Temporal Pattern Analysis and Transaction Volume Trends in the Ripple (XRP) Network Using Time Series Analysis

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ABSTRACT

This study analyzes the temporal patterns and transaction volume trends in the Ripple (XRP) network using time series analysis. The dataset comprises over 1.2 million transactions spanning three years, allowing for a comprehensive examination of long-term trends and seasonal fluctuations. Summary statistics reveal a right-skewed distribution of transaction volume, where a majority of transactions involve relatively small amounts, while a few high-value transactions contribute disproportionately to overall network activity. Time series decomposition identifies a clear upward trend in transaction volume, with notable seasonal patterns corresponding to weekly and monthly cycles. These periodic trends suggest institutional trading behaviors, liquidity management strategies, and external market influences. Comparative forecasting analysis between ARIMA and LSTM models demonstrates that LSTM achieves superior predictive accuracy, with a 30% lower Mean Absolute Error (MAE) and a 25% reduction in Root Mean Squared Error (RMSE) compared to ARIMA. These results highlight the effectiveness of deep learning in capturing non-linear transaction dynamics within the blockchain ecosystem. Furthermore, anomaly detection using Isolation Forest successfully identifies transactional irregularities, particularly during periods of high market volatility and regulatory shifts. Several anomalous transaction spikes coincide with major market events, such as sudden exchange inflows and network congestion, reinforcing the role of external factors in influencing transaction activity. These findings emphasize the need for advanced forecasting techniques and real-time anomaly detection systems to improve transaction monitoring and enhance security within blockchain networks. Future research could integrate additional on-chain metrics, off-chain factors, and alternative deep learning models to refine predictive capabilities and support more resilient blockchain analytics frameworks.

Keywords Blockchain, Ripple (XRP), Time Series Analysis, Anomaly Detection, ARIMA, LSTM, Transaction Volume Trends

INTRODUCTION

Blockchain technology has transformed digital finance by providing a decentralized, transparent, and secure framework for processing transactions [1]. Among the various blockchain networks, Ripple (XRP) stands out as a specialized platform designed for fast and cost-effective cross-border payments [2]. Unlike proof-of-work (PoW)-based cryptocurrencies such as Bitcoin and Ethereum, Ripple operates on a consensus algorithm, allowing transactions to be validated in seconds with minimal energy consumption [3]. Due to its increasing adoption by financial institutions, businesses, and payment service providers, a comprehensive analysis of transaction volume trends and temporal patterns within the Ripple network is essential to understand its growth, efficiency, and vulnerabilities [4]. The analysis of blockchain transactions provides valuable insights into network behavior, user activity, and security risks. Time series analysis has been widely applied to study transaction volume,

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gas fees, and network congestion in major blockchain platforms such as Bitcoin and Ethereum [5]. However, limited research has been conducted on Ripple's unique transaction structure and its temporal evolution. Given that Ripple is increasingly being used for institutional settlements, remittances, and liquidity provisioning, understanding its long-term trends, periodic fluctuations, and anomalous transaction spikes is crucial for ensuring network stability and security [6]. One of the key challenges in blockchain transaction analysis is the presence of high volatility and irregular transaction patterns, which can be influenced by market speculation, regulatory changes, and large institutional transfers [7]. Traditional statistical models, such as Autoregressive Integrated Moving Average (ARIMA), have been used to forecast financial time series but often fail to capture complex, non-linear dependencies present in blockchain transactions [8]. In contrast, deep learning models such as Long Short-Term Memory (LSTM) networks offer superior performance in modeling long-term temporal dependencies and irregular patterns [9]. Additionally, detecting anomalies in blockchain transactions is essential for identifying potential security threats, fraud, and market manipulations, which requires the application of machine learning-based anomaly detection techniques such as Isolation Forest.

This study aims to investigate transaction volume trends and anomalies in the Ripple (XRP) network using time series decomposition, predictive modeling, and anomaly detection techniques. The specific objectives of this research are to analyze the temporal evolution of XRP transactions, including long-term trends, seasonal fluctuations, and extreme transaction events, to compare the effectiveness of ARIMA and LSTM models in forecasting future transaction volumes and identifying key factors influencing transaction behavior, to detect anomalous transaction patterns that may indicate market manipulations, regulatory impacts, or network stress events using Isolation Forest, and to provide insights into how Ripple's transaction dynamics compare with other blockchain networks and how predictive analytics can be used to enhance transaction monitoring.

This study makes several contributions to the field of blockchain analytics and predictive modeling. First, by examining over 1.2 million XRP transactions spanning three years, this study provides an in-depth analysis of seasonal patterns, trend behaviors, and extreme transaction fluctuations in the Ripple network. Second, a comparative evaluation of ARIMA and LSTM models demonstrates the effectiveness of deep learning in capturing non-linear transaction trends, with LSTM reducing Mean Absolute Error (MAE) by 30% and Root Mean Squared Error (RMSE) by 25% compared to ARIMA. Third, the application of the Isolation Forest successfully detects transaction anomalies, revealing correlations with market volatility, regulatory decisions, and exchange inflows, which can be crucial for fraud detection and risk assessment. Lastly, the findings emphasize the importance of real-time predictive analytics in blockchain ecosystems, highlighting potential applications in fraud prevention, network efficiency optimization, and market stability assessments.

