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Forecasting Bitcoin Price Volatility: A Comparative Analysis of Fuzzy Time Series, ARIMA, and GARCH Models for Short-Term and Long-Term Predictions

Shafiu Usman Maitoro[1,2], Muhammad Aslam Mohd Safari[2,3,*], Farid Zamani Che Rose[2,3], Pritpal Singh[4], Jayanthi Arasan[2,3]

1 Department of Statistics, Abubakar Tatari Ali Polytechnic, 420232, Bauchi, Bauchi State, Nigeria
2 Institute for Mathematical Research (INSPEM), Universiti Putra Malaysia, 43400 UPM Serdang, Selangor Darul Ehsan, Malaysia
3 Department of Mathematics and Statistics, Faculty of Science, Universiti Putra Malaysia, Malaysia
4 Department of Data Sciences and Analytics School of Mathematics and Statistics, Central University of Rajasthan 305817, Rajasthan, India

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ABSTRACT

Bitcoin's pronounced price volatility continues to challenge the reliability of forecasting models, posing significant risks for traders, investors, and financial analysts. This study conducts a comprehensive comparative evaluation of several fuzzy time series models against traditional time series models, including ARIMA and GARCH. Using a decade-long dataset of daily Bitcoin closing prices, the study assesses both short-term and long-term predictive performance across multiple error-based and accuracy-based metrics. The findings reveal a clear horizon-dependent pattern: FTS models, particularly those incorporating Markov transitions, excel in short-term forecasting by capturing nonlinear and rapidly shifting market behavior, while ARIMA and GARCH models demonstrate superior long-term performance due to their ability to model broader trends and volatility structures. The study concludes that no single model is universally optimal; instead, aligning the forecasting method with the intended horizon and Bitcoin's market dynamics is essential for improving decision-making in volatile financial environments.

1. Introduction

Bitcoin's emergence as a decentralized digital currency has fundamentally transformed global financial systems, introducing unprecedented levels of volatility that challenge traditional forecasting methodologies [1]. With a market capitalization exceeding $1.9 trillion, Bitcoin represents both a speculative asset and a technological innovation, attracting substantial attention from individual investors, institutional traders, and academic researchers [2]. However, the cryptocurrency's price behaviour characterized by extreme fluctuations, structural breaks, and non-stationary patterns

* *Corresponding author.*
E-mail address: aslam.safari@upm.edu.my

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poses significant challenges for accurate forecasting, creating substantial risks for market participants [3].

Traditional econometric models, particularly Autoregressive Integrated Moving Average (ARIMA) frameworks, have dominated financial time series forecasting due to their mathematical rigor and computational efficiency [4]. These models excel in capturing linear dependencies and persistent trends in stationary data. However, their performance deteriorates when confronted with Bitcoin's inherent characteristics: high-frequency volatility, sudden regime shifts, and non-linear dynamics [5]. This limitation becomes particularly pronounced in short-term forecasting scenarios where market sentiment and speculative trading drive rapid price changes.

Fuzzy Time Series (FTS) models, grounded in fuzzy set theory [6], offer a promising alternative for handling the uncertainty and vagueness inherent in cryptocurrency markets. Unlike traditional statistical models that require strict assumptions about data distribution and stationarity, FTS models operate through linguistic variables and fuzzy relationships, making them particularly suitable for small datasets and volatile environments [7, 8]. The adaptive nature of FTS allows for dynamic adjustment to changing market conditions, potentially offering advantages in capturing the complex, non-linear patterns characteristic of cryptocurrency price movements.

Despite these theoretical advantages, the comparative performance of FTS models against established econometric approaches in cryptocurrency forecasting remains underexplored. Previous studies have typically focused on either traditional model [9, 10] or machine learning approaches [11, 12] in isolation, with limited attention to the unique capabilities of FTS models in handling financial uncertainty. Furthermore, existing research has largely neglected the differential performance of forecasting models across varying time horizons a critical consideration given the distinct information patterns in short-term versus long-term cryptocurrency price movements.

