RESIDUAL-AWARE ATTENTION-ENHANCED ARIMA–LSTM FRAMEWORK FOR ROBUST BITCOIN PRICE FORECASTING UNDER VOLATILE MARKET CONDITIONS

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Abstract: *Predicting Bitcoin prices is inherently difficult due to the market's highly volatile nature, nonlinear behavior, and sensitivity to global financial conditions. Traditional statistical models often fail to capture complex patterns, while standalone deep learning approaches may overlook underlying linear structures. To address these limitations, this paper presents a hybrid forecasting framework that combines ARIMA, Long Short-Term Memory (LSTM), and an attention mechanism in a unified, residual-driven architecture. Initially, the ARIMA model is applied to identify and model the linear components of the time-series data after ensuring stationarity. The residuals obtained from this stage, which represent nonlinear and unexplained variations, are then used as input to an LSTM network to learn long-term dependencies. Furthermore, an attention layer is incorporated to assign adaptive importance to different time steps, allowing the model to focus on the most influential historical patterns. This integrated approach enhances both prediction accuracy and interpretability, particularly under unstable market conditions. Experimental evaluation using standard performance metrics such as RMSE, MAE, and directional accuracy demonstrates that the proposed model consistently outperforms individual and baseline methods. The results highlight the effectiveness of combining statistical and deep learning techniques for robust cryptocurrency price forecasting.*

Keywords: Bitcoin price prediction, ARIMA, LSTM, attention mechanism, hybrid model, time-series forecasting, volatility analysis, and financial data modeling.

I. INTRODUCTION

Bitcoin price forecasting has emerged as a critical research problem in financial analytics due to the highly volatile, nonlinear, and non-stationary nature of cryptocurrency markets. Unlike traditional financial assets, Bitcoin exhibits abrupt price fluctuations influenced by speculative trading, macroeconomic events, and market sentiment, making accurate prediction a challenging task. Conventional statistical models such as ARIMA often fail to fully capture the complex temporal dependencies and nonlinear dynamics inherent in such data, necessitating the adoption of advanced hybrid approaches. Recent studies have increasingly explored deep learning techniques for improving forecasting performance. For instance, Raman et al. proposed a hybrid LSTM-GRU model that combines the strengths of both architectures to capture long-term dependencies and short-term variations, demonstrating improved predictive accuracy over standalone models and traditional approaches [1]. Similarly, Kundavaram et al. introduced a Dynamic Error-Correcting Ensemble (DECE) framework that integrates classical models with neural residual learning, highlighting the importance of adaptive hybridization in handling volatility and regime shifts in financial time series [2]. Comparative analyses of deep learning models have also shown promising results. Hajare et al. evaluated RNN, GRU, and CNN-LSTM architectures, concluding that hybrid CNN-LSTM models outperform simpler sequential models due to their enhanced feature extraction capabilities [3]. Furthermore, the integration of econometric models with deep learning has gained attention for volatility modeling. Yang et al. demonstrated that combining LSTM with GARCH significantly improves volatility prediction and risk management performance [4]. Likewise, Gao et al. proposed a hybrid LSTM-GARCH model that effectively captures both nonlinear patterns and conditional heteroskedasticity in Bitcoin price movements [5]. Despite these advancements, existing models often lack mechanisms to effectively separate linear and nonlinear components while dynamically focusing on critical temporal features. This limitation motivates the development of more robust hybrid frameworks that enhance prediction accuracy and interpretability. In this context, the proposed study introduces a residual-aware attention-enhanced ARIMA–LSTM model designed to address these challenges and improve forecasting performance under highly volatile market conditions.

