

Long Memory Analysis and Directional Return Forecasting in Cryptocurrency Markets: An Application of the PATSOS Method *

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Abstract

This study aims to investigate the volatility dynamics of five major cryptocurrencies (Bitcoin, Ethereum, Binance Coin, Solana, and Ripple) to determine whether they exhibit long memory properties, reveal their market efficiency, and perform directional return forecasts using PATSOS, a hybrid machine learning method. This study uses daily data on cryptocurrencies from 2014 to 2022. According to the study results, long memory in volatility is found in the return series of Bitcoin, Binance Coin, Solana, and Ripple. Therefore, this finding reveals that the Efficient Markets Hypothesis does not hold for these cryptocurrencies' return series, except Ethereum. Based on the tests, the most appropriate models for predicting volatility are HYGARCH(1, d, 1) for Bitcoin, IGARCH(1, 1) for Ethereum, FIGARCH(1, d, 0) for Binance Coin, FIGARCH(1, d, 1) and FIAPARCH(1, d, 1) for Solana and Ripple. Predicting future prices using past price movements is possible in these inefficient cryptocurrencies. In this context, we conduct return forecasts using the PATSOS method, which yields successful results in non-linear data. As a result, the PATSOS method produces lower RMSE, MSE, and MAE values and higher accuracy rates than the ANFIS method for all cryptocurrencies in the analysis. These findings highlight the effectiveness of hybrid models in capturing the non-linear structure of cryptocurrency returns.

Keywords: PATSOS, Cryptocurrencies, Volatility Modelling, Long Memory, Market Efficiency.

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1. INTRODUCTION

Technological advances have facilitated a significant shift towards online payment systems and digital transactions, accelerating the emergence of digital money as an alternative to traditional currencies. The combination of digital currency with advanced cryptography and blockchain technology has paved the way for the emergence of the concept of "encrypted money". This concept was first introduced to the literature in an article titled "Bitcoin: A Peer-to-Peer Electronic Cash System", published in 2008 by a person or group using the pseudonym Satoshi Nakamoto (Nakamoto, 2008); thus, Bitcoin entered the market and later led to the development of various alternative digital assets, such as Ethereum, Litecoin, and Tether. Nowadays, these digital assets are used as valid tools in different payment transactions.

The rapid adoption of cryptocurrencies in the financial world has been influenced by the integration of new-generation technologies based on decentralized structures into financial systems. In this process, blockchain infrastructure can ensure the security and efficacy of direct transactions without intermediary institutions (Böhme et al., 2015; Chen et al., 2024). Unlike typical fiat currencies, cryptocurrencies do not rely on a central governing authority; people are able to conduct their transactions without involving third parties (Budree & Nyathi, 2023). To illustrate, Bitcoin is such a case in which the miners, who collaborate in a decentralized process, are responsible for the consensus mechanism, and they apply cryptographic security methods. Thus, transaction security is enhanced, and risks like fraud or double spending are reduced (Böhme et al., 2015; Chen et al., 2024;).

In this context, the unique structure of cryptocurrencies has raised the question of how efficient and predictable they are. For investors, in particular, the ability to predict future price movements of these assets is critical. Therefore, the question of whether the efficiency of cryptocurrency markets and price behaviors are random or predictable is increasingly discussed in the academic literature.

The Efficient Market Hypothesis (EMH), proposed by Fama in 1965, implies that the information and knowledge of the market are learned simultaneously by all the investors present; thus, no one can earn abnormal profits by using inside information. Under the assumption that prices get into a random or unbiased state, one ultimately cannot use previous or past price data to make price predictions (Malkiel, 2003). In markets that exhibit long memory, one can deploy past price data to predict future price movements. This perspective is in contradiction to the efficient market hypothesis (EMH) thesis, which states that all the relevant information is immediately reflected in the present market price (Mensi et al., 2019). Cryptocurrencies displaying more significant variance have consequently become a riskier investment choice as compared to traditional assets (Bouri et al., 2019; Liu & Tsyvinski, 2018). That is a significant reason that investors are preoccupied with the use of methodologies that are based on historical prices to predict the future price movements of crypto assets. The assessments may lack considerably lower confidence if the cryptocurrency under discussion has neither a long memory feature in its return series nor its volatility series. Consequently, it is essential to

consider whether cryptocurrencies have a long memory effect on the returns or volatility series (Soylu et al., 2020).

The research examines cryptocurrency volatility patterns alongside their long memory characteristics to evaluate market risk and efficiency. The return direction predictions are made using the PATSOS. This method combines Fuzzy Logic and Artificial Neural Networks (ANN) in a closed-loop configuration to improve forecasting accuracy. The model enhances forecasting accuracy by integrating two ANFIS subcomponents, PR-ANFIS and CON-ANFIS.

Within the scope of the study, the five cryptocurrencies with the highest market capitalization—Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Solana (SOL), and Ripple (XRP)—are examined. Daily price data are used for the following periods: September 20, 2014, to May 30, 2022, for Bitcoin; November 12, 2017, to May 30, 2022, for ETH, BNB, and XRP; and April 13, 2020, to May 30, 2022, for SOL. Unlike most literature focusing on a single or small number of cryptocurrencies, this study examines five major cryptocurrencies simultaneously. Since these coins' total market capitalization represents a significant cryptocurrency market share, the findings are expected to be more generalizable.

Furthermore, this study contributes to the literature by employing models considering the asymmetry effect in long memory detection and a hybrid machine learning method (PATSOS), which is especially effective with non-linear time series. Consequently, the results are expected to provide more accurate return forecasts for individual and institutional investors interested in cryptocurrencies.

The rest of the study is structured as follows: The second section includes previous studies in the literature. The third section discusses the research model, while the fourth section explains the methodology used. The fifth section presents the data analysis results, and the sixth section evaluates the findings. Finally, the seventh section includes the general results of the study.

2. LITERATURE REVIEW

This section presents a comprehensive review of the relevant literature, focusing on the evolution of volatility modeling and the increasing adoption of machine learning techniques in financial and cryptocurrency markets. The literature is structured across four subsections, allowing for a more apparent distinction between domains and methodologies.

