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Gold Price Forecasting in Kuala Pilah, Negeri Sembilan, Malaysia Using Long Short-Term Memory (LSTM)

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ABSTRACT

Gold is the most popular investment in the world because it has proven to be the most effective haven in many countries. It is challenging to use technical analysis to predict gold's value. Many prediction problems involving time components require time series forecasting, an important topic in machine learning. This paperpresents a prototype for predicting the gold price in Kuala Pilah, Negeri Sembilan, Malaysia, using the Long Short-Term Memory (LSTM) time-series method. To address the problem, a dataset of daily gold prices was collected from Telegram Kedai Emas Nur Jannah and the Bullion Rates website. The main feature of the system is to predict the gold price and to visualise the predicted value. The waterfall method has been chosen as the project's methodology to ensure the project’s flow is correct. The predictive model was also evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). As a result, the system achieved an MAE of 0.108 at the daily time scale. The RMSE was 0.131 at the daily time scale, and the MAPE was 17%. The system can also improve the visualisation to make it more interactive and include another timescale, such as a daily timeframe.

Keywords: Gold, Prediction, Long Short-Term Memory (LSTM), Time Series

INTRODUCTION

The gold price prediction system in Kuala Pilah, Malaysia, is an interesting area of research because the gold price here is unpredictable. The reason for this is that the price in Kuala Pilah, Negeri Sembilan, Malaysia is a factory price, which differs from the MS Bullion website. Predicting gold prices can be a gold mine —very beneficial for investors, traders, and anyone who needs to plan ahead. The price of gold is constantly changing and it cannot be easily predicted. Now that prices are rising, many customers who come to this shop are interested in selling their gold. However, some exchange old gold for new designs to use the gold as savings and a 'backup' to cash savings (Assan, 2023). This project aims to analyse the factors influencing gold prices in Kuala Pilah and to develop a reliable model for predicting future price trends. Understanding the dynamics of the gold market in this specific geographical location will enhance existing knowledge and provide practical implications for stakeholders involved in gold trading in Kuala Pilah. This is because the gold price in Kuala Pilah is the lowest in Malaysia. People prefer to buy gold here (Kuala Pilah) because of the low prices, which are not tied to associations, and the reasonable wages, depending on the chosen design (Hamzah, 2021). The low price of gold for decades has made gold shops in the town of Kuala Pilah, here, too often the frequent focus of customers, especially every month and at weekends (Hasbi, 2023).

Problem Statement

There is a lack of accurate, reliable gold price predictions, which hinders individuals and businesses from making informed decisions about buying, selling, and investing in gold. However, the price of gold fluctuates unpredictably (Makala et. al, 2021). Current gold price prediction methods in Kuala Pilah are limited and often unreliable, leading to uncertainties and potential financial losses for those involved in gold-related activities. To address this problem, machine learning and deep learning methods, specifically recurrent neural networks

(RNNs) and Long Short-Term Memory (LSTMs), can be used to predict future gold prices. A comprehensive and data-driven approach must be implemented, utilising historical gold price data to develop an accurate predictive model for gold prices in Kuala Pilah.

Additionally, the problem at hand is the need for daily gold price predictions to identify optimal buying and selling opportunities, ensuring purchases are made at lower prices and sales at higher prices (Setyowibowo et al., 2022). This requires a solution that can accurately predict daily gold price movements. One possible solution is to employ machine learning algorithms, such as RNNs, which are specifically designed to handle time-series data. Training an RNN model on historical gold price data enables it to learn patterns and trends, enabling reliable predictions of future prices. The model can then be utilised daily to forecast gold prices, allowing traders and investors to time their buying and selling decisions to maximise profits strategically. Regularly updating the model with the latest data ensures that predictions remain accurate and relevant.

Related Work

In predictive applications, LSTMs are particularly valuable for their ability to learn from historical data and identify complex temporal patterns. For instance, in financial forecasting, an LSTM model can analyse past stock prices to predict future values, capturing intricate dependencies that traditional models like ARIMA may overlook (Zhang, 2003). LSTM architecture allows it to effectively manage sequences with long-term dependencies, a crucial feature for predicting outcomes in which earlier inputs significantly influence future outputs. This makes LSTMs particularly suitable for tasks such as weather forecasting, where current conditions are influenced by historical climatic patterns (Greff et al., 2017).

