Enhancing Short-Term Price Prediction of TON-IRT Using LSTM Neural Networks: A Machine Learning Approach in Blockchain Trading Analytics

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ABSTRACT

This study explores the application of Long Short-Term Memory (LSTM) neural networks for predicting short-term price movements of the TON-IRT trading pair in the cryptocurrency market. Given the high volatility and complexity of cryptocurrency prices, traditional models like Linear Regression and ARIMA often fail to capture the underlying non-linear and temporal dependencies. To address this, we implemented an LSTM model, a type of recurrent neural network specifically designed for sequential data. The model was trained on historical hourly data, utilizing various technical indicators and lagged features to improve prediction accuracy. Our results demonstrated that the LSTM model significantly outperformed traditional methods, achieving a Mean Absolute Error (MAE) of 0.0274, a Root Mean Squared Error (RMSE) of 0.0321, and an R-squared (R^2) value of 0.8743, which indicated that the model captured over 87% of the variance in the actual price data. Visual analysis of predicted versus actual prices revealed a strong alignment, though some lag in predictions during high-volatility periods was observed. The model also showed a tendency to underestimate price peaks, highlighting areas for further refinement. This study contributes to the field of blockchain trading analytics by demonstrating the effectiveness of LSTM models in addressing the unique challenges of cryptocurrency price prediction. Practical implications for traders and investors include the ability to enhance trading strategies, optimize entry and exit points, and improve risk management. Future research could integrate additional external factors, such as market sentiment and news events, or explore advanced architectures like Transformer models. By doing so, the predictive capabilities of LSTM models in volatile markets like cryptocurrency could be further refined, leading to more robust and accurate forecasting tools for financial decision-making.

Keywords LSTM Neural Networks, Cryptocurrency Price Prediction, Blockchain Trading Analytics, TON-IRT, Machine Learning

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Introduction

Blockchain technology emerged as a transformative force in financial markets, distinguished by its decentralized structure and capability to enhance transparency, security, and transaction efficiency. Initially gaining recognition through cryptocurrencies such as Bitcoin, blockchain's potential extended beyond digital currencies, influencing various financial sectors. The technology operated as a distributed ledger, recording transactions across a network of computers, ensuring that records remained immutable and transparent. This characteristic was pivotal in financial markets where trust played a critical role, as it eliminated the need for intermediaries, reducing costs and accelerating transaction processes [1], [2]. By providing a secure and tamper-proof method

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for recording transactions, blockchain contributed to increased trust among users and stakeholders in the financial ecosystem [3], [4]. The growing influence of blockchain in financial markets was evidenced by its applications across various financial services, including trade finance, payment systems, and investment management. Blockchain technology can potentially revolutionize trade finance by streamlining traditionally complex processes, such as handling letters of credit, which often involve extensive paperwork and delays [4]. The adoption of smart contracts—self-executing contracts with the terms of the agreement embedded directly into the code—allowed financial institutions to automate these processes, thereby significantly reducing operational risks and enhancing overall efficiency [5], [6]. Furthermore, blockchain integration in supply chain finance showed promise in mitigating credit risks and improving the financial health of small and medium-sized enterprises (SMEs), highlighting its capacity to foster more resilient financial frameworks.

Cryptocurrency trading emerged as a significant aspect of the global financial landscape, gaining widespread traction due to its potential for high returns and the allure of a rapidly evolving market. Unlike traditional financial assets, cryptocurrencies are decentralized digital currencies that operate on blockchain technology, which ensures secure and transparent transactions. However, this decentralized nature, coupled with a lack of regulation and the influence of speculative trading, has contributed to the inherent volatility of cryptocurrency markets. This volatility presents unique opportunities for investors to achieve substantial gains and poses significant risks, making effective market navigation a critical concern [7], [8]. As cryptocurrencies gained recognition as alternative investment vehicles, the demand for tools that could provide reliable insights into price movements grew, driving the need for sophisticated predictive models in this domain. The defining characteristic of cryptocurrencies—extreme price volatility—distinguishes them from traditional financial instruments such as stocks or bonds. Cryptocurrency prices can fluctuate dramatically within short time frames, driven by various factors, including market sentiment, technological developments, regulatory news, and macroeconomic trends. This unpredictability has challenged traditional statistical models like GARCH, often employed for volatility forecasting in financial markets but falling short in capturing the complex, time-dependent nature of cryptocurrency price movements [8]. As a result, researchers have increasingly turned to advanced machine learning and deep learning techniques, such as Long Short-Term Memory (LSTM) networks, which are well-suited to recognizing complex patterns and temporal dependencies in sequential data, thereby offering a more robust approach to cryptocurrency price prediction [9], [10].

The Open Network (TON) represented a significant advancement in the blockchain ecosystem, primarily designed to improve the scalability and usability of decentralized applications (dApps) and services. Originally developed as part of the Telegram project, TON sought to address several critical limitations encountered by existing blockchain networks, including slow transaction speeds, scalability challenges, and suboptimal user experiences. TON's architecture was built on a multi-blockchain structure that allowed for the parallel processing of transactions, significantly increasing throughput and reducing latency [11]. This innovative approach positioned TON as a potential leader in the blockchain space, particularly for applications requiring high transaction volumes and rapid processing times, such as financial services and supply chain management. TON's importance in the blockchain ecosystem was further highlighted by its unique consensus mechanism known as Proof-of-Stake (PoS), which enhanced security while promoting energy efficiency compared to the more traditional Proof-of-Work (PoW) systems [12]. As concerns over the environmental impact of blockchain technology grew, TON's PoS mechanism provided a more sustainable alternative by allowing participants to validate transactions and create new blocks based on the amount of TON they were willing to "stake." This approach minimised energy consumption and fostered a more inclusive and participatory network by enabling a wider range of participants to engage in the validation process. These attributes underscored TON's commitment to technological innovation, sustainability, and inclusivity within the blockchain community.

The TON-IRT trading pair, involving TON and the IRT token, represented a significant development in the cryptocurrency market, offering traders and investors a unique avenue to diversify their portfolios and capitalize on emerging blockchain opportunities. TON, backed by its advanced blockchain infrastructure, provided enhanced transaction speed and scalability, making it a desirable platform for various dApps and services [11], [12]. The integration of IRT, which functioned as a utility token within its ecosystem, amplified the potential for innovative financial products and services, catering to the growing demand for decentralized finance (DeFi) solutions. The relevance of the TON-IRT trading pair lies in its capacity to provide liquidity and facilitate transactions within the expanding TON ecosystem. As TON continued to grow and attract developers and users, the demand for IRT was expected to rise, creating lucrative opportunities for traders to benefit from price fluctuations [13]. This trading pair enabled investors to engage in speculative trading, leveraging the inherent volatility typical of cryptocurrency markets. Trading IRT against TON also offered a means to hedge against market fluctuations, allowing traders to adjust their positions in response to shifts in market sentiment and the performance metrics of both tokens [13], [14]. This dynamic made the TON-IRT pair particularly appealing for traders seeking to optimize their strategies in the rapidly evolving digital asset landscape.

