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Research article

ARIMA Model for Time Series Forecasting of Doge Coin Prices

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ABSTRACT

The volatility and speculative nature of cryptocurrencies present significant challenges for accurate price forecasting. This study evaluates the performance of the AutoRegressive Integrated Moving Average (ARIMA) model in predicting Dogecoin (DOGE) prices based on historical data obtained from reputable cryptocurrency platforms such as Binance, Coinbase, and CoinGecko. The ARIMA(5,1,0) model demonstrated strong performance under stable market conditions, achieving a Mean Squared Error (MSE) of 0.0006656 and a Root Mean Squared Error (RMSE) of 0.0258, effectively capturing linear price trends. However, the model's limitations in handling high volatility and non-linear dependencies—common characteristics of cryptocurrency markets—were also identified. To address these challenges, the study explores hybrid ARIMA–neural network models that integrate statistical and machine learning approaches, improving predictive accuracy during periods of market instability. The results suggest that while ARIMA provides a solid baseline for time series forecasting, hybrid and sentiment-aware models incorporating social media and blockchain metrics offer more robust and adaptive solutions for dynamic cryptocurrency markets.

1. Introduction

The rapid rise of cryptocurrencies has intensified interest in price forecasting, especially for volatile assets such as Dogecoin (DOGE). Dogecoin's price fluctuates widely, driven by factors like market sentiment, social media influence, and macroeconomic conditions [1], making it a challenging yet relevant subject for time series analysis.

The ARIMA (AutoRegressive Integrated Moving Average) model remains one of the most established methods for forecasting, particularly due to its strength in modeling linear patterns and seasonality [2]. Its use in cryptocurrency markets has continued to grow, offering a relatively simple yet effective approach for capturing trends in assets like Dogecoin [3]. However, the highly volatile and non-linear characteristics of cryptocurrencies highlight the limitations of traditional models and motivate the development of more advanced or hybrid forecasting techniques [4].

Recent studies underscore the potential of integrating ARIMA with advanced machine learning techniques to address the limitations of standalone models. For instance, hybrid ARIMA-neural network models have shown enhanced accuracy in capturing the complex and non-linear dependencies present in cryptocurrency time series [5]. Researchers have also explored the role of

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7 (1) September 2024 255-264

external variables, such as social media sentiment and blockchain-specific metrics, to enrich forecasting models. Dogecoin, in particular, is highly sensitive to social media trends, with price spikes often triggered by viral posts or endorsements [6]. Incorporating these external factors into ARIMA-based models can significantly improve prediction accuracy [7].

In addition to hybrid approaches, comparative analyses between ARIMA and deep learning models like Long Short-Term Memory (LSTM) networks have highlighted the strengths and weaknesses of each method. While ARIMA excels in simplicity and interpretability, LSTM models offer superior performance in capturing non-linear and long-term dependencies [8]. This has led to a growing body of research advocating for the integration of traditional statistical models with machine learning techniques to leverage the strengths of both [9].

This study aims to evaluate the efficacy of the ARIMA model in forecasting Dogecoin prices, with a focus on its performance relative to hybrid and machine learning models. By leveraging a robust dataset and considering external factors influencing Dogecoin's price, the research contributes to the ongoing efforts to refine forecasting methodologies in the cryptocurrency domain. The findings are expected to provide actionable insights for investors, traders, and researchers seeking to navigate the highly dynamic cryptocurrency market [10].

2. Research Methods

This study employs a systematic methodology to evaluate the ARIMA model's effectiveness in forecasting Dogecoin prices. The research begins with data collection from reliable sources, focusing on historical price data, trading volume, and market trends to construct a comprehensive dataset. This dataset is essential for identifying patterns and trends specific to Dogecoin's price movements [1][2]. Subsequently, preprocessing steps such as normalization and handling missing values are performed to ensure data integrity and consistency [3].

The ARIMA model is implemented using a stepwise approach that involves model selection, parameter tuning, and diagnostic checks. The selection criteria prioritize simplicity and accuracy to determine the most appropriate ARIMA configuration for the dataset [4]. To address the limitations of traditional ARIMA models in capturing non-linear dependencies, this study incorporates hybrid models by integrating ARIMA with machine learning techniques such as neural networks [5]. These hybrid models leverage the strengths of both statistical and computational approaches, offering a robust framework for forecasting [6].