Implementing LSTM for prediction involves structuring data into appropriate input-output pairs, where the model is trained to map sequences of past observations to future values. After training, the LSTM can generate predictions by processing the most recent data points. The model's performance is typically evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to assess accuracy and reliability (Brownlee, 2017). This robust framework enables LSTMs to achieve significant improvements in prediction accuracy, making them a powerful tool for handling complex time-series prediction tasks.

Equation

The accuracy test determines whether the model performs well. This test utilised three methods to evaluate the model's performance: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Accuracy testing validates the results produced by the developed model using the formulas MAE, RMSE, and MAPE shown in Figure 1.

Root mean squared error	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$
Mean absolute error	$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} \lvert e_t \rvert$
Mean absolute percentage error	$\mathrm{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n} \left\lvert \frac{e_t}{y_t} \right\rvert$

Fig 1. Equation Formula for Accuracy Testing

Model

In the gold price prediction system, a function named define_model was created to define the LSTM model. The model was designed to accept input data with shape (128, 1), corresponding to 128 time steps with one feature each. The model's architecture consisted of three LSTM layers, each with 64 units. The return_sequences=true parameter in the first two LSTM layers ensured that the entire sequence of outputs was returned, enabling sequence predictions. After each LSTM layer, a Dropout layer with a rate of 0.2 was added to prevent overfitting.

The final layer of the model was another Dense layer with a single unit, serving as the model's output and predicting the future gold price. The model was compiled using the Nadam optimiser and mean squared error as the loss function, both of which are suitable for a regression problem like this one. The model.summary() function was called to print the model architecture. The function define_model then returned the constructed model. Figure 2 shows the code for the LSTM model.

```
#Creating LSTM Network
#Model Definition
def define_model():
    input1 = Input(shape=(window_size,1))
    x = LSTM(units = 128, return_sequences=True)(input1)
    x = Dropout(0.2)(x)
    x = LSTM(units = 128, return_sequences=True)(x)
    x = Dropout(0.2)(x)
    x = LSTM(units = 128)(x)
    x = Dropout(0.2)(x)
    x = Dense(64, activation='relu')(x)
    dnn_output = Dense(1, activation='linear')(x)

    model = Model(inputs=input1, outputs=[dnn_output])
    model.compile(loss='mean_squared_error', optimizer='Nadam')
    model.summary()

    return model
```

Fig 2. The Coding for the LTSM Model

METHODOLOGY

This phase involved tasks such as Research Design, Use Case Diagram, and Flow Chart.

Research Design

The process begins by collecting daily gold price data from Telegram Kedai Emas Nur Jannah for Kuala Pilah and from the Bullion Rates website for Malaysia. The telegram displays the price of gold with wages, without wages, and the trade-in price. It is cheaper than the price in the rest of Malaysia. This is because most gold shops in Kuala Pilah use factory-set gold prices. Next, data cleaning and preprocessing steps are performed to prepare the data for the LSTM model. This process includes handling missing values and transforming the data into sequences for the model. The LSTM model, a type of neural network designed for time series data, is trained on these sequences to learn historical price patterns. Finally, the trained model can be used to forecast future gold prices by feeding it new sequences of past prices, as shown in Figure 3.