2.1. Studies Investigating Volatility Dynamics in the Field of Finance

Numerous studies have addressed long memory and volatility dynamics in financial markets. Sadique and Silvapulle (2001) investigated long memory in Japan, New Zealand, the US, Singapore, Korea, and Malaysia stock markets using GPH and R/S tests. They found evidence of long memory in some markets but not in Japan and the US. Similarly, Kılıç (2004) found a long memory in volatility in

the BIST 100, while Cavalcante and Assaf (2004) found a long memory in both returns and volatility in the Brazilian stock market.

Similar results have been observed in emerging markets such as Brazil, Russia, and Turkey. For example, Saleem (2014) found long memory in all sectors of the Russian stock market, while Çevik and Topaloğlu (2014) and Türkyılmaz and Balıbey (2014) reported the existence of long memory and asymmetric effect in conditional variance in BIST indices. Özdemir and Çelik (2020) found no long memory in Turkish and US returns but confirmed long memory in volatility. When structural breaks are considered, the results become closer to market efficiency. Similarly, Umore et al. (2024), focusing on African currencies, found that strong long memory effects persist in currency returns, with a high shock persistence.

A study by Festic et al. (2012) on Eastern European stock markets such as Hungary and Croatia indicates a long memory effect on market volatility. Similarly, Horobet et al. (2016) stated that they detected a long memory effect lasting between 7 and 9 months in their analysis of exchange rates in Russia, Hungary, Romania, Czechia, Serbia, Turkey, and Croatia. Different studies (Aslam et al., 2020; Ibrahim et al., 2018) determined that some currencies exhibit long memory properties against the US dollar. Also, Caporale et al. (2024) found evidence of long memory between various European stock indices for returns and volatility.

2.2. Studies Investigating Volatility Dynamics in the Cryptocurrency Market

As for the cryptocurrency market, it attracts attention with its dynamic structure, which includes high volatility and long memory. Studies using various models based on the GARCH family show that Bitcoin and similar digital assets have features such as long memory, asymmetric shocks, and heavy tails (Bouri et al., 2017; Fakhfekh & Jeribi, 2020; Katsiampa, 2017; Phillip et al., 2018). However, these features may not be fully reflected when structural breaks are not considered (Aharon et al., 2023). In addition, Nadarajah et al. (2025) also show that machine learning and artificial intelligence-based approaches (e.g., ANFIS) exhibit higher accuracy rates than GARCH-type models.

Similarly, Bariviera (2017) reported that although he could not detect a long memory effect in Bitcoin returns, he encountered this effect in volatility. Al-Yahyaee et al. (2018) argue that Bitcoin exhibits more pronounced multifractal and long memory features than foreign exchange, stock, and gold markets. Charfeddine and Maouchi (2019) revealed that cryptocurrencies such as BTC, LTC, ETH, and XRP exhibit long memory properties, especially in volatility. Mensi et al. (2019) also reached similar results on BTC and ETH data and stated that the long memory effect becomes more pronounced during periods of structural breaks. On the other hand, machine learning models based on candlestick data are used as an effective tool in detecting trend breaks (Kapur et al., 2024).

Bouri et al. (2019) emphasize shocks' persistent and non-mean-reverting nature, while Khuntia and Pattanayak (2020) argue that BTC trading volume impacts long memory during bull-bear periods.

Using wavelet-based analysis, Assaf et al. (2022) reported a decline in long-term memory after the 2017 crypto bubble and a further significant decline during COVID-19. On the other hand, Münyas and Kadooğlu-Aydın (2023), who tested weak-form efficiency, reported that the market was inefficient, as the seven cryptocurrencies they examined did not exhibit a random walk.

2.3. Studies Employing Machine Learning Methods in the Field of Finance

The interest in machine learning techniques in the field of finance has increased in recent years. ANN-based approaches (Karaatlı et al., 2005; Khan et al., 2011; Özçalıcı, 2016; Tektaş & Karataş, 2004) have generally yielded more successful results than statistical models in predicting stock prices on a daily, weekly, or monthly basis. In addition, studies using methods such as Support Vector Machines (SVM) and Particle Swarm Optimization (PSO) have shown that they achieve high accuracy rates in the analysis of financial news and S&P 500 stocks (Hagenau et al., 2013; Hegazy et al., 2013). Again, examples such as the successful prediction of gold prices using Artificial Neural Networks (ANN) (Yüksel & Akkoç, 2016) and the superior performance achieved in the S&P 500 index (Addai, 2016) reveal the advantages of machine learning techniques over traditional methods. In addition, the classification of customer profiles in the electricity retail sector with Recency, Frequency, Monetary (RFM), and clustering methods supported the effectiveness of the methods by revealing differences in financial behavior (Gülcü & Çalışkan 2020).

2.4. Studies Employing Machine Learning Methods in the Cryptocurrency Market

Studies on price and yield predictions in cryptocurrency markets have similarly increased. In the early periods, high accuracy rates were achieved using SVM, Neural Networks, Bayesian Regression, and Time Mixture models (Greaves & Au, 2015; Guo et al., 2018; Shah & Zhang, 2014), while MLP, LSTM, GRU and RNN models, which are among the deep learning techniques, were also widely preferred. McNally et al. (2018) made a comparison between MLP and LSTM, while LSTM and GRU attracted much attention from Awoke and co-workers (2020). Jiang (2020) presented that these two models achieve outstanding results even under high volatility conditions. Chen et al. (2020) have pointed out that a particular model's performance might differ, for instance, due to the time-frequency (5-minute or daily data) employed. Seabe et al. (2023) demonstrated the Bi-LSTM model, which has superiority over traditional statistical models in BTC, ETH, and LTC price predictions.

AI systems based on the new models, such as SDAE, 1D-CNN, and BRNN, have also exhibited an accurate capacity to predict the price direction of Bitcoin (Cavalli & Amoretti, 2021; Lahmiri & Bekiros, 2020; Liu et al., 2021). Recent findings by Wang et al. (2023) showed that Random Forest and LSTM, which consider both internal and external influences, are superior to classical GARCH models regarding forecasting. In the same way, Chen et al. (2021) have noted that the LSTM models, judging from joint economic and technology indicators, give much more accurate predictions than classical statistical methods, particularly in high-frequency data. These studies show that deep learning-based

models are better instruments for capturing cryptocurrency markets' complex and rapidly changing nature.

In line with these developments, the PATSOS method—combining artificial neural networks with fuzzy logic in a closed-loop structure—has demonstrated superior accuracy in predicting the directional changes of BTC compared to ANN and ANFIS (Atsalakis et al., 2019). This result shows that PATSOS can produce robust and reliable forecasts even in highly volatile market environments.