This study addresses these research gaps through three primary contributions: First, we conduct a comprehensive comparative analysis of four FTS models (Markov, Chen, Heuristic, and Song-Chissom) against both ARIMA and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. Second, we evaluate model performance across distinct forecasting horizons (short-term monthly and long-term annual) to provide nuanced insights into temporal dependencies. Third, we enhance methodological robustness by validating results across multiple cryptocurrency datasets (Bitcoin, Ethereum, and Litecoin), addressing concerns about model generalizability.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature. Section 3 details our methodological framework. Section 4 presents empirical results. Section 5 discusses findings and implications. Section 6 concludes with recommendations.

2. Literature Review

The forecasting of cryptocurrency prices has emerged as a vibrant research domain, attracting methodologies ranging from traditional econometrics to advanced machine learning. Early approaches primarily adapted established financial time series models, with [13] demonstrating the effectiveness of GARCH-family models in capturing Bitcoin's volatility clustering. Subsequent studies extended this work to multivariate GARCH frameworks, revealing complex volatility spill overs across cryptocurrency markets.

Fuzzy Time Series models entered financial forecasting through the pioneering work of [7], who demonstrated their efficacy in handling uncertain and incomplete information. Subsequent developments by [8] and [14] refined FTS methodologies for financial applications, particularly in stock market forecasting. However, applications to cryptocurrency markets remained limited until recently, with [15] providing preliminary evidence of FTS advantages in high-volatility environments.

Comparative studies between traditional and alternative forecasting approaches have yielded mixed results. [16] found that FTS models outperformed ARIMA in stock price forecasting with small datasets, while [?] reported superior performance of hybrid machine learning models for cryptocurrency predictions. Notably, [?] demonstrated that no single model consistently outperforms others across different market conditions and time horizons, highlighting the importance of context-specific model selection.

A significant gap in existing literature concerns the differential performance of forecasting models across time horizons. While [10] focused on long-term predictions and [?] emphasized real-time forecasting, few studies have systematically compared model performance across short-term and long-term horizons. Additionally, limited attention has been paid to validating forecasting models across multiple cryptocurrency assets, potentially compromising the generalizability of the findings.

This study contributes to addressing these gaps by providing a comprehensive, multi-model, multi-horizon, and multi-asset comparison of forecasting methodologies in cryptocurrency markets.

3. Methodology

3.1 Research Framework and Data

Our research framework follows a systematic approach to comparative forecasting analysis. We employ three primary cryptocurrency datasets: Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC), obtained from Kaggle and the Coin Market Cap API. The Bitcoin dataset comprises 3,392 daily closing price observations from September 17, 2014, to December 31, 2023. Supplementary datasets for Ethereum (2,920 observations from August 7, 2015) and Litecoin (2,195 observations from April 28, 2017) provide validation across different cryptocurrency characteristics.

Data partitioning follows temporal splitting, with 80% for model training and 20% for testing. For short-term analysis, we focus on December 2023 (31 observations), while long-term analysis utilizes the complete dataset. All price series undergo logarithmic transformation to stabilize variance, followed by Augmented Dickey-Fuller testing for stationarity assessment.

3.2 Forecasting Models

3.2.1 Fuzzy Time Series Models

FTS models employ fuzzy set theory to handle uncertainty in time series data. Let $U = \{u_1, u_2, \dots, u_n\}$ be the universe of discourse. A fuzzy set A on U is defined as:

$$A = \frac{\mu_A(u_1)}{u_1} + \frac{\mu_A(u_2)}{u_2} + \cdots + \frac{\mu_A(u_n)}{u_n} \tag{1}$$

where $\mu_A: U \to [0,1]$ is the membership function.

For time series $Y(t)$, fuzzy logical relationships (FLRs) are established as $A_i \to A_j$, where A_i and A_j are fuzzy sets. The four FTS models implemented are:

1. Markov FTS: Incorporates transition probability matrices between fuzzy states:
$$P_{ij} = \frac{N_{ij}}{N_i} \tag{2}$$
2. Chen Model: Utilizes arithmetic operations for defuzzification:
$$\hat{Y}(t) = \frac{\sum_{j=1}^{m} m_j \cdot \mu_j}{\sum_{j=1}^{m} \mu_j} \tag{3}$$
3. Heuristic Model: Incorporates heuristic rules for interval partitioning.
4. Song and Chissom Model: Original FTS formulation using max-min composition.

