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XRP Price Prediction Using Advanced Deep Learning Models

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Abstract
Virtual currencies have been declared as one of the financial assets that are widely recognized as exchange currencies. The cryptocurrency trades caught the attention of investors as they can be considered highly profitable investments. To optimize the profit of cryptocurrency investments, accurate price prediction is essential. The model proposed in the paper will leverage deep learning algorithms such as LSTM, Bi-LSTM, GRU, which are popular and reliable models for time series datasets and forecasting. The model will incorporate daily closing prices of XRP, including features such as Volume, High, Low, Open and Change percentage. It will provide a prediction of prices using a historical dataset as well as live data according to the traders' needs within the current market trend of XRP. This system can also forecast the prices and provide what will be the market trend of XRP in the coming time frame. This model system will make the trading of XRP tokens for the traders more convenient and time saving. This model system can also provide valuable insight into the trends of the crypto currency market.

Keywords: *Ripple, Cryptocurrency, Deep learning, Tokenization.*

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I. INTRODUCTION

Cryptocurrencies have drastically pioneered since their initial appearance in 2008, gaining ever-increasing popularity and social acceptance. However, in recent years, in addition to their use as a medium of deficiency, cryptocurrencies have emerged as an alternative investment asset, reaching a total market capitalization of 1.76 trillion USD in 2022. Although the digital currency market is attractive due to its unique characteristics, such as potential high return, no association with classical financial assets, and governmental restrictions, it should also be regarded as volatile and risky. In the literature, it proposes profitable transaction approaches based on those predictions. Since digital currencies are powerful investment tools for buyers, it is necessary to apply forecasting methods in this new evolving market.

Due to the highly volatile nature of digital currencies, traditional statistical approaches and econometric models used to predict traditional financial assets are proven to be ineffective when used for cryptocurrency prediction. It is necessary to develop smart systems that do not require pre-determined assumptions about the data. Deep learning algorithms are based on neural networks that aim to extract hidden patterns, integrate them, and elaborate the valuable featural information by eliminating noise in the input data. Several studies showed that deep learning algorithms provide highly effective results in forecasting financial asset data.

Ripple enables global financial institutions, businesses, governments, and developers to move, manage and tokenize value to help to unlock greater economic opportunity for their users. The token deployed for ripple is called XRP. It is a trusted agent between two parties in a transaction, as the network can quickly confirm that the exchange went through properly. Ripple can facilitate exchanges for a variety of fiat currencies and cryptocurrencies, such as Bitcoin, to name one example.

Researchers from various scientific disciplines have studied the factors influencing cryptocurrency prices and have leveraged techniques from the fields of statistics, machine, and deep learning in order to predict it with high accuracy. However, most of these models operate as a black box without considering the contribution of each feature to the prediction accuracy. The goal of this work is to overcome the limitations of a black-box approach and present an efficient method for selecting the features that influence cryptocurrency prices the most. We shall proceed with domain knowledge feature selection as well as automatic feature selection using python libraries.

We propose a framework of feature selection techniques to identify the best features for predicting the future price of Ether and then develop a set of deep learning models consisting of LSTM, GRU, and TCN layers that indicate both the exact price of XRP as well as its direction in the short and long term (one and seven days respectively). We focused on XRP because of its Fast settlement transactions, low fees, and Versatile exchange network. It also supports much more functionality and has a more complex nature than Bitcoin due to the way it is transferred.

The purpose of making XRP price predictions using deep learning models is to forecast the future price movements of XRP, a cryptocurrency that is traded on various exchanges. LSTM and GRU are advanced deep learning techniques that have been proven to be effective in predicting time series data, including cryptocurrency prices.

By using these techniques to analyze historical price data of XRP, we can create a predictive model that can forecast the future price of XRP with a certain degree of accuracy. This information can be useful for traders, investors, and other market participants who are looking to make informed decisions about buying, selling, or holding XRP.

Moreover, XRP price prediction can also assist in risk management by identifying potential price fluctuations that can impact investment decisions. Additionally, it can provide insight into the market trend and help market participants to understand the underlying factors driving the price movements of XRP. Overall, the purpose of making XRP price prediction using LSTM GRU is to provide valuable insights and help market participants make more informed decisions.

This project also lies down a comparative study between different deep learning models in different scenarios. It could be useful to researchers as well as students who are trying to understand the effectiveness of models in varied scenarios.

