Hybrid Transformer–LSTM for Accurate AAVE Price Forecasting Using Technical Indicators in Decentralized Finance Ecosystems through Deep Learning Models

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ABSTRACT

The rapid growth of decentralized finance (DeFi) has increased the importance of accurate cryptocurrency price forecasting to support intelligent financial decision making in emerging metaverse ecosystems. However, the high volatility and nonlinear characteristics of cryptocurrency markets make reliable prediction a challenging task. This study proposes a Hybrid Transformer LSTM model for forecasting AAVE cryptocurrency prices using historical price data and technical indicators. Daily OHLC data collected from November 2020 to March 2026 were employed to compute multiple technical indicators, including Simple Moving Average, Exponential Moving Average, Relative Strength Index, Moving Average Convergence Divergence, Average True Range, Rate of Change, Momentum, Bollinger Bands, Williams %R, Commodity Channel Index, and Stochastic Oscillator. The proposed model was compared with four benchmark approaches, namely the Naïve model, LSTM, GRU, and Transformer, using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), coefficient of determination (R^2), and Directional Accuracy (DA). Experimental results show that all deep learning models successfully captured the general trend of AAVE price movements and achieved stable convergence during training. The Naïve model obtained the lowest prediction errors and the highest R^2, while the GRU achieved the highest Directional Accuracy. Although the proposed Hybrid Transformer LSTM did not achieve the best numerical performance, it produced stable prediction trajectories and a balanced residual distribution, demonstrating consistent forecasting behavior under different market conditions. These findings indicate that hybrid attention and recurrent learning architectures provide a robust framework for cryptocurrency forecasting, while also highlighting that increased model complexity does not necessarily lead to superior predictive accuracy when only technical indicators are used. The study contributes to intelligent financial analytics for decentralized finance and metaverse applications by providing a comprehensive comparison of contemporary deep learning architectures for cryptocurrency price prediction.

Keywords Cryptocurrency Price Forecasting, Decentralized Finance (Defi), Hybrid Transformer–LSTM, Technical Indicators, Metaverse Financial Systems

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INTRODUCTION

The rapid development of blockchain technology has accelerated the growth of decentralized finance (DeFi), creating a new digital financial ecosystem that enables peer to peer financial services without relying on centralized intermediaries [1]. DeFi platforms provide various financial services, including lending, borrowing, asset trading, and liquidity provision through smart

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contracts, while cryptocurrencies function as the primary medium of exchange within these ecosystems. Along with the emergence of metaverse platforms that integrate virtual economies with blockchain based digital assets, cryptocurrencies have become increasingly important for supporting intelligent financial activities in immersive digital environments [2]. Consequently, accurate cryptocurrency price forecasting has become essential for facilitating investment decision making, financial risk management, and digital asset valuation in decentralized financial systems [3].

Despite its growing importance, cryptocurrency price forecasting remains a challenging task because cryptocurrency markets exhibit high volatility, nonlinear behavior, abrupt trend reversals, and rapidly changing market conditions. Unlike traditional financial assets, cryptocurrency prices are influenced by multiple interacting factors, including investor behavior, market sentiment, liquidity, and speculative trading activity. These characteristics reduce the effectiveness of conventional statistical forecasting methods, which generally assume relatively stable data distributions and linear relationships among variables. As a result, machine learning and deep learning techniques have attracted considerable attention because of their ability to automatically learn complex nonlinear relationships directly from historical market data [4].

Recent studies have demonstrated the effectiveness of recurrent neural network architectures, particularly Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU), for cryptocurrency price forecasting due to their capability to model sequential temporal dependencies. LSTM has been widely adopted to address long term dependency problems encountered in conventional recurrent neural networks, while GRU provides a simpler architecture with fewer parameters and faster convergence. More recently, Transformer based architectures have emerged as an alternative approach by utilizing self attention mechanisms to capture long range contextual relationships without relying on recurrent computations. Several studies have reported promising forecasting performance using Transformer models, especially for complex financial time series that exhibit long range dependencies. Furthermore, hybrid deep learning architectures have been introduced to integrate the complementary strengths of multiple neural network models, aiming to improve forecasting accuracy and learning stability in highly dynamic financial markets [5].

Although substantial progress has been achieved in cryptocurrency forecasting, several research gaps remain. First, many previous studies primarily focus on major cryptocurrencies such as Bitcoin and Ethereum, while relatively limited attention has been given to decentralized finance tokens such as AAVE, whose market characteristics differ because they are closely associated with DeFi lending and liquidity protocols. Second, previous research frequently evaluates individual deep learning architectures independently, whereas comprehensive comparisons among recurrent, attention based, and hybrid architectures under the same experimental setting remain relatively limited. Third, although hybrid Transformer based models have recently attracted increasing interest, empirical evidence regarding their effectiveness when trained solely on technical indicators derived from historical prices remains insufficient. Consequently, it remains unclear whether increasing architectural complexity consistently produces superior forecasting performance in decentralized finance cryptocurrency markets.

The state of the art in cryptocurrency forecasting has shifted from conventional recurrent neural networks toward attention based and hybrid deep learning architectures capable of modeling increasingly complex temporal patterns. Hybrid Transformer LSTM models represent one of the latest developments by integrating the global contextual representation capability of self attention mechanisms with the sequential memory modeling of recurrent neural networks. This combination is expected to improve the representation of both long term market trends and short term temporal dependencies, thereby providing a more comprehensive understanding of cryptocurrency price dynamics. However, the practical effectiveness of such hybrid architectures should be validated through systematic comparisons with established benchmark models using multiple evaluation metrics under identical experimental conditions.