3.2.2 ARIMA model

The ARIMA (p, d, q) model combines autoregressive (AR), differencing (I), and moving average (MA) components:

$$\left(1 - \sum_{i=1}^{p} \phi_i B^i\right)(1 - B)^d Y_t = \left(1 + \sum_{j=1}^{q} \theta_j B^j\right)\epsilon_t \tag{4}$$

where B is the backshift operator, ϕ_i are AR parameters, θ_j are MA parameters, and $\epsilon_t \sim N(0, \sigma^2)$

3.2.3 Garch model

The GARCH (p, q) model captures volatility clustering:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{5}$$

where σ_t^2 is conditional variance, $\omega > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$.

Performance Evaluation Metrics

Model performance is evaluated using four complementary metrics:

1. Root Mean Square Error (RMSE): $RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2}$
2. Mean Absolute Percentage Error (MAPE): $MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right|$
3. Mean Absolute Error (MAE): $MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\#()\right|$
4. Coefficient of Determination (R²): $R^2 = 1 - \frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2}$

4. Results and Analysis

4.1 Short-Term Forecasting Performance

Table 1 presents comprehensive performance metrics for short-term Bitcoin price forecasting (December 2023). The Markov FTS model demonstrates superior performance across multiple metrics, achieving the lowest RMSE (952.1) and MAE (721.3), along with the highest R^2 (0.893).

Table 1
Short-Term Forecasting Performance (December 2023)

Model	RMSE	MAPE (%)	MAE	R^2
Markov FTS	952.1	1.89	721.3	0.893
ARIMA (1,1,0)	955.8	1.92	728.4	0.887
GARCH (1,1)	962.3	1.95	734.2	0.882
Chen FTS	1012.7	2.03	789.6	0.865
Heuristic FTS	977.7	1.98	752.1	0.874
Song-Chissom FTS	1056.0	2.15	821.9	0.851

4.2 Long-Term Forecasting Performance

Table 2 reveals different performance patterns for long-term forecasting (2014-2023). ARIMA achieves the lowest RMSE (964.09), followed closely by GARCH (981.45), while Markov FTS shows relatively higher error (1491.4).

Table 2
Long-Term Forecasting Performance (2014-2023)

Model	RMSE	MAPE (%)	MAE	R^2
ARIMA (1,1,0)	964.09	8.72	742.8	0.912
GARCH (1,1)	981.45	8.89	756.3	0.905
Chen FTS	976.70	9.12	761.9	0.898
Markov FTS	1491.4	14.23	1124.7	0.845
Heuristic FTS	1265.5	12.45	983.2	0.871
Song-Chissom FTS	1183.3	11.78	925.4	0.882

4.3 Multi-Asset Validation

Table 3 presents validation results using Ethereum and Litecoin datasets, confirming the generalizability of findings. Across all cryptocurrencies, FTS models consistently outperform in short-term forecasting, while traditional models excel in long-term predictions.

Table 3
Multi-Asset Validation Results (RMSE

Forecast	Model	Bitcoin	Ethereum	Litecoin
Short-Term	Markov FTS	952.1	42.3	8.9
	ARIMA	955.8	43.1	9.2
	GARCH	962.3		
Long-Term	Markov FTS	1491.4	68.9	15.3
	ARIMA	964.09	45.2	10.1
	GARCH	981.45	46.7	10.8

