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Recent Advances in Machine Learning and Statistical Approaches for Imputation and Forecasting in Financial and Cryptocurrency Data: A Review

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Abstract— The proliferation of data-driven methods in financial analytics has underscored the importance of effectively handling missing data and accurately forecasting market behaviors. This review consolidates recent advancements in missing data imputation within financial datasets, alongside machine learning (ML) and statistical models applied to cryptocurrency forecasting. We highlight classical approaches, such as expectation-maximization and k-nearest neighbors, and explore contemporary frameworks involving deep learning architectures like LSTM and generative adversarial networks (GANs). Additionally, we compare hybrid optimization methods tailored to the volatility of cryptocurrency markets. This study synthesizes key findings, identifies prevailing challenges, and outlines promising directions for future research in financial data analytics.

Keywords— Missing Data, Financial Time Series, Cryptocurrency, Machine Learning, LSTM, GAN.

1. INTRODUCTION

The accelerated digitization of global financial systems has ushered in an era where vast volumes of data underpin critical investment and risk management decisions. However, the quality and completeness of financial datasets remain persistent challenges, with missing data frequently arising from irregular reporting, market closures, or technological disruptions. Simultaneously, the meteoric rise of cryptocurrencies has introduced new complexities into financial markets, characterized by extreme volatility, fragmented regulation, and sentiment-driven price movements. In response, researchers have increasingly turned to machine learning (ML) and advanced statistical techniques to enhance data reliability through robust imputation methods, as well as to develop predictive models capable of capturing intricate, non-linear market behaviors. This review systematically examines recent progress in these two intertwined areas: (i) the treatment of missing data in financial time series and (ii) the application of ML and statistical models for forecasting in cryptocurrency markets. By consolidating methodologies, comparative results, and identified challenges across these

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domains, this study aims to provide a coherent foundation for future advancements in data-driven financial analytics.

2. METHODOLOGY OF THE LITERATURE REVIEW

This review was conducted to synthesize recent developments in machine learning and statistical methods applied to financial data imputation and cryptocurrency forecasting.

2.1. Data Sources and Search Strategy:

Relevant literature was identified by searching major scientific databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The search was performed using combinations of keywords such as “financial time series imputation,” “missing data,” “cryptocurrency forecasting,” “LSTM,” “GAN,” “support vector machines,” and “deep learning in finance.”

2.2. Time Frame and Scope:

The primary focus was on articles published between 2020 and 2024, reflecting the rapid advancements in machine learning applications during this period. However, seminal earlier works were also referenced when necessary to provide foundational context.

Inclusion and exclusion criteria:

The review prioritized peer-reviewed journal articles and reputable conference proceedings that:

- proposed new or significantly enhanced methods for handling missing financial data,
- or applied machine learning and statistical models to cryptocurrency forecasting with quantitative performance evaluation.

Papers purely descriptive in nature, lacking empirical validation, or focusing solely on traditional stock markets without a machine learning component were generally excluded.

2.3. Data Extraction and Synthesis:

Key information extracted from the selected studies included the type of datasets used (financial time series or cryptocurrency), imputation or forecasting methodologies, performance metrics, and main findings. Comparative insights were then synthesized to identify prevailing trends, advantages, and existing gaps in the literature.

This approach enabled a comprehensive overview of the state-of-the-art, while also ensuring the inclusion of a diverse set of methods and perspectives across the two intertwined domains of financial data quality and predictive analytics.

3. LITERATURE REVIEW

Recent studies have extensively explored various imputation techniques to address missing data in the financial time series. These efforts aim to improve prediction accuracy and data completeness, thereby enhancing decision-making processes in finance. First, a study conducted a comparative analysis and quantitative assessment of several imputation techniques using K-NN, expectation-maximization, classification and regression tree, and random forest (RF) methodologies. The findings indicated that the expectation-maximization technique exhibited favorable performance relative to other methods [1].

Another study assessed the effectiveness of modeling stock market volatility using RF. The study highlighted that RF achieves high performance in scenarios with large feature sizes and effectively manages intricate datasets, making it a robust tool for financial volatility modeling [2]. A paper by [3] aimed to build a prediction model for forecasting stock prices, utilizing LSTM, Extreme Gradient Boosting, Linear Regression, Moving Average, and Last Value models. The experimental findings confirmed that these models could acquire patterns in time series data, with the LSTM model demonstrating superior performance for the intended objective.

