Cryptocurrency Predictive Analytics: A Comparative Study of LSTM, CNN, and GRU Models

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Abstract

This paper investigates the efficacy of deep learning models such as Long-Short Term Memory (LSTM), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU) for cryptocurrency price prediction, examining their short-term and long-term forecasting accuracy for investor guidance and advancing AI in financial analysis. The study uses time series analysis with LSTM, CNN, and GRU models on daily cryptocurrency prices from Investing.com, preprocessing data before testing on Bitcoin, Ethereum Classic, Ethereum, Litecoin, Monero, and the other 37 cryptocurrencies. RMSE, MAE, and accuracy rates measure performance. Findings revealed that only six cryptocurrencies were selected for final analysis, including Bitcoin, Ethereum Classic, Ethereum, Litecoin, and Monero. Results indicate that the deep learning models, particularly the LSTM and GRU, can predict cryptocurrency prices with high accuracy, especially for short-term forecasts within a 7-day window. The CNN model demonstrates significant predictive power, suggesting its utility for immediate trading decisions. Across the models, short-term precision was remarkably high, while long-term predictions maintained a moderate level of accuracy. This study presents a comparative analysis of LSTM, GRU, and CNN models for forecasting cryptocurrency prices, emphasizing LSTM and GRU's ability to navigate price volatility and suggesting their use for real-time trading analysis. The study's historical data reliance curtails forecasting unforeseen market shifts. Future studies should include new variables like social sentiment and blockchain analytics and test real-time adaptive models to enhance predictive strength. Model validation in actual market conditions is recommended for practical application.

Keywords: Cryptocurrency; price prediction; deep learning; time series analysis; financial forecasting.

JEL Classification: C45, G17, C53

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1. Introduction

In traditional economy systems, payments are processed exclusively by financial institutions like banks, regardless of their form (cash or electronic). These institutions act as intermediaries during fund transfers, thereby exercising complete control of the financial transaction as it works well for it, it restricts the amount of money that is transacted and lacks the necessary trust, security, transparency, and adaptability (Badawi & Al-Haija, 2021). To tackle these shortcomings, we desire a system that eliminates financial intermediaries, enabling direct money transfers between parties. This change would transform the economy (Abdul et al., 2022).

A scholar named Satoshi Nakamoto introduced a P2P Electronic Cash System of Bitcoin in 2008, proposing a cash transfer method based on it for online payments, eliminating the need for the financial sector as an intermediary. The idea demonstrated the decentralized valid transaction chains known as blockchains (Derbentsev et al., 2020). The implementation of this concept relies on the mechanism of proof-of-work (PoW), which relies on hashes and timestamps. It is used to generate blocks in the chains and validate the transaction. This new system eliminates the transparency challenge and increases its reliability since no third party is involved in the execution of a transaction (Nasirtafreshi, 2022). It is transparent because the chain was shared among P2P. To the traditional setup of financial institutions, P2P systems offer the advantage of quicker and cheaper transitions than regular financial organizations, which in totality means enhanced uptake of financial services to the people in the areas that have little or no access to banking services (Abdul et al., 2022). This shift decentralizes concentration on the central authorities and provides more users with financial freedom and security. As a result, such systems may benefit underprivileged groups of society, allowing them to contribute fully to the global economy (Seabe et al., 2023).

This innovative concept paves the way for a new kind of digital currency, cryptocurrency (Derbentsev et al., 2020). It is a digital currency that is used in financial systems. It is secured by cryptography to prevent counterfeiting or double-spending. The fact is that they are not issued by central banks or from central authorities and that they can be converted through cryptographic procedures, which separate them from traditional currencies (Nasirtafreshi, 2022). Hence, the cryptocurrency markets have experienced unexpected growth recently. In the short time it has existed, this market has evolved irregularly and rapidly fluctuated (Derbentsev et al., 2020).

In addition, cryptocurrencies are built on blockchain technology, which is designed to store data securely, making it resistant to alteration, hacking, or fraud. According to CoinMarketCap, there are approximately 23,000 cryptocurrencies, including well-known names like Bitcoin, Dogecoin, Ethereum, Litecoin, Cardano, XRP, and Monero. Despite their rise and expansion, cryptocurrencies are still in their infancy, and their widespread adoption in global markets remains unpredictable (Patel et al., 2020). It relies on blockchain technology. The central authority does not control its transactions. Therefore, consensus algorithms are used to validate and confirm the transaction to resolve trust issues among stakeholders (Seabe et al., 2023).

Additionally, blockchain's complexity stems from its decentralized structure, cryptographic security, and immutable data storage capabilities, which collectively ensure transparency and trust. The decentralization of blockchain means that no signal entity controls the system, making it less susceptible to manipulation or fraud. Cryptographic security ensures that transactions are securely verified, protecting against unauthorized changes and counterfeiting. Furthermore, immutable data storage ensures that once information is recorded on the blockchain, It cannot be altered or erased, providing a transparent and trustworthy record of all transactions. Together, these features create a robust system that enhances accountability and security.

The price-accurate prediction can help investors get accurate information and make timely decisions that prevent unbiased information dissemination by fraudsters and profiteers (Sohaib et al., 2019). Across the globe, researchers have been curious about the highly volatile prices and depend on various factors, including sentiments, stock markets, price of alternate coins, popularity, market trends, mining difficulty, transaction costs, and some other legal aspects. These factors increase the instability of prices and fluctuate them rapidly over time, which makes prediction difficult (Ibrahim et al., 2021).

The popularity of this currency has grown to become a global phenomenon that has attracted many users in recent years. In contrast, prices fluctuate rapidly. Therefore, forecasting future prices has become a primary concern (Ammer & Aldhyani, 2022). Previously, researchers have tried deep and machine learning algorithms to predict the prices of precious metals and Bitcoin, Ripple, Monero, Stellar, Tron, Chainlink, Ethereum, Binance Coin, and Monero; Ethereum, Litecoin, and Bitcoin (Wei et al., 2023; Kok et al., 2022; Kumar et al., 2022; Luo et al., 2022), recently gained investors' attention (Smyl et al., 2023). The digital currency Litecoin is ranked among the top ten cryptocurrencies, offering a transaction time four times faster than Bitcoin, making it a strong competitor for future applications. Monero, ranked 15th in terms of currency rankings, is recognized as a privacy coin due to its analysis-resistant, unlinkable, and untraceable features.

This study contributes to predicting the prices of Ethereum, Ethereum Classic, Bitcoin, LItecoin, and Moero. The study used AI algorithms named the Gated Recurrent Unit (GRU), the Convolutional Neural Network (CNN), and the Long Short-Term Memory (LSTM) to predict the prices of digital currencies. Predicting cryptocurrency prices is difficult due to their dynamic and volatile nature. However, many individuals globally have been investing in CC and seeking the best method to predict high-return currencies. This paper aims to offer a suitable scheme for predicting cryptocurrency prices and providing returns on digital currency. There has been an increase in interest in its forecasting. As a result of the volatile and dynamic nature of digital markets and investments, the existing papers have not yet provided a comprehensive solution (Al-Haija, 2022). A significant approach using deep algorithms is required to uncover the hidden pattern within the data and enable efficient prediction. Thus, investors would receive a reliable and actionable return forecast by addressing the research gap (Al Hawi et al., 2023).

2. Literature Review

The study explores the prediction of cryptocurrency prices (Ethereum, Ethereum Classic, Bitcoin, LItecoin, and Moero). The study uses AI Algorithms including (GRU), (CNN), and (LSTM). The theory applied to this study is the theory of machine learning. Arthur Samuel proposed the machine learning theory. It enables computers to adapt and imitate human-like behavior. It is central to performing tasks that involve data analyzing patterns and using the learned experience for future predictions. It is used to perform actions and interactions learned by the system. This action can be used as an experience in the future (Al-Hawi et al., 2023). It draws elements from statistics and computation theory that involve tasks, which include creating mathematical models that capture aspects of ML that analyze the inherent difficulty and ease of different learning problem types. Previously, it used to forecast prices due to the inherent complexities in identifying patterns in dynamic markets (Al-Haija, 2022). The methods have previously been applied to predict cryptocurrency prices by gathering data on various factors such as prices, market sentiments, trading volume, technological development, regulatory changes, and other relevant factors and predict the future price accurately by linear regression, decision trees, random forests, neural networks, and LSTM (Abdul et al., 2022).

Previously, many studies have applied different methods to predict the prices of cryptocurrencies via LSTM and GRU models together. Tanwar et al. (2022) argued that it is less stable, uncertain, and highly volatile than the traditional markets. Previously, researchers found that legal, sentimental, and technical factors influenced it. This study proposed LSTM and GRU models to forecast the prices of Zeash and Litecoin. The study found that the prices are more accurate than existing models. However, it does not provide insights by employing multiple prediction models. Patel et al. (2020) investigated the best model to predict cryptocurrency prices accurately. The study argued that it is a medium of blockchain digital exchange in which the records are secured by utilizing its algorithms, including (MD5) (Moreover, there is still dynamism and uncertainty arising in the prices that influence investment decisions. Every problem has a solution. However, this study identified limitations in explaining price dynamics. It only used two predicted models, i.e., GRU and LSTM, that only focused on Monero and Litecoin prices. The results found that both schemes predicted prices with high price accuracy, respectively. Patel et al. (2022) argued that deep learning algorithms GRU, LSTM, and ARIMAX are utilized to forecast and examine the elements affecting cryptocurrency prices. Moreover, an individual currency called dash coin is significantly affected by Litecoin and Bitcoin prices. It found hierarchical dependency among these coins. Litecoin and Bitcoin Prices affect the Dash coin prices. The proposed scheme forecasts the prices with high precision and low misfortune.