Therefore, this study proposes a Hybrid Transformer LSTM model for forecasting the closing price of the AAVE cryptocurrency using historical daily OHLC data and multiple technical indicators, including Simple Moving Average, Exponential Moving Average, Relative Strength Index, Moving Average Convergence Divergence, Average True Range, Rate of Change, Momentum, Bollinger Bands, Williams %R, Commodity Channel Index, and Stochastic Oscillator. The proposed model is evaluated against four benchmark approaches, namely the Naïve model, LSTM, GRU, and Transformer, using Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error, coefficient of determination, and Directional Accuracy. The findings provide a comprehensive assessment of contemporary deep learning architectures for decentralized finance cryptocurrency forecasting and contribute to the development of intelligent financial analytics for metaverse financial systems by examining the effectiveness of hybrid attention and recurrent learning models under a unified experimental framework.

Literature Review and Related Works

Cryptocurrency price forecasting has become one of the most active research areas in financial analytics because digital asset markets exhibit high volatility, nonlinear behavior, and rapidly changing market conditions. Traditional statistical approaches often struggle to capture these complex temporal dynamics, encouraging researchers to adopt machine learning and deep learning methods that are capable of learning nonlinear relationships directly from historical data [6], [7]. Recent review studies have also shown that deep learning models consistently outperform many conventional forecasting techniques, particularly when sufficient historical observations and informative input features are available [8], [9].

Among deep learning approaches, recurrent neural network architectures have received considerable attention because of their ability to model sequential financial data. Long Short Term Memory (LSTM) has been widely employed to capture long term temporal dependencies while alleviating the vanishing gradient problem encountered in conventional recurrent neural networks. Similarly, the Gated Recurrent Unit (GRU) has emerged as an efficient alternative by utilizing a simpler gating mechanism that reduces computational complexity while maintaining competitive forecasting performance. Numerous studies have demonstrated that both LSTM and GRU are effective for cryptocurrency forecasting, particularly when historical market information and technical indicators are used as predictive features [10], [11], [12].

The introduction of Transformer architectures has significantly expanded the capabilities of deep learning for financial time series forecasting. Unlike recurrent neural networks, Transformer models employ self attention mechanisms that enable simultaneous processing of entire input sequences while capturing long range contextual dependencies. This characteristic improves computational efficiency and allows the model to learn complex relationships that extend across long observation windows. Recent studies have reported promising forecasting performance of Transformer based models for cryptocurrency prediction, especially when combined with multivariate financial indicators and optimized attention mechanisms [13], [14], [15].

To further improve prediction accuracy, recent research has increasingly focused on hybrid deep learning architectures that combine complementary learning mechanisms. Hybrid models integrate the contextual representation capability of attention based networks with the temporal memory characteristics of recurrent neural networks, enabling simultaneous modeling of global market structures and sequential price dynamics. Several studies have demonstrated that hybrid architectures can achieve improved forecasting stability and predictive accuracy under certain market conditions compared with individual deep learning models [16], [17]. Nevertheless, comparative studies have also shown that the performance of hybrid architectures is strongly influenced by feature selection, prediction horizon, dataset characteristics, and market conditions, indicating that increased model complexity does not always guarantee superior forecasting performance [18], [19].

Although substantial progress has been achieved, several limitations remain in the existing literature. Most previous studies primarily focus on Bitcoin and Ethereum, whereas decentralized finance tokens such as AAVE have received considerably less attention despite their growing importance within blockchain based financial ecosystems. Furthermore, many studies evaluate different forecasting architectures using distinct datasets, preprocessing strategies, and feature configurations, making direct performance comparisons difficult. Comprehensive evaluations that compare Naïve, LSTM, GRU, Transformer, and Hybrid Transformer LSTM models under the same experimental framework using identical technical indicators remain relatively limited [20]. Motivated by these limitations, this study performs a unified comparative evaluation of these forecasting models using daily AAVE historical prices and multiple technical indicators to provide a more comprehensive understanding of their effectiveness for decentralized finance cryptocurrency forecasting.

Methodology

Research Framework

The overall research methodology adopted in this study is illustrated in figure 1. The proposed framework consists of five sequential stages, namely data collection, data preprocessing and feature engineering, model development, model training, and performance evaluation. Initially, historical daily OHLC data of the AAVE cryptocurrency were collected and organized chronologically. The raw data were subsequently preprocessed to remove missing values and generate multiple technical indicators representing market trends, momentum, and volatility. The processed dataset was then normalized and transformed into sequential samples using a sliding window approach before being divided into training, validation, and testing datasets. In the model development stage, five

forecasting approaches, namely the Naïve model, LSTM, GRU, Transformer, and the proposed Hybrid Transformer LSTM, were implemented and trained under identical experimental settings. Finally, the forecasting performance of each model was evaluated using multiple statistical metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), coefficient of determination (R^2), and Directional Accuracy (DA), to provide a comprehensive comparison of prediction accuracy and forecasting capability.