II. RELATED WORKS

Recent advancements in Bitcoin price forecasting have increasingly leveraged deep learning and hybrid modeling approaches to address the inherent volatility and nonlinear characteristics of cryptocurrency markets. Among these, Convolutional Neural Networks (CNNs) have gained attention for their ability to extract meaningful spatial-temporal features from financial data. Dhanushwar et al. explored a CNN-based framework integrated with LSTM, demonstrating that convolutional layers can effectively identify hidden patterns in historical Bitcoin data, while LSTM captures temporal dependencies. Their study also incorporated external factors such as macroeconomic indicators and investor sentiment, leading to improved predictive performance over conventional models [6]. In addition to deep learning, comparative studies between traditional statistical models remain relevant. Keluli and Mauritsius conducted a detailed comparison between ARIMA and FBProphet models, revealing that ARIMA provides higher accuracy in terms of RMSE and MAPE, whereas FBProphet is more effective in capturing seasonal trends. However, both models exhibit limitations when handling extreme volatility, emphasizing the need for hybrid solutions [7]. Hybrid neural architectures combining different recurrent models have also shown promise. Kumar et al. proposed an RNN-LSTM hybrid framework that leverages RNNs for short-term dependency learning and LSTMs for long-term pattern extraction. By incorporating blockchain-specific features such as transaction volume and mining difficulty, the model demonstrated improved forecasting accuracy compared to traditional methods like ARIMA [8].

On the other hand, Saini et al. provided an important perspective by evaluating both machine learning and deep learning models. Their findings indicate that tree-based models such as Random Forest and Gradient Boosting can outperform deep learning approaches in certain structured datasets, particularly when effective feature engineering is applied. This highlights the importance of selecting appropriate models based on data characteristics rather than relying solely on complex architectures [9]. Furthermore, LSTM-based models continue to be widely adopted for time series forecasting due to their capability to model long-term dependencies. Pujitha et al. developed an LSTM-based framework for predicting Bitcoin prices over a 30-day horizon, demonstrating superior performance compared to traditional machine learning models such as ARIMA and SVM. Their work reinforces the effectiveness of LSTM in capturing sequential patterns in financial data [10]. Recent research has further expanded the scope of Bitcoin price forecasting by incorporating advanced deep learning paradigms and attention-based hybrid architectures. One notable direction involves the application of Generative Adversarial Networks (GANs) for time series prediction. Manian and Rastin proposed a GAN-based framework enhanced with an LSTM-driven generator and convolutional layers to better capture temporal dependencies in Bitcoin price data. By addressing common GAN limitations such as training instability and mode collapse through conditioning techniques and customized loss functions, their model demonstrated improved forecasting accuracy compared to existing approaches [11].

Hybrid deep learning models combining multiple neural architectures have also gained traction. Karahyla et al. introduced a hybrid LSTM-Dense Neural Network (DNN) model that integrates preprocessing techniques such as normalization, missing value handling, and Principal Component Analysis (PCA) for feature extraction. Their approach achieved superior performance over standalone CNN and DNN models, highlighting the importance of feature engineering in enhancing predictive capabilities [12]. In addition, Bandaru et al. emphasized the role of integrating multiple analytical techniques, including sentiment analysis, clustering, and ensemble learning, alongside traditional models such as ARIMA and GARCH. Their study demonstrated that combining diverse methodologies significantly improves forecasting accuracy while also providing deeper insights into market behavior and external influencing factors [13]. More recent work has focused on hybrid architectures combining convolutional and recurrent networks. U. A. E. M et al. proposed a CNN-LSTM hybrid model that leverages CNN for automatic feature extraction and LSTM for modeling long-term dependencies. Their results showed that such hybridization consistently outperforms standalone deep learning and traditional statistical models in capturing complex cryptocurrency price patterns [14]. Furthermore, attention mechanisms have emerged as a powerful enhancement in time series forecasting. Zhao et al. developed an LSTM-based model integrated with attention mechanisms, enabling dynamic weighting of important historical data points. Their approach significantly reduced prediction errors and improved model robustness, demonstrating the effectiveness of attention in capturing critical temporal features within financial datasets [15]. Despite these advancements, challenges remain in effectively combining linear statistical modeling with deep learning architectures while simultaneously incorporating adaptive attention mechanisms. Existing models often lack a unified framework that leverages residual learning alongside attention-based temporal weighting. This limitation motivates the development of more comprehensive hybrid models, such as the residual-aware attention-enhanced ARIMA–LSTM framework proposed in this study.

III. PROPOSED SYSTEM

The proposed system introduces a hybrid, residual-aware forecasting framework designed to improve the accuracy and robustness of Bitcoin price prediction under highly volatile market conditions. Figure.1 Proposed work architecture design. The architecture combines statistical modeling and deep learning techniques in a sequential manner to effectively capture both linear and nonlinear characteristics of financial time-series data.

