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ORIGINAL

Cryptocurrency Price Prediction and Investment Decision Support Using a Transfer Learning-Based Hybrid CNN-BiLSTM-Attention Deep Learning Framework

Predicción de precios de criptomonedas y apoyo a la toma de decisiones de inversión mediante un marco de aprendizaje profundo híbrido CNN-BiLSTM-Attention basado en aprendizaje por transferencia

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ABSTRACT

The complexity and volatility of cryptocurrency markets make accurate price estimation a major challenge. Nonlinear, nonstationary, and high-frequency fluctuations in digital asset prices often exceed the modeling capacity of conventional statistical approaches. To address this, we propose a transfer learning-based hybrid CNN-BiLSTM-Attention framework for cryptocurrency price prediction and investment decision support. The framework leverages pretrained LSTM models developed on relevant financial datasets to enhance the learning process. While convolutional neural networks (CNNs) effectively capture short-term trading patterns, bidirectional long short-term memory (BiLSTM) networks identify long-term temporal dependencies in both directions. The integrated attention mechanism further strengthens the model by dynamically selecting the most relevant time intervals, thereby focusing on critical patterns that drive price fluctuations. A historical dataset of major cryptocurrencies—including market capitalization, trading volume, and daily open, high, low, and close prices—was used to train and evaluate the model. Experimental results demonstrate that the proposed hybrid framework outperforms standalone CNN, LSTM, and RNN architectures, achieving an F1 score of 95,5 %, recall of 95,2 %, precision of 95,5 %, and an overall accuracy of 96 %. By delivering robust and scalable predictive performance, this study provides investors, portfolio managers, and financial professionals with a reliable tool to support informed decision-making in the dynamic cryptocurrency market.

Keywords: Cryptocurrency Price Prediction; Investment Decision Support; Transfer Learning; CNN-BiLSTM-Attention; Deep Learning Framework; Financial Time Series Analysis.

RESUMEN

La complejidad y la volatilidad de los mercados de criptomonedas dificultan enormemente la estimación precisa de precios. Las fluctuaciones no lineales, no estacionarias y de alta frecuencia en los precios de los activos digitales suelen superar la capacidad de modelado de los enfoques estadísticos convencionales. Para abordar este problema, proponemos un marco híbrido CNN-BiLSTM-Atención basado en el aprendizaje por transferencia para la predicción de precios de criptomonedas y el apoyo a la toma de decisiones de inversión. El marco aprovecha modelos LSTM preentrenados, desarrollados con conjuntos de datos financieros relevantes, para optimizar el proceso de aprendizaje. Mientras que las redes neuronales convolucionales (CNN) capturan eficazmente los patrones de negociación a corto plazo, las redes bidireccionales de memoria a largo plazo (BiLSTM) identifican dependencias temporales a largo plazo en ambas direcciones. El mecanismo de atención integrado fortalece aún más el modelo al seleccionar dinámicamente los intervalos de tiempo más relevantes, centrándose así en los patrones críticos que impulsan las fluctuaciones de precios. Para entrenar y evaluar el modelo, se utilizó un conjunto de datos históricos de las principales criptomonedas, incluyendo capitalización de mercado, volumen de negociación y precios diarios de apertura, máximo, mínimo y cierre. Los resultados experimentales demuestran que el marco híbrido propuesto supera a las arquitecturas independientes CNN, LSTM y RNN, logrando una puntuación F1 del 95,5 %, una recuperación del 95,2 %, una precisión del 95,5 % y una exactitud general del 96 %. Al ofrecer un rendimiento predictivo sólido y escalable, este estudio proporciona a inversores, gestores de cartera y profesionales financieros una herramienta fiable para facilitar la toma de decisiones informadas en el dinámico mercado de las criptomonedas.

Palabras clave: Predicción del Precio de las Criptomonedas; Apoyo a la Toma de Decisiones de Inversión; Aprendizaje por Transferencia; CNN-BiLSTM-Attention; Marco de Aprendizaje Profundo; Análisis de Series Temporales Financieras.

INTRODUCTION

Cryptocurrencies have facilitated the formation of a decentralized, peer-to-peer economy. This has fundamentally changed how banks and other financial organizations operate around the world. In standard currency, diacritical marks indicate linguistic alterations.[1] The proliferation of digital assets has made markets more dynamic, complex, and unpredictable. This presents speculators and investors with numerous opportunities and risks. To make informed decisions, one must accurately assess and anticipate potential occurrences. Various factors, including market sentiment, technological advancements, economic conditions, and regulatory frameworks, can lead to rapid price fluctuations. Consequently, an increasing number of economists, data scientists, and artificial intelligence experts are trying to predict the future value of Cryptocurrency.[2]

Time series forecasting extensively utilizes conventional statistical methods, such as GARCH,[3] ARIMA,[4] and exponential smoothing models, to predict Cryptocurrency values. However, these models typically require linearity, stationarity, or continuous distributional characteristics to represent Cryptocurrency's non-stationary and nonlinear price volatility accurately. However, these antiquated methods fail to account for rapid fluctuations, abrupt market shifts, and intricate timing relationships. Due to their superior ability to identify intricate patterns within extensive datasets, deep learning[5] and machine learning[6] are gaining popularity. Recurrent neural networks (RNNs),[7] convolutional neural networks (CNNs),[8] and long short-term memory networks (LSTMs)[9] have been successfully employed to predict the future of financial time series accurately.