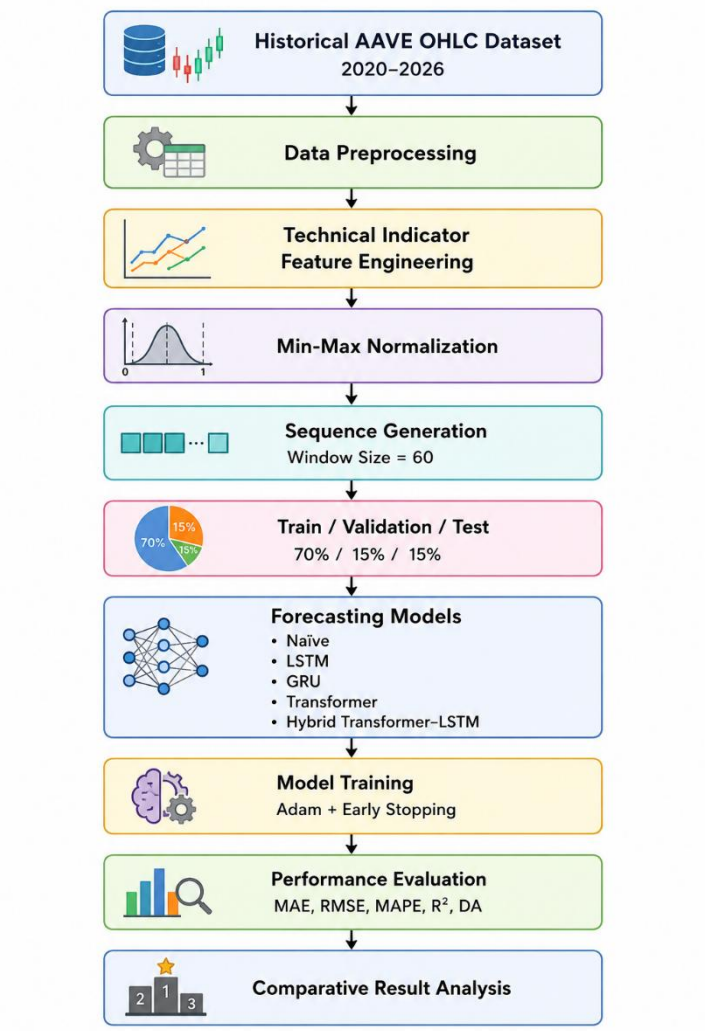

Figure 1 Research Framework

Dataset

The dataset used in this study consists of daily historical AAVE cryptocurrency prices covering the period from 28 November 2020 to 27 March 2026. Each observation contains the Open, High, Low, and Close (OHLC) prices arranged chronologically. Duplicate observations and missing values were removed during preprocessing to ensure data consistency. After calculating all technical indicators and eliminating rows containing undefined indicator values, 1,897 observations remained for model development.

Feature Engineering

To enhance the representation of cryptocurrency market behavior, multiple technical indicators were generated from the OHLC price series. These indicators capture different aspects of market dynamics, including trend, momentum, volatility, and market strength.

Trend indicators consist of the Simple Moving Average (SMA) with periods of 5, 10, 20, and 50 days, and the Exponential Moving Average (EMA) with periods of 5, 12, 20, 26, and 50 days. Momentum indicators include Momentum, Rate of Change (ROC), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), MACD Signal, MACD Histogram, Williams %R, Commodity Channel Index (CCI), and the Stochastic Oscillator. Volatility related indicators include the Average True Range (ATR), Bollinger Bands, Bollinger Band Width, Bollinger Band Percentage, rolling volatility, daily return, logarithmic return, daily trading range, and daily price change. Overall, 45 input features were generated for model training.

Data Normalization and Sequence Construction

Since the input variables have different numerical scales, Min Max normalization was applied before model training. The normalized feature value is calculated as:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

$x$is the original feature value, $x_{\min}$and $x_{\max}$denote the minimum and maximum values of the corresponding feature, and x'represents the normalized value.

To preserve temporal dependencies, a sliding window approach was employed with a sequence length of 60 trading days. Each input sequence consists of observations from the previous sixty days, while the corresponding target represents the closing price on the next trading day.

The processed dataset was divided chronologically into training, validation, and testing subsets using a ratio of 70:15:15, resulting in 1,267 training samples, 285 validation samples, and 285 testing samples.

Forecasting Models

Five forecasting models were evaluated in this study.

The Naïve model predicts the next closing price using the previous day's closing price and serves as the baseline model.

The LSTM model employs memory cells and gating mechanisms to capture long term temporal dependencies in sequential financial data.

The GRU model adopts a simplified recurrent architecture with fewer parameters while maintaining effective sequential learning capability.

The Transformer utilizes multi head self attention mechanisms to model long range contextual dependencies across the input sequence without relying on recurrent computations.

The proposed Hybrid Transformer LSTM integrates Transformer encoder layers with an LSTM network. The Transformer first extracts contextual representations through self attention, after which the extracted features are processed by the LSTM layer to capture sequential temporal dependencies

before generating the final price prediction.

Model Training

All deep learning models were implemented using TensorFlow. Model parameters were optimized using the Adam optimizer with a learning rate of 0.001, while Mean Squared Error (MSE) was used as the loss function. Training was conducted for a maximum of 100 epochs with a batch size of 32. Early stopping with a patience value of 15 epochs was applied to prevent overfitting by monitoring validation loss during training.

Performance Evaluation

The forecasting performance of each model was evaluated using five quantitative metrics.

Mean Absolute Error (MAE)

MAE measures the average magnitude of prediction errors.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (2)$$

Root Mean Square Error (RMSE)

RMSE gives greater penalties to larger prediction errors.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

Mean Absolute Percentage Error (MAPE)

MAPE expresses the prediction error as a percentage.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} | \frac{y_i - \hat{y}_i}{y_i} | \quad (4)$$

Coefficient of Determination (R^2)

The coefficient of determination evaluates how well the forecasting model explains the variance of the observed data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (5)$$

Directional Accuracy (DA)

Directional Accuracy measures the percentage of correctly predicted market directions.

$$DA = \frac{1}{n}\sum_{i=1}^{n} I\left[(y_i - y_{i-1})(\hat{y}_i - \hat{y}_{i-1}) > 0\right] \times 100\% \quad (6)$$

$I(\cdot)$is the indicator function that returns 1 when the predicted price movement has the same direction as the actual market movement and 0 otherwise.