3. RESEARCH MODEL

This section explains the study's main objectives, the characteristics of the dataset used, and the hypotheses tested in the study, and the conceptual framework that underpins the subsequent analysis.

3.1. Research Objective

The study aims to explore the volatility dynamics of the most popular cryptocurrencies with the highest market capitalization, analyze whether these assets display long memory features, and use a hybrid machine learning method called PATSOS for predicting returns' direction. The PATSOS method, which integrates Fuzzy Logic and ANN within a closed-loop structure, is the algorithm used to make a more accurate directional prediction in highly volatile financial time series with non-linear structures.

The existence of a long memory effect in the return or volatility series of cryptocurrencies demonstrates that the previous price movements may determine future prices. In the first step of the study, the long memory effect in the return and volatility series of the chosen cryptocurrencies is tested. Then, the most suitable volatility prediction models are selected. In the second stage, the PATSOS method is utilized to predict the return directions.

According to the EMH, investors cannot achieve a higher return than the market by analyzing past price movements. The existence of long memory in an asset means that predictions can be made about future prices using past price movements, potentially challenging the EMH in its weak form. In such markets, it becomes possible for investors to generate abnormal returns using historical information. Therefore, determining the volatility dynamics of cryptocurrencies is important for those who want to invest in the cryptocurrency market.

As of March 2, 2022, the total market capitalization of the five cryptocurrencies selected within the scope of the research was \$1.32 trillion, representing 69.1% of the total cryptocurrency market (\$1.91 trillion) (CoinMarketCap, 2022). Including a substantial portion of the overall cryptocurrency market in the study enhances the findings' consistency, significance, and generalizability.

Although there are studies testing the existence of long memory in cryptocurrencies, very few have used models that account for long memory and asymmetry. To fill this gap, this study uses advanced models such as Fractionally Integrated GARCH (FIGARCH) and Hyperbolic GARCH

(HYGARCH), which capture fractional integration, and Fractionally Integrated Asymmetric Power Autoregressive Conditional Heteroskedasticity (FIAPARCH), which also consider the asymmetry in volatility.

Furthermore, while a large body of literature utilizes machine learning techniques such as Fuzzy Logic and ANN to predict the price or return of cryptocurrencies, the number of studies using PATSOS, which combines the strengths of these two models, is quite limited. Therefore, this study aims to contribute significantly to the existing literature. By applying PATSOS to forecast the direction of cryptocurrency returns, this study not only expands the methodological toolkit in financial forecasting but also makes a new contribution to the literature by integrating fractional volatility modeling with hybrid artificial intelligence.

3.2. Data Set of the Study

The five cryptocurrencies with the highest market capitalization as of March 2, 2022, BTC, ETH, Tether (USDT), BNB, and USD Coin (USDC), were initially considered for analysis.

However, due to their structural features—specifically, their values being pegged to 1 USD—return forecasting for USDT and USDC would be meaningless. Thus, instead of these two cryptocurrencies, XRP and SOL, which rank sixth and seventh in market capitalization, were included in the dataset (CoinMarketCap, 2022).

In the PATSOS method, the dataset is typically divided into two subsets: training and testing. Although splitting the dataset such as 50:50, 60:40, 70:30, and 80:20 are common, a 90:10 split is considered the most appropriate to ensure that the model has sufficient historical data for learning (Guiu et al., 1999; Oppenheim & Shani, 2017). For this reason, the study adopts a 90:10 split, where 90% of the data is used for model training and the remaining 10% for testing.

The daily price data used in the study were obtained from the Yahoo Finance platform and converted into a return series. The sample periods and splits for each cryptocurrency are as follows:

- Bitcoin (BTC): September 20, 2014 – May 30, 2022 (Total: 2,810 days)
 - Training set: September 20, 2014 – August 22, 2021 (2,529 days)
 - Test set: August 23, 2021 – May 30, 2022 (281 days)
- Ethereum (ETH), Binance Coin (BNB), Ripple (XRP): November 12, 2017 – May 30, 2022 (Total: 1,661 days)
 - Training set: November 12, 2017 – December 15, 2021 (1,495 days)
 - Test set: December 16, 2021 – May 30, 2022 (166 days)
- Solana (SOL): April 13, 2020 – May 30, 2022 (Total: 778 days)
 - Training set: April 13, 2020 – March 13, 2022 (700 days)
 - Test set: March 14, 2022 – May 30, 2022 (78 days)

3.3. Research Hypotheses

This study intends to examine whether the return series of five major cryptocurrencies – Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Solana (SOL), and Ripple (XRP) – exhibit long memory properties and whether their return directions can be accurately predicted using advanced machine learning techniques.

Accordingly, the following research questions are posed:

1- Is the Efficient Market Hypothesis (EMH) valid for the selected cryptocurrencies?

2- Can the return directions of the selected cryptocurrencies be accurately forecasted using the PATSOS method?

In order to find answers to these two fundamental questions, the following hypotheses were tested in the study:

H_{0A} : The return series of the selected cryptocurrencies do not exhibit long memory.

H_{1A} : The return series of the selected cryptocurrencies exhibit long memory.

H_{0B} : The return directions of the selected cryptocurrencies cannot be accurately forecasted using the PATSOS method.

H_{1B} : The return directions of the selected cryptocurrencies can be accurately forecasted using the PATSOS method.

4. RESEARCH METHODOLOGY

This section presents the methodological framework for the study and introduces the statistical and machine learning-based models utilized in the analysis of cryptocurrency market volatility dynamics and return direction forecasts. In the initial phase, volatility structures of the selected cryptocurrencies were examined by employing short memory models such as GARCH and IGARCH, as well as long memory models like FIGARCH, FIAPARCH, and HYGARCH. In the subsequent stage, return direction forecasts were made using the PATSOS method, a hybrid algorithm with a closed-loop structure explicitly designed to enhance predictive accuracy for financial time series exhibiting high volatility and non-linear characteristics. The following subsections provide the theoretical background and fundamental equations for short and long memory volatility models, followed by a detailed description of the operational structure of the PATSOS method.

4.1. Volatility Models

This section presents short and long memory volatility models to capture the unique dynamics of cryptocurrency time series more successfully. While short memory models serve primarily as benchmarks, long memory models are favored for their ability to effectively uncover the persistent volatility patterns observed in these markets.