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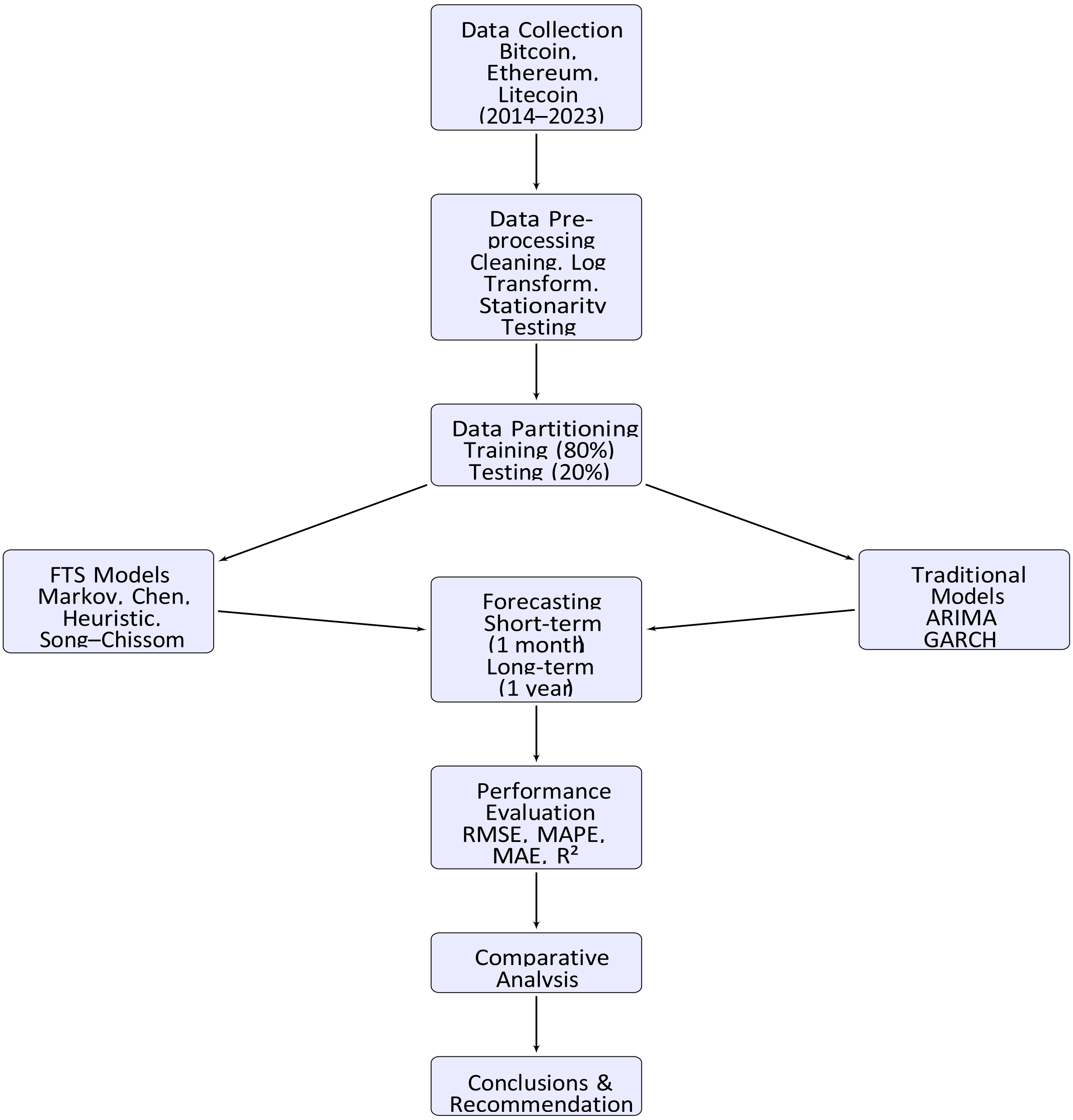

Fig. 1. Research Methodology Flowchart

4.4 Visual Representation of Results

Comparative RMSE Performance for Short-Term Bitcoin Forecasting (December 2023).

