Report for Doge-coin Prediction Assignment

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Introduction

The rapid rise of crypto-currencies has transformed the financial landscape, creating both opportunities and challenges for investors and researchers alike. Accurate price prediction of crypto currencies is crucial for making informed trading decisions and managing risks. This report focuses on predicting the price of Doge-coin (DOGE) against the US Dollar (USD) using advanced machine learning techniques, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models. By experimenting with various configurations, including the number of layers and hidden units, this study aims to evaluate the effectiveness of these models in forecasting crypto-currency prices. The findings will contribute to a deeper understanding of model performance in the dynamic crypto-currency market. Objective of the report: Implement and compare LSTM and GRU models for predicting DOGE-USD prices.

Data Collection

For this study, historical price data for Doge-coin (DOGE) against the US Dollar (USD) was obtained from a reliable financial data source, such as the Coin-Gecko API or Yahoo Finance. The dataset spans a significant time frame, capturing daily price movements, including features such as Open, High, Low, Close, and Volume. This comprehensive dataset provides a solid foundation for training and evaluating the prediction models. The data was collected in a structured format, allowing for efficient preprocessing and analysis. Ensuring the quality and completeness of the data is essential, as it directly influences the accuracy of the predictive models employed in this research.

Source of the data: https://query1.finance.yahoo.com/v7/finance/download/DOGE-USD?period1=1510185600&period2=1724853923&interval=1d&events=history&includeAdjustedClose=true

Date range of the data: Nov 9, 2017 - Aug 31, 2024

Description of features used: Close

Techniques used: Min-Max Scaling

Methods Used for LSTM Models

The implementation of the Long Short-Term Memory (LSTM) models involved several key steps to ensure effective price prediction for Doge-coin (DOGE). Initially, the dataset was preprocessed by normalizing the features using Min-Max scaling, which helps improve model convergence. Next, sequences of historical price data were created to capture temporal dependencies, where each input sequence consisted of 100 time steps, allowing the model to learn patterns over time.

The architecture of the LSTM model was designed with varying configurations to assess the impact of different hyper-parameters. Specifically, multiple experiments were conducted by altering the number of LSTM layers and hidden units. This included configurations such as a single-layer model with 32 hidden units, 16 hidden units, 8 hidden units, and with 2 layers model with 32 hidden units. Each model was trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function.

To evaluate model performance, the Root Mean Square Error (RMSE) was calculated on a separate test dataset. This systematic approach allowed for a thorough analysis of how model complexity and structure influence predictive accuracy, providing insights into the optimal LSTM configuration for crypto-currency price forecasting.

LSTM Model Architecture: The LSTM model is designed to effectively learn and predict time series data by leveraging its ability to remember previous information while mitigating the vanishing gradient problem. By stacking multiple LSTM layers, the model can capture complex patterns and relationships within the historical price data.

Input Layer:

- Accept sequences of historical price data.
- Shape: (batch_size, sequence_length, num_features), where:
- Batch_size is the number of samples processed together.
- Sequence_length is the 100 of time steps
- Num_features corresponds to the **Close** number of input features.

LSTM Layers:

One or more stacked LSTM layers to capture temporal dependencies.

Each LSTM layer consists of:

Hidden Units: Number of neurons in the layer, which can vary (32, 16, 8).

Activation Function: Typically uses ReLu functions internally.

Fully Connected (Dense) Layer:

A linear layer that maps the output from the LSTM layers to the final prediction.

