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RESEARCH ARTICLE

An Improved Machine Learning-Driven Framework for Cryptocurrencies Price Prediction With Sentimental Cautioning

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ABSTRACT Cryptocurrencies, recognized by their extreme volatility due to dependency on multiple direct and indirect factors, offer a significant challenge regarding precise price forecasting. This uncertainty has led to investment hesitation within the digital currency market. Previous research attempts have presented methodologies for price forecasting and trend prediction in cryptocurrencies. However, these forecasts have typically suffered from increased error rates, leaving the opportunity for improvement in this field. Furthermore, the influence of sentiment-based factors could compromise the reliability of price predictions. In this research, we have proposed a machine learning-driven framework that provides precise cryptocurrency price projections and adds an alert mechanism to guide investors. Our fundamental analyzer, Bi-LSTM and GRU hybrid model use historical data of digital currencies to train and reliably anticipate future values. Complementing this, a sentiment analyzer, utilizing a BERT and VADER hybrid model, analyzes sentiments to assess the forecast price as trustworthy or uncertain. Besides assisting investor decision-making, this technique also helps risk management in the dynamic realm of cryptocurrency. Our suggested approach delivers highly precise price predictions with dramatically decreased error rates compared to prior competitive studies. The proposed Bi-LSTM-GRU-BERT-VADER (BLGBV) model is tested for three cryptocurrencies, namely BTC, ETH, and Dogecoin and reports an average root mean square error (RMSE) of 0.0241%, 0.0645%, and 0.0978%, respectively.

INDEX TERMS Cryptocurrency, price prediction, machine learning, technical analysis, sentiment, bullish, bearish, candlestick, Bi-LSTM, GRU.

I. INTRODUCTION

As the world becomes increasingly digital, cryptocurrencies are the evolution of our traditional money. We all are familiar with the money transaction paradigm, shifting from physical commodities like cash and cheques to online digital transactions. In the last two decades, we have seen the next phase of this digitization, where digital currencies, known as cryptocurrencies, have emerged and keep dominating traditional currencies.

Cryptocurrency is a digital currency that uses cryptography, a decentralized system, and a consensus mechanism to secure and verify transactions made between individuals or groups [1]. This combination of cryptography techniques and a digital ledger of transactions is distributed across the entire network on the blockchain [2], [3]. Most cryptocurrencies rely on blockchain technology, which provides a secure, decentralized, transparent, and immutable transaction record registration and verification process [4]. Additionally,

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using cryptography makes it impossible to counterfeit or double-spent digital currency. Moreover, the added or altered record is broadcast to all network nodes for verification. If verified, it is added to the digital ledger, which ensures security and temper-proofing by consensus mechanism [5].

In 2021, as per the statistics, the total market value of cryptocurrencies has reached a staggering $2 trillion. The cryptocurrency market is anticipated to generate US $37.9 billion in revenue by 2023. By 2027, revenue is predicted to increase at a 14.40% annual rate, reaching a total estimated value of US $64.9 billion [6]. As of May 2023, there are over 12,000 cryptocurrencies in existence [7]. Bitcoin (BTC) remains the most prominent, market-dominant, and well-known cryptocurrency. However, many others are gaining ground, such as Binance coin, Ethereum (ETH), Litecoin, Cardano, Monero, and Dogecoin (DOGE).

The popularity and adaptation of cryptocurrencies are due to their decentralised nature, giving consumers more privacy, freedom, and anonymity. This implies that cross-border transactions can be facilitated without using middlemen such as banks and payment processors, which is costly and time-consuming in a traditional financial system. Despite having several advantages, including decentralisation, lower costs, enhanced security, and transparency. Digital currencies are exposed to security attacks, which may lead to transaction data manipulation. Most digital currencies, including BTC, ETH, and Litecoin, are based on blockchain technology.

A blockchain-based cryptocurrency transaction proceeds safely and openly. Beginning with the creation of a digital message containing the recipient's wallet address and the amount of BTC to be transferred, the sender initiates the transaction. This message is broadcast to the decentralized nodes of the network that make up the blockchain. The nodes confirm the transaction's legitimacy by ensuring the sender has enough money and that the transaction follows the cryptocurrency's protocol.

The nodes undertake intricate mathematical computations, called mining, as part of this verification process. The transaction is combined with other confirmed transactions into a block once it has received confirmation from many nodes. Following that, this block is included through a consensus-based mechanism in the already-existing chain of blocks, thus the name "blockchain".

A simple illustration of a digital currency transaction using a blockchain database between two clients (a sender and a receiver) is shown in Figure 1. When the sender initiates a transaction, it is verified through the distributed digital ledger or blockchain, which all clients in the network maintain. The transaction validity is checked at the senders' end, and this information is then stored at the receivers' end in the global storage. This systematic procedure guarantees an authenticated and secure transaction.