Additionally, a study evaluated and compared the effects of various imputation methods for estimating missing values in a time series. The methodologies included Mean, LOCF, MICE, K-NN, and NOCB. The results showed that the K-NN technique was the most effective in reconstructing missing data and positively contributed to time series forecasting compared with other imputation methods [4]. Then, a study proposed a novel imputation method to obtain a fully observed panel of firm fundamentals by exploiting time series and cross-sectional data dependency. This approach, which utilized statistical methods and various backward and forward strategies, documented significant consequences for risk premia calculations, cross-sectional anomalies, and portfolio building [5].

Another study compared new approaches for imputing missing time steps with traditional and state-of-the-art methods. The study found that resampling the Financial Index dataset by the week's mean yielded the best results when imputed using a sequence of Kalman, Nature, and Decomposition methods. Additionally, resampling by Friday yielded the best results when imputed using Kalman, Regression, and Missing Indicators, with the mean tied for third place [6].

In the same year, [7] proposed a Modified Genetic Algorithm (MGA) to address the local optima problem of the Genetic Algorithm (GA). By comparing MGA with GA and PSO, the study found that MGA performed better in terms of accuracy, precision, recall, and F-score. Researchers in [8] introduced the unique Rolling Mice Forest (RMF) approach for handling missing values in financial panel data. This method employed RFs to impute missing data, reducing future observation leakage and improving the prediction performance of Gradient Boosted Regression Trees (GBRTs) in stock return prediction. The study found that RMF and median imputations enhanced GBRT predictions in the U.S. and Norway, whereas list-wise deletion negatively impacted performance.

Lastly, a novel framework leveraging generative adversarial networks (GANs) and an iterative approach using the gradient of the complementary was proposed. The experimental findings demonstrated that imputeGAN exhibited superior performance compared with conventional complementation techniques in terms of complementation accuracy [9].

3.1. Recent Machine Learning and Statistical Model Studies on Cryptocurrency Datasets

In this section, existing relevant research on the topic addressed in this thesis is reviewed comprehensively. With the global economy becoming increasingly interconnected, the performance of individual countries is becoming more strongly linked to financial markets. Thus, currency is a key determinant of a country's economic health.

[10] combined the particle swarm algorithm and ARIMA to create an optimal prediction model. Moreover, they presented the mean-variance model, Sharpe ratio, and efficient frontier to achieve risk-return equilibrium. Their findings highlighted the importance of investor personality in investment strategies and emphasized the ARIMA model's efficacy in financial forecasting and portfolio optimization.

[11] conducted a comparative analysis of ARIMA and long short-term memory (LSTM) models across five cryptocurrencies and found that the LSTM model has better accuracy than ARIMA and can better visualize cryptocurrency price trends. According to their findings, accuracy can be improved by adjusting model parameters and integrating other ML methods.

[12] categorized tweets and data from various sources according to whether they were positive, negative, or neutral. Then, they examined the relationships between Bitcoin movements and tweet sentiments. Their method achieved a high forecasting accuracy of 98.75%, and this technique was compared with established methods through the use of visualization tools.

[13] proposed the use of a multi-input deep neural network to predict Bitcoin price and movement. The model analyzed cryptocurrency data inputs to gain insights from each coin. Experimental analysis showed that this method has less overfitting and processing load than fully connected deep neural networks do.

[14] integrated the XGBoost algorithm with enhanced PSO to fine-tune hyperparameters and make them more suitable to optimize the prediction rate. Superior prediction results were obtained by this method.

[15] assessed the performance of various deep learning models, including convolutional neural networks (CNNs), deep feedforward networks, and gated recurrent units (GRUs), along with boosted tree-based approaches, in predicting cryptocurrency closing prices. Six Bitcoin datasets were used to evaluate these methods on the basis of key performance indicators. Findings show that forecasting accuracy was considerably improved.

[16] conducted non-time series analysis to compare the performance of k-nearest neighbors (k-NN) and multiple polynomial regression (MPR) algorithms in predicting Ethereum prices through non-time series analysis. Mean squared error (MSE) and mean absolute error (MAE) were used as evaluation parameters. Findings show that k-NN with $K = 2$ provided the most accurate predictions, outperforming MPR.

