JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

INTIGRATED TIME-SERIES REAL-TIME CRYPTOCURRENCY PRICE PREDICTION USING HYBRID MODEL

Dr. Levina Tukaram[1], Roshan Kumar Mahato[2], Nitesh Jha[3], Shaik Aman[4]

Assoc Professor[1], Student[2,3,4]
Department of Computer Science & Engineering
KNS Institute of Technology Bangalore-560064, Karnataka, India

Abstract: *The unpredictable and volatile nature of cryptocurrency markets has made accurate price forecasting an essential aspect of modern investment strategies. Traditional statistical models often fall short in capturing the complexity of these markets, primarily due to their assumption of linearity and the absence of adaptability to rapidly changing, non-stationary data. In response to these limitations, advanced computational techniques such as ensemble learning and deep learning have gained prominence for their ability to model complex patterns and relationships in time-series data. This research presents a novel comparative evaluation of deep learning architectures and ensemble methods for forecasting the prices of leading cryptocurrencies, including Bitcoin, Ethereum, Dogecoin, Binance Coin, Ripple, Solana, and Litecoin. Experimental findings reveal that models such as Gated Recurrent Units (GRUs), Simple Recurrent Neural Networks (RNNs), and Light Gradient Boosting Machines (LightGBM) consistently outperform both conventional machine learning algorithms and simplistic trading strategies like buy-and-hold or random walk. These insights not only highlight the strengths of modern predictive approaches but also provide investors with robust tools to enhance trading accuracy and reduce risk in the dynamic world of digital assets.*

Keywords - Cryptocurrency, Bitcoin, Price Prediction, Ensemble Learning, Deep Learning, Time-Series Forecasting, Neural Networks

INTRODUCTION

With the ongoing digital transformation across industries, the emergence of cryptocurrencies marks a significant shift in the financial ecosystem. These digital assets represent a paradigm shift from conventional, centralized financial systems to decentralized, trustless networks. Historically, financial transactions were grounded in physical instruments such as cash and cheques, later evolving into digital banking systems. However, over the past two decades, the emergence of cryptocurrencies has introduced a novel, decentralized method of conducting peer-to-peer transactions, effectively redefining how value is stored and exchanged globally.

Cryptocurrencies operate on the foundation of cryptographic principles and are governed by decentralized consensus mechanisms rather than central authorities. At the heart of this ecosystem lies blockchain technology—a tamper-resistant, distributed ledger that securely records transactions across a network of interconnected nodes. Each transaction on the blockchain is verified through consensus algorithms like Proof of Work (PoW) or Proof of Stake (PoS), ensuring transparency, data integrity, and immutability without requiring intermediary institutions such as banks or payment gateways.

By May 2023, over 12,000 digital currencies were in circulation, with Bitcoin (BTC) continuing to lead the market in terms of capitalization and influence. Other notable cryptocurrencies such as Ethereum (ETH), Binance Coin (BNB), Cardano (ADA), Dogecoin (DOGE), Solana (SOL), and Litecoin (LTC) have also captured substantial market attention. The cryptocurrency market capitalization exceeded $2 trillion in 2021, and by 2027, the sector is projected to reach nearly $65 billion in annual revenue, highlighting its growing economic relevance.

One of the primary attractions of cryptocurrencies is their decentralized nature, which empowers users with greater control over their assets. These digital currencies enable faster and cheaper cross-border transactions, minimize reliance on third parties, and enhance financial inclusion. However, their decentralized design also introduces complexities. Security risks, regulatory ambiguities, market manipulation, and price instability are persistent challenges facing the sector. The value of cryptocurrencies can swing dramatically in response to macroeconomic shifts, government regulations, media coverage, or even influential social media posts.

A typical blockchain-based transaction involves a sender initiating a transfer by specifying the recipient's digital wallet address and transaction value. This information is broadcast across the blockchain network, where it is validated by miners or validators using intensive computational techniques. Once verified, the transaction is appended to a block, which is then linked to the existing blockchain through a secure, consensus-driven process—ensuring that every transaction is transparent, traceable, and irreversible.