Engaging with cryptocurrency is challenging despite many advantages, like safe and verified transactions. The inherent volatility and intricate correlation between transaction volumes and price variations pose complexities, resulting in an unpredictable fluctuation in value over time. The most common factors influencing cryptocurrency prices are mainly the crypto-market, economy, politics, and other factors associated with digital currencies, shown in Figure 2. The challenge lies in deciphering the interplay between these factors and their effects on cryptocurrency prices. Thus, cryptocurrency price prediction is challenging.

Regardless of these challenges, the demand for accurate forecasting in this dynamic field has increased. Precise forecasts enable investors to maximize their trading tactics, proficiently handle hazards, and profit from developing market prospects. So, cryptocurrency investors seek trustworthy models and tools to help them make well-informed decisions. To offer a solution, scholars and researchers are driven to expand our knowledge of market behavior, which propels the development of financial modeling and prediction techniques.

Using cutting-edge statistical and computational technologies, researchers must analyze vast volumes of transactional and market data while considering several elements and their interdependencies. Several techniques, including technical, fundamental, and sentiment analysis, have been employed to accurately anticipate cryptocurrency values while considering their volatility and the wide range of factors that affect them. Recurring patterns and trends in price charts are identified for the technical analysis. The basic variables influencing the cryptocurrency industry, including legislative modifications, technical developments, market uptake, and investor mood, are examined in fundamental analysis. On the other hand, sentiment analysis can determine the market's mood, revealing short-term market dynamics and prospective price changes.

In the past, uni-domain multi-factors were mostly used to conduct crypto price predictions, which is inadequate due to several interdependent factors influencing crypto prices. To address this gap, we propose a multi-domain, multi-factors-based model in this study to predict the cryptocurrency price precisely.

The main contributions of this study are:

1) Presents an effective model for cryptocurrency price forecasting based on historical data.
2) Incorporate a precautionary mechanism to promptly notify investors of negative sentiments that might undermine the validity of predictions.
3) Mitigate risk factors and empower investors to make informed decisions for effective risk management.

The manuscript's structure follows a logical flow, starting with an extensive review of relevant literature. After that, the "Methodology" section explains the first part of our suggested framework for cryptocurrency price prediction, followed by a second part that is sentiment analysis. A thorough description of the dataset and evaluation metrics can be found in the "Materials and Evaluation Metrics" section. Next, the "Results" section delves deeply into the results of our suggested model. Finally, the "Discussion" and "Conclusion and Future Work" sections are provided.

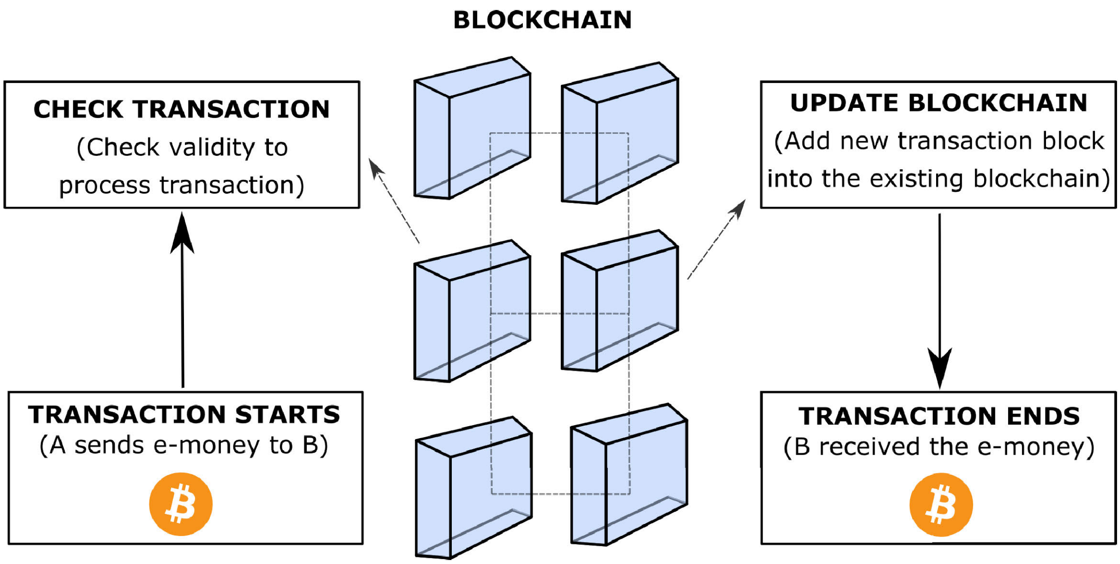

FIGURE 1. Illustration of the utilization of blockchain technology in cryptocurrency workflow.

II. RELATED WORK

Substantial attention has been given by researchers to cryptocurrency price prediction, as it is becoming a rapidly expanding industry. Due to the existing challenges in digital currency price anticipation, various techniques have been developed, including fundamental analysis, sentiment analysis, technical analysis, market and order book analysis, and econometric models, that may use machine learning (ML) and artificial intelligence (AI), statistical analysis, previous records etc. The following section discusses recent competitive studies performing technical, fundamental and sentiment analysis using ML and AI-based methods.