Results

Exploratory Data Analysis

Exploratory data analysis (EDA) was conducted to understand the characteristics of the AAVE cryptocurrency market before model development. Figure 2 illustrates the historical closing price of AAVE from November 2020 to March 2026. The price series exhibits substantial fluctuations throughout the observation period, reflecting the highly volatile nature of decentralized finance (DeFi) assets. A significant price surge occurred during the cryptocurrency bull market in 2021, followed by a prolonged bearish period throughout 2022 and 2023. Subsequently, the market gradually recovered beginning in 2024, although frequent upward and downward movements continued to occur until the end of the observation period. These pronounced fluctuations indicate that the AAVE market is characterized by nonlinear behavior and rapidly changing price dynamics, making accurate forecasting particularly challenging. The observed variability also highlights the need for forecasting models capable of learning complex temporal dependencies while adapting to different market regimes.

The correlation heatmap presented in figure 2 summarizes the relationships among the selected input variables used in this study. Strong positive correlations are observed among the Open, High, Low, and Close (OHLC) variables, reflecting their close dependence within daily trading activities. Similarly, trend-based indicators such as the Simple Moving Average (SMA) and Exponential Moving Average (EMA) exhibit high correlations with the closing price because they are derived directly from historical price movements. In contrast, momentum indicators including the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Rate of Change (ROC), and Williams %R demonstrate moderate correlations, indicating that they capture complementary market information beyond price trends alone. Volatility-related indicators, such as the Average True Range (ATR) and Bollinger Bands, provide additional insights into the magnitude of price fluctuations under different market conditions. Collectively, the combination of trend, momentum, and volatility indicators provides a comprehensive representation of market behavior, enabling the forecasting models to learn diverse patterns associated with cryptocurrency price movements and potentially improve predictive performance.

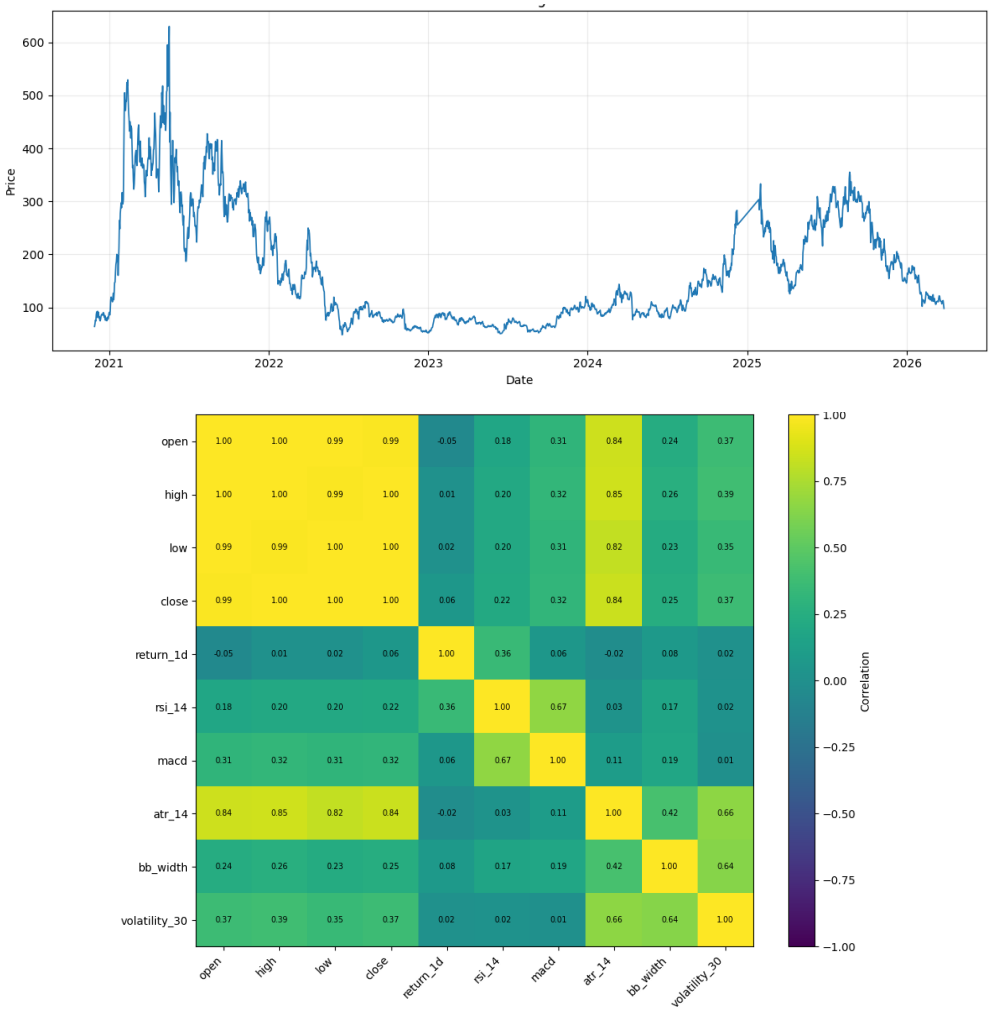

Figure 2 Exploratory Data Analysis of the AAVE Dataset. Historical closing price of AAVE (2020–2026) and Correlation heatmap of the selected input features.

Model Training Performance

The convergence behavior of the four deep learning models is illustrated in figure 3. All models exhibit a consistent reduction in both training and validation losses throughout the optimization process, indicating that the networks successfully learned meaningful patterns from the input data. Although fluctuations are observed during the initial training epochs, the loss values gradually stabilize as training progresses, suggesting that the optimization procedure effectively minimized the prediction error. The close agreement between the training and validation loss curves further indicates that none of the models experienced severe overfitting, demonstrating satisfactory generalization performance on unseen validation data.

As shown in figure 3(a) and figure 3(b), the LSTM and GRU models converge relatively quickly during the early training epochs and achieve stable validation losses after a limited number of iterations. This behavior reflects the effectiveness of recurrent neural networks in modeling sequential financial data by capturing temporal dependencies from historical observations. Among the recurrent architectures, the GRU exhibits a slightly smoother convergence pattern, whereas the LSTM experiences minor fluctuations before reaching

stability. These results suggest that both recurrent models are capable of learning the temporal dynamics of AAVE price movements while maintaining stable optimization throughout the training process.

