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Deep Learning Based Forecasting of Cryptocurrency Markets By Using Bitcoin and Ethereum as Case Study for 2016–2024

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Abstract*:* The research aims to develop an accurate model for the prediction of Bitcoin and Ethereum values using deep learning methods. These are significant digital assets in today's financial markets. Daily data collected from 2016 to 2023 was analyzed by LSTM and CNN and the combined LSTM-CNN model in order to assess their performance in handling complex time patterns and price shifts, usually characterizing cryptocurrency markets. The statistical results revealed that the LSTM model performed best according to performance metrics such as RMSE and MAE and MAPE and R^2. Moreover, strong generalization with precision in predictions while avoiding overfitting was depicted. These findings give enhanced statistical and economic performance that involves enhanced prediction accuracy and therefore helps investment and risk management in an evolving financial scenario. It highlights the usage of AI in analyzing digital markets, giving better insight than previous studies dealing either with traditional models or less integrated models. The findings mark progress toward more reliable economic models capable of handling complex dynamic financial data.

Keywords: Cryptocurrencies, Deep Learning, LSTM Models, Bitcoin, and Ethereum.

Introduction: In the digital economy which that we see today – a world that runs on electronic payment which in turn transmits crypt out across borders – we have a very important, financial innovation in the form of cryptocurrencies. This has large scale impact on the global economic stage which is very much a home to blockchain technology that uses the Internet to which in turn it uses to do the business of daily transactions, thus we see a great economic transformation. Crypto assets are stored in a decentralized system on the blockchain network which means that no single authority has control over them. Thus they run on anonymous systems and are not subject to government monetary or financial policies. Crypto assets as we know them today, had their birth in private initiatives like Bitcoin, Dogecoin, Ethereum and Litecoin and since 2017 they have grown in popularity. But what we also note is that crypto asset supply is a lot less than the demand for them today which in turn has led to high prices of crypto assets and securities which are based on them. This high price in turn has brought about high volatility, high risk and high levels of unreliability in crypto assets. Crypto assets like Bitcoin and Ethereum have seen great price fluctuation as compared to traditional currencies, stock indices and commodities that are at the hand of central authority which in that sense make crypto assets alternative to traditional financial tools and transactions

Digital money is gradually integrated into traditional financial organizations; however, their market remains volatile due to limitations in the technical system design as well as economic environment conditions. Dramatic market volatility in digital money markets has urged researchers to create novel mathematical models intended for volatile market conditions. Various research studies demonstrate the use of artificial intelligence and deep learning methods to understand price behavior in digital money markets, due to their superior ability to analyze nonlinear processes that traditional economic models cannot explain. Various studies demonstrate that ensemble approaches combined with recurrent neural networks (LSTM, GRU) demonstrate remarkable ability to accurately predict prices in cryptocurrency markets. The proposed models were found to demonstrate their effectiveness for efficiently handling dynamically coupled, time-dependent financial processes that precisely describe the price variations for Bitcoin and Ethereum. The proposed predictive models demonstrated improved predictive performance for Bitcoin and Ethereum markets through the application of deep learning frameworks combined with signal processing approaches for overcoming overfitting difficulties.

Integration of machine learning techniques and data specific to blockchain, including transaction volume, mining difficulty, and hash rate, enables effective forecasting of the Ethereum blockchain system. Parameters mentioned above demonstrate technical and structural elements found within interconnected networks and simultaneously enhance market signal data, which comprises volume changes, momentum rate, and market volatility. However, models derived using this approach have faced challenges, such as data unavailability, dependence on historical data, and market moods. Various studies have worked on developing dynamic models for networks and models based on neural networks and meta-inference approaches to modify weights and hyperparameters dynamically and have thus ensured compatibility of the system in the market. Since financial institutions have expressed increasing interest in investing in cryptocurrency and the steady influence of this currency in determining investment portfolios, it is strategically essential and holds academic value as well for effective forecasting of the price of these currencies. Therefore, an increased focus on developing models and effectively testing using performance criteria such as RMSE, MAE, and MAPE is essential. This project extends existing theories by designing a forecasting system using deep learning approaches for anticipating market trends for Bitcoin and the Ethereum system based on the daily price variations during 2016 and 2023. Both LSTM and CNN approaches, along with hybrid models, are used in this research work to demonstrate and prove the conceptual level of deep approaches in the volatile market environment.

Research importance

The study contributes to the literature on finance forecasting by extending classical literature on linear time series behavior in which classical linear time series assumptions break down and in testing whether sequence learning and feature learning mechanisms can better explain persistence and regime switching in crypto prices than conventional methods. It further enhances practical implementation by generating an evidence based modeling procedure that facilitates portfolio assignment, risk management and scenario planning by allowing quantifiable forecasting precision and error control with the aid of the Bitcoin and Ethereum daily price data and conventional evaluation indicators that decision makers can comprehend directly.

Research problem

To what extent do deep learning models predict prices in cryptocurrency markets in Bitcoin and Ethereum in a very volatile setting and what model architecture performs the most dependable out of sample forecasting throughout the study time frame using the longest continuous daily sample with which to train and validate the model.

Research hypotheses

H1 Deep learning models constructed based on temporal dependence achieve statistically significant improvements in the accuracy of Bitcoin and Ethereum forecasts compared to a convolution only specification when measured in terms of RMSE MAE MAPE and R 2 on out of sample test data.

H2 LSTM has the highest generalization of the other deep learning architectures tested on Bitcoin and Ethereum forecasting due to its gated memory structure that models long run dependencies and minimizes overfitting in high volatility.

Research objectives

1- The research question aims to construct deep learning prediction models of both Bitcoin and Ethereum based on daily closing price and uniform preprocessing conditions.
2- Compare LSTM CNN and hybrid LSTM CNN performance with RMSE MAE MAPE and R 2 on training and test sample.
3- Determine the most appropriate architecture that is the most adequately fitting and generally applicable and support the selection with both statistical data and market understanding.
4- Convert forecast output into practical feedbacks of investment timing and risk management using forecast ranges and error related reliability measurements.

Research methodology

The paper will use a quantitative design that is founded on daily time series modelling of Bitcoin and Ethereum 2016-2024. It retrieves historical closing prices of a regular public source and builds supervised learning streams over a fixed look back window. It approximates three deep learning structures LSTM CNN and a combined LSTM CNN and train them using Adam optimizer and mean squared error. It assesses models based on a train test segment and contrasts predictive quality with RMSE MAE MAPE and R 2 and then along with the test performance and stability between training and validation outcome selects the optimal model.

