows users to save the graph as an image, enabling easy sharing and analysis. Pan enables seamless navigation across the chart by dragging the view to explore specific data points. Zooming allows users to focus on specific areas, providing a closer look, while zooming out broadens the view. Autoscaling adjusts axes based on data, optimizing the visual representation for a clearer exploration. The reset axes feature allows users to revert to the original scaling, providing a quick way to reset the view. Together, these features contribute to a rich interactive experience, enabling users to analyze and communicate data effectively.

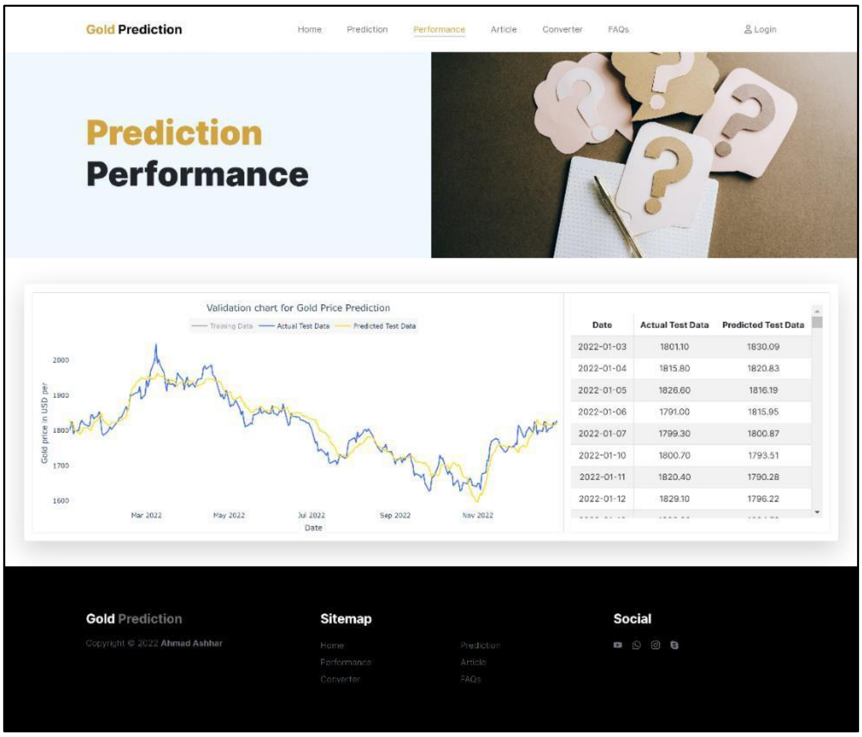

Figure 5: Prediction Page Interface

Figure 5 shows the performance page that consists of a validation chart and table for the gold price prediction system. It will visualize how close the actual test data is to the predicted test data. The features that this graph has are just like the previous page, which is the prediction page, but there are more features that our system provides. For example, the user can click any label on the top of the graph that is below the title to hide the specific plot in graph. For example, clicking on the training data label will hide its plot, represented by a black line, and only display the blue and yellow lines. Another feature is that the user can try to put a cursor on any plot on the graph, and the system will display the data details. Furthermore, users can perform a double click on any point in the graph, drag the cursor to a desired location, and release it to zoom into the selected area, offering a flexible and dynamic exploration experience. Figure 4.8 shows the prediction page of this system.

RESULT AND DISCUSSION

To conduct the accuracy test, historical gold price data is used to train the LSTM model. The model generates predictions for this test dataset, and the MAPE is calculated by comparing the predicted values with the actual prices. A lower MAPE indicates higher accuracy, as it signifies a smaller average percentage difference between predicted and actual values. In the MAPE formula, n is the number of data, Ai is the actual value at time i and Fi is the predicted value at time i. Eq. (1) shows the formula of MAPE.

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|A_i - F_i|}{A_i} \qquad 1$$

The code for MAPE evaluation techniques was implemented in the system. The variable MAPE is calculated by calling the mean_absolute_percentage_error function with two parameters which are y_test and y_pred, y_test represents the actual gold prices and y_pred represents the corresponding predicted prices. Subsequently, the variable Accuracy is computed by subtracting the MAPE from 1 and multiplying with 100. This is done to express the accuracy as a percentage, where a higher value indicates better predictive performance. Figure 4 shows the code for calculating MAPE and accuracy.

```
y_pred = model.predict(X_test)
MAPE = round(mean_absolute_percentage_error(y_test, y_pred),3)
Accuracy = round((1 - MAPE)*100,3)
```

Figure 4: Code for calculating MAPE and Accuracy

Table 3 shows the accuracy of LSTM model across different numbers of epochs, ranging from 40 to 180. Notably, as the number of epochs increases from 40 to 150, there is a general trend of improvement in accuracy, as measured by Mean Absolute Percentage Error (MAPE) and overall accuracy percentage. Particularly, at 150 epochs, the model achieves a MAPE of 0.037 and an accuracy of 96.32%. This signifies a balance between model complexity and performance, where the model demonstrates significant learning without overfitting to the training data. While further increasing the number of epochs beyond 150 may initially lead to marginal improvements in accuracy, the subsequent epochs from 160 onwards show a decline in performance, indicating potential overfitting. Therefore, the choice of 150 epochs appears optimal, as it strikes a balance between capturing meaningful patterns in the data and preventing overfitting, thereby enhancing the model's generalization capability for gold price prediction using LSTM.

Table 3: Result of MAPE and accuracy Based on Epochs

Epochs	**MAPE**	**Accuracy (%)**
40	0.050	95.01
50	0.038	96.17
60	0.025	97.53
70	0.033	96.70
80	0.026	97.38
90	0.026	97.44
100	0.039	96.06
110	0.037	96.32
120	0.038	96.19
130	0.033	96.67
140	0.026	97.38
150	0.023	97.68
160	0.056	94.39
170	0.058	94.20
180	0.088	91.21

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