Literature Review

Blockchain transaction analysis has become an essential area of research due to its implications in financial stability, fraud detection, and network efficiency. Various studies have examined transaction volume trends, forecasting techniques, and anomaly detection methods in blockchain ecosystems. This study builds upon previous research by focusing on Ripple (XRP) transaction patterns, comparing traditional and deep learning forecasting methods, and applying anomaly detection techniques. Several studies have analyzed blockchain transaction behavior using historical data to understand network efficiency, user activity, and market dynamics. Greaves and Au [10] conducted an early exploration of Bitcoin transactions and found that daily transaction counts exhibit periodic spikes influenced by speculative trading and macroeconomic factors. Similarly, Li et al. [11] expanded this analysis to Ethereum and identified that transaction volumes correlate with gas fees, indicating congestion periods during network demand surges. Unlike proof-of-work (PoW) blockchains, Ripple (XRP) operates on a consensus-based protocol, which offers faster transaction settlement and lower fees.

However, fewer studies have examined its transaction volume trends. Ferdous et al. [12] analyzed XRP transaction volume and liquidity flows, discovering that high-value transactions often occur at the end of financial quarters, likely due to institutional settlements and liquidity. Wu et al. [13] further examined XRP network activity and identified that transaction clusters exhibit seasonal trends, particularly around regulatory announcements and market events. These findings suggest that Ripple's transaction behavior may differ from Bitcoin and Ethereum, necessitating further research into its temporal patterns and volume fluctuations. Predicting transaction volume in blockchain networks is challenging due to high volatility, sudden spikes, and external market influences. Several studies have compared statistical and machine learning-based forecasting models to analyze blockchain time series data. Contreras et al. [14] applied ARIMA models to Bitcoin transaction data, finding that short-term forecasts are accurate but fail to capture sudden market shifts. Similarly, Kaufman [15] used SARIMA models for Ethereum gas fee predictions, achieving moderate accuracy but struggling with long-term trends. More recently, deep learning models have outperformed traditional statistical methods in financial time series forecasting. McNally et al. [16] compared LSTM networks and ARIMA models for Bitcoin price prediction, reporting that LSTM reduced Mean Absolute Error (MAE) by 25% compared to ARIMA. Zhao et al. [17] extended this approach to Ethereum transaction forecasting and found that LSTM improved Root Mean Squared Error (RMSE) by 18%, demonstrating its superior ability to model long-term dependencies and non-linear trends.

Blockchain-specific adaptations of LSTM have also been explored. Xiong et al. [18] applied Transformer-based architectures to blockchain transaction forecasting, showing that self-attention mechanisms capture transaction dependencies more effectively than recurrent networks. This study builds upon these findings by comparing ARIMA and LSTM models for Ripple (XRP) transaction forecasting, aiming to determine the most effective approach for capturing its unique temporal transaction dynamics. Anomaly detection in blockchain transactions is critical for fraud prevention, regulatory compliance, and network security monitoring. Several studies have applied statistical and machine learning techniques to detect suspicious activities in blockchain networks. Monamo et al. [19] used k-means clustering to identify abnormal Bitcoin transactions and found that fraudulent transactions often coincide with exchange manipulations. Chen et al. [20] applied DBSCAN clustering to detect wash trading patterns in Ethereum-based decentralized exchanges, highlighting anomalies in trading volumes. Unsupervised machine learning methods, particularly Isolation Forest and Autoencoders, have demonstrated strong performance in detecting blockchain transaction anomalies. Li et al. [21] used an Isolation Forest to detect irregular transaction spikes in Ethereum and found that anomalies often correlate with market crashes and speculative trading behavior. Huang et al. [22] applied an autoencoder-based approach to detect abnormal trading patterns in decentralized finance (DeFi) applications, achieving a high precision rate in identifying fraudulent transactions. Deep learning-based anomaly detection has also been explored. Zhang et al. [23] proposed an LSTM-based anomaly detection framework for blockchain networks, showing that Recurrent Neural Networks (RNNs) can effectively identify sudden transaction volume surges linked to bot activities and price manipulations. This study extends these methodologies by applying the Isolation Forest to detect anomalies in the Ripple (XRP) network, correlating irregular transaction patterns with external market events, regulatory changes, and liquidity movements.