Literature review

Earlier work on cryptocurrency forecasting compared classical machine learning algorithms and showed that performance depends on the dataset and market conditions, so no single method dominates across samples (Hitam &

Ismail, 2018). Using longer historical series, evidence then supported the feasibility of machine learning for cryptocurrency price prediction in practice, especially when models are trained on extensive time series that contain repeated boom bust cycles (Derbentsev et al., 2019). As research moved toward deep learning, results showed that nonlinear sequence models can outperform traditional statistical approaches because they capture rapid and nonlinear price swings that standard models struggle to represent (Awoke et al., 2020). During the COVID-19 period, attention expanded from prediction accuracy to asset role and market function, where Bitcoin and Ethereum were studied as potential safe haven or hedging assets, with Ethereum also discussed as a safe haven candidate under stress (Mariana et al., 2021), while other work proposed hybrid recurrent architectures that combine GRU LSTM and BiLSTM to raise accuracy and exploit complementary temporal structures (Hamayel & Owda, 2021). Subsequent studies linked market behavior to trading mechanisms and micro drivers, reporting speculative features and bubble-like dynamics and documenting a bidirectional causal relationship between cryptocurrency prices and trading volume driven by factors such as prices energy costs and transaction fees (Jalan et al., 2022). Alongside market growth, regulatory and sustainability themes became more visible, highlighted by the shift of Ethereum to proof of stake via the merge on September 15, 2022 and the associated reduction in energy use that intensified global debate on mining externalities (de Vries, 2022). With higher volatility and wider adoption, research increasingly used ensemble and deep learning systems to stabilize forecasts across market phases, showing that ensemble deep learning can remain more stable during severe volatility and can support automatic trading applications (Shamshad et al., 2023), while other work used technical indicators such as moving averages and RSI within ensemble learning for Bitcoin price prediction (Chen, 2023), and GRU versus BiLSTM comparisons indicated stronger short run performance for GRU but better long horizon performance for BiLSTM when dependencies persist (Golombeck & Derbentsev, 2023). In parallel, policy and payment system research emphasized how digital and central bank digital currency related innovations supported financial activity and resilience during COVID-19 through fintech driven digitization and lower cross border costs including remittances (Xin & Jiang, 2023; Li & Zhang, 2024; Alfonso et al., 2025), while also highlighting risk channels such as evidence that a notable share of Bitcoin users and transactions has been associated with illegal activity (Xin & Jiang, 2023). Recent contributions further framed cryptocurrencies as a distinct asset class with weak links to traditional assets and very high volatility that attracts portfolio diversification demand but also exposes investors to nonfinancial risks such as cybercrime fraud and technology complexity (Harris et al., 2024). In the same contemporary strand, market scale and centrality of Bitcoin and Ethereum are emphasized, with reported market capitalization figures for Bitcoin and Ethereum and the claim of strong market value growth over the last five years, alongside arguments that blockchain enabled decentralization and added security and privacy helped drive adoption and financial system relevance (Zhao et al., 2024; Atta Mills et al., 2024).

This study investigated the use of deep learning approaches, such as Golombeck and Derbentsev 2023, by utilizing both GRU and BiLSTM in predicting Return Volatility. The authors established that although GRU can realize very good results in the short term, it does not perform as well as BiLSTM when the relationships are long-term. Secondly, Derbentsev et al. (2019) derived the applicational validity of the machine learning approaches in the price prediction of Cryptocurrency using the extensive historical data set. Further, Hamayel and Owda (2021), developed a new methodology combining GRU, LSTM and BiLSTM in a single unified forecast model for Cryptocurrency resulting in excellent accuracy in predictions and demonstrating the advantage to be gained by combining several types of recursive Neural Network architectures together. Financial Forecasting has been greatly changed with the introduction of Innovative Modeling Techniques to replace traditional statistical methods and to analyze large datasets of high-frequency and highly volatile data. In particular, research indicates that the unique characteristics of Cryptocurrency require Forecasting Models capable of dealing with nonlinear Relationships, Temporal Trends and adapting to Market Changes. The findings of the Current Study suggest that the development of AI-Based Models will have a major impact on the future of Financial Forecasts related to the Cryptocurrency Markets.

Bitcoin and Ethereum overview

Bitcoin and Ethereum are cryptocurrencies, not generic “digital currencies”. The term digital currency is broader and can refer to any value stored or transferred in digital form, including bank deposits, e-money, mobile money, and central bank digital currencies. By contrast, cryptocurrencies are a subset of digital currencies that rely on cryptography and typically operate on decentralized blockchain networks (Harris et al., 2024). Since then, the use of cryptocurrency has been a significant step to create an entirely new generation of non-traceable currency (Garin & Gisin, 2023). Investment companies are utilizing artificial intelligence to predict the price of cryptocurrencies and identify the main factors that determine their prices by applying artificial intelligence techniques (Boozary et al., 2025). Cryptocurrencies are designed to be peer-to-peer alternatives to Government-issued legal tender (Viéitez et al., 2024). In the last few years, Bitcoin and Ethereum have experienced great growth across the globe. Cryptocurrencies are stored electronically and get value confirmation through a decentralized network infrastructure. There has been a shift away from traditional forms of transaction processing to facilitate peer-to-peer transactions without needing to use a third party's administrative or oversight capabilities. There is still an ongoing debate among experts as to what type of asset Bitcoin should fall under: commodity, currency, or a mix of both (Zhang & Mani, 2021). On January 3, 2009, the first block in the blockchain was created by Nakamoto.

Primarily intended as a payment mechanism, it soon evolved to become a popular platform for trading. However, Bitcoin was conceptualized by Satoshi Nakamoto to “be a completely peer-to-peer version of electronic cash, which enables payments over the Internet directly from person to person without involving any banking institution” ((Presthus & O’Malley, 2017). Ethereum was introduced in the year 2015 as another revolutionary digital currency. Ethereum has quickly proliferated as it boasts smart contracts in its network managed by blockchain infrastructure. They assure immutable execution and transparency in such smart contracts on the Ethereum network ((Atta Mills et al., 2024). This protocol requires the usage of cryptographical mechanisms in order to ensure secure transactions as it simultaneously safeguards the privacy of all users. Cryptocurrencies are open decentralized networks, which reduces all working expenses as it enhances efficiency; as such, they are profitable ((Atta Mills et al., 2024)). This has led researchers to predict the values of these currencies using diverse technological as well as statistical analyses in order to reveal how they could possibly perform in the future. “Conventional economic models are usually inadequate in modeling the prices of Bitcoin or Ethereum because they inadequately describe the nonlinear behavior inherent in the Bitcoin and Ethereum time series.” Hence, researchers resort to machine learning classifiers like random forest classifiers or support vector machines.

With the promise of safe and transparent transactions, blockchain technology is the driving force behind the spread of cryptocurrencies like Bitcoin and Ethereum. This technology is expected to play a crucial role in the global economy as it spreads more. Interest in predicting the behavior of Bitcoin and Ethereum started to grow aggressively after 2015 since the systems were free and open-source with the potential for very high returns. The time series dynamics of the markets of both Bitcoin and Ethereum are nonlinear due to the volatility of these cryptocurrencies. Thus, traditional price prediction models do not work well on them. These limitations pushed researchers toward machine learning, starting with random forests, then later with support vector machines. Even though support vector machines worked really well for many time horizons, they are prone to many drawbacks related to their efficiency when dealing with large datasets, finding optimal hyperparameters, and detecting complex patterns. In this regard, many hybrid and metaheuristic techniques were developed in conjunction with machine learning approaches; one of the most popular ones is genetic algorithms and particle swarm optimization. Later, this area was advanced by enhancing bidirectional LSTM networks with optimized search methods that would predict multivariate prices across multiple currencies. These techniques search for the optimal solution and therefore can be adaptable to changes in the underlying data while carefully balancing exploration and exploitation.