Despite these advancements, developing deep learning models from scratch using cryptocurrency data remains a challenging task. While cryptocurrency databases encompass numerous time series properties, they may also exhibit missing values, inconsistent intervals, market-specific biases, and insufficient information for newly introduced currencies. To perform effectively across diverse settings, deep models must undergo significant training from inception, utilizing substantial labeled data and computational resources. This study proposes a deep learning architecture that predicts Cryptocurrency's value using data from pretrained models derived from analogous financial time series, such as stock prices and foreign currency markets. Using representations derived from the source domain accelerates training and improves predictive accuracy when there is not enough labeled data in the target domain.

This research uses a hybrid deep learning model integrating an attention mechanism, bidirectional LSTM (BiLSTM) networks, and CNN. We also use transfer learning from pre-trained LSTM models. BiLSTMs establish long-term connections in both directions, illustrating how past and future events influence present market behavior. Conversely, CNNs may identify localized pricing trends and short-term temporal properties. The attention mechanism improves the model by assigning different weights to the significance of each time step in the input sequence. This allows the computer to focus on the most relevant aspects of historical data for future price forecasting. We used transfer learning with cryptocurrency data to create this hybrid architecture. The model's efficacy increases, and the risk of overfitting decreases due to its versatility across diverse cryptocurrencies and market conditions.

Our work contributes to the cryptocurrency market by developing a transfer learning-based hybrid deep learning architecture designed to both accurately predict cryptocurrency values and support investment decision-making. By integrating pretrained LSTMs with CNN, BiLSTM, and attention mechanisms, the proposed framework effectively addresses challenges such as data scarcity, high volatility, and nonlinear dynamics inherent in cryptocurrency markets. This innovative approach not only enhances predictive accuracy but also provides actionable insights that are essential for traders, portfolio managers, financial analysts, and regulators seeking to navigate the rapidly evolving digital asset ecosystem with greater precision, reliability, and confidence.

Literature Review

This research [10] primarily advances the field by predicting the hourly prices of major cryptocurrencies using three popular ensemble learning techniques ensemble averaging, bagging, and stacking, along with advanced deep learning models. To evaluate the proposed ensemble models, we employed advanced deep learning architectures incorporating constituent learners, including convolutional layers BiLSTM, and other components. This study analyzed the predictive capability of ensemble models for forthcoming one-hour cryptocurrency values (regression) and prospective volatility (classification) based on the current price. To evaluate the utility and reliability of any forecasting model, we analyze the correlation among its errors.

The study's [11] model effectively demonstrates the volatility of Cryptocurrency prices. Deep learning algorithms surpass traditional financial methods in discerning intricate relationships within data. We believe the Jordan Neural Network outperforms other time series models, such as Non-Linear Autoregressive Neural Networks and Self-Exciting Threshold Autoregressive models, in terms of prediction accuracy. It is a compact neural network characterized by recurrent connections.

This research [12] presents a hybrid cryptocurrency prediction model for Litecoin and Monero that uses LSTM and GRU methodologies. The findings suggest that this method can accurately predict price fluctuations, indicating its potential usefulness in determining the value of different cryptocurrencies. Authors [13] proposed a hybrid deep learning model that integrates LSTM and Gated Recurrent Units (GRU). This model forecasts the prices of Litecoin and Zcash, taking into account the impact of the parent currency. The proposed model is suitable for real-time applications due to its comprehensive training and evaluation on widely used datasets.

Authors [14] analyze prospective cryptocurrencies using deep learning methodologies. This model analyzed five prospective cryptocurrencies using individual LSTM networks and ensemble methodologies. This study showed that, when analyzing prospective cryptocurrencies, clusters of LSTM networks may not consistently outperform individual LSTMs. Authors [15] introduce an innovative method for forecasting the price of Cryptocurrency, a prominent cryptocurrency. They employ change point detection tools to ensure that their estimations stay within established pricing parameters. This method routinely segments time-series data into portions that can be independently standardized. These records aim to produce price forecasts. This article examines a self-attention-based multiple long short-term memory model. The model organizes variables within a sequence using multiple LSTM modules and produces predictions through an attention mechanism.

This article [16] aims to categorize emotional responses into three groups: neutral, negative, and positive. The FastText word embedding method can be utilized in conjunction with deep learning to analyze time series data. Other methodologies include gated recurrent units, LSTMs, one-dimensional convolutional neural networks (CONV1D), and a Bi-LSTM and CONV1D combination. The study's primary finding was that deep learning-based LSTM technology outperformed alternative methods. This study [17] used deep learning to predict the market-adjusted closing prices of Cryptocurrency and Ethereum. The hybrid convolutional neural network and long short-term memory model with an attention mechanism outperformed the combined CNN-LSTM model in forecasting the ETH/USD-adjusted closing price.