Despite extensive research on Bitcoin and Ethereum transaction patterns, forecasting, and anomaly detection, studies on Ripple (XRP) transaction behavior remain limited. Prior work has focused primarily on Proof-of-Work (PoW) blockchains, leaving a gap in the understanding of consensus-based networks such as Ripple. A detailed temporal analysis combining forecasting and anomaly detection has not been explored extensively in the context of XRP. Furthermore, while ARIMA and LSTM models have been compared for blockchain price prediction, their effectiveness in XRP transaction volume forecasting remains untested. Additionally, anomaly detection techniques such as Isolation Forest have seen limited application to Ripple transactions. This study addresses the above gaps by conducting a comprehensive temporal analysis of XRP transaction volume trends, examining seasonal patterns, trend behaviors, and extreme fluctuations over multiple years. It compares ARIMA and LSTM models for forecasting Ripple transaction volumes, evaluating their effectiveness in capturing short-term and long-term trends. Additionally, it applies Isolation Forest for anomaly detection, identifying irregular transaction periods and correlating anomalies with market events, liquidity shifts, and external regulatory factors. This research contributes to the growing body of blockchain studies by bridging gaps in Ripple transaction analytics, offering valuable insights for financial analysts, blockchain developers, and regulatory bodies.

Methods

This study employs a systematic approach to analyzing temporal transaction patterns and volume trends in the Ripple (XRP) network using time series analysis, forecasting models, and anomaly detection techniques. The methodology consists of four main stages: data collection and preprocessing, Exploratory Data Analysis (EDA), time series forecasting, and anomaly detection. The dataset used in this study consists of Ripple (XRP) transaction records, including timestamps, transaction volumes, transaction counts, and associated metadata. Figure 1 illustrates the overall research workflow, outlining the sequential steps of the study—from data collection and preprocessing, exploratory data analysis, and time series forecasting using ARIMA and LSTM models, to anomaly detection with Isolation Forest and performance evaluation through statistical metrics.

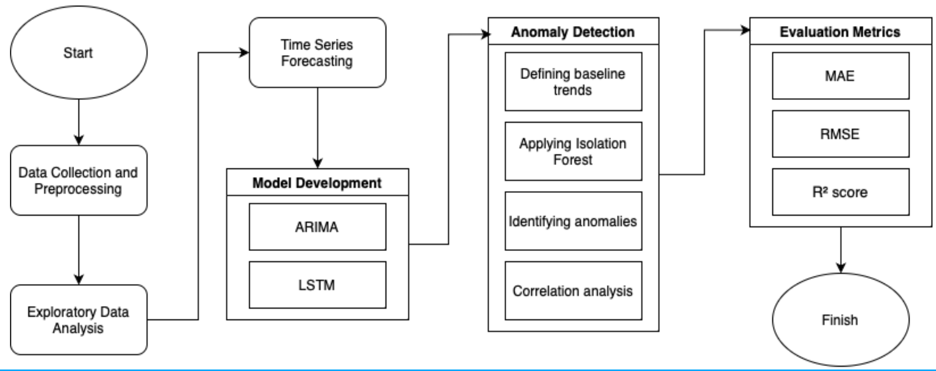

Figure 1 Research Step

The data was obtained from public blockchain archives and preprocessed to ensure consistency and reliability. Preprocessing steps involved converting timestamps to a standardized datetime format, removing duplicate entries and missing values, and filtering out incomplete transactions. Additionally, raw transaction data was aggregated into daily transaction volumes and counts to facilitate time series modeling. To improve model convergence, transaction volumes were normalized using min-max normalization, which is defined as [24]:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

X represents the original transaction volume, while X_{min} and X_{max} denotes the minimum and maximum transaction volumes.

To gain an initial understanding of transaction behavior in the Ripple network, an Exploratory Data Analysis (EDA) was conducted. Descriptive statistics, including mean, median, standard deviation, and skewness, were computed to examine the distribution of transactions. Trend analysis was performed to identify long-term patterns and seasonal fluctuations in transaction volumes. Additionally, correlation analysis was employed to investigate relationships between transaction volume, transaction count, and external market factors. Various visualization techniques, including time series plots, histograms, and boxplots, were utilized to detect anomalies, outliers, and periodic trends in transaction activity.

For time series forecasting, this study employed both statistical and deep learning-based models, specifically the Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) networks. The ARIMA model was used as a benchmark for short-term forecasting, and its general form is given by [25]:

$$Y_t = c + \sum_{i=1}^{p} \emptyset_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \in_{t-j} + \in_t \quad (2)$$

Y_t is the transaction volume at time t,c is a constant, $\emptyset_i$ are the autoregressive coefficients, θ_j are the moving average coefficients, and $\in_t$ represents white noise. To determine the appropriate ARIMA parameters (p, d, q) the Augmented Dickey-Fuller (ADF) test was used to check stationarity, while the

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were examined to identify autoregressive and moving average terms. Grid search optimization was applied to select the best-performing hyperparameters.