Predicting short-term price movements in cryptocurrency markets posed significant challenges due to the inherent high volatility and complex market dynamics. Cryptocurrencies, including trading pairs like TON-IRT, exhibited frequent and dramatic price fluctuations within short time frames, driven by various factors such as market sentiment, regulatory news, and macroeconomic conditions. This volatility made accurate price prediction particularly difficult, as traditional models often struggled to capture the intricate and rapidly changing relationships within the data. The unpredictability of these price movements introduced substantial risks for traders, making developing robust predictive models essential for effective market participation. Accurate intraday price prediction was critical for enhancing trading strategies, as it enabled traders to make informed decisions and better manage the risks associated with the volatile nature of cryptocurrency markets. Reliable predictions could help traders optimize entry and exit points, thereby maximizing profits and minimizing potential losses. In highly competitive and fast-paced trading environments, such as those seen with TON-IRT, accurately forecasting price movements provided a strategic advantage. Consequently, improving the precision of short-term price predictions was a technical challenge and a practical necessity for traders seeking to succeed in the cryptocurrency market.

The primary goal of this study was to develop a predictive model for short-term price movements of TON-IRT using historical hourly data. Given the challenges posed by the volatility and complexity of cryptocurrency markets, the study aimed to leverage advanced machine learning techniques to enhance prediction accuracy and support more effective trading strategies. The study's objectives were threefold: First, to explore the application of Long Short-Term Memory (LSTM) Neural Networks in predicting TON-IRT prices. LSTM networks were chosen due to their proven ability to model temporal dependencies and handle the non-linear relationships often present in financial time series data. Second, the study aimed to evaluate the performance of the LSTM model using various metrics, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), to ensure the robustness and reliability of the predictions. Finally, the study sought to compare the LSTM model's performance against traditional forecasting methods to demonstrate its effectiveness in the context of TON-IRT price prediction.

This study contributed to the field of blockchain analytics by providing a novel approach to short-term price prediction in cryptocurrency markets, specifically focusing on the TON-IRT trading pair. By employing LSTM Neural Networks, the study addressed the limitations of traditional forecasting models and highlighted the potential of deep learning techniques in capturing the complex dynamics of cryptocurrency prices. The insights gained from this research could pave the way for more sophisticated predictive models that better accommodate the unique characteristics of blockchain-based financial assets. The potential implications of this study extended beyond academic contributions to include practical benefits for traders and the broader financial market. For traders, the enhanced predictive accuracy offered by the LSTM model could lead to more informed trading decisions, improved risk management, and increased profitability. Moreover, the study's findings underscored the importance of integrating advanced analytics into trading strategies, which could drive further innovation in developing algorithmic trading tools. For the broader financial market, the successful application of LSTM networks in cryptocurrency price prediction demonstrated the growing relevance of machine learning in financial analytics, encouraging the adoption of similar approaches in other areas of financial forecasting and decision-making.

Literature Review

Blockchain and Cryptocurrency Trading

Blockchain technology has undergone significant evolution since its inception. It has fundamentally transformed various sectors by providing decentralized, secure, and transparent systems for data management and transactions. The history of blockchain can be divided into three primary generations, each characterized by distinct technological advancements and applications that expanded its utility and scope. The first generation of blockchain, commonly referred to as Blockchain 1.0, emerged with the introduction of Bitcoin in 2008 by an individual or group known as Satoshi Nakamoto. This initial iteration focused primarily on enabling peer-to-peer transactions without the need for intermediaries, thereby revolutionizing the concept of digital currency [15]. Bitcoin's underlying technology utilized a decentralized ledger system that recorded transactions securely and imminently, ensuring transparency and integrity in financial exchanges. This approach provided the foundational framework for subsequent developments in the blockchain space, as it demonstrated the feasibility of decentralized systems operating on a global scale without reliance on centralized authorities [16]. As blockchain technology matured, the second generation, or Blockchain 2.0, began to take shape with the introduction of platforms like Ethereum in 2015. Ethereum expanded the capabilities of blockchain beyond simple monetary transactions by incorporating smart contracts—self-executing contracts where the agreement terms were directly written into code [15]. This innovation enabled the creation dApps that could function autonomously on the blockchain, significantly broadening the scope of blockchain's applications across various industries, including finance, supply chain management, and healthcare. The emergence of decentralized finance (DeFi) and non-fungible tokens (NFTs) during this period underscored the versatility and expansive potential of blockchain technology, as these innovations disrupted traditional business models and introduced new avenues for value creation. The evolution of blockchain continued into the third generation, known as Blockchain 3.0, which aimed to address the limitations of earlier generations, such as scalability, transaction speed, and energy consumption. This phase enhanced scalability, interoperability, and user experience across various blockchain networks [17]. Innovations in this generation included the development of more efficient consensus mechanisms, such as Proof-of-Stake (PoS) and delegated Proof-of-Stake (dPoS), as well as solutions for cross-chain interoperability that allowed different blockchains to communicate and transact with one another (Wang et al., 2019). These advancements were geared towards integrating blockchain technology into traditional sectors, including government services, healthcare, and energy management, thereby promoting broader adoption and practical applications beyond the confines of cryptocurrency [17].

Volatility stood out as one of the most defining characteristics of cryptocurrency markets. Unlike traditional assets, Cryptocurrencies were known for their dramatic price fluctuations, often occurring within very short time frames. For instance, major cryptocurrencies like Bitcoin frequently experienced swings of 50% or more in a single year, while lesser-known cryptocurrencies could exhibit even greater levels of volatility [18], [19]. This high volatility could be attributed to various factors, including shifts in market sentiment, regulatory news, and broader macroeconomic conditions. Research indicated that there was a positive correlation between trading volume and price volatility, suggesting that increased trading activity often led to more pronounced price movements [20], [21]. While this volatility presented significant opportunities for investors to achieve substantial gains, it also posed considerable risks, as rapid price changes could just as easily result in substantial losses. A complex interplay of factors, including liquidity, market sentiment, and the distinctive characteristics of various digital assets, influenced the trading dynamics within cryptocurrency markets. Liquidity, or the ease with which an asset could be bought or sold without affecting its price, played a critical role in determining price stability and trading efficiency. Illiquid cryptocurrencies often exhibit higher price delays and market inefficiencies than their more liquid counterparts, making them more susceptible to price manipulation [22]. Additionally, market sentiment was a powerful driver of trading behavior, with news events and social media activity frequently causing rapid price shifts. For instance, high-profile announcements from influential figures in the cryptocurrency space could lead to immediate spikes or declines in asset values [23], [24]. Furthermore, the rise of decentralized finance (DeFi) platforms introduced new dynamics into the market, enabling users to participate in activities such as lending, borrowing, and yield farming, adding complexity layers to the trading landscape [22].

