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Time Series Analysis with Cryptocurrency

Ankit Raj
Student, Computer Science and Engineering, Parul University, Vadodara
ar1046662@gmail.com

Dr. Shiv Shakti Shrivastava
Department of Computer Science and Engineering, Parul University, Vadodara, India
shivshakti.shrivatava33694@paruluniversity.ac.in

Abstract

Cryptocurrency markets are characterized by extreme volatility, rapid price fluctuations, and complex nonlinear behavior, making accurate forecasting a significant challenge for investors, analysts, and researchers. This study investigates the application of Time Series Analysis techniques to model and predict cryptocurrency prices using historical market data. Both traditional statistical approaches, such as the AutoRegressive Integrated Moving Average (ARIMA) model, and advanced deep learning methods, including Long Short-Term Memory (LSTM) networks, are implemented to capture underlying temporal patterns. The dataset consists of daily open, high, low, close prices, and trading volume obtained from reliable financial data sources.

Data preprocessing steps such as handling missing values, normalization, stationarity testing using the Augmented Dickey-Fuller test, and time series decomposition are performed to ensure model efficiency and accuracy. Exploratory Data Analysis (EDA) is conducted to identify trends, seasonality, and volatility characteristics. Model performance is evaluated using statistical metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The comparative analysis demonstrates that while ARIMA performs adequately for short-term forecasting, LSTM models provide superior performance in capturing nonlinear and long-term dependencies within cryptocurrency price movements. However, external factors such as market sentiment and regulatory changes continue to influence prediction accuracy. This research contributes to a better understanding of cryptocurrency forecasting techniques and highlights the effectiveness of deep learning approaches in financial time series analysis.

Keywords: Cryptocurrency, Time Series Analysis, ARIMA, LSTM, Price Prediction

Introduction

Cryptocurrency has emerged as one of the most transformative innovations in the global financial ecosystem. Since the introduction of Bitcoin in 2009 **[1]**, digital currencies have gained widespread attention from investors, researchers, and financial institutions. Unlike traditional currencies regulated by central authorities, cryptocurrencies operate on decentralized blockchain technology, ensuring transparency, security, and immutability of transactions **[1]**. Following Bitcoin's success, other major cryptocurrencies such as Ethereum have expanded the scope of digital assets by enabling smart contracts and decentralized applications **[2]**. The rapid growth of this market has led to increased interest in understanding and predicting cryptocurrency price behaviour.

Cryptocurrency markets are highly volatile compared to traditional financial markets **[3]**, **[4]**. Prices fluctuate significantly within short periods due to factors such as investor sentiment, market demand and supply, regulatory announcements, macroeconomic events, and technological developments. This high volatility makes cryptocurrency forecasting both challenging and essential. Accurate price prediction can assist traders in making informed investment decisions, help financial institutions manage risk, and support policymakers in understanding market stability.

Time Series Analysis plays a crucial role in analyzing sequential data collected over time **[5]**. Since cryptocurrency prices are recorded at regular intervals (hourly, daily, or weekly), they naturally form time series data. Traditional statistical models like the AutoRegressive Integrated Moving Average (ARIMA) have been widely used for financial forecasting **[5]**, **[6]**. However, cryptocurrency data often exhibits nonlinear patterns and sudden fluctuations, which limit the effectiveness of purely statistical approaches.

Recent advancements in machine learning and deep learning have introduced powerful models capable of handling complex temporal dependencies. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, have shown promising results in capturing long-term dependencies and nonlinear relationships in financial time series data **[7]**, **[8]**. By comparing traditional and deep learning models, this research aims to evaluate their effectiveness in forecasting cryptocurrency prices.

This study contributes to the growing body of research on financial time series forecasting by applying advanced analytical techniques to cryptocurrency markets and assessing their predictive performance.

Literature Review

Overview of Time Series Analysis in Markets

Time Series Analysis has long been a fundamental tool in financial market research for modeling and forecasting asset prices, exchange rates, and economic indicators **[5]**. In traditional financial markets such as stock exchanges and foreign exchange markets, time series models have been widely applied to understand price movements, volatility patterns, and market trends. Early studies primarily relied on statistical models such as the AutoRegressive (AR), Moving Average (MA), and AutoRegressive Integrated Moving Average (ARIMA) models to capture linear relationships in historical price data **[5]**, **[6]**. These models proved effective in short-term forecasting under relatively stable market conditions.