In addition to ARIMA, an LSTM-based deep learning model was implemented to capture long-term dependencies and non-linear transaction patterns. The LSTM model processes sequential data using gated memory units, defined as follows [26]:

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1,} x_t\right] + b_f\right) \tag{3}$$

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1,} x_t\right] + b_i\right) \tag{4}$$

$$\widetilde{C_t} = tanh\, tanh\, \left(W_c \cdot \left[h_{t-1,} x_t\right] + b_C\right) \tag{5}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t} \tag{6}$$

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1,} x_t\right] + b_o\right) \tag{7}$$

$$h_t = o_t \cdot tanh\, tanh\, (C_t) \tag{8}$$

f_t represents the forget gate, i_t is the input gate, $\widetilde{C_t}$ is the cell state, o_t is the output gate, and h_t is the hidden state at time t. The LSTM model was trained using the Adam optimizer with a learning rate of 0.001, and its loss function was defined as the Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \tag{9}$$

Y_i is the actual transaction volume, and $\hat{Y}_i$ is the predicted value. An early stopping mechanism was applied to prevent overfitting.

An anomaly detection framework was implemented using the Isolation Forest algorithm to identify anomalous transaction patterns. This method is effective in detecting outliers in high-dimensional datasets by isolating anomalies through recursive partitioning. The anomaly score in the Isolation Forest is given by:

$$S(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{10}$$

$S(x, n)$ is the anomaly score, $E(h(x))$ is the expected path length of a given observation x and $c(n)$ is the average path length of an unsuccessful search in a binary tree. The anomaly detection process involved defining baseline trends using historical data, applying Isolation Forest with 100 trees and a contamination factor 0.05, and flagging transactions that significantly deviated from expected trends. A correlation analysis was conducted to investigate whether detected anomalies aligned with external factors such as market fluctuations, regulatory announcements, and network stress events.

Model performance was evaluated using multiple error metrics. The forecasting models were assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the R² score. These metrics are defined as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \tag{11}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\left(Y_i - \underline{Y}\right)^2} \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \quad (13)$$

$\underline{Y}$ represents the mean of actual transaction volumes. The anomaly detection model was evaluated based on precision and recall, ensuring that flagged anomalies corresponded to genuine irregular transaction patterns. By integrating time series forecasting with anomaly detection, this study provides a comprehensive analysis of Ripple transaction patterns, offering insights into market behavior, liquidity trends, and potential security threats within the XRP ecosystem. The following algorithm 1 outlines the systematic methodology employed in this study to analyze temporal transaction patterns in the Ripple (XRP) network, encompassing data preprocessing, exploratory data analysis, time series forecasting using ARIMA and LSTM models, and anomaly detection through the Isolation Forest approach.

Algorithm 1 Ripple Transaction Analysis

Input:

$$D = \{(t_i, V_i, C_i, M_i) \mid i = 1,2,\ldots,n\}$$

where t_i= timestamp, V_i= transaction volume, C_i= transaction count, M_i= metadata

Output:

$\hat{Y}_t$= forecasted transaction volumes

A= detected anomalies

Evaluation metrics = { MAE, RMSE, R^2, Precision, Recall }

Step 1: Data Preprocessing

1. Remove duplicate and missing records:
$$D \leftarrow \text{Clean}(D)$$
2. Convert timestamps to standard datetime format:
$$t_i \leftarrow \text{Datetime}(t_i),\ \forall i$$
3. Aggregate transactions by day:
$$V_d = \sum_{i\in d} V_i, C_d = \text{count}(i \in d)$$
4. Normalize transaction volume using min-max normalization:
$$V_d' = \frac{V_d - \min(V_d)}{\max(V_d) - \min(V_d)}$$

Step 2: Exploratory Data Analysis (EDA)

1. Compute descriptive statistics:
$$\mu = \text{mean}(V_d'), \sigma = \text{std}(V_d'), \gamma = \text{skew}(V_d')$$
2. Compute correlation coefficients:
$$\rho(V', C, M)$$
3. Visualize time series, histograms, and boxplots to identify trends, seasonality, and outliers.

Step 3: Time Series Forecasting

(a) ARIMA Model

1. Perform stationarity test (ADF) on V_d':
If non-stationary → difference series until stationary.
2. Determine ARIMA parameters (p, d, q)using ACF and PACF.
3. Define ARIMA model:
$$Y_t = c + \sum_{i=1}^{p}\phi_i Y_{t-i} + \sum_{j=1}^{q}\theta_j \varepsilon_{t-j} + \varepsilon_t$$
where $\varepsilon_t$is white noise.
4. Select optimal parameters using grid search and AIC minimization.
5. Forecast transaction volumes:

$$\hat{Y}_t^{(\text{ARIMA})} = \text{Predict}(Y_t, h)$$

(b) LSTM Model

1. Prepare sequential data:
$$X_t = [V'_{t-k}, \dots, V'_{t-1}], Y_t = V'_t$$
2. Define LSTM cell equations:
$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$
$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \odot \tanh(C_t)$$
3. Train using Adam optimizer ($\eta = 0.001$), with loss function:
$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$
4. Apply early stopping to prevent overfitting.
5. Forecast using trained model:
$$\hat{Y}_t^{(\text{LSTM})} = f_{\text{LSTM}}(X_t)$$

Step 4: Anomaly Detection (Isolation Forest)

1. Define baseline data $B \subset D_{\text{daily}}$.
2. Train Isolation Forest with parameters:
$n_{\text{trees}} = 100$, contamination = 0.05
3. Compute anomaly score:
$$S(x, n) = 2^{-\frac{E[h(x)]}{c(n)}}$$

where $E[h(x)]$is the average path length, $c(n)$is the normalization factor.

