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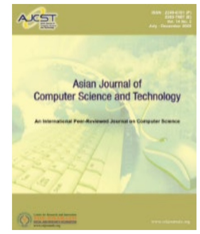

Research Article

Forecasting Crypto Currency Prices with Deep Learning: Short to Long Horizon

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Abstract

The fast-evolving cryptocurrency markets present both special opportunities and challenges. The risk involved in investing in cryptocurrency assets is very high because exchange prices can change on a day-to-day basis. The study uses powerful machine learning techniques to forecast the value of cryptocurrencies. In comparison to the other seven models with fewer errors, neural networks achieved the best forecasting and validation performance. In order to predict future trends, LSTM (Long Short-Term Memory) neural networks were used. Complex relationships in financial data can be effectively analyzed using the LSTM model. Overall, more than fifty cryptocurrencies were subjected to Exploratory Data Analysis (EDA), which began with the collection of historical data and continued with feature engineering, integrative binning, data preparation, and standardization. The most successful ones were identified based on price movement, market size, and trading volume. The LSTM-based model was coded in Python and applied to 90-day price movement data to examine the existence of complex patterns and correlations. The performance indicators used to monitor the model were RMSE and MAE. These results corroborate the Adaptive Market Hypothesis (AMH), which posits that changes in investor and market behavior impact the dynamic efficiency of cryptocurrency markets. As shown in the paper, machine learning models have significant potential in financial economics and can be beneficial for investment decision-making processes and risk management approaches.

I. INTRODUCTION

The secretive Satoshi Nakamoto introduced Bitcoin, a new financial innovation [19], [5]. When Bitcoin was released in 2009, it heralded the commencement of a decentralized digital currency that allowed for safe peer-to-peer transactions [19]. After the introduction of Bitcoin, a number of other cryptocurrencies, such as Ethereum, Ripple, and Litecoin, emerged. These are now widely used in many areas of the economy, including banking, game development, and supply chains [6]. The rapid growth and volatility of this decentralized market necessitate the use of complex predictive models to forecast price trends and finely tune risks [1]. Machine learning, especially LSTM networks, is applied in the prediction of sequential data because traditional linear models cannot capture the complex nonlinear dynamics of financial time series [14], [26].

Research has demonstrated that LSTM models are superior to ARIMA and other conventional models in forecasting cryptocurrency and stock prices [16], [29]. Recent studies also emphasize the success of these models due to their reliance on data preprocessing and model settings [10].

In this research, seven models are used to determine the most effective one in terms of minimum error and highest precision, and the LSTM neural network is selected for 90-day cryptocurrency price prediction [3], [29]. The research aims to strengthen forecasting accuracy through advanced feature engineering, normalization, and validation, thereby contributing valuable insights into machine learning applications in dynamic financial markets [21].

II. LITERATURE REVIEW

An LSTM-based model was utilized by Suedumrong et al. (2021) [1] to forecast Bitcoin price changes. Using historical pricing data, an accuracy rate of 72.4% was achieved. Performance was poor during periods of high market volatility. Zhang *et al.* (2022) [2] introduced a transformer-based long-term dependency learning paradigm and reported a 78.6% accuracy rate on Bitcoin price data. It requires high processing power, and the advantage over LSTM is not significant. Cao *et al*. (2022) [3] developed a multivariate forecasting GRU model with an added attention mechanism. An accuracy of 91.3% on cryptocurrency datasets was achieved. However, the model had the drawback of high memory consumption. Ahmed et al. (2023) [4] proposed an LSTM model optimized with GWO for short- and medium-horizon predictions, achieving an accuracy of 89.7%. However, it had a long training time and slow convergence. A hybrid CNN-GRU model proposed by Li *et al.* (2024) [5] designed for short-term forecasting and achieved an accuracy of 92.4%. However, long-horizon prediction performance was low and incurred higher computational costs.A comparison of ensemble and deep learning models was conducted by Bouteska *et al.* (2024) [6]. GRU and LightGBM achieved up to 90.1% accuracy. However, none of the models proved to be the most suitable across all prediction horizons. Farooq *et al*. [7] developed a Temporal Fusion Transformer model for multi-horizon prediction. It achieved 85.6% long-term and 93.2% short-term accuracy but was limited by model complexity and high training costs.