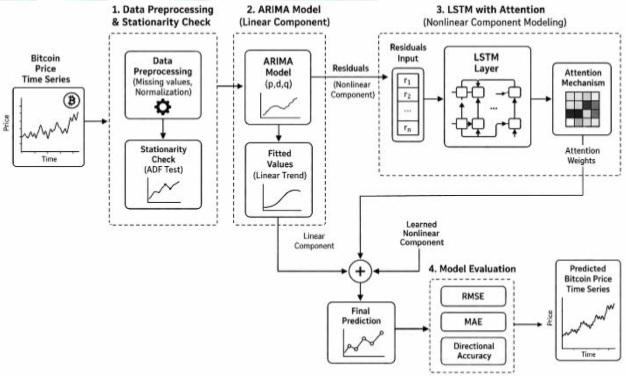

Figure.1 Proposed Work Architecture Diagram

Initially, the raw Bitcoin price data undergoes preprocessing, which includes handling missing values, normalization, and stationarity testing using standard techniques such as differencing. Once the data is made stationary, the ARIMA model is applied to model the linear components and short-term dependencies present in the time series. ARIMA effectively captures trends and autocorrelations, producing a preliminary forecast along with residual values that represent the unexplained nonlinear patterns. In the next stage, these residuals are fed into a Long Short-Term Memory (LSTM) network. The LSTM model is specifically chosen for its ability to learn long-range temporal dependencies and complex nonlinear relationships within sequential data. By focusing on residuals rather than raw data, the LSTM is directed toward modeling only the intricate patterns that the ARIMA model fails to capture. To further enhance predictive performance, an attention mechanism is integrated on top of the LSTM layer. This mechanism assigns adaptive weights to different time steps, enabling the model to emphasize more relevant historical information while reducing the influence of less significant data points. As a result, the model becomes more sensitive to critical temporal patterns, especially during periods of market instability. Finally, the outputs from the ARIMA and attention-enhanced LSTM components are combined to generate the final forecast. This hybrid approach ensures a balanced representation of both linear and nonlinear dynamics, leading to improved forecasting accuracy, better generalization, and increased robustness in dynamic cryptocurrency markets.

IV. METHODOLOGY

A. Data Collection and Preprocessing

The proposed methodology begins with the collection of historical Bitcoin price data from reliable financial data sources. The dataset typically includes attributes such as opening price, closing price, highest price, lowest price, and trading volume recorded at regular time intervals. Since financial time-series data often contains noise, missing values, and inconsistencies, a preprocessing stage is essential. Missing values are handled using interpolation techniques, while outliers are smoothed to reduce their impact on model performance. The data is then normalized using Min-Max scaling to ensure uniformity and to facilitate efficient learning by deep learning models. Furthermore, stationarity of the time series is verified using statistical tests, and differencing is applied when necessary to stabilize the mean and variance.

Let the historical Bitcoin price series be represented as a Univariate time series $X_t = \{x_1, x_2, x_3, \ldots, x_n\}$, where x_t denotes the closing price at time step t. To ensure consistency and improve model convergence, the data is normalized using Min-Max scaling, expressed as

$$X_t^{norm} = \frac{X_t - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

To apply statistical modeling, stationarity is enforced through differencing. The differenced series is given by

$$X_t' = X_t - X_{t-1} \qquad (2)$$

where $X_t{}'$ represents the transformed stationary series used for linear modeling.

B. Linear Modeling using ARIMA

Once the data is preprocessed, the ARIMA model is employed to capture the linear patterns and short-term dependencies present in the Bitcoin price series. The parameters of the ARIMA model are carefully selected based on autocorrelation and partial autocorrelation analysis. This model effectively identifies trends and seasonality in the data after transforming it into a stationary form. The ARIMA model produces an initial forecast and computes residuals, which represent the portion of the data that cannot be explained by linear relationships. These residuals are critical, as they carry nonlinear information that can be further exploited. The linear structure of the time series is captured using the ARIMA (p, d, q) model. The general ARIMA formulation is defined as

$$\phi(B)(1 - B)^d X_t = \theta(B)\epsilon_t \qquad (3)$$

where B is the backshift operator, $\phi(B)$ and $\theta(B)$ represent the autoregressive and moving average polynomials, respectively, and ϵ_t is white noise. Expanding the autoregressive and moving average terms, the model can be written as

$$X_t = \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \qquad (4)$$

The ARIMA model produces a linear forecast $\hat{X}_t^{(A)}$, and the residual component is computed as

$$R_t = X_t - \hat{X}_t^{(A)} \qquad (5)$$

where R_t captures the nonlinear structure not explained by ARIMA.