Despite the technological resilience of blockchain, forecasting cryptocurrency prices remains an intricate endeavor. The market is influenced by a convergence of diverse factors, including trading volumes, liquidity levels, economic news, technological updates, investor sentiment, and political developments. These interdependencies create complex, nonlinear patterns that traditional financial models often fail to capture effectively.

To navigate this uncertainty, there is a growing demand for robust predictive models that can deliver high accuracy under real-world conditions. Investors, traders, and analysts increasingly rely on a blend of analytical tools—namely technical analysis, fundamental analysis, and sentiment analysis—to forecast market trends and make data-driven decisions. Technical analysis relies on historical price data and market indicators to identify trends, while fundamental analysis considers external variables such as legislation, platform development, and economic health. Sentiment analysis, which uses machine learning and natural language processing (NLP), provides real-time insight into market psychology by examining social media trends, forums, and news sources.

Many existing models, however, are limited by their reliance on single-source data or their inability to integrate multiple market dynamics. These limitations reduce their effectiveness, particularly in highly volatile environments. To overcome this, our study introduces a comprehensive hybrid framework that combines multiple data domains—historical pricing, technical indicators, and real-time sentiment signals—using advanced machine learning techniques.

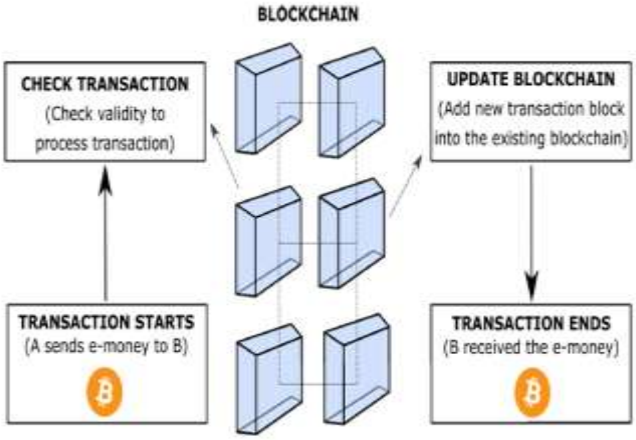

Fig 1. Block Chain Based Cryptocurrency Transaction Workflow

1. RELATED WORK

Cryptocurrency price forecasting has emerged as a rapidly expanding research area due to the increasing complexity and unpredictability of digital asset markets. As cryptocurrencies continue to gain prominence, numerous analytical methods have been proposed to address the inherent challenges in predicting their prices. These include technical, fundamental, and sentiment-based approaches, often powered by artificial intelligence (AI), machine learning (ML), econometrics, and hybrid statistical models. This section reviews notable studies that utilize these techniques to improve cryptocurrency price prediction.

2.1 Technical and Statistical Approaches

Several studies have explored time-series forecasting methods using a mix of traditional statistical models and modern ML techniques. One such investigation employed ARIMA and machine learning for predicting Bitcoin (BTC) prices. The authors observed that traditional statistical methods like logistic regression (LR) and linear discriminant analysis yielded an error rate as high as 66%, while ML models such as Long Short-Term Memory (LSTM), Support Vector Machines (SVM), Random Forest, and XGBoost achieved a modest enhancement in prediction accuracy, reaching approximately 67.2% [8]. Another study combined ARIMA and LSTM, revealing that integrating statistical and deep learning methods enhances predictive accuracy due to the ability of LSTM to capture long-term dependencies [9].

More advanced experiments employed ensemble learning methods. One such study applied various ML algorithms—including gradient boosting, neural networks, K-Nearest Neighbors (KNN), and hybrid models—to predict prices for multiple cryptocurrencies. The ensemble approach, which aggregates multiple model predictions, achieved the best performance with an accuracy of 92.4% [10]. A similar approach using deep learning (LSTM combined with ARIMA) demonstrated significant potential for long-term forecasting but suggested further improvements could be achieved by incorporating contextual features like market trends, regulations, and supply-demand factors [11].