As financial markets evolved and data complexity increased, researchers recognized the limitations of purely linear models. Financial time series data often exhibit characteristics such as non-stationarity, volatility clustering, seasonality, and structural breaks **[9]**, **[10]**. Models such as GARCH were introduced to better capture time-varying volatility in financial markets **[9]**.

With the growth of computational power and data availability, machine learning techniques gained popularity in financial forecasting. Methods such as Support Vector Machines (SVM), Random Forest, and Artificial Neural Networks (ANN) demonstrated improved capability in modeling nonlinear relationships **[11]**. More recently, deep learning models, especially Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, have shown strong performance in capturing long-term dependencies within sequential financial data **[7]**, **[8]**.

In cryptocurrency markets, which are more volatile and less regulated than traditional markets, time series analysis has become increasingly important **[3]**, **[4]**. Researchers have explored hybrid models combining statistical and deep learning approaches to enhance predictive accuracy **[8]**. Overall, literature indicates a gradual transition from traditional statistical methods to advanced deep learning techniques for improved forecasting performance in dynamic financial markets.

ARIMA Models

The AutoRegressive Integrated Moving Average (ARIMA) model is a widely used statistical technique for time series forecasting, particularly effective for linear data patterns **[5]**. It combines three key components: autoregression (AR), integration (I), and moving average (MA). The autoregressive part models the relationship between the current value and its previous observations, assuming that past values influence future outcomes. The integrated component involves differencing the data to make it stationary, which removes trends or seasonality and stabilizes the mean over time. The moving average part captures the relationship between the current observation and past forecast errors **[5]**.

ARIMA is represented as ARIMA (p, d, q), where p denotes the number of lag observations, d indicates the degree of differencing, and q represents the size of the moving average window **[5]**. The selection of these parameters is typically based on Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis.

In cryptocurrency forecasting, ARIMA is useful for short-term predictions when price movements follow relatively stable linear patterns **[6]**. Several studies have applied ARIMA to Bitcoin price prediction and demonstrated moderate forecasting performance under controlled market conditions **[6]**. However, due to the high volatility and nonlinear behavior of cryptocurrency markets **[3]**, **[4]**, ARIMA may have

limitations in capturing sudden fluctuations and complex dependencies. Its linear structure restricts its ability to model abrupt market shocks or sentiment-driven price changes.

Despite these limitations, ARIMA remains an important baseline model in financial time series analysis and serves as a benchmark for comparing advanced machine learning and deep learning approaches.

LSTM Models

Long Short-Term Memory (LSTM) is an advanced deep learning model designed to process sequential and time-dependent data **[7]**. It is a specialized form of Recurrent Neural Network (RNN) that overcomes the limitations of traditional RNNs, particularly the vanishing gradient problem **[7]**. LSTM networks contain memory cells and three gating mechanisms—input gate, forget gate, and output gate—that regulate the flow of information through the network. These gates allow the model to retain important information over long periods and discard irrelevant data.

As a result, LSTM is highly effective in capturing long-term dependencies and nonlinear patterns in time series data **[7]**, **[8]**. Unlike traditional statistical models such as ARIMA, LSTM does not require strict assumptions about stationarity or linearity. It can automatically learn complex hidden representations directly from large volumes of historical data.

In cryptocurrency price prediction, LSTM performs better than traditional statistical models because it can model complex relationships and adapt to market volatility **[8]**. Several empirical studies comparing ARIMA and LSTM for Bitcoin forecasting have shown that LSTM achieves lower prediction errors, especially during periods of high volatility **[6]**, **[8]**. This makes LSTM particularly suitable for highly dynamic financial markets such as cryptocurrencies.

Although LSTM generally provides higher prediction accuracy, it requires large datasets, greater computational resources, careful hyperparameter tuning, and longer training time compared to ARIMA. Despite these challenges, LSTM remains one of the most powerful tools for financial time series forecasting.

