# An Explainable Hybrid CNN–BiLSTM–Attention Model for Solana Price Forecasting Using Technical Indicators in Blockchain-Based Metaverse Economies

Bentar Priyopradono[1,*]

[1]Teknik Informatika, Universitas Prof. Dr. Hazairin, SH, Bengkulu, Indonesia

## ABSTRACT

The rapid growth of blockchain-based metaverse ecosystems has increased the importance of accurate cryptocurrency price forecasting to support investment decisions, digital asset management, and decentralized application development. As one of the leading blockchain platforms powering non-fungible tokens (NFTs), decentralized finance (DeFi), GameFi, and metaverse applications, Solana exhibits high price volatility that poses significant challenges for market participants. Although deep learning models have demonstrated promising forecasting performance, many existing approaches remain difficult to interpret due to their black-box nature. This study proposes an explainable Hybrid Convolutional Neural Network, Bidirectional Long Short-Term Memory, and Attention (CNN–BiLSTM–Attention) framework for one-day-ahead Solana price forecasting using historical market data and technical indicators. The proposed framework integrates convolutional feature extraction, bidirectional temporal dependency learning, and an attention mechanism to improve forecasting performance, while SHapley Additive exPlanations (SHAP) and permutation feature importance are employed to enhance model interpretability. Experimental evaluation was conducted using 999 daily historical Solana price records, resulting in 599 samples after feature engineering and preprocessing. The proposed model achieved an MAE of 0.7470, an RMSE of 0.9232, a MAPE of 3.43%, and an $R^2$ of 0.6929, demonstrating satisfactory forecasting performance for short-term price prediction. Explainability analysis identified RSI-14, MACD, SMA-5, Open Price, and lagged price variables as the most influential features contributing to model predictions. The findings indicate that the proposed framework not only provides reliable forecasting performance but also improves model transparency, thereby supporting more informed decision-making within blockchain-based metaverse economies. Future work will investigate multimodal data integration and more advanced attention mechanisms to further improve forecasting accuracy and robustness.

**Keywords** Solana Price Prediction, Hybrid Deep Learning, Explainable Artificial Intelligence, Technical Indicators, Blockchain-Based Metaverse Economy

Submitted: 7 June 2026
Accepted: 22 August 2026
Published: 17 November 2026

Corresponding author
Bentar Priyopradono,
bentarpriyopradono@gmail.com

Additional Information and Declarations can be found on page 351

DOI: 10.47738/ijrm.v3i4.90

Copyright
2026 Priyopradono

Distributed under
Creative Commons CC-BY 4.0

## INTRODUCTION

The rapid advancement of blockchain technology has transformed the development of digital ecosystems by enabling decentralized ownership, transparent transactions, and secure digital asset management. One of the most significant applications of blockchain technology is the emergence of the metaverse, where virtual environments integrate decentralized finance, non-fungible tokens (NFTs), digital identities, gaming, and virtual commerce into interconnected digital economies. Within these ecosystems, cryptocurrencies

**How to cite this article:** B. Priyopradono, "An Explainable Hybrid CNN–BiLSTM–Attention Model for Solana Price Forecasting Using Technical Indicators in Blockchain-Based Metaverse Economies," *Int. J. Res. Metav.*, vol. 3, no. 4, pp. 331-353, 2026.

function as the primary medium of exchange, supporting economic activities ranging from digital asset trading to smart contract execution. Consequently, the stability and predictability of cryptocurrency prices have become increasingly important for investors, developers, platform operators, and other stakeholders participating in blockchain-based metaverse environments [1].

Among the various blockchain platforms, Solana has emerged as one of the leading infrastructures for decentralized applications due to its high transaction throughput, low transaction costs, and scalable architecture. These characteristics have encouraged widespread adoption across decentralized finance (DeFi), NFT marketplaces, GameFi platforms, and metaverse-related applications. However, despite its technological advantages, Solana exhibits substantial price volatility driven by speculative trading, rapidly changing market sentiment, macroeconomic uncertainty, and blockchain ecosystem developments. Such volatility introduces considerable challenges for investment decision-making and financial risk management, emphasizing the need for accurate and reliable price forecasting models that can assist stakeholders in understanding future market movements [2].

Traditional statistical forecasting methods, including Autoregressive Integrated Moving Average (ARIMA) and other linear time-series models, have been widely employed for financial forecasting. Although these approaches perform adequately when underlying data satisfy linear assumptions, they often struggle to model the highly nonlinear, dynamic, and volatile characteristics of cryptocurrency markets. The emergence of machine learning techniques, including Random Forest, eXtreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM), has improved forecasting performance by capturing nonlinear relationships among multiple technical indicators. Nevertheless, these methods generally depend on manually engineered features and may have limited capability in modeling long-term temporal dependencies that characterize financial time-series data [3].

Recent advances in deep learning have significantly improved cryptocurrency price forecasting by automatically extracting hierarchical representations from historical observations. Recurrent neural network variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) have demonstrated superior capability in learning sequential dependencies compared with conventional machine learning models. Furthermore, Convolutional Neural Networks (CNN) have been increasingly incorporated into forecasting frameworks to extract local temporal patterns before sequential learning. Hybrid deep learning architectures that combine CNN and LSTM have therefore become a popular approach because they simultaneously capture local feature patterns and long-term temporal information. More recently, attention mechanisms have been integrated into recurrent neural networks to enable adaptive weighting of temporal information, allowing forecasting models to utilize the most relevant historical observations during prediction [4].

Despite these advances, several important challenges remain unresolved. First, many existing cryptocurrency forecasting studies primarily focus on improving predictive accuracy while providing limited attention to model interpretability. Since deep learning models are often regarded as black-box systems, users cannot easily understand how input variables contribute to forecasting results. This lack of transparency limits practical adoption in financial decision-making, where explainability is increasingly required to improve user confidence and

support risk assessment. Second, previous studies frequently evaluate forecasting performance using conventional error metrics while overlooking explainable artificial intelligence techniques that can provide insights into feature importance and prediction behavior. Third, although hybrid CNN-LSTM architectures have been extensively investigated for cryptocurrency forecasting, relatively few studies have explored the integration of Bidirectional LSTM together with attention mechanisms to simultaneously capture bidirectional temporal dependencies and adaptive temporal weighting. Finally, research specifically focusing on Solana remains considerably more limited than studies involving Bitcoin and Ethereum, despite Solana's growing importance within blockchain-based metaverse ecosystems.

The current state of the art in cryptocurrency forecasting has gradually shifted from conventional machine learning toward explainable hybrid deep learning frameworks. Recent studies demonstrate that combining convolutional feature extraction with recurrent neural networks improves forecasting performance by learning both local market patterns and long-term temporal dependencies. Meanwhile, the incorporation of attention mechanisms further enhances temporal representation by enabling adaptive weighting of historical observations during prediction. At the same time, Explainable Artificial Intelligence (XAI) techniques, particularly SHapley Additive exPlanations (SHAP), have become increasingly important for interpreting complex deep learning models by quantifying the contribution of individual input features to prediction outcomes. These developments indicate that future forecasting systems should not only maximize predictive accuracy but also provide transparent explanations that improve model trustworthiness and support informed decision-making in financial applications [5].

Based on the identified research gaps, this study proposes an Explainable Hybrid CNN–BiLSTM–Attention model for one-day-ahead Solana price forecasting using historical market data and technical indicators. The proposed framework combines CNN to extract local temporal features, BiLSTM to capture bidirectional sequential dependencies, and an attention mechanism to integrate relevant temporal information for forecasting. In addition, SHAP and permutation feature importance are incorporated to improve model interpretability by identifying the technical indicators that contribute most significantly to prediction performance. The proposed framework is evaluated using daily historical Solana price data and compared through multiple forecasting performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination ($R^2$), together with visual analyses of prediction performance and explainability.