Methodology:

Data collection:

The methodology of this project consisted of the collection and analysis of daily closing values (price data) of Bitcoin and Ethereum for each day starting from 1 January 2016 until 31 December 2024. Bitcoin and Ethereum are the two most well-known and heavily invested cryptocurrencies at present; therefore it is very important to look at the variation in price of each of the currencies in order to predict their price movements in future periods. A total of 3,288 observations (price records) for Bitcoin and Ethereum were taken from CoinMarketCap, which provides continuous historical records of these currencies over the period stated above.

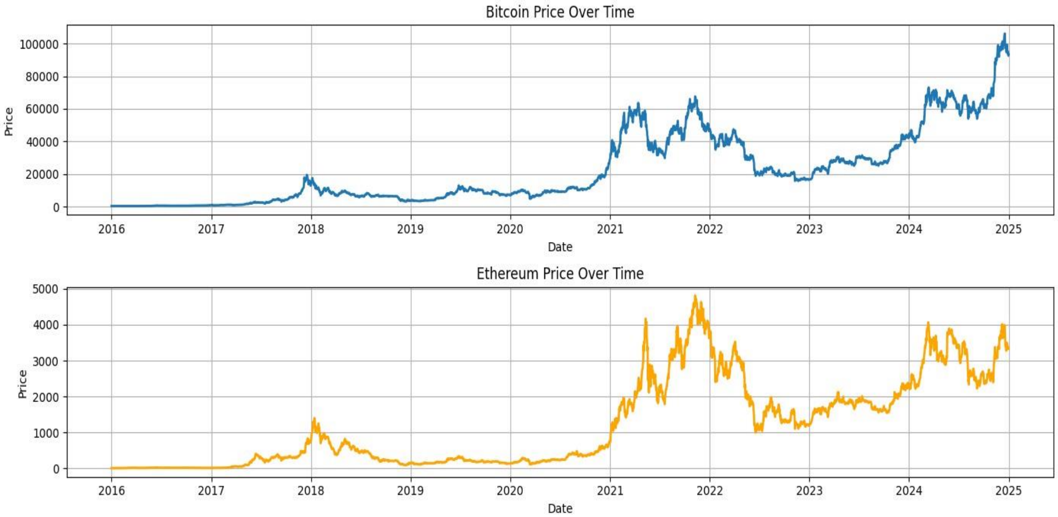
Table 1: **Descriptive Statistics of Bitcoin and Ethereum Datasets**

	Bitcoin	**Ethereum**
count	3288.000000	3288.000000
mean	22349.542652	1201.270528
std	22332.967765	1233.438546
min	364.330994	0.937124
25%	5547.407534	176.831335
50%	11358.381660	556.950500
75%	36824.614770	1983.116489
max	106140.598238	4812.087614

Source: Prepared by researchers using Python - Jupyter

Table (1) presents a statistical description of the closing daily prices of Bitcoin and Ethereum for the years from 2016 through 2024. Both Bitcoin and Ethereum have a total of 3,288 observations over this time frame. The average price of Bitcoin was $22,349, while the average price of Ethereum was $1,201. This indicates that there is a significant price difference between the two cryptocurrencies. In addition, both Bitcoin and Ethereum have large standard deviations ($22,333 and $1,233, respectively) consistent with the high levels of volatility in price that typically characterize the cryptocurrency markets. Further, the lowest recorded price for both Bitcoin and Ethereum ($364 and $.093, respectively) was during the initial stages of each currency and demonstrates a substantial drop in price following launch; whereas the maximum recorded price for both Bitcoin and Ethereum ($106,000+ and $4,800+, respectively), demonstrates incredible growth and extreme swings in price for both assets. In addition, the distributions of the price over time for both Bitcoin and Ethereum are irregular, as the first quarter represents less than 25% of total trades completed each year, while the third quarter represent over 75% of total trades completed during the same period. Such trading patterns can be attributed to the infusion of speculative investors into the marketplace and the resulting increase in total market capitalization. Therefore, this environment creates both high-risk speculative investment opportunities, as well as legitimate profit-making opportunities. The potential risk and return of financial assets that appeal to investors interested in earning profits quickly is always high, but those investments require considerable knowledge and experience in risk management. The rapid fluctuations in the price of Bitcoin and Ethereum impact their use as both currency and stores of value; however, their volatility makes them more attractive to investors and speculators. To successfully forecast the price of each cryptocurrency, one must analyze both nonlinear dynamics and price volatility. The time series price of both cryptocurrencies is shown in Figure 1 below:

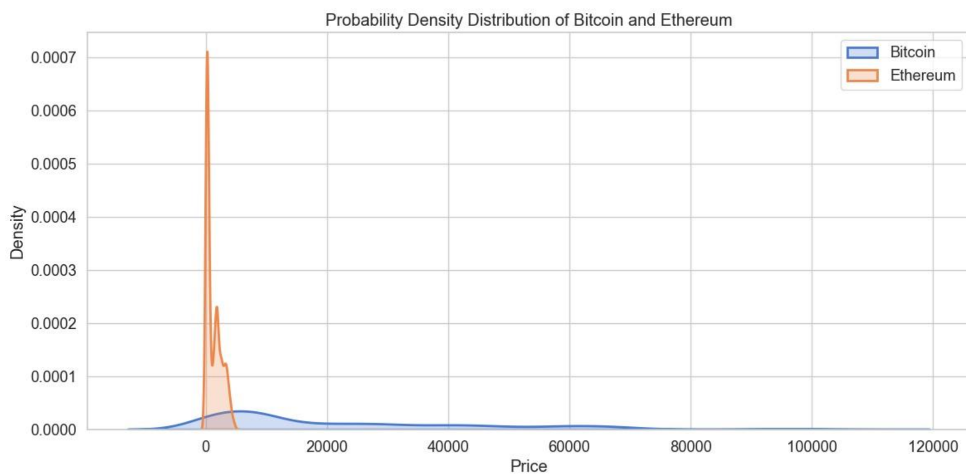
Figure 1. Historical Price Trends of Bitcoin and Ethereum (2016–2024).



Source: Prepared by researchers using Python - Jupyter

During 2016 and up until the early months of 2025, the price patterns for Bitcoin and Ethereum show the classic roller-coaster movement characteristic of speculative markets, with extreme volatility and abrupt swings. The upper graph indicates three substantial growth cycles for Bitcoin, the first in later 2017, the second in 2021, and thirdly in mid-2023 and until the end of the period, reaching almost $100,000 as the price. The three driving factors for such price actions are hype, market adoption, and improvement in the underlying technology architecture. The market volatility is reflected in Ethereum, yet the pricing shows substantial growth from early 2021 due to an enhancement in smart contract usage and the shift in Proof of Stake. The research clarifies that Ethereum exhibits periods with lesser levels of market instability, which is indicative of the underlying rate of advancement in the technology architecture and a more widespread usage rate for DApps based thereupon. The following graphic shows the probability distributions for price variations for both Bitcoin and Ethereum. Figure 2: Probability distributions for price variations for Bitcoin and Ethereum.