Despite these advancements, gaps persist in understanding how AI-driven techniques account for nuanced market behavior and investor sentiments. Previous studies investigated the prediction of various asset prices via different machine learning and deep learning models (Chowdhury et al., 2020; Gomez et al., 2023; Haq et al., 2021; Guo et al., 2021). Hassan et al. (2022) developed an optimal method for forecasting cryptocurrency prices based on users' social media opinions. As a result, this study examines cryptocurrency fluctuations. Litecoin, Monero, Bitcoin, and Ethereum's prices are predicted using a deep learning algorithm and convolution neural networks. 98.75% accuracy was demonstrated in forecasting prices using the proposed method. While their model excels in accuracy, it does not fully address factors like technical influences or cross-currency dependencies.

Murray et al. (2023) forecasted digital currency prices and compared these currencies using ensembles, deep learning, and machine learning. Nasirtafreshi (2022) argued that recent developments have been seen in cryptocurrency over the last few decades. It is one of the most ambiguous and controversial innovations in the modern era. The fluctuations in rates are not predictable, increasing the distrust of investors. Hence, this issue has been resolved by offering the appropriate methods and models for forecasting the prices of assets. It used a deep learning model to predict the prices of digital assets. It was found that the proposed method was superior to the other method. It presented deep learning models to forecast prices but did not comprehensively address hierarchical dependencies among digital currencies. Sulistio et al. (2023) predicted the stock prices in the energy sector using the LSTM, GRU, and CNN Hybrid Algorithm. Hasan et al. (2022) predicted the cryptocurrency price fluctuations using optimum CNN.

Behera et al. (2023) argued that cryptocurrency price fluctuations due to irregular movement of prices have become hot topics. Moreover, various econometric and statistical models can predict digital asset prices (Maciel et al., 2022). Still, there is a lack of advanced AI intelligence models to determine the behavior of these price movements. The study examined comparative performance analysis of Friedman tests and forecasting models to reveal the statistical significance and superiority. The study found that ANNs with trained FWA, TLBO, and CRO obtained an average rank of 2.75, 2, and 1, respectively. Previous studies focused on price prediction accuracy; they did not analyze the dynamic dependencies among cryptocurrencies. The theoretical framework of this study is grounded in advanced machine learning theories, particularly those relevant to financial forecasting. By integrating principles from artificial intelligence with economic forecasting, we hypothesize that deep learning models like LSTM, CNN, and GRU can effectively predict market trends in this sector. This hypothesis is supported by existing literature that underscores the growing role of technology in financial analysis.

3. Methodology

The methodology incorporates three specialized neural networks: the gated recurrent unit (GRU), the Convolutional Neural Network (CNN), and the Long Short-Term Memory (LSTM). Each of these models is meticulously crafted for time series analysis. In this approach, the models focus on daily data from a select group of cryptocurrencies: Bitcoin, Ethereum Classic, Ethereum, Litecoin, and Monero.

3.1 Data Collection and Preprocessing

This research employs a dataset encompassing historical data related to cryptocurrency prices, which have been transformed into daily returns. The period of the data for each selected cryptocurrency is detailed below in Table 1.

Table 1
Data Collection

Crypto Currency Name	From	To
Bitcoin	18-Jul-10	21-Jul-23
Ethereum Classic	28-Jul-16	21-Jul-23
Ethereum	10-Mar-16	21-Jul-23
Litecoin	24-Aug-16	21-Jul-23
Monero	29-Jan-15	21-Jul-23

Data for this study is sourced daily from Investing.com. Initial data was gathered for 42 different cryptocurrencies (price data subsequently converted to returns). However, after applying our deep learning algorithms for filtering, we distilled the list to the five most suitable cryptocurrencies, as previously mentioned. Firstly, data cleaning techniques are used to remove any outliers or inconsistencies, thereby safeguarding the precision of our models.

3.2 Time Series Models

It is dedicated to forecasting cryptocurrency returns, relying solely on the return data of each cryptocurrency. During preprocessing, the data values are normalized with the MinMaxScaler to ensure they fall within the 0 to 1 range. The dataset is then partitioned into training and testing segments, with 80% allocated for training. These models utilize a 65-day lookback window, meaning they harness the historical data from the preceding 65 days to project the return for the subsequent day. Scaling the data increases numerical stability, and the convergence during training is improved, which is essential for deep learning models such as CNN, LSTM, and GRU, which are known to be scale-sensitive.

Table 2
Hyperparameters Settings for Models

Parameter	LSTM	GRU	CNN
No. of Layers	2	2	3
Filters	50 per layer	50	64, 128, 256
Activation Function	ReLU for dense layers	ReLU	ReLU
Optimizer	Adam	Adam	Adam
Learning Rate	0.001	0.001	0.001
Batch Size	32	32	64
Epochs	50	50	50
Lookback Window	65 days	65	65

Table 2 presents an overview of hyperparameter settings for each model to ensure the study's reproducibility and aid model comparison in cryptocurrency return forecast efficiency.

3.3 Model Architectures and Equations

3.3.1 Long Short-Term Memory Models

Hochreiter (1997) described how LSTM controls the flow of information inside a network due to its gates. This can prevent both the vanishing and exploding gradient problems when training LSTM with long sequences based on the research of Ergen and Katlav (2024) The LSTM models are built on the sequential architecture using the Keras interface from TensorFlow following the methodology of Chollet and Chollet (2021).

$$f\_t = \sigma\,(W\_f \cdot [h\_(t-1), x\_t]) \longrightarrow \text{(i)}$$

$$i\_t = \sigma\,(W\_i \cdot [h\_(t-1), x\_t]) \longrightarrow \text{(ii)}$$

$$g\_t = tanh\,(W\_g \cdot [h\_(t-1), x\_t]) \longrightarrow \text{(iii)}$$

$$o\_t = \sigma\,(W\_o \cdot [h\_(t-1), x\_t]) \longrightarrow \text{(iv)}$$

$$h\_t = o\_t * tanh(C\_t) \longrightarrow \text{(v)}$$

$$C\_t = f\_t * C\_(t-1) + i\_t * g\_t \longrightarrow \text{(vi)}$$

Where: f_t: Forget gate; i_t: Input gate; g_t: Candidate memory cell; o_t: Output gate; h_t: Hidden state; C_t: Memory cell.

These are actually the gates in the LSTM model that regulate the flow of information. These make the model decide whether to remember or forget particular data, which is important for modeling long-term dependency. It also makes it possible for LSTM to predict prices, considering past and more recent data.

3.3.2 Gated Recurrent Units Models

The Gated Recurrent Units (GRUs), as mentioned by the authors (Cho et al., 2014). The sequential structure is also evident in TensorFlow's Keras API, and using layers is beneficial for analyzing temporal patterns in data. A significant issue with the applicability of the GRUs is that there is a problem of capacity decrease of the hidden cell state because the input and forget gates are intertwined with the update gate, as concluded by (Greff et al., 2017). Several academic works have backed up the archival of GRUs as credible forecasting models recorded by Dautel, Härdle, and Lessmann (2020).

The mathematical formulations for the GRU models are presented subsequently.

$$z\_t = \sigma\,(W\_z \cdot [h\_(t-1), x\_t]) \longrightarrow \text{(vii)}$$

$$r\_t = \sigma\,(W\_r \cdot [h\_(t-1), x\_t]) \longrightarrow \text{(viii)}$$

$$h{\sim}t = tanh\,(W\_h \cdot [r\_t * h(t-1), x\_t]) \longrightarrow \text{(ix)}$$

$$h\_t = (1 - z\_t) * h\_(t-1) + z\_t * h{\sim}\_t \longrightarrow \text{(x)}$$

Where, *r_t*: Reset gate; *z_t*: Update gate; *h_t*: Hidden state.

It employs update and reset gates to determine exactly how much of the earlier data should be retained and how much should be released. These equations allow the model to capture the necessary temporal relations, and the model is extremely efficient for short-term forecasting in the given fluctuating market.

3.3.3 Convolutional Neural Network Models

The CNN (Convolutional Neural Network) was pioneered by (LeCun, Bottou, Bengio, & Haffner, 1998). This structure is composed of pivotal layers, namely the input, convolutional, pooling, and fully connected layers, with each having its own distinct function, as elucidated by (Balaji, Ram, & Nair, 2018). The convolutional layer is at the core of the CNN, primarily dedicated to feature extraction via the convolution operation, a notion underscored by (Chen et al., 2024). By pooling, the dimensionality of the data is reduced, thereby reducing the number of parameters and minimizing the chances of over-fitting. The above-mentioned models use Conv1D, MaxPooling1D, Flatten, and Dense layers. Below are the mathematical expressions that define the CNN models.

$$y\_t = f\,(W\_c * X\_t + b\_c) \longrightarrow \text{(xi)}$$

$$z\_t = max\_pool\,(y\_t) \longrightarrow \text{(xii)}$$

$$h\_t = g\,(W\_h * z\_t + b\_h) \longrightarrow \text{(xiii)}$$

Where, f_t: Convolutional filters; p_t: Max-pooling; h_t: Flattened features; h_t': Hidden state.