4.1.1. Short Memory Models

Models from the ARCH/GARCH family (Bollerslev, 1986; Engle, 1982) are widely preferred in the analysis of financial time series. The GARCH(p,q) model structures the conditional variance as a function of lagged conditional variances and squared past error terms. The basic form of the model is presented below:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i u_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (1)$$

In Equation 1, the ARCH coefficient α_i captures the immediate impact of short-term shocks, while the GARCH coefficient β_j represents the long-term effect. The sum of $\alpha + \beta$ reflects the degree of volatility persistence in the market. Here, q indicates the number of lags in the ARCH component, p refers to the number of lags in the GARCH component and u_{t-1} represents the error term.

Exponential GARCH (EGARCH) (Nelson, 1991) and Threshold GARCH (TGARCH) (Rabemananjara & Zakoian, 1993) models, which are asymmetric variations of the GARCH model, work on the assumption that the effects of positive and negative shocks on volatility may differ from each other

4.1.2. Long Memory Models

While the effect of shocks decreases exponentially over time in short memory models, this effect fades more gradually following a hyperbolic pattern in long memory models (Baillie et al., 1996). At this point, the FIGARCH(p,d,q) model comes to the fore:

$$\sigma_t^2 = \alpha[1 - \beta(L)]^{-1} + [1 - \beta(L)]^{-1}\gamma(L)(1 - L)^d \varepsilon_t^2 \quad (2)$$

In this equation, α represents the constant term, β is the GARCH component, γ represents the ARCH term, L denotes the lag operator, and d represents the long memory parameter. A fractional differencing parameter (d) value between 0 and 1 indicates a long memory effect in the series. FIAPARCH (Tse, 1998) and Fractionally Integrated Exponential GARCH (FIEGARCH) (Bollerslev & Mikkelsen, 1996) are further enhancements, which, in addition to the long memory structure, also consider the asymmetric shock effect. Additionally, the new model Davidson (2004) offered, HYGARCH, is practically efficient as it adequately catches hyperbolic decay behavior.

The application of these models makes a notable stride in understanding the long-term effects and the asymmetric structure of volatility in cryptocurrency markets. Furthermore, identifying the long memory property might reflect the market's weakly efficient state, which could lead to more market predictability.

4.2. PATSOS Method

In this study, the PATSOS method—a hybrid machine learning technique for forecasting the return directions- was employed apart from the traditional statistical approach. Fuzzy Logic and ANN

types of machine learning are among the most successful in the non-linear time series field (Jang, 1993; Zadeh, 1965). PATSOS is a hybrid prediction model developed by Atsalakis and Valavanis (2009), which combines these two methods in a closed-loop structure.

The PATSOS method consists of two subcomponents:

1. CON-ANFIS (ANFIS Controller): Generates a control signal based on the difference between the current and the following trends.

2. PR-ANFIS (ANFIS Process): Forecasts the next value using the control signal generated by CON-ANFIS.

The forecasting process includes two stages: learning and application. PATSOS structurally integrates two ANFIS modules—PR-ANFIS and CON-ANFIS—in a closed-loop system to facilitate forecasting accuracy. The inverse learning technique is utilized in the learning stage. CON-ANFIS, acting as the ANFIS controller, generates a control signal, which PR-ANFIS subsequently uses to predict the next value. As an illustration, the model can predict the movement of the following day when daily data is used (Atsalakis et al., 2019).

The following equations are carried out in the training phase of CON-ANFIS.

$$y(k + 1) = f(y(k), u(k)) \quad (3)$$

$$u(k) = g(y(k)) \quad (4)$$

Here, $y(k + 1)$ represents the value of the analyzed data at the time $(k + 1)$, $y(k)$ is the value at time k , $u(k)$ denotes the control signal at time k .

The first subsystem of the PATSOS method, CON-ANFIS, is trained using the data $y(k)$, $y(k + 1)$ and $u(k)$. The inputs of the model are $y(k)$, the current trend value of the asset under study, and $y(k + 1)$, the actual trend value of the asset 1 day later. The output of this model is the control signal $u(k)$. Then, the control signal $u(k)$ is used as one of the inputs to the model in the PR-ANFIS process. In the training process, $u(k)$ is calculated as a positive control signal as follows:

$$u(k) = \sqrt{(y(k) - y(k + 1))^2} \quad (5)$$

During the training process, the model is designed to predict the price one step ahead (e.g., hour, day, week). However, since the CON-ANFIS input $y(k + 1)$ is unknown during the evaluation phase, $y_d(k + 1)$ is used instead. $y_d(k + 1)$ is calculated as follows:

$$SMA(k) = \frac{\text{Closing price of day } k + \text{Closing price of day } k-1 + \text{Closing price of day } k-2}{3} \quad (6)$$

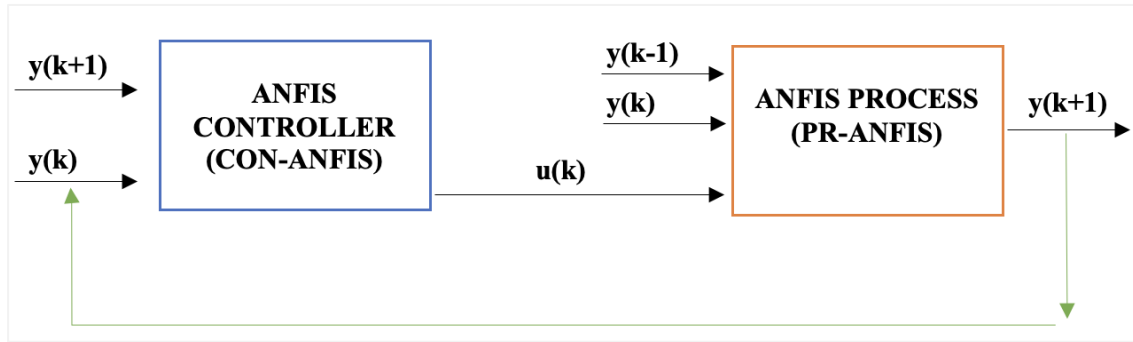
$$\text{Moving Average Ratio} = \frac{SMA(k) - SMA(k-1)}{SMA(k-1)} \quad (7)$$

According to Equations 6 and 7, the first step involves calculating the simple moving average $SMA(k)$, by taking the average of closing prices for days k , $k - 1$, and $k - 2$. Then, using this value, the moving average ratio is calculated. This ratio is used as one of the model inputs in the CON-ANFIS stage. So, the inputs of CON-ANFIS consist of the moving average ratio defined in Equation 7 and the current price value $y(k)$; the model's output is the control signal $u(k)$.