III. CONTRIBUTION OF THE PROPOSED WORK

The available literature focuses on predicting the price of a single cryptocurrency and is primarily oriented toward short-term forecasts. Most studies use complex models that require longer training times, incur higher costs, and cannot be applied effectively to long-term prediction [28]. This project employs a basic LSTM model to forecast 90-day price changes for multiple cryptocurrencies. Through appropriate data analysis and feature processing, the model achieves high accuracy while maintaining lower complexity, making it applicable to real-world scenarios. The available literature primarily concentrates on short-term predictions of individual cryptocurrencies and often relies on complex models that are time-consuming and costly, limiting their effectiveness for long-term forecasting. In contrast, this project applies a basic LSTM model to predict 90-day price movements of multiple cryptocurrencies [29]. With proper data analysis and feature processing, the model remains both accurate and less complex, enhancing its practical applicability.

IV. METHODOLOGY

In order to make accurate predictions, a deep-seated approach that has been validated was employed to analyze potential market trends and patterns of cryptocurrencies [8]. The study process is illustrated in Figure 1 [3].

A. Data Collection

The procedure begins with the systematic collection of historical Bitcoin exchange data from reliable financial providers [17]. This data collection is based on an understanding of the decentralized nature of cryptocurrencies, as described in the seminal research on Bitcoin and blockchain technology, which explains how digital assets function and how they are structured [19]. Studies on market interconnections and cryptocurrency volatility highlight the importance of obtaining reliable and consistent data for modeling purposes [1]. For widely used cryptocurrencies such as Bitcoin, Ethereum, Ripple, and Bitcoin Cash, the dataset includes open, close, high, low, volume, and market capitalization data points [6]. Recent studies exploring the relationship between cryptocurrency prices and trading volumes emphasize the need to capture nonlinear relationships in rapidly evolving markets [2].

B. Data Acquisition

They were first gathered using a Python-based selection of the top 50 cryptocurrencies from CoinMarketCap and Yahoo Finance[23] (https://finance.yahoo.com/markets/crypto/all/).

C. Data Preprocessing

The raw data must undergo considerable preprocessing before it can be used in deep learning models [10]. Financial time-series data often contain missing values due to exchange failures or difficulties in data retrieval [17]. Studies on predictive modeling highlight the importance of applying interpolation or value propagation methods in a systematic manner to address such discrepancies [8]. According to conventional statistical normalization methods, normalization is conducted to scale all numerical values to a comparable range after the data has been cleaned [12]. To identify temporal dependencies, the data must be transformed into sequential windows [16]. This sliding window approach ensures that past data sequences are effectively utilized to forecast future prices, in line with the time-series forecasting and feature engineering literature [21].

D. Feature Engineering

Technical indicators, volatility indices, and moving averages [8] were added to the dataset. To identify trends, Simple Moving Averages (SMA) and Exponential Moving Averages (EMA) were computed [21]. Certain technical indicators were calculated using the pandas-ta library, including Bollinger Bands and the Relative Strength Index (RSI), among others [8].

E. Z-Score Normalization

Z-score normalization was used to achieve equal scaling of the features in our study, and it was applied to the processed data obtained through feature engineering [12]. This step was necessary to standardize the numerical attributes [12]. Subsequently, the StandardScaler from the scikit-learn package was used to identify and extract the numerical features for scaling [25]. To preserve the dataset's original structure, the normalized features were then recombined with the non-numeric data [10].