The convolution layers used in Convolutional Neural Networks learn or identify important features in the data, including repetitive market price trends. The pooling layer makes it less complex which makes it more generalized. It helps CNNs forecast future prices in terms of trend indication from the underlying data patterns.

Enduring 80% of the data for training enables the models to be competent with historical data, which is compulsory for identifying intricate behaviors in price movement. Only 20% of the data is set aside for validation and testing, enabling the models to be tested on new data. This approach reduces cases of overfitting and also improves the overall generality of the models developed.

3.4 Model Evaluation

To understand how well each model works, we use several performance measures. Two of the most common are the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). These help us see how close the model's predictions are to the actual values. We divided our data into two parts: used for training the model at 80% while the remaining 20% was used to test the model. In the training phase, we modify the model's parameters through the Adam optimizer to minimize the difference between calculated and expected vectors. The other are Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SMAPE), Mean Squared Logarithmic Error (MSLE) as well and R-squared value.

3.5 Parameter Tuning and Model Selection

To tune the parameters of each model, we changed the number of epochs and the batch size by interchanging them. Out of the numbers generated in the previous step, we selected the model that yielded the least errors on the test data set (both RMSE and MAE inclusive). In this way, it was ensured that only the model capable of yielding an accurate and reliable forecast of crypto returns was selected.

3.6 Statistical Analysis

We use some statistical tests to understand better how well the models work and how strong they are. These help us see how good the model is at making predictions and spotting patterns in the data. We also use charts like time series graphs and scatterplots to show how the model's predictions compare to actual outcomes and to highlight any odd or mismatched results.

3.7 Computational Environment

We built all the models using Python and tools in the TensorFlow and Keras libraries. We ran the calculations on a powerful computer system to ensure everything worked fast and smoothly, especially during the training and testing stages.

4. Results Analysis

4.1 Correlation Analysis

A comprehensive analysis is conducted to identify the most crucial variables for predicting cryptocurrency returns. The procedure initiated with a correlation study to assess the interrelationships among the various cryptocurrencies presented in Table 1. However, Table 3 represents the Pearson correlation matrix, which evaluates the linear association between the prices of cryptocurrencies. Notably, a strong correlation is evident, especially between Bitcoin, Ethereum Classic, Litecoin, and Monero, with coefficients of 0.93 and 0.85. All cryptocurrencies displayed a correlation coefficient of at least 0.75 exhibit baseline correlation, indicating synchronous price movements.

Table 3
Pearson correlation matrix

	Bitcoin	Ethereum Classic	Ethereum	Litecoin	Monero
Bitcoin	100.00%				
Ethereum Classic	72.35%	100.00%			
Ethereum	93.27%	83.37%	100.00%		
Litecoin	72.72%	70.76%	66.11%	100.00%	
Monero	74.56%	80.15%	73.83%	91.25%	100.00%

4.2 Data Analysis for CNN

The CNN time series algorithm has been applied across several cryptocurrencies, and its performance across them can be summarized and compared as follows:

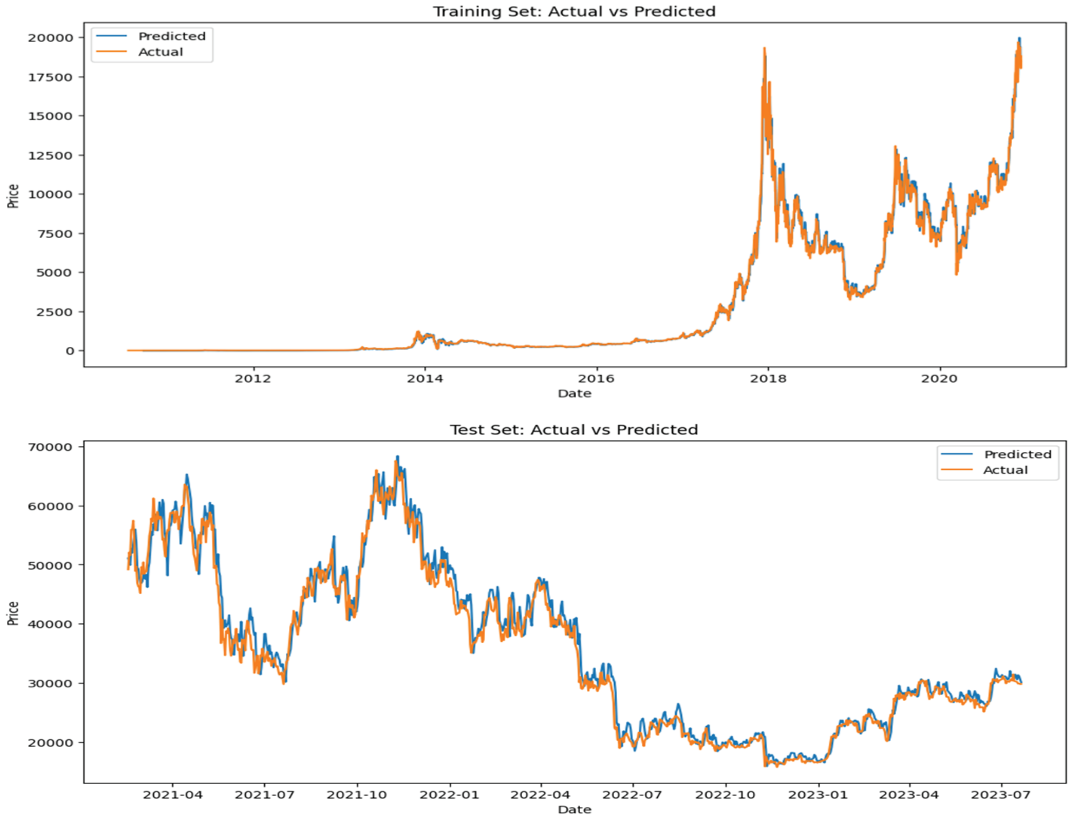
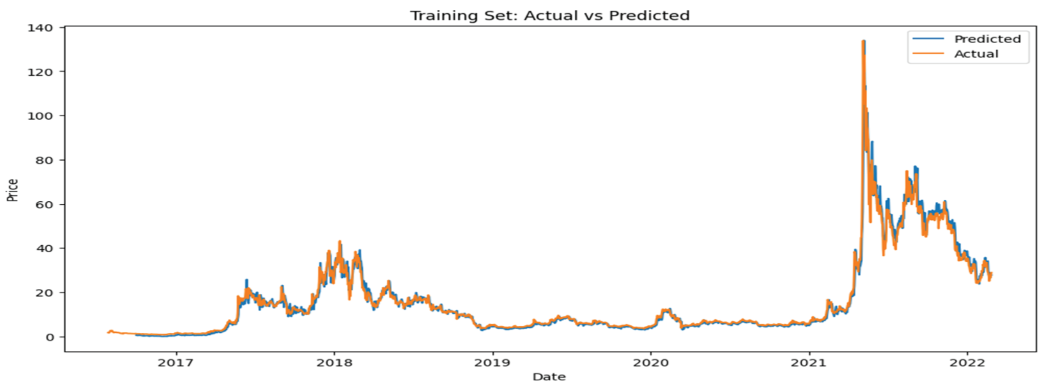


Figure 1: Bitcoin Price Forecasting by CNN

Bitcoin price forecasting is shown in Figure 1. The CNN model for Bitcoin showcases a strong ability to capture the price trends of both training and test sets, even anticipating significant price events like the 2021 surge, dip, and subsequent recovery. Ethereum Classic price forecasting is shown in Figure 2 The algorithm displays a particular proficiency in short-term forecasting for ETC, predicting prices within a 5% range up to a month in advance.