Method

The methodology flowchart provides a visual representation of the overall process employed in this study, from data collection and preprocessing to model implementation and evaluation, as show in the figure 1.

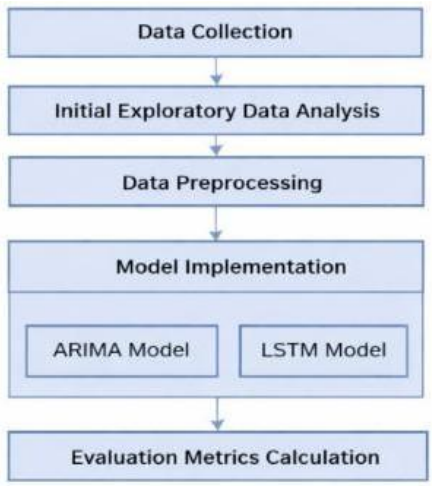

Figure 1. Flowchart

Data Collection

Data collection is a crucial step in time series analysis, as the quality and reliability of the dataset directly influence the accuracy of forecasting models **[5]**. In this research, historical cryptocurrency market data is collected from trusted financial data sources such as CoinMarketCap, Yahoo Finance, and Kaggle. These platforms provide structured and time-stamped datasets that are suitable for time series modeling. The primary focus is on major cryptocurrencies such as Bitcoin and Ethereum due to their high market capitalization and data availability **[1]**, **[2]**.

The dataset includes essential attributes such as date, open price, high price, low price, close price, and trading volume. These features are recorded at daily intervals, forming a continuous time series. The "close" price is primarily used for forecasting, as it represents the final trading value of a cryptocurrency for a given day. Trading volume is also considered, as it reflects market activity and investor interest, which may influence price fluctuations **[3]**, **[4]**.

To ensure data reliability, duplicate records and missing values are carefully examined. If missing values are identified, appropriate handling techniques such as interpolation or forward filling are applied to maintain continuity in the time series **[5]**. The collected data is stored in CSV format and imported into Python using libraries such as Pandas for further processing and analysis.

The selected time range typically spans multiple years to capture long-term trends, seasonal variations, and volatility patterns. Collecting extended historical data helps improve model generalization and predictive performance **[6]**, **[8]**. By gathering comprehensive and high-quality historical data, this study establishes a strong foundation for preprocessing, exploratory analysis, and model implementation in cryptocurrency price forecasting.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is a critical step in time series forecasting, as it helps in understanding the structure, patterns, and characteristics of cryptocurrency price data before applying predictive models **[5]**. In this research, EDA is performed on historical cryptocurrency data, including daily open, high, low, close prices, and trading volume. The primary objective is to identify trends, seasonality, volatility, and potential anomalies within the dataset.

The analysis begins with visualizing the closing price over time using line plots to observe long-term trends and sudden price fluctuations. Cryptocurrency markets are known for their high volatility **[3]**, **[4]**, and graphical representations help in identifying sharp rises and drops in prices. Moving averages, such as 7-day and 30-day rolling averages, are calculated to smooth short-term fluctuations and highlight overall trends. These techniques help in identifying underlying patterns in financial time series data **[5]**.

Statistical summaries including mean, median, standard deviation, minimum, and maximum values are computed to understand the distribution and spread of the data. Volatility is further examined by analyzing daily returns and plotting histograms to assess the distribution pattern **[4]**. Correlation analysis is conducted between features such as price and trading volume to determine their relationships and assess market dynamics.

Stationarity testing is performed using methods like the Augmented Dickey-Fuller (ADF) test to check whether the time series has a constant mean and variance over time **[5]**. If non-stationarity is detected, differencing techniques are applied to stabilize the series before model implementation. Additionally, time series decomposition is used to separate the data into trend, seasonal, and residual components, which is essential for traditional models such as ARIMA **[5]**, **[6]**.