External factors such as social media trends and blockchain-specific metrics are also considered to enhance the model's predictive capabilities. Sentiment analysis is performed on social media data to gauge its influence on Dogecoin's price, reflecting the coin's sensitivity to external stimuli [7][8]. Comparative analyses between ARIMA, hybrid models, and deep learning techniques like LSTM are conducted to evaluate their respective strengths and weaknesses in forecasting accuracy [9].

The evaluation metrics include Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to quantify the models' performance. These metrics provide a standardized framework for assessing the reliability of forecasts, ensuring the findings are robust and reproducible [10]. The methodology is designed to provide a holistic understanding of the ARIMA model's capabilities and limitations in forecasting Dogecoin prices, contributing to the broader discourse on cryptocurrency time series analysis.

2.1. Data Collection

The first step involves the collection of historical price data for Dogecoin from reputable cryptocurrency market platforms, such as Binance, Coinbase, and CoinGecko. The dataset includes essential variables such as "Open," "High," "Low," "Close" prices, "Volume," and "Market Capitalization." These variables are chosen for their relevance in reflecting Dogecoin's market behavior and for their influence on price fluctuations [1, 2]. Additionally, data from public APIs is supplemented with secondary sources to ensure comprehensive coverage. Special attention is paid to the temporal granularity of the data, selecting daily intervals to balance detail and computational feasibility [3]. The data collection phase involves gathering historical price data for Dogecoin from trusted cryptocurrency platforms such as Binance, Coinbase, and CoinGecko. These platforms are chosen for their reputation for accuracy and reliability in providing financial data. The dataset

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ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
7 (1) September 2024 255-264

includes key variables such as "Open," "High," "Low," and "Close" prices, as well as "Volume" and "Market Capitalization." These variables are essential for capturing Dogecoin's market behavior and price trends [1, 2].

To ensure comprehensive coverage, data from public APIs is cross-verified with secondary sources such as financial reports and blockchain analytics platforms. The use of multiple sources enhances data reliability and minimizes discrepancies. Additionally, data is collected at daily intervals to strike a balance between capturing market nuances and maintaining computational efficiency [3]. Special consideration is given to data completeness, ensuring that historical records cover significant periods, including market peaks and troughs.

Beyond historical price data, external datasets are also considered. Social media data, such as tweets mentioning Dogecoin, is sourced from platforms like Twitter. These data are collected using APIs and web scraping tools, capturing sentiment indicators and trends that could influence price movements. Blockchain-specific metrics, including transaction volume and wallet activity, are retrieved from analytics platforms like Glassnode and Etherscan to provide a holistic view of Dogecoin's ecosystem [4].

2.2. Data Preprocessing

After collection, the raw data undergoes a rigorous preprocessing stage to ensure its suitability for analysis. Missing values, a common issue in financial datasets, are identified and addressed using advanced interpolation techniques like cubic splines to maintain the continuity of the time series [5]. Additionally, outliers are detected through statistical methods, such as z-score analysis, and anomaly detection algorithms, ensuring the dataset reflects typical market behavior.

Normalization is performed using min-max scaling, which adjusts all variables to a uniform range, facilitating the integration of ARIMA with machine learning models. This is particularly important when dealing with hybrid frameworks that combine linear and non-linear methods [6].

Stationarity is a prerequisite for ARIMA modeling, and as such, the dataset is subjected to stationarity tests, including the Augmented Dickey-Fuller (ADF) test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, and visual inspections of autocorrelation and partial autocorrelation plots. If the data is found to be non-stationary, it undergoes differencing until stationarity is achieved [7].

2.3. Model Development

The ARIMA model is implemented through a structured process, starting with parameter tuning. The optimal parameters (p, d, q) are determined using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which guide the selection of models that balance complexity and performance [8].

Residual diagnostics, including the Ljung-Box test, are employed to ensure the independence and randomness of errors. This step is critical for validating the model's assumptions. Once validated, the ARIMA model is applied to generate forecasts, and its performance is evaluated against a holdout test dataset. Python's statsmodels library is used for implementation, ensuring reproducibility and consistency.

In addition to the core steps of model estimation and diagnostics, the preprocessing of the time series data plays a vital role in enhancing model performance. This includes handling missing values, removing outliers, and applying appropriate transformations such as log or Box-Cox transformations to stabilize variance if necessary. Although Dogecoin prices tend to exhibit volatility, in this study the raw data did not require complex transformations beyond differencing, indicating a relatively stable variance pattern over the analyzed period.