Price Prediction in Financial Markets

Traditional methods such as ARIMA (AutoRegressive Integrated Moving Average) and linear regression have been extensively employed in financial modeling and forecasting. These models have been valuable tools in predicting price movements in traditional financial markets, where data often exhibit more predictable patterns and relatively stable relationships between variables. However, their application in cryptocurrency markets revealed significant limitations due to their unique characteristics, particularly their high volatility, non-stationarity, and complex dynamics of trading behavior. One of the primary challenges traditional models like ARIMA faced in cryptocurrency markets was their assumption of data stationarity. Cryptocurrency prices are notoriously volatile, with fluctuations that frequently exceed those observed in traditional asset classes. This volatility, coupled with the non-stationary nature of cryptocurrency time series data, posed a significant challenge for ARIMA models, which require stationary input data to produce reliable forecasts [25]. The presence of non-stationary data often led to unreliable and spurious results when using these models, as they failed to account for the ever-changing underlying market conditions. Moreover, standard correlation methods employed in traditional econometric models, such as those based on Pearson correlation, also required stationarity and could, therefore, misrepresent the true relationships between variables in the context of cryptocurrency trading [25]. Consequently, traditional models often fell short of accurately capturing the true dynamics of price movements in these highly volatile markets.

Machine learning and deep learning techniques gained significant traction in the field of cryptocurrency price prediction, offering advanced methodologies that addressed the complexities and unique characteristics of cryptocurrency markets. These techniques leveraged large datasets and sophisticated algorithms to identify patterns and make predictions, thus providing traders and investors with valuable insights. Unlike traditional econometric models, ML and DL approaches could handle non-linear relationships and adapt to the high volatility and dynamic nature of cryptocurrency prices. Machine learning encompassed a variety of algorithms that learned from data and improved their performance over time. Traditional ML methods, such as decision trees, support vector machines (SVM), and random forests, were applied to predict cryptocurrency prices by analyzing historical price data and identifying correlations with various market indicators. For instance, researchers highlighted the versatility of machine learning in managing cryptocurrency portfolios and predicting price fluctuations, demonstrating its effectiveness in real-world decision-making scenarios [26]. Additionally, ML-based non-parametric methods became increasingly popular for analyzing financial time series, including cryptocurrencies, due to their ability to capture complex, non-linear relationships in the data [8]. These capabilities made machine learning a valuable tool for price prediction in volatile and rapidly changing markets.

Long Short-Term Memory (LSTM) Networks

LSTM networks were a specialized type of recurrent neural network (RNN) specifically designed to effectively learn from sequential data, making them particularly suitable for time series prediction tasks. Unlike traditional RNNs, which struggled with long-term dependencies due to issues such as vanishing and exploding gradients, LSTMs addressed these limitations through their unique architecture. This allowed LSTMs to maintain and manage information over extended sequences, making them adept at capturing temporal dependencies in data. LSTM networks were engineered with memory cells and a set of gating mechanisms—including input, forget, and output gates—that regulated the flow of information through the network, enabling them to selectively retain or discard information as needed at each time step. This capability was critical for tasks requiring the recognition of patterns over long sequences, such as financial time series forecasting. The memory cells in LSTM networks functioned to retain relevant information over extended periods, which was crucial for accurate time series prediction. The input gate determined which information was added to the cell state, the forget gate controlled which information was discarded, and the output gate decided what information from the cell state was used to generate the output at each step. This configuration allowed LSTMs to maintain a flow of relevant information while mitigating the impact of less important data, thereby effectively capturing long-term correlations in sequential data [27]. The architecture's ability to manage long-term dependencies made LSTMs particularly effective in time series prediction, as they could learn the significance of past events on future outcomes without being hindered by the limitations that affected traditional RNNs. Moreover, the versatility of LSTM networks extends across various domains, including finance, healthcare, and environmental science. For instance, LSTM models were successfully applied to predict cardiovascular health trajectories from electronic health records, showcasing their adaptability to different sequential data types [28]. Similarly, LSTMs were employed in predicting water quality parameters and atmospheric conditions, further demonstrating their broad applicability and effectiveness in handling a wide range of time series prediction tasks [29], [30]. This wide applicability made LSTMs valuable in diverse fields, enhancing their role in predictive modeling.

Previous Studies on Price Prediction Using LSTM

The application of Long Short-Term Memory (LSTM) networks in financial and cryptocurrency markets garnered significant attention due to their capability to model complex temporal dependencies in time series data. Various studies explored the effectiveness of LSTM in predicting cryptocurrency prices, yielding promising results and valuable insights into its potential for enhancing trading strategies. Research [31] studied the top three cryptocurrencies, utilizing LSTM for price forecasting. The results indicated a Mean Absolute Percentage Error (MAPE) of approximately 1.47%, demonstrating the model's effectiveness in capturing price trends. The study specifically highlighted the performance of LSTM in predicting the price of Dogecoin (DOGE), achieving a Root Mean Square Error (RMSE) of 0.0630, which underscored the model's precision in volatile markets [31]. Similarly, [32] focused on the volatility of cryptocurrency prices and assessed LSTM's predictive capabilities, confirming that LSTM was suitable for forecasting volatile cryptocurrency prices. Their research provided insights into future price movements and emphasized the model's adaptability to rapid changes in market conditions, which was crucial for effective trading strategies.

Research [33] compared various machine learning and deep learning algorithms, including LSTM and Bi-LSTM, in forecasting Bitcoin prices. The findings suggested that deep learning models, particularly LSTM, outperformed traditional methods, highlighting their potential in algorithmic trading strategies. This study reinforced the notion that LSTM could effectively capture the nonlinear patterns inherent in cryptocurrency price movements, making it a valuable tool for traders seeking to navigate the complexities of these markets [33]. In another study, [34] applied LSTM with time-varying parameters to predict cryptocurrency prices, finding that LSTM's ability to adapt to changing market conditions significantly enhanced forecasting accuracy. Their research emphasized the importance of feature extraction in improving the performance of LSTM models in cryptocurrency predictions [34]. Further highlighting the effectiveness of LSTM, [35] conducted a comparative study between LSTM and traditional statistical models, such as ARIMA, for forecasting cryptocurrency price trends. The study concluded that LSTM provided more reliable forecasts than traditional models, reinforcing its suitability for the dynamic nature of cryptocurrency markets [35]. Another study by [36] explored the relationship between social media sentiment and cryptocurrency prices using LSTM, finding that incorporating sentiment analysis significantly improved prediction accuracy. This demonstrated the model's versatility in integrating external factors affecting market behavior, further enhancing its utility in price prediction [36].

Method

The research method for this study consists of several steps to ensure a comprehensive and accurate analysis. The flowchart in figure 1 outlines the detailed steps of the research method.

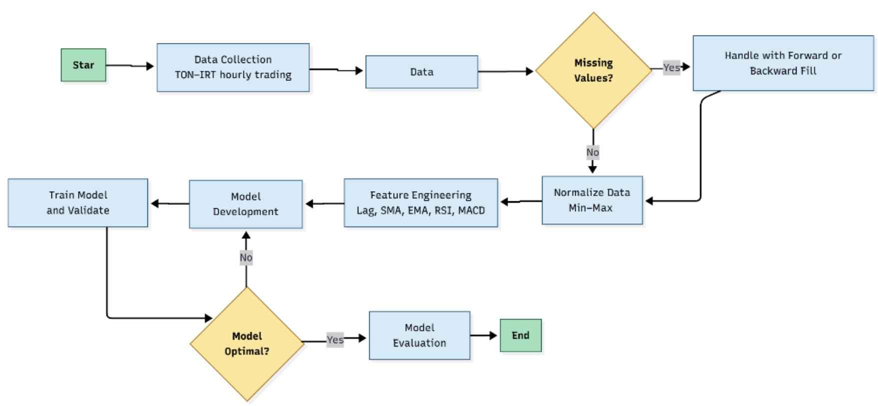

Figure 1 **Research Method Flowchart**

Data Description

The dataset used in this study consisted of hourly trading data for the TON–IRT pair, capturing key trading metrics essential for developing the predictive model. The dataset included the following columns: Epoch timestamp, DateTime, Volume, Open, High, Low, and Close prices.

