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Forecasting Crypto Market Prices Using Stacked Bidirectional LSTM

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ABSTRACT

The crypto market refers to the marketplace for cryptocurrencies, which are digital or virtual currencies that rely on cryptography to ensure security and prevent counterfeiting. This market has significantly influenced global financial systems, introducing decentralised finance and blockchain-based transactions. By offering faster, more transparent, and borderless financial operations, it has revolutionised the traditional financial industry and challenged conventional banking and payment methods. Amid the rising geopolitical and economic challenges, global currency values have declined, stock markets have struggled, and investors have faced losses. This has renewed the interest in digital currencies. Due to the decentralised nature of cryptocurrency networks, predicting their prices is challenging, given their complexity, lack of central authority, and high market volatility. Our objective is to accurately forecast cryptocurrency price fluctuations to support profitable investments. This study employs Long Short-Term Memory (LSTM) networks, a deep learning approach, to predict prices, focusing on Ethereum and Bitcoin using reliable historical data. Experimental results indicate that the projected model outstrips other algorithms in terms of mean absolute error (MAE), mean square error (MSE), and overall accuracy. This model aims to help investors reduce the financial risks and make informed decisions.

KEYWORDS Long Short-Term Memory, cryptocurrency, Exponential Moving Average, Stacked Bidirectional LSTM

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1. Introduction

Accurate price forecasting is difficult in cryptocurrency markets because of their extreme volatility and complexity. This synopsis outlines the methodology, including preprocessing, data collection, model architecture, training, evaluation, and deployment. Additionally, it emphasises the importance of fine-tuning models, monitoring performance, and integrating other factors such as trading volume and sentiment analysis. While LSTM models can offer valuable insights into cryptocurrency price movements, it is crucial to acknowledge the inherent uncertainty and risks associated with cryptocurrency markets. Nonetheless, with careful implementation and continuous refinement, LSTM-based approaches can contribute to more knowledgeable decision making in cryptocurrency transactions and assets. However, due to the complexity and volatility of cryptocurrency prices, these methods are not as effective at precisely predicting them. As a result, there is increasing interest in forecasting cryptocurrency prices using cutting-edge machine learning methods like deep learning algorithms.

As a specialised form of recurrent neural network, LSTMs are compatible for processing time-series data and effectively utilised in areas like image analysis, speech recognition, and language translation. This approach offers valuable insights for sectors such as investment firms, individual investors, risk management services, media, insurance, and cryptocurrency lending platforms.

1.1. Scope

LSTM networks provide a robust approach to analysing the sequential outlines in cryptocurrency price data, allowing for the detection of complex trends that traditional statistical methods might miss. By utilising LSTM models, analysts and traders can more accurately forecast future price movements, supporting better decision making and risk management in the highly volatile cryptocurrency market. Furthermore, the application of LSTM-based price prediction extends beyond individual cryptocurrencies to encompass portfolio management, algorithmic trading strategies, and risk assessment for investors and financial institutions. But, it is important to admit the essential challenges in cryptocurrency price prediction, including market unpredictability, data noise, and the requirement for continual model adaptation. Despite these challenges, the enduring advancements in machine learning techniques, coupled with the growing availability of high-quality data and computing resources, present significant opportunities for further refining and optimising LSTM models for cryptocurrency price forecasting. As such, the scope for LSTM-based cryptocurrency price prediction remains a dynamic and evolving field with immense potential for innovation and practical application in the cryptocurrency ecosystem.

• Significance: In the current global financial environment, especially amid the economic uncertainties and volatile fiat currencies, the cryptocurrency market has gained significant traction as an alternative to traditional investment avenues. However, the decentralised and most unstable nature of cryptocurrencies presents significant challenges in predicting their price movements. Traditional forecasting models often fail to catch complex, linear, and time-based forms in crypto data. For this, it is necessary to use advanced mechanical learning techniques such as long short-term memory (LSTM) networks, which are more relevant for handling continuous data and dynamic trends. The study addresses the urgent need for strong and reliable prediction equipment that can help investors, financial analysts, and policymakers by using stacked LSTM models, reducing financial risk, and leading to an unpredictable cryptocurrency arena.

• Motivation: The motivation in the context of this research has developed from the increasing number of digital assets such as Bitcoin and Ethereum for investment and commercial purposes. Despite their capacity for higher income, the lack of standard and accurate forecasting equipment has prevented the market from enjoying confident participation. The inner complexity of cryptocurrency pricing, which is influenced by factors such as market sentiment, social media trends and global events, demands a prognostic approach that can adapt to rapid fluctuations. The study is implemented not only to learn from historical pricing, but also to create an intelligent, data-based forecasting model that suits the market's mechanics. By proposing the stacked bilateral LSTM structure, the research aims to contribute to the growth of the most accurate and responsible equipment for the pricing of cryptocurrency, which will eventually support the best strategic planning and risk management in the growing digital economy.