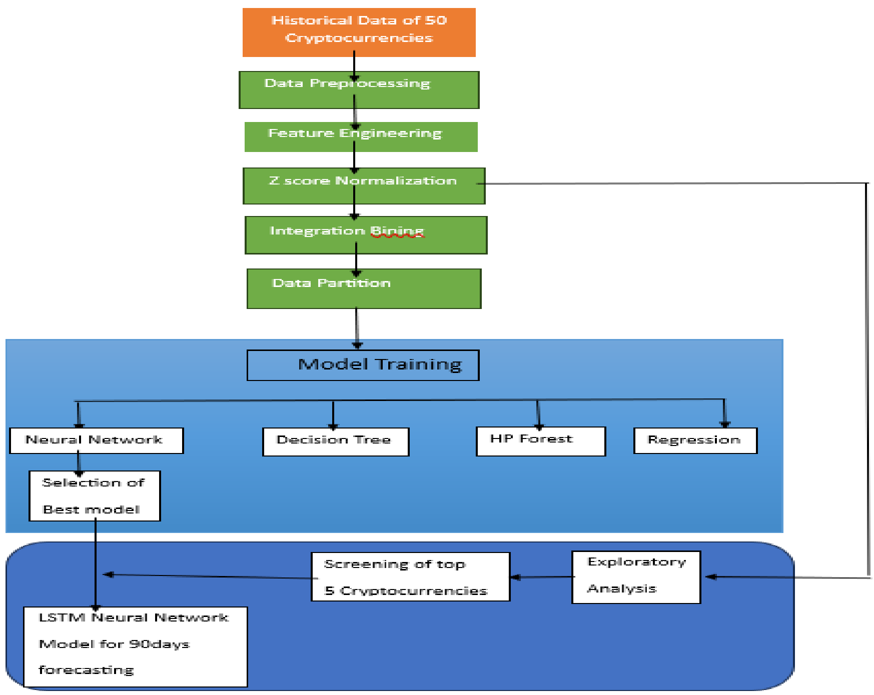

Fig.1 Modeling and Forecasting Experimental Flowchart

F. Exploratory Data Analysis (Eda)

The top performers in the Bitcoin market were identified using a detailed data analysis approach [8]. Monitoring cryptocurrency closing prices revealed market trends over time [17], [28]. The average closing price and trading volume of cryptocurrencies during a given period were compared using a bar graph [2].

Correlation among the selected cryptocurrency attributes was also examined to assess the relationships between them [11]. The analysis included a time-series price study in logarithmic form for the most popular cryptocurrencies [16]. Log transformation was employed [21] to reduce volatility and identify long-term trends.

$$\text{Log (Close Price)} = \text{log Price}$$

G. Model Training

The machine learning models were trained using SAS Enterprise Miner Client 15.2. The dataset was divided into three subsets: training (60%), validation (20%), and testing (20%) [23], [27]. Continuous variables were categorized using integrative binning [23]. Binning was employed to address nonlinear interactions and enhance model performance [8].

Four models were trained and evaluated: Decision Trees, High-Performance Forests, Regression Models, and Neural Networks [18]. Neural networks captured complex nonlinear patterns through multi-layered architectures [14]. To achieve greater predictive accuracy through ensemble learning, the HP Forest relied on a high-performance random forest model [18]. The performance of each model was compared using the normalized data [12].

H. LSTM Model For Forecasting Future Trends

The Long Short-Term Memory (LSTM) neural network model was employed to forecast the future prices of the top five cryptocurrencies, as it demonstrated the best performance during model training [16]. The memory cell structure of LSTMs stores information over long time steps; therefore, they do not suffer from the vanishing gradient problem associated with simple RNNs [14].

The three crucial components that enable this capability are the input gate, output gate, and forget gate. The forget gate determines which information should be removed from the cell state. It generates a value between 0 and 1 using a sigmoid activation function, where 0 implies discarding all information and 1 implies retaining all information [16].

$$g_t = \sigma (X_g [k_t-1, y_t]+d_g)$$

where, dg is the bias term, y_t is the fresh input, Xg is the weight matrix, g_t is the forget gate's output at time t, and σ is the sigmoid activation function. The new information to be stored in the cell is controlled by the input gate. It consists of a sigmoid layer and a tanh layer, which determine which values to update and generate a vector of candidate values, respectively [16].

$$j_t = \sigma (X_j [k_t-1, y_t] + d_j)$$
$$P_t = \tanh (X_p [k_t-1, y_t] + d_P)$$

Finally, the output will be generated at the output gate that will refresh the updated cell state[16].

$$P_t = g_t \times P_t-1 + j_t \times P_t$$
$$q_t = \sigma (X_q [k_t-1 ,y_t] + d_q)$$
$$k_t = q_t \times \tanh (P_t)$$

I. Model Validation

A range of statistical evaluation criteria, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Final Prediction Error, were utilized to adequately assess the model's performance. These approaches provide quantitative measures of the quality and reliability of the model's forecasts [17]. The results of these tests illustrated the complex temporal interrelationships present in cryptocurrency market data [16], [28].