[17] used support vector machine (SVM) and KNN algorithms to predict Bitcoin prices, showing that SVM was better than the more commonly used KNN.

[18] used ML to predict cryptocurrency volatility using internal and external factors. The study demonstrated that applying optimization models significantly enhanced forecasting performance. The SHapley Additive Explanations interpretation also showed that models trained with multiple cryptocurrency determinants performed better than those trained with a single coin.

[19] introduced three recurrent neural network (RNN) algorithms for predicting the prices of three cryptocurrencies. GRU outperformed the LSTM and bidirectional LSTM (Bi-LSTM) models in predicting various cryptocurrency types.

[20] suggested using three types of RNNs—LSTM, GRU, and Bi-LSTM—to predict exchange rates of important cryptocurrencies. Bi-LSTM achieved the highest prediction accuracy, having better results in terms of root mean squared error (RMSE) and mean absolute percentage error (MAPE) than those of LTSM and GRU.

[21] utilized random forest to analyze three scenarios based on input variables—technical indicators, candlestick patterns, and a combination of both—finding that candlestick patterns were more efficient than technical indicators.

[22] examined the daily and minute-level prediction of the top 12 cryptocurrencies by using ML algorithms such as SVM, LR, artificial neural networks, and random forests. The categorization accuracy of these algorithms consistently exceeded 50% for all coins and timelines, with SVM in particular having superior performance.

[23] evaluated the effectiveness of RNN and LSTM deep learning approaches in predicting Bitcoin and Ethereum prices and found that LSTM outperformed RNN, showing lower RMSE and MAPE values.

[24] applied SVM to estimate financial returns for six major digital currencies from the top 10 cryptocurrencies using sensor data. The study focused on the pre- and post-COVID-19 periods and showed that SVM can effectively create profitable trading strategies with accurate results.

[25] introduced an optimized least squares SVM (OLS-SVM) model for predicting return rates in Blockchain financial products. Grey wolf optimization was combined with differential evolution to optimize the model parameters. Simulation results based on MSE and MAPE shows that the OLS-SVM model predicted financial product return rates better.

Many studies have presented different ML and statistical models, such as ARIMA, LSTM, SVM, RNN, and random forest, as indicated by a review of literature on cryptocurrency price prediction. [10] noted that ARIMA was effective in finance and portfolio management, while [11] observed that LSTM models had better accuracy and trend analysis.

Comparative studies show that ML methods produce better results than conventional methods can. [12] improved the forecast performance by establishing relationships between Bitcoin fluctuations with Twitter sentiments, while [13] proposed a multi-input deep neural network to minimize overtraining. Other studies such as those of [14] and [15] used advanced algorithms and optimization techniques to improve the outputs that are used to predict cryptocurrency markets. Findings show that such algorithms can help in understanding the fluctuations of cryptocurrency markets.

Error! Reference source not found. provides an overview of various studies that have u sed different forecasting algorithms and models for cryptocurrency price prediction. These studies apply different cryptocurrencies and were conducted during various time periods, showing that diverse approaches are being used in the field.

Table 1.Summary of Selected Studies on Cryptocurrency Forecasting Algorithms

Reference	Year	Crypto	Period	Model	Approach
[10]	2022	Bitcoin	2016–2021	ARIMA	Forecasting
[11]	2023	Bitcoin, Ethereum, Binance Coin, Tether, and Cardano	2017–2021	ARIMA, LSTM	Forecasting
[12]	2022	Litecoin, Monero, Bitcoin, and Ethereum	2015–2020	CNN	Forecasting
[13]	2021	Bitcoin, Ethereum, and Ripple	2017–2020	CNN-LSTM	Forecasting
[14]	2023	Bitcoin, Dogecoin, and Ethereum	2010–2020	Regression Algorithm, Particle Swarm Optimization with XGBoost	Forecasting
[15]	2023	Bitcoin, Ethereum, Binance Coin, Litecoin	2018–2021	XGBoost, GBoostM, Adaptive boosting, GRU, CNN	Forecasting
[16]	2021	Ethereum	2017–2021	KNN	Forecasting
[17]	2020	Bitcoin	2014–2017	SVM, KNN	Forecasting
[18]	2023	Bitcoin, Ethereum, Litecoin and Ripple	2017–2022	RF, LSTM	Forecasting
[19]	2021	Bitcoin, Litecoin, and Ethereum	2018–2021	LSTM	Forecasting
[20]	2023	Bitcoin, Ethereum, and Litecoin	2018–2023	LSTM	Forecasting
[21]	2023	Bitcoin	2013–2020	RF	Forecasting
[22]	2021	Bitcoin Cash, Bitcoin, Dash, EOS, Ethereum Classic, Ethereum, Iota, Litecoin, OmiseGO, Monero, Ripple, and Zcash	2013–2018	SVM LR, ANN, and RF	Forecasting
[23]	2023	Bitcoin, Ethereum	2013–2021	RNN and LSTM	Forecasting
[24]	2021	Binance Coin, Bitcoin, Cardano, Dogecoin, Ethereum, and Ripple	2020–2021	SVM	Forecasting
[25]	2020	Ethereum		LSSVM	Forecasting