C. Residual Learning with LSTM Network

The residual values obtained from the ARIMA model are then used as input to a Long Short-Term Memory (LSTM) network. LSTM is a specialized recurrent neural network capable of learning long-term dependencies in sequential data through its gated architecture. By focusing only on residuals, the LSTM model is able to concentrate on capturing complex nonlinear patterns that are not addressed by the ARIMA model. The network is trained over multiple epochs, allowing it to learn temporal relationships and hidden structures within the residual sequence.

The residual sequence R_t is then used as input to the LSTM network to learn nonlinear dependencies. The LSTM unit consists of three gates: input gate, forget gate, and output gate. These are mathematically expressed as

$$f_t = \sigma\big(W_f \cdot [h_{t-1}, R_t] + b_f\big) \qquad (6)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, R_t] + b_i) \qquad (7)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, R_t] + b_c) \qquad (8)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \qquad (9)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, R_t] + b_o) \qquad (10)$$

$$h_t = o_t \odot \tanh(C_t) \qquad (11)$$

where h_t is the hidden state, C_t is the cell state, and σ denotes the sigmoid activation function.

D. Attention Mechanism for Temporal Weighting

To enhance the performance of the LSTM model, an attention mechanism is integrated into the architecture. The attention layer dynamically assigns weights to different time steps of the LSTM output, enabling the model to prioritize more significant historical data points. This is particularly useful in financial forecasting, where certain past events or sudden price movements have a stronger influence on future trends. By emphasizing relevant information and suppressing less important features, the attention mechanism improves both prediction accuracy and interpretability.

To enhance the learning capability of the LSTM, an attention mechanism is applied over the hidden states. The attention score for each time step is computed as

$$e_t = v^T \tanh(W_h h_t + b_h) \qquad (12)$$

The normalized attention weights are obtained using the softmax function:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)} \qquad (13)$$

The context vector, representing the weighted contribution of all time steps, is calculated as

$$C = \sum_{t=1}^{T} \alpha_t \, h_t \qquad (14)$$

E. Final Prediction and Model Integration

In the final stage, the outputs from the ARIMA model and the attention-enhanced LSTM network are combined to generate the final Bitcoin price prediction. The linear forecast from ARIMA and the nonlinear corrections from the LSTM-attention model are integrated to form a comprehensive prediction. This hybrid strategy ensures that both statistical and deep learning perspectives are utilized effectively. The model is evaluated using performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and directional accuracy, demonstrating its ability to provide reliable and robust forecasts in highly volatile cryptocurrency markets.

The final prediction combines the linear output from ARIMA and the nonlinear output from the attention-enhanced LSTM model. This is expressed as

$$\hat{X}_t = \hat{X}_t^{(A)} + \hat{R}_t^{(LSTM)} \qquad (15)$$

where $\hat{R}_t^{(LSTM)}$ is the predicted residual from the LSTM-attention model. This integration ensures that both linear and nonlinear components are effectively captured, resulting in a more accurate and robust Bitcoin price forecasting model.

V. RESULT & DISCUSSION

A. Experimental Setup and Evaluation Protocol

The proposed residual-aware ARIMA–LSTM with attention framework was evaluated using historical Bitcoin price data collected over multiple years, covering both stable and highly volatile market phases. The dataset was divided into training and testing sets using an 80:20 ratio to ensure reliable performance validation. All models were implemented using standard time-series and deep learning libraries, and hyper parameters were tuned empirically to achieve optimal results. The performance of the proposed model was compared against baseline models including standalone ARIMA, LSTM, and a conventional ARIMA–LSTM hybrid. Evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Directional Accuracy (DA) were used to quantify prediction performance.