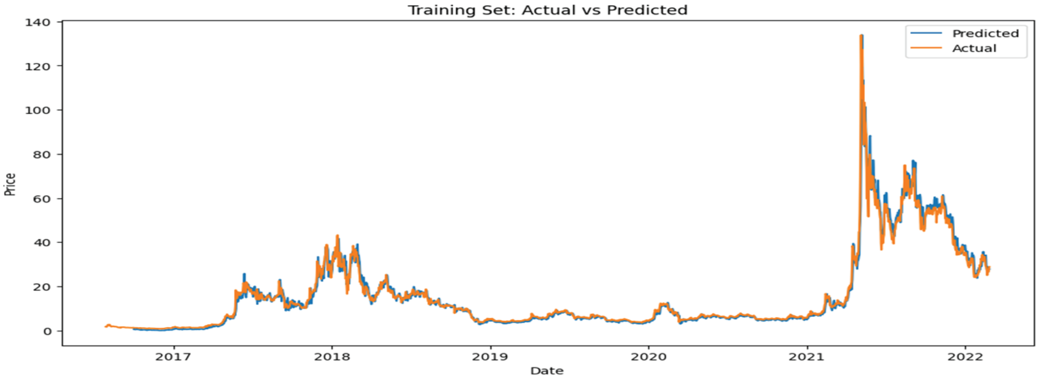


Figure 2: Ethereum Classic Price Forecasting by CNN

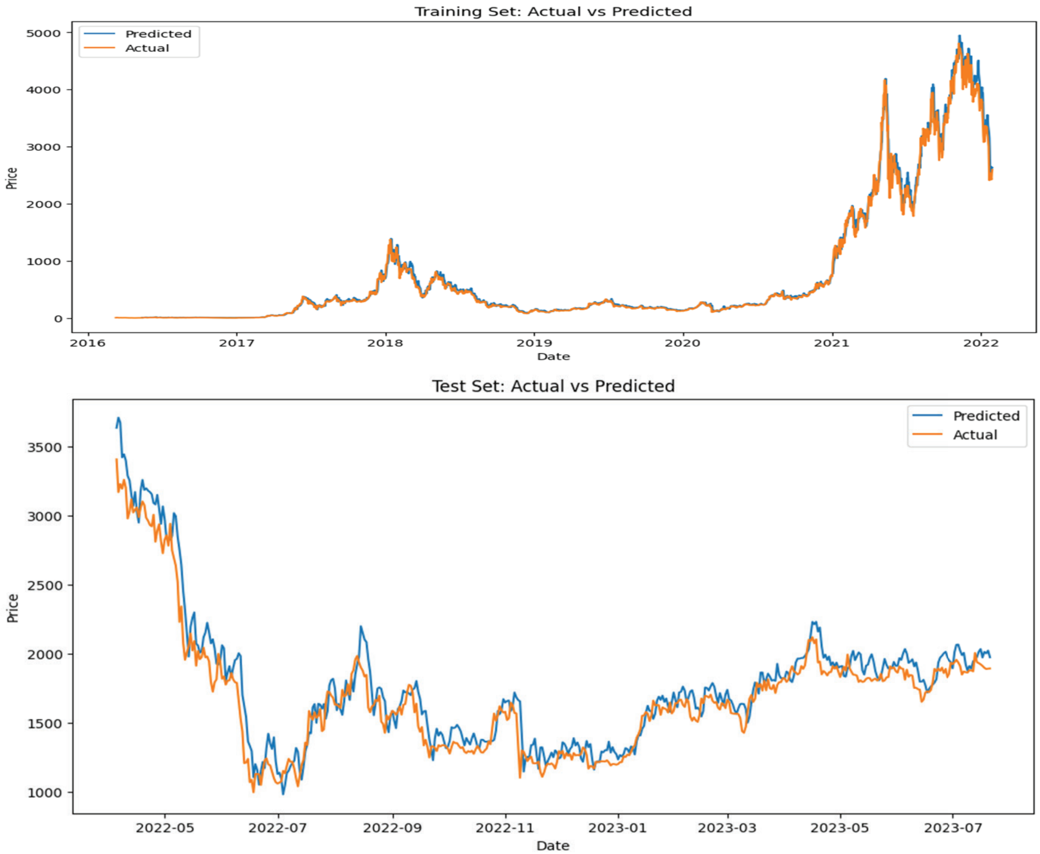


Figure 3: Ethereum Price Forecasting by CNN

Ethereum price forecasting is shown in Figure 3. In the case of ETH, the utilization of the CNN algorithm shows efficiency in predicting prices over the next 30 days with deviations not exceeding 5% for short-term oscillations and trends, both major and minor. They sought to elaborate on two things: the inherent volatility of crypt markets and the firm's capacity to adapt it. This precision makes it possible for the CNN model to be a powerful tool for short-term trading strategies so that traders can act appropriately in the market.

Figure 4: Litecoin Price Forecasting by CNN

Litecoin price forecasting is shown in Figure 4. The Litecoin forecast can be considered accurate because predictions vary by 5% for 30 days and 1% for 7-day short-term forecasts.

Figure 5: Monero Price Forecasting by CNN

Monero price forecasting is shown in Figure 5. The forecast of the Monero is similar to Litecoin's: 5% accuracy for 30 days with 1% increased accuracy for the 7-day outlook. The trend it depicts and the significant movements in the Monero market confirms its proficiency in visualizing details.

Across all cryptocurrencies, the CNN algorithm consistently demonstrates strength in short-term forecasting, especially within a 7-day timeframe, with heightened precision often within the 1% range. Each model capably identifies price peaks and troughs with over 80% accuracy and captures the broader market trends with over 90% accuracy. Regarding the model, Bitcoin does remarkably well regarding low variance and capturing major price movements. Ethereum Classic and Ethereum: There is a slight inaccuracy in the long-term forecast, but short-term predictions are good. Litecoin and Monero are notable for their accuracy in short-term predictions.

4.3 Results Analysis for GRU

The GRU time series algorithm has been applied across several cryptocurrencies, and its performance across them can be summarized and compared as follows:

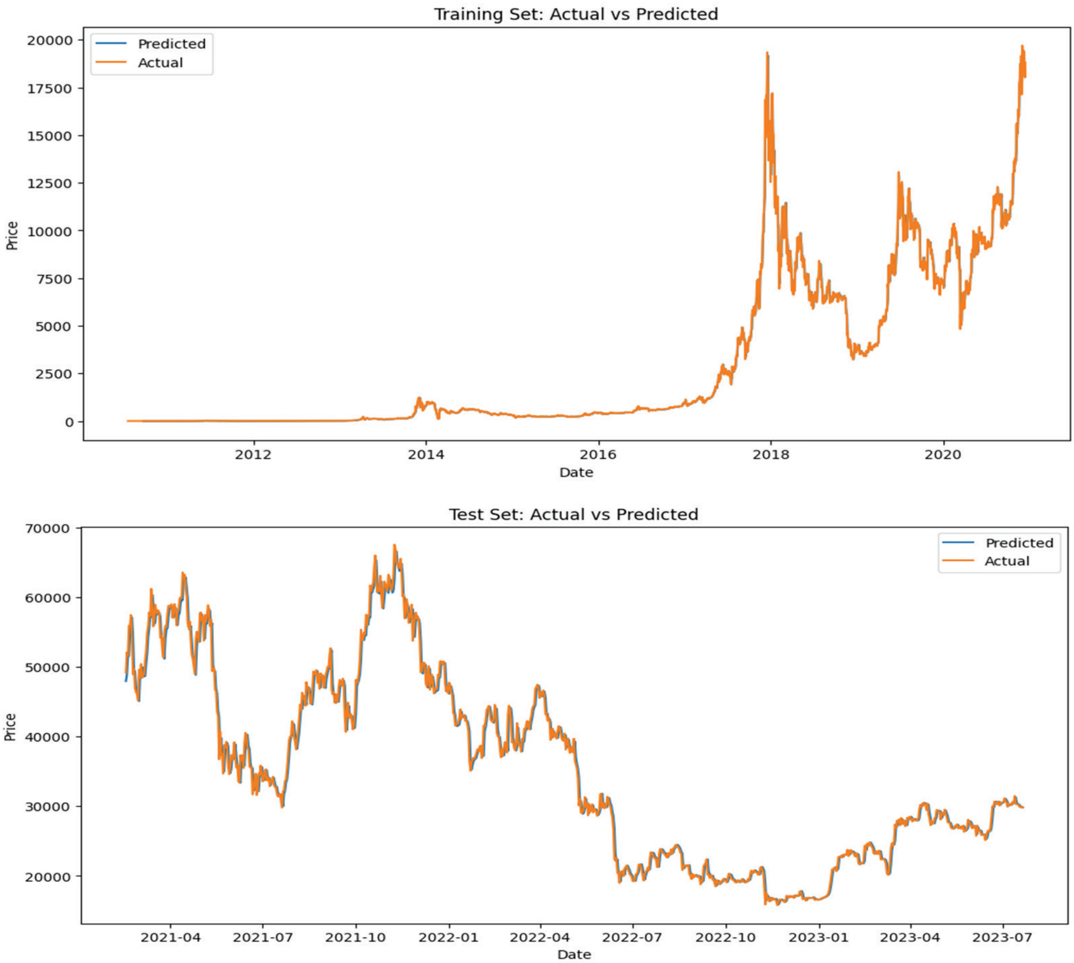


Figure 6: Bitcoin Price Forecasting by GRU

Bitcoin price forecasting is shown in Figure 6. The results obtained in this paper show that the GRU model performs well in forecasting Bitcoin prices. It has a daily forecast accuracy of +/—5% for up to 30 days into the future and the highest accuracy of +/—1% for the 7-day forecast.