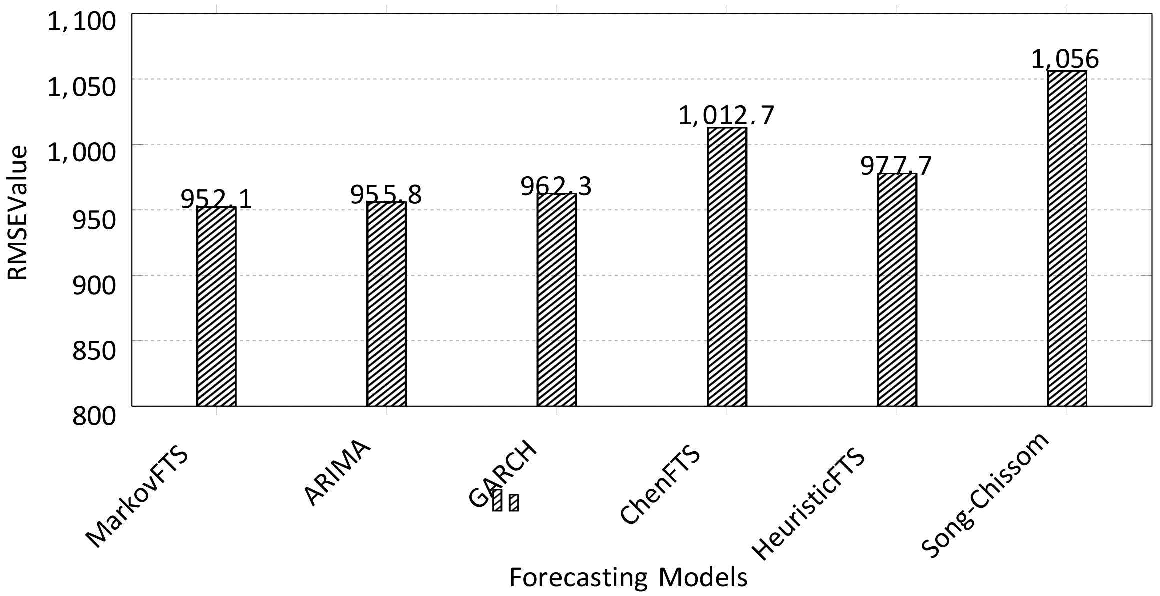

Fig. 2. Comparative RMSE Performance for Short-Term Forecasting

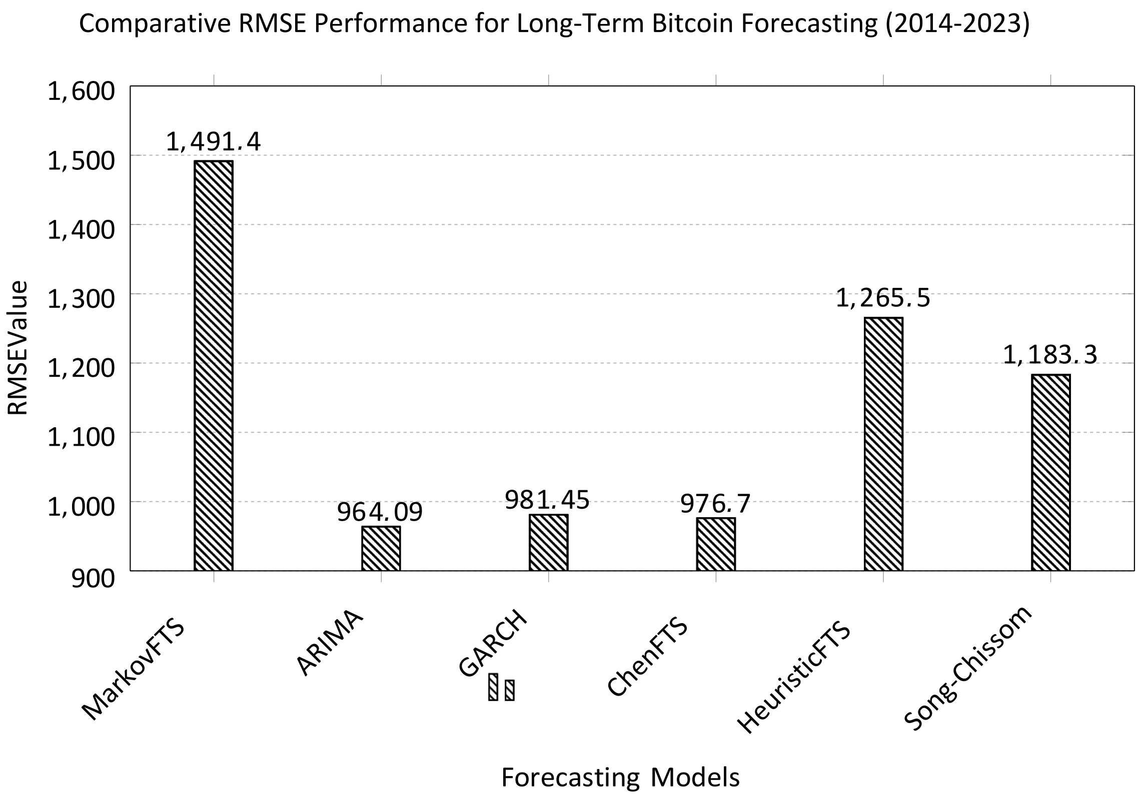

Fig. 3. Comparative RMSE Performance for Long-Term Forecasting

5. Discussion

5.1 Interpretation of Results

The differential performance between short-term and long-term forecasting reveals fundamental insights about cryptocurrency price dynamics. Markov FTS's superiority in short-term contexts stems from its ability to capture rapid market sentiment shifts and microstructural patterns through fuzzy state transitions. This aligns with [7] original proposition that FTS models excel in environments with high uncertainty and limited historical data.