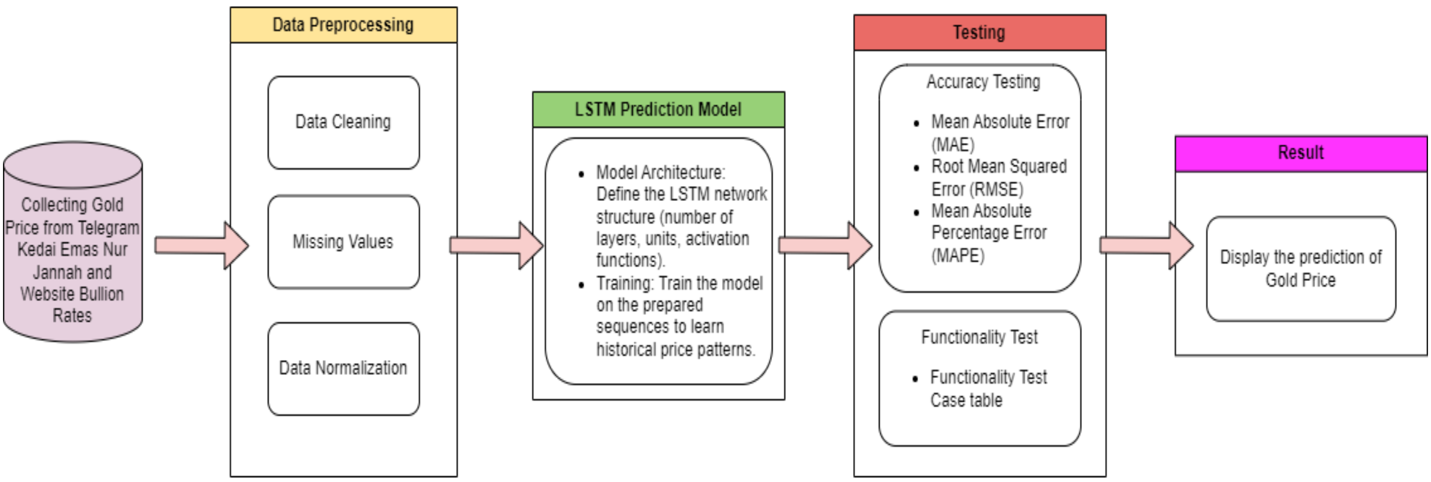

Fig3. Research Design Flow

Use Case

Figure 4 displays the use case diagram for this prototype, summarising the details of the prediction system and the users involved. The admin user is responsible for adding daily gold prices from the Kuala Pilah datasets.

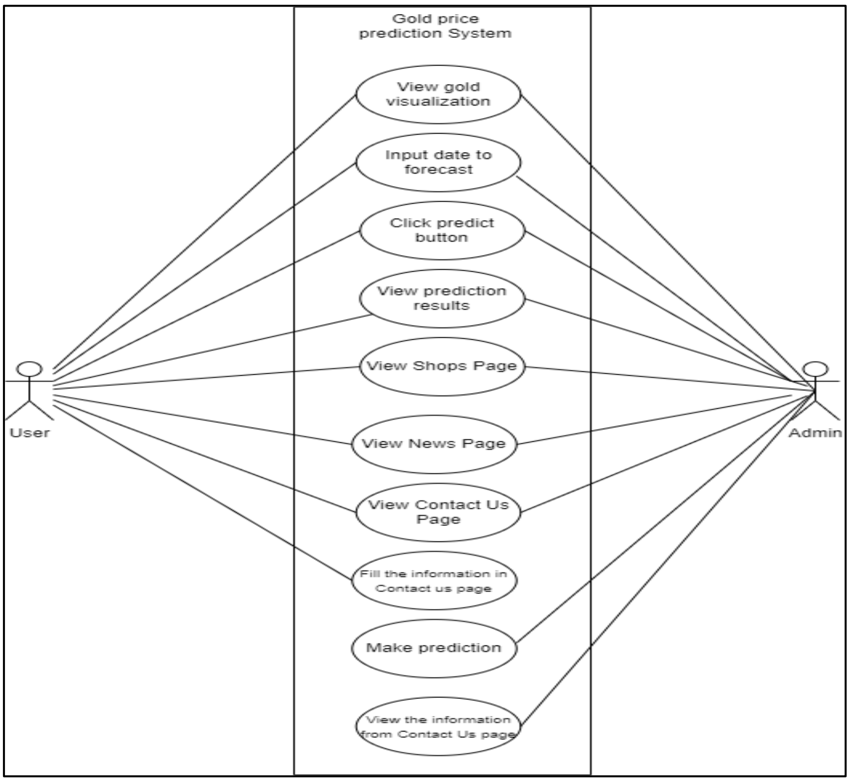

Fig 4. Use Case Diagram

Flow Chart

Figure 5 shows the flow chart of the prediction system. The homepage will provide the users with various options for navigating the system.