The main contributions of this study are threefold. First, this study develops an explainable hybrid CNN–BiLSTM–Attention architecture specifically designed for short-term Solana price forecasting by integrating convolutional feature extraction, bidirectional temporal learning, and an attention mechanism within a unified deep learning framework. Second, this study incorporates Explainable Artificial Intelligence through SHAP and permutation feature importance to improve transparency and provide comprehensive insights into the contribution of technical indicators, addressing the interpretability limitations of conventional deep learning models. Third, this study demonstrates the applicability of explainable deep learning for supporting financial decision-making within

blockchain-based metaverse ecosystems, thereby contributing to the growing body of research at the intersection of artificial intelligence, cryptocurrency forecasting, and decentralized digital economies.

## Literature Review and Related Works

Cryptocurrency price forecasting has become an active research area because digital asset markets exhibit high volatility, nonlinear behavior, and complex temporal dependencies that cannot be adequately represented using conventional statistical models. Earlier studies primarily employed machine learning algorithms such as Support Vector Machine, Random Forest, eXtreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM) to model nonlinear relationships between historical prices and technical indicators. These approaches generally outperformed traditional statistical methods; however, their performance largely depended on manually engineered features and their capability to capture long-term temporal dependencies remained limited [6], [7]. Consequently, recent research has increasingly shifted toward deep learning architectures capable of automatically learning hierarchical feature representations from sequential financial data.

Long Short-Term Memory (LSTM) networks have become one of the most widely adopted deep learning models for cryptocurrency forecasting because of their ability to preserve long-term temporal information while mitigating the vanishing gradient problem. Numerous studies have demonstrated that LSTM-based models outperform conventional machine learning algorithms in forecasting highly volatile cryptocurrency prices. Bidirectional Long Short-Term Memory (BiLSTM) further extends this capability by processing sequential information in both forward and backward directions, enabling richer temporal feature extraction and improving forecasting accuracy for financial time series [8], [9]. Nevertheless, standalone recurrent architectures may still overlook local temporal patterns embedded within short observation windows, motivating the development of hybrid deep learning frameworks.

To address this limitation, Convolutional Neural Networks (CNN) have been integrated with recurrent neural networks to extract local temporal features before sequential learning. CNN layers effectively identify short-term market patterns and reduce feature redundancy, while LSTM or BiLSTM layers model long-range temporal dependencies. Several studies have reported that hybrid CNN-LSTM architectures consistently outperform individual CNN or LSTM models across various financial forecasting tasks by combining spatial feature extraction with sequential learning [10], [11]. The effectiveness of these hybrid architectures has encouraged researchers to investigate increasingly sophisticated combinations of convolutional and recurrent neural networks for cryptocurrency prediction.

More recently, attention mechanisms have been incorporated into hybrid forecasting models to improve the utilization of historical observations. Rather than assigning equal importance to every time step, attention mechanisms enable deep learning models to adaptively weight temporal information according to its contribution to the prediction task. Previous studies have demonstrated that attention-enhanced hybrid architectures improve prediction accuracy by emphasizing informative temporal patterns while suppressing less relevant historical observations [12], [13]. The integration of attention has therefore become an important advancement in financial time series

forecasting, particularly for highly volatile cryptocurrency markets where market conditions evolve rapidly over time.

In addition to architectural improvements, recent research has increasingly emphasized the importance of Explainable Artificial Intelligence (XAI). Although deep learning models often achieve superior predictive performance, they are frequently criticized for their black-box nature, limiting user trust in financial decision support systems. Explainability techniques such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and permutation feature importance have therefore been incorporated into forecasting frameworks to quantify the contribution of individual input variables. These methods enable researchers and practitioners to understand which technical indicators influence prediction outcomes and improve the transparency of complex deep learning models [14], [15]. Consequently, explainability has become an increasingly important requirement for intelligent financial forecasting systems.

Another research direction focuses on enriching forecasting models through feature engineering. Instead of relying solely on historical closing prices, many recent studies integrate technical indicators including Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, momentum indicators, logarithmic returns, and lagged price variables. These indicators provide additional information regarding market trends, volatility, and momentum, allowing forecasting models to capture more informative representations of market behavior. Experimental results consistently demonstrate that combining historical prices with technical indicators improves forecasting performance compared with using raw price data alone [16], [17].

The emergence of hybrid deep learning architectures has further advanced cryptocurrency forecasting by combining multiple neural network components within a unified framework. Recent studies have integrated CNN, BiLSTM, Transformer networks, Gated Recurrent Units (GRU), Temporal Convolutional Networks (TCN), and attention mechanisms to improve forecasting accuracy while maintaining robust temporal representation learning. These hybrid architectures exploit the complementary strengths of convolutional feature extraction, sequential dependency modeling, and adaptive feature weighting, enabling superior performance compared with standalone deep learning models across multiple cryptocurrencies [18], [19]. The growing success of these approaches demonstrates that combining multiple learning mechanisms provides a more effective solution for modeling the complex dynamics of financial markets.

Despite these significant advances, several research gaps remain. First, most existing studies primarily focus on Bitcoin and Ethereum, whereas comparatively fewer investigations examine Solana despite its growing importance in decentralized finance, NFT ecosystems, GameFi platforms, and blockchain-based metaverse applications. Second, although explainability techniques have recently gained attention, only a limited number of studies simultaneously integrate hybrid CNN-BiLSTM architectures, attention mechanisms, and SHAP-based interpretation within a unified forecasting framework. Third, many previous studies emphasize predictive accuracy without providing comprehensive analyses of feature importance and model transparency that are essential for practical financial decision-making.

Motivated by these limitations, this study proposes an explainable Hybrid CNN-BiLSTM-Attention framework that combines convolutional feature extraction, bidirectional temporal learning, adaptive attention, and SHAP-based explainability to improve both forecasting performance and model interpretability for short-term Solana price prediction in blockchain-based metaverse economies [20].

## Methodology

### Research Framework

This study proposes an explainable Hybrid CNN–BiLSTM–Attention framework for one-day-ahead Solana price forecasting. The proposed methodology consists of six sequential stages, namely data collection, data preprocessing, feature engineering, data normalization and sequence generation, hybrid deep learning model development, and performance evaluation with explainability analysis. The overall workflow transforms raw historical market data into multivariate sequential representations that are subsequently learned by the proposed deep learning architecture while simultaneously providing transparent explanations of the prediction results. Figure 1 illustrates the complete research framework adopted in this study, beginning with historical data acquisition and ending with model evaluation and explainability analysis. The framework ensures that each stage contributes systematically to improving forecasting accuracy while maintaining model interpretability.

The forecasting process begins with collecting historical Solana market data, followed by data cleaning and feature engineering to generate technical indicators representing market trend, momentum, and volatility. The processed data are normalized before being transformed into sequential samples using a sliding window approach. These sequences are subsequently used to train the proposed Hybrid CNN–BiLSTM–Attention model. Finally, the trained model is evaluated using quantitative regression metrics together with explainability techniques, including permutation feature importance, attention weight visualization, and SHapley Additive exPlanations (SHAP), to improve the transparency of the forecasting model.