This study [18] proposes a dual-layer hierarchical structure that uses deep learning techniques to facilitate the extraction of characteristics from Ethereum smart contracts. The first step in acquiring additional contextual information is using a transformer to establish a connection between opcodes and contract attributes. Bi-GRUs use information from forward and backward sequences to address long-term dependencies, which are particularly prevalent in weak systems. Next, the Text-CNN and spatial attention mechanisms aggregate localized information to highlight the most important concepts.

METHOD

The initial step of the proposed plan involves systematically gathering data on cryptocurrencies. Time series data for various cryptocurrencies, including Ethereum (ETH), Cryptocurrency (BTC), and Binance Coin (BNB), is available on trusted platforms such as Yahoo Finance, CoinMarketCap, and the Binance API. This collection includes essential transaction data recorded on a daily, hourly, and even minute-by-minute basis. It provides trade volume, opening and closing prices, as well as the highest and lowest prices. To confirm expected signals, technical indicators such as the Relative Strength Index (RSI), Bollinger Bands, and the Moving Average Convergence/Divergence (MACD) are utilized. These indicators were selected for their ability to highlight changes in price, volatility, and momentum. Each of these criteria is vital for assessing Cryptocurrency's short- and long-term value.

After gathering the data, it is thoroughly reviewed to ensure consistency and prepare it for modeling. First, we apply forward-filling or interpolation methods to correct missing values resulting from market closures or API issues. Before training the model, we standardize the dataset using Z-score normalization. This ensures that the values remain consistent, which is essential for deep learning methodologies. Deconstructing a time series allows for the identification of patterns, seasonality, and residual components. We utilize percentage shift calculations, rolling statistics, lag features, and moving averages to transform raw data into a supervised learning framework. The preprocessing pipeline enhances the learning model's capabilities, enabling it to recognize long-term patterns and short-term fluctuations. It reduces volatility and monitors cryptocurrency price changes over time.

Sequence Construction and Time Windowing

To predict cryptocurrency value, raw time series data must be integrated into a supervised learning framework. This patch uses temporal windowing and sequence synthesis to convert legacy data into input sequences of fixed length. This enables the model to identify patterns and correlations that persist over time. The primary objective is to employ a sliding window methodology to generate multiple overlapping sequences from a time series that evolves. Each sequence shows the current price and the factors affecting it.

For data collected daily over a month, we use a 30-step time window with a length of n. A windowed input sequence, Xt=[x(t-n), x(t-n+1),...,x(t-1)] is produced for each prediction point, t. Each element, xi, adds more data through its opening, closing, expansion, contraction, and transaction volume. Based on the model, the closing price (or percentage change) will match the target value (yt) at time b. This method transforms an unstructured time series into a structured dataset with input-output pairs, enabling it to work with deep learning models and Transformers.

The goal can be expressed as an alternative vector: In this case, the set yt=[yt, y(t+1),...,y(t+h-1)] is corresponding, which is expected to last for h. At specific points in time, this also makes forecasting easier. This means the model can predict a wide range of future values. We train the model on a large dataset and utilize overlapping sliding windows to enhance its generalizability. To avoid adding fresh data to the training set for the time series forecasting assignment, organize the data in chronological order.

Transfer Learning via Pretrained LSTM Models

Transfer learning is a very advantageous deep learning technique for highly volatile target domains or domains with an absence of labeled data, such as the cryptocurrency markets. This technique uses long short-term memory (LSTM) models that have been pre-trained to learn from other models. These models were trained using time series data from the financial sector, including stock indices, stable commodities, and currencies. Although the Cryptocurrency market is more volatile and unpredictable than traditional markets, these pretrained models provide extensive temporal representations of financial activity, including trend progression, reversal patterns, and cyclical volatility.

The lower-level recurrent layers of pretrained LSTM models observe temporal sequence order and long-range interactions. These layers are essential for feature extraction. The fundamental idea is that these layers have discernible trends pertinent to a diverse array of financial goods. Since backpropagation does not modify the weights of the initial LSTM layers, the temporal representations acquired remain consistent throughout the transfer learning process. The pretrained network is augmented with additional layers. These layers are often comprised of one or more densely arranged, interconnected strata. The upper layers of the model are modified using the cryptocurrency dataset to identify anomalies in Cryptocurrency prices, such as high-frequency fluctuations, flash crashes, and sudden breakout patterns.