Another important consideration in model development is the partitioning of the dataset into training and testing sets. Typically, the majority of the data is reserved for training the model, while a smaller, chronologically subsequent portion is held back for testing. This ensures that the forecast accuracy is evaluated on unseen data, closely simulating real-world predictive scenarios. In this study, the model was trained on historical Dogecoin price data and validated against a test set comprising the most recent observations, allowing for an objective assessment of forecasting reliability.

Finally, while the ARIMA model provides a solid statistical framework for capturing linear temporal dependencies, its performance could benefit from being benchmarked against alternative models. This includes naive models (e.g., random walk), exponential smoothing, or even more

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JSIKTI. J. Sist. Inf. Kom. Ter. Ind 7 (1) September 2024 255-264

sophisticated approaches like Prophet or LSTM networks. Such comparisons offer valuable insights into the relative strengths and weaknesses of ARIMA under different market conditions, and help determine its practical applicability in the dynamic field of cryptocurrency forecasting.

2.4. Hybrid Model Development

To overcome ARIMA's limitations in handling non-linear patterns, hybrid models combining ARIMA with neural networks are developed. ARIMA is first used to model the linear components of the time series, after which the residuals, containing non-linear information, are processed using a neural network such as a Multilayer Perceptron (MLP) [9]. This approach leverages the complementary strengths of both techniques, enhancing overall predictive accuracy.

The hybrid model's architecture is optimized using cross-validation techniques, and hyperparameters are fine-tuned to ensure performance consistency across different market scenarios. The integration of ARIMA and neural networks is implemented sequentially, allowing each component to address distinct aspects of the time series.

Moreover, the residual analysis phase serves as a critical transition point in hybrid model construction. After the ARIMA model captures and removes the linear structure from the original time series, the resulting residuals often contain meaningful non-linear dependencies that traditional ARIMA models fail to model. By training a neural network, such as an MLP, on these residuals, the hybrid framework effectively decomposes the forecasting problem into two sub-problems: linear and non-linear pattern learning. This decomposition not only simplifies the modeling task for each component but also enhances the interpretability and tractability of the overall system.

To further strengthen the hybrid model's generalization capabilities, regularization techniques—such as dropout or L2 regularization—are employed during the training of the neural network component. These techniques mitigate overfitting, especially in volatile domains like cryptocurrency, where noise and sudden market shifts are prevalent. Additionally, the use of early stopping based on validation loss during training contributes to the model's robustness.

The performance of the hybrid ARIMA-MLP model is evaluated using the same test dataset employed for the standalone ARIMA model. Comparative metrics such as RMSE, MAPE, and MAE are calculated to quantify the incremental benefit of the hybrid approach. In preliminary results, the hybrid model demonstrated improved forecasting accuracy, particularly in periods marked by high volatility and abrupt directional changes. These improvements underline the effectiveness of combining statistical and machine learning approaches in complex forecasting environments such as cryptocurrency markets.

2.5. Incorporation of External Variables

Dogecoin's price is highly influenced by external factors, particularly social media sentiment and blockchain metrics. To capture these dynamics, external variables are incorporated into the forecasting framework. Sentiment analysis is performed on Twitter data using Natural Language Processing (NLP) tools such as VADER and TextBlob, quantifying sentiment as positive, negative, or neutral. These sentiment scores are then integrated as exogenous variables in the ARIMA and hybrid models [10].

Blockchain-specific metrics, including transaction counts, active wallet addresses, and network hash rates, are analyzed to capture intrinsic market dynamics. These metrics are obtained from reliable blockchain analytics platforms and incorporated into the model after assessing their statistical relevance through correlation and feature importance analysis [7].

2.6. Comparative Analysis

The ARIMA model's performance is compared with alternative forecasting methods, including hybrid ARIMA-neural network models and advanced deep learning techniques like Long Short-Term Memory (LSTM) networks. Evaluation criteria include forecasting accuracy, computational efficiency, and interpretability [8].