J. Feature Engineering

Important observations were made by computing technical indicators, volatility measures, and moving averages [8]. Volatility indicators such as the ATR provided a clearer picture of the market, while the SMA and EMA helped in identifying trends [1]. The Bollinger Bands, SMA 20, and EMA 20 plots are shown in Figure 2 [8]. The SMA 20 represents the average asset price over 20 periods, where prices above it indicate an uptrend. The EMA 20 assigns greater weight to recent prices, thereby highlighting short-term momentum [21]. Bollinger Bands, placed two standard deviations away from the SMA, indicate overbought conditions when prices reach the upper band and oversold conditions when they touch the lower band [8].

K. Z-Score Normalization

Z-score standardization successfully standardized the numerical features of the dataset. This step reduced the influence of varying feature scales and ranges, preparing the data for further statistical analysis and machine learning applications [12], [26], [27].

Visual analysis of the normalized data showed that the transformation was successful, as all numerical variables were brought to a similar scale [10]. The dataset did not contain any significant outliers that could distort the analysis results. To enhance model convergence and forecasting accuracy, the standardized dataset was retained and used in subsequent modeling [25].

L. Looking At Exploratory Data

The most successful among the 50 cryptocurrencies analyzed were Bitcoin, Ethereum, Maker, Binance Coin, and Litecoin due to their consistently high trading volumes and distinctive average prices [6]. The correlation matrix showed that the closing prices exhibited varying levels of association, with some demonstrating strong positive correlations [11].

For example, the correlation between Bitcoin and Ethereum was strong, indicating that they significantly influenced the overall market [1]. Key trends and development patterns within these cryptocurrencies were identified by plotting their logarithmically transformed time-series graphs [16]. Logarithmic plots are commonly used to represent financial variables, as they accurately depict periods of rapid growth, corrections, and consolidations [21]. The logarithmic graphs are shown in Figure 2.