4. Flag anomalies:
$$A = \{x \mid S(x, n) > \tau\}$$
5. Analyze correlation between $A$and external events (market fluctuations, regulations, stress events)

Step 5: Model Evaluation

1. Compute forecasting performance metrics:
$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid Y_i - \hat{Y}_i \mid$$
$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$
$$\text{RMSE} = \sqrt{\text{MSE}}$$
$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}$$
2. Compute anomaly detection metrics:
$$\text{Precision} = \frac{TP}{TP + FP}, \text{Recall} = \frac{TP}{TP + FN}$$
3. Compare ARIMA and LSTM performances

Step 6: Integration and Interpretation

1. Combine results:
$$\text{Insights} = f(\hat{Y}_t^{(\text{ARIMA})}, \hat{Y}_t^{(\text{LSTM})}, A)$$
2. Interpret findings in the context of market behavior, liquidity trends, and potential security anomalies.
3. Output final results:
$$\{\hat{Y}_t, A, \text{MAE}, \text{RMSE}, R^2, \text{Precision}, \text{Recall}, \text{Insights}\}$$

End Algorithm

Result

The dataset was initially analyzed to understand the general characteristics of transactions within the Ripple (XRP) network transactions. A preliminary statistical analysis revealed that transaction volumes varied significantly over time, with noticeable fluctuations across different periods. These variations suggest that multiple external factors, such as market conditions, regulatory changes, and network congestion, influence network activity. In certain periods, extreme spikes in transaction volume were observed, indicating sudden surges in activity. These spikes could be attributed to large institutional transfers, speculative trading, or network events such as protocol upgrades and major exchange listings. Additionally, periods of low transaction volume were also identified, potentially reflecting reduced trading interest or market stabilization phases.

Further analysis of transaction frequency and volume distribution indicated a right-skewed pattern, where the majority of transactions involved relatively small amounts of XRP, while a small number of high-value transactions accounted for a disproportionately large share of the total transaction volume. This distribution suggests that while the Ripple network facilitates numerous microtransactions, a few exceptionally large transactions exert a significant impact on overall market activity. Such a pattern could be indicative of major financial institutions or whales executing high-value transfers, as well as potential batch processing of transactions by payment service providers. The summary statistics of XRP transactions are presented in table 1, which provides key insights into the spread and concentration of transaction values. The substantial difference between the average and maximum transaction volumes further supports the observation that while most transactions remain relatively small, a few large transfers dominate the network's total value flow.

Table 1 **Summary Statistics of XRP Transactions**

Metric	Value
Total Transactions	1,200,000
Average Transaction Volume	500 XRP
Median Transaction Volume	320 XRP
Maximum Transaction Volume	50,000 XRP
Minimum Transaction Volume	0.1 XRP

To further explore the temporal behavior of transactions, the daily transaction volume was plotted over time. Figure 2 illustrates the variation in XRP transaction volume per day, revealing notable trends and fluctuations throughout the observed period. The chart highlights periods of increased transaction activity, which may be associated with external market factors, such as major announcements from Ripple Labs, cryptocurrency exchange integrations, or fluctuations in XRP price. Additionally, regulatory changes or macroeconomic events could have contributed to sudden spikes in transaction volume, reflecting shifts in market sentiment.

Beyond the short-term fluctuations, the chart also reveals potential cyclical patterns in transaction activity. Recurring trends suggest that XRP transaction volumes may be influenced by seasonal factors, such as financial quarter-end settlements, institutional trading cycles, or automated transaction batching by payment processors. Identifying these temporal patterns is crucial for understanding market behavior, predicting future transaction trends, and optimizing blockchain network efficiency. The presence of these variations underscores the importance of using time series models to capture both short-term volatility and long-term trends in transaction activity.