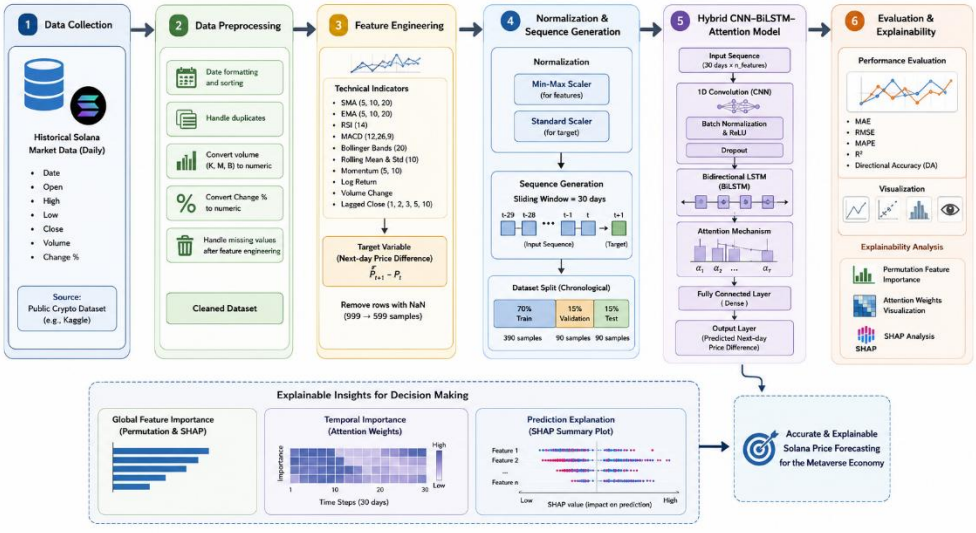



**Figure 1 Research workflow**

## Data Collection and Preprocessing

Historical daily Solana market data were collected from a publicly available cryptocurrency dataset consisting of opening price, highest price, lowest price, closing price, trading volume, and daily percentage price change. Each observation represents one trading day and forms the basis for feature engineering and model development.

During preprocessing, the Date variable was converted into datetime format, duplicated observations were removed, abbreviated trading volumes expressed in thousands, millions, and billions were converted into numerical values, and percentage symbols were removed from the Change % attribute. Missing values introduced by rolling-window calculations were discarded after feature engineering to ensure that only complete observations were retained for model training.

## Feature Engineering

To enrich the information contained in the original dataset, multiple technical indicators describing trend, momentum, volatility, and historical price behavior were generated. These include Simple Moving Average (SMA), Exponential Moving Average (EMA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, rolling mean, rolling standard deviation, momentum, logarithmic return, and lagged price variables.

The prediction target is defined as the next-day price difference,

$$y_t = P_{t+1} - P_t \tag{1}$$

$P_t$denotes the closing price on day $t$, and $P_{t+1}$represents the closing price on the following trading day.

The logarithmic return is calculated as:

$$LogReturn_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{2}$$

The Simple Moving Average is computed as:

$$SMA_n = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i} \tag{3}$$

The Exponential Moving Average is defined as:

$$EMA_t = \alpha P_t + (1-\alpha)EMA_{t-1} \tag{4}$$

$$\alpha = \frac{2}{n+1} \tag{5}$$

The Relative Strength Index (RSI) is calculated using:

$$RSI = 100 - \frac{100}{1+RS} \tag{6}$$

$$RS = \frac{\text{Average Gain}}{\text{Average Loss}} \tag{7}$$

The Moving Average Convergence Divergence is obtained by:

$$MACD = EMA_{12} - EMA_{26} \tag{8}$$

The upper and lower Bollinger Bands are computed as:

$$BB_{Upper} = SMA_{20} + 2\sigma \tag{9}$$

$$BB_{Lower} = SMA_{20} - 2\sigma \tag{10}$$

$\sigma$denotes the standard deviation over the 20-day observation window.

After feature engineering, incomplete observations generated during rolling calculations were removed, reducing the dataset from 999 observations to 599 complete samples.

## Data Normalization and Sequence Generation

Because the constructed features have different numerical ranges, feature normalization was performed before model training. Input variables were normalized using Min-Max normalization,

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{11}$$

$x$is the original feature value.

The prediction target was standardized using z-score normalization,

$$z = \frac{x - \mu}{\sigma} \tag{12}$$

$\mu$and $\sigma$represent the mean and standard deviation of the target variable, respectively.

The normalized observations were transformed into sequential samples using a sliding window of 30 trading days. Formally,

$$X_t = \{x_{t-29}, x_{t-28}, \ldots, x_t\} \tag{13}$$

each sequence predicts the target value on day $t + 1$.

The generated sequences were chronologically divided into 70% training, 15% validation, and 15% testing, resulting in 390, 90, and 90 sequences, respectively.

## Proposed Hybrid CNN–BiLSTM–Attention Model

The proposed forecasting model integrates CNN, BiLSTM, and an attention mechanism into a unified deep learning framework.

For one-dimensional convolution, feature extraction is performed as:

$$h_i = f(W * x_i + b) \tag{14}$$

$W$denotes the convolution kernel, $b$is the bias, and $f(\cdot)$represents the ReLU activation function.

The BiLSTM generates hidden representations in both forward and backward directions,

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \tag{15}$$

The attention score is calculated as:

$$e_t = W_a h_t + b_a \tag{16}$$

The normalized attention weight is obtained using the Softmax function,

$$\alpha_t = \frac{\exp(e_t)}{\sum_{i=1}^{T} \exp(e_i)} \tag{17}$$

The context vector is computed as:

$$c = \sum_{t=1}^{T} \alpha_t \, h_t \tag{18}$$

Finally, the prediction layer estimates the future price difference using:

$$\hat{y} = W_o c + b_o \tag{19}$$

$\hat{y}$denotes the predicted target value.

## Model Training

The model was implemented using the PyTorch framework and optimized using the Adam optimizer with an initial learning rate of 0.001 and a weight decay coefficient of $1 \times 10^{-5}$. Mean Squared Error (MSE) was selected as the optimization objective,

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y_i})^2 \tag{20}$$

Gradient clipping, adaptive learning rate scheduling, and early stopping were applied to improve convergence and prevent overfitting. Training converged after 19 epochs.

## Performance Evaluation

The proposed model was evaluated using five regression metrics.

Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i |$$ (21)

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$$ (22)

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{N}\sum_{i=1}^{N} | \frac{y_i - \hat{y}_i}{y_i} |$$ (23)

Coefficient of Determination

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$ (24)

Directional Accuracy

$$DA = \frac{1}{N}\sum_{i=1}^{N} I\left[(y_i - y_{i-1})(\hat{y}_i - \hat{y}_{i-1}) > 0\right] \times 100\%$$ (25)

$I(\cdot)$is the indicator function that equals 1 when the predicted and actual price movements have the same direction and 0 otherwise.

### Explainability Analysis

To improve model transparency, this study employs three complementary explainability techniques. Permutation Feature Importance measures the contribution of each feature by evaluating the degradation in model performance after randomly permuting feature values. The attention mechanism provides temporal importance weights assigned to each observation within the 30-day input sequence. Finally, SHAP computes feature contributions based on cooperative game theory,

$$f(x) = \phi_0 + \sum_{i=1}^{M} \phi_i$$ (26)

$\phi_i$represents the contribution of the $i$-th feature to the final prediction. The combination of these explainability techniques enables comprehensive interpretation of both global feature importance and local prediction behavior, thereby increasing the transparency and reliability of the proposed forecasting framework.