A previous study on BTC price prediction was performed using both statistical methods and ML [8]. For the statistical approach, the authors claim an accuracy of 66% using logistic regression (LR) and linear discriminant analysis. The ML models used were long short-term memory (LSTM), support vector machine (SVM), Random Forest, and XGBoost, which achieved an accuracy of 67.2%. A study proposed a gated recurring unit (GRU) model as a better approach for BTC price prediction [9]. In conclusion, recurrent machine learning models are suggested to have much better accuracy than other traditional prediction methodologies

In a study, multiple machine learning techniques, including gradient boosted trees, neural net, k-nearest neighbor (KNN), and ensemble learning methods, were implemented for price prediction of several cryptocurrencies [10]. The ensemble learning method achieved the best results among all the models used. The accuracy achieved with the ensemble model was reported at 92.4%. An efficient deep learning-based prediction model, LSTM and GRU were proposed for BTC price forecasting [11]. The authors claim the long-term dependencies are better handled using GRU and LSTM. However, the results could be improved by adding other related features like market trends, government policies, demand-supply gap, etc.

A stochastic neural network-based model for cryptocurrency price forecast was proposed [12]. To replicate market volatility, the proposed approach introduces layer-wise randomization into the observed feature activations of neural networks. Another research study suggested a GRU and LSTM hybrid model with interdependence to the parent currency [13]. A deep neural network used Google, BTC market data, and blockchain datasets to predict the BTC price [14]. A primary deep neural network was used to forecast the ideal window size based on the observed BTC price trend over the previous days and its volatility. Then, using the first step's anticipated window as a guide, the secondary deep neural network forecasts the price of BTC [15]. Comparative analysis and predictor importance measures point to a recent shift in the focus of BTC market investing from trend-following to exaggerated momentum and sentiment [15].

Another study [16] identifies LSTM and wavelet decomposition models for this purpose. This research supports the hypothesis that very accurate cryptocurrency return predictions may be achieved using cutting-edge machine-learning algorithms. A comparison of non-linear and linear BTC forecasting techniques to decide which model is the most accurate outside of a sample is provided [17]. Their findings imply that less complex models can outperform more complex ones. However, there are limitations on the kind of elements that may be employed in this argument to achieve that goal. The above-mentioned studies provide a deep knowledge of previous methodologies on technical analysis. We will now look into the studies made for fundamental analysis.

Fundamental analysis entails determining digital currency's inherent worth by looking at its underlying components and macroeconomic data when predicting its price. A study used 59 fundamental factors categorized into five groups: traditional fundamental, currency, stock indices,

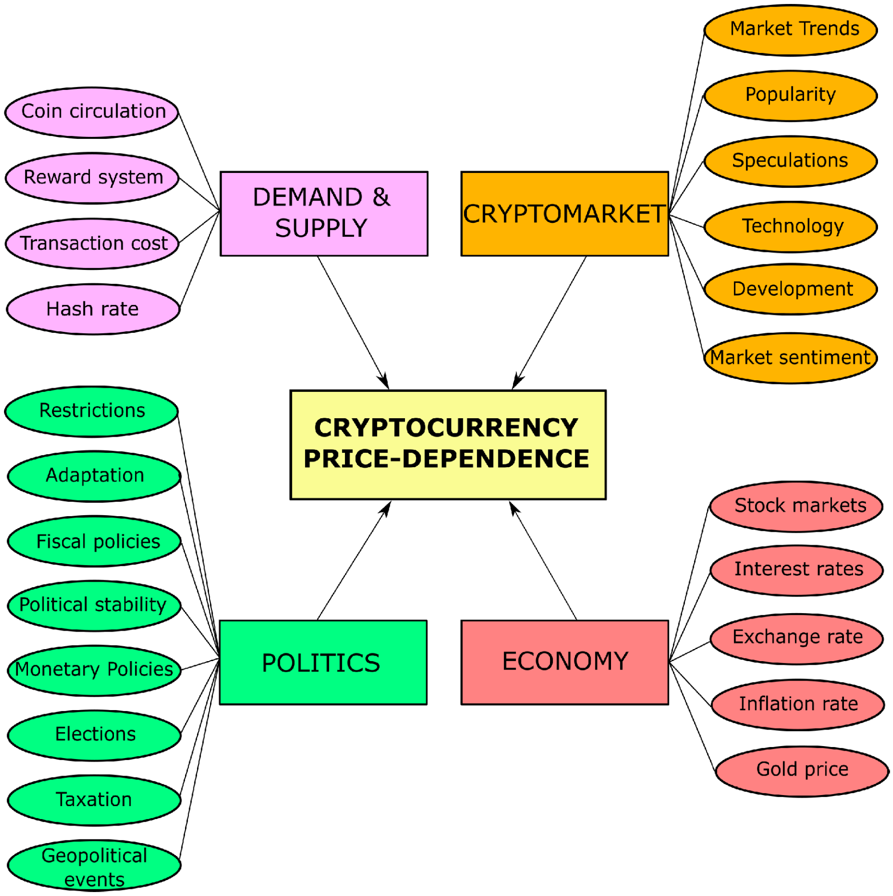

FIGURE 2. Key factors driving volatility and influencing cryptocurrency price.