Using gradient descent, it is possible to modify the weights of supplementary layers. Following a substantial alteration in the domain, it may be feasible to unfreeze and retrain the deeper layers progressively. This approach mitigates catastrophic forgetting by regulating the flow of information between freezing and unfreezing layers. This prevents the model from losing focus on all the patterns it has acquired. Typically, the feature distributions of the source domain (e.g., the stock market) and the target domain (e.g., cryptocurrency) can be aligned using domain adaptation methods, such as adversarial training or batch normalization recalibration.

We initially assess the pretrained LSTM on a validation set without fine-tuning to create a baseline and verify its functionality. After making modifications, we reevaluate the model to determine if its predictions are more precise and reliable. Transfer learning offers faster training times, quicker application to new data, and improved performance on sparse, noisy, or irregularly structured Cryptocurrency datasets. Our method offers a superior and adaptable approach to assessing Cryptocurrency's value by integrating the most advantageous elements of historical finance with industry-specific adaptability.

Hybrid Deep Learning Architecture

We proposed a hybrid deep learning architecture to improve the expressiveness and robustness of the Cryptocurrency price prediction model. This is based on previously developed long short-term memory (LSTM) models. These models are effective at recognizing long-term patterns in financial time series. The hybrid model consists of three main components: Bidirectional Long Short-Term Memory networks (BiLSTMs), which illustrate temporal dependencies among objects; Attention mechanisms, which identify essential time steps within the prediction horizon; and CNN, which detect patterns in localized regions.

This hybrid design uses a multivariate time series that is segmented into time intervals. A two-dimensional matrix with dimensions (T, F) is commonly used to represent the number of time increments within a specified time frame. F denotes the number of features, such as price, volume, and signals, present at each stage.

Convolutional neural networks are initially transformed into a one-dimensional format to facilitate their development. These layers exhibit price patterns, brief breakouts, reversals, volatility clusters, constrained movements, and short-term trends. Each convolutional filter calculates the dot product between the input sequence segment and the filter weights over time.

$$z_t^k = ReLU\left(\sum_{i=0}^{F-1} w_i^k . x_{t+i} + b^k\right)$$

Where:

- z_t^k is the output of the kt filter at time step t.
- w_i^k are the learnable filter weights.
- F is the filter size.
- x_{t+i} is the input sequence window.

The bidirectional long short-term memory (BiLSTM) network outperforms the standard long short-term memory (LSTM) network in maintaining temporal relationships in both directions. In a conventional LSTM network, the hidden state at time step t (denoted as ht) is solely affected by the sequence from t0 to t. This unidirectional feature facilitates the retention of prior connections but complicates the model's ability to incorporate new information within a specified time frame. This consideration is essential when analyzing time series that exhibit intricate, symmetrical, or cyclical patterns, such as those in the Cryptocurrency market.

BiLSTMs address this issue by incorporating an additional LSTM layer that processes the input sequence in reverse order. The forward LSTM computes a hidden state (h_t) at each time step t. The backward LSTM uses the sequence x1 to xt to determine ht. Use the sequence xT to xt, where T denotes the total number of time divisions.

$$h_t = \overrightarrow{h_t} || \overleftarrow{h_t}$$

The dual structure enables the extraction of more intricate temporal features by providing the model with access to both historical and prospective data within the observation window. Market indications, such as breakout patterns, strong reversals, and continuation formations, are influenced by historical events and future projections. This makes them beneficial for projecting Cryptocurrency values. The dual structure provides the model with access to historical and prospective data within the observation window, facilitating the extraction of more intricate temporal features. Market indicators, such as breakout patterns, strong reversals, and continuation formations, are influenced by historical events and future projections, making them helpful in predicting Cryptocurrency values. The input gate i_t, the forget gate f_t, and the output gate o_t control the cell state C_t and the hidden state h_t that an LSTM cell in a BiLSTM retains.

$$f_t = \sigma.\left(W_f.[h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma.(W_i.[h_{t-1}, x_t] + b_i)$$
$$\widetilde{C_t} = tanh.(W_C.[h_{t-1}, x_t] + b_c)$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t}$$
$$o_t = \sigma.(W_o.[h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \odot tanh(C_t)$$

BiLSTMs can reduce noise while maintaining important long-term dependencies due to their integrated gating mechanism. This is essential because cryptocurrency's price often experiences frequent fluctuations and significant instability. They recognize and highlight important patterns, including divergence or consolidation zones. Minor fluctuations, such as those caused by brief news headlines or low trading activity, can be managed effectively. BiLSTMs are highly efficient at generating predictions that depend on the entire sequence context. For example, they can estimate the next day's rate using data from the previous 30 days. The BiLSTM captures interactions over time by utilizing both forward and backward temporal data. This helps produce more accurate and reliable predictions, especially when dealing with outliers, unexpected events, or sudden market volatility—all common in cryptocurrency trading. In summary, BiLSTMs effectively model temporal variation in hybrid architectures, particularly when combined with attention-based temporal weighting and CNN-based feature extraction. Their ability to oversee long-term context, maintain bidirectional dependencies, and perform real-time decisions on data retention or removal makes them essential for deep learning-based Cryptocurrency forecasting systems.