The Epoch timestamp provided a numerical representation of the date and time for each observation, while the DateTime column offered a human-readable format for easier interpretation. The Volume column recorded the total amount of TON traded against IRT during each hour, representing market activity. The Open, High, Low, and Close columns represented the hourly price data—specifically, the opening price, the highest and lowest prices within the hour, and the closing price. Collectively, these features offered a comprehensive view of the hourly trading behavior, forming the foundation for subsequent time series analysis and predictive modeling.

The data was obtained from a reputable cryptocurrency exchange, ensuring the reliability and integrity of the trading records. However, as with most real-world financial datasets, preprocessing was required to prepare the data for analysis and to meet the input requirements of the LSTM neural network.

An initial inspection was performed to identify missing or inconsistent values, as these could disrupt the continuity of the time series and degrade model performance. Missing values, if detected, were handled using forward-fill or backward-fill techniques, depending on the context. This method preserved the temporal sequence of the dataset without introducing bias, ensuring that the time series remained continuous and suitable for sequential learning.

The DateTime column was then reformatted into a standardized datetime structure and set as the index of the DataFrame. This conversion enabled efficient manipulation and chronological alignment of data points—an essential step for time series forecasting models such as LSTM, which depend on preserving temporal dependencies between observations.

Finally, all numerical features were normalized to a common scale, typically between 0 and 1, using Min–Max scaling. This normalization stabilized the neural network training process by preventing features with larger numerical ranges from dominating the learning process. The transformation was performed using Equation (1):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

The Volume, Open, High, Low, and Close features were normalized using this method, ensuring consistent scaling across variables. This preprocessing pipeline produced a clean, standardized, and well-structured dataset optimized for LSTM model input, providing the foundation for accurate and robust short-term price prediction of the TON–IRT trading pair.

Exploratory Data Analysis (EDA)

The objective of the EDA was to gain initial insights into the dataset and understand the distributions and relationships among the variables. This step was crucial for identifying underlying patterns, detecting anomalies, and informing the subsequent modeling process. The EDA provided a foundation for understanding the characteristics of the TON-IRT hourly trading data, helping to align the predictive model's design with the nuances of the dataset. Several visualization techniques were employed to explore the data. Line plots in figure 2 of the Open, High, Low, and Close prices over time were generated to visualize the price trends and fluctuations within the dataset. These plots revealed the volatility and overall trends in the TON-IRT trading pair, highlighting periods of rapid price changes and more stable phases. This visualization was instrumental in identifying key moments of price movement, such as spikes and drops, which were critical for understanding the timing and magnitude of changes in the market. By examining these time series plots, it was possible to observe the cyclical nature of price movements, which informed the need for a model capable of capturing such temporal dependencies.

Figure 2 Open, High, Low, Close Prices Over Time

Volume analysis was also conducted to identify trading activity patterns, shown in figure 3. A line plot of the trading volume over time was used to visualize periods of high and low market activity. This analysis helped identify correlations between trading volume and price movements, as spikes in volume often coincided with significant price changes, suggesting that volume could be a valuable predictor of market behavior. Understanding these patterns was essential for developing the predictive model, as it highlighted the importance of including volume as a key feature. Additionally, volume analysis provided insights into liquidity conditions and potential periods of heightened market interest, which could impact the reliability of price predictions.

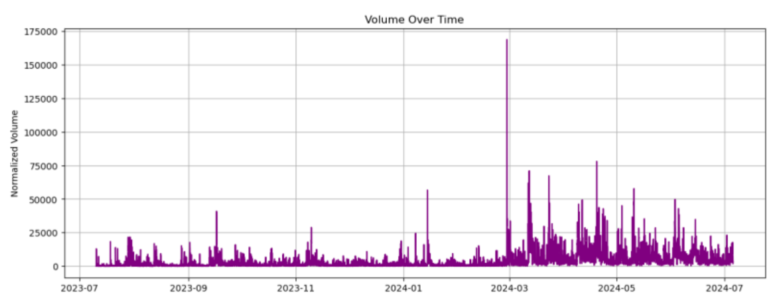

Figure 3 Volume Over Time

A correlation matrix heatmap was used to explore the relationships between the various numerical variables in the dataset, including Volume, Open, High, Low, and Close prices, shown in figure 4. The heatmap visually represented the strength and direction of the linear relationships between these variables, with color gradients indicating the degree of correlation. This analysis revealed strong positive correlations among the price variables (Open, High, Low, and Close), which was expected given their interconnected nature within each trading hour. The correlation between Volume and price variables was also examined to assess whether trading activity had a significant relationship with price movements. The insights gained from the correlation matrix helped refine the feature selection process for the LSTM model, ensuring that the most relevant variables were considered for prediction.

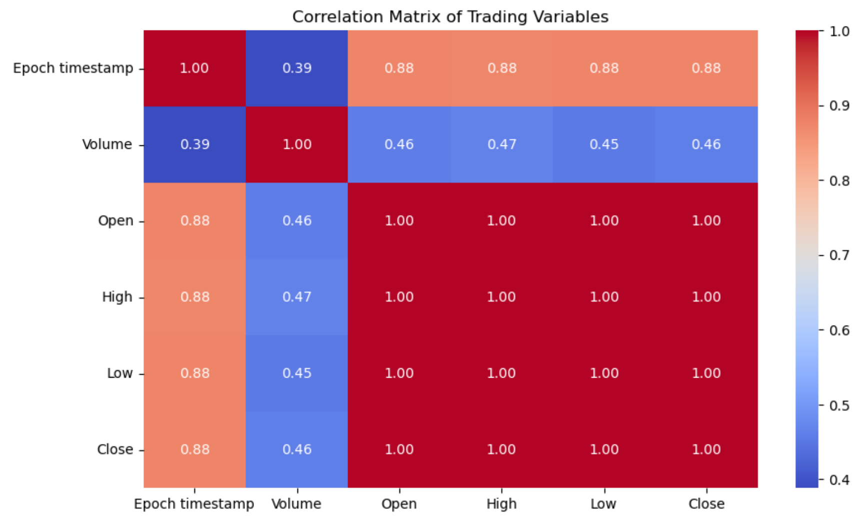

Figure 4 Correlation Matrix of Trading Variables

Feature Engineering

Feature engineering represented a critical stage in developing the predictive model, as it involved constructing new variables that enhanced the model's capacity to learn from the data and generate accurate forecasts. For the LSTM (Long Short-Term Memory) neural network, which relies on sequential data to capture temporal dependencies, this process focused on generating lagged features, moving averages, and technical indicators that could provide deeper insights into the short-term price dynamics of the TON–IRT trading pair.