Blockchain technology-based, BTC and blockchain trend-based factors [18]. These fundamental and technical factors were used to predict and calculate the returns for 12 cryptocurrencies. Another study proposed a classification tree-based model to predict the BTC price based on 124 price-based technical indicators [19]. According to the study's findings, technical analysis can be helpful in a market like BTC, where non-fundamental factors mostly determine price.

The values of cryptocurrencies are highly impacted by mainstream news and social media posts in their dynamic universe. As a result, a key area for precise cryptocurrency price prediction is sentiment analysis. A study uses BTC price data and sentiment indicators to forecast the price [20]. The proposed model works in four steps: collection of Twitter data into CSV format, market sentiment score is calculated, BTC price data is processed using python library (TA-LIB) for technical indicators, and data is merged by time indexes to evaluate models. The study claims that the near-real-time forecast performs better, with a mean absolute error of 88.74%. Another study used Twitter data to formulate a model for learning [21]. The correlations with many other stochastic occurrences were examined using tensor networks.

A study used Twitter and Google trends for short-term main cryptocurrencies price prediction [22]. The study proposed a hybrid model to alleviate the deficiencies of any one model. Another hybrid model composed of multiple linear regression and recurrent neural network was proposed [23]. In a study of BTC-related posts from online forums, their price and transaction count data were gathered. The deep learning model used Only the selected data with higher score ratings to predict the BTC price [24]. A study used Chinese social media posts to predict cryptocurrency prices using historical records of cryptocurrency prices and LSTM-based recurrent neural network [25].

A study used three models to predict the digital currency price trend: neural networks (NN), SVM, random forest using Twitter data, market data, or a combination of both. The study claims that NN outperforms the other models in predicting the price trend of Ripple, BTC, ETH, and Litecoin. It's important to be aware of the limits of sentiment analysis. The cryptocurrency market is wildly speculative and is impacted by various variables, including macroeconomic trends, technology advancements, regulatory announcements, and market sentiment. To increase the precision of cryptocurrency price forecasts, sentiment analysis should be combined with other fundamental and technical analysis techniques. A resilient and hybrid architecture, DL-Gues, was developed for cryptocurrency price prediction, taking into account its interdependencies with other cryptocurrencies and market sentiments [26].

Granger Causality analysis was used in a study project to forecast fluctuations in cryptocurrency prices. The study concentrated on Dogecoin using a time series of public sentiment gathered from quantifying a large collection of daily tweets (5 million). The authors used a customized version of the lexicon-based sentiment polarity analysis technique known as VADER to examine the textual content of each tweet mentioning Dogecoin.

A study uses large datasets and variables based on daily time series to investigate the relationship between sentiment scores and financial metrics in a thorough analysis. The results demonstrate a cointegration between sentiment and cryptocurrency prices, revealing an overall positive sentiment toward all cryptocurrencies.

In an investigation, the BERT model was used to investigate sentiments and was used for both sentiment analysis and emotion recognition in Twitter data. The researchers created unique classifiers for every task and used real-world tweet datasets to evaluate the models' efficacy. Impressive accuracy rates of 0.92 for sentiment analysis and 0.90 for emotion recognition were shown in the experiment results [27]. Instead of using a standard BERT tokenizer, a study suggested a method to integrate an Arabic BERT tokenizer. Different instances were used for different tests (dialect and standard). Compared to Arabic BERT and AraBERT models, the experimental study demonstrates the suggested strategy's effectiveness in classification quality and accuracy [28].

In a related study, opinion mining using the TextBlob model was used to conduct sentiment analysis on Twitter. The suggested method included gathering tweets, preprocessing the data, extracting features, and classifying the labeled and unlabeled data. Applying machine learning classifiers proved efficient and accurate, as evidenced by the several practical implications [29], [30], [31], [32], [33].

Some investigations have employed hybrid or ensemble models to enhance sentiment analysis. A study used TextBlob and VADER analyzer to examine the historical tweets for people's feelings about the coronavirus pandemic. 1,048,575 tweets were collected from Twitter to create a dataset. An ensemble learning approach that combined the Random Forest, SVM, Decision Tree, and Logistic Regression algorithms was developed. Sentences in the dataset were successfully converted into numerical vectors to improve model performance [34].

In short, technical analysis is based on previous data and is therefore vulnerable to bias. Consequently, integrating technical and sentiment analysis, can present a more thorough and reliable picture of the possible price movements of the cryptocurrency. By incorporating many aspects of research, price projections may be made more accurate and reliable, giving investors more confidence to make well-informed decisions about their investments and foresee future returns. Hence, our novel methodology would be a breakthrough in cryptocurrency price prediction by revealing hidden patterns, uncovering untapped insights, and offering a greater grasp of market dynamics.