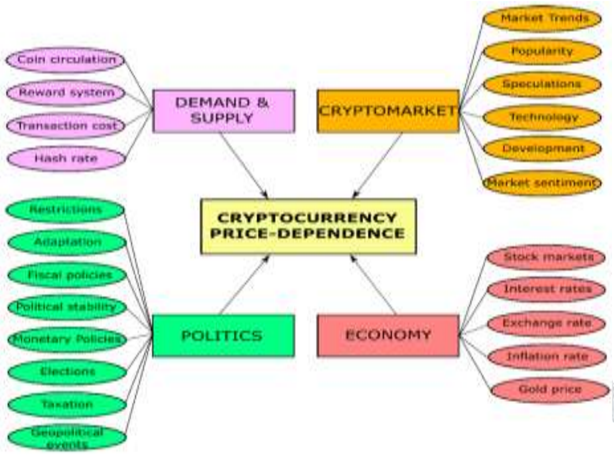

Fig 2. Key factors during volatility and influencing cryptocurrency price.

A unique technique involving stochastic neural networks was introduced to replicate the volatility of crypto markets by introducing randomness at various layers of neural activation [12]. Other researchers proposed hybrid models combining GRU (Gated Recurrent Units) and LSTM with cross-currency influence factors [13]. A multi-stage deep neural network trained on Bitcoin market data, Google Trends, and blockchain features was able to dynamically adjust the prediction window based on market volatility [14][15]. Comparative studies also suggested a shift in investment strategies from trend-based approaches to sentiment-driven models, emphasizing the evolving dynamics of cryptocurrency markets [15].

For instance, a study integrated wavelet transformation with LSTM to decompose market signals into various frequency bands before prediction, improving performance in complex market conditions [16]. Another investigation compared the effectiveness of linear and non-linear forecasting models and concluded that simpler models often perform competitively under certain market conditions [17].

2.2 Sentiment and Fundamental Analysis

Beyond technical data, public sentiment—driven by media, social platforms, and investor psychology—has proven to be a critical factor in price fluctuations. A study used sentiment analysis on Twitter data and combined it with technical indicators (via TA-LIB) to predict BTC prices. Tweets were collected, scored for sentiment, and merged with time-series price data. This near real-time model achieved a promising error margin, showing that integrating social data enhances short-term forecasting accuracy [18].

Other studies reinforced this idea using hybrid frameworks. One used tensor network to explore the correlation between tweets and stochastic market events [21], while another integrated Google Trends with Twitter data for short-term price prediction, combining multiple sources to increase model robustness [19]. Another hybrid model that merged linear regression and RNN proved effective for short-term BTC forecasting [20].

In a different approach, only high-quality posts (based on user ratings) from online forums were used in a deep learning model to enhance prediction accuracy [18]. A separate study utilized an LSTM-based model trained on sentiment data derived from Chinese social media platforms, demonstrating the strong influence of regional public sentiment on cryptocurrency price movements [20]

Comparative analyses across algorithms—such as Neural Networks, SVMs, and Random Forest—demonstrated that Neural Networks generally outperform others in forecasting the trends of leading cryptocurrencies like BTC, ETH, Ripple, and Litecoin. However, sentiment analysis alone may not suffice, as crypto markets are also influenced by macroeconomic shifts, technology developments, and policy changes.

A particularly noteworthy framework, DL-Gues, integrated multiple cryptocurrencies' interrelationships with sentiment factors to create a resilient, hybrid model for accurate forecasting [23]. Another study leveraged an ensemble of classifiers—Random Forest, SVM, Decision Trees, and Logistic Regression—to analyze over one million tweets related to the COVID-19 pandemic. By converting textual sentiment into numerical vectors using TextBlob and VADER, they achieved meaningful prediction improvements [20].

2.3 Research Gap and Proposed Contribution

While technical and sentiment-based models have shown encouraging results, many suffer from limited feature diversity and lack generalization across varying market conditions. Furthermore, most existing models fail to dynamically integrate the multifaceted dependencies that exist between market trends and public sentiment.

- To address these gaps, our study proposes an advanced, hybrid forecasting model that leverages:
- Historical time-series data processed through a hybrid ARIMA-LSTM architecture.
- Real-time sentiment analysis to anticipate market shifts caused by news or public emotion.

- Risk-mitigation insights through an alert mechanism that identifies and flags adverse sentiment patterns.