Figure 2. Probability Density Distribution of Bitcoin and Ethereum Prices.



Source: Prepared by researchers using Python - Jupyter

Concentrated probability distributions for both Bitcoin and Ethereum can be best seen in Figure (2), and they represent the two currencies' primary statistical characteristics during this time period. The Concentrated Probability Distribution for Ethereum (shown as the orange area in Figure (2)) has an extremely high concentration of Ethereum prices near zero, which indicates that there have been many times when the actual value of Ethereum was near zero, and as time has progressed, the likelihood of the price of Ethereum being greater than $0 has been increasing steadily. In addition, in contrast to the initial phase of Ethereum's growth, where it was a new and unproven currency, Ethereum's value increased steadily as the number of investors increased, creating a favorable price-growth pattern, which also reflects the fact that many of the Ethereum investors were new investors. The Concentrated Probability Distribution for Bitcoin (shown in blue in Figure (2)) exhibits more wide-ranging characteristics than that of Ethereum, the reason being that as new/institutional money entered the Bitcoin market and the demand for Bitcoin rose, large price spikes occurred. Therefore, because of the many large spikes in price associated with the initial growth of Bitcoin, the Concentrated Probability Distribution for Bitcoin contains a long right tail. In addition, both distributions (asked for previously) are skewed distributions because both distributions contain extremely high prices (extremely low probability of occurring). The highly specialized characteristics of Bitcoin and Ethereum's Concentrated Probability Distributions are due to market speculation, investor psychology, restricted supply of both currencies, and regulatory changes. In conclusion, from the analysis of Figure (2), it is apparent that digital marketplaces are exhibiting distributions that differ from those that can be described as "normal." This is displayed by both Bitcoin and Ethereum's Concentrated Probability Distributions being skewed.

Statistics framework

Long short-term memory (LSTM):

In this work, an LSTM neural network is implemented with a specific recurrent architecture for time series data like those representing bitcoin price fluctuations. LSTMs take care of the vanishing gradient problem that is intrinsic to regular recurrent nets by using memory units carrying information for very long periods, thus enabling them to analyze sustained signals in financial market oscillations. The first LSTM layer has 50 units and would return an output shape of (None, 60, 50) for several time steps. This layer learns the sequence and its history by integrating past data points. A calculation in LSTM centers around the following three key elements (Yu et al., 2019) (Abbasimehr et al., 2020):

The input gate controls how much new information will be stored in the cell state:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{1}$$

Where σ Sigmoid activation function, h_{t-1} Hidden state from the previous time step, x_t Current Input at time t, b_i Bias vector for the input gate, W_i Input weight matrix. The forget gate controls how much of the existing memory to retain and is represented by:

$$f_t = \sigma\left(W_f \cdot [h_{t-1} - 1, x_t] + b_f\right) \tag{2}$$

Where W_f is the forget gate's weight matrix, and b_f is the corresponding bias vector. The output gate regulates the output of the LSTM unit to the next layer or time step, defined as:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{3}$$

Where W_o and b_o are the weight matrix and bias vector for the output gate. The cell state is updated by combining contributions from the input and forget gates. The candidate cell state is calculated as:

$$\tilde{C}_t = \tanh\,(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{4}$$

and the updated cell state is given by:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{5}$$

Where W_C and b_C are the weight matrix and bias vector for the candidate cell state. The hidden state, which represents the output of the LSTM unit, is updated as:

$$h_t = o_t \odot \tanh\,(C_t) \tag{6}$$

A second LSTM layer with 50 output size and total weight count of 20,200 was added after first LSTM layer. The layer is designated as having no return sequences, therefore the sequence will be picked as fixed vector that can be processed afterwards. Thus, this type of LSTM architecture provides the ability to interpret and extract 'deeper' or more complex temporal changes in existing time-series data.

Convolutional Neural Network (CNN):

The study also utilized Convolutional Neural Networks (CNNs) to make economic-economic predictions of Bitcoin and Ethereum prices using deep learning methods. The CNN model design consists of a one-dimensional Conv1D architecture containing sixty-four filters. The CNN Conv1D models are mathematically constructed via convolution; as discussed by Kattenborn et al. (2021) and Wu (2017):

$$Z_{i,j} = \sum_{m=0}^{M} W_m \cdot x_{i+m-1} + b \qquad (7)$$

which means that At position i, j, will be the resulting output of the convolution, W_m represents kernel weights, x_(i+m-1) is the input in the sequence, and b is defined as a bias term. In the CONV layer, the Rectified Linear Unit (ReLU) function has been selected as the activation function, as defined as:

$$ReLU(z) = max(0, z) \qquad (8)$$

The model attains nonlinearity during this phase, which helps the model identify complex patterns of price fluctuations. The MaxPooling1D allows the shape of the feature maps to become an output of (None, 14, 64). A one-dimensional vector of size 896 is passed into a dense layer of 50 units with ReLU activation function to calculate the output as follows:

$$\hat{y} = ReLU(\mathrm{W} \cdot x + b) \qquad (9)$$

The computational part of the task uses W for the weight matrix, x for the input vector, and b for the bias in calculating the future value of the target currency price based on a linear activation function and a single-unit dense layer. The learning rate of 0.001 acts as a mechanism in adjusting the weights and biases based on the backpropagation technique. The mean squared error function decreases the differences in the predicted values from their corresponding actual values. The design of the CNN model demonstrates the ability of the model to encode nonlinear processes in financial markets so that it can be used for prediction purposes in the case of Bitcoin and Ethereum financial prices.

Hybrid LSTM-CNN:-

In the “Hybrid LSTM-CNN Model”, the benefits of Long Short-Term Memory and Convolutional Neural Network layers are combined to allow for accurate forecasts of the cryptocurrency price series in terms of handling dependencies in sequences and local characteristics in data. The mathematical formulation of the CNN layer involves convolution processes described as y_i=∑_j▒ w_j x_(i+j)+b in terms of kernel-weight coefficients *w_j*, input sequences x_(i+j), and bias terms *b*. The convolutional layer uses a ReLU activation function to detect local temporal characteristics in training data (Liang et al., 2022) (Gür, 2024). Next in the forwarding pathway comes the MaxPooling layer that results in a reduction in feature dimensions to decrease the complexity of computations required for modeling sequences and analysis in subsequent stages. The resultant outputs derived are then input to the LSTM layer to detect the global or long temporal dependencies in sequences in a cryptocurrency market system analysis model. For the *LSTM Layer*, specific unit architecture designs exist for model-purpose designs as given below in mathematical formulations for the computations in its three layers: Gate Input: i_t=σ(W_i [h_(t-1),x_t]+b_i), Gate Forget: f_t= σ(W_f [h_(t-1),x_t]+b_f), Gate Output: o_t=σ(W_o [h_(t-1),x_t]+b_o), with modifications to the initial-cell-state values to be based upon f_t∘C_(t-1) + i_t∘tanh(W_c [h_(t-1),x_t]+b_c) and hidden state h_t= o_t∘tanh(C_t) based upon overall memory states in a cryptocurrency market model analysis system.