Our study suggests an improved analytical approach, including cutting-edge ML techniques and the use of data sources for accurate results. This research-based study aims to develop an advanced framework for cryptocurrency price forecasting that incorporates a precautionary mechanism and employs historical data to improve the precision of predictions. The main aim is to give investors a trustworthy system that could precisely predict cryptocurrency prices and quickly alert them to unfavorable sentiments that might jeopardize the validity of predictions. The main objectives of this study are listed below:

- Design and implement an effective cryptocurrency price forecasting model utilizing historical data.
- Integrating a preventative measure in the forecasting model to identify negative sentiments related to cryptocurrency.
- Assess and improve the model to guarantee its accuracy and resilience in making trustworthy forecasts.
- Provide investors with practical advice for efficient risk management, based on the forecasting model's identification of mitigated risk factors.
- Development of predictive modeling in cryptocurrency space, giving market players an important tool for decision-making.

III. METHODOLOGY

This comprehensive study revolutionizes digital currency price prediction by proposing a unique ML-driven framework, as shown in Figure 3. Leveraging historical data as training input, our hybrid model combines the capability of Bi-LSTM and GRU to generate accurate and robust predictions. Beyond technical analysis, our methodology takes a step further by including a sentiment analysis module. This module functions as a vigilant sentinel, instantly raising a red signal in the presence of unfavorable conditions that might be detrimental to the value of the cryptocurrency. We apply a sophisticated hybrid model integrating Bidirectional encoder representations from the Transformers (BERT) and ValenceAware Dictionary and Sentiment Reasoner (VADER) to grasp the complicated geography of online sentiments.

In Figure 3, historical price data is fetched as input to train the Bi-LSMT and GRU hybrid model. Similarly, for sentiment analysis, the recent sentiments are fetched to analyze by the BERT and VADER hybrid model. After the training on previous data, the Bi-LSTM and GRU hybrid model predicts the price with high precision. This prediction's reliability depends on the sentiment analyser's three possible outcomes. In the presence of positive or neutral sentiments, the anticipated prices are considered trustworthy, whereas in the face of negative sentiment, the forecast price becomes unreliable. The proposed technical and sentiment analyzers are discussed in detail in the following subsections.

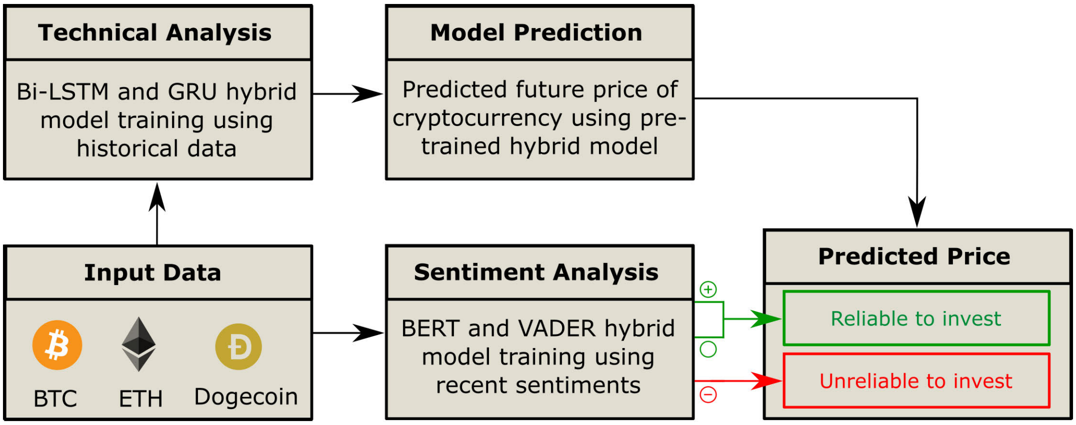

FIGURE 3. Proposed framework for cryptocurrencies price prediction and generating sentiment-based alerts.

A. TECHNICAL ANALYSIS

Technical analysis examines past price and volume data to forecast cryptocurrency prices. It basically finds trends and patterns from historical data. This historical data entails chart analysis utilizing line, bar, and candlestick charts. Trend lines can identify horizontal, upward, or downward trends. Levels of support and resistance indicate potential buying and selling points. Triangles head and shoulder charts indicate trend continuations or reversals.

Technical analysis is based on three main principles: the first is that stock prices already reflect all available information in the market; the second is that stock prices often follow trends; and the third is that history repeats itself. We used technical charts from reliable websites like Binance, Trading View, and Investing.com to achieve this. With these charts' aid, we could demonstrate technical analogies, analyze the technical charts, and explain how indicators and other technical analysis tools impact price and decision-making regarding when to enter and exit the market.

The technical indicators considered in our study are trends, volumes, behavior of traders, support and resistance levels, moving averages, moving average convergence divergence (MACD), relative strength index, and strategy for stop-loss. A detailed description of these indicators is mentioned [35]. However, a brief concept of these indicators is mentioned below.