This study demonstrates that the proposed Stacked Bidirectional LSTM model, especially for Bitcoin and Ethereum, significantly surpasses traditional forecasting techniques in predicting the prices of cryptocurrency. By effectively capturing past and future dependencies on the time series data, the sample achieves advanced accuracy and strength, which has been proven by the MAE and the MSE values. Key innovations highlight the ability of the model in improving investment strategies and reducing the risk of unstable market conditions. The remaining part of the thesis is configured as follows: Section 2 provides the value of the relevant literature and the existing instructions; Section 3 outlines the proposed model and its components; Section 4 describes the test system, data pre-processing, and activation; Section 5 discusses the results and performance assessment; finally, Section 6 concludes the study with future research directions.

2. Literature review

Patrick Jaquart, Sven Kopke, and Christof Weinhardt (2022) conducted an empirical examination of several machine learning models' efficacy in predicting cryptocurrency market movements. It systematically generates features for classifiers with and without memory functions. For deep learning models such as LSTM, TCN, and, GRU, consistent daily return sequences, each consisting of 90 data points, are created. In order to do this, daily returns are normalised by deducting the mean from each training batch and dividing the result by the standard deviation. The meticulous method of creating features enhances the prediction models' resilience and dependability. Ultimately, this methodology facilitates a comprehensive analysis of the models' performance and their ability to discern meaningful patterns within the complex cryptocurrency market dynamics. Such detailed feature engineering underscores the study's commitment to methodological rigour and its contribution to advancing the understanding of machine learning applications in financial forecasting. The model's reliability and forecasting method, using normalized 90-day revenue time series data, employs ML models such as LSTM, GRU, and TCN for cryptocurrency price prediction. However, the study of historical income data is dependent on the market or real-time fluctuations.

Akila V., Nitin M.V.S., Prasanth I., Sandeep Reddy M., and Akash Kumar G. (2023) propose an innovative approach to cryptocurrency price prediction by utilising practical gauges and antique price data as inputs for an LSTM model. This model enhances the accuracy by identifying underlying data patterns and trends. Additionally, the forecasting precision is further improved through the integration of the Pruned Exact Linear Time (PELT) technique combined with a Change Point Detection (CPD) method. By detecting notable fluctuations in currency prices, this methodology makes it possible to modify the LSTM model and enhance its prediction capabilities. The study mostly concentrates on

Bitcoin, but other cryptocurrencies can also use the model if reliable historical price data is available. With the potential to improve bitcoin price forecasting capabilities, this creative technique offers a promising path towards more informed decision making in the turbulent cryptocurrency markets.

Suhwan ji, Jongmin Kim and Hyeonseung Im (2019) delve into the recent surge of interest in Bitcoin, driven by its highly publicised price fluctuations. Acknowledging the significant attention from both the public and media, numerous researchers have explored the multifaceted factors influencing Bitcoin's price dynamics, with a particular focus on leveraging machine learning methods for analysis. This study contributes by comprehensively investigating and comparing state-of-the-art deep learning techniques, including long short-term memory (LSTM), deep neural networks (DNNs), deep residual networks, convolutional neural networks, and their groupings, for Bitcoin price prediction. By means of experimental evaluation, it was observed that DNN-based models performed exceptionally well in classifying Bitcoin price changes, while LSTM-based replicas somewhat improved in regard to regression. Additionally, a profitability analysis showed that for algorithmic trading methods, categorisation models performed better than regression models. However, the reliability of the study of historical tendencies controls its response to rapidly growing market sentiment and external trauma.

Arun Kumar K, Prajith Krishnan, Rashid K, and Rigil Renji (2023) and others present a comprehensive overview of contemporary approaches and techniques for machine learning-based Bitcoin prediction. The study examines a range of factors used to forecast cryptocurrency prices, with antique price data, marketplace sentiment, newscast procedures, and social media sentiment. It evaluates the efficiency of several machine learning procedures such as decision trees, support vector machines, neural networks, and linear regression in predicting Bitcoin prices. Additionally, the research explores ensemble methods that combine multiple machine learning models to improve prediction exactness. By analysing these techniques, the study aimed to assess their ability to capture the complexities of cryptocurrency market dynamics, while also addressing the contests and confines of using machine learning for cryptocurrency prediction. But, the width of the study can be compromised, and the real-time applicability is limited by the inherent setback and noise in the consciousness and news data.

Franco Valencia, Alfonso Gomez-Espinosa, and Benjamin Valdes Aguirre (2019) assessed and likened the recital of three prediction model neural networks (NNs), support vector machines (SVMs), and random forest (RF) utilising both market data and Twitter data for sentiment analysis. By integrating essentials from market data and Twitter as inputs, the study aimed to capture the collective sentiment of both the media and public perception surrounding the cryptocurrency market. The results of the analysis demonstrated the feasibility of predicting cryptocurrency markets through the fusion of machine learning and sentiment analysis techniques. Nevertheless, the performance of the model is vulnerable to misinformation and the fluctuation of sensation on social media sites, which may distort the prognostic consequences.

This finding revealed that Twitter data alone could serve as a viable predictor for certain cryptocurrencies, underlining the significance of social media sentiment in shaping market dynamics. The comparative analysis of prediction models revealed that neural networks outperformed SVM and RF models in terms of predictive accurateness and heftiness. This superiority of NN models underscores their efficacy in taking composite patterns and nuances present in the combined Twitter and market data (Zeinab Shahbazi and Yung-Cheol Byun, 2021). They proved that Twitter data alone can effectively predict certain cryptocurrencies, and that neural networks used for modeling complex sentiment-driven market systems perform better than SVM and RF models. Yet, relying on social media data may introduce dependencies and noise, which can affect the model's stability and robustness under varying market conditions.