In the PR-ANFIS stage, which is the second component of the PATSOS method, the model takes the values $u(k)$, $y(k)$, and $y(k - 1)$ as inputs in the training process and forecasts the future trend value $y(k + 1)$ as output.

Figure 1 illustrates the structure explained above and the forecasting system of the PATSOS method.

Figure 1. PATSOS' Forecasting System



Note: Adapted from Atsalakis et al. (2019).

Root Mean Square Error (RMSE), Mean Square Error (MSE), and Mean Absolute Error (MAE) are commonly used performance metrics to evaluate how well machine learning model predictions align with the actual observed values. This study uses these error metrics to evaluate and compare the prediction performance of the ANFIS and PATSOS methods. The mathematical formulations of these metrics are presented below.

$$RMSE = \sqrt{\frac{\sum_{t=1}^N e_t^2}{N}} \quad (8)$$

$$MSE = \frac{1}{N} \cdot \sum_{t=1}^N e_t^2 \quad (9)$$

$$MAE = \frac{1}{N} \cdot \sum_{t=1}^N |e_t| \quad (10)$$

5. DATA ANALYSIS

This section presents the empirical results of the analyses. First, the long memory and volatility dynamics of selected cryptocurrencies are examined. Then, the forecasting performance of machine learning models is evaluated based on return predictions.

5.1. Market Efficiency and Volatility Analysis

In this section, market efficiency (i.e., whether there is long memory in returns) and the volatility dynamics of the cryptocurrencies included in the scope of the research are analyzed. First, descriptive statistics and unit root test results for the selected cryptocurrencies are presented; then, the most appropriate volatility model is determined, along with an evaluation of the EMH.

5.1.1. Descriptive Statistics and Unit Root Tests

Table 1. Descriptive Statistics for BTC, ETH, BNB, SOL, and XRP

	BTC	ETH	BNB	SOL	XRP
Number of Observation	2,810	1,661	1,661	778	1,661
Mean	0.001561	0.0011123	0.0031672	0.0051143	0.00041345
Standard Deviation	0.039024	0.051813	0.06094	0.081827	0.06591
Skewness	-0.76695	-0.96751	0.38583	-0.095842	0.82963
Kurtosis	13.011	13.147	17.150	6.4473	18.851
Minimum	-0.46473	-0.55073	-0.54308	-0.46535	-0.5505
Maximum	0.22512	0.23474	0.52922	0.38718	0.60689
Jarque-Bera: Prob.	14,470 [0.0000]	7,384.2 [0.0000]	13,899 [0.0000]	386.42 [0.0000]	17,580 [0.0000]
ARCH (2)	22.960 [0.0000]***	6.3839 [0.0017]***	66.022 [0.0000]***	15.545 [0.0000]***	44.025 [0.0000]***
ARCH (5)	12.276 [0.0000]***	7.0073 [0.0000]***	29.556 [0.0000]***	12.379 [0.0000]***	19.474 [0.0000]***
ARCH (10)	8.7921 [0.0000]***	4.6042 [0.0000]***	24.264 [0.0000]***	6.5588 [0.0000]***	13.754 [0.0000]***
Q (5)	2.69684 [0.7466]	12.7080 [0.0262]**	13.8046 [0.0168]**	9.22364 [0.1004]	6.83784 [0.2329]
Q (10)	19.8649 [0.0305]**	26.2203 [0.0034]***	39.9643 [0.0000]***	15.2588 [0.1229]	20.3392 [0.0262]**
Q (20)	30.3061 [0.0650]*	37.0239 [0.0116]**	54.4262 [0.0000]***	36.7417 [0.0125]**	39.9742 [0.0050]***
Q (50)	70.0372 [0.0321]**	55.9520 [0.2613]	79.1990 [0.0053]***	59.0313 [0.1788]	99.3636 [0.0000]***
Q ² (5)	70.7293 [0.0000]***	39.0859 [0.0000]***	170.867 [0.0000]***	82.2462 [0.0000]***	107.577 [0.0000]***
Q ² (10)	108.862 [0.0000]***	51.6936 [0.0000]***	285.558 [0.0000]***	88.0448 [0.0000]***	174.944 [0.0000]***
Q ² (20)	132.322 [0.0000]***	56.6435 [0.0000]***	386.169 [0.0000]***	91.0743 [0.0000]***	269.916 [0.0000]***
Q ² (50)	155.656 [0.0000]***	72.3566 [0.0209]**	433.093 [0.0000]***	121.040 [0.0000]***	407.431 [0.0000]***
Long Memory Test Statistics					
%90 (0.861, 1.747)					
%95 (0.809, 1.862)					
%99 (0.721, 2.098)					
Lo R/S (Returns)	1.56948	1.65548	1.3764	1.6987	1.30324
Hurst-Mandelbrot R/S (Returns)	1.55124	1.61804	1.38176	1.63898	1.30802
Lo R/S (Squared Returns)	1.92297	1.10764	2.17996	2.4848	2.87478
Hurst-Mandelbrot R/S (Squared Returns)	2.03827	1.15344	2.45345	2.71019	3.07608

As seen in Table 1, the skewness and kurtosis values of the return series for all cryptocurrencies indicate asymmetric and leptokurtic (heavy-tailed) distributions. Jarque-Bera test values also confirm that the series is not normally distributed. Moreover, the ARCH-LM and Box-Pierce (Q and Q²) tests reveal that the residuals of the series exhibit heteroskedasticity and autocorrelation at specific lags. Moreover, the long memory test statistics (Lo R/S and Hurst-Mandelbrot R/S) applied to both return and squared return series show that the squared returns for BTC, BNB, SOL, and XRP fall outside the 95% confidence interval, providing evidence of long memory behavior in volatility. These results are significant as squared returns represent volatility clustering in financial time series. In contrast, ETH does not exhibit such behavior, which is consistent with the EMH.