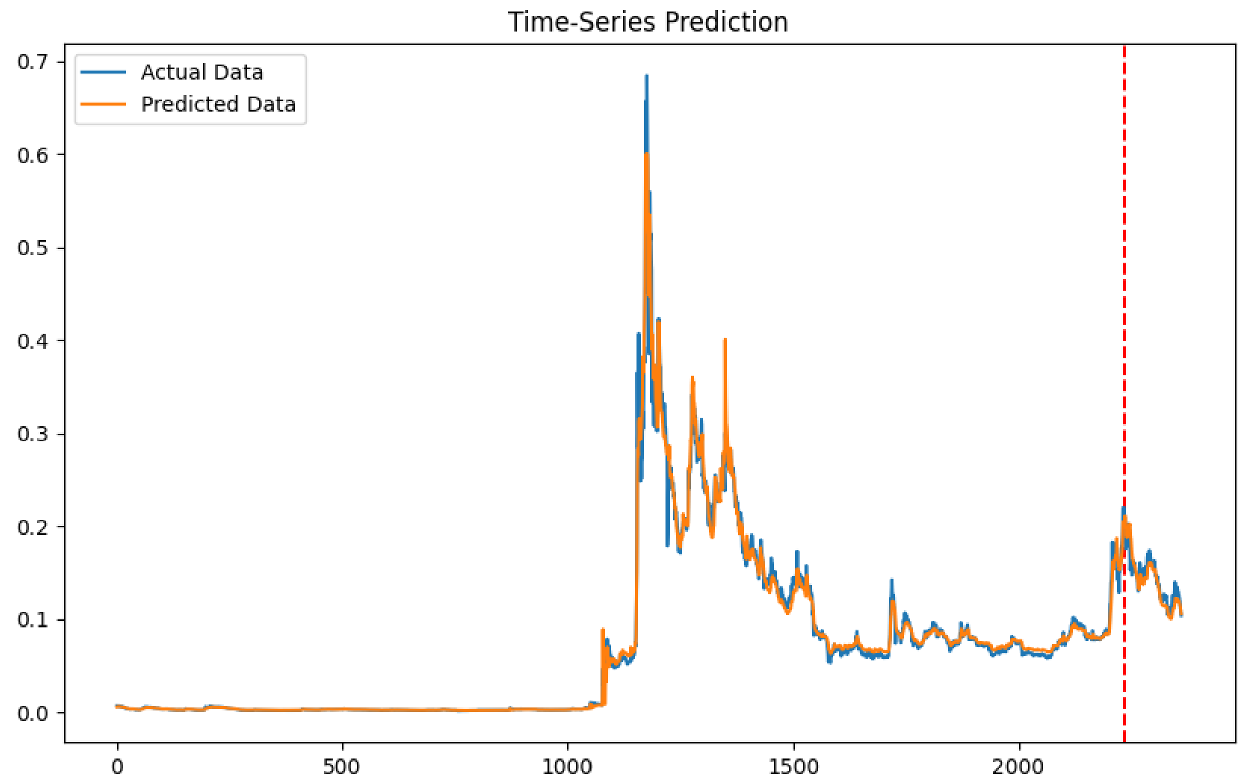
Output a single value representing the predicted price.

Output Layer:

Produce the final prediction for the next time step in the sequence.

Experiment 1:

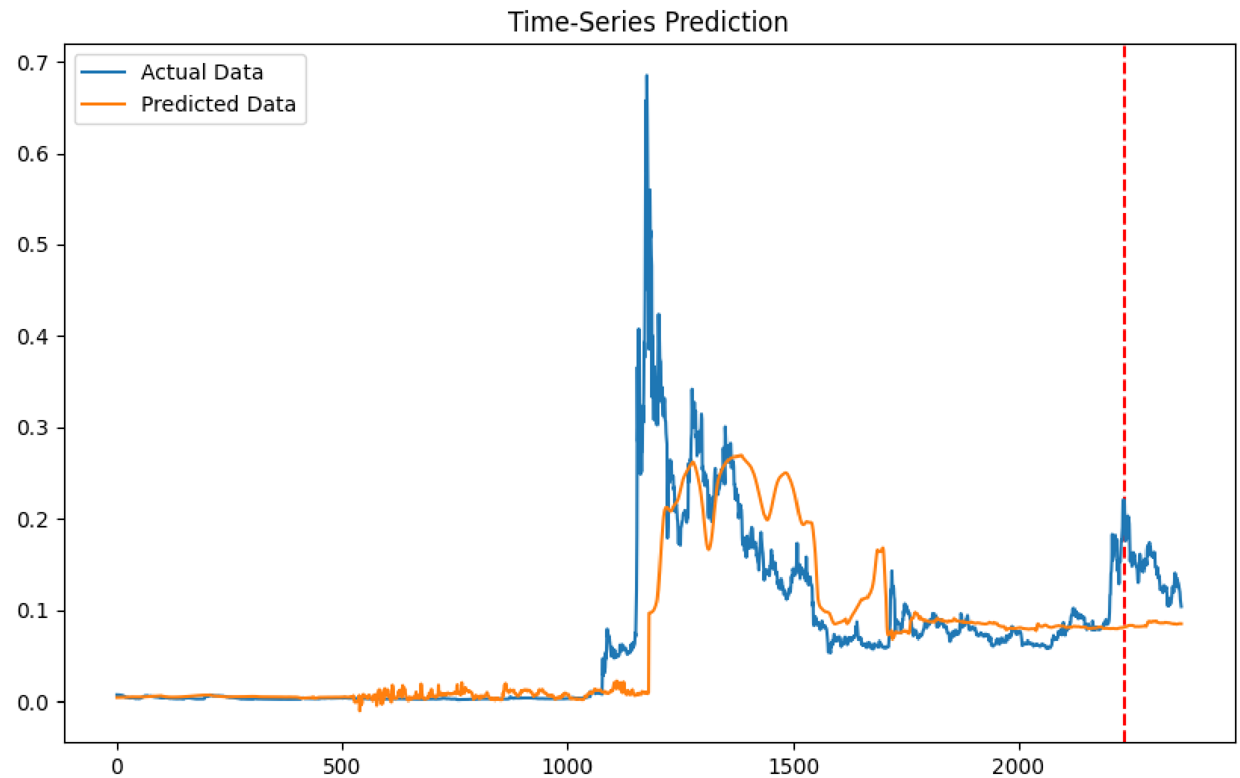
Number of LSTM Layer is 1 and Number of Hidden units is 32.