Helder Sebastiao and Pedro Godinho (2021) delved into the effectiveness assessment of transaction policies planned for machine learning methodologies, particularly linear models, support vector machines, and random forest.

The methodology entails using antique price data and practical indicators as inputs for the LSTM model, allowing it to identify original designs and tendencies in the dataset. To enhance prediction accurateness, the study integrates a Change Point Detection (CPD) method that employs the Pruned Exact Linear Time (PELT) system. This methodology facilitates the identification of significant variations in cryptocurrency prices, thereby enabling adjustments to the LSTM model to ensure more accurate predictions. By integrating CPD with LSTM, the study aimed to refine the predictive capabilities of the model, consequently enhancing the profitability of trading strategies reliant on cryptocurrency price forecasts. Evaluated trading strategies using machine learning models such as Linear Regression, SVM, Random Forest, and an enhanced LSTM to improve forecasting accuracy. Nevertheless, the approach may face limitations in dealing with real-time market disruptions and the measurement of different cryptocurrency properties.

Rashika Bangroo, Utsav Gupta, Roshan Sah, and Anil Kumar (2022) highlight the burgeoning trend of cryptocurrency, underscoring its increasing significance in the financial sector. Recognising the imperative for accurate predictions in cryptocurrency trading, the study conducts a thorough analysis of datasets to comprehend market behaviour. Employing various machine learning algorithms such as Random Forest Regressor, Linear

Regression, XGBoost, and Gradient Boosting Regressor, the study aims to forecast the regular price behaviour of four prominent cryptocurrencies: Bitcoin, Ethereum, XRP, and Stellar. Through rigorous experimentation, the study achieves impressive validation correctness extending from 95% to 97%. These results signify the efficacy of machine learning algorithms in forecasting cryptocurrency price movements, thus offering valuable insights for traders seeking profitable investment strategies amidst the dynamic cryptocurrency market landscape. But, samples may not be suitable for sudden market disruptions and may not be continuously reusable in updated data.

Mareena Fernandes, Saloni Khanna, Leandra Monteiro, Anu Thomas, and Garima Tripathi (2022) address the rapid evolution of virtual currency exchange methods, particularly for Bitcoin, Litecoin, and Ethereum, propelled by technological advancements. Cryptocurrencies aim to streamline transactions by bypassing financial intermediaries, fostering direct peer-to-peer exchanges. Amidst the global Coronavirus pandemic, the correlation between Bitcoin and the equity market expanded, highlighting the growing significance of cryptocurrencies. Despite their inherent volatility, cryptocurrencies present lucrative investment opportunities. However, the influx of misinformation on social media often influences cryptocurrency prices, adding to investor confusion. The study integrates public mood data from Reddit and Twitter with deep learning models (RNN, LSTM, and GRU) to predict Bitcoin prices. The study intends to maximise investment strategies and reduce investor risks by utilising these tactics. In the end, the use of precise prediction models can boost investor trust and perhaps establish cryptocurrencies as commonplace payment methods. The revolutionary potential of digital currencies in contemporary financial ecosystems is emphasised by this study.

Aleksandar Petrovic, Ivana Strumberger, Timea Bezdan, Hothefa Shaker Jassim, and Said Suleiman N (2021) utilise the strong cryptography for transaction security and ownership verification, which has garnered substantial popularity within the financial sector, facilitated by blockchain technology thereby ensuring transaction security, transparency, and traceability. However, their inherent unreliability and unpredictability pose significant investment risks. Predicting cryptocurrency prices has thus become a focal point in contemporary research. This paper introduces a novel approach for price prediction, employing a hybrid machine learning and swarm intelligence methodology. The results strongly indicate that the projected model achieves superior accuracy compared to recent similar approaches, showcasing its efficacy in addressing this critical task. The integration of machine learning and swarm intelligence offers a promising avenue for enhancing cryptocurrency price prediction accuracy, potentially mitigating the investment risks associated with the volatile cryptocurrency market. The proposed hybrid engine learning and swarm intelligence sample significantly improves the accuracy of the price forecasting, which provides a trusted solution to alleviate investment risks in the turbulent market. The performance of the model may still be affected by market anomalies and external factors, and further testing throughout various cryptocurrency markets is required to ensure its generalisation.

The study integrated public mood data from Reddit and Twitter with deep learning models (RNN, LSTM, and GRU) to predict Bitcoin prices. The study intended to maximise investment strategies and reduce investor risks by utilising these tactics. In the end, the use of precise prediction models can boost investor trust and perhaps establish cryptocurrencies as commonplace payment methods. The revolutionary potential of digital currencies in contemporary financial ecosystems is emphasised by this study. By integrating stochastic neural network models, they inject layer-wise randomness into neural network activations, enabling the simulation of market volatility within the model architecture. Furthermore, they introduce a unique technique designed to capture the nuanced reaction patterns exhibited by cryptocurrency markets, enhancing the model's predictive capabilities. Through empirical experimentation, they trained Long Short-Term Memory (LSTM) models and Multi-Layer Perceptron (MLP) specifically tailored for Litecoin, Bitcoin, and Ethereum. Their comprehensive analysis revealed the superior performance of the proposed stochastic model over traditional deterministic approaches in cryptocurrency price forecasting. By harnessing the power of stochasticity and incorporating market reaction patterns, the approach not only offers more precise estimates but also proposes treasured insights into the complex dynamics of cryptocurrency markets. Coordination of mood data and random neurological networks improves the cryptocurrency price prediction, and improves the confidence and decision making of investors. The reliability of the emotional data is not due to all market factors, but also controls its performance under changing conditions.