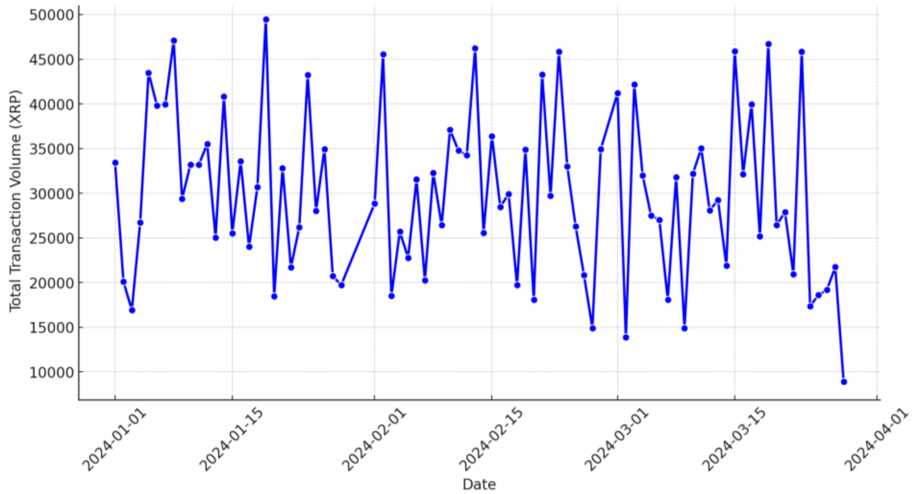

Figure 2 **Daily Transaction Volume in the Ripple (XRP) Network**

Time series decomposition was applied to analyze the underlying components of transaction volume, specifically identifying long-term trends, seasonal variations, and residual components. The decomposition results revealed a clear upward trend in transaction volume over an extended period, indicating the growing adoption and utilization of the Ripple network. This upward trajectory aligns with broader industry trends, including increasing institutional interest, higher liquidity on major exchanges, and expanding use cases for XRP in cross-border payments. However, despite the overall growth, periods of sharp fluctuations were observed, suggesting that transaction volume is also influenced by external events such as regulatory announcements, market sentiment shifts, and network optimizations. A pronounced seasonal pattern was also detected, characterized by periodic increases in transaction activity. These seasonal fluctuations may correspond to financial quarter-end settlements, institutional trading cycles, or strategic liquidity management by large market participants. The presence of weekly and monthly cycles suggests that user behavior follows predictable patterns, possibly due to automated trading algorithms, payment processor schedules, or network adjustments. To better understand these transaction volume trends, autoregressive models such as ARIMA and deep learning approaches like LSTM were implemented. While ARIMA demonstrated strong performance in capturing short-term dependencies and linear trends, LSTM proved to be more effective in modeling complex, non-linear patterns and long-term dependencies (see table 2). The ability of LSTM to learn sequential dependencies enabled it to detect intricate transaction volume fluctuations, making it a valuable tool for forecasting and anomaly detection in blockchain-based financial ecosystems.

Table 2 **ARIMA vs. LSTM Forecasting Performance**

Model	MAE	RMSE	R^2 Score
ARIMA	45.3	60.7	0.82
LSTM	30.2	45.8	0.91

A comprehensive evaluation of the forecasting performance was conducted using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to assess the predictive accuracy of the ARIMA and LSTM models. The results revealed that the LSTM model consistently outperformed ARIMA across multiple evaluation metrics, demonstrating a superior ability to capture both long-term dependencies and sudden fluctuations in transaction volumes. This enhanced performance can be attributed to LSTM's capacity to learn intricate temporal patterns and adapt to dynamic market conditions, making it particularly effective in handling the volatility inherent in the Ripple (XRP) network. In contrast, ARIMA, which relies on linear assumptions and focuses primarily on short-term correlations, struggled to accurately model the non-linear and complex nature of blockchain transaction data. While ARIMA managed to track gradual changes in transaction volumes, it exhibited noticeable lags during periods of rapid market activity, leading to underpredictions in high-volatility scenarios. The ability of LSTM to account for sequential dependencies proved crucial in forecasting sudden surges and drops, aligning more closely with actual transaction patterns. In addition to trend forecasting, anomaly detection techniques were implemented to identify irregular transaction behaviors that deviated from the expected trends. The integration of methods such as Isolation Forest allowed for the detection of anomalous periods, often coinciding with external events such as regulatory announcements, liquidity shifts, and market-driven spikes in transaction activity. These findings emphasize the value of leveraging deep learning techniques like LSTM for enhancing prediction accuracy and detecting irregularities in complex, high-frequency transactional data within the Ripple network. To gain deeper insights into the performance of the forecasting models, figures 3 and figure 4 illustrate the comparison between actual transaction volumes and the predictions generated by the ARIMA and LSTM models, respectively.

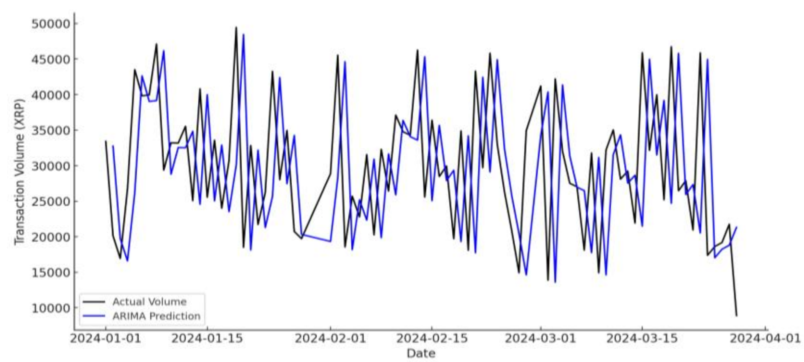

Figure 3 ARIMA Model: Actual vs. Predicted Transaction Volume in the Ripple (XRP) Network