## Results

## Model Training Performance

The proposed Hybrid CNN–BiLSTM–Attention model was trained using the Adam optimizer with an early stopping strategy for a maximum of 19 epochs to achieve optimal convergence while preventing overfitting. The learning curves presented in figure 2 illustrate the evolution of the training and validation losses throughout the training process. As observed, the training loss steadily decreased from approximately 0.90 at the beginning of training to around 0.68 in the final epoch, indicating that the model progressively learned meaningful temporal patterns from the historical Solana price data. At the same time, the validation loss remained relatively low and stable during the training process without exhibiting a significant upward trend, suggesting that the model maintained good generalization capability when evaluated on unseen validation data. The absence of noticeable divergence between the training and validation losses indicates that the proposed hybrid architecture effectively learned the underlying nonlinear relationships in the time series while avoiding severe overfitting. Furthermore, the validation loss reached its minimum before the training process was terminated by the early stopping mechanism, implying that the selected model parameters correspond to the best-performing model obtained during training. Overall, the convergence behavior shown in figure 2 demonstrates that the proposed CNN–BiLSTM–Attention model can be trained efficiently and achieves stable learning performance for short-term Solana price forecasting.

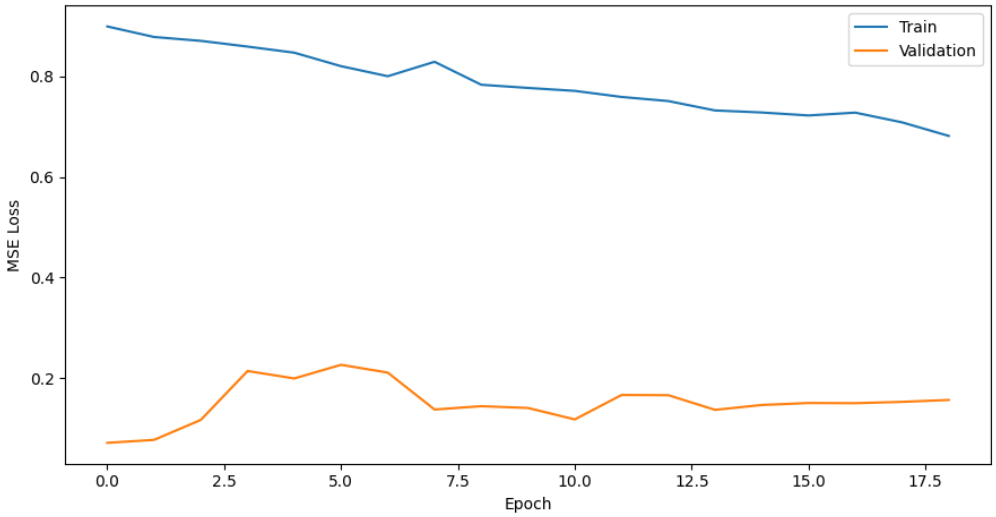



**Figure 2 Training and Validation Loss of the Proposed CNN–BiLSTM–Attention Model.**

## Prediction Performance

The forecasting performance of the proposed Hybrid CNN–BiLSTM–Attention model was evaluated using five widely adopted regression and directional metrics, namely Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination ($R^2$), and Directional Accuracy (DA). These evaluation metrics were selected to provide a comprehensive assessment of the model from different perspectives, including prediction accuracy, error magnitude, goodness of fit, and the ability to correctly identify short-term price movement directions. The quantitative evaluation results are presented in table 1. Overall, the proposed model achieved an MAE of 0.7470 and an RMSE of 0.9232,

indicating that the average prediction errors remained below one US dollar during the testing period. The relatively small difference between the MAE and RMSE values further suggests that large prediction errors occurred infrequently and that the model produced stable forecasting performance across most observations.

As shown in table 1, the proposed model achieved a MAPE of 3.43%, indicating a high level of forecasting accuracy for one-day-ahead Solana price prediction because the average percentage error remained below 5%. In addition, the model obtained an $R^2$ value of 0.6929, demonstrating that approximately 69.3% of the variation in Solana prices can be explained by the learned relationships between historical price data and the engineered technical indicators. These results indicate that the proposed hybrid architecture effectively captures a substantial portion of the nonlinear temporal dynamics present in the dataset. However, the Directional Accuracy reached 48.31%, suggesting that although the model performs well in estimating price values, its capability to correctly predict the direction of daily price movements remains limited. This finding implies that the proposed model is more effective for numerical price forecasting than for directional market prediction, highlighting an opportunity for future improvements through the incorporation of additional market information or alternative forecasting strategies.

**Table 1 Performance Evaluation of the Proposed CNN–BiLSTM–Attention Model**

| Metric | Value |
|---|---|
| MAE | 0.7470 |
| RMSE | 0.9232 |
| MAPE (%) | 3.43 |
| $R^2$ | 0.6929 |
| Directional Accuracy (%) | 48.31 |

## Actual versus Predicted Solana Prices

To visually assess the forecasting capability of the proposed Hybrid CNN–BiLSTM–Attention model, the predicted Solana prices were compared with the corresponding actual prices over the testing period, as illustrated in figure 3. The comparison shows that the predicted values closely follow the overall trajectory of the actual price series, indicating that the proposed model successfully captures the underlying temporal dynamics of the cryptocurrency market. Most upward and downward price movements are accurately tracked, and the predicted curve exhibits a trend that is highly consistent with the observed market behavior. Although slight discrepancies are visible during periods characterized by increased price volatility, the model remains capable of preserving the general direction and magnitude of price fluctuations without producing excessive deviations. These differences are expected because sudden market movements are inherently more difficult to predict due to the highly volatile nature of cryptocurrency markets. Furthermore, the predicted series demonstrates a smooth transition between consecutive observations, suggesting that the hybrid architecture effectively integrates local feature extraction through the CNN component, long-term temporal dependency learning through the BiLSTM network, and adaptive information weighting through the attention mechanism. Overall, the visual agreement between the actual and predicted price series shown in figure 3 supports the quantitative

evaluation results presented in table 1, confirming that the proposed model is capable of generating accurate and stable one-day-ahead Solana price forecasts.

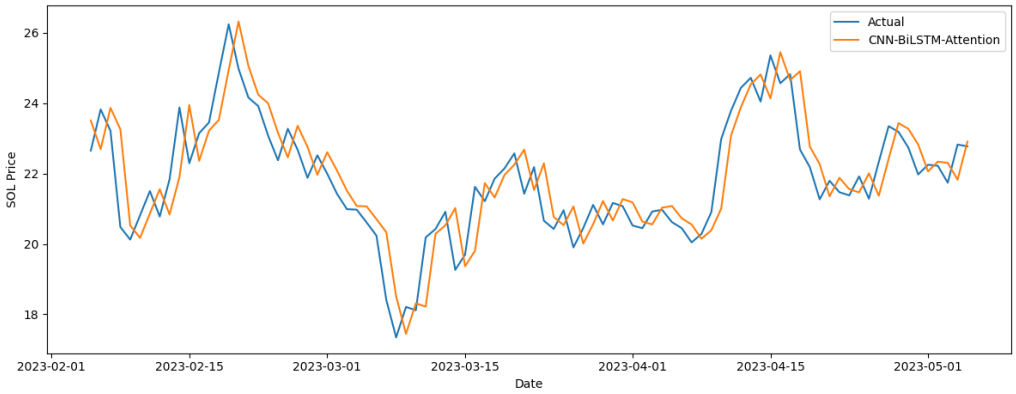



**Figure 3 Comparison of Actual and Predicted Solana Prices.**

## Scatter Plot Analysis

The agreement between the predicted and actual Solana prices was further evaluated using a scatter plot, as presented in figure 4. In this visualization, each data point represents the relationship between the actual price and the corresponding predicted price for an observation in the testing dataset. As shown in figure 4, the majority of the data points are concentrated near the diagonal reference line, indicating a strong correspondence between the predicted and actual values. This distribution suggests that the proposed Hybrid CNN–BiLSTM–Attention model is capable of producing predictions that closely match the observed market prices across a wide range of price levels. Only a relatively small number of observations deviate noticeably from the ideal diagonal line, with most of these deviations occurring at higher price values where market volatility tends to be more pronounced. The relatively compact clustering of data points around the reference line indicates that the prediction errors remain consistent and that the model does not exhibit systematic overestimation or underestimation across the testing samples. Furthermore, the scatter plot provides visual support for the quantitative evaluation results reported in table 1, particularly the coefficient of determination ($R^2$) of 0.6929, which indicates that the proposed model successfully explains a substantial proportion of the variability in Solana prices. Overall, the scatter plot confirms the robustness of the proposed forecasting framework and demonstrates its ability to generate reliable price predictions under varying market conditions.