Eventually, if the model gives optimal accuracy, we shall be using this model as a strategy and shall automate trade on Trading View using Pine Script.

II. DATA DESCRIPTION

XRP is a cryptocurrency and digital payment protocol that Ripple Labs Inc. Binance created is one of the largest cryptocurrency exchanges in the world, providing a platform for individuals to trade cryptocurrencies and digital assets. The data in this dataset represents the comprehensive historic information for the XRP token on the Binance exchange.

II.1. Data Collection

The data in this dataset was collected using the Binance API, which provides access to real-time and historical data for various cryptocurrencies and digital assets on the Binance exchange. The API allows for data to be fetched for specific time intervals, such as daily, hourly or even minute-by-minute data. This dataset includes the most comprehensive and relevant data fields for the analysis of XRP token performance on the Binance exchange.

2.2. API Data Retrieval

The Binance API provides a secure and flexible way to access real-time and historical data for various cryptocurrencies and digital assets on the Binance exchange. To retrieve the data, an API key must be generated through the Binance website. The API key is a unique identifier that allows for programmatic access to the data on the exchange. To fetch the data, a script or application can be written that makes API requests utilizing the API key. The API allows for data collection for specific time intervals, such as daily or hourly, and to data fields, such as the open price, high price, low price, close price, volume, quote volume, and the weighted average price of XRP. Binance API can retrieve the data in various file formats, such as CSV or JSON. The Binance API is subject to change. It is important to regularly check and update any scripts or applications that utilize it to ensure that the data remains accurate and up to date.

2.3 Data Fields

- Timestamp: The date and time of the data point in UTC format.
- Open The opening price of XRP at the start of the interval.
- High: The highest price of XRP reached during the interval.
- Low: The lowest price of XRP reached during the interval.
- Close: The closing price of XRP at the end of the interval.
- Volume: The total volume of XRP traded during the interval.
- Quote Volume: The total volume of the quote currency traded for XRP during the interval.
- Weighted Average Price: The weighted average price of XRP during the interval.

2.4 Notes

- The interval of the data points may vary depending on the specific API request made.
- The data should be used for informational purposes only and not intended as investment advice.
- The Binance API is subject to change, and the data may become outdated.

III. METHODOLOGY

III.1. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is specifically designed to process sequential data such as time series, natural language text, or speech. RNNs are a popular choice for processing sequential data because they can remember previous information and use it to inform their predictions for the next step in the sequence. However, traditional RNNs suffer from a problem known as the vanishing gradient problem, which occurs when the gradients of the parameters become very small over time, making it difficult to train the network effectively.

LSTMs are designed to overcome the vanishing gradient problem by incorporating memory cells that can retain information over a long period and input, output, and forget gates that control the flow of information through the network. The input gate determines which information from the sequence should be passed to the memory cell, the output gate determines which information should be passed from the memory cell to the output, and the forget gate determines which information should be forgotten by the memory cell. By selectively retaining, updating, or discarding information, LSTMs are able to capture and process long-term dependencies in sequential data effectively.

LSTMs have been widely used in various applications such as speech recognition, machine translation, and natural language processing and have been shown to outperform traditional RNNs and other deep learning models in many cases. The ability of LSTMs to capture long-term dependencies in sequential data and overcome the vanishing gradient problem makes them a powerful tool for processing sequential data.

III.2. Gated Recurrent Units (GRUs)

Gated Recurrent Units (GRUs) are another type of RNN that is designed to be a simplified alternative to LSTMs. Like LSTMs, GRUs are designed to process sequential data and overcome the vanishing gradient problem encountered in traditional RNNs. However, GRUs have a simpler architecture than LSTMs, consisting of only two gates: the reset gate and the update gate. The reset gate determines which information should be discarded from the previous time step, and the update gate determines which new data should pass information to the next time step.

GRUs have been shown to perform competitively with LSTMs in various applications, such as speech recognition and natural language processing, despite their simpler architecture. The simplicity of GRUs also makes them computationally more efficient than LSTMs, as they require fewer parameters and fewer computational resources. This makes GRUs a popular choice for sequential data processing tasks that require high computational efficiency, such as real-time streaming data processing.

III.3. Bidirectional Long Short-Term Memory (bi-LSTM)

Bidirectional Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is capable of processing sequential data such as time series, natural language text, or speech. Unlike traditional RNNs, which process sequential data in only one direction, bidirectional LSTMs process sequential data in both forward and backward directions, which allows the model to learn context from both past and future information in the sequence.