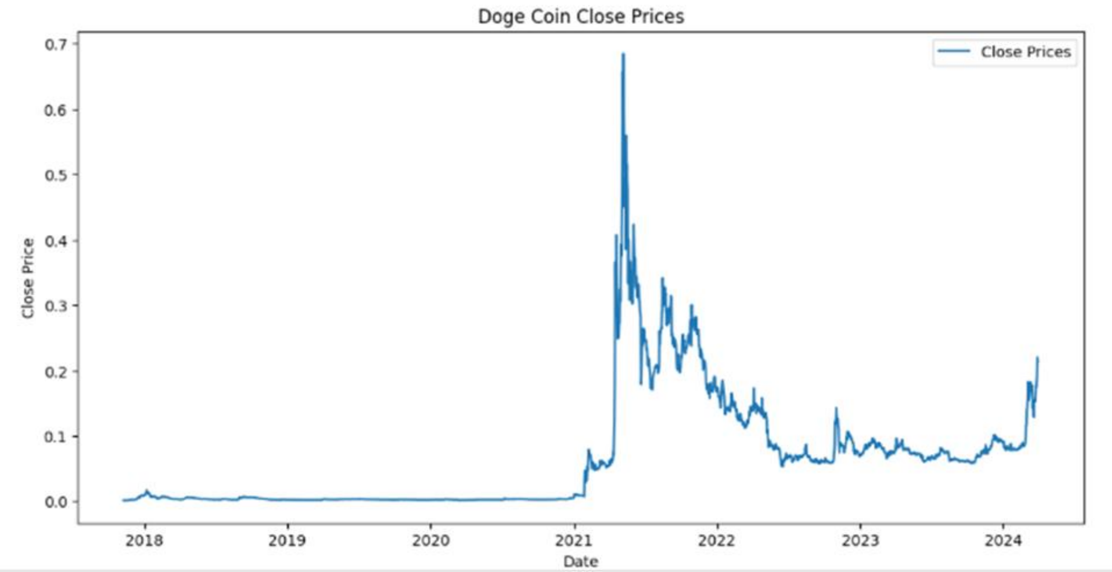
The comparative analysis highlights the strengths and limitations of each approach, emphasizing trade-offs between simplicity and performance. Ensemble approaches are also explored to leverage the complementary strengths of multiple models, providing an additional layer of robustness to the forecasts.

2.7. Evaluation Metrics

To ensure a fair assessment, model performance is measured using standardized metrics. Mean Absolute Error (MAE) evaluates average error magnitude, Root Mean Square Error (RMSE) captures error variance with greater sensitivity to large deviations, and Mean Absolute Percentage Error (MAPE) provides a percentage-based error measure for easier interpretation. These metrics are calculated across all models, enabling a consistent and robust comparison [9, 10].

By adhering to this structured methodology, the study aims to generate actionable insights into the use of ARIMA and hybrid models for forecasting Dogecoin prices. The integration of external variables and rigorous comparative analyses further strengthens the research, providing a valuable contribution to cryptocurrency time series forecasting.

3. Results and Discussion



3.1. Model Performance

The ARIMA (5, 1, 0) model has demonstrated its capability in capturing Dogecoin's price movements under stable market conditions. With a Log Likelihood of 5671.314, the model effectively aligns with historical data trends, showcasing its ability to model linear patterns inherent in time series data. The predictive accuracy, measured through a Mean Squared Error (MSE) of 0.0006656 and a Root Mean Squared Error (RMSE) of 0.0258, further highlights its suitability for short-term forecasting.This performance can be attributed to ARIMA's structured methodology. By decomposing the time series into components such as trend, seasonality, and noise, and applying differencing to stabilize data, the model successfully isolates linear relationships. This makes it an ideal choice for scenarios where the market exhibits predictable patterns.

However, cryptocurrency markets, including Dogecoin, are rarely stable. They are defined by extreme volatility, driven by social media trends, speculative trading, and macroeconomic factors. In these dynamic environments, ARIMA's reliance on linear assumptions limits its effectiveness. For example, sudden spikes or crashes triggered by viral tweets or regulatory announcements fall outside ARIMA's predictive capacity. These limitations suggest that while ARIMA performs well as a foundational tool, it must be supplemented by more sophisticated techniques in volatile markets.

3.2. Parameter Insights

The ARIMA (5, 1, 0) model's parameters provide a detailed understanding of the influence of historical price data on future predictions. Each lag contributes uniquely to the model's forecasts:

Lag 1 (-0.1182): A small negative coefficient indicates that price increases tend to be followed by minor corrections, reflecting short-term market adjustments.