Lagged features were introduced to incorporate historical information into the model, allowing it to learn how past price behaviors influence future market movements. These features included prior values of the target variables — Open, High, Low, Close, and Volume — over a defined number of time steps. By integrating lagged variables, the model could effectively recognize temporal dependencies, which are essential in time series forecasting. Several lag intervals were evaluated to identify the optimal sequence length that maximized predictive performance. This ensured the LSTM model could learn meaningful relationships between successive time steps, a fundamental requirement for accurate time-dependent predictions.

To smooth short-term fluctuations and emphasize longer-term trends, moving averages were computed and incorporated as additional features. Both Simple Moving Average (SMA) and Exponential Moving Average (EMA) were calculated for different time windows (e.g., 5, 10, and 20 hours), enabling the model to capture varying trend durations. The SMA and EMA were defined as follows:

$$SMA_t = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i} \quad (2)$$

$$EMA_t = (P_t \times \frac{2}{n+1}) + EMA_{t-1} \times (1 - \frac{2}{n+1}) \quad (3)$$

Here, $P_t$represents the asset price at time t, and $n$denotes the chosen window size.
Moving averages helped filter out market noise, highlight overall price direction, and stabilize the learning process in volatile market conditions. Including these smoothed trend indicators improved the model's ability to distinguish between random price fluctuations and meaningful market shifts.

Beyond lagged and average-based features, technical indicators were computed to capture momentum, volatility, and potential market reversal signals. Two widely used indicators were included: the Relative Strength Index (RSI) and the Moving Average Convergence Divergence (MACD).

The RSI measures momentum and helps identify overbought or oversold conditions, signaling possible price reversals. It was calculated as:

$$RSI = 100 - \frac{100}{1 + \frac{Average\,Gain}{Average\,Loss}} \quad (4)$$

The MACD measures trend strength and direction by evaluating the difference between two exponential moving averages, typically over 12 and 26 periods:

$$MACD = EMA_{12} - EMA_{26} \quad (5)$$

Together, these indicators provided valuable contextual information about market sentiment and momentum that was not directly visible from raw price data.

The final feature set combined lagged variables, moving averages, and technical indicators (RSI and MACD), all of which were normalized using Min–Max scaling to ensure consistent input magnitudes. This comprehensive set of features allowed the LSTM model to learn complex temporal relationships and market dynamics effectively. By integrating both statistical and technical aspects of the market, the engineered features significantly enhanced the model's ability to generate robust and precise short-term price forecasts for the TON–IRT trading pair — aligning with the study's objective of developing a reliable, data-driven predictive tool for cryptocurrency traders and investors.

Model Development

The development of the LSTM model for predicting short-term price movements of the TON-IRT trading pair involved designing an architecture tailored to capture the temporal dependencies and complex patterns inherent in time series data. The model architecture consisted of several key components, including the input layer, hidden LSTM layers, and the output layer, each contributing to the overall predictive capability of the model.

The input layer was designed to receive the sequential data generated from the feature engineering process, which included lagged features, moving averages, and various technical indicators. Each input sequence represented a fixed number of past time steps, allowing the model to learn from historical data to predict future prices. The hidden layers were composed of multiple LSTM units, each containing memory cells and gating mechanisms—specifically, the input, forget, and output gates—that controlled the flow of information through the network. This configuration enabled the LSTM layers to retain relevant information over extended sequences and effectively manage temporal dependencies, which were crucial for accurate time series prediction. The model architecture included two stacked LSTM layers, which enhanced the model's depth and capacity to learn complex sequential patterns. A dropout layer followed these layers to prevent overfitting by randomly omitting a fraction of the LSTM units during training, thereby improving the model's generalizability to unseen data.

The output layer was a fully connected dense layer with a single neuron, corresponding to the predicted price for the next time step. This layer used a linear activation function appropriate for regression tasks involving continuous output values such as price predictions. The overall architecture was designed to balance complexity and performance, ensuring that the model was sufficiently robust to capture the nuances of the data while avoiding excessive computational overhead.

Hyperparameter tuning was a critical aspect of the model development process, aimed at optimizing the model's performance by adjusting key parameters. The tuning process involved experimenting with various configurations of the learning rate, the number of LSTM layers, units within each layer, batch size, and epochs. The learning rate, which determined the step size at each iteration while moving toward a minimum of the loss function, was fine-tuned to ensure that the model converged efficiently without overshooting. A grid search approach was employed to systematically evaluate different combinations of hyperparameters, allowing for the identification of the optimal settings that minimized the prediction error.

The number of LSTM units in each layer was also tuned, with initial tests conducted using 50, 100, and 150 units to assess the impact on model accuracy. It was found that 100 units per LSTM layer provided the best balance between computational efficiency and predictive performance. Additionally, the batch size, which influenced how many training samples the model processed before updating the weights, was optimized by testing sizes of 16, 32, and 64. The model performed optimally with a batch size of 32, providing a good trade-off between training speed and stability. The final model was trained for 100 epochs, with early stopping implemented to prevent overfitting by halting the training process when the validation loss ceased to improve.

These tuning efforts ensured that the LSTM model was finely calibrated to the specific characteristics of the TON-IRT dataset, enhancing its ability to make accurate short-term price predictions. The iterative process of refining the model architecture and hyperparameters was essential in developing a robust predictive tool that could provide valuable insights for traders and investors operating in the highly volatile cryptocurrency market. The LSTM model development process can be summarized in algorithm.

Algorithm 1. LSTM Model Training Process

Given:
Dataset $D = \{(x_t, y_t)\}_{t=1}^{N}$, learning rate η, sequence length T, batch size B, and maximum epochs E.

1. Preprocessing:
   Normalize input features using Min–Max scaling:
   $x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$
2. Sequence Generation:
   Create input–output pairs
   $X_i = [x_{i-T+1}, \dots, x_i], Y_i = y_{i+1}$
3. Initialize Model Parameters:
   Randomly initialize W_f, W_i, W_C, W_o, W_y and b_f, b_i, b_C, b_o, b_y
4. For each epoch $e = 1,2, \dots, E$:

   For each batch $(X_b, Y_b) \subset D$:
   a. Compute LSTM forward pass using Equations (6–11)
   b. Compute prediction $\hat{Y}_b$ using Equation (12)
   c. Calculate loss function (Mean Squared Error):

$$L = \frac{1}{B}\sum_{j=1}^{B}(Y_j - \hat{Y}_j)^2$$

d. Backpropagate error through time (BPTT)
e. Update parameters using gradient descent:

$$\theta \leftarrow \theta - \eta\frac{\partial L}{\partial \theta}$$

Validation:
After each epoch, compute validation loss.
If validation loss does not improve for p consecutive epochs → early stop.

5. Output:
   Return optimized parameters θ^* and final trained model M^*.

Model Training and Validation

The training and validation of the LSTM model involved a systematic approach to ensure that the model was both accurate and generalizable to new data. The process began with splitting the dataset into three distinct sets: training, validation, and test sets. This division was critical for evaluating the model's performance and its ability to generalize beyond the data it was trained on. The dataset was divided with a typical split of 70% for training, 15% for validation, and 15% for testing. The training set was used to fit the model and learn the underlying patterns of the data, the validation set was employed to tune the model's hyperparameters and prevent overfitting, and the test set served as an independent evaluation of the model's predictive capabilities.