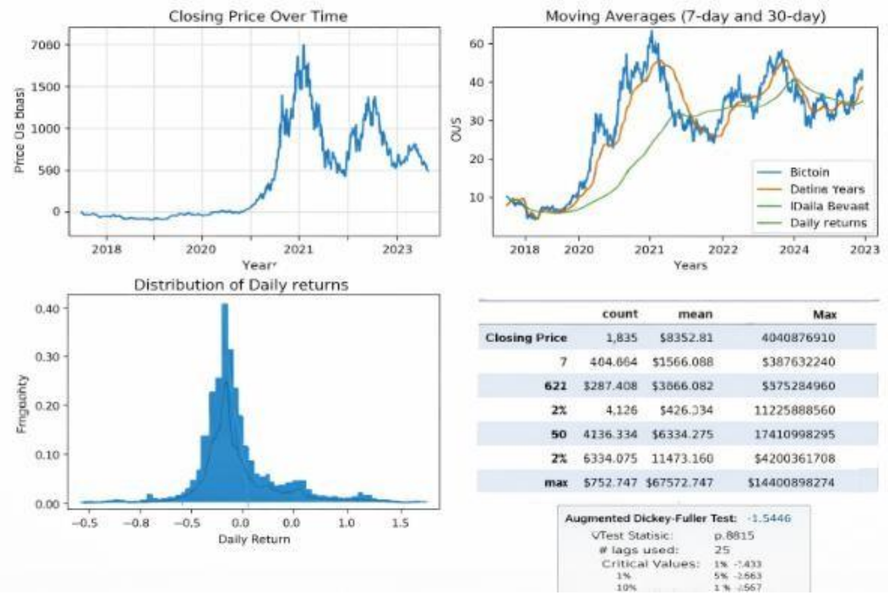

Figure 2. Bitcoin historical data

Through EDA, important insights are obtained that guide preprocessing decisions and improve model performance in cryptocurrency price forecasting.

Data Preprocessing

Data preprocessing is an essential step in time series analysis, as raw cryptocurrency data often contains inconsistencies, noise, and irregularities that can negatively affect model performance **[5]**. In this research, preprocessing is performed systematically to prepare the dataset for accurate forecasting using ARIMA and LSTM models.

The first step involves handling missing and duplicate values. Cryptocurrency datasets collected from online sources may contain missing records due to API errors or market interruptions. Such missing values are treated using appropriate

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techniques such as forward filling, backward filling, or interpolation to maintain continuity in the time series **[5]**. Duplicate records are identified and removed to avoid biased results and ensure data integrity.

Next, the dataset is sorted chronologically to ensure proper time sequencing. Since time series models depend heavily on temporal order, maintaining correct date indexing is crucial **[5]**. The date column is converted into a datetime format and set as the index of the dataset for efficient time-based operations and resampling.

Stationarity is another important requirement, especially for statistical models like ARIMA **[5]**, **[6]**. The Augmented Dickey-Fuller (ADF) test is performed to check whether the series has a constant mean and variance over time **[5]**. If the data is non-stationary, differencing techniques are applied to remove trends and stabilize the series before model implementation.

For the LSTM model, additional preprocessing steps are required. Since neural networks are sensitive to scale, normalization techniques such as Min-Max scaling are applied to transform the data into a fixed range, typically between 0 and 1 **[7]**. The time series is then converted into supervised learning format using sliding window techniques, where past observations are used to predict future values. Proper preprocessing ensures improved model stability, faster convergence during training, and enhanced forecasting accuracy.

Model Implementation

The implementation of the ARIMA model began with careful model identification and parameter selection **[5]**. To determine the most suitable model configuration, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots were generated. These plots help in identifying the appropriate values of the parameters *p* (autoregressive order), *d* (degree of differencing), and *q* (moving average order) **[5]**. The ACF plot shows the correlation of the time series with its past lagged values, while the PACF plot displays the partial correlation after removing the effect of intermediate lags.