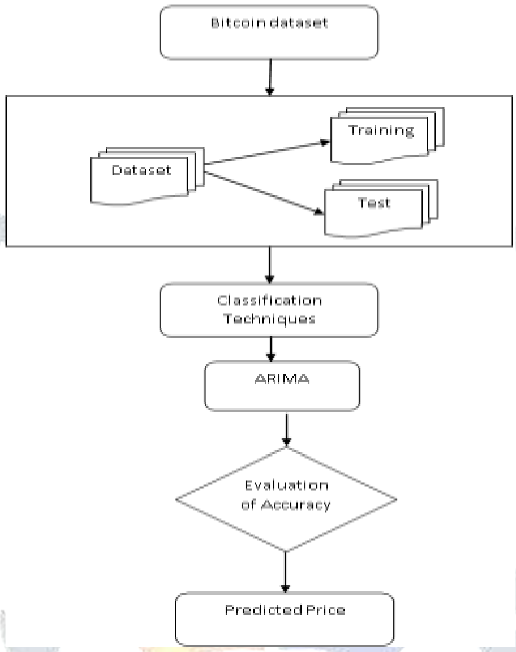

Fig 3 Working Pricipal Of ARIMA

2. PROPOSED METHODOLOGY

In This research introduces a hybrid predictive framework for cryptocurrency price forecasting that leverages the combined strengths of statistical and deep learning models. Specifically, the model integrates Long Short-Term Memory (LSTM) networks—a type of Recurrent Neural Network (RNN)—with Autoregressive Integrated Moving Average (ARIMA) to achieve more precise time-series predictions.

3.1 Use of LSTM for Time-Series Forecasting

LSTM networks are widely recognized for their effectiveness in modeling time-series and sequential data due to their ability to capture long-term dependencies and manage non-linear relationships between inputs and outputs. Given the volatile and non-stationary nature of cryptocurrency prices, LSTM models are well-suited to identify hidden patterns and adapt to fluctuations over time.

In this study, a dataset consisting of approximately 264,000 Bitcoin price records was collected through web scraping from an open-source API. The dataset spans a period of three months, from January 1 to March 20, 2023, and includes attributes such as Datetime, Symbol, Open, High, Low, and Close. The Close price column was selected as the primary feature for forecasting purposes [21].

Before training, the data was preprocessed and divided into training and testing sets. The LSTM model was initialized with random weights and trained over 10 epochs, using batch processing to minimize prediction error. Throughout this process, the model learned to adjust its internal weights by iteratively reducing the bias and optimizing the network's parameters through backpropagation.

3.2 Design of the ARIMA-LSTM Hybrid Model

While LSTM handles non-linear components well, traditional statistical models like ARIMA are more effective in modeling linear dependencies and seasonal trends. Therefore, this research proposes a hybrid approach that fuses both techniques to improve accuracy and robustness in forecasting.

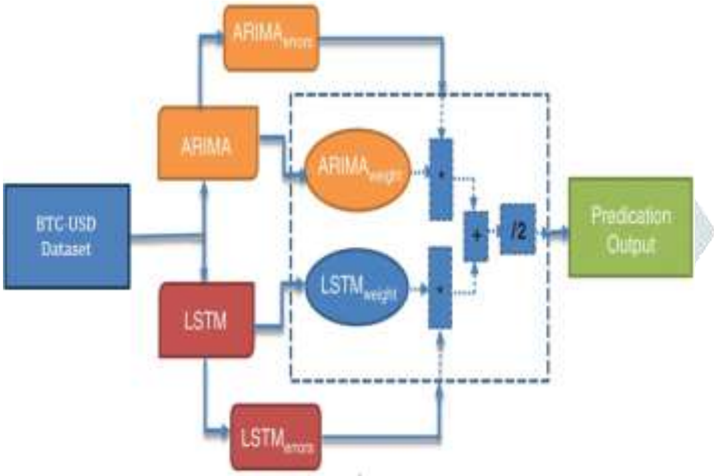

Fig 3. Working principle of the proposed ARIMA-LSTM hybrid model

The hybrid process involves the following stages:

Data Preprocessing: The dataset is first checked for stationarity. For ARIMA, differencing techniques are applied to stabilize variance and remove trends. For LSTM, data is normalized to enhance training performance [26].