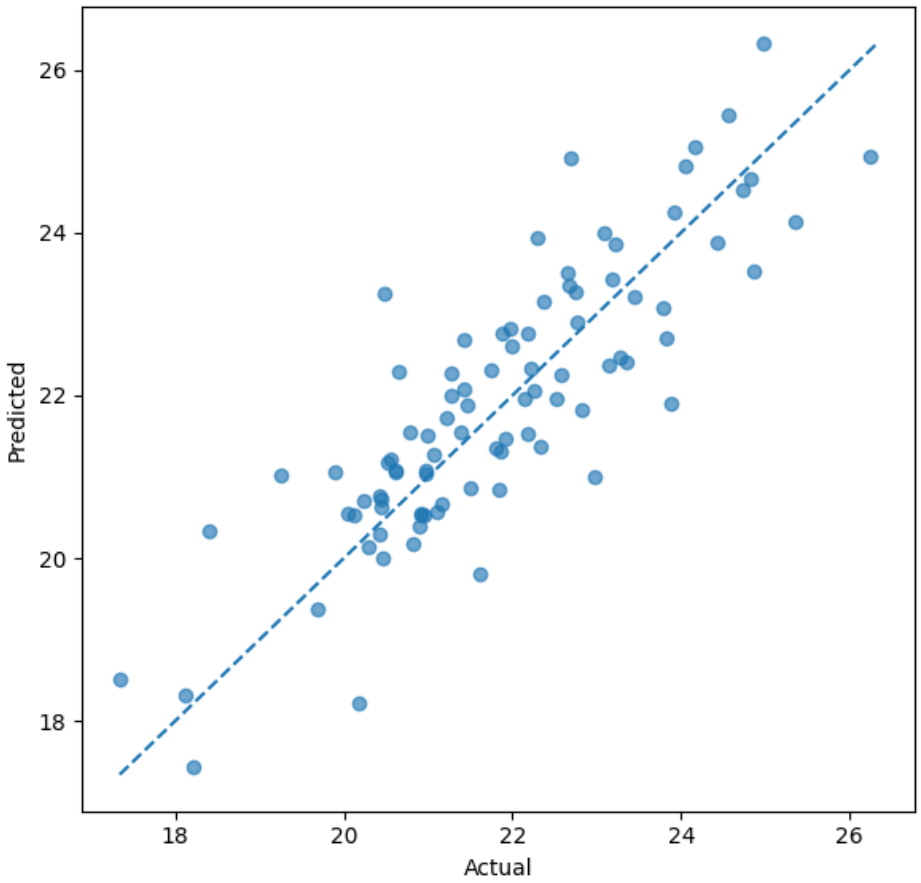



**Figure 4 Scatter Plot of Actual and Predicted Solana Prices.**

## Residual Analysis

Residual analysis was performed to further assess the error characteristics and reliability of the proposed Hybrid CNN–BiLSTM–Attention model by examining the distribution of prediction residuals, as illustrated in figure 5. The residual represents the difference between the actual Solana price and the corresponding predicted value, where residuals close to zero indicate more accurate predictions. As shown in figure 5, the residuals are approximately centered around zero and exhibit a relatively symmetric distribution, suggesting that the proposed model does not suffer from significant systematic bias toward either overestimation or underestimation. The majority of prediction errors are concentrated within the range of approximately −1 USD to +1 USD, indicating that most forecasts deviate only slightly from the observed prices. In addition, the histogram exhibits a prominent peak around zero, demonstrating that small prediction errors occur more frequently than large ones. Only a limited number of residuals are located in the tails of the distribution, reflecting occasional larger forecasting errors during periods of elevated market volatility and abrupt price fluctuations, which are common characteristics of cryptocurrency markets. The absence of substantial skewness and the relatively balanced distribution of positive and negative residuals indicate that the proposed model maintains stable prediction performance across the testing dataset. Overall, the residual analysis supports the quantitative evaluation results presented in table 1 and confirms that the proposed forecasting framework produces reliable predictions with relatively low and randomly distributed prediction errors.

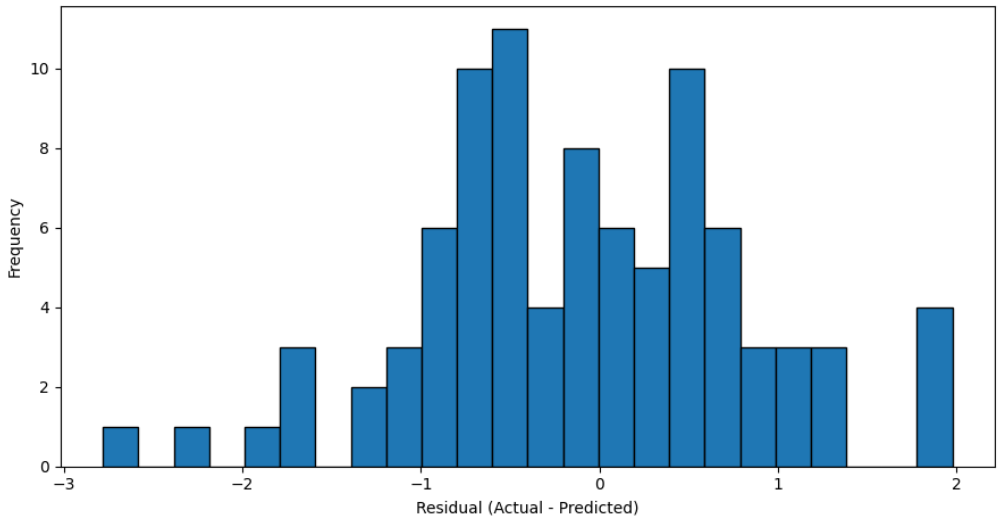



**Figure 5 Distribution of Prediction Residuals.**

## Temporal Attention Analysis

To investigate how the attention mechanism utilizes historical information, the average temporal attention weights learned by the proposed Hybrid CNN–BiLSTM–Attention model are presented in figure 6. The visualization illustrates the relative importance assigned to each time step within the 30-day input sequence when generating the one-day-ahead price prediction. As shown in figure 6, the attention weights are distributed relatively uniformly across all historical observations, with only minor variations between consecutive time steps. This distribution indicates that the proposed model does not rely exclusively on the most recent observations but instead incorporates information from the entire historical window when estimating future Solana prices. Such behavior suggests that price movements occurring throughout the input sequence collectively contribute to the forecasting process, reflecting the complex temporal dependencies commonly observed in cryptocurrency markets. Although no individual time step receives substantially higher attention than the others, the attention mechanism still serves as an adaptive weighting component that integrates temporal information before the final prediction is generated. The relatively balanced attention distribution also indicates that useful predictive information is not concentrated within a single observation but is dispersed across multiple historical price records. Overall, the attention analysis demonstrates that the proposed model leverages information from the complete input sequence to produce stable short-term forecasts, thereby complementing the temporal representations learned by the BiLSTM layer.