In contrast, the Transformer model shown in figure 3(c) requires additional training epochs before reaching a stable validation loss, reflecting the greater complexity of its attention-based architecture. Although the Transformer eventually converges, its validation loss displays larger oscillations compared with the recurrent models, indicating higher sensitivity during optimization. Figure 3(d) shows that the proposed Hybrid Transformer LSTM also achieves stable convergence while integrating the strengths of both architectures. By combining the Transformer's capability to capture long range contextual relationships with the LSTM's effectiveness in modeling sequential temporal dependencies, the hybrid model maintains a stable learning process throughout training. Overall, the convergence patterns demonstrate that all four models successfully learned from the training data and achieved satisfactory generalization performance for cryptocurrency price forecasting.

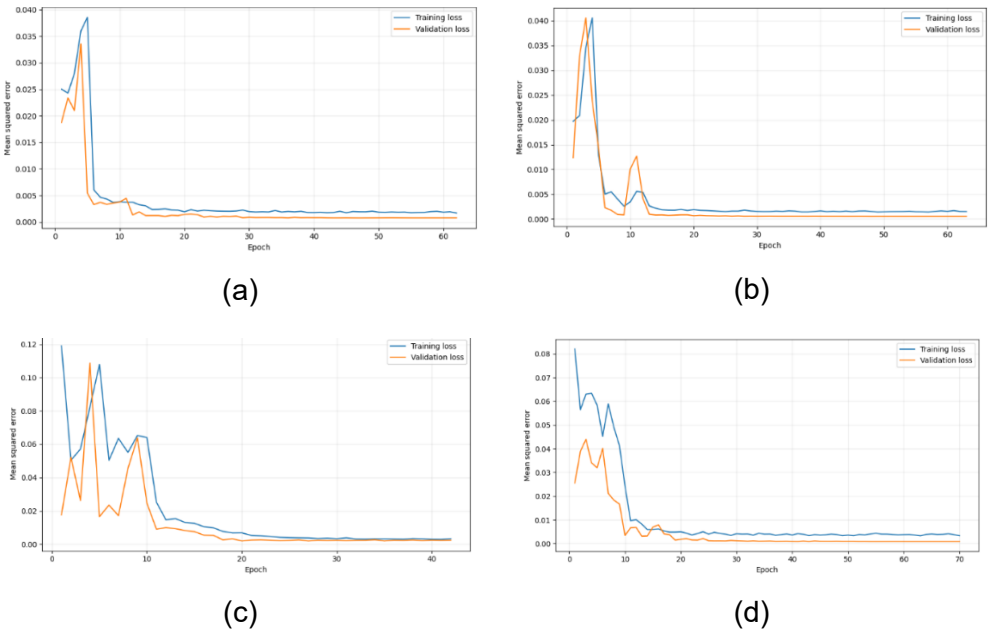

Figure 3 Training and Validation Loss of Deep Learning Models (a) LSTM. (b) GRU. (c) Transformer. (d) Hybrid Transformer–LSTM.

Prediction Performance

The forecasting performance of all models on the testing dataset is presented in figure 4. Overall, each deep learning model is able to capture the general trend of AAVE closing prices, indicating that the selected technical indicators provide sufficient information for learning the underlying market dynamics. Although all models follow the overall direction of price movements, differences in predictive capability become more evident during periods of increased market volatility, where rapid price fluctuations present greater forecasting challenges. The LSTM model successfully tracks the overall market movement but tends to generate smoother predictions, resulting in slight underestimation or overestimation during sharp price reversals. The GRU model produces predictions that more closely follow the actual price trajectory across most of the

testing period, suggesting a stronger ability to capture short term temporal dependencies while maintaining stable prediction accuracy. In comparison, the Transformer model exhibits larger deviations, particularly during the final months of the evaluation period, indicating that its attention based architecture is less effective in adapting to abrupt market changes within the selected forecasting framework. The proposed Hybrid Transformer LSTM combines the contextual learning capability of the Transformer with the sequential memory mechanism of the LSTM, enabling it to capture both long term market trends and short term temporal variations. As illustrated in figure 4, the hybrid model generates stable predictions that remain consistent with the observed price movement across different market conditions, demonstrating its capability to model the complex and nonlinear behavior of cryptocurrency prices.