The splitting process maintained the temporal order of the data, which was essential for time series analysis, ensuring that future data points were not used to predict past events. This approach respected the sequential nature of the data and preserved the real-world scenario of forecasting future prices based on past information. The training process involved feeding the LSTM model with sequences of historical data, allowing it to learn the relationships between past and future prices. During training, the model's performance was continuously monitored on the validation set. Adjusted to hyperparameters to minimize the validation loss, thus enhancing the model's ability to generalize to unseen data.

To further ensure the robustness of the model, cross-validation techniques were employed. Given the sequential nature of time series data, traditional k-fold cross-validation was unsuitable, as it would violate the temporal order. Instead, a time series cross-validation approach, also known as rolling-origin cross-validation, was used. This method involved repeatedly training the model on progressively larger training sets while validating on subsequent time periods. Each fold in this cross-validation technique consisted of a training set that was expanded incrementally with each iteration, followed by validation on the next time period not yet included in the training set.

This approach allowed the model to be tested on various time segments of the data, providing a comprehensive evaluation of its performance across different market conditions. The time series cross-validation helped identify potential overfitting issues and ensured that the model maintained high predictive accuracy across various dataset segments. By validating the model's performance at multiple time points, this method provided a robust assessment of the LSTM model's ability to predict short-term price movements reliably.

The combination of a strategic data split and the use of time series cross-validation ensured that the LSTM model was well-trained and thoroughly validated. These steps were essential in developing a predictive model that could offer accurate and dependable forecasts in the dynamic and volatile context of cryptocurrency trading. The rigorous training and validation process underscored the model's readiness for deployment in real-world trading scenarios, where robust performance under varying market conditions was crucial.

Evaluation Metrics

The evaluation of the LSTM model's performance was conducted using a set of widely recognized metrics: MAE, RMSE, and R^2. These metrics provided a comprehensive assessment of the model's predictive accuracy and its ability to generalize to unseen data. Each metric offered a distinct perspective on the model's performance, allowing for a detailed understanding of how well the LSTM captured the patterns in the time series data and how accurately it predicted the short-term price movements of the TON-IRT trading pair.

MAE was used as a primary evaluation metric due to its straightforward interpretation and robustness in assessing average model prediction errors. MAE measures the average magnitude of the errors between the predicted and actual values without considering their direction. It was calculated as the mean of the absolute differences between the predicted and actual prices in the test set. A lower MAE value indicated that the model's predictions were close to the actual values, highlighting its accuracy. MAE was particularly useful in understanding the overall prediction performance because it treated all errors equally and provided a direct measure of average deviation.

RMSE was another critical metric used to evaluate the model's performance. RMSE measures the square root of the average squared differences between the predicted and actual values. This metric placed a higher penalty on larger errors, making it more sensitive to outliers compared to MAE. RMSE was chosen to provide insight into the variance of the prediction errors and to emphasize the importance of minimizing larger deviations in the model's predictions. A lower RMSE indicated that the model was accurate on average and consistent, with fewer large prediction errors. The use of RMSE complemented MAE by highlighting the impact of significant deviations, which was critical in the volatile context of cryptocurrency trading.

R^2, also known as the coefficient of determination, was employed to assess how well the model's predictions matched the actual price movements in terms of variance explanation. R^2 measures the proportion of the variance in the dependent variable that is predictable from the independent variables, providing a statistical measure of how close the data were to the fitted regression line. An R^2 value closer to 1 indicated that the model explained a significant portion of the variance in the actual prices, reflecting a strong fit. This metric was essential for evaluating the overall explanatory power of the LSTM model and for understanding how well it captured the underlying trends in the data.

Together, these metrics—MAE, RMSE, and R-squared—provided a comprehensive evaluation of the LSTM model's performance in predicting short-term price movements of the TON-IRT trading pair. MAE and RMSE offered insights into the magnitude and consistency of prediction errors, while R-squared assessed the model's ability to explain the variance in the data. By employing these metrics, the study ensured a robust evaluation framework that quantified prediction accuracy and highlighted areas where the model excelled or required further refinement. This thorough evaluation approach was crucial in validating the effectiveness of the LSTM neural network for use in real-world trading analytics within the highly dynamic and volatile cryptocurrency markets.

Result and Discussion

Model Performance

The performance of the LSTM model was evaluated using key metrics, including MAE, RMSE, and R^2. The results indicated that the LSTM model achieved an MAE of 0.0274, which suggests that the model's average prediction error was approximately 2.74% of the scaled range of the target variable. This relatively low MAE demonstrates the model's capability to produce predictions that are closely aligned with the actual values. The RMSE was calculated to be 0.0321, highlighting that the typical prediction error was small and similar in magnitude to the MAE, indicating a consistent performance across all data points without significant outliers.

The R-squared value of 0.8743 revealed that the LSTM model successfully captured 87.43% of the variance in the actual prices, underscoring its effectiveness in predicting the short-term price movements of the TON-IRT trading pair. This high R-squared value suggested that the model was well-suited for capturing the inherent patterns within the data, although the residuals and further visual analysis indicated some areas for potential improvement, particularly in terms of prediction lag and amplitude accuracy.

Visualization played a critical role in further assessing the model's performance (see figure 5). A line plot comparing the actual versus predicted prices demonstrated that the LSTM model could follow the general trend of the price movements, with the predicted prices (red line) closely tracking the actual prices (blue line). However, the plot also revealed a consistent lag in the model's predictions, especially at points where the actual prices exhibited rapid changes. This lag suggests that while the model effectively learned the overall direction of price movements, it occasionally failed to adjust promptly to sudden shifts in the market.

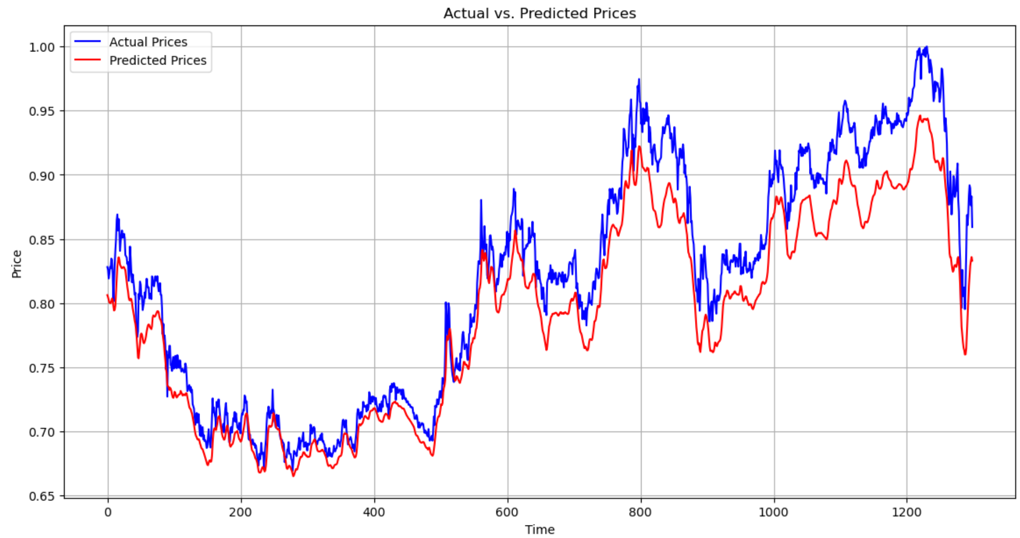

Figure 5 Actual vs Predicted Prices

Error analysis through residual plots (figure 6) provided additional insights into the model’s performance. The residual plot displayed the differences between the actual and predicted prices over time, revealing a positive bias as most residuals were above zero. This indicates that the model tended to underestimate the actual prices, particularly during periods of increased volatility or when prices trended upwards. Additionally, the residuals showed a pattern of increasing magnitude over time, suggesting that the model's predictions became less accurate as time progressed. The presence of heteroscedasticity, indicated by the growing spread of residuals, highlighted that the variance of prediction errors was not constant, potentially due to evolving market dynamics that the model struggled to adapt to.