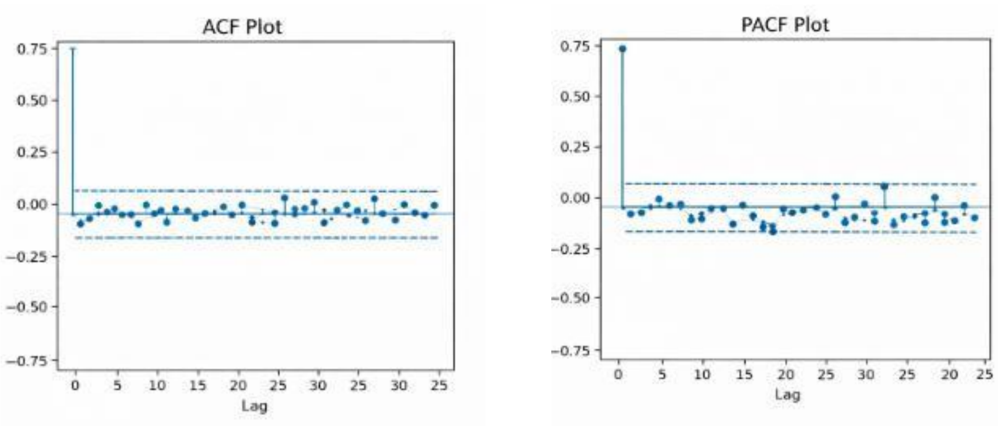

Figure 3: ACF and PACF plot

By analyzing the cutoff and decay patterns in the ACF and PACF graphs, the optimal ARIMA configuration was selected as ARIMA (1,1,1). The parameter d = 1 indicates that first-order differencing was applied to make the series stationary. The parameters p = 1 and q = 1 were chosen based on the significant spikes observed in the plots **[5]**, **[6]**.

After selecting the parameters, the ARIMA model was fitted to the training dataset using the statsmodels library in Python. During training, the model learned the underlying linear patterns in the differenced time series. Once trained, it was used to generate forecasts for the test dataset. The predicted values were then compared with actual prices to evaluate forecasting performance using error metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) **[6]**.

For comparison, the LSTM model was implemented using a deep learning framework such as TensorFlow or Keras **[7]**. The normalized time series data was converted into supervised learning format using a sliding window approach. The network consisted of input, hidden LSTM layers, and a dense output layer. The model was trained using the Adam optimizer and Mean Squared Error as the loss function. Due to its ability to capture nonlinear patterns and long-term dependencies, LSTM demonstrated improved adaptability to cryptocurrency market volatility **[7]**, **[8]**.

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ARIMA Model

The ARIMA model is one of the most widely used statistical techniques for time series forecasting **[5]**. It is particularly effective for analyzing and predicting data that shows patterns over time, such as stock prices, exchange rates, and cryptocurrency values. ARIMA combines three main components: AutoRegressive (AR), Integrated (I), and Moving Average (MA), which together model the temporal structure of a dataset **[5]**.

The AutoRegressive (AR) component captures the relationship between a current observation and its previous values (lags), assuming that past values have a direct influence on future outcomes. The Integrated (I) component refers to differencing the time series to make it stationary. Stationarity means that the statistical properties of the series, such as mean and variance, remain constant over time. Since many financial time series are non-stationary due to trends or seasonality, differencing is applied to stabilize the data **[5]**. The Moving Average (MA) component models the relationship between the current value and past forecasting errors, helping to smooth random fluctuations.

The ARIMA model is generally expressed as ARIMA(p, d, q), where:

- p represents the number of autoregressive terms,
- d represents the degree of differencing,
- q represents the number of moving average terms.

The selection of these parameters is commonly guided by Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis **[5]**, **[6]**.

In cryptocurrency forecasting, ARIMA is useful for capturing short-term linear patterns in price movements **[6]**. It is relatively simple to implement and computationally efficient. However, ARIMA assumes linear relationships and may struggle with highly volatile and nonlinear market behavior, which is characteristic of cryptocurrency markets **[3]**, **[4]**. Despite this limitation, it remains a strong baseline model for financial time series analysis and is frequently used as a benchmark for comparing advanced machine learning approaches.