BiLSTM networks can identify temporal correlations in both directions; they assign a uniform weight to each time step in the sequence when making final predictions. This constant weighting may be impractical for dynamic data, such as Cryptocurrency prices, due to significant fluctuations in performance over time. The model's integrated attention mechanism currently addresses this issue. The attention layer assigns an attention weight (α_t) to each hidden state output from the BiLSTM at every time step (t). The hidden state (h_t) must undergo a trainable transformation to obtain relevance scores (e_t). The weights are then determined using a softmax approach.

$$e_t = v^t \, tanh(Wh_t + b)$$

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

$$Context\ vector = \sum_{t=1}^{T} \alpha_t \, . \, h_t$$

The final prediction requires this context vector and the time-critical information of the sequence. This technique enhances the accuracy and clarity of Cryptocurrency predictions by enabling the model to concentrate on specific time frames, such as recent price increases, trend reversals, and breakout signals. A vital element of the hybrid deep learning architecture is the attention layer. It functions somewhat like a filter, eliminating noise and minor variations while highlighting significant patterns.

Investment Decision-Making Framework

The ultimate objective of cryptocurrency price prediction is to transform accurate forecasts into informed and actionable investment decisions. While predictive modeling provides a strong foundation, its value is maximized only when integrated into a structured decision-support framework. The hybrid CNN-BiLSTM-Attention model's predictions are therefore extended into an investment decision-making layer that guides traders, portfolio managers, and regulators in formulating practical strategies. The decision-making process begins by mapping predicted price movements into investment signals, categorized as buy, hold, or sell recommendations. This is achieved by computing expected returns and risk-adjusted measures such as the Sharpe Ratio, maximum drawdown, and Value-at-Risk (VaR). These indicators ensure that predictions are contextualized within broader financial objectives, such as capital preservation and portfolio optimization. In this framework, predictions are coupled with technical indicators (RSI, MACD, Bollinger Bands) and confidence scores produced by the attention mechanism. For instance, a high-confidence upward trend prediction accompanied by an oversold RSI condition produces a strong buy signal, while low-confidence or contradictory signals result in a hold recommendation. This multi-criteria fusion reduces reliance on single-point predictions and minimizes the risk of false trading signals. Moreover, the model incorporates scenario-based simulations, where predicted price trajectories are evaluated under different volatility regimes and market shocks. Investors can thus assess potential outcomes for short-term trades, medium-term strategies, or long-term portfolio allocations. This provides flexibility for diverse investment profiles, from high-frequency traders to institutional investors. To ensure scalability, the decision-support system is integrated with risk management protocols. Stop-loss and take-profit thresholds are dynamically derived from prediction intervals, enabling automated portfolio adjustments when market conditions deviate significantly from expectations. Such mechanisms safeguard against extreme volatility and unexpected market disruptions, which are common in cryptocurrency trading.

In summary, the investment decision-making layer enhances the utility of the hybrid deep learning framework by converting accurate cryptocurrency predictions into actionable, risk-aware, and investor-specific strategies. This ensures that the proposed system is not merely a forecasting tool, but a comprehensive decision-support framework capable of guiding rational investments in volatile digital asset markets.