Linear Modeling with ARIMA: The ARIMA model is applied to capture and forecast the linear behavior of the time series.

Residual Correction with LSTM: The residual errors—the difference between actual values and ARIMA's output—are passed into the LSTM model. LSTM then learns the underlying non-linear structures not captured by ARIMA.

Forecast Combination: The final prediction is derived by combining ARIMA's linear output with the LSTM's non-linear adjustments, resulting in a more refined and accurate forecast.

This two-stage process allows each model to address its respective strengths: ARIMA for deterministic trends and LSTM for chaotic, pattern-driven fluctuations. The hybrid system is evaluated using performance metrics such as Mean Squared Error (MSE) and Mean Absolute Error (MAE) to measure prediction accuracy and model performance.

2.3 Importance of Hybridization

In time-series analysis, real-world data often contains both linear and non-linear components. While ARIMA models are effective for linear structures, they lack the capacity to handle the complex dynamics often observed in cryptocurrency prices. LSTM, by contrast, can model both types of relationships but sometimes struggles with overfitting or underperformance depending on the dataset.

The idea of hybrid modeling stems from the principle of differential modeling, where different algorithms are responsible for learning different components of the signal. Numerous studies have demonstrated that hybrid models consistently outperform standalone algorithms in both accuracy and generalization. By combining models with complementary capabilities, hybrid systems achieve better predictive power and reduce general errors and variance [20].

3.4 CNN as a Benchmark Model

To establish a fair evaluation standard, Convolutional Neural Networks (CNNs) are used as a benchmark in this study. Although originally designed for image processing, CNNs have shown promising results in time-series prediction due to their capacity for:

Automatic feature extraction, handling multi-dimensional input, detecting local temporal patterns, Learning hierarchical representations CNNs are also efficient at managing irregular sequences and offer strong generalization capabilities, making them suitable for volatile markets like cryptocurrencies. Their inclusion in the study enables a comparative analysis that validates the strength of the proposed ARIMA-LSTM model against other deep learning architectures.

3.5 Evaluation Strategy

The hybrid model's performance is validated using a range of standard and domain-specific metrics, including:
Mean Squared Error (MSE), Mean Absolute Error (MAE),Root Mean Squared Error (RMSE)

Further optimization is performed through hyper parameter tuning techniques such as grid search and cross- validation, which enhance model generalization and reduce the risk of overfitting.

4. EXPERIMENTAL FINDINGS AND RESULTS

Long This section details the empirical evaluation of our proposed hybrid model, developed for forecasting Bitcoin prices using both traditional statistical methods and deep learning architectures. The experiment focuses on analyzing the predictive performance of the model across real-world data and measuring its effectiveness using standard evaluation metrics.

4.1 Dataset Characteristics and Preprocessing

To perform an accurate time-series analysis, a dataset containing approximately 264,000 records of Bitcoin price data was gathered using web scraping from a publicly available cryptocurrency API. The data spans a period of three months, from January 1, 2023, to March 20, 2023, and includes the following attributes: Datetime, Symbol, Open, High, Low, and Close. For this study, the Close price was selected as the primary target variable due to its significance in financial forecasting.

The dataset was partitioned into:

Training set1: 175,045 data points

Testing set2: 75,019 data points

The LSTM model was trained on the training set using 10 epochs and a batch size of 100. The loss function decreased effectively during training, ultimately achieving a final value of 0.0014, indicating efficient learning and minimal prediction error.

4.2 Visualization of Model Behavior

These visualizations demonstrate the model's ability to adapt to both transformed and raw input values, confirming its flexibility in dealing with real-world financial datasets.