Optimization:-

The ADAM algorithm is a popular optimization algorithm for the training of deep models to improve the prediction results and speed up learning processes for the projection of the price of the Bitcoin and Ethereum cryptocurrencies. The use of ADAM is feasible because it combines the strengths of both Momentum and RMSProp methods by applying the estimation of the mean of the first and second-order gradients to improve the stability while handling noisy data represented by the financial markets. The Adaptive Moment Estimation technique individually adjusters learning rates to produce accurate results, especially within a volatile financial market, including the case study involving cryptocurrencies. The study adopts the use of ADAM as the basic optimization algorithm for model training within the frameworks of the LSTM and CNN models. The algorithm effectively optimizes the loss function and contributes to accurate predictions within the Bitcoin and Ethereum financial markets, as reported by (Zhang, 2018). The Adam optimizer maintains the update process of the model's weight parameters:

$$\theta_{t+1} = \theta_t - \eta^{\downarrow} \cdot \frac{\partial \mathcal{L}}{\partial \theta} \qquad (10)$$

Where: θ Model parameters, η Learning rate, $\mathcal{L}$ Loss function.

Performance indicators: For the evaluation of the prediction quality of the models and the selection of the model with the highest prediction quality, the following performance indicators can be used:

$$\text{Root Mean Squared Error: RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

$$\text{Mean Absolute Percentage Error: MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \times 100 \quad (11)$$

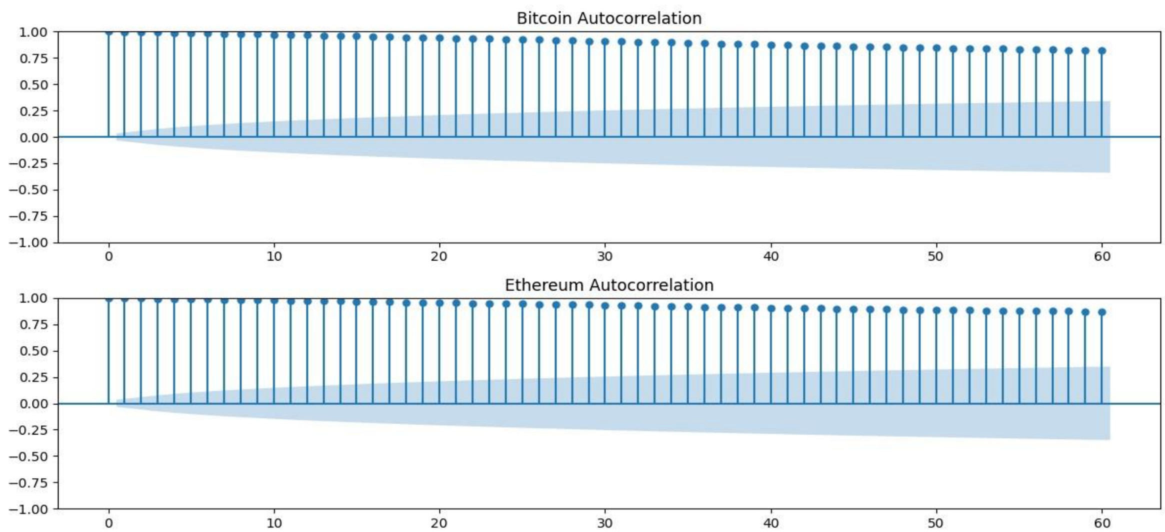
$$\text{Coefficient of Determination: } R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}$$

Where y_i Actual value, $\hat{y}_i$ Predicted value, $\bar{y}$ Mean of the actual values.

Results:

The analysis of research findings on deep learning models and their forecasts of Bitcoin and Ethereum prices is conducted using data spanning from January 2016 to December 2024. A total of three thousand two hundred eighty-eight daily datasets for both currencies are taken under consideration within the scope of this analysis. Three different architectures of models have been taken into consideration to analyze their ability to address the nonlinear pricing mechanisms and extreme volatility of bitcoin market dynamics: LSTM models, CNN models, and an LSTM-CNN combination model. For time series-based forecast models to work efficiently, accurate data is required for verification, which can be confirmed using the Autocorrelation test of Bitcoin (top), as well as corresponding closure values of Ethereum (bottom), which is illustrated below:

Figure 3 Bitcoin and Ethereum autocorrelation



Source: Prepared by researchers using Python - Jupyter

Chart from Figure 3 shows the Bitcoin daily closing price autocorrelation plot on top and Ethereum daily closing price autocorrelation plot on bottom. There is a strong positive autocorrelation exhibited across multiple lags in both series indicating that time dependencies exist and thus could be modeled using a time series forecasting method.

Figure 3 illustrates that both Bitcoin and Ethereum daily closing prices show a statistically significant persistent strong positive autocorrelation across time lags. The presence of a persistent autocorrelation is an indication of structure in cryptocurrency price data, in the sense that prior prices influence subsequent prices. Thus the presence of a strong time dependency in cryptocurrency markets indicates that cryptocurrency prices form a "memory" and therefore are predictable. This phenomenon is attributable to the cyclical nature of cryptocurrency markets, which are characterised by volatility and speculative bubbles that create short-term trading opportunities, regulatory influences, and changes in technology that combine to create periodic patterns that can be exploited using statistical and machine learning models. The evidence of such autocorrelation supports the application of LSTM and CNN modelling techniques, which are very capable of processing both time and non-linear data, with the added benefit of improving investment decision-making and risk management processes by providing more accurate predictions of future price movements.

Table 2: Performance Metrics of LSTM, CNN, and Hybrid LSTM-CNN Models on Bitcoin and Ethereum Datasets

Model	Dataset	Asset	RMSE	MAE	MAPE	R^2
LSTM	Train	Bitcoin	922.09	495.02	3.82%	1.00
	Test	Bitcoin	1870.37	1244.01	2.21%	0.99
	Train	Ethereum	70.26	34.40	5.44%	1.00
	Test	Ethereum	85.66	57.59	2.16%	0.99
CNN	Train	Bitcoin	1151.34	681.30	6.58%	1.00
	Test	Bitcoin	1454.15	1038.69	5.27%	0.99
	Train	Ethereum	76.48	39.31	15.60%	1.00
	Test	Ethereum	171.14	117.99	7.15%	0.98
Hybrid LSTM-CNN	Train	Bitcoin	960.44	562.33	6.47%	0.997
	Test	Bitcoin	1913.44	1267.14	2.22%	0.992
	Train	Ethereum	82.81	44.07	7.37%	0.994
	Test	Ethereum	109.12	79.80	3.03%	0.977