Trends show which way the price is likely to move. Trends are a combination of up moves and down moves. Three categories of trends exist. Uptrend: When higher highs and lower lows are reached, an uptrend is created. Lower highs and lower lows indicate the formation of a downtrend. A sideways trend is created when highs and lows fall within the same range.

A volume measures how many deals are made during a specific period. Volumes may be a good indicator of market strength since growing markets with rising volumes are often considered robust and healthy. One of the most well-known elements of technical analysis is candlestick charts, which enable the analysis of price changes. In essence, this aids in monitoring the asset class's open and close prices and daily highs and lows.

Candlesticks come in a variety of forms, but the most popular ones for usage as indicators are i) Bullish Engulfing Pattern, ii) Bearish Engulfing Pattern, iii) Morning Star Candlestick, iv) Evening Star Candlestick, v) Hammer, and vi) hanging man. Mathematical tools that can be used to anticipate trends are volatility and the price of various securities. The moving average is a useful indication, but because it is regarded as a lagging indicator, it produces "Buy and Sell" signals somewhat later than other indicators. The average of the most recent closing prices over time calculates moving averages.

MACD is a leading indicator which declares the price moves later but first exhibits indications of strength and weakness. Price movements and MACD trends provide a variety of bullish and bearish reversal signs. Another indicator is the relative strength index, which assesses if the price of a stock or other asset is oversold by calculating the size of the most recent price fluctuations.

One of the most important and disciplined things in trading is to set a stop-loss in the transaction. The stop-loss is the limit of one's will to lose to a certain level. To summarize, technical analysis is a technique to assess cryptocurrencies by looking at data produced by historical prices, volumes, and market activity.

We have proposed a ground-breaking hybrid model that combines the advantages of the Bidirectional Long Short-Term Memory (Bi-LSTM) and GRU architectures in our attempt to improve the digital currency price prediction. We have incorporated several other benchmark models in our comparative research to ensure a thorough assessment of the performance of our model. These models include the LSTM, Convolutional Neural Network (CNN), MLP, and LR. The architecture of our suggested model is explained in detail in the following parts.

1) PROPOSED HYBRID MODEL

A feed-forward neural network with internal memory is known as an RNN, unlike a normal neural network with distinct inputs and outputs for each component. The outputs of one stage in an RNN are used as the input for the following stage. This trait gives RNNs a remarkable capacity to extract the temporal components of data. An RNN resembles several neural networks placed side by side, with the output from one network as input to the next. A simple recurrent neural network can be defined as in equation 1.

$$S_n = \theta(W_h S_{n-1} + W_i x_n) \tag{1}$$

where W_h is the weight of the recurrent neuron, W_i is the weight of the input neuron, S_t is a new state, S_{t-1} is the previous state, x_n is the current input, and is activation function, which is usually tanh. The output state O_n is calculated as in the equation 2 after the current hidden state has been determined.

$$O_n = W_o S_n \tag{2}$$

Back-propagation is typically used to train RNN. However, their cyclic construction makes them challenging to train, take longer to converge, and have the vanishing gradient issue. Consequently, an RNN cannot learn long-term dependencies more easily [36]. So, in this study, the Bi-LSTM and GRU-based hybrid model is used to solve this RNN challenge. The operation, architecture, advantages, and disadvantages of each model are covered in the section below before going into more detail about the proposed Bi-LSTM and GRU-based hybrid model. This supports the rationale for presenting a hybrid model that combines the benefits of these models for an improved methodology for predicting the price of cryptocurrencies.

Bi-LSTM model trains a network using past and future input data sequences. Based on the context of past and future elements, Bi-LSTM predicts each element's sequence using a limited sequence. Figure 4 shows the architecture diagram of the Bi-LSTM model. Fundamentally, it consists of two LSTMs operating simultaneously, one from left to right and the other from right to left. Composite output refers to a target signal's forecast. This approach has shown to be very helpful. Equations 3 and 4 are used to calculate the forward function of the Bi-LSTM using "I" units as inputs and "H" as the number of hidden units. The Bi-LSTM model architecture comprises input, forward, backwards, activation and output layers, as shown in Figure 4.

$$v_h^t = \sum_{i=1}^{I} x_i^t w_{ih} + \sum_{h',t>0}^{H} p_{h'}^{t-1} w_{h'h} \tag{3}$$

$$v_h^t = \theta_h(v_h^t) \tag{4}$$

Bi-LSTM can analyze input data forward and backward. It offers several special advantages over the basic LSTM model. The Bi-LSTM analyzes data in both directions concurrently, going beyond the standard LSTM, which processes data sequentially from the past to the future. With this bidirectional approach, Bi-LSTM can capture the influence of future events on the current price and the impact of previous events on future price movements, leading to a more thorough understanding of bidirectional relationships. With the use of historical and prospective data, Bi-LSTM provides a more comprehensive grasp of the dynamics of the cryptocurrency market.