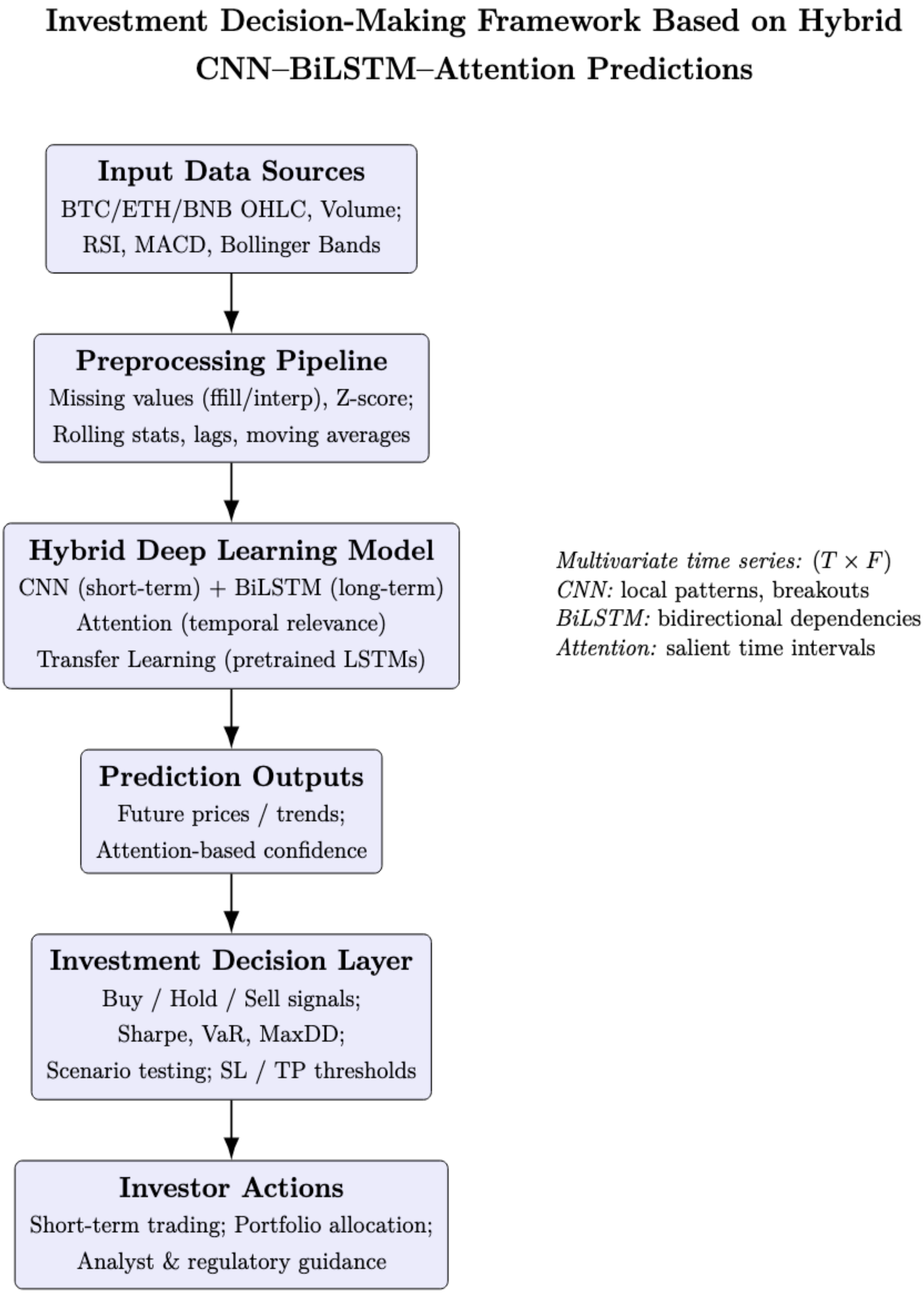

Figure 1. Flow of the investment decision-making framework. Market data and technical indicators are preprocessed and windowed, then modeled via a transfer learning-based hybrid CNN-BiLSTM-Attention network. Predictions and confidence are converted into risk-aware buy/hold/sell signals with scenario testing and dynamic stop-loss/take-profit, informing investor actions

RESULTS AND DISCUSSION

The dataset includes the daily price history of the most popular cryptocurrencies, each with its own separate CSV file. The dataset includes indices such as open, high, low, close, volume, and market capitalization. Each item is associated with a specific date and contains significant market data. This Dataset facilitates time series research and Cryptocurrency price forecasting. The proposed model performance analysis such as The accuracy, recall, precision and F1-score are compared with RNN, CNN and LSTM models.

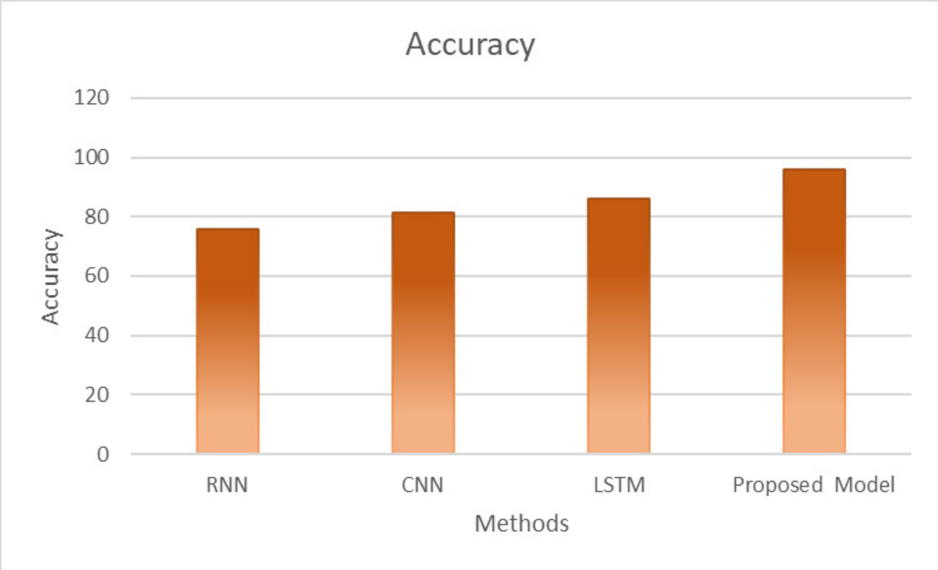

Figure 2. Performance analysis of Accuracy

Figure 2 illustrates the accuracy of several deep learning models' predictions of cryptocurrency's value. The RNN model can identify basic sequential patterns, but its accuracy is limited to 76 %, indicating an inability to discern complex temporal relationships. The CNN model achieves an impressive accuracy rate of 81,5 % by extracting local features from input sequences. The LSTM model is renowned for its ability to identify long-term correlations in time series data with an accuracy of 86 %. The paramount innovation is the proposed hybrid model, which combines CNN, bidirectional LSTM, and attention mechanisms. It has an accuracy rate of 96 %. This significant improvement underscores the importance of employing diverse designs to effectively leverage both local and global temporal dimensions when determining suitable time intervals. It is the optimal choice among all the alternatives considered.