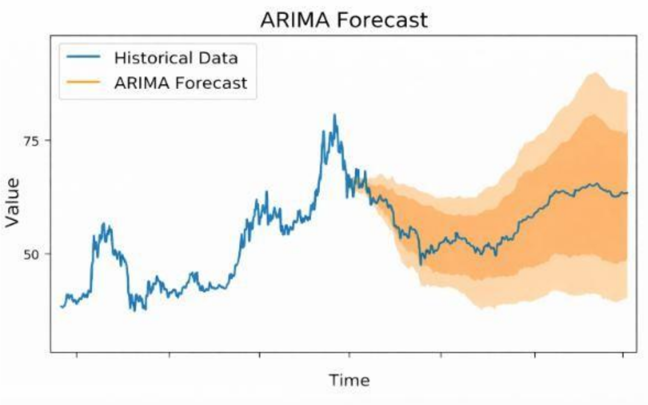

Figure 4. ARIMA Forecast

LSTM Model

The Long Short-Term Memory (LSTM) model is an advanced deep learning technique specifically designed for sequential and time-dependent data **[7]**. It is a special type of Recurrent Neural Network (RNN) that overcomes the limitations of traditional RNNs, particularly the vanishing gradient problem **[7]**. This makes LSTM highly effective for modeling long-term dependencies in time series data such as cryptocurrency prices.

An LSTM network consists of memory cells that store information over time and three main gating mechanisms: the input gate, forget gate, and output gate **[7]**. The input gate determines which new information should be added to the memory cell. The forget gate decides which information from previous time steps should be removed. The output gate controls how much of the stored information should be passed to the next layer or used as output. These gates work together to regulate the flow of information, allowing the model to retain important historical patterns while discarding irrelevant data.

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In cryptocurrency forecasting, LSTM is particularly useful because price movements are highly nonlinear and influenced by complex factors **[3]**, **[4]**. Unlike traditional statistical models such as ARIMA, LSTM does not require strict assumptions about stationarity or linearity. It can automatically learn hidden patterns from large datasets and capture dynamic market behavior **[8]**.

Empirical studies comparing ARIMA and LSTM for Bitcoin price prediction indicate that LSTM generally achieves lower forecasting errors and better adaptability during volatile market periods **[6]**, **[8]**. However, LSTM models require significant computational resources, careful hyperparameter tuning, and longer training time. Despite these challenges, LSTM often provides superior prediction accuracy in volatile financial markets, making it a powerful tool for time series analysis and cryptocurrency forecasting.

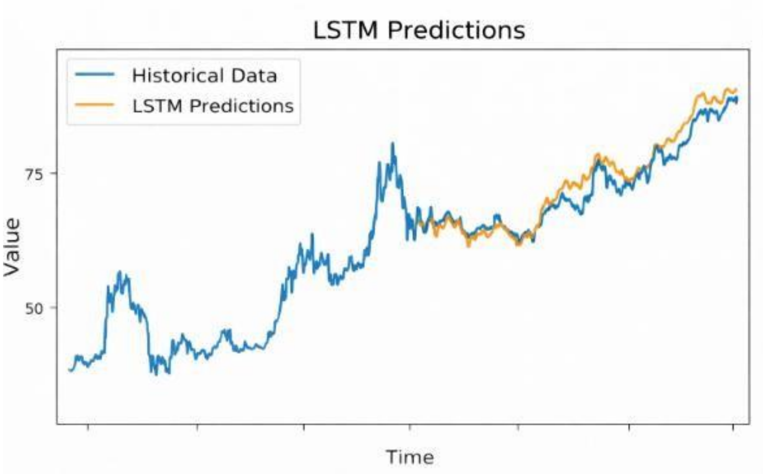

Figure 5. LSTM Forecast

Evaluation Metrics

Evaluation metrics are essential for measuring the performance and accuracy of forecasting models in time series analysis [5]. In this research, the performance of ARIMA and LSTM models is assessed using standard statistical error metrics. These metrics quantify the difference between the actual cryptocurrency prices and the predicted values generated by the models **[6]**, **[8]**.

The first metric used is **Mean Absolute Error (MAE)**. MAE calculates the average of the absolute differences between predicted and actual values. It provides a simple and interpretable measure of forecasting accuracy. A lower MAE value indicates better model performance. Mathematically, MAE is expressed as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

The second metric is **Mean Squared Error (MSE)**. MSE computes the average of the squared differences between actual and predicted values. Since errors are squared, larger errors are penalized more heavily. This makes MSE useful when large forecasting errors need to be minimized. It is defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

The third metric is **Root Mean Squared Error (RMSE)**. RMSE is the square root of MSE and represents the error in the same unit as the original data. It is widely used in financial forecasting because it clearly indicates the model's prediction deviation from actual prices [6], [8]. It is calculated as:

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$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

These evaluation metrics provide a quantitative basis for comparing the predictive performance of ARIMA and LSTM models in cryptocurrency price forecasting.