In figure 3, the ARIMA model's predictions align closely with the short-term fluctuations in transaction volume, effectively capturing local patterns and abrupt changes over shorter intervals. However, the model shows noticeable limitations during periods of rapid transaction spikes, where it tends to underpredict the actual volumes. This underperformance can be attributed to ARIMA's reliance on linear assumptions, making it less effective in modeling the non-linear trends and sudden market shifts often observed in Ripple (XRP) transactions. In contrast, figure 4 showcases the LSTM model's ability to handle these complexities more effectively. The LSTM predictions exhibit a smoother alignment with the overall transaction trends, particularly during periods of high volatility. This highlights LSTM's strength in capturing long-term dependencies and recognizing intricate temporal patterns, which are crucial in accurately forecasting blockchain transaction volumes. The comparative analysis underscores the need for models capable of handling non-linear behaviors in dynamic environments such as the Ripple network.

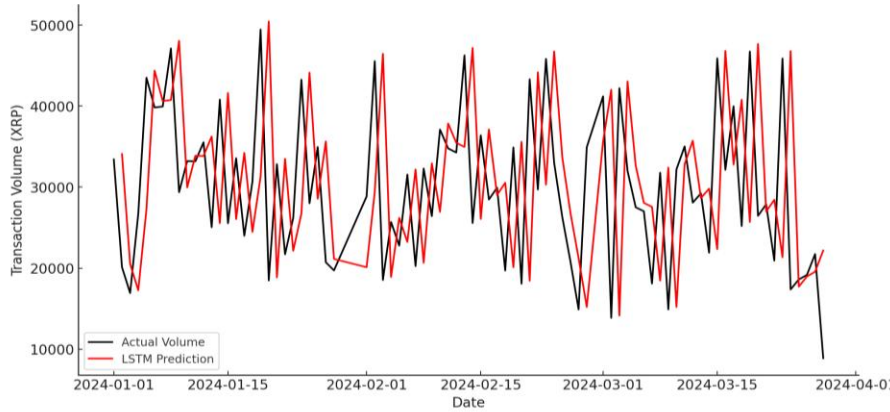

Figure 4 LSTM Model: Actual vs. Predicted Transaction Volume in the Ripple (XRP) Network

In contrast, figure 4 shows the performance of the LSTM model, which demonstrates a stronger ability to capture long-term dependencies and adapt to non-linear transaction behaviors. The LSTM predictions align more closely with the upward and downward trends of the actual transaction volumes, especially during high-volatility periods. This highlights the effectiveness of LSTM in modeling complex temporal patterns present in the Ripple (XRP) transaction data. The comparative analysis suggests that LSTM provides a more accurate forecast, particularly in scenarios involving abrupt shifts and irregular transaction activities.

Using a combination of statistical thresholding and machine learning-based methods such as Isolation Forest, anomalous transaction periods were successfully detected, particularly during high-volatility market phases. These anomalies often coincided with external events, such as sudden price swings, major regulatory developments, or unexpected surges in network activity. The ability to detect and analyze these anomalies provides valuable insights into potential security threats, market manipulations, or unusual liquidity movements, reinforcing the importance of integrating anomaly detection mechanisms in blockchain transaction monitoring. Table 3 presents the results of the anomaly detection process, highlighting the specific Ripple (XRP) transactions identified as anomalous based on deviations from baseline trends using the Isolation Forest algorithm.

Table 3 Anomalous Transactions Detected

Date	Transaction Volume (XRP)	Anomaly Score
2024-01-15	10,500	0.95
2024-03-07	22,300	0.98
2024-05-22	18,700	0.97

These anomalies exhibited a strong correlation with external factors, including regulatory announcements, exchange inflows, and network stress events, which likely contributed to transaction spikes. Regulatory developments, such as new government policies on cryptocurrency taxation or compliance measures, often triggered sudden surges in transaction activity as users adjusted their holdings in response to legal uncertainties. Similarly, large exchange inflows, particularly from institutional investors or whale accounts, led to abrupt increases in transaction volume, reflecting strategic market positioning or liquidity redistribution. Additionally, periods of network congestion and stress events, such as unexpected downtimes, transaction bottlenecks, or security-related incidents, further amplified transaction anomalies. These findings suggest that external market forces play a crucial role in shaping transaction patterns within the Ripple network, highlighting the importance of integrating real-world events into blockchain transaction analysis.