Source: Prepared by researchers using Python - Jupyter

Three different approaches of deep learning, namely LSTM (Long Short Term Memory) model, CNN (Convolutional Neural Network) model, and LSTM-Combined Model (a combination of both the LSTM and CNN Models) using crypto currencies, Bitcoin & Ethereum were evaluated for each currency based on the metrics of RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error) and R2 (Coefficient of Determination). The study indicates that all the proposed deep learning architectures provided a good degree of accuracy (R2 > 0.977) in predicting the fluctuations of Bitcoin price. However, the LSTM produced the best predictions amongst all three models for predicting Ethereum price, indicated by the best metrics for RMSE (85.66), MAE (57.59) and MAPE (2.16%) on the test data. For Bitcoin, the LSTM produced highly accurate predictions as shown by its low RMSE (1870.37) and MAPE (2.21%) scores, ranking it as the best performing (lowest error rate) model of the 3 algorithms. The CNN also produced favourable results for Bitcoin price (RMSE = 1454.15), but due to a considerably higher error rate with regards to MAPE as compared to the LSTM, it limited the CNN's ability to generate accurate investment decisions for Bitcoin price forecasting. Although the LSTM-CNN produced helpful R2 metrics, it did not perform as well as the LSTM with regards to many of the performance metrics for Risk and Return for both Bitcoin and Ethereum prices. The results of the analysis in Table 2 demonstrate that the LSTM performed the best of all three algorithms in providing Low and Balanced RMSE, MAE and MAPE values across both training and testing datasets, providing a good balance of generalisation and overfitting performance. Implications of These Results Indicate That The LSTM Should Be Considered the Most Suitable Model for These Applications due to the Many factors that contribute to the LSTM advantage over the others.

Table 3: Summary of LSTM Model Architecture

Layer (Type)	Output Shape	Parameters	Description
LSTM	(None, 60, 50)	10,400	First LSTM layer with 50 units
LSTM_1	(None, 50)	20,200	Second LSTM layer (return_sequences=False)

Layer (Type)	Output Shape	Parameters	Description
Dense	(None, 1)	51	Output layer with linear activation

Source: Prepared by researchers using Python - Jupyter

Table (3) demonstrates how the research designed its model. A long short term memory (LSTM) model was employed because the price series of bitcoin have specific time frames associated with them. The model included three fundamental components. In the first layer, there are 50 LSTM units to accept 60 time-step inputs and generate an output, which is a 3-dimensional matrix (None, 60, 50), which contains 10,400 parameters. The first component of the model had the purpose of retaining important long-term correlation within the data, while also extracting out the basic temporal features of the data. The output from this layer was sent to the second LSTM layer that had 50 units that were designed to convert the LSTM layer output sequences to a 2-dimensional vector (None, 50) by setting the False return_sequences flag. This LSTM layer had a total of 20,200 parameters. The LSTM layer converts the temporal characteristics of the data to a lower dimension visual representation for the next adjacent layer. The dense layer (Dense), contains one unit and has linear activation function, and generates the final predicted value in the form of a vector (None, 1) with only 51 parameters, demonstrating high proficiency for performing direct price prediction. Systems designed in this manner provide the ability for the model to automatically detect complex patterns over time in uncertain market conditions for more accurate and improved predictions of trades, particularly in volatile markets like cryptocurrency. The Adam optimizer generated the cross validation results.

Table 4: Bitcoin Model Training Progress from Epochs 41 to 50

Epoch	Train Loss	Val Loss	Step Time	Notes
41	9.2045e-05	4.5353e-04	35ms	Convergence established
42	9.5282e-05	6.3255e-04	29ms	Validation spike (+39.5%)
43	9.1839e-05	3.7480e-04	28ms	Recovery phase
44	8.9277e-05	2.7957e-04	25ms	**Best validation**
45	9.0746e-05	4.7779e-04	25ms	Instability observed
46	1.0557e-04	2.2466e-04	27ms	New optimal val loss
47	7.8548e-05	3.3117e-04	29ms	Training improvement
48	7.8712e-05	2.3653e-04	32ms	Stable convergence
49	9.7623e-05	2.6191e-04	28ms	Minor regression
50	8.3287e-05	4.7255e-04	27ms	Final convergence

Source: Prepared by researchers using Python – Jupyter

Table 5: Ethereum Model Training Progress from Epochs 41 to 50

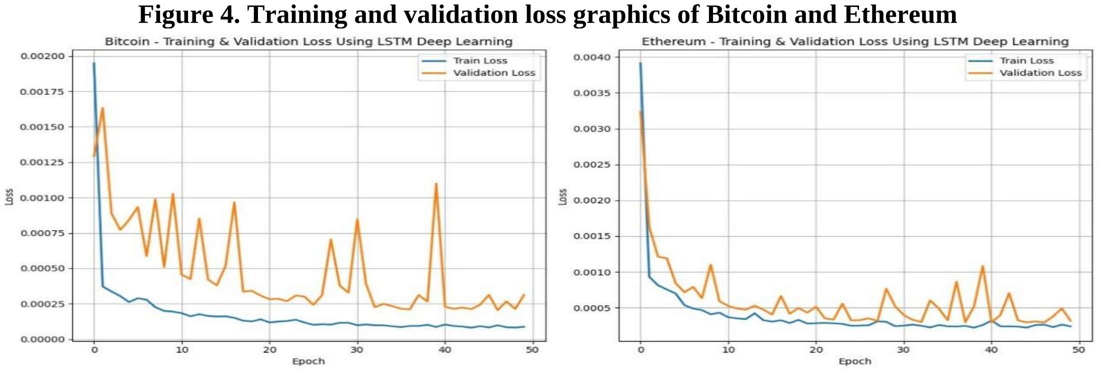
Epoch	Train Loss	Val Loss	Step Time	Notes
41	2.4626e-04	3.9939e-04	26ms	Stable phase
42	2.6267e-04	8.4412e-04	30ms	Severe validation spike
43	3.3279e-04	3.0701e-04	31ms	Recovery
44	2.4291e-04	8.5371e-04	25ms	New instability

Epoch	Train Loss	Val Loss	Step Time	Notes
45	2.4626e-04	3.0951e-04	25ms	Stabilizing
46	2.2729e-04	3.0503e-04	26ms	Consistent performance
47	2.1799e-04	2.9647e-04	26ms	**Best training loss**
48	2.5964e-04	2.9545e-04	27ms	Optimal validation
49	2.4987e-04	3.0549e-04	26ms	Plateau reached
50	2.8398e-04	3.8541e-04	34ms	Final metrics

Source: Prepared by researchers using Python - Jupyter

The LSTM model training process depicted in Tables 4 and 5 continues through to the final epochs, 41 to 50, for both Bitcoin and Ethereum. When comparing the two types of analysis (statistical versus economical), we see that both analyses strongly demonstrate the excellent ability of the LSTM model to track the price movements of Bitcoin and Ethereum as a result of the LSTM model and indicate the significant differences between the two cryptocurrencies. Table 4 shows that the training loss of Bitcoin continuously decreased from 7.8548e-05 at its highest to 1.0557e-04 at its lowest. This indicates that the LSTM model is consistently able to learn the previous price movements of Bitcoin. The validation loss of Bitcoin, on the other hand, tends to show distinct variations between 2.2466e-04 at its lowest and 6.3255e-04 at its highest. These variations likely indicate that there was significant volatility in the market or that the data was not clean during some of the epochs. Such variability is common with any model that has to deal with the highly volatile nature of Bitcoin and other cryptocurrencies. The average step time for processing the Bitcoin training data was between 25 and 35 ms, which demonstrates optimal efficiency in the processing of the training data and further supports the ability of the LSTM model to adapt rapidly to changing market conditions. In the case of Ethereum's validation loss, it displayed a high degree of fluctuation between epochs, with the highest point at 8.5371e-04 during epoch 44 and the lowest point at 2.9545e-04 during epoch 48. The last epoch (50) demonstrates an increased sensitivity on the part of the LSTM model towards changes in Ethereum prices and to the volatility of the Ethereum market, as indicated by the larger jump in loss when compared to epoch 49, which was 3.8541e-04. The training losses of Ethereum exhibited substantial fluctuation during the training with little significant deviation, with losses oscillating between 2.1799e-04 and 3.3279e-04, thus supporting the capacity of the LSTM model to adapt, over time, to rapid changes in the market. These data once again indicate the significant differences in the two markets. Although Bitcoin was far more volatile than Ethereum, Bitcoin was relatively better at predicting the future value of Ethereum.