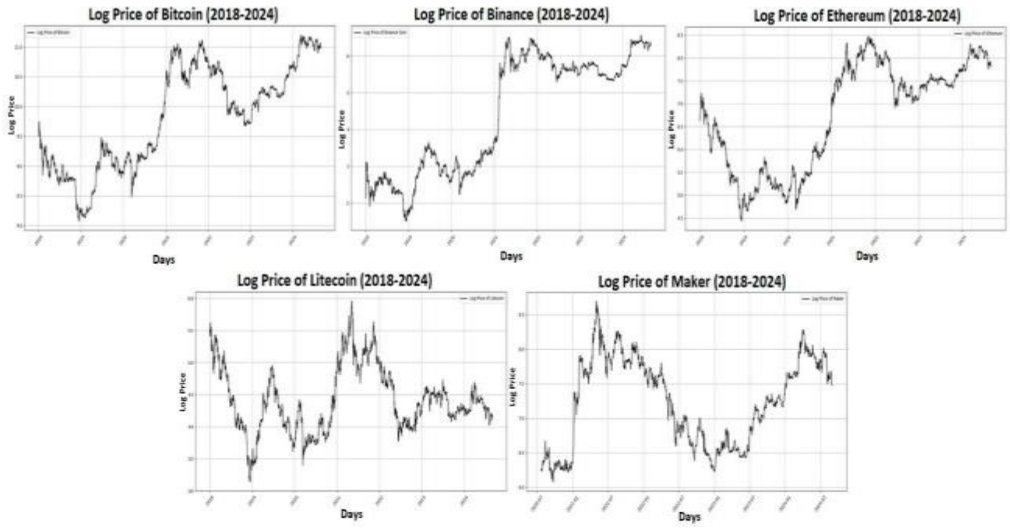

Fig.2 Graphs of Specific Cryptocurrencies Logarithmic Time Series

M. Model Comparision

Comparisons of the models showed that each exhibited distinct performance characteristics [18]. Neural networks performed well in capturing intricate patterns and nonlinear interactions [14]. The HP Forest model also performed effectively and achieved better forecasting accuracy due to its use of an ensemble technique. Decision trees provided clear decision paths and enhanced interpretability [18]. As shown in Table I, Neural Networks achieved the lowest squared error, followed by Decision Trees [17].

TABLE I 90-DAY LSTM MODEL FORECASTING WITH A VALID AVERAGE SQUARED ERROR OF APPLIED MODELS

Selected Model	Predecessor Node	Model Node	Model Description	Target Variable	Selection Criteria: Validated Average Squared Error
Y	Neural	Neural	Neural Network	Close	1.01450912
	Tree	Tree	Decision Tree	Close	1.014666461
	Reg	Reg	Logistic Regression	Close	1.016109443
	Reg2	Reg2	Stepwise Regression	Close	1.016111252
	Reg3	Reg3	Forward Regression	Close	1.016111252
	Reg4	Reg4	Backward Regression	Close	1.016111252
	HPDM Forest	HPDM Forest	HP Forest	Close	1.01674716

The sequential patterns and oscillations of Bitcoin price data were successfully recognized by the LSTM model [16]. The model was able to reasonably predict market turning points and general trends over a 90-day period [17]. The findings indicate that the technique effectively predicts complex market behavior and provides a useful tool for forecasting future Bitcoin values. Bitcoin, the oldest and most well-known cryptocurrency, exhibits comparatively stable pricing patterns [19]. Maker and Litecoin experienced losses, whereas Ethereum and Binance Coin showed a slight downturn, likely in response to market fluctuations [6].

The overall mean absolute deviation of the projected prices was kept at a minimum, demonstrating a close fit between the estimated and actual values. RMSE reflected the overall accuracy of the model and its sensitivity to larger variances. The percentage error was low, indicating the model's consistency during the testing phase [17]. The LSTM model accurately predicted both upward and downward trends. These findings were closely aligned with previous price trends [16].