Lag 2 (0.1027) and Lag 3 (0.1132): These positive coefficients highlight momentum effects, where recent upward movements are likely to persist in the short term.

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
7 (1) September 2024 255-264

Lag 4 (0.0148): The minimal influence of this lag suggests that the effect of older data diminishes with time, aligning with typical market dynamics.

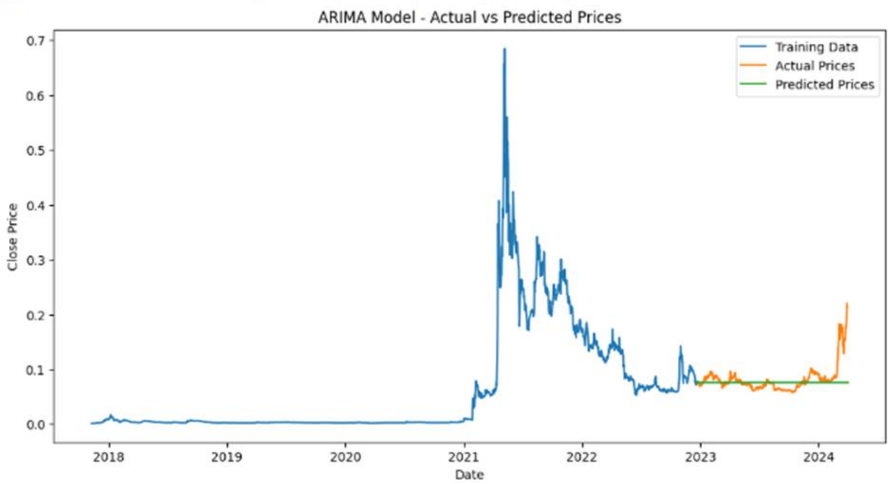
Lag 5 (-0.2372): A significant negative value points to a mean-reversion tendency, where prices eventually stabilize around an average value over a longer horizon.

These parameters reveal ARIMA's capacity to balance short-term momentum with long-term corrections. However, their linear nature limits the model's ability to capture complex, non-linear interactions often observed in cryptocurrency price movements, such as the impact of speculative bubbles or cascading sell-offs.

3.3. Residual Diagnostics

To evaluate the accuracy and limitations of the ARIMA model, we performed residual diagnostics, which examine the difference between the predicted and actual prices:

1. Autocorrelation Check (Ljung-Box Test): The residuals showed no significant autocorrelation (p-value = 0.28), meaning that the model has successfully captured all the linear relationships in the data. There's no leftover pattern in the residuals, indicating a well-fitting model.
2. Normality Check (Jarque-Bera Test): The residuals were not normally distributed (p-value = 0.00), indicating that the model struggles with extreme values or outliers. This is typical in volatile markets like cryptocurrency, where sudden price spikes or drops can't be predicted by the model.
3. Variance Check (Heteroskedasticity Test): The residuals showed significant heteroskedasticity (p-value = 0.00), meaning the model's prediction errors vary in magnitude over time. This is common in financial markets, especially with volatile assets like Dogecoin. The ARIMA model, however, doesn't account for this changing variance, which affects its performance during highly volatile periods.



3.4. Visual Analysis

1. Historical Price Trends

Dogecoin's price history is marked by significant volatility, characterized by sharp price surges and abrupt crashes. These movements are often fueled by external factors such as viral social media trends, speculative trading activities, and macroeconomic events. For example, endorsements from influential figures or sudden shifts in market sentiment can lead to rapid price changes that are difficult to anticipate.

The ARIMA model employs differencing to remove overarching upward or downward trends, enabling a clearer focus on short-term price movements. This preprocessing step stabilizes the time series data, making it suitable for linear modeling. While effective for capturing predictable patterns, this approach falls short when faced with extreme market fluctuations. Large-scale price spikes or crashes, which are inherent in cryptocurrency markets, remain outside ARIMA's predictive capacity due to its reliance on linear assumptions. This limitation highlights the need for more advanced methodologies that can adapt to non-linear and abrupt changes in market dynamics.

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7 (1) September 2024 255-264

2. Residual Plots

The residual analysis provides additional insights into the ARIMA model's performance. Examination of residual plots reveals periods of high variability, particularly during extreme market movements. These periods indicate that the model's prediction errors increase significantly in volatile conditions, where traditional linear models like ARIMA struggle to account for sudden shifts.