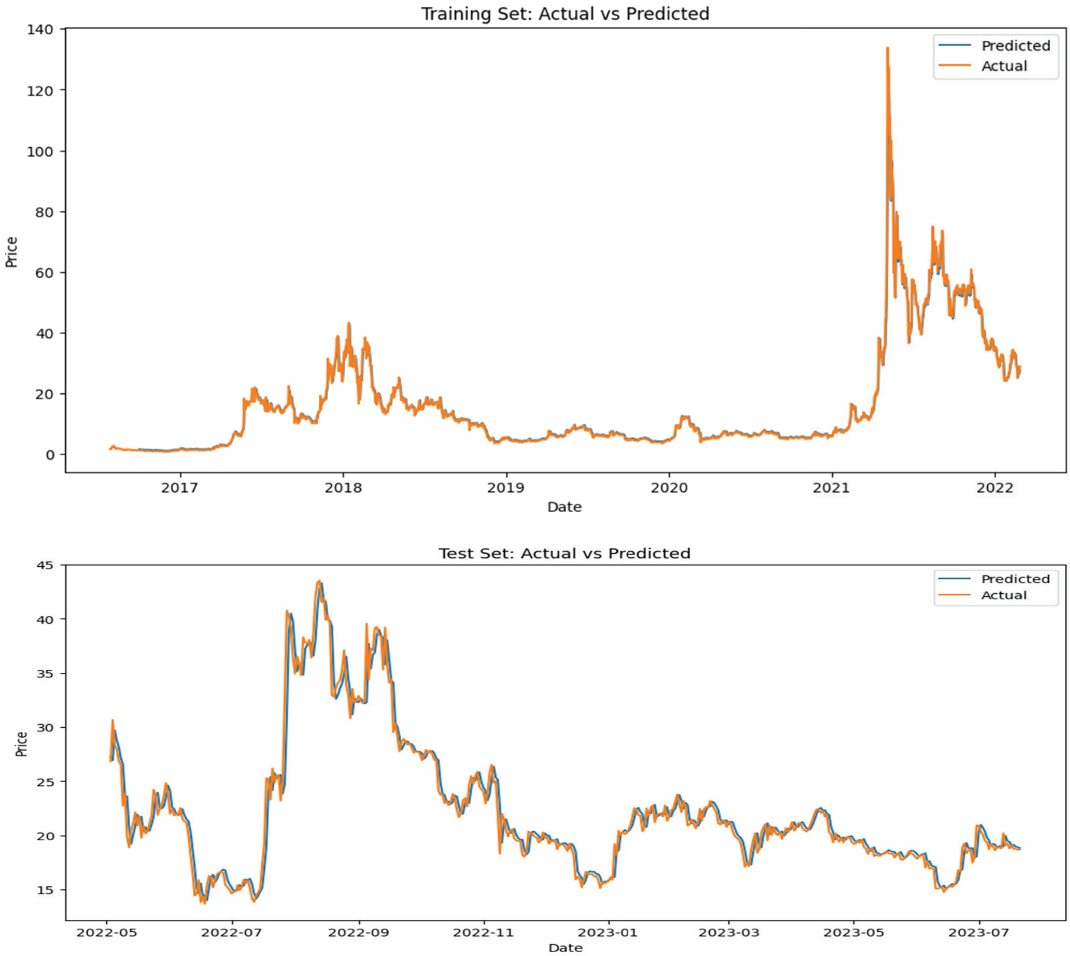


Figure 7: Ethereum Classic Price Forecasting by GRU

Ethereum Classic (ETC) price forecasting is shown in Figure 7. Like Bitcoin, the GRU model reveals relatively high accuracy for predicting ETC's prices. It gets to a 5% variation for 30 days, though these predictions are narrowed down to 1% for the short term.

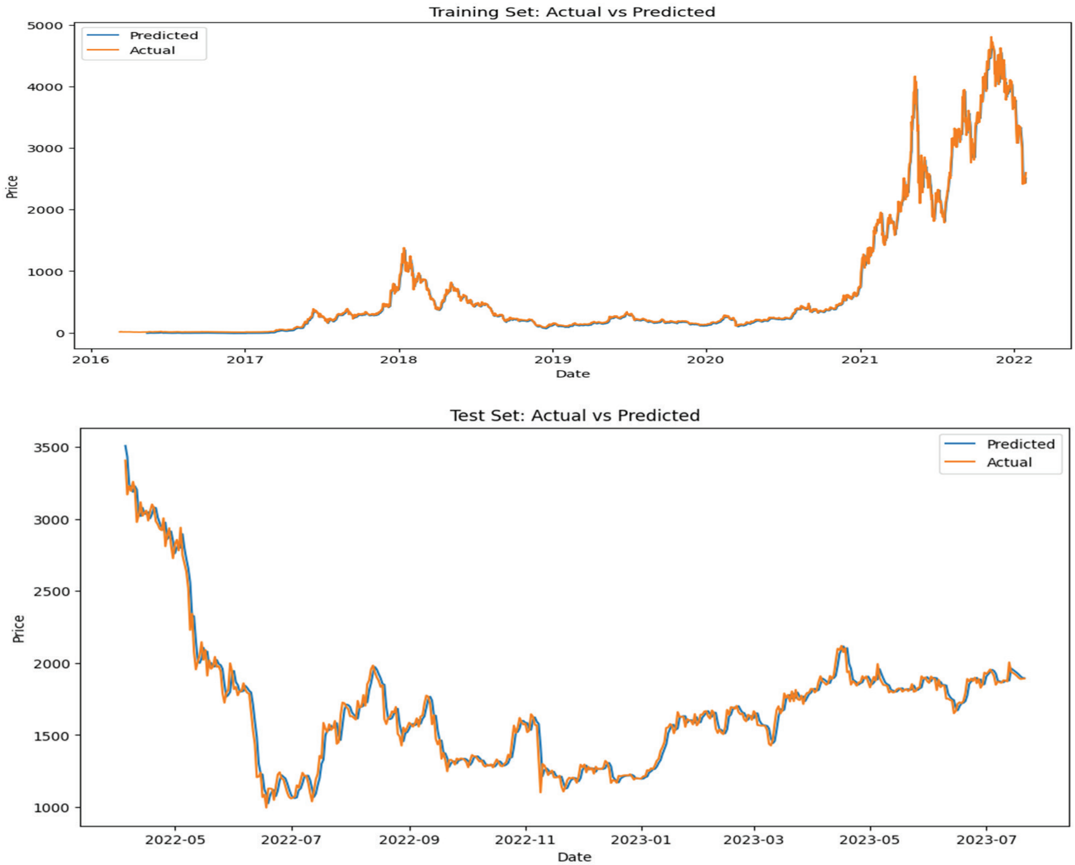


Figure 8: Ethereum Price Forecasting by GRU

Ethereum (ETH) price forecasting is shown in Figure 8. The same goes for the other measures from the GRU model for ETH, which are also kept within a 5% margin for up to 30 days. Interestingly, a short-term pin-point accuracy of 1% is ideal for short-term trading or intra-day trading strategies.

Figure 9: Litecoin Price Forecasting by GRU

Litecoin price forecasting is shown in Figure 9. The figures below show that predictions made using the GRU model for Litecoin are accurate. It has an error tolerance of roughly 5% for a month and even narrows this error to 1% for seven-day forecasts.

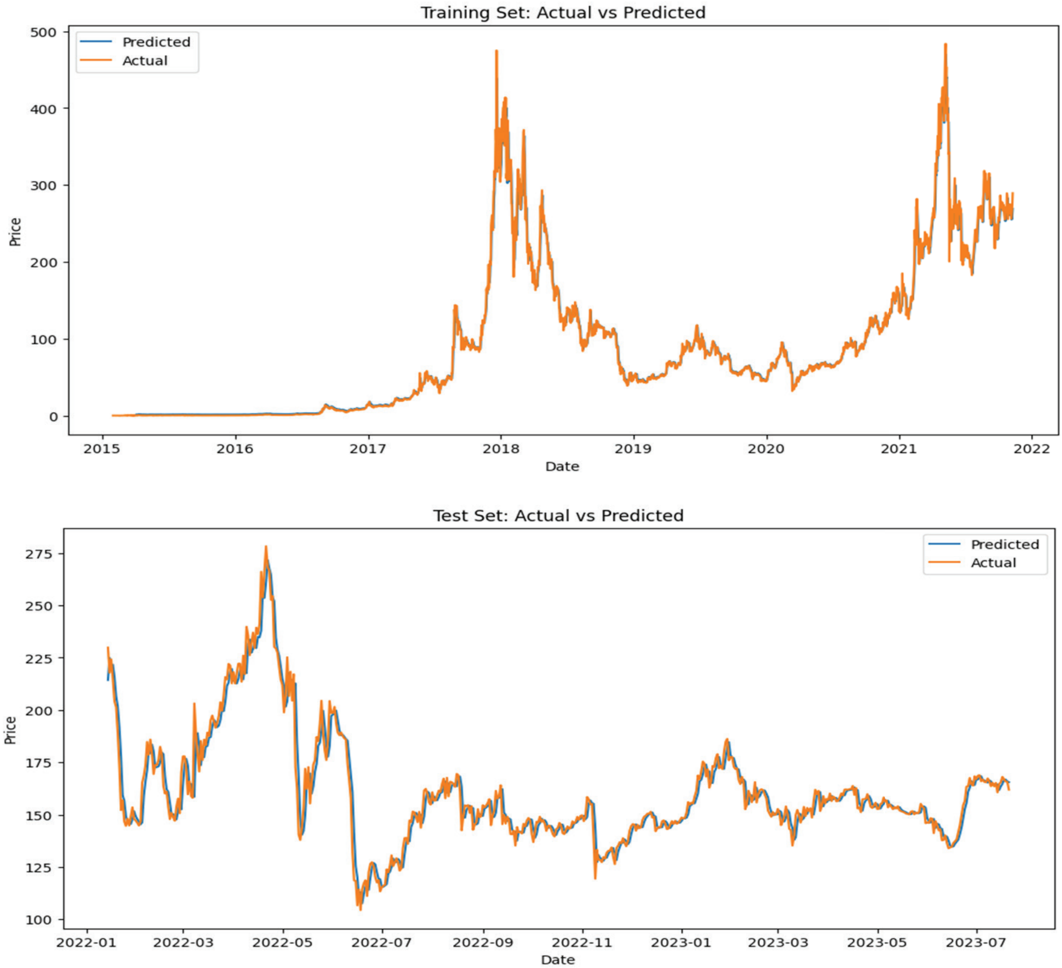


Figure 10: Monero Price Forecasting by GRU

Monero price forecasting is shown in Figure 10. The algorithm in question also holds up quite well in Monero. The predictions remain between 5% and 1% for a 30-day timeframe and possess a 1% tolerance for short-term forecasts.