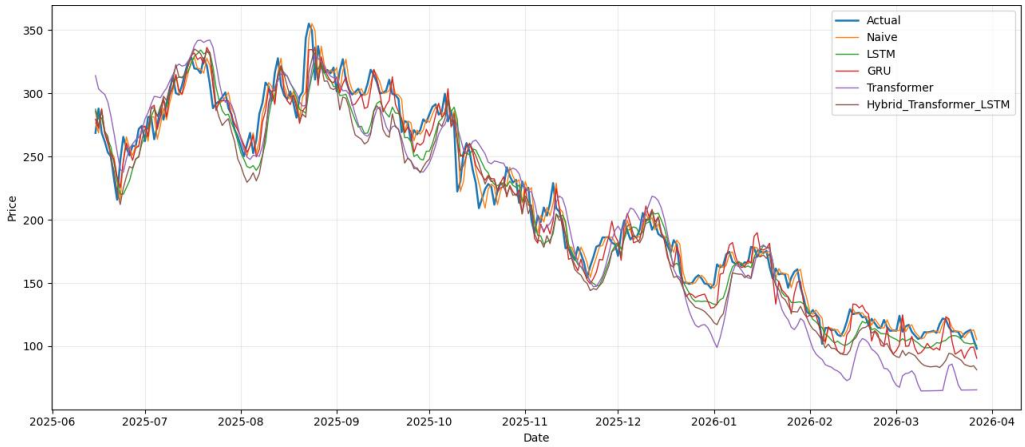

Figure 4 Actual and Predicted Closing Prices of the Forecasting Models

Quantitative Performance Comparison

The quantitative performance of the forecasting models is summarized in table 1 using five evaluation metrics, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), coefficient of determination (R^2), and Directional Accuracy (DA). These metrics were selected to provide a comprehensive evaluation of forecasting performance from different perspectives. MAE, RMSE, and MAPE measure the magnitude of prediction errors, where lower values indicate higher prediction accuracy. The coefficient of determination (R^2) evaluates the proportion of variance in the actual closing prices that can be explained by the forecasting model, with values closer to one indicating better goodness of fit. Meanwhile, Directional Accuracy measures the ability of a model to correctly predict the direction of price movement between consecutive observations, which is particularly important in financial forecasting because correctly identifying market trends can be as valuable as minimizing numerical prediction errors.

The results presented in table 1 demonstrate noticeable differences in forecasting performance among the evaluated models. The Naïve model achieved the lowest values for MAE, RMSE, and MAPE, as well as the highest R^2 value, indicating the smallest overall prediction errors on the testing dataset. In contrast, the GRU model obtained the highest Directional Accuracy, suggesting a stronger capability to correctly identify the direction of price movements despite producing larger numerical prediction errors than the Naïve approach. The LSTM model produced intermediate performance across all

evaluation metrics, whereas the Transformer exhibited the largest prediction errors and the lowest coefficient of determination among the evaluated deep learning models. The proposed Hybrid Transformer LSTM achieved better numerical performance than the standalone Transformer but did not outperform the recurrent architectures according to the selected evaluation metrics. Overall, these quantitative results provide an objective basis for comparing recurrent, attention based, and hybrid deep learning architectures for decentralized finance cryptocurrency price forecasting while highlighting the strengths and limitations of each approach under the experimental setting adopted in this study.

Table 1 Performance Comparison of Forecasting Models

Model	MAE	RMSE	MAPE (%)	R^2	Directional Accuracy (%)
Naïve	7.8216	10.5371	3.6565	0.9789	46.48
GRU	10.7871	13.2047	5.6521	0.9668	49.30
LSTM	13.1595	16.8965	6.3502	0.9457	45.07
Hybrid Transformer–LSTM	17.4199	20.8708	9.1429	0.9172	47.18
Transformer	22.2034	26.5713	12.9281	0.8657	46.83

Residual Analysis

Residual analysis was performed to further evaluate the prediction performance of the proposed Hybrid Transformer LSTM model by examining the distribution of forecasting errors on the testing dataset. As illustrated in figure 5, the residuals are predominantly concentrated around zero, indicating that the model does not exhibit substantial systematic overestimation or underestimation of AAVE closing prices. The approximately symmetric distribution of residuals suggests that most prediction errors are relatively small and randomly distributed, reflecting the model's ability to accurately capture the underlying relationship between historical market information and future price movements. Although a limited number of residuals with larger magnitudes are observed, these deviations primarily correspond to periods of elevated market volatility in which cryptocurrency prices change rapidly and unpredictably. Such behavior is expected in highly volatile financial markets and indicates that extreme price movements remain challenging to forecast with high precision. Overall, the residual distribution demonstrates that the proposed Hybrid Transformer LSTM produces stable and unbiased predictions across the testing period, providing additional evidence that the model is capable of learning the complex temporal patterns and nonlinear characteristics of decentralized finance cryptocurrency price data.

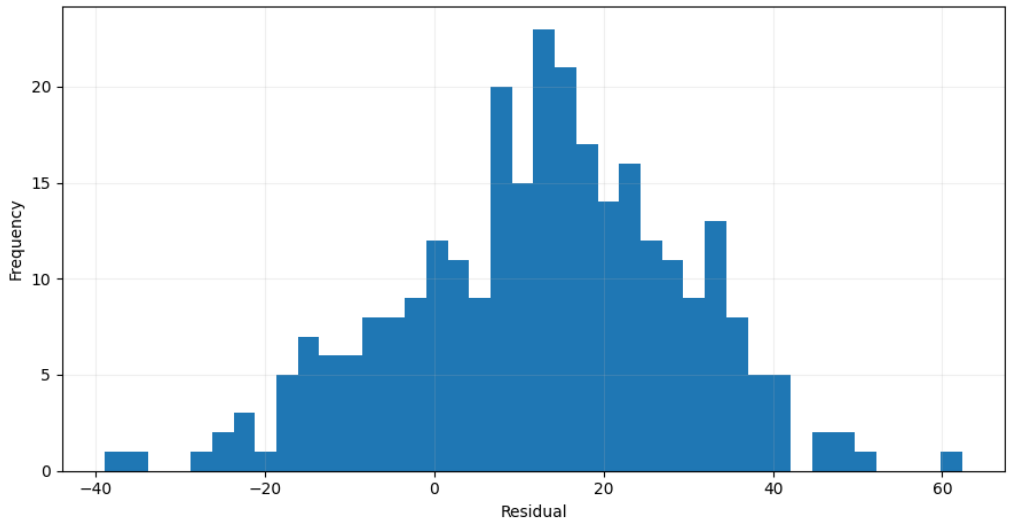

Figure 5 **Residual Distribution of the Proposed Hybrid Transformer–LSTM Model**

Discussion

The findings of this study demonstrate that forecasting decentralized finance cryptocurrency prices remains a challenging task because of the highly dynamic and nonlinear nature of the AAVE market. The exploratory data analysis revealed substantial price fluctuations, multiple trend reversals, and changing volatility levels throughout the observation period, indicating that the underlying data distribution continuously evolves over time. These characteristics increase forecasting complexity because prediction models must simultaneously capture long term market trends and short term price variations while adapting to different market conditions [21]. Despite these challenges, all deep learning models successfully converged during training, and the forecasting results showed that they were capable of following the general direction of AAVE price movements. This observation suggests that the selected technical indicators provide meaningful representations of market behavior and contain sufficient information for learning temporal patterns in historical cryptocurrency prices [22].