Given the extreme volatility of cryptocurrency markets and their interdependence, Raj Parekh, Nisarg P. Patel, Nihar Thakkar, Rajesh Gupta, Sudeep Tanwar, Gulshan Sharma, Innocent E. Davidson, and Ravi Sharma (2021) tackle the difficult task of predicting cryptocurrency prices. Robust forecasting models are required because cryptocurrencies, which were once utilised for investment objectives, have replaced traditional assets such as equities, real estate, and metals. Using information from social media sites like Twitter, researchers have examined the use of deep learning, sentiment analysis-based models, and machine learning to forecast Bitcoin prices. The study suggests a hybrid and reliable framework for Bitcoin price prediction dubbed DL-Gues in response to these difficulties. DL-Gues uses price history and tweets about different cryptocurrencies, like Dash, Litecoin, Bitcoin, and Bitcoin-Cash, to combine the interdependency of cryptocurrencies and market sentiment. The framework offers insights into market dynamics and potential applications in investment strategies, and it demonstrates its efficacy in predicting Bitcoin values through thorough validation using various loss function.

The DL-Kas structure effectively predicts Bitcoin prices by integrating price history and social media sentiment, providing valuable intelligence to investment strategies. The performance of the model may be affected by changing the variation and reliability and market conditions of social media data.

Integration of various mechanical learning models, including LSDM, GRU, and social media, provides significant improvements in predicting the prices of cryptocurrencies, improving investment strategies, and providing confidence in investors. The quality and reliability of social media data can affect the performance of the samples due to market fluctuations and real-time fluctuations, controlling their applicability under changing market conditions.

Ahamed, Samir, D. Radha, and VS Kirthika Devi (2025) highlight the performance of BI-LSTM and other advanced models in predicting Bitcoin prices, providing valuable intelligence to traders and investors to invest in the cryptocurrency markets. The performance of samples can be limited by the availability and quality of historical data, and their accuracy is due to market fluctuations and unexpected events.

Tiwari, D (2025) recommended an Improved optimal stacked-LSDM model multilingual, cross-platform consciousness analysis with particle optimisation, which significantly improves the accuracy of cryptocurrency pricing. The performance of the model is the factor which most changes the associated slang, creating online language forms or having no adequate environmental references.

Objective: The integration of various mechanical learning models, including LSDM, GRU, and social media, results in achieving significant improvements in predicting the prices of cryptocurrency, improving investment strategies, and providing confidence for investors. The quality and reliability of social media data can affect the performance of the samples due to market fluctuations and real-time fluctuations, controlling their applicability under changing market conditions.

3. Proposed model

This paper employs a Stacked Bidirectional LSTM model, a powerful tool for predicting cryptocurrency prices. This model combines the strengths of Bidirectional LSTMs, capable of understanding context from both future and past data, and stacking multiple layers for enhanced learning. It excels in seizing complex designs and associations in cryptocurrency market data, offering a more precise prediction framework. The system automates feature extraction, eliminating the need for physical involvement. With its advanced temporal analysis, it addresses the dynamic nature of the market. Stacked Bidirectional LSTMs efficiently handle high-dimensional data, improving overall performance. The model's adaptability to evolving market conditions makes it a robust choice, while its automatic learning capabilities minimise the risk of overfitting. Overall, the proposed system provides a sophisticated yet user-friendly approach to cryptocurrency price prediction.

Advantages:

i. The model excels at recognising complex patterns and relationships, leading to more accurate predictions compared to simpler approaches.

ii. The model's bidirectional nature enhances temporal analysis, allowing it to better capture and adjust to dynamic variations in the cryptocurrency market.

iii. The Stacked Bidirectional LSTMs capture framework from both future and past data provides a comprehensive understanding of cryptocurrency market dynamics.

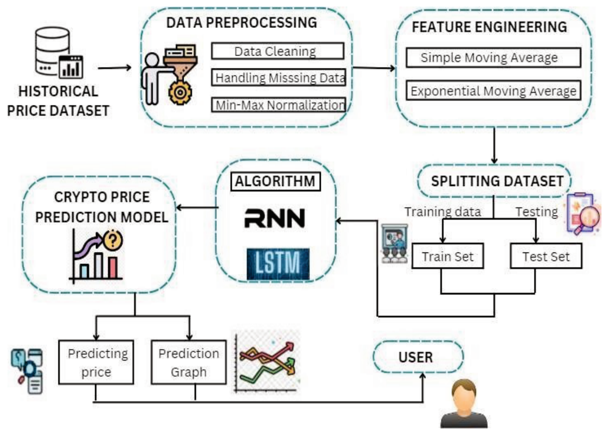


Figure 1. Model Architecture.