Given these statistics, the GRU algorithm accurately predicts in the short term, with 7-day forecasts having 1% accuracy in each cryptocurrency. The last column in Table 4 shows that the accuracy of the GRU model only deviates 5% from the actual value for the monthly forecasts. Thus, it is a valuable instrument for long-term investment planning. GRU algorithm retains high accuracy in identifying primary price targets with over 80% accuracy. In other words, for every cryptocurrency, the GRU model follows the overall market trend with up to 90% accuracy.

4.4 Results Analysis for LSTM

The LSTM time series algorithm has been implemented to predict the prices of various cryptocurrencies, and its performance can be summarized and compared as follows:

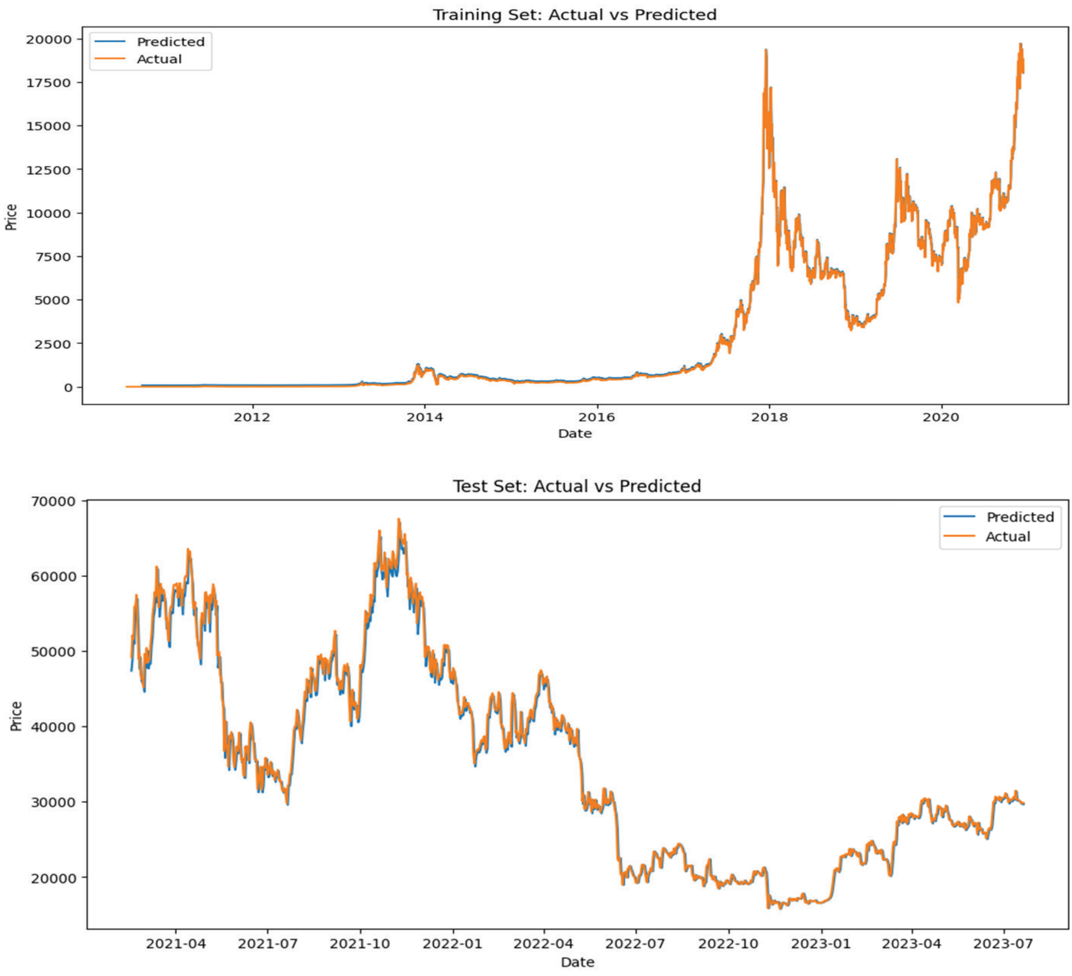


Figure 11: Bitcoin Classic Price Forecasting by LSTM

Bitcoin price forecasting is shown in Figure 11. From the given results of Bitcoin prices, the LSTM model is quite effective. The prices are explained well, and the forecasts are quite reasonable in application. This keeps a 5% accuracy on the prediction of up to 30 days and a 1% accuracy on the prediction of up to 7 days.

Figure 12: Ethereum Classic Price Forecasting by LSTM

Ethereum Classic (ETC) price forecasting is shown in Figure 12. For ETC, the LSTM algorithm's forecasting capability is well maintained, as depicted by the box plot indicating balanced forecast results compared to actual prices. As with Bitcoin, its weekly forecasts are within a 5% error, and it optimizes on 1% for daily forecasts.

Ethereum (ETH) price forecasting is shown in Figure 13. In the case of ETH as well, the model relating to the LSTM algorithm retains its precision once again. For a longer horizon of up to 30 days, it anticipates prices within the range of 5 percent; for the short-term horizon of 7 days, it gives an even narrower margin of 1 percent.