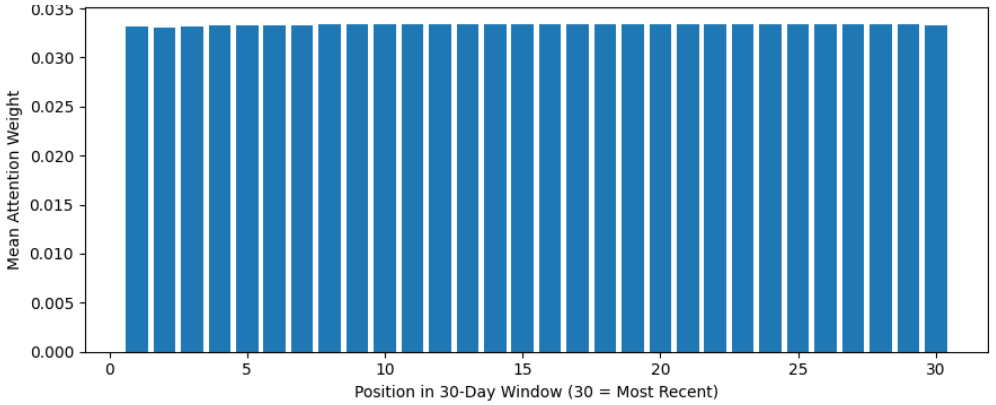



**Figure 6 Average Temporal Attention Weights across the 30-Day Input Window.**

## Explainability Analysis Using Permutation Feature Importance

To identify the technical indicators that contribute most significantly to the forecasting performance of the proposed Hybrid CNN–BiLSTM–Attention model, a permutation feature importance analysis was conducted. This approach evaluates the importance of each feature by randomly shuffling its values and measuring the corresponding increase in prediction error, where a larger increase indicates a greater contribution to the model's predictive capability. The results of the analysis are presented in figure 7. As shown, RSI-14 exhibits the highest feature importance, producing the largest increase in RMSE when permuted, indicating that it plays the most critical role in the prediction process. This is followed by MACD, Upper Bollinger Band, Log Return, and Price Lag-3, all of which contribute substantially to the forecasting performance. In contrast, indicators such as Rolling Standard Deviation, EMA-20, Change Percentage, Momentum-5, and SMA-10 demonstrate relatively smaller contributions, suggesting that the proposed model relies less heavily on these variables when generating predictions. The dominance of RSI-14 and MACD indicates that momentum-related indicators provide highly informative signals for capturing short-term market dynamics, while the importance of Bollinger Bands reflects the influence of market volatility on price movements. Furthermore, the inclusion of lagged price features among the most influential variables suggests that historical price behavior remains an essential source of information for forecasting future Solana prices. Overall, the permutation feature importance analysis demonstrates that the proposed hybrid model effectively exploits a combination of momentum, volatility, and historical price information to improve forecasting accuracy and provides valuable insights into the internal decision-making process of the model.

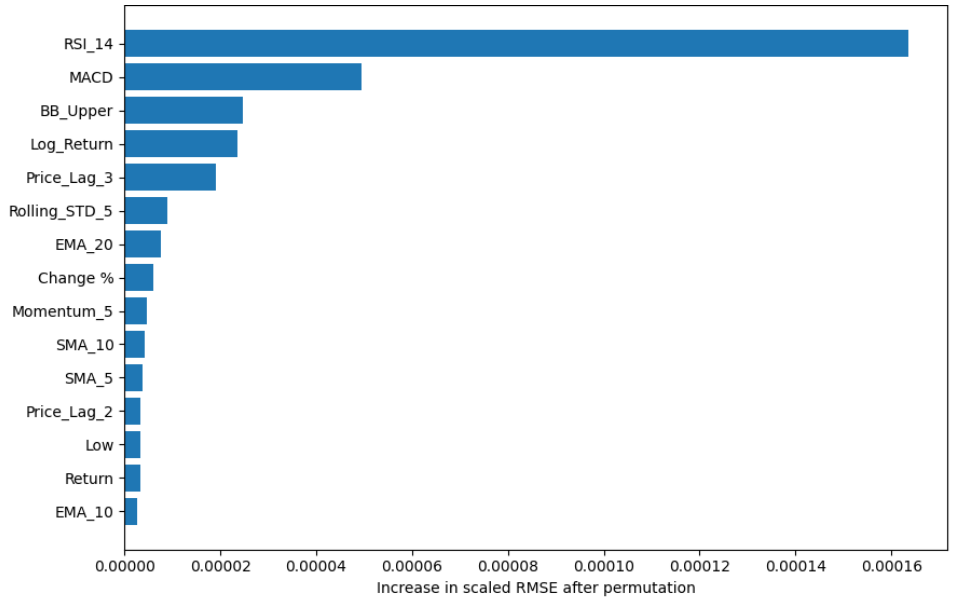



**Figure 7 Permutation Feature Importance of the Technical Indicators.**

## Global Explainability Using SHAP

To further enhance the interpretability of the proposed Hybrid CNN–BiLSTM–Attention model, SHapley Additive exPlanations (SHAP) analysis was employed to quantify the contribution of each input feature to the model predictions. Unlike conventional feature importance methods, SHAP estimates the average marginal contribution of each feature by considering its influence across all possible feature combinations, thereby providing a theoretically grounded explanation of the model's decision-making process. The global SHAP feature importance obtained from the testing dataset is presented in figure 8. As illustrated, SMA-5 is identified as the most influential feature, followed by Open, Price Lag-3, Price Lag-1, and Upper Bollinger Band, indicating that short-term trend information and historical price observations play a dominant role in forecasting future Solana prices. Other features, including RSI-14, Volume, Rolling Mean-5, Log Return, and Momentum-5, also contribute to the prediction process, although their average influence is comparatively smaller. The prominence of SMA-5 suggests that the proposed model relies heavily on recent price trends to capture short-term market dynamics, while the importance of lagged price variables confirms that historical price behavior remains a valuable predictor for subsequent price movements. In addition, the contribution of volatility-related indicators, such as the Upper Bollinger Band, indicates that the model also incorporates information regarding market uncertainty when generating forecasts. Although the ranking of features differs slightly from the permutation feature importance analysis presented in figure 7, both explainability methods consistently identify trend-related indicators, lagged prices, and momentum-based variables as the primary drivers of prediction performance. This difference is expected because permutation feature importance evaluates the reduction in model performance caused by randomly shuffling individual features, whereas SHAP quantifies the average contribution of each feature to every individual prediction while accounting for feature interactions. Consequently, the two approaches provide complementary perspectives on model interpretability, with permutation

importance emphasizing model sensitivity to feature perturbation and SHAP offering a more comprehensive explanation of how each feature influences the final prediction. Overall, the SHAP analysis demonstrates that the proposed forecasting framework not only achieves competitive predictive performance but also provides transparent and interpretable insights into the factors that govern Solana price prediction, thereby supporting more informed decision-making in blockchain-based metaverse ecosystems.