The quantitative evaluation further highlights that different neural network architectures exhibit distinct forecasting characteristics. The Naïve model achieved the lowest MAE, RMSE, and MAPE values together with the highest coefficient of determination, indicating the smallest numerical prediction errors on the testing dataset. This outcome suggests that one step ahead forecasting for daily AAVE prices retains a high degree of temporal continuity, allowing the previous closing price to serve as a competitive benchmark. Meanwhile, the GRU model achieved the highest Directional Accuracy, demonstrating a stronger capability to correctly identify future price movements even though its numerical prediction errors were larger than those of the Naïve model. The LSTM produced competitive but less accurate results than the GRU across most evaluation metrics, whereas the Transformer generated the largest prediction errors and exhibited greater deviations during highly volatile periods. Although the proposed Hybrid Transformer LSTM did not outperform the benchmark models according to the selected evaluation metrics, its prediction curves closely followed the overall market trajectory and the residual distribution remained centered around zero, indicating stable and unbiased forecasting

behavior throughout the testing period [23].

The performance of the Hybrid Transformer LSTM suggests that combining self attention mechanisms with recurrent temporal learning does not automatically guarantee superior predictive accuracy when forecasting cryptocurrency prices using only technical indicators. The Transformer component is designed to capture long range contextual relationships, whereas the LSTM component specializes in sequential temporal dependency modeling. However, the advantages of integrating these architectures may be constrained by the characteristics of the available data. The dataset consists of daily historical prices and technical indicators that primarily reflect past market behavior, without incorporating additional information such as investor sentiment, blockchain network activity, macroeconomic events, or regulatory developments that frequently influence cryptocurrency markets [24]. Consequently, the hybrid architecture may not fully exploit its representation capability under the current experimental setting. Nevertheless, the stable convergence during training, consistent forecasting patterns, and balanced residual distribution indicate that the proposed model remains a reliable forecasting framework for decentralized finance applications. These findings also provide valuable insights for intelligent metaverse financial systems, where robust cryptocurrency forecasting can support digital asset valuation, financial decision support, and risk management within blockchain based virtual economies. Future studies may improve forecasting performance by integrating multimodal data sources, exploring advanced Transformer architectures, and optimizing hybrid learning strategies to better capture the rapidly evolving dynamics of decentralized financial markets [25].

Conclusion

This study investigated the effectiveness of deep learning models for forecasting AAVE cryptocurrency prices in decentralized finance using historical price data and technical indicators. Five forecasting approaches, namely the Naïve model, LSTM, GRU, Transformer, and the proposed Hybrid Transformer LSTM, were evaluated using MAE, RMSE, MAPE, coefficient of determination (R^2), and Directional Accuracy. The experimental results demonstrated that all deep learning models successfully learned the nonlinear characteristics of cryptocurrency price movements and achieved stable convergence during training. However, their forecasting performance varied across different evaluation metrics. The Naïve model achieved the lowest prediction errors and the highest R^2, while the GRU model obtained the highest Directional Accuracy. Although the proposed Hybrid Transformer LSTM did not achieve the best numerical performance, it produced stable prediction trajectories and exhibited a balanced residual distribution, indicating its capability to generate consistent and unbiased forecasts under different market conditions.

The findings suggest that increasing model complexity does not necessarily guarantee improved forecasting accuracy when only technical indicators are used as input features. Nevertheless, the proposed hybrid architecture demonstrates the potential of integrating attention based learning with recurrent temporal modeling for capturing both long term contextual information and sequential market dynamics. These results contribute to the development of intelligent financial analytics for decentralized finance and metaverse ecosystems by providing a comparative evaluation of contemporary deep learning architectures for cryptocurrency forecasting. Future research should

investigate the incorporation of additional data sources, such as blockchain network activity, investor sentiment, and macroeconomic indicators, together with advanced Transformer architectures and optimized hybrid learning strategies, to further enhance forecasting accuracy and robustness in rapidly evolving digital asset markets.

Declarations

Author Contributions

Conceptualization: G.A.T., G.K.; Methodology: G.K.; Software: G.A.T.; Validation: G.A.T., G.K.; Formal Analysis: G.A.T., G.K.; Investigation: G.A.T.; Resources: G.K.; Data Curation: G.K.; Writing Original Draft Preparation: G.A.T., G.K.; Writing Review and Editing: G.K., G.A.T.; Visualization: G.A.T.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Informed Consent Statement

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] F. Schär, “Decentralized finance: On blockchain- and smart contract-based financial markets,” *Federal Reserve Bank of St. Louis Review*, vol. 103, no. 2, pp. 153–174, 2021, doi: 10.20955/r.103.153-74.

[2] Y. K. Dwivedi *et al.*, “Metaverse beyond the hype: Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy,” *International Journal of Information Management*, vol. 66, no. October, Art. no. 102542, pp. 1-55, 2022, doi: 10.1016/j.ijinfomgt.2022.102542.

[3] D. C. A. Mallqui and R. A. S. Fernandes, “Predicting the direction, maximum, minimum and closing prices of daily Bitcoin exchange rate using machine learning techniques,” *Applied Soft Computing*, vol. 75, no. February, pp. 596–606, 2019, doi: 10.1016/j.asoc.2018.11.038.

[4] P. L. Seabe, C. R. B. Moutsinga, and E. Pindza, “Forecasting cryptocurrency prices using LSTM, GRU, and bi-directional LSTM: A deep learning approach,” *Fractal and Fractional*, vol. 7, no. 2, Art. no. 203, 2023, doi: 10.3390/fractalfract7020203.