A bidirectional LSTM is composed of two separate LSTM models, one processing the input sequence in the forward direction and the other processing the input sequence in the reverse direction. The output from both LSTMs is then concatenated and used as input to the next layer of the network, allowing the model to learn context from both past and future information in the input sequence,

Bidirectional LSTMs have been shown to outperform traditional LSTMs in various applications, such as natural language processing and speech recognition, due to their ability to capture context from both past and future information in the input sequence. The bidirectional nature of the LSTM also helps mitigate the vanishing gradient problem that is commonly encountered in traditional RNNs, allowing for improved training and performance.

III.4. Ensemble Learning

Ensemble learning is a powerful machine learning technique that involves training multiple models and combining their predictions to produce a more robust and accurate result. In this technique, the predictions from different models are combined either by voting, averaging, or weighting. This approach helps to overcome the limitations of individual models and can improve the overall performance of the prediction.

In the case of Ripple price prediction, an ensemble of LSTM and GRU models can be used to leverage the strengths of both models. LSTM, short for Long Short-Term Memory, is a type of Recurrent Neural Network (RNN) that is specifically designed to handle the issue of vanishing gradients in traditional RNNs. It can effectively capture the long-term dependencies in the data and can be used for time-series prediction. GRU, short for Gated Recurrent Unit, is another type of RNN that uses a gating mechanism to control the flow of information. It is computationally efficient compared to LSTM and can be used for time-series prediction as well.

By combining the predictions from LSTM and GRU models, we can obtain a more robust prediction that can effectively capture the complex relationships in the data. This can be done by either weighting the predictions from the individual models or by taking the average of the predictions. Additionally, different ensemble techniques can be applied to obtain the best combination of models that can improve the overall performance of the forecast. Subsequently, we will apply the ensemble for all the different models used in the implementation for different market scenarios to achieve maximum accuracy.

IV. RESULT AND ANALYSIS

The LSTM model is a type of Recurrent Neural Network (RNN) that is well-suited for time series prediction due to its Fig. 1. System Architecture. Fig. 2. Data Flow Diagram. ability to remember previous input sequences and its internal memory cells. One advantage of LSTM is its ability to handle long-term dependencies in the data, which makes it suitable for predicting cryptocurrency prices where trends can persist over time. Another advantage is its ability to capture nonlinear relationships in the data, which is often present in the volatility of cryptocurrency prices. However, LSTM models can be computationally expensive and difficult to train, which can limit their ability to capture complex patterns in the data accurately.

The GRU model is another type of RNN that is similar to LSTM, but with a simpler architecture. GRUs are faster to train and less computationally expensive than LSTMs, making them well-suited for cryptocurrency price prediction tasks. However, their simpler architecture also means that they may not capture the same level of detail in the data as LSTMs, which can limit their accuracy in complex time series prediction tasks.

Bidirectional LSTMs take the standard LSTM architecture a step further by processing the input sequence in both forward and backward directions. This allows the model to make use of context from both the past and future, which can be particularly useful in time series prediction tasks where the future is dependent on both past and future events. However, bidirectional LSTMs are even more computationally expensive than regular LSTMs and can be more difficult to train.

Ensemble learning is a method where multiple models are combined to form a single prediction. In the context of cryptocurrency price prediction, an ensemble of LSTM, GRU, and bidirectional LSTM models can be used to take advantage of the strengths of each individual model. By combining multiple models, the ensemble can provide a more robust prediction by reducing the risk of overfitting to a single model. However, ensembles can also increase the complexity and computational expense of the prediction task, making them less practical for real-time prediction applications.

A. DL-GuesS

Deep Learning and Sentiment Analysis-Based Cryptocurrency Price Prediction is a study that combines deep learning and sentiment analysis to predict cryptocurrency prices. The study shows that combining these two approaches can lead to improved prediction accuracy compared to using deep learning models alone. Sentiment analysis involves using natural language processing techniques to analyze text data, such as news articles, to determine the overall sentiment about a particular cryptocurrency. This information can be used to augment the deep learning models, providing additional context about the current market conditions that can improve the accuracy of the prediction.