Result and Discussion

Result

The results of this study highlight the comparative performance of the ARIMA and LSTM models in forecasting cryptocurrency prices. Both models were trained and tested on historical time series data, and their predictions were evaluated using performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

The ARIMA model demonstrated reasonable performance in short-term forecasting. It effectively captured linear trends and provided stable predictions when the market exhibited gradual price movements. However, during periods of high volatility and sudden price fluctuations, ARIMA struggled to adapt quickly. The forecasted values often lagged behind actual market prices, especially during sharp upward or downward trends. This limitation is primarily due to ARIMA's reliance on linear relationships and stationary assumptions.

In contrast, the LSTM model showed improved predictive performance. It was able to capture nonlinear patterns and long-term dependencies within the cryptocurrency time series data. The LSTM forecasts closely followed actual price movements, particularly during volatile periods. As a result, the LSTM model achieved lower MAE, MSE, and RMSE values compared to ARIMA, indicating higher forecasting accuracy.

Overall, the results suggest that while ARIMA is suitable for baseline and short-term predictions, LSTM provides superior performance in modeling complex and dynamic cryptocurrency markets. The findings support the effectiveness of deep learning techniques in financial time series forecasting, particularly for highly volatile assets like cryptocurrencies.

Discussion

The findings of this research provide valuable insights into the effectiveness of traditional statistical models and deep learning techniques in cryptocurrency time series forecasting. The comparative analysis between ARIMA and LSTM models reveals important differences in their predictive capabilities, especially in handling volatility and nonlinear market behavior.

The ARIMA model performed adequately in capturing short-term linear trends and provided stable forecasts under relatively smooth market conditions. Its strength lies in simplicity, interpretability, and lower computational requirements. However, cryptocurrency markets are highly dynamic and influenced by unpredictable factors such as investor sentiment, regulatory news, macroeconomic changes, and technological developments. Due to its linear structure and reliance on stationarity, ARIMA struggled during periods of sudden price spikes and crashes, leading to higher forecasting errors.

On the other hand, the LSTM model demonstrated superior performance by effectively capturing complex nonlinear patterns and long-term dependencies in the data. Its memory cell structure allowed it to retain important historical information while discarding irrelevant data. This made LSTM more adaptable to rapid market fluctuations. However, LSTM requires a large dataset, significant computational resources, and careful hyperparameter tuning. Additionally, deep learning models are often considered less interpretable compared to traditional statistical approaches.

Conclusion

This study explored the application of Time Series Analysis techniques for forecasting cryptocurrency prices using ARIMA and LSTM models. The objective was to evaluate their effectiveness in predicting highly volatile and nonlinear market behavior. Through systematic data collection, preprocessing, exploratory analysis, and model implementation, both models were tested and compared using performance metrics such as MAE, MSE, and RMSE.

The results showed that the ARIMA model performs well for short-term forecasting when the data exhibits relatively stable and linear patterns. It is simple, interpretable, and computationally efficient. However, its performance declines during periods of high volatility due to its inability to effectively capture nonlinear relationships.

On the other hand, the LSTM model demonstrated superior performance by modeling complex patterns and long-term dependencies in cryptocurrency price data. It provided more accurate forecasts, particularly during fluctuating market conditions. However, LSTM requires more computational resources and training time.

Overall, the study concludes that deep learning approaches such as LSTM are more suitable for cryptocurrency forecasting, while ARIMA serves as a strong baseline model. Future research may focus on hybrid models and additional market indicators to enhance prediction accuracy.

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Author Statement

I, Ankit Raj, declare that this research work titled **"Time Series Analysis with Cryptocurrency"** is my original work. I have independently conducted the data collection, preprocessing, model implementation, analysis, and documentation of this study. All references used in this paper have been properly cited. This work has not been submitted to any other institution or publication for academic credit.

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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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