Table 2. Unit Root Tests for BTC, ETH, BNB, SOL, and XRP Series

		ADF	PP	KPSS
BTC	Price	-2.11168	-1.88046	11.9962*
	Return	-30.2614*	-51.0562*	0.109901
ETH	Price	-23.7764*	-40.8177*	0.15878
	Return	-22.5704*	-31.8991*	0.147811
BNB	Price	-2.13259	-1.87388	8.23353*
	Return	-22.5653*	-29.4022*	0.130861
SOL	Price	-1.03473	-1.27667	1.9412*
	Return	-15.9897*	-21.8414*	0.185794
XRP	Price	-3.45059	-3.34396	6.21135*
	Return	-22.5954*	-31.1719*	0.0720177

According to the unit root test results in Table 2, the return series of the five cryptocurrencies are stationary (H₀: 'the series is non-stationary' is rejected in the ADF and PP tests, while H₀: the series is stationary is not rejected in the KPSS test). A significant portion of the price series was found to be non-stationary. Therefore, volatility analysis and forecasting were conducted based on the return series.

5.1.2. Volatility Modeling and Long Memory Tests

The Lo R/S and Hurst-Mandelbrot R/S test results (see “Long Memory Test Statistics” at the bottom of Table 3) provide preliminary evidence supporting the presence of long memory in the volatility of all return series except ETH.

This finding indicates that while most of the selected cryptocurrencies exhibit persistent volatility patterns, Ethereum demonstrates a volatility structure that is better characterized by short term dependencies. Accordingly:

- Short memory models (GARCH, IGARCH) were applied to the ETH return series, which did not exhibit long memory characteristics.
- Long memory models (FIGARCH, FIAPARCH, HYGARCH) were applied to the BTC, BNB, SOL, and XRP return series, which showed statistical evidence of long memory in volatility.

Table 3. Summary of Estimation Performance for All Models and Cryptocurrencies

Crypto	Model	Log L	AIC	SIC	MSE	MAE	RMSE
BTC	FIGARCH (1,d,1)	5,200.33	-4.107818	-4.093973	0.001215	0.02556	0.03486
BTC	FIAPARCH (1,d,1)	5,206.22	-4.110890	-4.092430	0.001216	0.02556	0.03487
BTC	HYGARCH (1,d,1)	5,211.64	-4.115963	-4.099811	0.001215	0.02556	0.03486
ETH	GARCH (1,1)	2,470.41	-3.298218	-3.280459	0.001690	0.03143	0.04111
ETH	IGARCH (1,1)	2,469.74	-3.298660	-3.284453	0.001689	0.03143	0.04110
BNB	FIGARCH (1,d,0)	2,384.11	-3.182754	-3.164995	0.001625	0.02975	0.04031
BNB	FIAPARCH (0,d,1)	2,385.66	-3.182149	-3.157287	0.001628	0.02979	0.04035
BNB	HYGARCH (0,d,1)	2,383.97	-3.181235	-3.159925	0.001625	0.02975	0.04031
SOL	FIGARCH (1,d,1)	808.209	-2.292025	-2.253016	0.004518	0.05042	0.06722
SOL	FIAPARCH (1,d,1)	808.335	-2.286671	-2.234659	0.004523	0.05042	0.06725
XRP	FIGARCH (1,d,1)	2,464.25	-3.288633	-3.267322	0.002230	0.03386	0.04722
XRP	FIAPARCH (1,d,1)	2,468.18	-3.291212	-3.262798	0.002232	0.03387	0.04725

Table 3 provides a comparative summary of the estimation results from different volatility models (e.g., FIGARCH, FIAPARCH, HYGARCH, GARCH, IGARCH) applied to five major cryptocurrencies: BTC, ETH, BNB, SOL, and XRP. The table includes key model performance indicators such as log-likelihood (Log L), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Mean Squared Error (MSE), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Bolded values indicate the best performance for each cryptocurrency based on lower error metrics and higher Log L. Thick horizontal lines are used to visually separate results by cryptocurrency for clarity. Also, Kupiec backtest results at the 99% confidence level indicate that, except for one instance, all models pass the test, as the null hypothesis is not rejected ($p > 0.05$). Overall, the models appear appropriate for VaR estimation at the 99% confidence level.

The following provides a summary of key findings from Table 3:

- **BTC:** Among FIGARCH, FIAPARCH, and HYGARCH models, HYGARCH(1, d, 1) delivered the most favorable results in terms of both log-likelihood and error metrics. This suggests that volatility in BTC follows a long memory process, which implies the invalidity of the EMH in its weak form.
- **ETH:** Short memory models performed best for ETH, particularly IGARCH(1,1). Since ETH does not exhibit a long memory feature, EMH is considered valid for returns and volatility.
- **BNB:** Among FIGARCH(1, d, 0), FIAPARCH(0, d, 1), and HYGARCH(0, d, 1), FIGARCH(1, d, 0) performed best in terms of both log-likelihood and error metrics. The performance metrics support the presence of long memory and the tendency for volatility to revert to the mean.

- **SOL:** Both FIGARCH(1, d, 1) and FIAPARCH(1, d, 1) provided similar estimation quality. Although asymmetry effects were not prominent, the results suggest the presence of long memory in SOL's volatility.
- **XRP:** Both FIGARCH(1, d, 1) and FIAPARCH(1, d, 1) showed robust results. While FIGARCH slightly outperformed in terms of prediction error metrics, FIAPARCH yielded comparable results. Overall, XRP's volatility appears predictable and exhibits characteristics inconsistent with EMH.

Table 4. Summary of Market Efficiency and Volatility Model Forecast Results

Crypto	Best-Fit Model	Distribution	Efficient Markets Hypothesis
BTC	HYGARCH(1, d, 1)	ST	Valid in returns, not valid in volatility
ETH	IGARCH(1, 1)	ST	Valid in both returns and volatility
BNB	FIGARCH(1, d, 0)	ST	Valid in returns, not valid in volatility
SOL	FIGARCH(1, d, 1), FIACH1, d, 1)	ST	Valid in returns, not valid in volatility
XRP	FIGARCH(1, d, 1), FIAPARCH(1, d, 1)	ST	Valid in returns, not valid in volatility

Table 4 summarizes market efficiency and the optimal volatility models for five cryptocurrencies. Accordingly, long memory exists in the volatility of all cryptocurrencies except ETH; therefore, even if the EMH is valid in return, it is not valid in volatility. Conversely, ETH does not exhibit long memory, suggesting a relatively weaker volatility dynamic. The results indicate that most of the cryptocurrencies exhibit asymmetric shocks and that, in general, the student-t (ST) distribution captures the heavy-tailed structure more effectively.