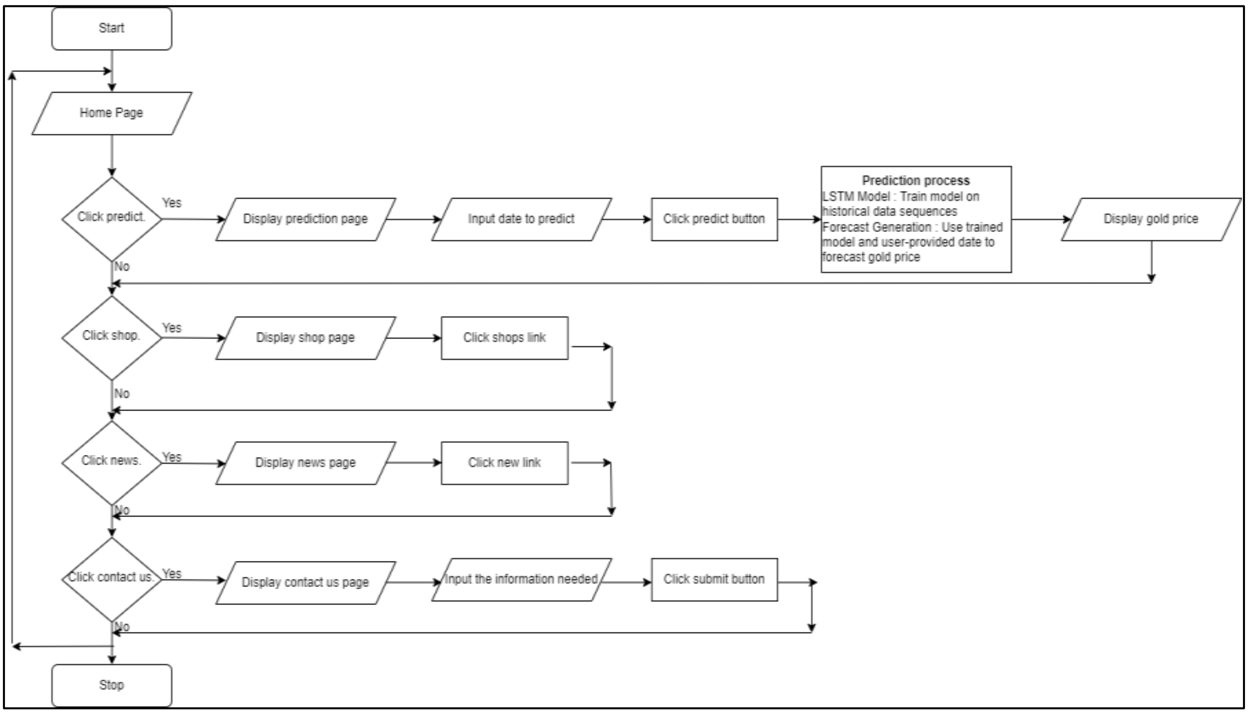

Fig 5. Flow Chart

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RESULT

Absolute errors and squared errors are the most widely used scale-dependent metrics, including mean square error, root mean square error, mean absolute error, mean absolute percentage error, and median absolute error. However, RMSE, MSE, and MAPE are the most popular because of their theoretical relevance in statistical modelling (Hyndman, 2006). Table I presents the results for this prototype.

Table I Accuracy Testing Result

Model of gold	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)	Mean Absolute Percentage Error (%)	Test Accuracy (%)
Daily	0.108	0.131	15	82.9

Table I shows that the MAE is 0.108, the RMSE is 0.131, and the MAPE is 15%. These are acceptable results, and 82.9% was achieved, which is viable for the LSTM model. The system's functionality was also tested using six test cases during this functionality testing. Table II summarises the test cases completed during this phase. Also, the functionality testing was successful, and the system is now functioning correctly and running as planned. This is one of the functionalities tested.

Table II Functionality Testing

Description	User select date and click on predict button
Test Summary	To prove user that display the predict price
Related Page	Predict Page
Testing Date	29/6/2024
Potential Output	Display prediction price in the text box
Activities	Select the date and click predict button
Expected Output	Prediction price was displayed
Actual Output	 Figure 5.4 Prediction Price Display
Status	Pass

CONCLUSION

In conclusion, Gold Predict is a system that provides a time-series prediction model using Long Short-Term Memory (LSTM). It predicts the daily gold price in Kuala Pilah at the daily time frame. The predicted values are listed in a table, and they are visualised in a line chart to help investors understand future trends in gold prices. The system also provides links to gold shops in Kuala Pilah, including their websites, for users who want to shop directly on the website, learn more, or obtain more information about the shops. Lastly, it includes a feature that lets users contact the admin directly to ask questions or request an explanation of our website. The system also helps the admin by providing visualisation of each model, along with its accuracy. For future work on this project, the gold price data should be pulled directly from financial websites by using a gold API. This recommendation will help improve the model’s performance and enhance system features. Another recommendation is to enhance the predictive model by using more advanced techniques, incorporating additional features, and gathering more historical data to improve accuracy. Regular evaluation and retraining will help maintain the model's performance. These steps will make the data analysis process more efficient and the predictions more reliable.

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