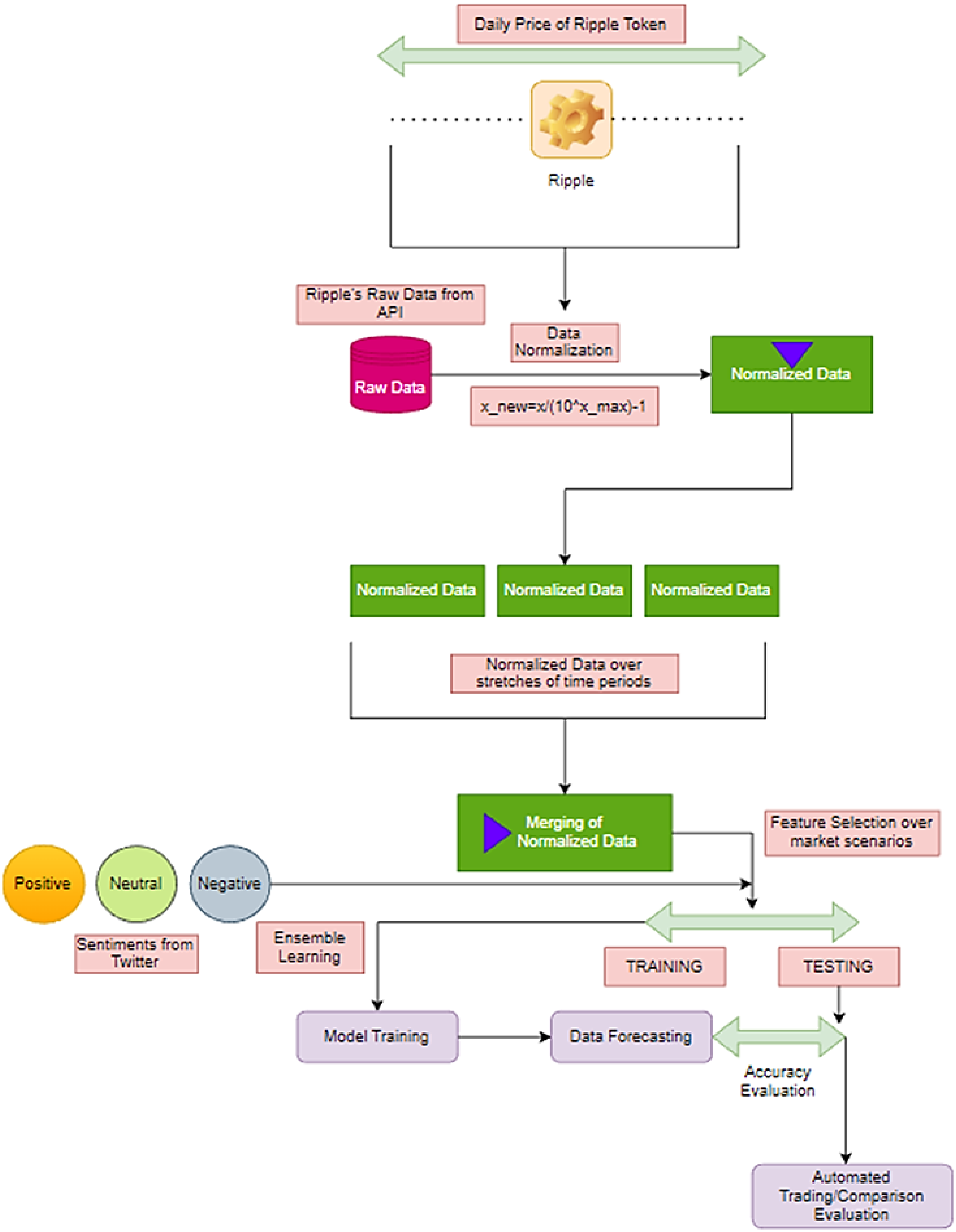

Fig. 1. Architectural diagram for Ripple price prediction Model

IV.1. Results / Predictions

Before prediction, inverse transform the outcome variable back to its original form and return it. Then making predictions to get the graphs as below:

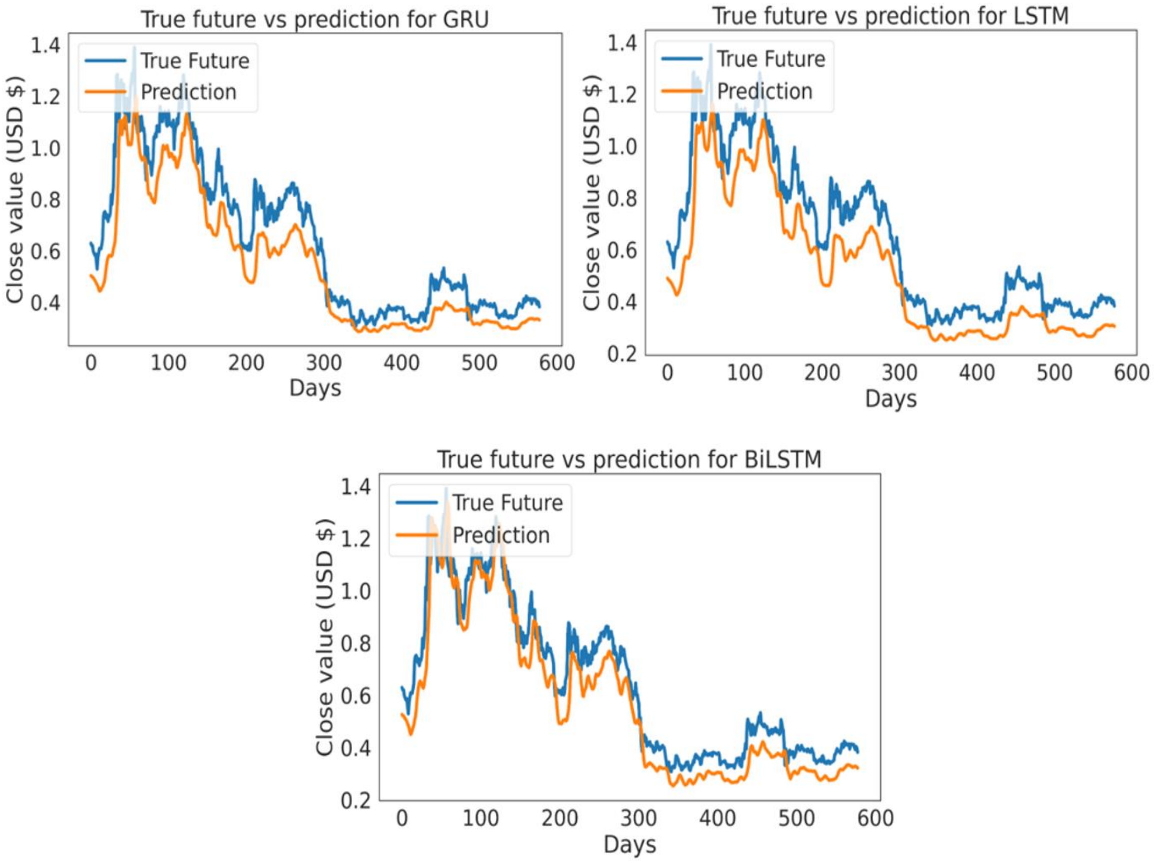

Fig. 2 Visual representation of true future vs predicted prices of GRU model.

IV.2. Metrics

Mean-Squared Error and Root Mean-Squared Error are the two metrics that are used to evaluate the performance of the models.

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Bidirectional LSTM:
Mean Absolute Error: 84.7181
Root Mean Square Error: 98.7336