GRU is another RNN variation that addresses the vanishing gradient issue [37]. A GRU has two gates, an update gate and a reset gate. These two gates work together to regulate the information flow through the network. The architecture of the GRU model is shown in Figure 5. The amount of historical data that must be passed on determines the update gate. The amount of information to be forgotten is decided by the reset gate, following equations 5, 6, 7, and 8 summarize the GRU working mechanism, whereas Figure 5 shows the architecture of a typical GRU model.

$$u_t = \sigma(X_u i_t + W_u o_{t-1} + p_u) \tag{5}$$

$$r_t = \sigma(X_r i_t + W_r o_{t-1} + p_r) \tag{6}$$

$$m_t = tanh(X_o i_t + W_o(r_t \odot o_{t-1} + p_o) \tag{7}$$

$$o_t = u_t \odot o_{t-1} + (1 - u_t) \odot m_t \tag{8}$$

Here, i_t, o_t, u_t, r_t are the inputs, outputs, update and reset gates, respectively. X, W and p are the weight matrices, whereas the $\odot$ denotes Hadamard product.

GRU provides a compelling foundation for increasing the accuracy of digital currency price prediction. Its usefulness in this area results from several essential benefits. First, GRUs excel at handling sequential data, making them perfect for simulating the complex, time-dependent patterns that distinguish cryptocurrency markets. It successfully handles the vanishing gradient issue, making it possible to identify long-term dependencies in price data, which is essential for reliably anticipating BTC trends. Additionally, GRUs contain an advanced gating system that enables effective memory management, enabling them to concentrate on pertinent information while removing noise present in cryptocurrency price data.

Moreover, GRUs have comparatively fewer parameters than their LSTM counterparts, which leads to quicker training times, a key advantage when working with the big datasets that are frequently encountered in digital currency historical price analysis. However, problems still exist. GRUs, like other deep learning models, can overfit, especially when there is a lack of prior cryptocurrency data.

Due to their high volatility and noise levels, cryptocurrency markets can be difficult to navigate. The interpretability of GRU-based models may be constrained, making it difficult to comprehend and have confidence in model predictions. In conclusion, GRUs are an effective tool for forecasting cryptocurrency prices, but realizing their full potential requires resolving issues like overfitting, poor data quality, non-stationarity, and model interpretability. Only then can forecasts in this volatile financial environment be sure to be accurate and dependable.

Hybrid model proposed in this study for the technical analysis comprised of Bi-LSTM and GRU. RNNs have sequential memory and are designed to model sequential

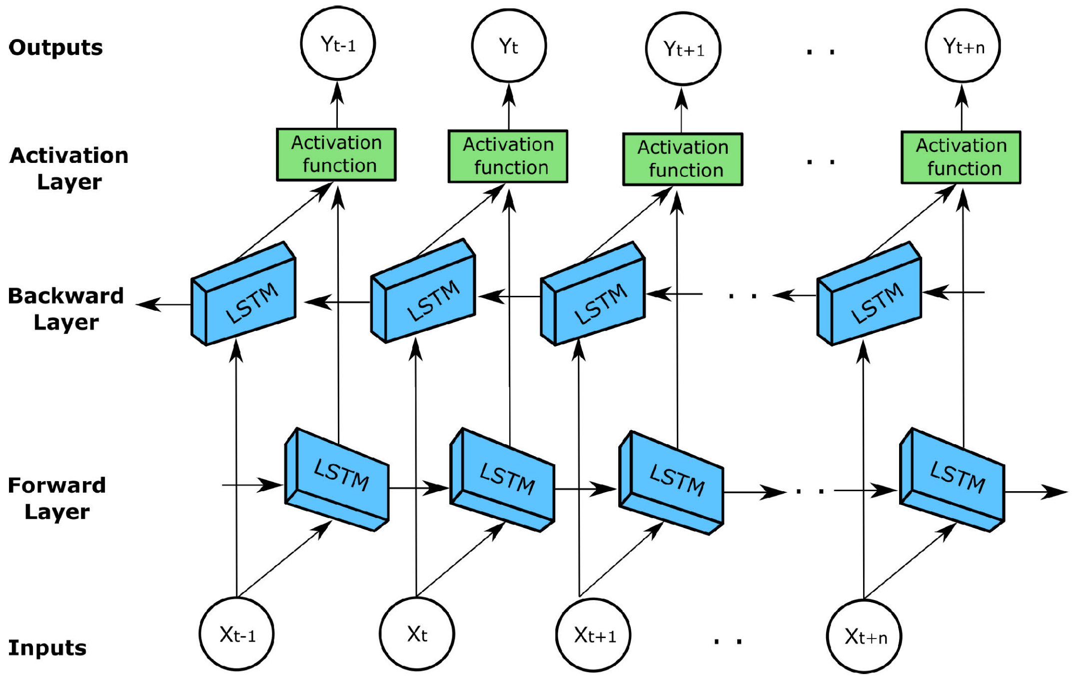

FIGURE 4. Architecture of Bi-LSTM model.