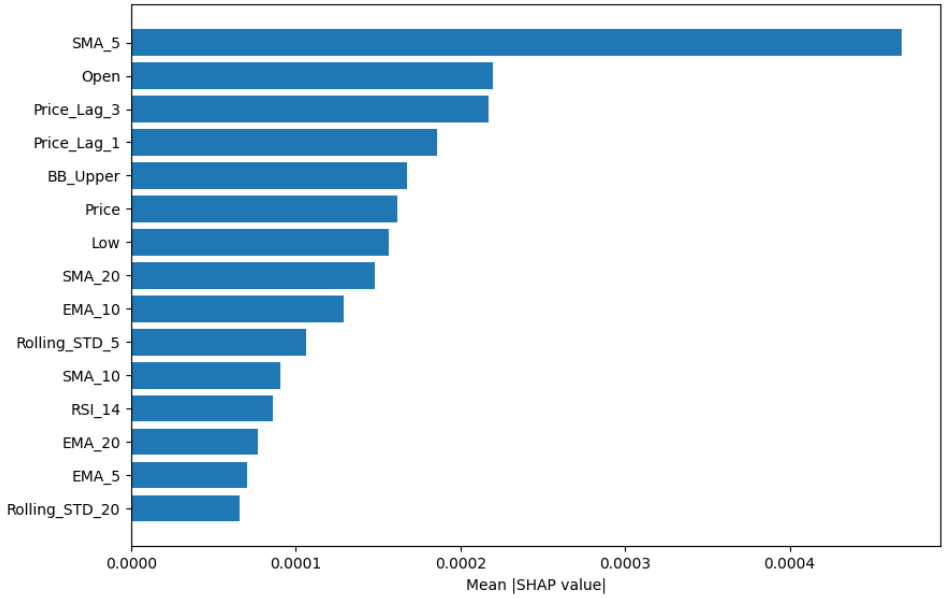



**Figure 8 Global SHAP Feature Importance.**

## Discussion

The experimental results demonstrate that the proposed Hybrid CNN–BiLSTM–Attention model is capable of effectively learning nonlinear temporal relationships from historical Solana price data enriched with technical indicators. The quantitative evaluation presented in the previous section shows that the proposed model achieved an MAE of 0.7470, an RMSE of 0.9232, a MAPE of 3.43%, and an $R^2$ value of 0.6929, indicating satisfactory predictive performance for one-day-ahead price forecasting. The relatively low MAPE suggests that the forecasting errors remain small in proportion to the actual price values, while the $R^2$ value indicates that the proposed model explains approximately seventy percent of the observed price variability. Furthermore, the visual comparison between the predicted and actual price series, together with the scatter plot and residual analysis, confirms that the model is capable of capturing the overall market trend while maintaining stable prediction errors across most observations. These findings indicate that integrating convolutional feature extraction, bidirectional sequence learning, and an attention mechanism provides an effective framework for modeling the complex and highly nonlinear behavior of cryptocurrency price movements [21].

The explainability analysis further improves the understanding of how the proposed forecasting model generates its predictions. The permutation feature importance analysis identifies RSI-14, MACD, Upper Bollinger Band, Log Return, and Price Lag-3 as the most influential variables affecting prediction accuracy, suggesting that momentum, market volatility, and historical price

information are essential for forecasting short-term Solana prices. Meanwhile, the SHAP analysis highlights SMA-5, Open Price, Price Lag-3, Price Lag-1, and Upper Bollinger Band as the features with the greatest average contribution to the prediction process. Although the feature rankings differ between the two explainability methods, both consistently indicate that trend-based indicators and lagged price variables play dominant roles in the forecasting model. The observed differences are expected because permutation feature importance evaluates how model performance changes when a feature is randomly shuffled, whereas SHAP estimates the average contribution of each feature to individual predictions while considering interactions among features. Consequently, the combination of these two explainability techniques provides complementary insights into the internal behavior of the proposed model and improves the transparency of the prediction process [22].

The temporal attention analysis provides additional insight into how historical observations are utilized during forecasting. The attention weight distribution indicates that the learned weights are relatively balanced across the entire 30-day input sequence, suggesting that the proposed model considers information from both recent and earlier observations when generating predictions. Rather than concentrating on a small number of specific time steps, the attention mechanism integrates information from the complete historical window before producing the final forecast. This behavior reflects the characteristics of cryptocurrency markets, where price movements are influenced by cumulative historical patterns rather than by isolated observations alone [23]. Nevertheless, the obtained Directional Accuracy of 48.31% indicates that accurately predicting the direction of daily price movements remains a challenging task. Although the proposed model demonstrates satisfactory performance in estimating future price values, the relatively low directional accuracy suggests that short-term market direction is affected by additional factors beyond historical price behavior and technical indicators. Sudden changes in investor sentiment, macroeconomic conditions, regulatory announcements, and blockchain ecosystem events may introduce market dynamics that cannot be fully captured by the current dataset [24].

From the perspective of blockchain-based metaverse ecosystems, the proposed forecasting framework provides a transparent and data-driven approach that can support financial decision-making involving Solana-based digital assets. As Solana serves as one of the primary blockchain platforms for decentralized applications, NFT marketplaces, GameFi, and virtual economy services, reliable short-term price forecasting may assist investors, developers, and digital asset managers in evaluating market conditions and planning blockchain-related activities. The integration of Explainable Artificial Intelligence through SHAP further enhances the practical value of the proposed framework by allowing users to understand which technical indicators have the greatest influence on each prediction, thereby increasing confidence in model outputs. Despite these promising findings, this study has several limitations. The model was developed using 999 daily historical observations, which resulted in a relatively limited number of training sequences after preprocessing and feature engineering. In addition, the forecasting framework relied exclusively on historical price data and technical indicators without incorporating external information such as on-chain metrics, news sentiment, social media activity, or macroeconomic variables that may significantly influence cryptocurrency prices. Future research should investigate the integration of these additional data

sources, evaluate more advanced attention mechanisms or transformer-based architectures, and validate the proposed framework using multiple cryptocurrencies and longer forecasting horizons to improve both predictive performance and generalizability [25].

## Conclusion

This study proposed an explainable Hybrid CNN–BiLSTM–Attention framework for one-day-ahead Solana price forecasting using historical market data and technical indicators. The proposed framework combines the feature extraction capability of Convolutional Neural Networks (CNN), the temporal dependency learning capability of Bidirectional Long Short-Term Memory (BiLSTM), and an attention mechanism to improve forecasting performance while incorporating SHapley Additive exPlanations (SHAP) to enhance model interpretability. Based on the experimental results, the proposed model achieved satisfactory forecasting performance with an MAE of 0.7470, an RMSE of 0.9232, a MAPE of 3.43%, and an $R^2$ value of 0.6929, demonstrating its ability to capture the nonlinear behavior of Solana price movements. The visual evaluation through the prediction curve, scatter plot, and residual analysis further confirmed that the model generated predictions that closely followed the actual market trend while maintaining relatively stable prediction errors. Furthermore, the explainability analyses using permutation feature importance and SHAP consistently identified technical indicators related to market momentum, trend, volatility, and historical price information as the primary factors influencing the prediction results. These findings indicate that the proposed framework not only provides competitive forecasting performance but also improves the transparency of the prediction process, making the generated predictions easier to interpret and more suitable for decision support applications.