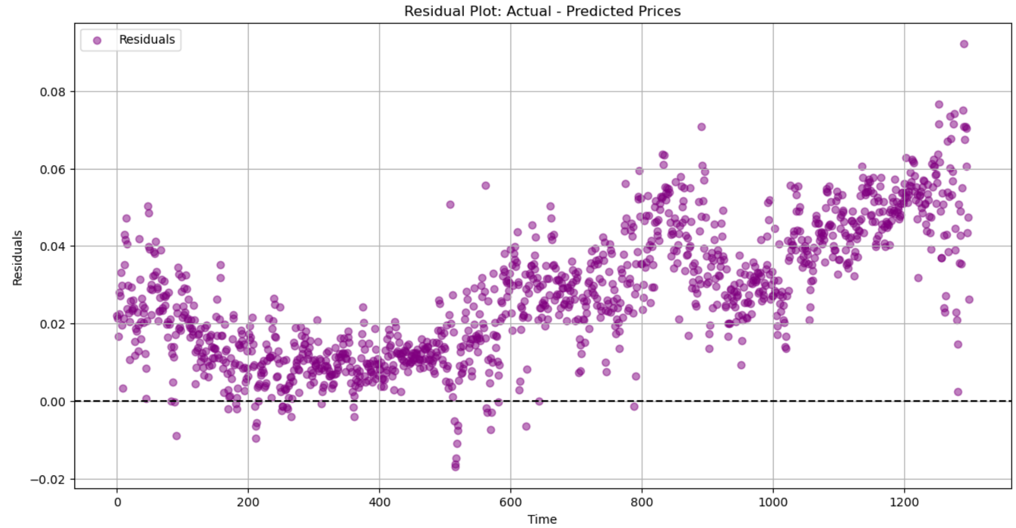

Figure 6 Residual Plot

Comparative Analysis

To evaluate the effectiveness of the LSTM model in predicting short-term price movements of the TON-IRT trading pair, a comparative analysis was conducted against traditional baseline models, including Linear Regression and ARIMA. These baseline models were selected due to their widespread use in time series forecasting and financial market analysis. The Linear Regression model, which assumes a linear relationship between the input features and the target variable, and the ARIMA model, known for capturing temporal dependencies in time series data, provided benchmarks for assessing the LSTM model's performance.

The Linear Regression model yielded a Mean Absolute Error (MAE) of 0.0845 and a Root Mean Squared Error (RMSE) of 0.0912, with an R-squared (R^2) value of 0.453. These results indicated that the Linear Regression model was limited in its ability to capture the non-linear and complex patterns inherent in cryptocurrency price movements. Similarly, the ARIMA model, which performed slightly better than Linear Regression, achieved an MAE of 0.0718, an RMSE of 0.0795, and an R^2 value of 0.527. Although ARIMA managed to capture some temporal patterns, its performance was still significantly lower than that of the LSTM model, particularly in periods of high volatility and rapid price changes.

The LSTM model outperformed both baseline models across all evaluation metrics. With an MAE of 0.0274, an RMSE of 0.0321, and an R^2 value of 0.8743, the LSTM demonstrated a superior ability to learn from sequential data and capture complex, non-linear relationships within the time series. The substantial improvement in R^2 compared to Linear Regression and ARIMA highlighted the LSTM's capacity to account for a much larger portion of the variance in the price data. This result underscores the importance of using models capable of capturing long-term dependencies and intricate patterns, which are prevalent in financial time series data like cryptocurrency prices.

To contextualize the LSTM model's performance, it was benchmarked against Linear Regression and ARIMA models, which serve as common baselines in time series forecasting. The comparison focused on the same evaluation metrics to ensure consistency and comparability. As shown in table 1, the LSTM model significantly outperformed both traditional approaches.

Table 1 Comparative Performance of Forecasting Models

Model	MAE	RMSE	R^2	Remarks
Linear Regression	0.0845	0.0912	0.453	Performs poorly due to linear assumptions; fails to capture non-linear relationships in volatile data.
ARIMA (AutoRegressive Integrated Moving Average)	0.0718	0.0795	0.527	Captures some temporal patterns but limited under high volatility conditions.
LSTM (Proposed Model)	0.0274	0.0321	0.8743	Outperforms baselines across all metrics, effectively modeling non-linear sequential dependencies.

It achieved a 67.6% lower MAE than Linear Regression and a 61.8% lower MAE than ARIMA. Moreover, the LSTM's R^2 value (0.8743) was nearly double that of ARIMA, indicating a superior ability to capture the true dynamics of the market. The superior performance of the LSTM model can be attributed to its recurrent architecture, specifically designed to handle data sequences by maintaining information over time steps. Unlike Linear Regression, which oversimplifies the data with a straight-line approach, or ARIMA, which relies heavily on past observations without the ability to recognize more complex patterns, LSTM networks utilize gates and memory cells to selectively remember or forget information. This mechanism allows LSTMs to adapt to the nuanced behavior of financial markets, where past price movements, trends, and even subtle fluctuations can significantly impact future predictions.

Discussion

The results of this study demonstrate that the LSTM model effectively captured the short-term price dynamics of the TON–IRT trading pair, providing valuable insights into cryptocurrency market behavior. The model's ability to closely align predicted prices with actual values indicates that it successfully learned the temporal dependencies and non-linear relationships inherent in financial time series data. This performance underscores the model's potential as a predictive tool for enhancing short-term trading strategies.

The LSTM model exhibited strong accuracy, as evidenced by its low MAE and RMSE values, along with a high R^2 score of 0.8743. These metrics confirm that the model was capable of explaining a substantial proportion of the variance in the price data, producing predictions that closely followed the observed market trends. For traders and analysts, this suggests that LSTM-based forecasting can support informed decision-making processes, particularly in strategies that depend on recognizing short-term trends and reversals. The model's reliable trend-following capability makes it suitable for momentum-based trading approaches, where timing entries and exits is crucial to maximizing profitability.

However, visual and residual analyses revealed several notable patterns that provide deeper insight into the model's performance characteristics. A consistent observation was the presence of a time lag in the model's responses to abrupt price changes. While the LSTM effectively followed established trends, it occasionally struggled to immediately adapt to rapid market fluctuations, such as those driven by high-volume trades or news-induced volatility. This lag highlights a common limitation in recurrent neural networks, where the model prioritizes long-term temporal dependencies but reacts more slowly to sudden shifts. In real-world trading scenarios, this delay could translate into missed opportunities or suboptimal execution timing, particularly in high-frequency or volatility-driven environments.