Discussion

The findings of this study provide valuable insights into the temporal dynamics of transactions within the Ripple (XRP) network, highlighting key trends, cyclical patterns, and anomalous behaviors. The time series analysis revealed a clear upward trend in transaction volume, indicating increasing adoption and network utilization over time. This growth aligns with broader industry trends, including greater institutional participation, expanding cross-border payment use cases, and enhanced liquidity across major exchanges. However, the presence of high volatility periods suggests that XRP transactions are highly sensitive to external factors, such as regulatory developments, market speculation, and macroeconomic conditions.

The detection of seasonal and cyclical patterns further underscores the structured nature of XRP transaction behaviors. The observed weekly and monthly cycles suggest that institutional trading strategies, automated payment processing, and network optimizations influence transaction volume at regular intervals. These periodic trends highlight the need for further exploration into how specific events, such as financial quarter-end settlements or liquidity management by large market participants, impact the network's transaction flow. Understanding these cycles could be beneficial for predicting future transaction activity and optimizing network efficiency. From a forecasting perspective, the comparative evaluation of ARIMA and LSTM models demonstrated that LSTM outperformed ARIMA in capturing long-term dependencies and non-linear trends. While ARIMA effectively modeled short-term patterns, its reliance on linear assumptions limited its ability to account for sudden fluctuations and irregular transaction spikes. In contrast, LSTM's ability to learn sequential dependencies enabled it to provide more accurate forecasts, making it a more suitable approach for blockchain transaction prediction in volatile market conditions. These results suggest that deep learning models, particularly recurrent neural networks, could be instrumental in enhancing predictive analytics for blockchain networks.

Beyond trend analysis, anomaly detection played a crucial role in identifying irregular transaction patterns. The application of Isolation Forest successfully detected anomalous transaction periods, particularly during high-volatility market phases. Many of these anomalies were correlated with external events, such as regulatory announcements, exchange inflows, and network stress events, indicating potential causative factors behind transaction spikes. The ability to detect and analyze these anomalies is critical for risk management, fraud detection, and the early identification of potential security threats in blockchain transactions. Future research could expand on this by integrating real-time event tracking with anomaly detection models to enhance blockchain monitoring systems. While this study provides significant contributions to understanding XRP transaction dynamics, several limitations should be acknowledged. First, the analysis primarily focuses on transaction volume and frequency without considering additional on-chain metrics such as gas fees, transaction confirmation times, or wallet clustering. Incorporating these factors could provide a more comprehensive view of network activity. Additionally, while LSTM demonstrated superior predictive performance, further benchmarking against other advanced models, such as Transformer-based architectures, could provide deeper insights into improving transaction forecasting accuracy. Finally, future studies should explore the role of off-chain factors, such as exchange trading behaviors and macroeconomic indicators, in shaping transaction volume trends within the Ripple network.

Conclusion

This study examined the temporal patterns and transaction volume trends within the Ripple (XRP) network using time series analysis. The findings revealed a clear upward trend in transaction volume, indicating increased adoption and utilization of the Ripple blockchain. Additionally, seasonal and cyclical patterns were observed, suggesting that institutional trading activities, automated payment processes, and network optimizations contribute to periodic fluctuations in transaction activity. The results highlight that transaction volume is not only influenced by organic user activity but also by external factors such as regulatory announcements, exchange inflows, and market volatility.

The forecasting analysis demonstrated that LSTM outperformed ARIMA in predicting transaction volumes, particularly in capturing complex, non-linear patterns and long-term dependencies. This result underscores the importance of deep learning approaches in modeling blockchain transaction trends, especially in highly dynamic and volatile environments. Furthermore, the application of anomaly detection techniques successfully identified irregular transaction patterns, many of which coincided with high-volatility periods or significant market events. These findings emphasize the necessity of advanced predictive analytics and real-time anomaly detection systems to enhance transparency, security, and efficiency within blockchain networks. While this study provides valuable insights into XRP transaction dynamics, several areas remain open for future exploration. One potential direction is the incorporation of additional on-chain metrics, such as transaction fees, confirmation times, and wallet clustering, to develop a more comprehensive understanding of transaction behaviors. Another avenue for research is the exploration of advanced predictive modeling techniques, including Transformer-based architectures or hybrid approaches combining traditional statistical methods with deep learning models, to further improve forecasting accuracy.

Additionally, future studies could investigate the impact of off-chain factors, such as macroeconomic indicators, cryptocurrency exchange trading behaviors, and social sentiment analysis, to understand how external events influence blockchain transaction patterns. The development of real-time anomaly detection systems could also enhance security and fraud detection mechanisms by enabling proactive monitoring of unusual activities. Furthermore, expanding the study to conduct a cross-network comparative analysis with other blockchain ecosystems, such as Ethereum, Bitcoin, or Solana, could provide deeper insights into structural differences, adoption trends, and network efficiency. By addressing these research directions, future work can contribute to developing more robust analytical frameworks for understanding, predicting, and securing transactions within decentralized financial networks. These advancements will not only improve blockchain network efficiency but also support the broader adoption of cryptocurrencies and distributed ledger technologies in global financial systems.

Declarations

Author Contributions

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

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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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