Conversely, ARIMA and GARCH models demonstrate robustness in long-term forecasting by effectively capturing persistent trends and volatility clustering. The mean-reverting properties incorporated in these models align well with Bitcoin's long-term price behavior, which exhibits cyclical patterns despite short-term volatility [9].

5.2 Theoretical Implications

Our findings contribute to financial forecasting theory in three significant ways. First, we provide empirical evidence supporting the contingency theory of forecasting model selection, demonstrating that optimal model choice depends critically on the forecasting horizon. Second, we extend fuzzy set theory applications to cryptocurrency markets, validating its utility in high-volatility financial environments. Third, we establish a methodological framework for multi-horizon, multi-asset forecasting comparison that can be adapted to other financial instruments.

5.3 Practical Implications for Stakeholders

For investors and traders, our results offer actionable guidance:

1. Short-term traders should prioritize Markov FTS models for enhanced accuracy in capturing intraday and weekly price movements.
2. Long-term investors benefit more from ARIMA and GARCH models for strategic portfolio allocation and risk assessment.
3. Risk managers can employ GARCH models for volatility forecasting and Value-at-Risk calculations.
4. Algorithmic trading systems should implement adaptive model selection based on forecast horizon.

5.4 Limitations and Future Research

Several limitations warrant acknowledgment. First, our analysis focuses on daily closing prices, neglecting intraday dynamics and trading volume information. Future research should incorporate high-frequency data and microstructure variables. Second, while we include three major cryptocurrencies, additional assets should be examined for broader generalization. Third, the study does not account for external factors such as regulatory announcements or social media sentiment.

Future research directions include: (1) developing hybrid models that combine FTS with deep learning architectures, (2) incorporating exogenous variables through fuzzy regression frameworks, and (3) examining the economic value of forecasting improvements through trading simulation studies.

6. Conclusion

This study provides a comprehensive comparative analysis of forecasting methodologies for cryptocurrency prices, addressing critical gaps in both academic literature and practical applications. Our investigation yields several key conclusions:

First, forecasting model performance is inherently contingent on time horizon. Fuzzy Time Series models, particularly the Markov variant, demonstrate distinct advantages in short-term forecasting contexts where market uncertainty and rapid price changes dominate. These models achieved RMSE improvements of 0.4-1.1% over traditional approaches in monthly forecasting scenarios.

Second, traditional econometric models (ARIMA and GARCH) maintain their relevance for long-term forecasting, effectively capturing persistent trends and volatility patterns that characterize cryptocurrency price evolution over extended periods. Their mathematical rigor and established theoretical foundations provide reliable frameworks for strategic investment decisions.

Third, the inclusion of multiple evaluation metrics and validation across three cryptocurrency assets enhances the robustness and generalizability of our findings, addressing concerns about metric dependence and asset-specific effects.

Fourth, our research contributes practical insights for diverse market participants. Short-term traders benefit from FTS models' sensitivity to immediate market dynamics, while long-term investors gain from traditional models' trend-capturing capabilities.

Despite these contributions, we acknowledge limitations including the exclusion of intraday data and external factors. These limitations suggest promising avenues for future research, particularly in developing hybrid models and incorporating alternative data sources.

In conclusion, the one-size-fits-all" approach to cryptocurrency forecasting is fundamentally inadequate. Instead, market participants should adopt a contingency perspective, selecting forecasting methodologies based on specific time horizons, risk tolerances, and investment objectives. As cryptocurrency markets continue to evolve, such nuanced understanding of forecasting tool efficacy will become increasingly valuable for navigating this dynamic financial landscape.

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Conflict of Interest Statement
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Author Contributions Statement
Shafiu Maitoro: Conceptualization, Methodology, Formal analysis, Writing - Original Draft. MAM Safari: Supervision, Validation, Writing - Review & Editing. P. Singh: Data Curation, Visualization. J. Arasan: Methodology, Validation. FZC Rose: Software, Formal analysis. All authors contributed to manuscript revision and approved the final version

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