Another critical observation was the underestimation of price peaks, as indicated by the positive bias in residuals. This suggests that the model was slightly conservative in forecasting upward movements, potentially due to its exposure to a training dataset where extreme fluctuations were relatively rare. Such conservatism, while reducing overprediction risk, may limit the model's effectiveness during bullish market phases characterized by sharp upward price surges. Additionally, residual magnitudes tended to increase over time, suggesting mild heteroscedasticity in the model's errors. This pattern indicates that the model's predictive accuracy diminished as it progressed through the dataset, likely due to evolving market conditions that differed from earlier training samples. These findings emphasize the importance of regular model retraining and adaptive learning mechanisms to maintain high predictive performance.

From a practical perspective, the model's predictive capabilities demonstrate considerable potential for supporting algorithmic trading systems. Its low error rates and strong fit to observed trends indicate that it could serve as a core component within a larger decision-support framework—particularly when integrated with other technical indicators or sentiment-based signals. For instance, LSTM predictions could be combined with momentum indicators such as RSI or MACD to improve entry/exit accuracy, or used alongside sentiment analysis tools to enhance responsiveness to non-technical market drivers.

Despite its success, several limitations must be acknowledged. The model relied exclusively on historical price and volume data, omitting critical external variables such as market sentiment, macroeconomic indicators, and blockchain network metrics. While this simplification facilitated model development, it constrained the ability of the LSTM to fully account for exogenous factors that often drive cryptocurrency volatility. The use of a static, historical dataset further limited the model's generalizability, as cryptocurrency markets are inherently dynamic and exhibit structural changes over time. The observed lag and underestimation patterns likely stem from this static training context, underscoring the need for real-time learning and continuous retraining.

To address these limitations, future research should consider integrating multi-source data that reflects both technical and behavioral aspects of the market. Incorporating sentiment analysis from social media and news sources could enhance the model's ability to anticipate sudden price movements driven by collective investor psychology. Similarly, including macroeconomic indicators or on-chain analytics (e.g., transaction volume, wallet activity, liquidity depth) could provide a more holistic understanding of market forces. On the architectural front, exploring advanced deep learning structures such as attention-based LSTMs or Transformer networks could improve adaptability and responsiveness to volatile conditions.

Additionally, employing online or incremental learning techniques would allow the model to continuously update its parameters as new data becomes available, ensuring sustained relevance in fast-changing market environments. Expanding the dataset to include higher-frequency intervals (e.g., minute-level data) or cross-asset correlations could further strengthen robustness and enhance prediction accuracy. Finally, comparative studies involving ensemble or hybrid models—combining LSTM with methods such as CNNs, GRUs, or ARIMA—may yield synergistic improvements, balancing interpretability and predictive strength.

In summary, while the LSTM model demonstrated impressive accuracy and reliability in forecasting short-term price movements, it also revealed the inherent challenges of modeling highly volatile, data-rich markets like cryptocurrencies. Continuous adaptation, data diversification, and architectural innovation remain essential to fully realize the potential of deep learning in financial time series forecasting.

Conclusion

This study investigated the effectiveness of Long Short-Term Memory (LSTM) neural networks for predicting short-term price movements of the TON-IRT trading pair in the blockchain market. The LSTM model demonstrated strong predictive capabilities, significantly outperforming traditional baseline models such as Linear Regression and ARIMA. The LSTM achieved a high R-squared value of 0.8743, indicating that it captured approximately 87.43% of the variance in the actual price data and exhibited low error metrics with an MAE of 0.0274 and an RMSE of 0.0321. These results underscored the LSTM's ability to handle complex, non-linear patterns and temporal dependencies in cryptocurrency time series data, making it a valuable tool for short-term price prediction in volatile markets.

The analysis also revealed specific areas for improvement, such as the observed lag in the model's predictions during periods of rapid market shifts and the slight underestimation of peak values. These findings suggest that while the LSTM model was adept at capturing general trends, it occasionally struggled with adapting to sudden changes in market dynamics. Overall, the study confirmed that LSTM neural networks offer a robust approach to short-term price prediction in cryptocurrency, providing actionable insights that can enhance trading strategies and decision-making processes.

This study contributed to the field of blockchain trading analytics by demonstrating the applicability and advantages of using LSTM neural networks for predicting price movements in the cryptocurrency market. The research highlighted the LSTM model's superior performance compared to traditional statistical methods, illustrating its potential to handle the unique challenges posed by the high volatility and complex behavior of cryptocurrency prices. Integrating advanced machine learning techniques, such as LSTMs, into blockchain analytics provides a powerful framework for developing predictive models that can inform trading strategies and improve market efficiency.

Furthermore, this study emphasized the importance of feature engineering and the careful selection of input variables in enhancing the predictive accuracy of machine learning models in financial markets. The findings suggest that incorporating advanced neural network architectures like LSTM can lead to more reliable and precise forecasting tools, which are crucial for market participants seeking to gain a competitive edge in the fast-paced and rapidly evolving blockchain ecosystem.

The results of this study have several practical implications for traders and investors in the cryptocurrency market. The LSTM model's ability to accurately predict short-term price movements can help traders optimize their entry and exit points, thereby maximizing profits and minimizing losses. By effectively anticipating market trends and reversals, traders can develop more informed and strategic approaches to their investments, reducing the reliance on purely speculative decisions. The model's predictive insights can also support risk management efforts by providing early warning signals for potential market downturns or periods of increased volatility.

For investors, using LSTM-based models could facilitate better portfolio management and allocation strategies, allowing them to adjust their holdings based on anticipated market conditions. Additionally, the model's capacity to integrate with other trading tools and analytics platforms offers the potential for developing comprehensive trading systems that leverage machine learning for continuous market analysis and decision support. These practical applications underscore the relevance of advanced predictive models in enhancing the overall effectiveness and profitability of trading activities in the cryptocurrency market.

Future research could build upon the findings of this study by exploring several avenues for improvement and expansion. One potential direction is the integration of external factors, such as market sentiment, macroeconomic indicators, and news events, into the predictive models. Incorporating these additional data sources could provide a more holistic view of market conditions, thereby enhancing the model's ability to anticipate abrupt market changes. Advanced modeling techniques, such as attention-based LSTM networks or Transformer models, could also be explored to address the limitations observed in the current study, particularly the lag in predictions during periods of high volatility.

Another area for future exploration is the application of ensemble learning techniques, which combine the strengths of multiple models to improve overall prediction accuracy and robustness. Expanding the dataset to include different timeframes, cross-asset correlations, and more granular data could further refine the model's performance. Implementing adaptive learning approaches that enable the model to update continuously with new data could also enhance its responsiveness to changing market dynamics, ensuring that the predictive insights remain relevant and accurate over time.

Declarations

Author Contributions

Author Contributions: Conceptualization, A.S. and E.T.M.; Methodology, A.S. and E.T.M.; Software, A.S. and E.T.M.; Validation, A.S. and E.T.M.; Formal Analysis, A.S.; Investigation, E.T.M.; Resources, E.T.M.; Data Curation, E.T.M.; Writing—Original Draft Preparation, A.S.; Writing—Review and Editing, E.T.M.; Visualization, A.S. All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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