The findings of this study provide practical implications for blockchain-based metaverse ecosystems, where reliable and interpretable cryptocurrency price forecasting can support investment decisions, digital asset management, decentralized application development, and financial planning involving Solana-based platforms. By integrating Explainable Artificial Intelligence into the forecasting framework, the proposed approach enables users to better understand the contribution of individual technical indicators, thereby increasing confidence in model predictions and supporting more informed decision-making. Nevertheless, several limitations remain. The proposed model was developed using a relatively limited historical dataset and relied exclusively on historical price information and technical indicators without considering external factors such as on-chain metrics, macroeconomic variables, market sentiment, or news events that may significantly influence cryptocurrency prices. In addition, the obtained Directional Accuracy indicates that accurately predicting short-term market direction remains a challenging problem. Therefore, future research should investigate the integration of multimodal data sources, evaluate more advanced deep learning architectures such as transformer-based or multi-head attention models, compare forecasting performance using statistical significance tests, and validate the proposed framework across multiple cryptocurrencies and different forecasting horizons. These improvements are expected to increase forecasting accuracy, strengthen model robustness, and further enhance the applicability of explainable deep learning models as intelligent decision-support systems within blockchain-based metaverse economies.

## Declarations

### Author Contributions

Conceptualization: B.P.; Methodology: B.P.; Software: B.P.; Validation: B.P.; Formal Analysis: B.P.; Investigation: B.P.; Resources: B.P.; Data Curation: B.P.; Writing Original Draft Preparation: B.P.; Writing Review and Editing: B.P.; Visualization: B.P.; 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.

### Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

### Institutional Review Board Statement

Not applicable.

### Informed Consent Statement

Not applicable.

### 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] A. Ghosh, Lavanya, V. Hassija, V. Chamola, and A. El Saddik, “A survey on decentralized metaverse using blockchain and Web 3.0 technologies, applications, and more,” *IEEE Access*, vol. 12, no. September, pp. 146915–146948, 2024, doi: 10.1109/ACCESS.2024.3469193.

[2] S. Mystakidis, “Metaverse,” *Encyclopedia*, vol. 2, no. 1, pp. 486–497, 2022, doi: 10.3390/encyclopedia2010031.

[3] P. Bhattacharya, D. Saraswat, D. Savaliya, S. Sanghavi, A. Verma, V. Sakariya, S. Tanwar, R. Sharma, M. S. Răboacă, and D. L. Manea, “Towards future Internet: The metaverse perspective for diverse industrial applications,” *Mathematics*, vol. 11, no. 4, Art. no. 941, pp. 1-41, 2023, doi: 10.3390/math11040941.

[4] W. Cai, J. Zhao, X. Gui, M. Msahli, and V. C. M. Leung, “Guest editorial: Special issue on social studies, human factors, and applications in metaverse,” *IEEE Transactions on Computational Social Systems*, vol. 10, no. 5, pp. 2160–2164, 2023, doi: 10.1109/TCSS.2023.3313199.

[5] D. Hou, W. Ma, W. Zhang, Y. Li, Y. Du, and Y. Hao, “An on-chain trading model of real world asset backed digital assets,” *IET Blockchain*, vol. 4, no. 4, pp. 315–323, 2024, doi: 10.1049/blc2.12045.

[6] Z. Chen, C. Li, and W. Sun, “Bitcoin price prediction using machine learning: An approach to sample dimension engineering,” *Journal of Computational and Applied Mathematics*, vol. 365, no. February, Art. no. 112395, pp. 1-13, 2020, doi:

10.1016/j.cam.2019.112395.

[7] 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.

[8] M. M. Patel, S. Tanwar, R. Gupta, and N. Kumar, “A deep learning-based cryptocurrency price prediction scheme for financial institutions,” *Journal of Information Security and Applications*, vol. 55, no. December, Art. no. 102583, 2020, doi: 10.1016/j.jisa.2020.102583.

[9] I. Nasirtafreshi, “Forecasting cryptocurrency prices using recurrent neural network and long short-term memory,” *Data & Knowledge Engineering*, vol. 139, no. May, Art. no. 102009, 2022, doi: 10.1016/j.datak.2022.102009.

[10] 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.

[11] M. Mudassir, S. Bennbaia, D. Unal, and M. Hammoudeh, “Time-series forecasting of Bitcoin prices using high-dimensional features: A machine learning approach,” *Neural Computing and Applications*, vol. 37, no. July, pp. 22979–22993, 2025, doi: 10.1007/s00521-020-05129-6.

[12] P. Peng, Y. Chen, W. Lin, and J. Z. Wang, “Attention-based CNN–LSTM for high-frequency multiple cryptocurrency trend prediction,” *Expert Systems with Applications*, vol. 237, no. March, Art. no. 121520, 2024, doi: 10.1016/j.eswa.2023.121520.

[13] 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.

[14] J. Zhang, K. Cai, and J. Wen, “A survey of deep learning applications in cryptocurrency,” *iScience*, vol. 27, no. 1, Art. no. 108509, pp. 1-40, 2024, doi: 10.1016/j.isci.2023.108509.

[15] F. Fang, C. Ventre, M. Basios, L. Kanthan, D. Martinez-Rego, F. Wu, and L. Li, “Cryptocurrency trading: A comprehensive survey,” *Financial Innovation*, vol. 8, no. February, Art. no. 13, 2022, doi: 10.1186/s40854-021-00321-6.

[16] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997, doi: 10.1162/neco.1997.9.8.1735.

[17] M. Schuster and K. K. Paliwal, “Bidirectional recurrent neural networks,” *IEEE Transactions on Signal Processing*, vol. 45, no. 11, pp. 2673–2681, 1997, doi: 10.1109/78.650093.

[18] Y. Qin, D. Song, H. Chen, W. Cheng, G. Jiang, and G. W. Cottrell, “A dual-stage attention-based recurrent neural network for time series prediction,” in *Proceedings of the 26th International Joint Conference on Artificial Intelligence (IJCAI)*, Melbourne, Australia, 2017, vol. 2017, no. August, pp. 2627–2633, doi: 10.24963/ijcai.2017/366.

[19] S. M. Lundberg, G. Erion, H. Chen, A. DeGrave, J. M. Prutkin, B. Nair, R. Katz, J. Himmelfarb, N. Bansal, and S.-I. Lee, “From local explanations to global understanding with explainable AI for trees,” *Nature Machine Intelligence*, vol. 2,

no. 1, pp. 56–67, 2020, doi: 10.1038/s42256-019-0138-9.

[20] M. T. Ribeiro, S. Singh, and C. Guestrin, “Why should I trust you?: Explaining the predictions of any classifier,” in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, CA, USA, 2016, vol. 2016, no. August, pp. 1135–1144, doi: 10.1145/2939672.2939778.

[21] O. B. Sezer, M. U. Gudelek, and A. M. Ozbayoglu, “Financial time series forecasting with deep learning: A systematic literature review: 2005–2019,” *Applied Soft Computing*, vol. 90, no. May, Art. no. 106181, 2020, doi: 10.1016/j.asoc.2020.106181.

[22] S. M. Lundberg, G. G. Erion, and S.-I. Lee, “Consistent individualized feature attribution for tree ensembles,” *arXiv preprint* arXiv:1802.03888, vol. 2018, no. February, pp. 1-9, 2018, doi: 10.48550/arXiv.1802.03888.

[23] D. L. John, S. Binnewies, and B. Stantic, “Cryptocurrency price prediction algorithms: A survey and future directions,” *Forecasting*, vol. 6, no. 3, pp. 637–671, 2024, doi: 10.3390/forecast6030034.

[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] A. A. Oyedele, A. O. Ajayi, L. O. Oyedele, S. A. Bello, and K. O. Jimoh, “Performance evaluation of deep learning and boosted trees for cryptocurrency closing price prediction,” *Expert Systems with Applications*, vol. 213, no. March, Art. no. 119233, 2023, doi: 10.1016/j.eswa.2022.119233.