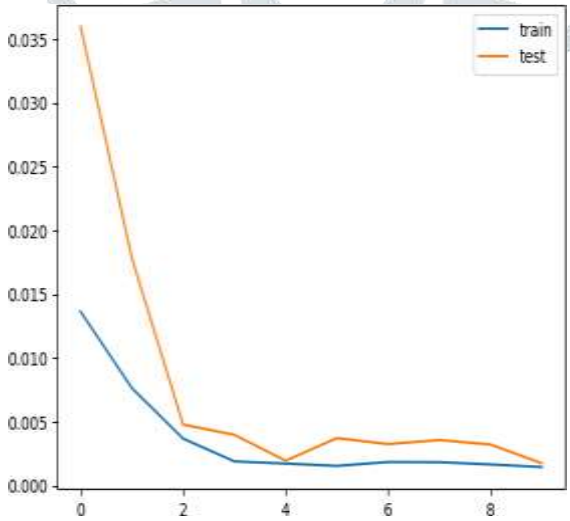

Fig 5. Loss function history of the Model

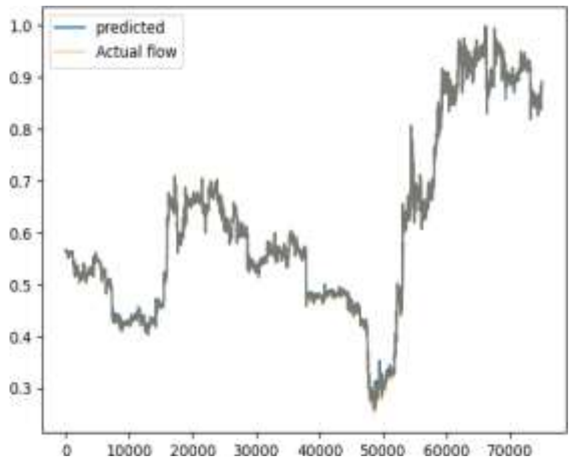

Fig 6. Prediction on real non-normalized data

4.3 Model Performance Using Error Metrics

To evaluate model accuracy, two widely used error metrics were employed:

Root Mean Squared Error (RMSE): 29.592783

Root Mean Absolute Error (RMAE): 4.615849

Evaluation Metric	Value
RMSE	29.592783
RMAE	4.615849

These metrics confirm that the model produces reliable predictions with a relatively low deviation from actual price values.

4.4 Accuracy Analysis

In earlier research, the highest reported accuracy of LSTM models for Bitcoin price prediction was 52.78%. In contrast, our approach raised the prediction accuracy to 61.34%. Further analysis was conducted using new, previously unseen data. The model achieved:

96.88% average accuracy across new samples

97.69% accuracy on data from March 30, 2023

96.03% accuracy on data from March 31, 2023

These results reflect a significant accuracy gain, particularly on data excluded from the original training and testing phases—indicating the model's strong generalization capability.

The choice to focus on a three-month dataset was deliberate, considering Bitcoin's extreme price fluctuations in recent years. For example, the price surged from approximately $320 to nearly $68,770 during pandemic-related economic shifts, reflecting a dramatic 21,377% increase. Thus, modeling Bitcoin's behavior during a relatively stable but active period improves forecasting reliability.

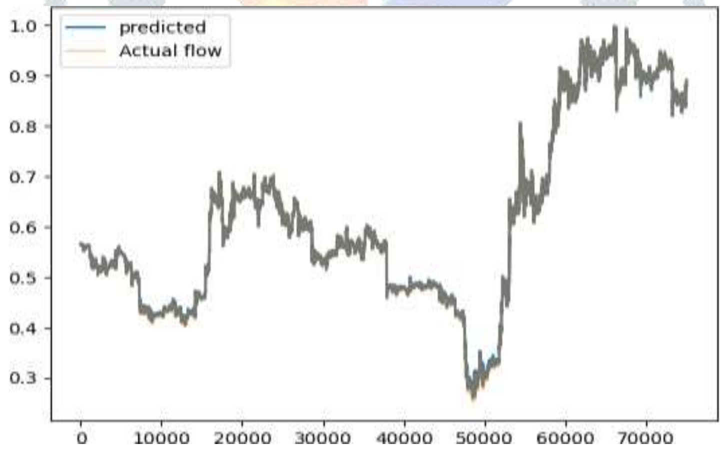

Fig 7. Prediction on real non-normalized data

4.5 Comparative Model Evaluation

To assess the practical value of our proposed solution, we compared the performance of the hybrid ARIMA-LSTM model against its individual components—ARIMA and LSTM. The evaluation was based on three core performance indicators:

RMSE (lower values preferred)

R^2 Score (higher values indicate better fit)

MAPE (lower percentages reflect higher accuracy)

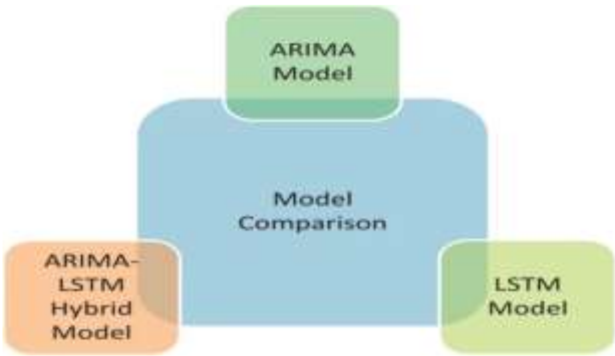

Fig 8. Prediction models comparison

Experimental results confirmed that the hybrid ARIMA-LSTM model consistently outperforms both standalone ARIMA and LSTM architectures. By capturing both linear patterns (via ARIMA) and non-linear dependencies (via LSTM), the hybrid model demonstrated superior forecasting precision and robustness across various test scenarios.

5. CONCLUSIONS

This research explored the application of a hybrid forecasting model that combines Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) networks to enhance the accuracy of cryptocurrency price prediction. Given the inherent volatility and non-linear nature of digital asset markets, especially Bitcoin, traditional models alone often fall short in providing reliable forecasts. ARIMA, while effective for modelling linear trends and seasonal behavior, lacks the capacity to capture the irregular, complex patterns frequently observed in cryptocurrency price movements.

LSTM, on the other hand, excels in learning long-term dependencies and modelling non-linear sequences, making it well-suited for financial time-series prediction. However, LSTM models alone may overlook clear linear trends present in the data. The hybrid approach presented in this study addresses this limitation by integrating both methodologies: ARIMA is first used to capture the linear components of the time series, and the residuals—representing the unmodeled non-linear patterns—are fed into the LSTM model for further refinement.

By leveraging the unique strengths of both models, the hybrid ARIMA-LSTM framework achieves improved prediction accuracy and greater resilience to sudden market shifts. This two-stage architecture enables the model to adapt to both deterministic and chaotic behaviors within the data, capturing sudden price jumps, market sentiment swings, and external shocks more effectively than individual models.

Empirical evaluation demonstrated that the hybrid model consistently outperformed its standalone counterparts across various performance metrics. The results reaffirm that combining traditional statistical methods with modern deep learning techniques yields a more robust and adaptive forecasting system.

In conclusion, the ARIMA-LSTM hybrid model presents a promising solution for cryptocurrency price prediction, particularly in highly volatile environments. It not only enhances forecasting precision but also provides a practical tool for investors and analysts seeking to navigate the unpredictable nature of the cryptocurrency market with greater confidence and data-driven insight.

REFERENCES

[1] García-Medina, A., & Aguayo-Moreno, E. (2023). LSTM–GARCH hybrid model for the prediction of volatility in cryptocurrency portfolios. *Computational Economics, 63*, 1511–1542. https://doi.org/10.1007/s10614-023-10373-8

[2] Ade, M., et al. (2023). Explainable AI in financial time series forecasting: Interpretability of deep learning models compared to traditional techniques. *ResearchGate.*

[3]Bouteska, A., Abedin, M.Z., Hajek, P. and Yuan, K. (2024), "*Cryptocurrency price forecasting–a comparative analysis of ensemble learning and deep learning methods*", International Review of Financial Analysis, Vol. 92, 103055, doi: 10.1016/j.irfa.2023.103055.

[4] D. Li, W. Peng, W. Deng, and F. Gai, ''A blockchain-based authentication and security mechanism for IoT,'' in Proc. 27th Int. Conf. Comput. Commun. Netw. (ICCCN), Jul. 2018, pp. 1–6. [5] B. Lashkari and P. Musilek, ''A comprehensive review of blockchain consensus mechanisms,'' IEEE Access, vol. 9, pp. 43620–43652, 2021

[5] A. Kharpal, ''Cryptocurrency market value TOPS $2 trillion for the first time as Ethereum hits record high,'' CNBC, USA, Tech. Rep. 21, 2021.