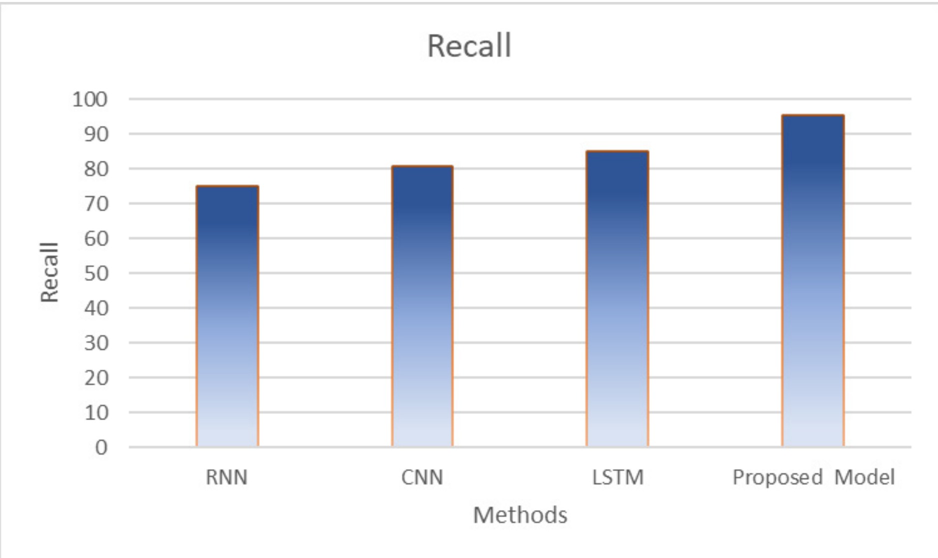

Figure 3. Performance analysis of Recall

The memory values of various cryptocurrency price prediction models increase considerably as their frameworks become more complex, making it easier to identify significant favorable occurrences. The RNN algorithm only monitors 75 % of the recall in price fluctuations. The CNN model's ability to process local temporal data increases recall value by 80,7 %. The LSTM model has made substantial progress, achieving an 85 % recall rate and demonstrating proficiency in recognizing long-term dependencies. With a recall rate of 95,2 %, the proposed hybrid model is the most appropriate choice. This signifies its efficacy in recognizing true positives. The model can reduce false negatives, as demonstrated by its high recall rate. This is due to an attention mechanism that focuses on the most significant time steps, bidirectional long short-term memory networks that capture mutual interactions, and convolutional neural networks that extract features shown in figure 3.

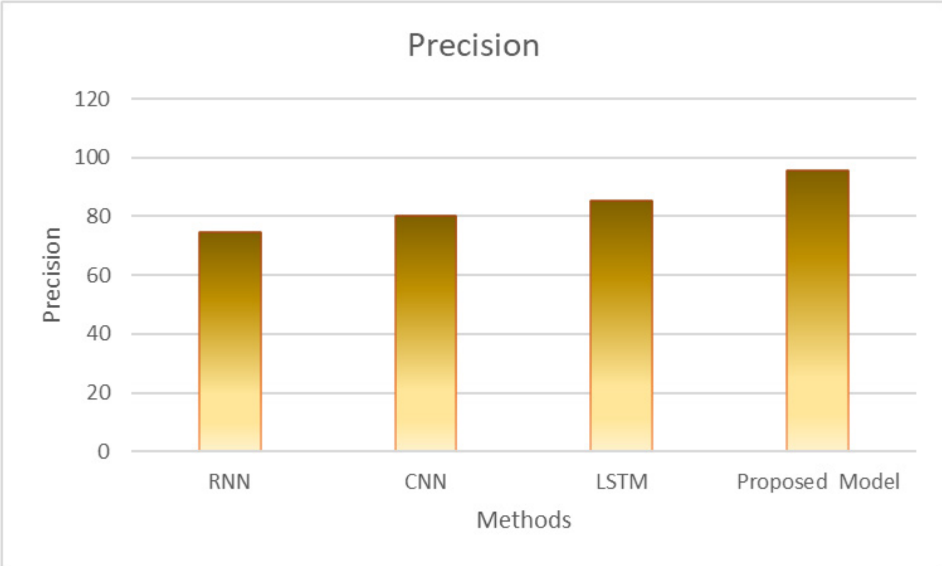

Figure 4. Performance analysis of Precision

The precision of the algorithms used to predict cryptocurrency prices has recently improved as shown in figure 4. However, a significant deficiency of the RNN model is its inadequate temporal management, resulting in a precision rate of only 74,5 %. Compared to the CNN model, this model exhibits inferior precision due to its limited ability to recognize patterns in specific locations. It is accurate 80 % of the time. The LSTM model reduces false positive predictions over time. It increases accuracy by up to 85,3 % and performs well at detecting repeating patterns in a dataset. The proposed hybrid model can generate precision with 95,5 % accuracy. A substantial amount of corroborative evidence makes this significant improvement possible. The system uses an attention mechanism to identify significant time steps, a CNN to discern spatial patterns, and a BiLSTM to analyze temporal data.