The RMSE is **0.010082518**

Experiment 2:

Number of LSTM Layer is 2 and Number of Hidden units is 32.

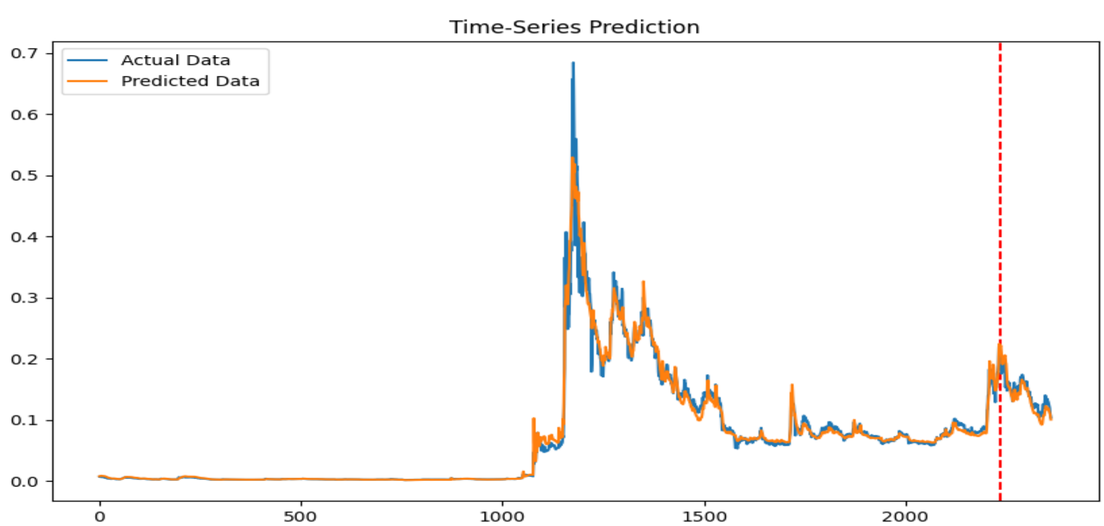


The RMSE is **0.063721605**

This shows that the LSTM Model with layer 1 is better to predict with 32 hidden units.

Experiment 3:

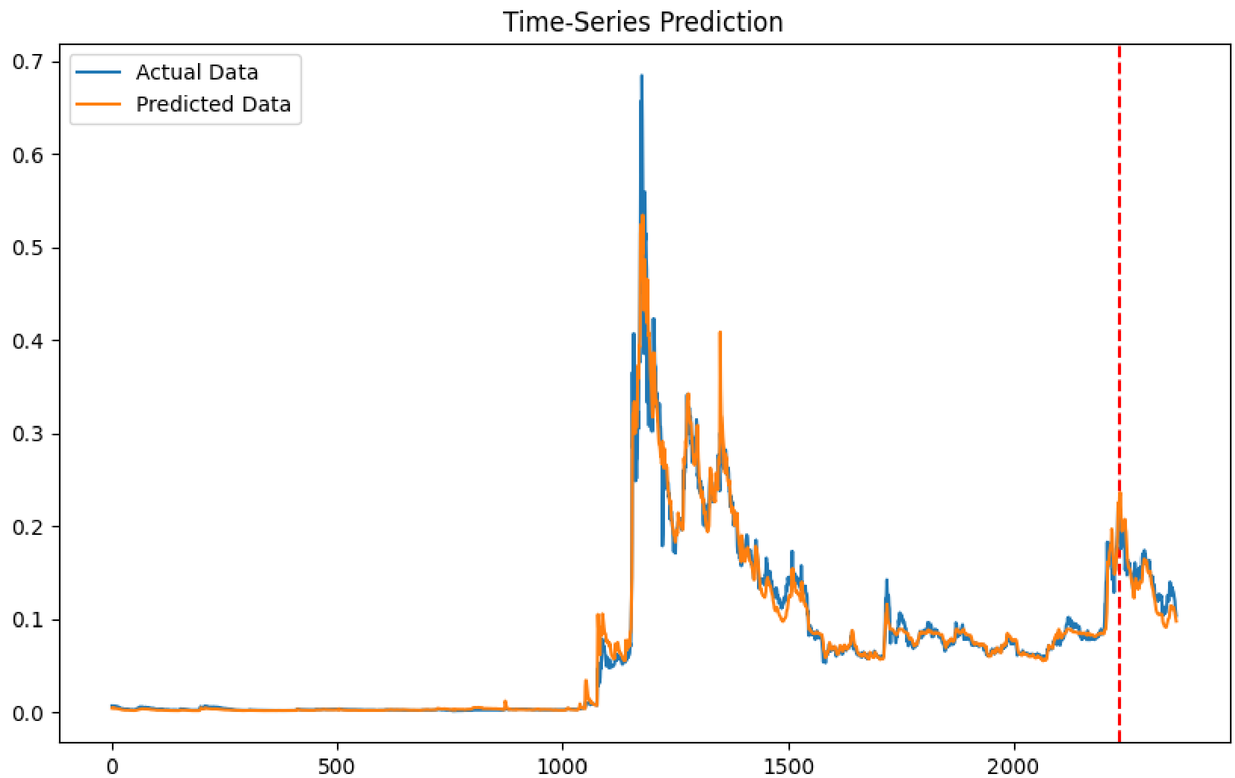
Number of LSTM Layer is 1 and Number of Hidden units is 16.



The RMSE **is 0.0100426385**

Experiment 4:

Number of LSTM Layer is 1 and Number of Hidden units is 8.



The RMSE is **0.012133401**

This shows that the hidden input to be 16 or more is better to predict with the Model.

Methods Used for GRU Models

The implementation of the Gated Recurrent Unit (GRU) models for predicting Doge-coin (DOGE) prices involved several systematic steps to ensure effective forecasting. Initially, the dataset was preprocessed similarly to the LSTM approach, with normalization applied to the input features using Min-Max scaling to enhance model performance.