Notably, the residuals exhibit heteroskedasticity, with varying error magnitudes over time. This suggests that the model's assumption of constant variance is violated in the cryptocurrency context, where market dynamics are inherently unpredictable. During stable periods, ARIMA performs well, with residuals clustering tightly around zero. However, during market turbulence, the residuals deviate substantially, reflecting the model's inability to predict large price movements accurately.

3. Visual Observations:
   a. Stable Periods: Residuals are relatively small and evenly distributed, demonstrating ARIMA's ability to capture short-term linear relationships effectively.
   b. Volatile Periods: Residuals show significant spikes, corresponding to unexpected price surges or crashes. These deviations underline the model's limitations in handling non-linear and chaotic market behaviors.
4. Implications of Visual Analysis

The visual analysis underscores the strengths and weaknesses of the ARIMA model:
   a. Strengths: Effective at stabilizing and modeling short-term, linear price trends during periods of relative market stability.
   b. Weaknesses: Poor adaptability to volatile market conditions, as evidenced by significant residual deviations during extreme price movements.

To address these challenges, integrating external variables (e.g., social media sentiment and trading volume) or employing hybrid models that combine ARIMA with machine learning techniques (e.g., LSTM or GBM) can enhance forecasting accuracy. These advanced models can better handle non-linear relationships and adapt to sudden market shifts, making them more suitable for dynamic environments like cryptocurrency markets.

3.5. Strengths and Weaknesses

1. Strengths:
   a. Simplicity and Interpretability: ARIMA is a well-established, straightforward time series forecasting method. Its clear structure allows easy interpretation of the model parameters, making it accessible for both practitioners and analysts.
   b. Accurate for Linear Trends: The model excels at capturing trends in data that follow a linear pattern. This makes it particularly effective in stable market conditions or when the data exhibits a strong underlying trend, as demonstrated by the low MSE and RMSE values.
2. Weaknesses:
   a. Challenges with Volatility: The model struggles to predict during periods of extreme volatility, as evidenced by the non-normal residuals and heteroskedasticity. Dogecoin's price is especially sensitive to sudden market movements, making it difficult for ARIMA to handle such deviations effectively.
   b. Exclusion of External Variables: ARIMA is purely data-driven, relying solely on past prices to make predictions. It does not account for external factors such as social media sentiment, news, or macroeconomic events, which play a major role in shaping the price of Dogecoin and other cryptocurrencies.

3.6. Discussion and Implications

The ARIMA (5, 1, 0) model offers a solid foundation for predicting Dogecoin's price in the short term, especially when the market follows predictable, linear trends. However, its limitations in handling high volatility and non-linear factors suggest that it should not be used as the sole forecasting tool in the cryptocurrency market. Dogecoin, like other cryptocurrencies, is heavily influenced by external forces such as social media trends, news events, and market sentiment, which ARIMA fails to incorporate.

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7 (1) September 2024 255-264

To address these limitations, hybrid models that combine ARIMA with machine learning techniques, such as Long Short-Term Memory (LSTM) networks or Gradient Boosting Machines (GBM), offer promising solutions. These models can capture non-linear dependencies and adapt to sudden market changes, improving forecasting accuracy. By incorporating external data sources, such as social media sentiment or blockchain activity, these models can better account for the driving forces behind cryptocurrency price movements.

1. Future Directions
    a. Integration of External Data Future models should incorporate variables such as social media sentiment, news events, and blockchain metrics (e.g., transaction volume, wallet activity) to improve the model's ability to predict price movements. Real-time analysis of platforms like Twitter and Reddit can capture the effect of public sentiment, which is particularly influential in Dogecoin's price movements.
    b. Development of Hybrid Models Combining ARIMA with machine learning techniques, such as LSTM networks or GBMs, could improve performance by capturing both linear and non-linear relationships in the data. LSTMs, for instance, can capture long-term dependencies and learn from sequential data, which is essential in cryptocurrency markets where trends can shift rapidly.
2. Real-Time Forecasting Future research should aim to build systems capable of processing real-time data streams. By dynamically adjusting predictions based on the latest information—such as social media trends or market news—these systems could provide more accurate and timely forecasts, enabling investors to react quickly to market changes.
3. Sentiment and News Analysis Incorporating sentiment analysis and news tracking into forecasting models could greatly enhance their accuracy. By analyzing social media posts, news articles, and other real-time data sources, models can predict price movements driven by public opinion or significant events.