Figure 1 implies the following: the process begins by acquiring historical price data for relevant cryptocurrencies. Following data acquisition, preprocessing steps involve cleaning and organising the dataset to handle outliers and missing values. Feature engineering involves selecting and transforming the relevant indicators, such as historical prices, trading volumes, and market sentiment scores. The algorithmic steps involve constructing a stacked bidirectional LSTM model and a deep learning architecture capable of capturing complex temporal patterns. The final step involves deploying the model in a user interface, where real-time or historical cryptocurrency prices can be input, and the model generates predictions for user analysis and decision making.

4. Experimental results

4.1. Data collection

Real-time price information for cryptocurrencies is provided by a variety of crypto pricing APIs. The most popular kind is API, which enables programmers to use HTTP queries to obtain pricing information. Another well-liked kind of cryptocurrency price API that offers real-time data streaming is WebSocket API (Figure 2). Daily price data for Bitcoin and Ethereum in USD was obtained from a reputable cryptocurrency exchange, covering the period from November 2018 to November 2023.

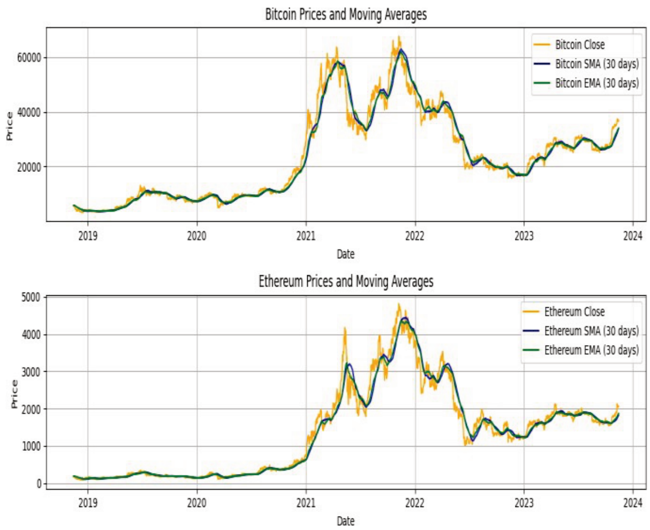


Figure 2. Moving Average Graph.

Simple Moving Average: A predetermined number of prices are added together over a predetermined amount of time, and the total is then divided by the number of periods to determine the SMA. A moving average graph is shown in Figure 2.

$$SMA = \frac{\sum_{i=1}^{N} P_i}{N}. \quad (1)$$

Pi represents the asset's price at period i, where N is the number of stages utilised in the computation.

Exponential Moving Average

The fact that EMA reacts to price changes faster than other tools makes it a useful tool for investors and traders, both long and short. Both the smoothing factor and the prior EMA value are necessary for EMA computation.

$$EMA = (Price - EMAprevious) * Smoothing\ Factor + EMAprevious. \quad (2)$$

EMA prior is a representation of the EMA value from the previous calculation. The weight given to the fresh data point is determined by a constant called the "Smoothing Factor".

4.2. Data Preprocessing and Validation

In the data preprocessing phase, missing values in the dataset were meticulously addressed through methods such as imputation or removal, ensuring the integrity of the dataset. To enhance model robustness, the identification and handling of outliers were conducted. Numerical features were carefully normalised to a consistent scale, preventing any variable's undue influence on the model due to varying magnitudes by using MinMaxScaler from the Scikit-Learn library (Figure 3).

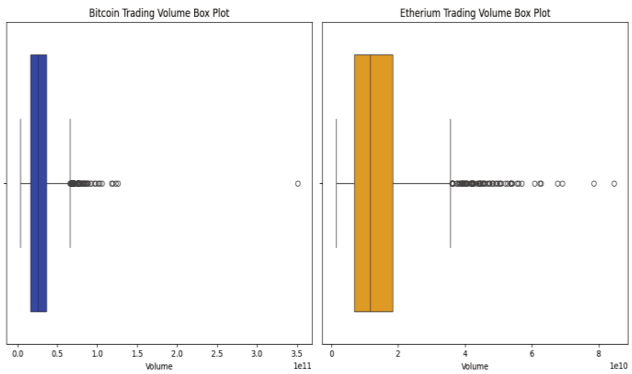


Figure 3. Data preprocessing—outlier analysis.

Feature Engineering

In this stage, a key focus was on incorporating relevant technical indicators to enrich the dataset. Various indicators, such as Relative Strength Index (RSI), Bollinger Bands, and simple moving averages, were computed to identify essential market trends and potential turning points. These indicators improved the model's capacity to identify intricate market dynamics by offering insightful information on market momentum, volatility, and possible reversal patterns (Figure 3).

5. Prediction model implementation

5.1. LSTM

An LSTM contains three gates—input, forget, and output gates—and a memory cell. The input gate controls the memory cell's capacity to accept new inputs. The forget gate determines how much of the memory cell's previous state should be discarded. The output gate regulates the output of the memory cell states, while the memory cell itself stores the data and passes it to the next time step. The

LSTM gates are formed using the sigmoid and tanh activation functions. The sigmoid function, which yields standards between 0 and 1, indicates whether the gates are open or closed. The tanh function, returning values between -1 and 1, represents the strength of the data.