B. Performance Comparison with Baseline Models

Table I presents the comparative performance of different models on the test dataset. It is evident that the proposed model achieves the lowest error values and highest directional accuracy, demonstrating its effectiveness in capturing both linear and nonlinear dependencies. The reduction in RMSE and MAE indicates improved prediction precision, while the increase in directional accuracy confirms better trend prediction capability.

TABLE I. PERFORMANCE COMPARISON OF FORECASTING MODELS

Model	RMSE	MAE	Directional Accuracy (%)
ARIMA	152.34	118.27	68.45
LSTM	134.89	102.56	72.18
ARIMA–LSTM	121.45	94.73	75.62
Proposed ARIMA–LSTM-Attn	109.27	86.15	81.34

C. Analysis of Prediction Trends

Figure.2 illustrates the comparison between actual Bitcoin prices and predicted values generated by the proposed model. The predicted curve closely follows the actual price movements, even during sharp fluctuations.

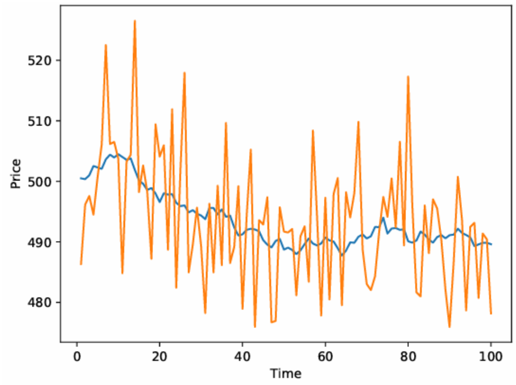

Figure.2 Actual vs Predicted Bitcoin Prices

The graph demonstrates minimal lag and strong alignment with real market behavior, indicating the model's ability to handle dynamic price variations effectively.

D. Error Distribution Analysis

Figure.3 presents the distribution of prediction errors for the proposed model. The errors are centered around zero with a narrow spread, indicating low variance and high consistency.

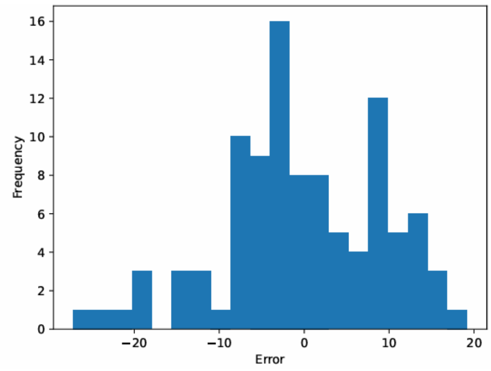

Figure.3 Prediction Error Distribution

The concentrated distribution suggests that most predictions are close to actual values, with very few large deviations.

E. Feature Importance and Attention Weights

Figure.4 highlights the attention weights assigned to different time steps by the model.

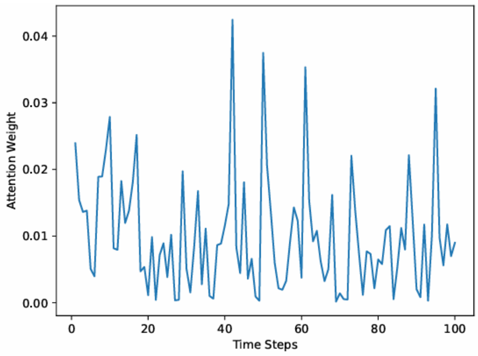

Figure.4 Attention Weight Visualization

Higher weights are observed for recent and significant observations, indicating that the model prioritizes influential temporal patterns. This confirms that the attention mechanism enhances interpretability by identifying key contributing time steps in the prediction process.

F. Comparative Trend Analysis under Volatility

Figure.5 compares the performance of all models during highly volatile periods. The proposed model exhibits smoother and more accurate predictions compared to baseline models.