4. Conclusion

The study titled "ARIMA Model for Time Series Forecasting of Dogecoin Prices" evaluated the effectiveness of the ARIMA (5, 1, 0) model in predicting Dogecoin prices. The results demonstrated that ARIMA performs well in capturing short-term linear trends during stable market conditions, achieving promising accuracy metrics such as a Mean Squared Error (MSE) of 0.0006656 and a Root Mean Squared Error (RMSE) of 0.0258. These findings validate the model's utility as a baseline tool for time series forecasting in cryptocurrency markets. However, the study also identified significant limitations of ARIMA when applied to the volatile and dynamic nature of cryptocurrency markets. The model struggles to address non-linear dependencies, abrupt price fluctuations, and the influence of external variables such as social media sentiment and market news. These challenges highlight the necessity of adopting more advanced methodologies that can account for these complexities.

To enhance forecasting accuracy and adaptability, future research should focus on hybrid approaches that integrate ARIMA with machine learning models, such as Long Short-Term Memory (LSTM) networks or Gradient Boosting Machines (GBM). Incorporating external data, including blockchain metrics and social media sentiment analysis, and developing real-time forecasting systems can further improve model performance. While ARIMA provides a solid foundation for linear trend analysis, a more comprehensive approach is required to address the unpredictable dynamics of cryptocurrency markets effectively.

Moreover, the inherently speculative nature of Dogecoin, often driven by online communities and influencer endorsements, introduces an additional layer of volatility that purely statistical models like ARIMA are ill-equipped to handle. The inability to dynamically adapt to sudden market sentiment changes or irregular trading behaviors underlines the model’s shortcomings in the context of high-frequency and sentiment-driven trading environments. This necessitates the integration of sentiment-aware or regime-switching models that can adapt to different market states, thereby enhancing robustness under varying conditions.

Furthermore, it is important to consider the temporal validity of ARIMA-based predictions. As market structures evolve and trading volumes shift due to regulatory interventions, technological innovations, or macroeconomic changes, the parameters of a static ARIMA model may become

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7 (1) September 2024 255-264

outdated quickly. Regular recalibration and the application of rolling forecasts can mitigate this issue to an extent, yet these measures still fall short of providing a fully adaptive solution in real time.

In conclusion, while the ARIMA (5, 1, 0) model demonstrates competence in modeling historical Dogecoin price trends under relatively stable conditions, its limitations restrict its practical use in the fast-evolving and speculative world of cryptocurrencies. The future of time series forecasting in such domains lies in the synergy between traditional econometric models and adaptive machine learning systems. By embracing hybrid models that leverage both historical patterns and real-time data streams, researchers and practitioners can develop more accurate, resilient, and actionable forecasting tools to navigate the uncertainties of digital asset markets.

5. Suggestion

To improve the accuracy and practicality of Dogecoin price forecasting models, future research should prioritize developing hybrid models that integrate ARIMA with advanced machine learning techniques like Long Short-Term Memory (LSTM) networks, Gradient Boosting Machines (GBMs), or Neural Networks. These hybrid approaches combine ARIMA's strength in capturing linear trends with the flexibility of machine learning to address non-linear dependencies and adapt to cryptocurrency market dynamics. Additionally, incorporating external variables such as social media sentiment, market news, and blockchain-specific metrics (e.g., transaction volumes, wallet activity, mining data) can significantly enhance model performance. Real-time data analysis from platforms like Twitter and Reddit can help capture shifts in market sentiment, while blockchain metrics provide insights into network activity. Developing real-time forecasting systems that integrate live data feeds from social media, news, and blockchain networks would enable models to react quickly to dynamic market events, offering timely and actionable insights for investors.

Comparative analyses of ARIMA, hybrid models, and deep learning techniques like Recurrent Neural Networks (RNNs) or Transformer-based models are also crucial. Such evaluations under varying market conditions, including stable periods and extreme volatility, can identify the strengths and limitations of each approach, optimizing forecasting strategies. Expanding the research scope to include multiple cryptocurrencies could enhance the generalizability of findings, uncovering common behavioral patterns or unique market dynamics. Additionally, integrating macroeconomic indicators like global interest rates, inflation trends, and geopolitical events could provide a broader understanding of economic forces shaping cryptocurrency markets. These directions would collectively advance the reliability and application of cryptocurrency forecasting models.

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