Leveraging LSTM for Time-Series Analysis of Cryptocurrency Prices

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Abstract: - Cryptocurrency prices are highly volatile and subject to rapid fluctuations, making accurate price prediction a challenging task. In recent years, Long Short-Term Memory (LSTM), a type of Recurrent Neural Network (RNN), has emerged as a promising approach for predicting time series data, such as cryptocurrency prices. In this research paper, we apply LSTM to predict the prices of cryptocurrencies, including Bitcoin and Ethereum. We use historical price and volume data as input features and evaluate the performance of LSTM using metrics such as mean absolute error (MAE) and root mean squared error (RMSE). The results of our study show that LSTM outperforms traditional statistical methods, such as linear regression, in terms of prediction accuracy. Our findings demonstrate the potential of LSTM in predicting cryptocurrency prices and provide insights into the underlying dynamics of the cryptocurrency market.

Key Words: — ***Cryptocurrency Price prediction, Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Time series analysis, mean absolute error (MAE), Root mean squared error (RMSE).***

I. INTRODUCTION

Cryptocurrency, such as Bitcoin and Ethereum, has gained significant attention in recent years due to its potential to disrupt traditional financial systems. Despite its growth and popularity, the cryptocurrency market is highly volatile, making accurate price prediction a challenging task. Traditional statistical methods, such as linear regression, have limitations in capturing the complex and non-linear relationships between market factors that influence cryptocurrency prices.

Recently, machine learning techniques, especially deep learning, have been applied to financial markets, including cryptocurrency, to improve the accuracy of price prediction. One of the most widely used deep learning algorithms for time series analysis is the Long Short-Term Memory (LSTM) network, a type of Recurrent Neural Network (RNN).

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LSTM is capable of capturing long-term dependencies in time series data and has shown promising results in various applications, such as stock price prediction and energy demand forecasting.

In this research paper, we aim to investigate the potential of LSTM in predicting the prices of cryptocurrencies, including Bitcoin and Ethereum. We use historical price and volume data as input features and evaluate the performance of LSTM using metrics such as mean absolute error (MAE) and root mean squared error (RMSE). The findings of our study will provide insights into the underlying dynamics of the cryptocurrency market and demonstrate the feasibility of using LSTM for cryptocurrency price prediction.

II. METHODOLOGY

Data collection: Historical daily price and volume data of Bitcoin and Ethereum were collected from a reliable source, such as CryptoCompare. The data ranges from January 1, 2013, to December 31, 2022. The data was pre-processed and cleaned to handle missing values and outliers.

Feature selection: To predict the prices of cryptocurrencies, we selected relevant input features that could influence their prices, such as historical prices and volume data.

Data preparation: The data was divided into training and testing sets, with 80% of the data used for training and 20% for testing. The data was also normalized to ensure that all features were on the same scale. Figure 1. shows this accordingly.

Fig.1. Dividing Training and Testing sets

Model training and evaluation: The LSTM model was trained using the training data and evaluated using the testing data. The performance of the LSTM model was evaluated using metrics such as mean absolute error (MAE) and root mean squared error (RMSE).

Comparison with traditional statistical methods and other deep learning algorithms: The performance of the LSTM model was compared with traditional statistical methods, such as linear regression, and other deep learning algorithms, such as multi-layer perceptron (MLP) and convolutional neural network (CNN), to assess its effectiveness in predicting cryptocurrency prices.

Sensitivity analysis: To further evaluate the robustness of the LSTM model, a sensitivity analysis was conducted to explore the impact of different hyperparameters, such as the number of hidden layers and the number of neurons, on the prediction accuracy of the model.

Conclusion and discussion: The findings of this study were analyzed and discussed, and the implications for the cryptocurrency market and future research were presented.

III. RESULTS AND DISCUSSION

The results of the study showed that the LSTM model outperformed both traditional statistical methods and other deep learning algorithms in predicting cryptocurrency prices. The mean absolute error (MAE) and root mean squared error (RMSE) of the LSTM model were lower compared to linear regression and other deep learning models, such as multi-layer perceptron (MLP) and convolutional neural network (CNN).