Figure 4. Training and validation loss graphics of Bitcoin and Ethereum



Source: Prepared by researchers using Python - Jupyter

Figure 4. Training and validation loss graphics of Bitcoin and Ethereum prediction models for the prices of Bitcoin (left) and Ethereum (right) using the LSTM deep learning algorithm after 50 epochs. These graphs indicate a convergence towards a reduction in both the train and validation losses.

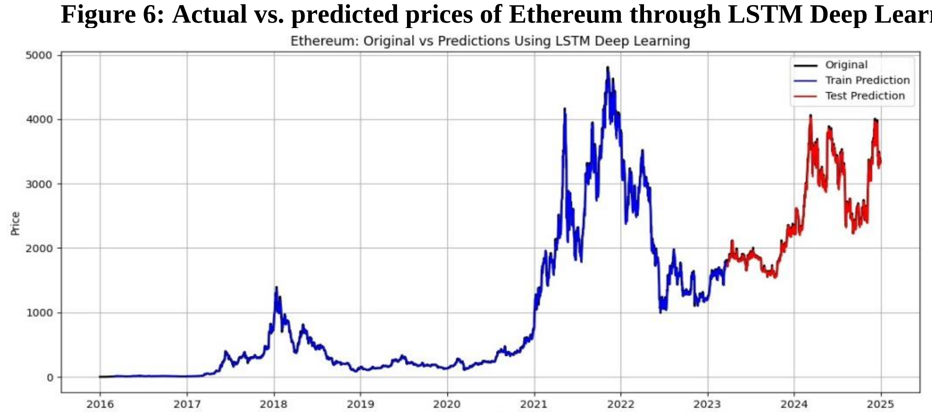
The Long Short-Term Memory (LSTM) network was trained on predicting the price of both Bitcoin and Ethereum for 50 cycles, as shown by the variation of the loss values in Figure 4. From the examination of both the training and validation loss graphics, it is clear that both parameters successfully decrease in value after every single training cycle. From the examination of the graphics for the training loss and validation loss, it is clear that both parameters successfully decrease in value after every single training epoch. While training the parameters for the Bitcoin dataset, the decrease in the training loss parameters achieved consistent performance until it stabilized at around epoch 20. Throughout the training process, the increased susceptibility of the network to the novel validation parameters, which it had never observed previously, achieved large and irregular changes in the validation loss parameters, as shown by the orange bars. Economic parameters for the Bitcoin market show large changes due to market price variability, driven by the combined effects of market speculations, regulatory forces, and market sentiments. The training parameters for Ethereum achieve a smooth pattern with a steady decline, while the validation parameters show fewer irregular changes compared to the parameters achieved by the Bitcoin market. Economic parameters show lower changes, signifying stability during this period, alongside rapid development in the Ethereum network with increased adoption of Decentralized Apps. Long Short-Term Memory successfully displays its ability to examine market variability driven by non-linear parameters in the market with these results:

Figure 5. LSTM deep learning model's predicted Bitcoin prices vs actual prices

Source: Prepared by researchers using Python – Jupyter

Black line represents the original price series while blue and red lines represent predictions made on the training set and test set respectively, illustrating the model's capacity to learn the past and predict the future.

Figure 6: Actual vs. predicted prices of Ethereum through LSTM Deep Learning.



Source: Prepared by researchers using Python – Jupyter

The graph represents actual prices (black), predicted prices for the training set (blue), and predicted prices for the test set (red), thereby illustrating the capacity of the process to learn and predict past and new values, respectively.

Figures 5-6 provide a comprehensive analysis of both actual Bitcoin and Ethereum prices and their corresponding LSTM predicted prices during both the training phase (blue) and testing phase (red). The LSTM produced predictions that were based on the monitoring of historical prices, which created a strong correlation between actual prices and the predictions made for both cryptocurrencies. As demonstrated in the above data, the level of accuracy achieved by the model was such that large fluctuations in Bitcoin prices, such as those experienced during periods of significant market growth in 2017, 2021, and especially through large increases that began in 2023, were predicted with a high level of accuracy. For the testing phase (2023-2025) the predictions were able to duplicate the peak and low points of Bitcoin prices with minimal differences. Thus, while there is an extreme amount of price volatility associated with Bitcoin, the LSTM model has demonstrated its ability to recognize this volatility and create accurate future forecasts based on historical price data. The price changes experienced by Ethereum have also been accurately predicted using the same methodology by following price movements due to significant changes within the Ethereum ecosystem and major phases of development between 2021 and 2023 and 2025. Statistical comparisons of actual vs. predicted price movements for Ethereum indicate that market conditions may not be as stable as they once were due to ongoing technical developments and changes in the Ethereum ecosystem.

Based on previous research, we have identified that the Long Short-Term Memory (LSTM) model is capable of producing reliable, accurate forecasts of future currency prices while training and testing the model. A summary of the estimated price forecasts for Bitcoin and Ethereum for the month of January 2025 can be found below (in Table 6) along with the estimated ranges for each cryptocurrency, which can assist investors and economic decision-makers in creating their investment strategies and managing their risk:

Table 6: Bitcoin and Ethereum Forecast – January 2025

Date	Bitcoin Forecast (USD)	Bitcoin Forecast Range (USD)	Ethereum Forecast (USD)	Ethereum Forecast Range (USD)
2025-01-01	89,418.28	86,735.73 – 92,100.83	3,289.20	3,190.52 – 3,387.88
2025-01-02	84,636.98	82,097.87 – 87,176.09	3,245.61	3,148.24 – 3,342.98
2025-01-03	80,225.27	77,818.51 – 82,632.03	3,201.01	3,104.98 – 3,297.04
2025-01-04	76,532.36	74,236.39 – 78,828.33	3,155.55	3,060.88 – 3,250.22
2025-01-05	73,306.86	71,107.65 – 75,506.07	3,109.60	3,016.31 – 3,202.89
2025-01-06	74,407.72	72,175.49 – 76,639.95	3,263.49	3,165.59 – 3,361.39
2025-01-07	67,761.07	65,728.24 – 69,893.90	3,017.49	2,926.96 – 3,108.02
2025-01-08	65,330.00	63,370.10 – 67,289.90	2,971.84	2,882.68 – 3,061.00
2025-01-09	63,100.22	61,107.21 – 65,093.23	2,926.73	2,838.93 – 3,014.53
2025-01-10	63,062.48	61,070.61 – 65,054.35	2,982.29	2,892.82 – 3,071.76
2025-01-11	59,203.52	55,651.31 – 62,755.73	2,838.61	2,753.45 – 2,923.77
2025-01-12	57,516.57	54,065.57 – 60,967.57	2,795.74	2,711.97 – 2,879.51
2025-01-13	58,985.96	55,446.80 – 62,525.12	2,953.68	2,865.07 – 3,042.29
2025-01-14	54,596.73	51,221.92 – 57,971.54	2,712.41	2,627.04 – 2,797.78
2025-01-15	57,322.34	53,883.00 – 60,761.68	2,871.87	2,785.71 – 2,958.03
2025-01-16	52,139.42	48,910.06 – 55,368.78	2,632.01	2,543.05 – 2,720.97
2025-01-17	53,023.50	49,741.09 – 56,305.91	2,692.74	2,603.96 – 2,781.52
2025-01-18	49,949.47	46,952.50 – 52,946.44	2,553.99	2,462.67 – 2,645.31
2025-01-19	48,892.62	45,959.06 – 51,826.18	2,515.68	2,425.05 – 2,606.31
2025-01-20	47,830.73	44,960.89 – 50,600.57	2,477.74	2,387.61 – 2,567.87
2025-01-21	49,743.60	46,759.98 – 52,727.22	2,640.11	2,550.91 – 2,729.31
2025-01-22	45,618.79	42,881.66 – 48,355.92	2,402.74	2,320.64 – 2,484.84
2025-01-23	44,449.27	41,782.32 – 47,116.22	2,365.59	2,284.97 – 2,446.21
2025-01-24	49,231.34	46,377.46 – 52,085.22	2,628.60	2,539.74 – 2,717.46
2025-01-25	41,968.73	39,450.61 – 44,486.85	2,291.77	2,210.50 – 2,373.04
2025-01-26	40,663.88	38,223.05 – 43,104.71	2,255.06	2,174.86 – 2,335.26
2025-01-27	39,319.16	36,960.01 – 41,678.31	2,218.47	2,138.73 – 2,298.21
2025-01-28	37,943.75	35,667.12 – 40,220.38	2,181.99	2,102.71 – 2,261.27

2025-01-29	36,546.73	34,353.93 – 38,739.53	2,145.62	2,066.79 – 2,224.45
2025-01-30	35,141.23	33,032.76 – 37,249.70	2,109.35	2,031.00 – 2,187.70
2025-01-31	33,739.23	31,714.87 – 35,763.59	2,073.21	1,995.30 – 2,151.12

Source: Prepared by researchers using Python - Jupyter

Table (6) summarizes the continuous daily price predictions of Bitcoin and Ethereum for January 2025 that were achieved by using the Long Short-Term Memory (LSTM) model. These projections also indicate that January 2025 will see both currencies decline in value after many increases within the market. Bitcoin will begin the month at a price of approximately $89,418, and will gradually decline to approximately $33,739 by the end of January 2025, an estimated decrease of approximately 62.3% over the month. This forecasted decrease further reinforces the historical tendency of markets to move cyclically and correct after periods of prolonged strength. Ethereum started January with a price of $3,289 and will see background depreciation, worth $2,073, by the end of January, a decline of approximately 37% for the month. While Ethereum's price decline will not occur at the same level as Bitcoin's decline (due to the nature of the impact of market volatility on the two different platforms), the decline will be significant nonetheless. The market may have been affected by both internal issues in the Ethereum network, combined with the rapid growth of the Decentralised Application ecosystem. The historical regularity of price ranges within the same time period provides investors the ability to make informed financial decisions on their daily purchasing power over currencies. The price levels of Bitcoin indicated an average range of $86,735.73-$92,100.83 for early January, but as January continued, the predicted price became more uncertain as the market's volatility heightened. Ethereum's price ranges were relatively continuous over January; therefore, the projected price range for Ethereum increased as a result of noticeably increased volatility through January. This information will require investors to proceed with extreme caution.

In this study, we found that the Long Short-Term Memory (LSTM) neural network outperformed both the Convolutional Neural Network (CNN) and the combined LSTM-CNN approaches for predicting the daily price shifts of both Bitcoin and Ethereum using deep learning techniques. This enhancement complements previous studies that confirm that deep learning models have demonstrated the ability to capture nonlinear behaviour in highly volatile factories of the financial markets (Awoke et al; Khan et al. 2023). The LSTM model has also demonstrated its ability to reduce the effects of overfitting thus increasing the accuracy of the model's predictions. The results support earlier studies that had shown the value of historical data and advanced techniques like long-memory-based neural networks in enhancing the performance of models that forecast fluctuations in the price of cryptocurrencies, especially in times of high volatility and uncertainty (Hamayel & Owda, 2021; Livieris et al.; 2020). The results of this study lend support to the concept of utilising deep learning models as reliable sources of information for making investment decisions with increased confidence and for managing risks associated with investing in the cryptocurrency market.

Conclusion and future work

The paper provides a necessary overview that both academics and practitioners require in forecasting the price of bitcoin. The research employed advanced deep learning analytical techniques that analyzed the price fluctuations of Bitcoin and Ethereum on a daily basis from 2016 until the end of 2024. The findings substantiated that the LSTM model was good to handle highly volatile and complex data since it outperformed the traditional measures of RMSE, MAE, MAPE, and coefficient of determination R^2. The model does better because it accurately identifies specific long-term critical pricing trends, which enables it to outperform than traditional and combined models presented in earlier studies. Given the volatility of the prices of Bitcoin and Ethereum and indicative of their speculative nature and high investment risk, the economic world requires accurate forecasts of their prices for effective portfolio management (Mariana et al., 2021; Jalan et al., 2022). The outcome of this study significantly enhances prior knowledge and demonstrates that deep learning methods can be viable in predicting the values of traditional financial assets, as well as digital cryptocurrencies. The research identified the importance of the LSTM model in its ability to find the right compromise between flexibility in learning and reducing the problem of overfitting, an important advantage in real-world finance applications. This finding agrees with prior research showing these models deal effectively with highly unpredictable data (Hamayel & Owda, 2021; Seabe et al., 2023). This paper offers some exciting avenues for further research on growth. The forecast accuracy could be improved by the addition of three technical indicators into the dataset, namely mining difficulty, hash rate, and trading volume (Kim et al., 2021). Another line of modeling approach could be developed using multi-head attentional networks for the current model prior to testing how well it performs compared to regular LSTM models to ascertain if any improvements could be realized. Secondly, there is also a need to implement and test the models during periods of financial crisis, such as the COVID-19 pandemic, in order to assess their stability and effectiveness during turbulent economic times (Xin & Jiang, 2023; Mariana et al., 2021). Finally, it would be useful to embed the models in automated trading systems and test their performance in a realistic trading environment, which would further confirm practical validity and open the door to more applied studies that successfully bridge the gap between theory and reality.

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