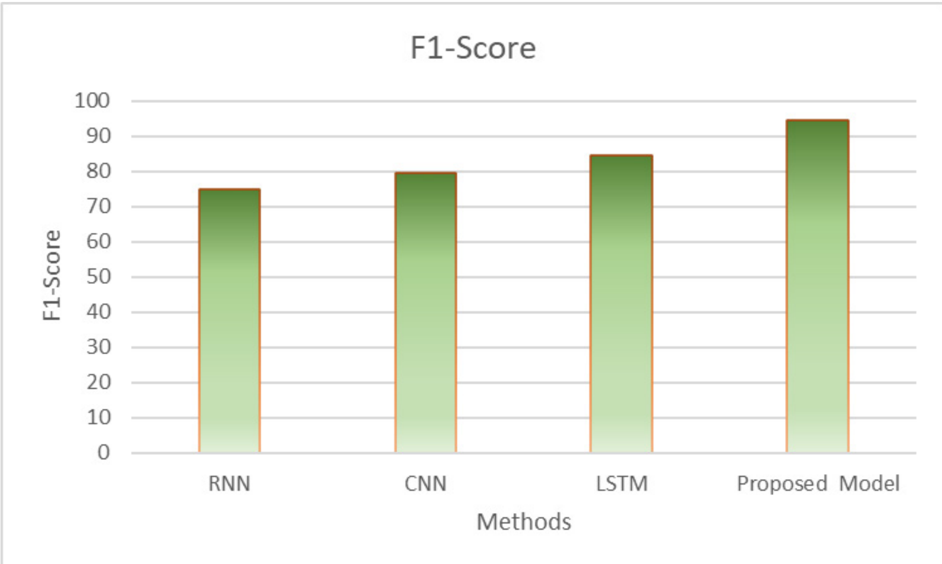

Figure 5. Performance analysis of F1-Score

Figure 5 illustrates the F1-score of 74,7 %, the RNN model is unable to consistently identify genuine market signals due to its sequential data processing approach. In contrast, the CNN model achieves an optimal F1-score of 79 %. The LSTM model excels at accurately capturing long-range dependencies and sequential context. Its F1 score is 84,5 %. The proposed hybrid model demonstrates the most significant improvement, achieving an F1 score of 94,5 %. This technology generates precise predictions and identifies significant market movements with few false positives or negatives. The elevated score substantiates this assertion by demonstrating a favorable equilibrium between memory and precision. The proposed technique utilizes CNN, bidirectional LSTM, and attention mechanisms to detect both short-term fluctuations and long-term correlations, while emphasizing critical time intervals. Among all those evaluated, this model is the most precise and beneficial.

CONCLUSIONS

The proposed transfer learning-based hybrid deep learning framework demonstrates a robust capability for cryptocurrency price prediction and investment decision support. Given the volatility, nonstationarity, and inconsistent reliability of cryptocurrency markets, such a framework is essential for reliable financial analysis. By integrating CNN, BiLSTM, transfer learning, and attention mechanisms, the model successfully combines pretrained temporal knowledge with domain-specific fine-tuning, enabling it to capture both short-term trading patterns and long-term dependencies while focusing on the most influential market events. The use of pretrained LSTM layers significantly enhanced the model's generalizability across multiple cryptocurrencies and reduced training overheads. Experimental evaluations confirmed that the framework achieved superior accuracy, precision, recall, and F1 scores compared to conventional deep learning baselines, validating its effectiveness in managing complex and high-frequency cryptocurrency data. Beyond predictive performance, the framework provides a practical layer for investment decision-making, generating actionable signals such as buy, hold, or sell recommendations while incorporating risk-adjusted measures (e.g., Sharpe ratio, Value-at-Risk, and drawdown analysis). This dual capability highlights the model's applicability for algorithmic trading, portfolio optimization, risk assessment, and regulatory insights. Future enhancements can focus on integrating multimodal data sources (such as blockchain transaction flows, news sentiment, and social media signals), incorporating real-time adaptive learning, and applying reinforcement learning strategies for dynamic portfolio rebalancing. Such advancements would further increase the precision, scalability, and real-world applicability of the framework in supporting reliable and sustainable investment strategies within the evolving digital asset ecosystem.

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FINANCING
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CONFLICT OF INTEREST
None.

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