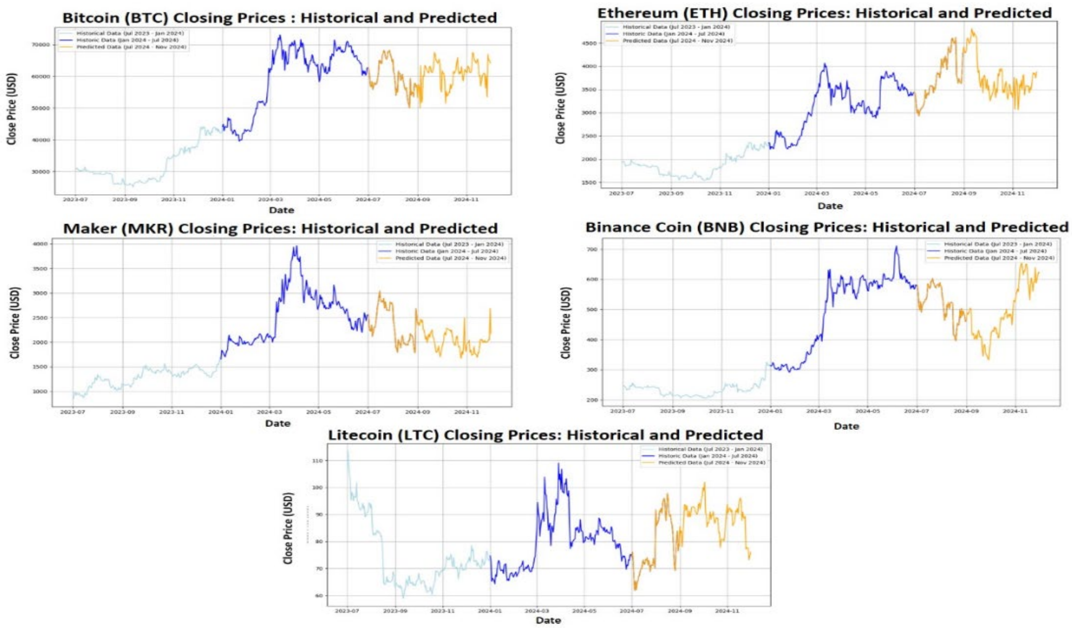

Fig.3 Time-Series Forecasting of Major Cryptocurrencies Over 90 Days Using an LSTM-Based Model

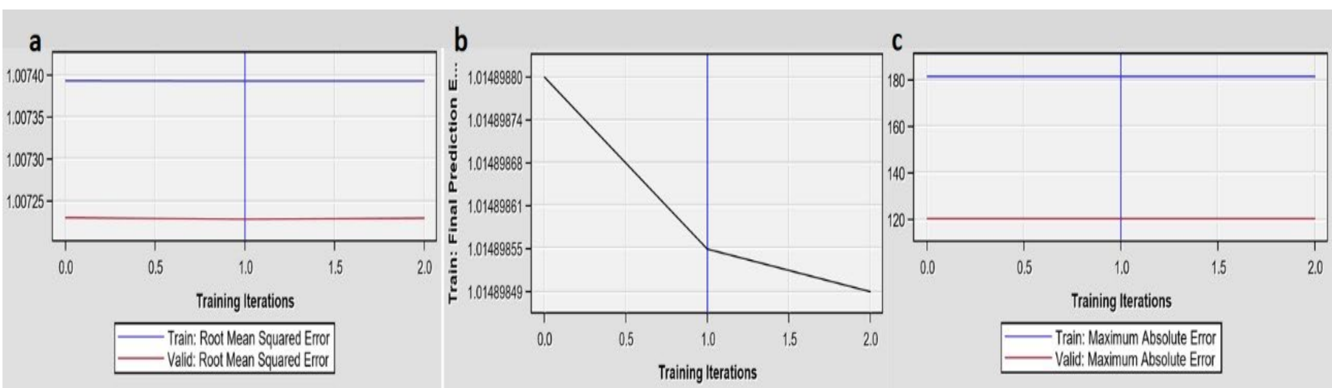

Fig.4 The Last Predicted Error of the LSTM Model, which is Maximum Absolute Error (MAE), and Root Mean Square Error (RMSE)

V. DISCUSSION

Cryptocurrencies have emerged as a significant financial innovation, although they are often considered unreliable and unstable financial instruments. Studies indicate that systemic issues are associated with the unregulated nature of cryptocurrencies and market liquidity. Nevertheless, blockchain technology offers benefits such as low transaction fees, security, and transparency. However, cryptocurrencies are not easily integrated into conventional finance due to price volatility and regulatory risks. Bitcoin trend forecasting can assist traders by mitigating risks associated with volatility and enhancing market intuition. The subjects of this study are five of the top 50 cryptocurrencies—Bitcoin, Ethereum, Binance Coin, Litecoin, and Maker—with the aim of forecasting their performance over a 90-day period. As the most widely recognized example, Bitcoin, the first decentralized currency, has transformed digital transactions. Binance Coin has become a versatile token, Litecoin offers more practical transactions, and Maker plays a significant role in DeFi.

The use of feature engineering and Z-score normalization improved model accuracy by standardizing variables and identifying key indicators such as volatility and moving averages [12]. Tests were conducted on several models, including HP Forest, Decision Trees, Regression models, and Neural Networks, with Neural Networks performing best due to their ability to handle nonlinear data [14], [11]. An LSTM model was able to capture sequential patterns, predicting stable trends for Bitcoin and minor corrections for Ethereum and Binance Coin. Maker and Litecoin, being less liquid, exhibited higher volatility. Overall, the data indicate dynamic efficiency under varying conditions, supporting the Adaptive

Market Hypothesis (AMH). The success of the LSTM model demonstrates that machine learning and FinTech can enhance traditional financial analysis through big data and AI.