5.2. Stacked Bidirectional LSTM

The stacked bidirectional LSTM model is a deep learning style designed for sequence prediction tasks, particularly well suited for time-series data like cryptocurrency prices. This model comprises multiple layers of bidirectional LSTM cells, each capable of capturing temporal dependencies in both backward and forward directions. Stacking these layers enables the extraction of intricate patterns and representations from sequential input data. The bidirectional aspect enhances the model's ability to comprehend context by considering data from future and past time steps simultaneously. For the purpose of capturing complex relationships in the ever-changing Bitcoin market, this bidirectional capability is essential. Additionally, the stacked configuration allows the model to learn hierarchical features, enabling it to capture both short-term fluctuations and long-term trends. The adoption of the Stacked Bidirectional Long Short-Term Memory (LSTM) architecture was driven by its proficiency in capturing intricate sequential dependencies within time series data, a crucial requirement for forecasting cryptocurrency price movements. Recognised for effectively addressing the vanishing gradient problem, the Stacked Bidirectional LSTM's dual-directional memory cells greatly enhance the model's size to discern and study composite patterns in time-sensitive economic data.

For training, 40 epochs were conducted using a batch size of 32, and the mean squared error (MSE) function was employed as the loss function. This enhanced Stacked Bidirectional LSTM configuration enables the model to leverage both past and future context, making it adept at capturing intricate market dynamics and further improving the accuracy of time-sensitive predictions.

6. Performance evaluation

Mean Square Error

A popular metric for calculating the discrepancy between projected values and a regression problem's actual values is the mean square error (MSE). The calculation includes an average of the squared deviations between the observed and expected values.

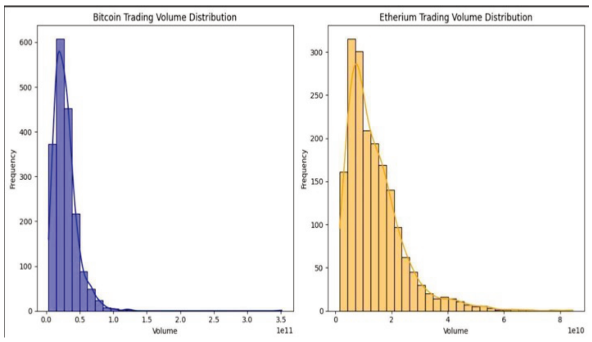
Root Mean Square Error

RMSE is used as the metric to estimate the performance of a predictive model, particularly in regression analysis.

$$RMSE = sqrt\ (1/n * sum\ ((predicted_i - actual_i). \qquad (3)$$

Figure 4(a) visualises the trends and patterns in the price data over time using line charts and candlestick charts. The candlestick chart reveals trends and patterns in the price movements of Bitcoin and Ethereum over five years. While both currencies experience significant volatility (Figure 4), an overall upward trend emerges despite periods of decline. Figure 4(b) shows the exploration of the distribution of trading volumes for both cryptocurrencies. The bars represent how often certain trade sizes occur. It can be seen that most trades are for smaller amounts (left side). Bitcoin's histogram suggests a higher overall trading volume compared to Ethereum during this period. However, without knowing the timeframe, broader conclusions are difficult.

(a)



(b)