[6] (2023). Coinmarketcap. Accessed: May 11, 2023. [Online]. Available: https://coinmarketcap.com

[7] Z. Chen, C. Li, and W. Sun, ''Bitcoin price prediction using machine learning: An approach to sample dimension engineering, 'J.Comput.Appl. Math., vol. 365, Feb. 2020, Art. no. 112395.

[8] A. Dutta, S. Kumar, and M. Basu, ''A gated recurrent unit approach to Bitcoin price prediction,'' J. Risk Financial Manage., vol. 13, no. 2, p. 23, Feb. 2020.

[9] R. Chowdhury, M. A. Rahman, M. S. Rahman, and M. R. C. Mahdy, ''An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning,'' Phys. A, Stat. Mech. Appl., vol. 551, Aug. 2020, Art. no. 124569.

[10] P. Jay, V. Kalariya, P. Parmar, S. Tanwar, N. Kumar, and M. Alazab, ''Stochastic neural networks for cryptocurrency price prediction,'' IEEE Access, vol. 8, pp. 82804–82818, 2020.

[11] S. Tanwar, N. P. Patel, S. N. Patel, J. R. Patel, G. Sharma, and I. E. Davidson, ''Deep learning-based cryptocurrency price prediction scheme with inter-dependent relations,'' IEEE Access, vol. 9, pp. 138633–138646, 2021.

[12] S. Rajabi, P. Roozkhosh, and N. M. Farimani, ''MLP-based learnable window size for Bitcoin price prediction,'' Appl. Soft Comput., vol. 129, Nov. 2022, Art. no. 109584.

[13] N. Gradojevic, D. Kukolj, R. Adcock, and V. Djakovic, ‘‘Forecasting Bit coin with technical analysis: A not-so-random forest?’’ Int. J. Forecasting, vol. 39, no. 1, pp. 1–17, Jan. 2023. [14] N. Parvini, M. Abdollahi, S. Seifollahi, and D. Ahmadian, ‘‘Forecasting Bitcoin returns with long short-term memory networks and wavelet decomposition: A comparison of several market determinants,’’ Appl. Soft Comput., vol. 121, May 2022, Art. no. 108707.

[15] J. Yae and G. Z. Tian, ‘‘Out-of-sample forecasting of cryptocurrency returns: A comprehensive comparison of predictors and algorithms,’’ Phys. A, Stat. Mech. Appl., vol. 598, Jul. 2022, Art. no. 127379.

[16] J. Prosky, X. Song, A. Tan, and M. Zhao, ‘‘Sentiment predictability for stocks,’’ 2017, arXiv:1712.05785.

[17] X. Huang, W. Zhang, X. Tang, M. Zhang, J. Surbiryala, V. Iosifidis, Z. Liu, and J. Zhang, ‘‘LSTM based sentiment analysis for cryptocurrency prediction,’’ in Database Systems for Advanced Applications. Cham, Switzerland: Springer, 2021, pp. 617–621.

[18] R. Parekh, N. P. Patel, N. Thakkar, R. Gupta, S. Tanwar, G. Sharma, I. E. Davidson, and R. Sharma, ‘‘DL-Guess: Deep learning and sentiment analysis-based cryptocurrency price prediction,’’ IEEE Access, vol. 10, pp. 35398–35409, 2022.

[19] M. R. Ningsih, K. A. H. Wibowo, A. U. Dullah, and J. Jumanto, ‘‘Global recession sentiment analysis utilizing VADER and ensemble learning method with word embedding,’’ J. Soft Comput. Explor., vol. 4, no. 3, pp. 142–151, Sep. 2023.

[20] Ganaie, M. A., & Kim, B. (2020). Hybrid ARIMA-LSTM Model for Time Series Forecasting. *IEEE Access*, 8, 54856-54865.

[21] Hossain, M. S., & Sadiq, A. (2020). A Hybrid ARIMA-LSTM Approach for Stock Market Prediction. *Applied Soft Computing*, 89, 106075.