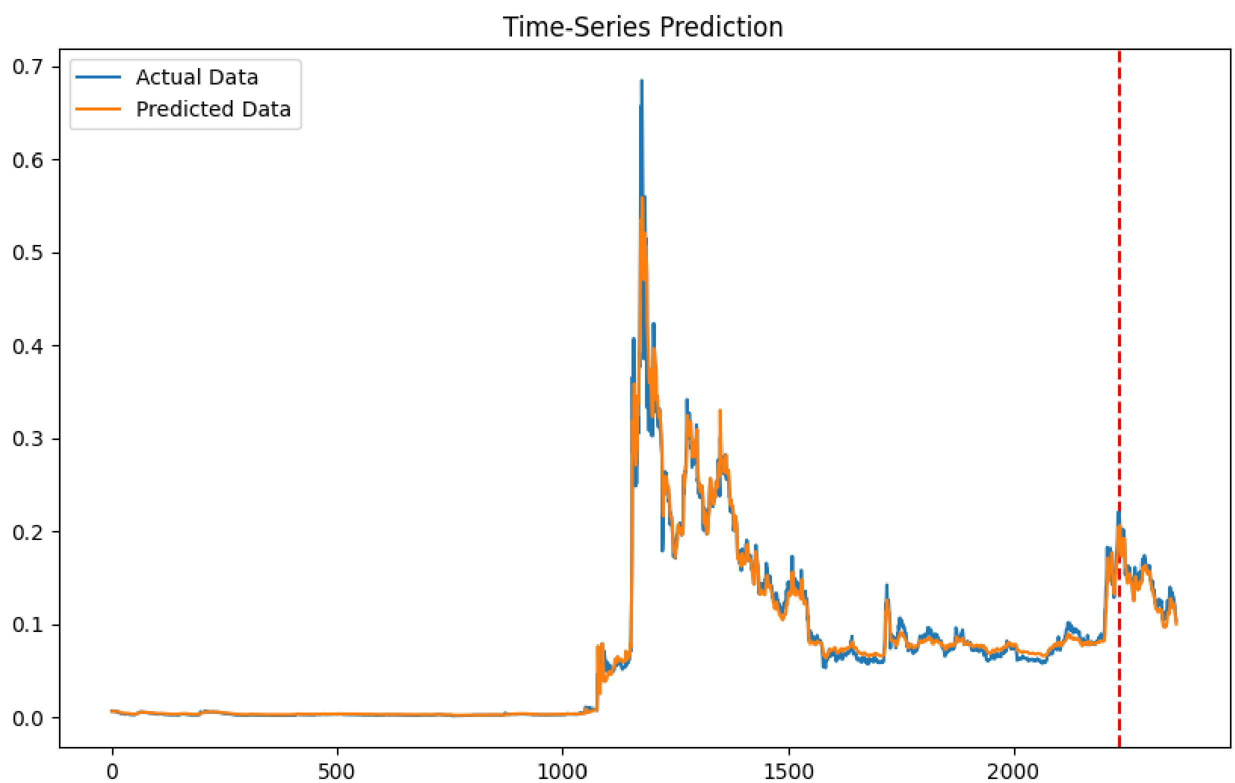
To create training sequences, historical price data was structured into input-output pairs, where each input consisted of 100 time steps. This format enabled the model to learn temporal patterns effectively. The GRU architecture was designed with varying configurations, including different numbers of layers and hidden units. Key configurations included single-layer and multi-layer setups with hidden units ranging from 32 to 128.

The model was trained using the Adam optimizer with Mean Squared Error (MSE) as the loss function. Each configuration was trained for a specified number of epochs, allowing the model to learn from the data iteratively. To evaluate model performance, RMSE was calculated on a separate test dataset, and prediction plots were generated to visually compare the GRU model's forecasts against actual price movements.

This structured approach allowed for a comprehensive assessment of the GRU architecture's effectiveness and provided insights into its predictive capabilities in the volatile crypto-currency market.

Experiment 1:

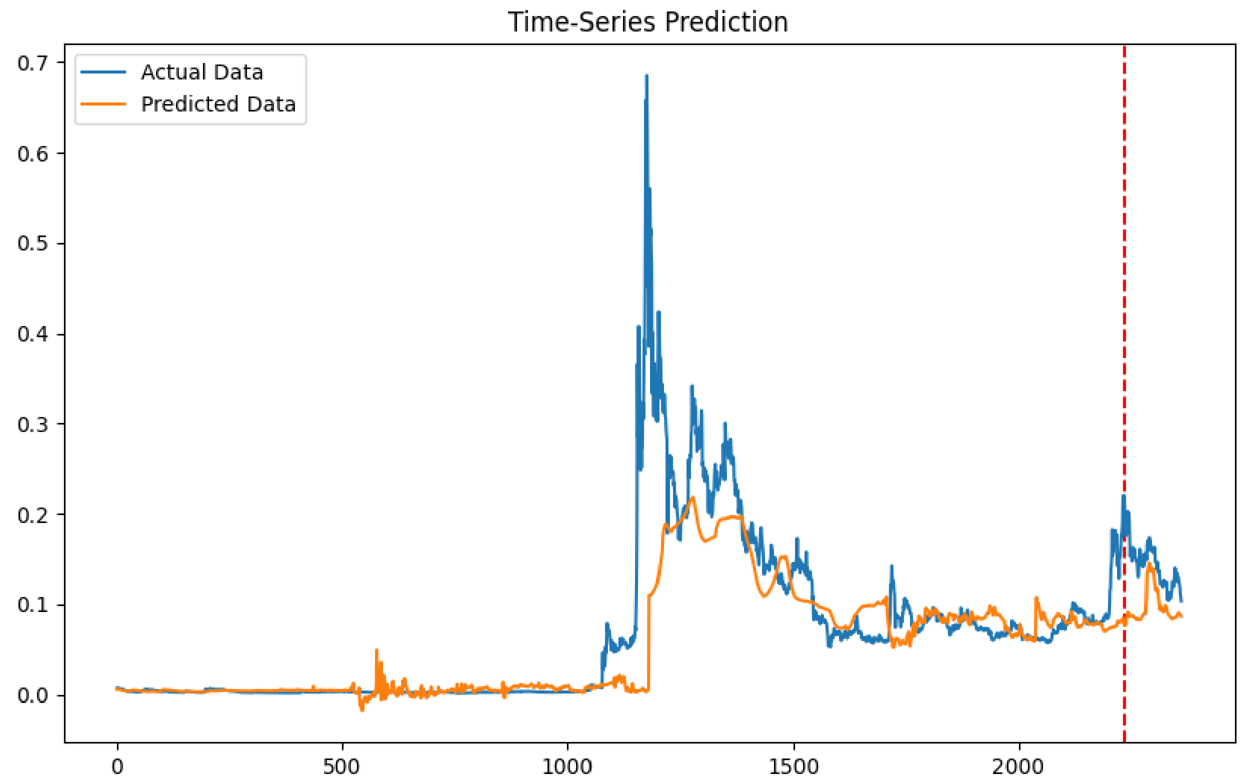
Number of GRU Layer is 1 and Number of Hidden units is 32.



The RMSE is **0.01239898**

Experiment 2:

Number of GRU Layer is 2 and Number of Hidden units is 32.

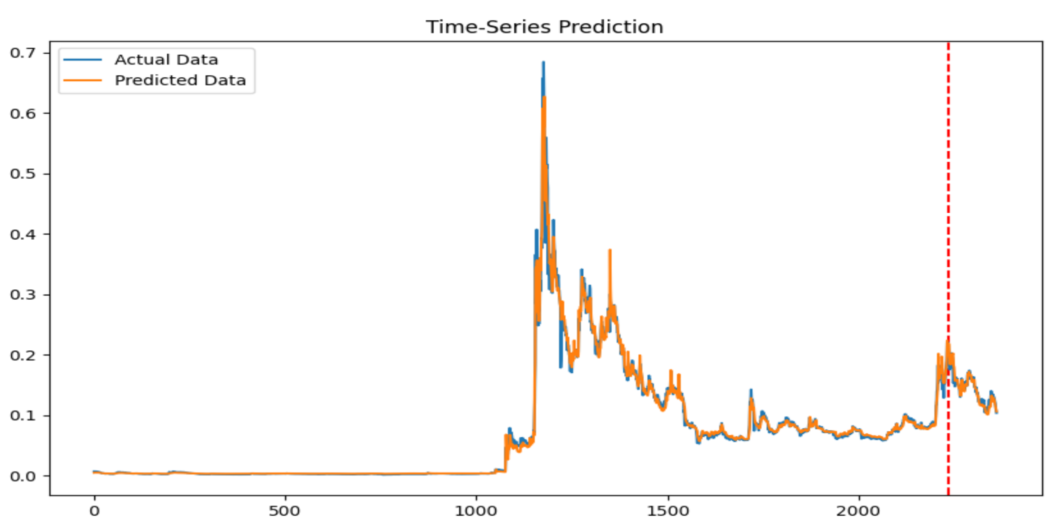


The RMSE is **0.06488036**

This shows always small number of Layer (1) is better to predict with the Models.