Fig 1 summarizes the number of articles that have examined cryptocurrencies, indicating that Bitcoin ranks first, followed by Ethereum.

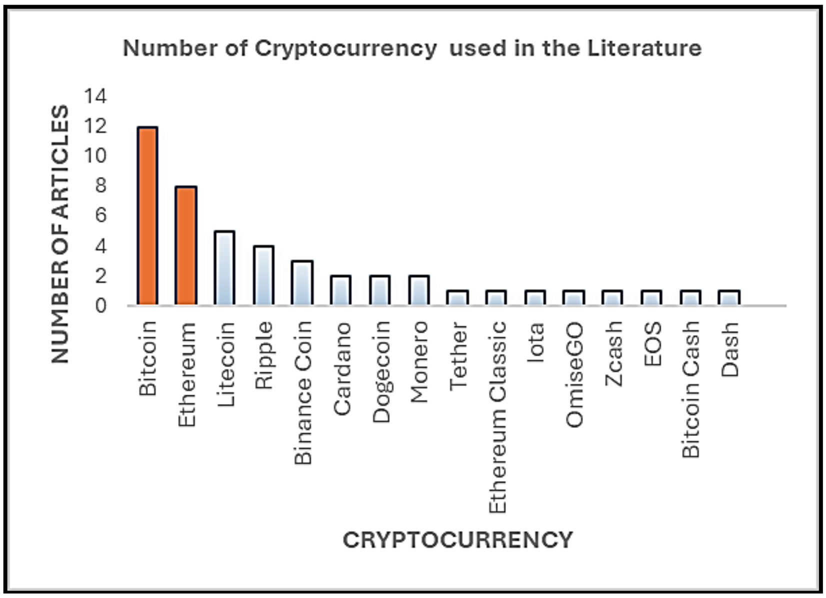

Fig 1. Summary of Cryptocurrency Used in the Literature

Fig 2 illustrates the number of articles that used algorithms, showing that LSTM was the most frequently used algorithm, followed by SVM.

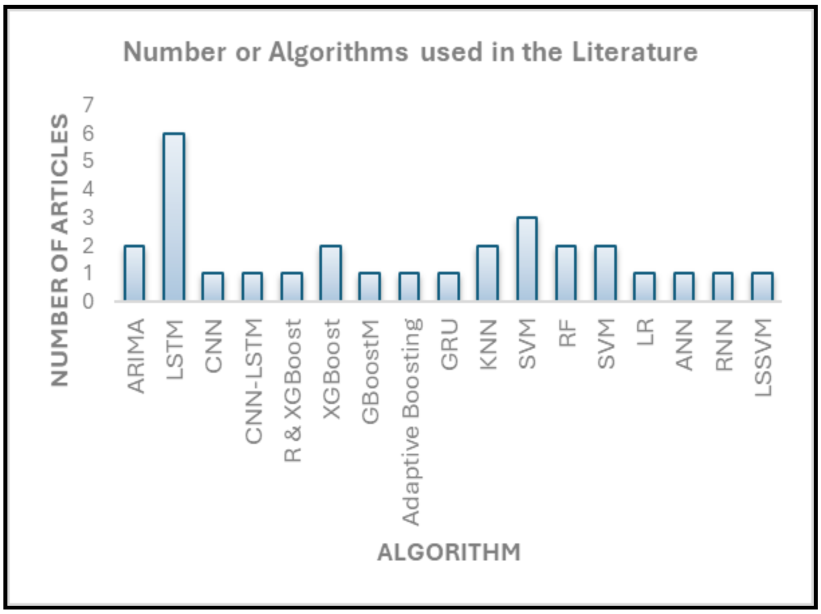

Fig 2. Summary of Algorithms Used in Literature

4. CHALLENGES AND FUTURE DIRECTIONS

Despite the remarkable progress highlighted throughout this review, the application of machine learning and advanced statistical techniques to financial time series imputation and cryptocurrency forecasting still faces significant challenges that warrant further investigation.