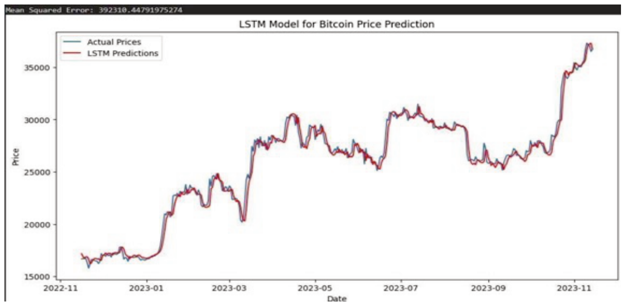
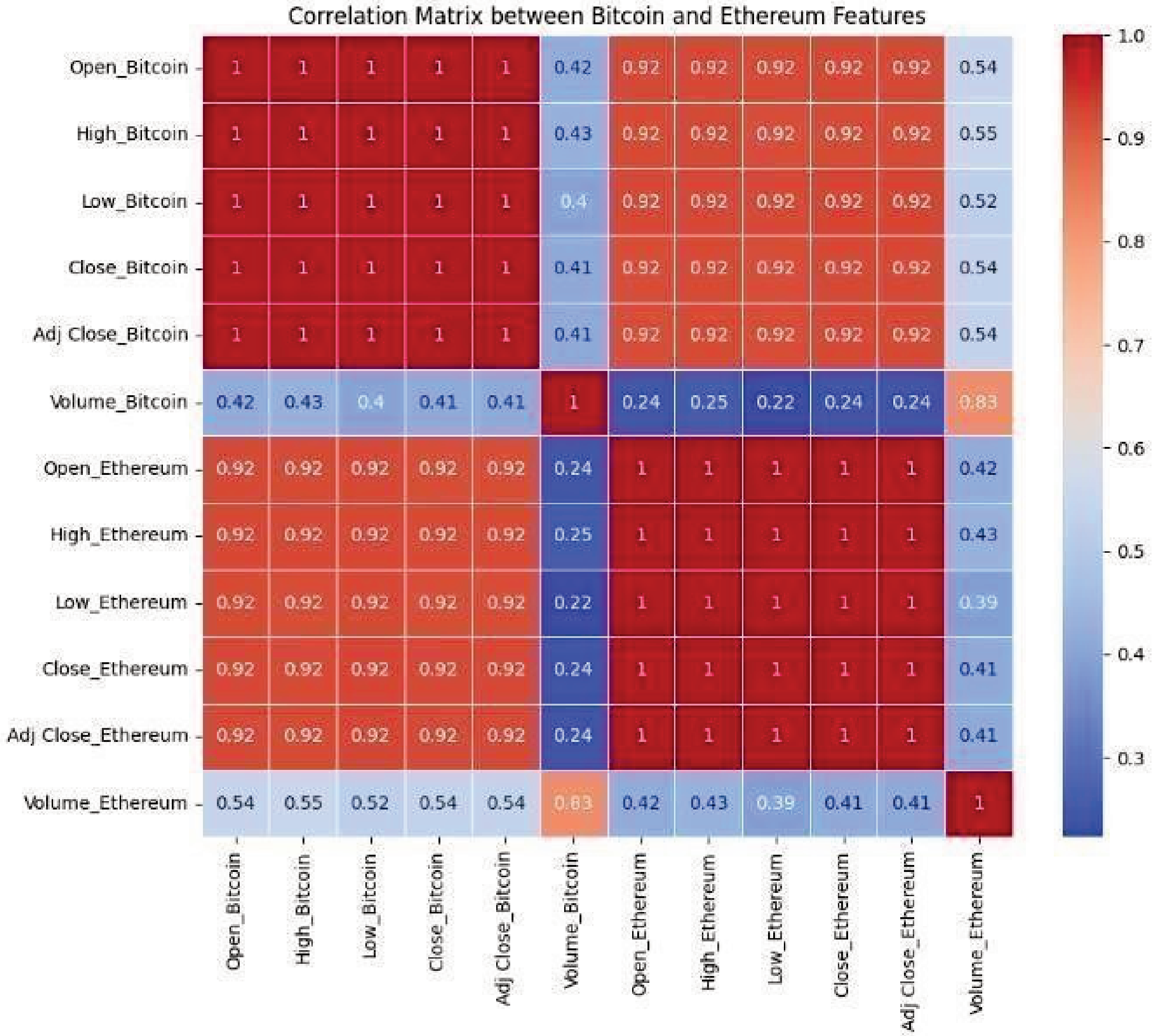


Figure 4. (a) Trend and Pattern Visualisation; and (b) Distribution of trading volume.

7. Results

Predicting cryptocurrency market prices involves analysing historical movements. Techniques such as machine learning algorithms, time-series analysis, and sentiment analysis are commonly used. However, due to the volatile nature of the market, predictions may not always be accurate and carry inherent risks. Investors should conduct thorough research and use multiple sources of information before making any trading decisions. The diagram below represents the prediction graph of the model where the Bitcoin price is predicted accurately.

Correlation Matrix



	Open_Bitcoin	High_Bitcoin	Low_Bitcoin	Close_Bitcoin	Adj Close_Bitcoin	Volume_Bitcoin	Open_Ethereum	High_Ethereum	Low_Ethereum	Close_Ethereum	Adj Close_Ethereum	Volume_Ethereum
Open_Bitcoin	1	1	1	1	1	0.42	0.92	0.92	0.92	0.92	0.92	0.54
High_Bitcoin	1	1	1	1	1	0.43	0.92	0.92	0.92	0.92	0.92	0.55
Low_Bitcoin	1	1	1	1	1	0.4	0.92	0.92	0.92	0.92	0.92	0.52
Close_Bitcoin	1	1	1	1	1	0.41	0.92	0.92	0.92	0.92	0.92	0.54
Adj Close_Bitcoin	1	1	1	1	1	0.41	0.92	0.92	0.92	0.92	0.92	0.54
Volume_Bitcoin	0.42	0.43	0.4	0.41	0.41	1	0.24	0.25	0.22	0.24	0.24	0.83
Open_Ethereum	0.92	0.92	0.92	0.92	0.92	0.24	1	1	1	1	1	0.42
High_Ethereum	0.92	0.92	0.92	0.92	0.92	0.25	1	1	1	1	1	0.43
Low_Ethereum	0.92	0.92	0.92	0.92	0.92	0.22	1	1	1	1	1	0.39
Close_Ethereum	0.92	0.92	0.92	0.92	0.92	0.24	1	1	1	1	1	0.41
Adj Close_Ethereum	0.92	0.92	0.92	0.92	0.92	0.24	1	1	1	1	1	0.41
Volume_Ethereum	0.54	0.55	0.52	0.54	0.54	0.83	0.42	0.43	0.39	0.41	0.41	1

Figure 5. Correlation matrix.