Experiment 3:

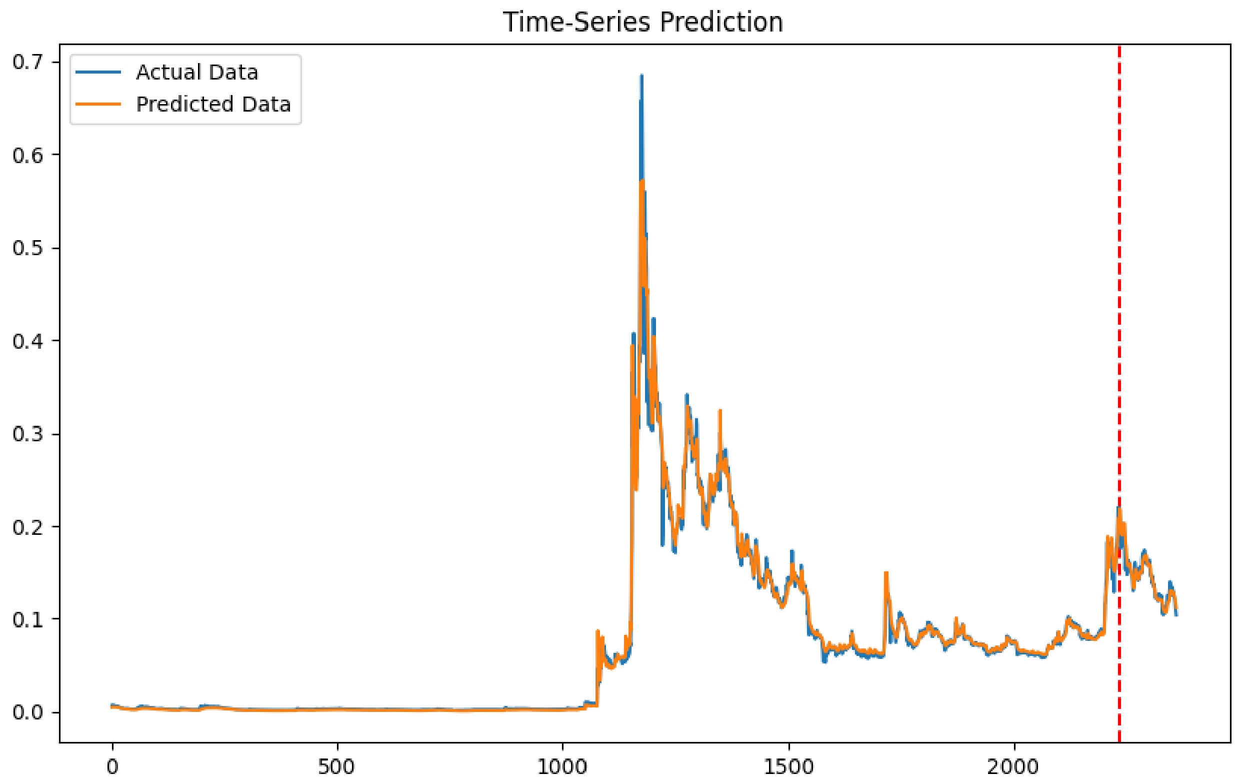
Number of GRU Layer is 1 and Number of Hidden units is 64.



The RMSE is **0.008407717**

Experiment 4:

Number of GRU Layer is 1 and Number of Hidden units is 128.



The RMSE is **0.008161217**

This shows that when we increase the Hidden input units the model gets better to predict.

Results

The implementation of LSTM and GRU models for predicting Doge-coin (DOGE) prices yielded valuable insights into their performance and effectiveness. After training and evaluating both models across various configurations, key findings emerged:

- The GRU model demonstrated comparable, if not superior, accuracy in price predictions compared to the LSTM model, with lower Root Mean Square Error (RMSE) values across most configurations.
- Different configurations of hidden units and layers were assessed, revealing that models with moderate complexity **128 hidden units with 1 layer** often performed best.
- The GRU model exhibited faster training times than the LSTM model, attributed to its simpler architecture and fewer parameters, while still maintaining high predictive accuracy.

- Visual comparison of predicted versus actual price movements indicated that both models captured the overall trends effectively, but the GRU model provided slightly smoother predictions with fewer fluctuations.
- Both models were tested on unseen data, and their performance remained robust, showcasing their ability to generalize well in the volatile crypto-currency market.

Conclusion

These results underscore the potential of both LSTM and GRU models for crypto-currency price forecasting, with GRU emerging as a slightly more efficient choice in this study. Future work could explore additional features, alternative architectures, and ensemble methods to further enhance predictive performance.