LSTM:
Mean Absolute Error: 127.6249
Root Mean Square Error: 143.8323

GRU:
Mean Absolute Error: 104.7163
Root Mean Square Error: 124.7553
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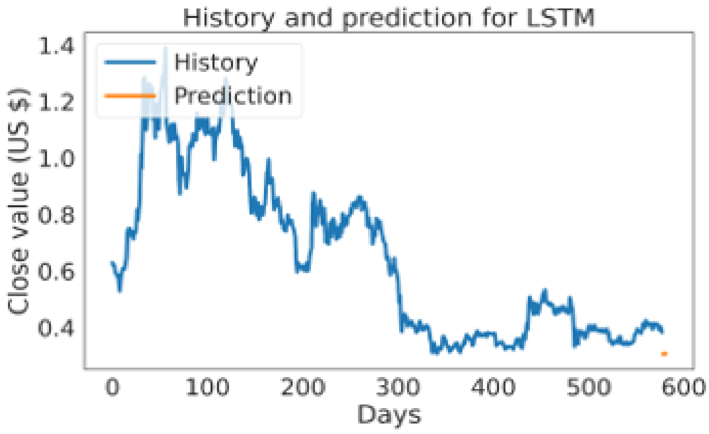
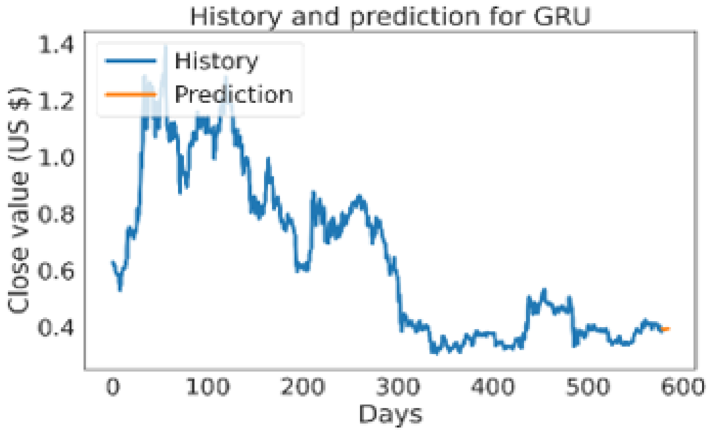
Fig. 3 Evaluation metrics

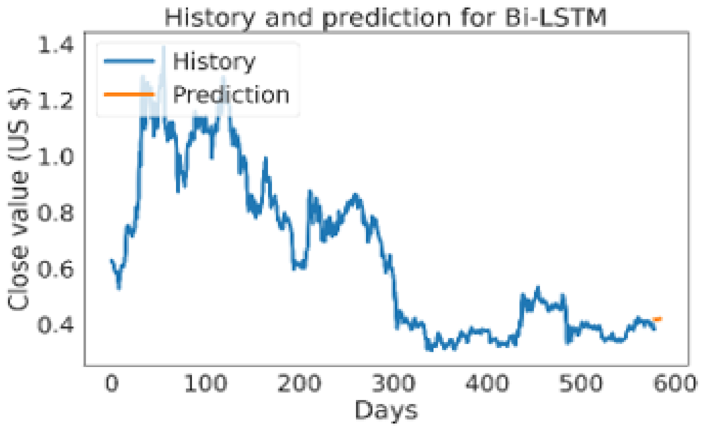
IV.3. Forecasting

The chosen parameters are TIME_STEPS = 10; and time frame of 1 month that means the trained data of 1 month is used to analyze the trend of the market and 10 days previous values of price of XRP to forecast the next 4 days of price.

There is freedom of change in these parameters according to the needs and forecasting potential. As in Fig 4, the visual analysis shows that the trend following potential of Bi-LSTM is much better than that of LSTM and overall, the GRU model seems to have the best fit potential of the market trend of the XRP-Ripple; almost aligning with the trend.







V. CONCLUSION

Our goal in this study was to forecast the XRP cryptocurrency's future pricing over a certain period. We evaluated the performances of several widely used models to the overall market trend and chose the most promising to use as a baseline. The Bi-Directional Long Short-Term Memory (Bi-LSTM) and Gated Recurrent Unit (GRU) models both demonstrate higher performance, precisely predicting the future prices of XRP, according to our implementation and analysis. The Bi-LSTM model achieves the lowest Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) scores, suggesting the most overall accuracy in predicting XRP values, even if the GRU model best reflects the overall market trend. Our results confirm that our forecasting approach is reliable and effective for predicting cryptocurrency prices, providing valuable insights for investment decisions and risk management in the dynamic and rapidly evolving digital asset market.

VI. FUTURE WORK

Since cryptocurrency market is highly volatile, there is a need for more accurate and advanced systems for price prediction. This model system is just an approach to a more advanced system that can be developed according to the research done here. Comparison of models show a better insight that which models work better according to the market trends. Certainly, these models can work more precisely by changing the parameters and adding more predictor variables to the system as well as sentimental analysis which can result in more accuracy.

We intend to include more parameters that are responsible for price fluctuations in this coin like supply and demand, investor and user sentiments, government regulations, and media hype. All these parameters could be included to develop a more concrete model for predicting the price.

We also intend to use the result to develop an automated trading bot which would use data the result to make trades and decide stop loss for the placed trades. This bot could particularly be useful in short term trades to yield a profit.

A comparative analysis webiste on real time data could also be developed which would give researchers and traders an opportunity watch and observe the price fluctuations and thereby make informed decisions.

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