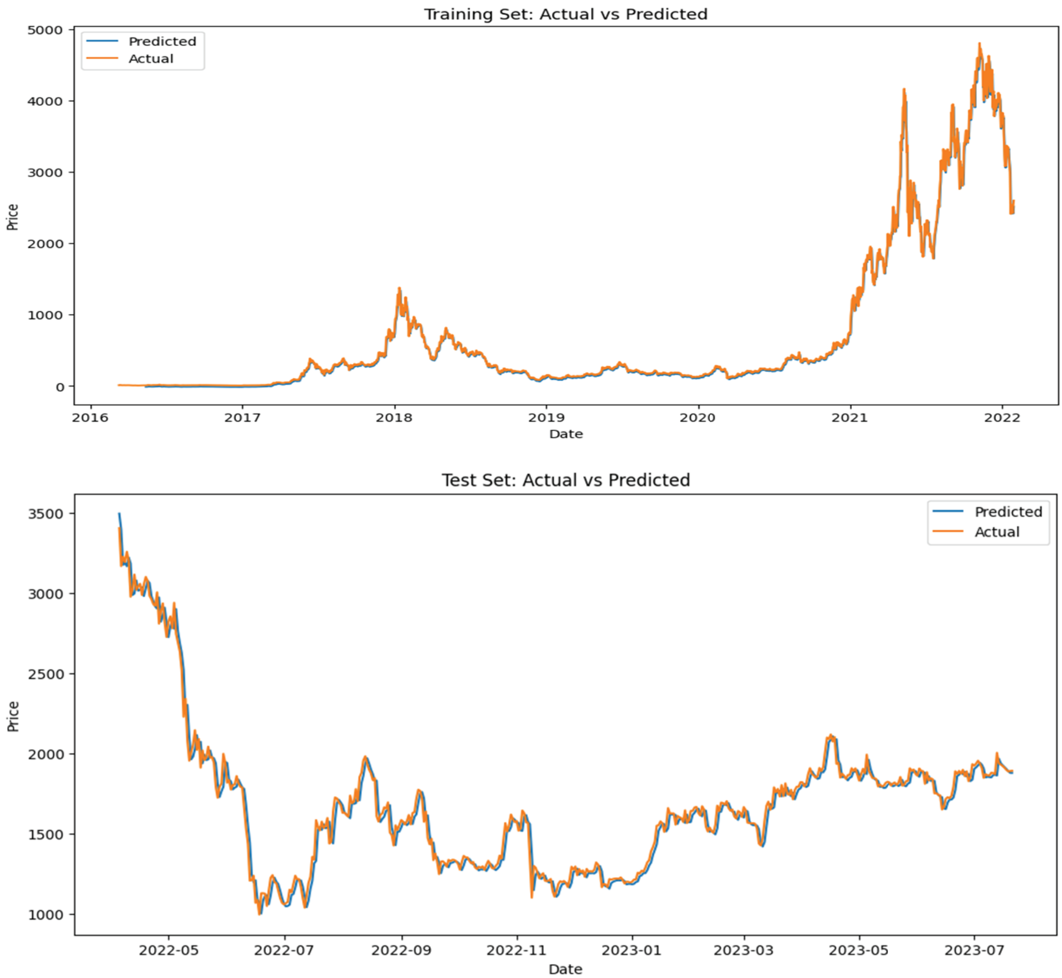


Figure 13: Ethereum Price Forecasting by LSTM

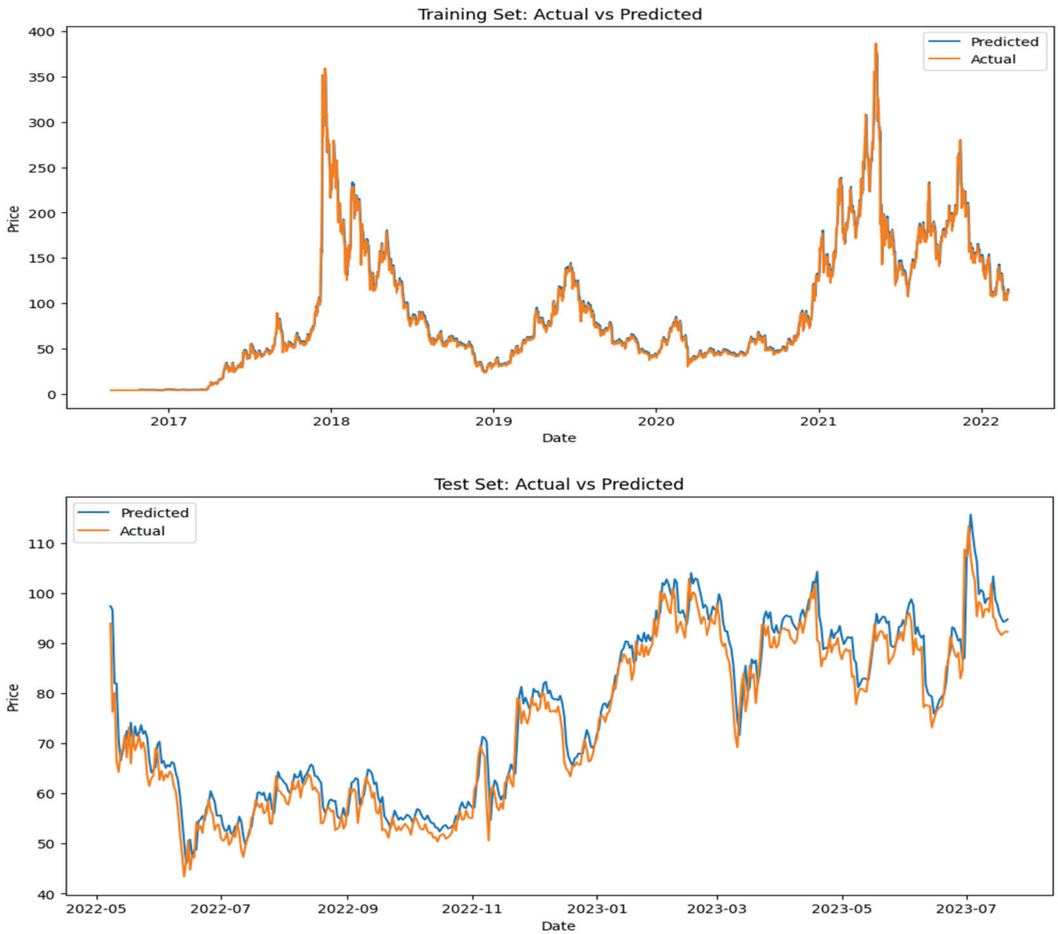


Figure 14: Litecoin Price Forecasting by LSTM

Litecoin price forecasting is shown in Figure 14. For Litecoin, therefore, the LSTM model stays the same, where most forecast prices may be closer to actual prices in most circumstances. It works to a 5 percent accuracy margin for a month and reduces this accuracy to 0.1 percent in the case of a 7-day forecast.

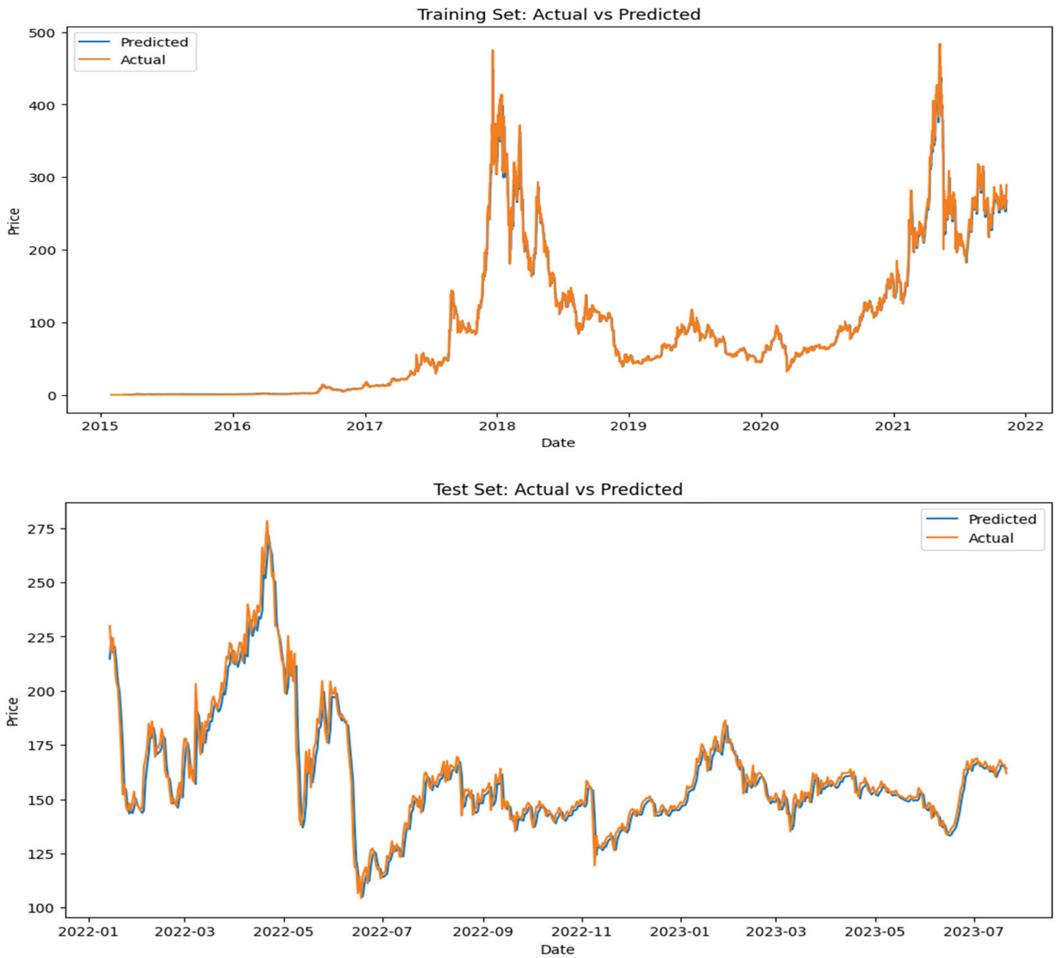


Figure 15: Monero Price Forecasting by LSTM

Monero price forecasting is shown in Figure 15. The LSTM applied to Monero reaffirms its effectiveness and accurate results. General forecasts for up to the 30-day horizon are stable within the 5% forecasting error range, while the model continues the 1% trend for short-horizon forecasts.

The LSTM has the same train and test prediction accuracy of 1% for the short-term forecast for all the Cryptocurrencies and can be a valuable tool for day-to-day trading strategies. In any case, the LSTM limits its forecast confines to within a ± 5% variation level for a month-long forecast horizon range, which is quite supportive of its slightly longer-term market forecasting capability. Regardless of the specific cryptocurrency in focus, the LSTM model accurately detects average significant price changes of over eighty percent. For each crypto, LSTM captures the overall trending of the market with over 90% accuracy, showing that the algorithm has knowledge of the market trends.

4.5 All Models Comparison

Table 4

Comparison of Crypto Currencies by CNN

	Time-Series CNN				
Performance Evaluation	**Bitcoin**	**Ethereum Classic**	**Ethereum**	**Litecoin**	**Monero**
R2 Score (Average => 30 Iterations)	0.974	0.873	0.907	0.907	0.849
MSE (Average => 30 Iterations)	4,867,069	5	18,761	25	111
RMSE (Average => 30 Iterations)	2,206	2	137	5	11
MAE (Average => 30 Iterations)	1,584	1	105	4	7
SMAPE Score (Average => 30 Iterations)	4.37	6.19	6.11	5.11	4.45
MAPE Score (Average => 30 Iterations)	4.33	6.21	6.39	5.06	4.42
MSLE (Average => 30 Iterations)	0.00	0.01	0.01	0.00	0.00
Minutes Taken (Average => 30 Iterations)	11.43	7.47	7.71	6.52	10.41

4.5.1 CNN Comparison

When employing a (CNN) algorithm for the prediction process of various types of ‘’cryptocurrency coins’’, separate and different results indicating variations in the accuracy of the prediction models and the time taken to train the models were recorded and shown in Table 4. Bitcoin Classic coin was notable, as it revealed the highest R^2 score, meaning that CNN was good at portraying much of the variance in the kind of coin. This superior predictive ability was further supported by the fact that the same coin had the lowest values in metrics. However, the Ethereum classic coin posed some difficulties for CNN. It gave the most miniature R^2 score and the most significant values across error measures, suggesting that CNN cannot learn or accurately predict its performance. Furthermore, the Ethereum Classic also underwent the longest training time; this indicates the continued difficulties of pattern recognition. However, Litecoin and Monero yielded slightly higher R^2 scores, but the error metrics show similar levels of prediction accuracy by the CNN. Also, the training times were identical, indicating that CNN achieved a similar training speed for these coins.