A correlation matrix in trading represents the pairwise relationships between different financial assets or instruments. Traders can better appreciate the advantages of diversification and portfolio risk by examining the price movements of different assets in connection to one another, as seen in Figure 5. Positive correlations with high values imply that two assets typically move in the same direction, whilst negative correlations show the opposite. Correlation matrices are used by traders to find possible hedging opportunities or to choose assets with low correlations in order to optimise portfolio allocations. Diversification is beneficial under the conditions of low or negative contacts between property, because it helps to reduce improper risk. Portfolio risk is usually administered by property allocation, communication analysis, and fluctuation monitoring. This study contributes to these features by combining a connection (Figure 5) to evaluate property relationships, thereby leading to the most effective diverse strategies. Comprehending correlations using a correlation matrix is crucial for managing risk and creating solid trading strategies that take into account the interactions between various market assets.

Figure 6 shows the simple moving average prediction graph.

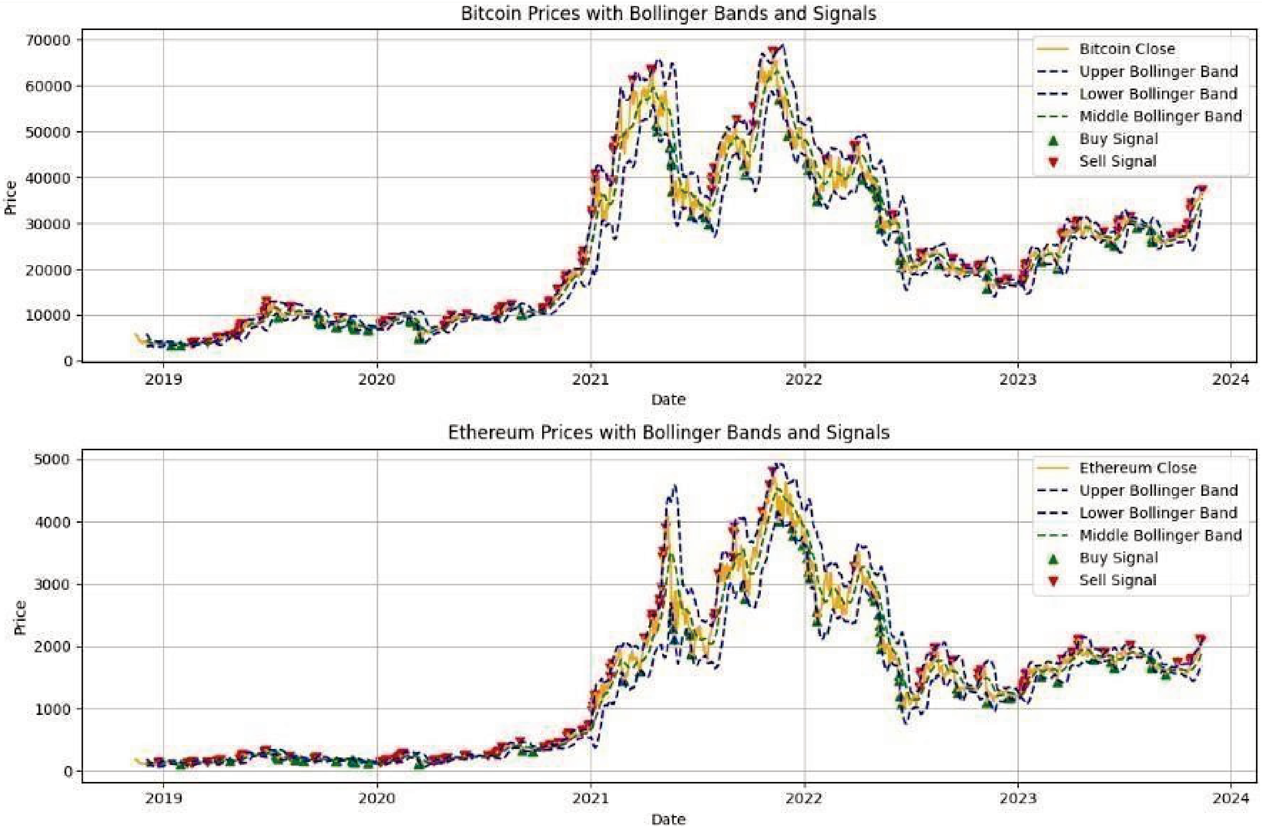


Figure 6. Simple Moving Average prediction graph.

8. Conclusion

This study focused on forecasting the prices of cryptocurrency using a Stacked Bilateral LSTM model, enhancing historical market data and technical indicators to address the challenges caused by market fluctuations. Key innovations enable the proposed model to surpass traditional approaches in accuracy and robustness. A new contribution to this research is the integration of bilateral temporary learning with a stacked structure, which enables an enhanced environmental understanding of time-series data. Theoretically, this approach improves deep learning applications in financial forecasting, providing a strong tool for the decision making and risk management for investors and financial institutions. These approaches may guide policymakers in creating a framework that supports responsible investment in the growing digital property environment system.

9. Future enhancement

The further future enhancement aims to incorporate attention mechanisms, allowing the model to focus more on relevant historical data points, thereby enhancing its ability to identify and respond to crucial market events. Additionally, integrating external data sources, such as social media sentiment or macroeconomic indicators, could provide a more comprehensive understanding of the market context, further refining the prediction accuracy. Furthermore, to improve model performance, fine-tuning of the hyperparameters and optimising the model architecture can be performed. Moreover, continuous monitoring and adaptation to emerging trends in deep learning and financial modelling methodologies will be crucial for maintaining the project's relevance.

Notes on contributors

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