These findings imply that the EMH is not entirely valid for cryptocurrencies at the weak-form level (especially in volatility processes) and that past volatility shocks of most crypto assets tend to have a persistent effect. Therefore, volatility forecasting using long memory models may yield more reliable results for investors and risk managers.

5.2. Return Forecasting Using the PATSOS Method

In this section, the return directional forecasts of BTC, ETH, BNB, SOL, and XRP are conducted using a hybrid machine learning method, PATSOS, which also delivers successful results on non-linear data. Since previous analyses have identified long memory in the volatility of cryptocurrencies other than ETH, past price movements in these markets may be more effective in predicting future trends. Given this nature and the high volatility of cryptocurrencies, PATSOS, which combines Fuzzy Logic and ANN approaches, can potentially enhance directional forecasting performance.

For each cryptocurrency, the PATSOS method, which consists of CON-ANFIS and PR-ANFIS stages, was first applied and then compared with the results obtained through the standard ANFIS

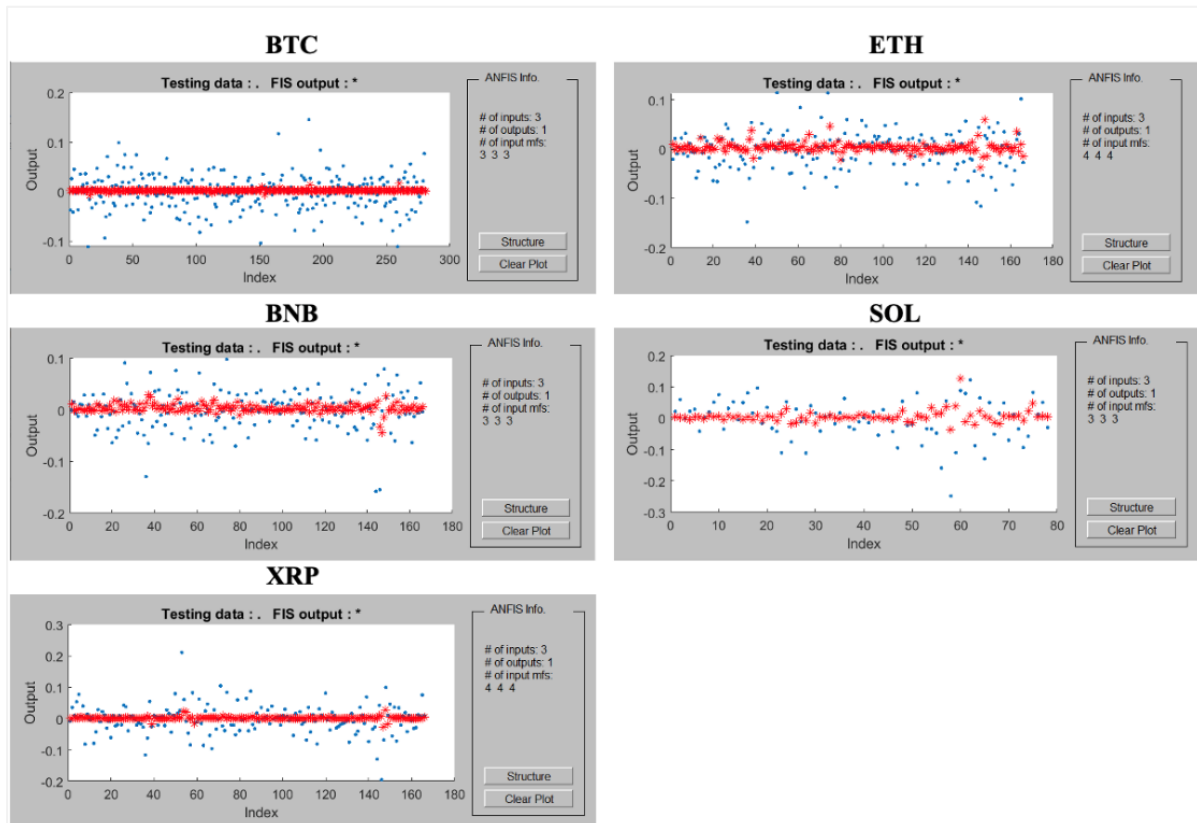
method. The forecasting performance of PATSOS and ANFIS is evaluated using RMSE, MSE, MAE, and correct directional prediction rate (i.e., whether the predicted and actual return signs match).

5.2.1. Forecasting Performance: PATSOS vs. ANFIS

The structural details of the PATSOS method, which consists of two subsystems—CON-ANFIS and PR-ANFIS—have been explained in Section 4.2. The model is applied to each cryptocurrency in this section, and the forecasting process results are presented.

Figure 2 illustrates the predicted and actual return series for five major cryptocurrencies—BTC, ETH, BNB, SOL, and XRP—using PATSOS. Red stars denote the model's forecasted returns, while blue dots represent the actual observed values. The visual alignment between predicted and actual returns demonstrates the model's effectiveness in capturing the return values across different cryptocurrencies

Figure 2. Forecasted vs. Actual Returns Using the PATSOS Method



Although Figure 2 displays return values rather than directions, directional accuracy—calculated by comparing the signs of actual and predicted returns—demonstrates that the PATSOS method performs better than traditional ANFIS, particularly for cryptocurrencies exhibiting long memory behavior. Table 5 summarizes the RMSE, MSE, MAE, and correct prediction rate values obtained by the PATSOS and ANFIS methods during the testing phase for five cryptocurrencies (BTC, ETH, BNB, SOL, and XRP).

Table 5. ANFIS and PATSOS Return Forecast Performance Comparison

Correct Prediction Rate (%)				Error Values					
Crypto	ANFIS	PATSOS	Crypto	RMSE		MSE		MAE	
				ANFIS	PATSOS	ANFIS	PATSOS	ANFIS	PATSOS
BTC	50.1	<u>52.6</u>	BTC	0.03477	<u>0.03469</u>	0.00120	<u>0.00120</u>	0.02556	<u>0.02531</u>
ETH	49.3	<u>54.2</u>	ETH	0.04074	<u>0.04021</u>	0.00165	<u>0.00161</u>	0.03131	<u>0.03085</u>
BNB	52	<u>53.8</u>	BNB	0.03907	<u>0.03869</u>	0.00152	<u>0.00149</u>	0.02890	<u>0.02867</u>
SOL	53.8	<u>55.1</u>	SOL	0.06636	<u>0.06150</u>	0.00440	<u>0.00378</u>	0.04885	<u>0.04677</u>
XRP	48.1	<u>49.3</u>	XRP	0.04676	<u>0.04642</u>	0.00218	<u>0.00215</u>	0.03339	<u>0.03313</u>

As seen in Table 5, the PATSOS method consistently outperforms ANFIS by achieving higher correct prediction rates and lower RMSE, MSE, and MAE values for all cryptocurrencies in the dataset. These results underscore the PATSOS method's ability to capture and adapt to the non-linear patterns inherent in cryptocurrency return series.