Table 5

Comparison of Crypto Currencies by GRU

	Time-Series GRU				
Performance Evaluation	**Bitcoin**	**Ethereum Classic**	**Ethereum**	**Litecoin**	**Monero**
R2 Score (Average => 30 Iterations)	0.990	0.940	0.976	0.957	0.933
MSE (Average => 30 Iterations)	1,834,669	2	4,791	12	49
RMSE (Average => 30 Iterations)	1,354	2	69	3	7
MAE (Average => 30 Iterations)	893	1	47	2	5
SMAPE Score (Average => 30 Iterations)	2.43	3.86	2.82	3.20	2.74
MAPE Score (Average => 30 Iterations)	2.43	3.85	2.84	3.21	2.77
MSLE (Average => 30 Iterations)	0.00	0.00	0.00	0.00	0.00
Minutes Taken (Average => 30 Iterations)	5.15	11.55	3.90	12.55	17.82

4.5.2 GRU Comparison

As for all four compared cryptocurrencies, the obtained R^2 scores were above 0.90. It implies that the GRU algorithm could explain more than 90 percent of the performance fluctuation of such coins, as shown in Table 5. More precisely, bitcoin had the highest value of R^2, which implies that the GRU explains the most variance in this coin's prices better solely, while Ethereum has the lowest value of R^2, pointing out a slightly weaker capability of the exact predictor to forecast it is performance solely. Interestingly, both Litecoins yielded values similar to Monero's, which suggests that the GRU is equally capable of addressing similar variances in the coins' performances. More evidence to support that the GRU made accurate predictions was that the metrics were especially low for all four coins. Bitcoin was/stayed the most substantial coin in terms of these markers, which further confirms the highest accuracy of the GRU's predictions. On the other hand, Ethereum yielded the highest values on these parameters, indicating a slight decline in the predictive power. In these scores, Litecoin and Monero remained parallel, thus magnifying the GRU's steady accuracy for both.

Table 6

Comparison of Crypto Currencies by LSTM

	Time-Series LSTM				
Performance Evaluation	**Bitcoin**	**Ethereum Classic**	**Ethereum**	**Litecoin**	**Monero**
R2 Score (Average => 30 Iterations)	0.987	0.950	0.977	0.938	0.935
MSE (Average => 30 Iterations)	2,436,101	2	4,595	17	48
RMSE (Average => 30 Iterations)	1,561	1	68	4	7
MAE (Average => 30 Iterations)	1,154	1	46	3	5
SMAPE Score (Average => 30 Iterations)	3.32	3.69	2.77	4.67	2.75
MAPE Score (Average => 30 Iterations)	3.39	3.70	2.80	4.55	2.76
MSLE (Average => 30 Iterations)	0.00	0.00	0.00	0.00	0.00
Minutes Taken (Average => 30 Iterations)	69.33	41.05	43.01	39.83	48.47

4.5.3 LSTM Comparison

It can be noted that the R^2 coefficients for all analyzed cryptocurrencies were above 0.90, which means that the LSTM algorithm successfully describes more than 90% of fluctuations in the performance of those four coins shown in Table 6. Bitcoin, specifically, exemplified this accuracy in the model's predictive ability, boasting the highest R^2 score. The results indicate that LSTM performs better at decomposing the complexities of Bitcoins than the other models. In contrast, Ethereum brought about the lowest R^2 score, which signifies the relatively lower effectiveness of the LSTM in modeling its performance variation. Namely, Litecoin and Monero demonstrated comparable R^2 scores while using the same algorithm, proving it has high prediction performance. Adding further credibility to the high degree of accuracy of the LSTM was its result for all the coins. Here, again, Bitcoin had the lowest values of these parameters, which confirmed the exceptional accuracy of LSTM's forecast for this coin. Similarly, the performance of Litecoin and Monero in these metrics was almost equal, showing that the LSTM model performs evenly in the prediction of these cryptocurrencies. Additionally, the number of epochs to train the LSTM algorithm is relatively small across the coins, meaning that the model is fast at learning patterns inherent to their performance.

5. Discussion and Conclusion

The analyses in this study on LSTM, CNN, and GRU neural network models reveal how they can be used to analyze and forecast future trends of cryptocurrencies. The ability to attain the short-term price range variability for the duration of one within a prediction error of 1%. The given week proves that the models are efficient and helpful for traders and investors. Most especially, the GRU and LSTM models proved to have the highest accuracy, ensuring the prediction error in not more than five percent of the actual stock price for up to 30 trials. to explain their usefulness in informing long-term investment decisions. Both models had distinct features, and the ability of the GRU model was promising in capturing more of the broad trend of the market with a margin of error of +/- 0.90%.

On the other hand, the GRU model performs better with information proving that longer-term patterns exist and that there are smooth deviations and vast, well-defined changes in demand. It seems more suitable to keep track of overreaching trends in a less volatile market segment. At the same time, the LSTM model was shown to have an excellent ability to understand the details of the price movement, contributing to more than 90% of the total fluctuation in the cryptocurrencies. The characteristics of LSTM allow it to capture the subtle nuances and minute patterns of price movement, making it ideal for modeling volatile and fast-moving price dynamics in the short term. It provides short-term predictions.

From this CNN model, the accuracy was tested within a 7-day forecast, showing higher accuracy in the short-term rather than long-term and revealing its appropriateness for short-term trading signals. It also demonstrated a very efficient capability to respond to major market rate shifts such as increased or decreased rates; this showcases the balanced model that is not over-training based on the training data. This reveals that CNN excels at identifying local patterns and anomalies significantly influencing price movements over short periods, making it particularly effective for real-time trading decisions. We have concluded that our studies relevant to everyday life have substantial consequences in terms of economics. The findings concerning the predictive accuracy of LSTM, CNN, and GRU models in this work set the direction for risk-adjusted outperformance in the cryptocurrency market. This implies that these models could be used by investors/financial analysts to obtain significant abnormal gains from technological applications, thus ensuring congruence of technological and economic value additions. Incorporating machine learning in economic strategies is a milestone in modern-day financial practices. Integrating machine learning into economic strategies represents a milestone in advancing financial practices, enabling more informed, data-driven investment decisions.

Finally, although the performance differences between Bitcoin, Ethereum Classic, Litecoin, and Monero were marginal in terms of the tested factors, the research affirms the effectiveness of the developed elaborate ANNs in forecasting cryptocurrencies' prices. These AI algorithms, therefore, come in handy when dealing with the volatile and unpredictable environments of cryptocurrencies. This paper signifies the feasibility of the analytical techniques of the LSTM, CNN, and GRU models in identifying the short-term trend price range of cryptocurrency with a reasonable level of accuracy. However, it also recognizes some of its shortcomings in that it uses history, which sometimes fails to echo things, especially in the volatile aspect of the cryptocurrency markets occasioned by distinct and divergent factors. The research may not capture the whole essence of the market owing to the limited number of cryptocurrencies examined.

The application of AI in financial forecasting presents several regulatory challenges and ethical considerations, including compliance with data privacy laws, ensuring transparency in algorithmic decisions, and preventing potential misuse of market manipulation. Ethical concerns also extend to mitigating biases in AI models that could disproportionately affect specific market participants and safeguarding against the exploitation of predictions to destabilize financial systems. Looking ahead, integrating hybrid models that combine the sequential pattern recognition strengths of LSTMs and GRUs with the spatial feature extraction capabilities of CNNs offers a promising avenue for future research. Such approaches can enhance predictive accuracy and robustness, paving the way for more reliable and ethical AI-driven forecasting tools.

The study would benefit researchers, investors, and academia as it describes the unique characteristics of the LSTM and GRU models, notably how GRU excels at capturing broad market trends. At the same time, LSTM specializes in understanding detailed price fluctuations. It expands on the potential implications of these models for real-world applications in cryptocurrency trading and could provide a clearer understanding. Furthermore, future research should explore integrating rad time data, market indices, and social sentiment analysis to improve forecasting accuracy and adapt to the ever-changing dynamics of markets, which would better address the evolving challenges investors and analysts face in making informed decisions.

Further studies can consider integrating current data, different market indexes, and market sentiment into the prediction system. Future studies can enhance these models by incorporating real-time data, market indices, and social sentiment data. It will be gathered from community forums, news outlets, and social media platforms, which can play a crucial role in driving its prices. Incorporating social sentiment analysis into predictive models would allow for a more comprehensive understanding of market dynamics and could lead to more accurate price forecasts. In particular, further progress toward real-time prediction models could be greatly helpful in investment planning and risk handling. Constant updates and upgrades to such models are thus fit for the process since cryptocurrency markets are constantly evolving. It would also be beneficial to apply them to live trading within the stock market due to the gained understanding of the models themselves and to identify the practical difficulties arising from their implementation.

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