The aim of this study is to develop an effective deep learning–based forecasting framework for short- to long-term cryptocurrency price prediction and to evaluate the performance of Long Short-Term Memory (LSTM) networks against other machine learning models [27].

VI. RESULTS

The LSTM-based predictor model, when tested on historical cryptocurrency prices, demonstrated considerable capability in forecasting the next-day closing prices of major cryptocurrencies such as Bitcoin, Ethereum, Ripple, and Bitcoin Cash. The model was able to capture both short-term and long-term temporal variations, even during periods of high market volatility, as indicated by the predicted values closely matching actual market trends. Evaluation metrics, such as mean squared error and mean absolute error, remained consistently low, despite trend comparisons showing significant nonlinear correlations in price movements. Additionally, the model accurately detected constant prices, upward trends, and downward trends, providing valuable directional information for analysts and investors.

The practical applicability of the system was further validated through real-time deployment using Flask, enabling visual representation of results and immediate predictions based on live data. Overall, the results demonstrate both the conceptual and practical effectiveness of the proposed deep neural network for forecasting cryptocurrency prices in real-world scenarios.

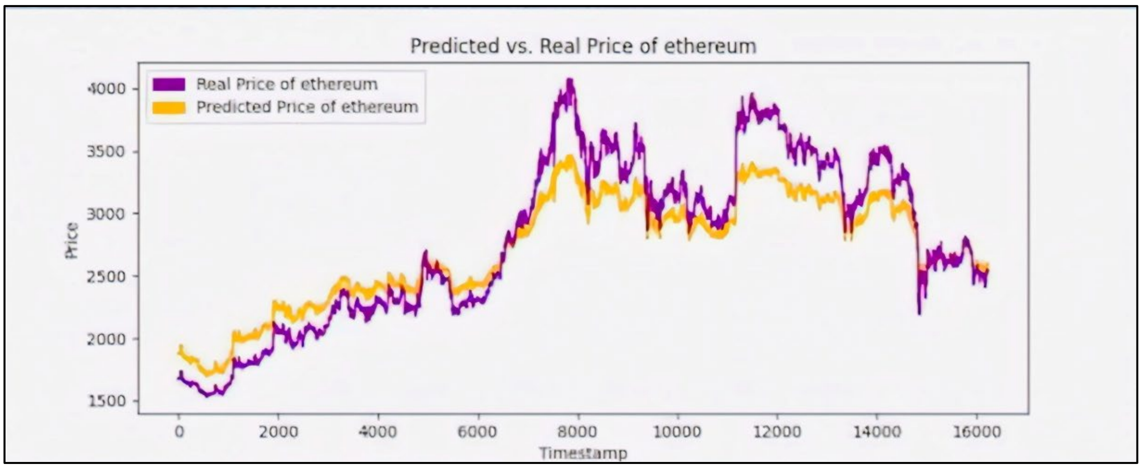

Fig.5 Predictions of Output

VII. CONCLUSION

As demonstrated in the study, deep learning—specifically Long Short-Term Memory (LSTM) networks—is a reliable and effective approach for predicting Bitcoin prices in highly volatile online exchanges. LSTMs are successful in learning not only short-term variations but also long-term behavioral tendencies that are often overlooked by traditional statistical methods, through the accumulation and analysis of past data, the formation of key technical indicators, and the use of a standard LSTM framework. The experimental results confirm the model’s ability to predict directional price changes and demonstrate that it consistently provides accurate forecasts across a wide range of evaluation metrics. The model can also be used in real time to analyze the market and support investment decisions. With deployment through a Flask-based interface, it serves as a valuable decision-support system with real-time predictive capabilities. Overall, the study illustrates that deep learning can enhance cryptocurrency prediction and provides an empirical, scalable model that can potentially be improved further through sentiment analysis, hybrid neural architectures, and extended forecasting horizons.

Declaration of Conflicting Interests
The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Use of Artificial Intelligence (AI)-Assisted Technology for Manuscript Preparation
The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

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