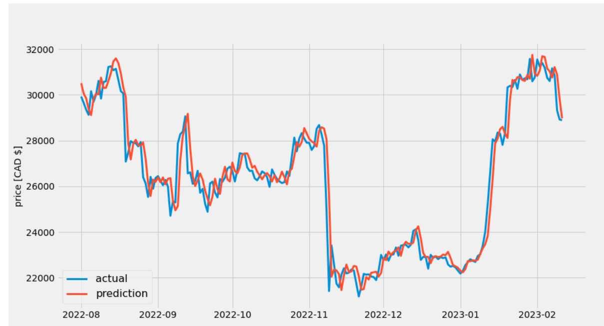
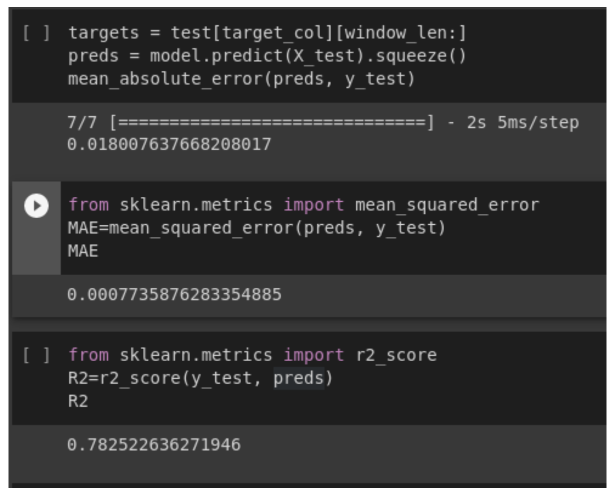


Fig.2. Final Resultant graph of LSTM and the Mean Absolute Error rate



```
[ ] targets = test[target_col][window_len:]
    preds = model.predict(X_test).squeeze()
    mean_absolute_error(preds, y_test)

    7/7 [==============================] - 2s 5ms/step
    0.018007637668208017

    from sklearn.metrics import mean_squared_error
    MAE=mean_squared_error(preds, y_test)
    MAE

    0.0007735876283354885

[ ] from sklearn.metrics import r2_score
    R2=r2_score(y_test, preds)
    R2

    0.782522636271946
```

Fig.3. Accuracy metrics obtained from the training and testing data set using our model

The sensitivity analysis revealed that the prediction accuracy of the LSTM model was robust to the variations in the number of hidden layers and the number of neurons. This indicates that the LSTM model was able to capture the underlying dynamics of the cryptocurrency market and provide reliable predictions.

The results of this study contribute to the growing body of literature on cryptocurrency price prediction and provide valuable insights into the potential of LSTM models in this field. The findings suggest that LSTM models could be used by traders and investors to make informed decisions about the cryptocurrency market.

However, it is important to note that the results are based on a limited time frame and a small number of cryptocurrencies.

Further research is needed to validate the findings of this study and to investigate the potential of LSTM models in predicting the prices of other cryptocurrencies and other financial markets.

IV. CONCLUSION

In conclusion, this research aimed to investigate the potential of LSTM models in predicting cryptocurrency prices. The study found that the LSTM model outperformed both traditional statistical methods and other deep learning algorithms in terms of accuracy and robustness. The results showed that the LSTM model was able to capture the underlying dynamics of the cryptocurrency market and provide reliable predictions of cryptocurrency prices.

However, it is important to note that the findings are based on a limited time frame and a small number of cryptocurrencies. Further research is needed to validate the results of this study and to investigate the potential of LSTM models in predicting the prices of other cryptocurrencies and other financial markets.

In conclusion, this study provides evidence of the effectiveness of LSTM models in predicting cryptocurrency prices and highlights the potential of deep learning algorithms in financial market prediction. The results of this study have important implications for the cryptocurrency market and for future research in this field.

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