[5] B. Lim, S. Ö. Arık, N. Loeff, and T. Pfister, "Temporal fusion transformers for interpretable multi-horizon time series forecasting," *International Journal of Forecasting*, vol. 37, no. 4, pp. 1748–1764, 2021, doi: 10.1016/j.ijforecast.2021.03.012.

[6] P. Katsiampa, "Volatility estimation for Bitcoin: A comparison of GARCH models," *Economics Letters*, vol. 158, no. January, pp. 3–6, 2017, doi: 10.1016/j.econlet.2017.06.023.

[7] S. Lahmiri and S. Bekiros, "Cryptocurrency forecasting with deep learning chaotic neural networks," *Chaos, Solitons & Fractals*, vol. 118, no. January, pp. 35–40, 2019, doi: 10.1016/j.chaos.2018.11.014.

[8] F. Sabry, W. Labda, A. Erbad, and Q. Malluhi, "Cryptocurrencies and artificial intelligence: Challenges and opportunities," *IEEE Access*, vol. 8, no. September, pp. 175840–175858, 2020, doi: 10.1109/ACCESS.2020.3025211.

[9] N. P. Patel *et al*., "Fusion in cryptocurrency price prediction: A decade survey on recent advancements, architecture, and potential future directions," *IEEE Access*, vol. 10, no. March, pp. 34511–34538, 2022, doi: 10.1109/ACCESS.2022.3163023.

[10] S. Ji, J. Kim, and H. Im, "A comparative study of Bitcoin price prediction using deep learning," *Mathematics*, vol. 7, no. 10, Art. no. 898, 2019, doi: 10.3390/math7100898.

[11] S. Tanwar *et al*., "Deep learning-based cryptocurrency price prediction scheme with inter-dependent relations," *IEEE Access*, vol. 9, no. October, pp. 138633–138646, 2021, doi: 10.1109/ACCESS.2021.3117848.

[12] A. S. Girsang and Stanley, "Hybrid LSTM and GRU for cryptocurrency price forecasting based on social network sentiment analysis using FinBERT," *IEEE Access*, vol. 11, no. October, p. 120530–120540, 2023, doi: 10.1109/ACCESS.2023.3324535.

[13] H. Zhou *et al*., "Informer: Beyond efficient Transformer for long sequence time-series forecasting," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 35, no. 12, pp. 11106–11115, 2021, doi: 10.1609/aaai.v35i12.17325.

[14] M.-C. Lee, "Bitcoin trend prediction with attention-based deep learning models and technical indicators," *Systems*, vol. 12, no. 11, Art. no. 498, 2024, doi: 10.3390/systems12110498.

[15] M.-C. Lee, "Temporal fusion transformer-based trading strategy for multi-crypto assets using on-chain and technical indicators," *Systems*, vol. 13, no. 6, Art. no. 474, 2025, doi: 10.3390/systems13060474.

[16] R. Parekh *et al*., "DL-GuesS: Deep learning and sentiment analysis-based cryptocurrency price prediction," *IEEE Access*, vol. 10, no. March, pp. 35398–35409, 2022, doi: 10.1109/ACCESS.2022.3163305.

[17] E. Mahdi, C. Martín-Barreiro, and X. Cabezas, "A novel hybrid approach using an attention-based Transformer + GRU model for predicting cryptocurrency prices," *Mathematics*, vol. 13, no. 9, Art. no. 1484, 2025, doi: 10.3390/math13091484.

[18] H. Hewamalage, C. Bergmeir, and K. Bandara, "Recurrent neural networks for time series forecasting: Current status and future directions," *International Journal of Forecasting*, vol. 37, no. 1, pp. 388–427, 2021, doi: 10.1016/j.ijforecast.2020.06.008.

[19] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, “Statistical and machine learning forecasting methods: Concerns and ways forward,” *PLOS ONE*, vol. 13, no. 3, Art. no. e0194889, 2018, doi: 10.1371/journal.pone.0194889.

[20] J. Zhang, K. Cai, and J. Wen, “A survey of deep learning applications in cryptocurrency,” *iScience*, vol. 27, no. 1, Art. no. 108509, 2024, doi: 10.1016/j.isci.2023.108509.

[21] Y. Liu and A. Tsyvinski, “Risks and returns of cryptocurrency,” *The Review of Financial Studies*, vol. 34, no. 6, pp. 2689–2727, 2021, doi: 10.1093/rfs/hhaa113.

[22] M. Ortu, N. Uras, C. Conversano, S. Bartolucci, and G. Destefanis, “On technical trading and social media indicators for cryptocurrency price classification through deep learning,” *Expert Systems with Applications*, vol. 198, no. July, Art. no. 116804, 2022, doi: 10.1016/j.eswa.2022.116804.

[23] M. J. Hamayel and A. Y. Owda, “A novel cryptocurrency price prediction model using GRU, LSTM and bi-LSTM machine learning algorithms,” *AI*, vol. 2, no. 4, pp. 477–496, 2021, doi: 10.3390/ai2040030.

[24] O. Kraaijeveld and J. De Smedt, “The predictive power of public Twitter sentiment for forecasting cryptocurrency prices,” *Journal of International Financial Markets, Institutions and Money*, vol. 65, no. March, Art. no. 101188, 2020, doi: 10.1016/j.intfin.2020.101188.

[25] V. Gurgul, S. Lessmann, and W. K. Härdle, “Deep learning and NLP in cryptocurrency forecasting: Integrating financial, blockchain, and social media data,” *International Journal of Forecasting*, vol. 41, no. 4, pp. 1666–1695, 2025, doi: 10.1016/j.ijforecast.2025.02.007.