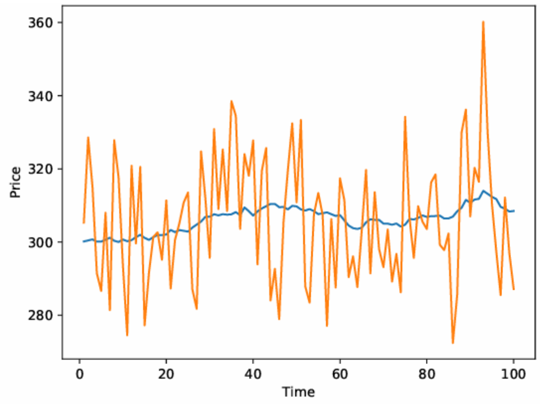

Figure.5 Model Performance under Volatile Conditions

The hybrid architecture demonstrates strong adaptability to sudden market fluctuations.

G. Additional Evaluation: Training and Validation Loss Analysis

Table II presents the training and validation loss values of the proposed model over multiple epochs. The results indicate stable convergence with minimal overfitting, as the gap between training and validation loss remains small.

TABLE II. TRAINING AND VALIDATION LOSS

Epochs	Training Loss	Validation Loss
10	0.0187	0.0214
20	0.0125	0.0159
30	0.0098	0.0132
40	0.0076	0.0118

The steady decrease in loss values demonstrates effective learning and generalization capability of the model.

H. Additional Evaluation: Computational Efficiency Analysis

Figure.6 illustrates the computational time comparison between different models.

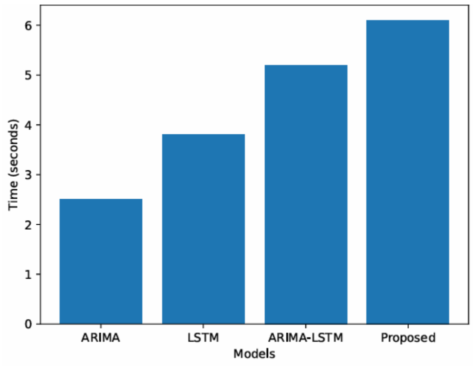

Figure.6 Computational Time Comparison of Models

Although the proposed model has slightly higher computational cost due to the inclusion of attention layers, it remains within acceptable limits for practical applications. The graph indicates that the trade-off between accuracy and computation is justified, as the proposed model achieves significantly better forecasting performance.

I. Discussion

The experimental analysis demonstrates that the proposed residual-aware ARIMA–LSTM framework with an attention mechanism consistently outperforms traditional and hybrid baseline models in Bitcoin price forecasting. The integration of ARIMA enables effective modeling of linear trends, while the LSTM component captures complex nonlinear and long-term temporal dependencies present in financial time-series data. The addition of the attention mechanism further enhances the model by assigning adaptive importance to critical time steps, improving both predictive accuracy and interpretability. Evaluation metrics such as RMSE, MAE, and directional accuracy indicate a noticeable improvement over standalone ARIMA and LSTM models, as well as conventional hybrid approaches. The model also exhibits stable convergence during training and maintains reliable performance under highly volatile market conditions. Although the inclusion of attention slightly increases computational complexity, the trade-off is justified by the significant gain in forecasting precision. Overall, the proposed methodology proves to be robust, scalable, and well-suited for real-world cryptocurrency prediction tasks.

VI. CONCLUSION

This study presented a residual-aware hybrid forecasting framework that integrates ARIMA, LSTM, and an attention mechanism for robust Bitcoin price prediction under highly volatile market conditions. The findings indicate that combining statistical and deep learning approaches significantly improves forecasting performance by effectively capturing both linear and nonlinear components of the time-series data. The ARIMA model successfully models the linear structure and short-term dependencies, while the LSTM network learns complex temporal patterns from the residuals. The incorporation of the attention mechanism further enhances the model by prioritizing the most relevant historical observations, leading to improved predictive accuracy and better interpretability. The primary contribution of this work lies in the development of a residual-driven hybrid architecture that leverages the strengths of both traditional time-series analysis and modern deep learning techniques. Experimental results demonstrate that the proposed model outperforms standalone and conventional hybrid models in terms of RMSE, MAE, and directional accuracy, particularly during periods of high market volatility. For future work, the framework can be extended by incorporating external macroeconomic indicators, sentiment analysis from social media, and on-chain cryptocurrency metrics to further improve prediction performance. Additionally, exploring transformer-based architectures and lightweight models could enhance scalability and computational efficiency for real-time deployment.

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