4.1. Lack of Standardized Benchmarks

A prominent limitation in current research is the absence of unified benchmark datasets and evaluation protocols. Most studies rely on proprietary or domain-specific datasets, often spanning different time periods, currencies, or market conditions, making it difficult to perform direct comparisons or reproduce results reliably.

4.2. Model Interpretability and Trustworthiness

As the financial sector is highly sensitive to transparency and regulatory scrutiny, the black-box nature of many advanced models—particularly deep learning architectures like LSTM and CNN-LSTM—poses challenges for adoption. While explainability tools such as SHAP and LIME have been explored, there is still a pressing need for frameworks that inherently combine high predictive accuracy with interpretable outputs.

4.3. Handling Market Regime Shifts and External Shocks

Current models often perform well under stable conditions but may struggle during structural breaks, such as those caused by economic crises, pandemics, or abrupt regulatory changes. Developing models that can adapt to or detect these regime shifts remains an open research question.

4.4. Integration of Multi-Modal Data Sources

Although some studies have incorporated sentiment data from platforms like Twitter, most forecasting approaches still predominantly rely on historical price and volume data. Future systems could benefit from more comprehensive multi-modal inputs, including macroeconomic indicators, blockchain activity data, and geopolitical event signals.

4.5. Transfer Learning and Generalization

While transfer learning has shown promise in other domains, it remains underexplored in financial applications. Leveraging knowledge from well-established markets (such as Bitcoin) to improve predictive performance in emerging cryptocurrencies or across different asset classes could significantly enhance generalization and mitigate data scarcity issues.

4.6. Robustness Against Adversarial Manipulation

Given the susceptibility of financial systems to manipulation, ensuring that machine learning models are robust against adversarial inputs or coordinated misinformation campaigns (particularly relevant when integrating social media data) is a critical area for future exploration.

Addressing these challenges will be essential for advancing the practical utility of machine learning frameworks in financial analytics, paving the way for systems that are not only accurate but also reliable, interpretable, and resilient in dynamic market environments.

5. CONCLUSION

This review has systematically examined the landscape of recent machine learning and statistical approaches applied to two critical domains in financial analytics: missing data imputation in financial time series and forecasting in cryptocurrency markets.

For the imputation of missing financial data, the literature reveals a strong evolution from classical statistical techniques, such as expectation-maximization, mean imputation, and k-nearest neighbors, toward more sophisticated machine learning frameworks. Notably, ensemble methods like random forests and novel solutions such as the Rolling Mice Forest and GAN-based architectures have demonstrated considerable promise in preserving temporal and cross-sectional dependencies, ultimately leading to improved data quality and predictive power.

In the context of cryptocurrency forecasting, the reviewed studies underscore the dominance of deep learning models, especially LSTM and GRU networks, which outperform traditional models like ARIMA in capturing the non-linear, highly volatile dynamics characteristic of digital currencies. Furthermore, the integration of hybrid techniques — such as CNN-LSTM architectures, optimization-augmented XGBoost models, and sentiment-driven frameworks leveraging social media data — highlights a methodological shift toward multi-source, multi-model strategies designed to tackle the complexities inherent in cryptocurrency markets.

This article contributes to the financial machine learning literature by synthesizing a diverse body of recent work, comparing methodologies across different datasets and evaluation metrics, and offering a consolidated view of current best practices. It also brings attention to critical challenges that remain, including the need for standardized benchmarking datasets, improvements in model interpretability, and more robust frameworks capable of adapting to structural shifts in market conditions.

Looking forward, the insights gathered here suggest a fertile ground for future research to explore transfer learning across financial instruments, integrate explainable AI methodologies for greater transparency, and develop adaptive systems responsive to emerging market phenomena. By advancing these directions, researchers and practitioners can build more reliable, interpretable, and effective tools for financial decision-making in an increasingly data-centric and algorithm-driven economy.

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