Moreover, for long memory series such as BTC, BNB, SOL, and XRP, PATSOS's closed-loop structure appears particularly effective in capturing the "influence of past price movements on future values" discussed in earlier sections. This suggests that hybrid machine learning models like PATSOS are better equipped to handle the complex dynamics and persistent fluctuations observed in crypto asset behavior.

6. DISCUSSION

In this study, the volatility dynamics and long memory properties of the five cryptocurrencies with the highest market capitalization (BTC, ETH, BNB, SOL, XRP) are analyzed in detail. Our findings reveal the existence of long memory in the volatility series of BTC, BNB, SOL, and XRP but not in ETH. Since the long memory property is inconsistent with the weak form of the EMH, we conclude that these crypto assets exhibit a predictive structure. ETH, in particular, stands out with its short memory and is more consistent with market efficiency.

Models that consider fractional and asymmetric impacts—like FIGARCH, FIAPARCH, and HYGARCH—have made a strong forecast on volatility with their performance. This, in return, has demonstrated the superiority of such models in accurately modeling the intricate and non-linear nature of crypto markets. Besides, the different impacts of positive and negative shocks on the volatility increase support the concept that behavioral factors are also significant in the cryptocurrency markets.

In the return forecasting phase, PATSOS yields lower error values and higher directional prediction accuracy across all cryptocurrencies than the benchmark ANFIS method. This suggests that machine learning methods such as PATSOS are particularly effective for volatile and non-linear financial time series.

The superior performance of the PATSOS method can be attributed to its closed-loop architecture, which incorporates dynamic feedback between the controller (CON-ANFIS) and the process (PR-ANFIS). This enables the model to capture the persistent volatility patterns and asymmetries in return behaviour more effectively than classical ANFIS, which relies on a one-way prediction mechanism. Moreover, this feedback mechanism mimics investor learning and adaptation over time, aligning well with behavioural finance insights regarding market inefficiencies in cryptocurrency markets.

Both academics and investors can benefit from these outcomes. For the researchers, it emphasizes the necessity of simultaneously modeling both long memory and asymmetry for crypto markets. On the other hand, for the investors, the evidence that predictability provides opportunities for using advanced trading risk management and algorithmic strategies with better model accuracy.

7. CONCLUSION

This research centers on the five cryptocurrencies with the highest market value (BTC, ETH, BNB, SOL, and XRP) using advanced volatility models and a hybrid forecasting method. The first step in the volatility analysis illustrated that models such as FIGARCH, FIAPARCH, and HYGARCH capture both long memory and asymmetric volatility effects very efficiently. The discovery of long memory in all of these assets except ETH proves the existence of market inefficiency; thus, the price movements in these markets may be predictable.

In the second stage, return forecasts were conducted using both ANFIS and the hybrid PATSOS approach. Directional accuracy rates, along with RMSE, MSE, and MAE error measures, were calculated and compared for ANFIS and PATSOS. The results demonstrated a clear improvement with PATSOS, as directional accuracy increased from 50.1% to 52.6% for BTC, from 49.3% to 54.2% for ETH, from 52% to 53.8% for BNB, from 53.8% to 55.1% for SOL, and from 48.1% to 49.3% for XRP. Across all cryptocurrencies, the PATSOS method achieved lower error values and higher correct prediction rates than the ANFIS. These results show the potential of closed-loop, hybrid machine learning methods like PATSOS in capturing the non-linear behavior of digital asset markets.

This study contributes to the literature in several ways. First, while most studies focus on a single cryptocurrency, this study simultaneously analyzes volatility and return forecasts for the top five cryptocurrencies regarding market capitalization. Second, more in-depth analyses are provided using advanced fractional models that accommodate both long memory and asymmetric effects in volatility modeling. Studies that consider these two elements together are quite limited. Third, PATSOS, a closed-loop hybrid method combining Fuzzy Logic and ANN, is used for return forecasting. Although machine learning techniques are widely used in cryptocurrency forecasts, applications of the PATSOS method are limited. Therefore, this study provides a multidimensional and novel contribution to the literature.

One limitation of this study is the exclusion of macroeconomic or regulatory variables that may influence cryptocurrency returns. While the model focuses solely on price-based features, incorporating macro-financial indicators in future studies could further enhance prediction accuracy and model robustness.

Given the dataset and methodological framework, the study's results provide valuable insights for those considering investing in cryptocurrencies. The high accuracy of the PATSOS method for all cryptocurrencies suggests that it may provide more effective return forecasting for individual and institutional investors. Moreover, the findings from these five cryptocurrencies, representing a large portion of the total market capitalization, can provide a benchmark for future research on other cryptocurrencies.

The results provide meaningful information for cryptocurrency investors interested in predicting price movements. Moreover, the findings are highly generalizable, as the selected cryptocurrencies constitute a significant portion of the market (69.1%).

However, this study has some limitations. First, it focuses on five cryptocurrencies and does not include other asset classes. Second, daily data is used; higher frequency data may provide different insights. Finally, the models do not account for external macroeconomic or regulatory variables that may affect future returns. Future research could address these aspects to improve forecast performance further.

Ethics Committee approval was not required for this study.

The authors declare that the study was conducted in accordance with research and publication ethics.

The authors declare that, during the writing process of this manuscript, AI tools (such as language improvement assistants) were occasionally used to enhance the clarity and fluency of the English language. All content, analysis, and interpretations were solely developed by the authors.

The authors declare that there are no financial conflicts of interest involving any institution, organization, or individual associated with this article. Additionally, there are no conflicts of interest among the authors.

The authors state that the first and corresponding author conducted the entire research process, including the planning, data collection, analysis, and manuscript preparation. The second author, who supervised the doctoral dissertation from which this article is derived, provided academic guidance during the thesis stage.

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