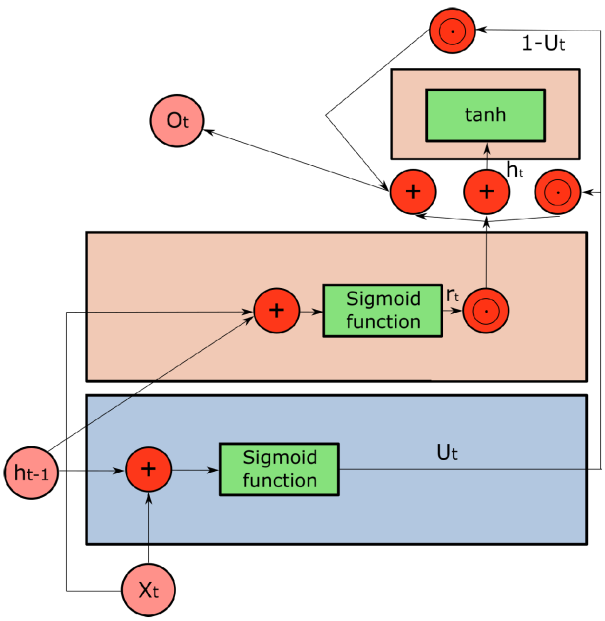

FIGURE 5. Architecture of GRU model.

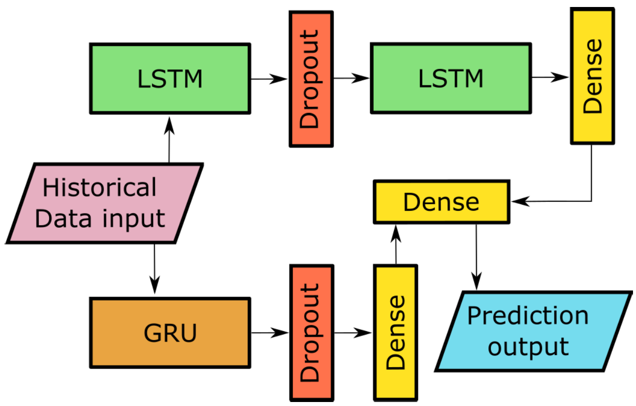

FIGURE 6. Architecture of the proposed Bi-LSTM and GRU hybrid model.

data. Their architecture enables them to produce outputs while considering both recent inputs and information learned from earlier inputs and outputs. Because of this quality, they are particularly suited for applications requiring time-series prediction. Both LSTM and GRU are RNN versions made to get around the vanishing gradient issue that RNN has. Several studies from the past [38], [39], [40], [41] have demonstrated the superiority of LSTM and GRU in time-series prediction.

We, therefore, provide a strategy for combining the two models to profit from both. Figure 6 shows the architectural diagram of the proposed framework.

The framework first perform pre-data processing to make it appropriate for the model's input [42]. The data is split up into many input-output pairs. A series of previous values or observations will be used as the input, and an output value will be mapped to them. This sequence's length (n) is a hyperparameter. We use $[x_0, x_1, \ldots, x_{n-1}]$ as input and get x_n as the output. Similarly, we use $[x_1, x_2, \ldots, x_n]$ as the following input and produce x_{n+1}. This technique is employed to prepare the dataset.

The Algorithm 1 explains the hybrid model working. The model combines a Bi-LSTM network with a GRU. Each model has a standard input, and when both networks

Algorithm 1 Pseudocode of Data Preparation

Input: $X_{in} \in$ {Cryptocurrency prices}
Output: $X_{out1} \in$ features, $X_{out2} \in$ target
procedure PROCESS DATA $\left(X, \omega_{features}^{Count}\right)$
  $X_{out1} \leftarrow \varnothing, \forall X_{out1} \in X_{training \rightarrow Features}$
  $X_{out2} \leftarrow \varnothing, \forall X_{out2} \in X_{training \rightarrow Target}$
  $n \leftarrow lambda(X)$
  for $\eta = 1, 2, 3, \ldots$ to n **do**
    $\xi \leftarrow \eta + \omega_{features}^{Count}$
    if $(\xi > (n - 1))$ **then**
      break
    end if
    $\psi_{out1} \leftarrow data[\eta : \xi]$
    $\psi_{out2} \leftarrow data[\xi]$
    $X_{out1 \rightarrow append}(\psi_{out1})$
    $X_{out2 \rightarrow append}(\psi_{out2})$
  end for
  $\mathscr{R} = (X_{out1}, X_{out2})$
end procedure=0

Algorithm 2 Pseudocode for Cryptocurrency Price Prediction

Input: $X_{out1} \in$ features, $X_{out2} \in$ target, $\mathscr{P} \in$ prediction window time
Output: $\mathscr{P} \in$ Predicted prices
procedure PREDICTION $\left(X_{out1}, X_{out2}, \mathscr{P}_{window}\right)$
  $\mathscr{R} \leftarrow \upsilon(X_{out1}, X_{out2})$
  $\mathscr{P}_{values} \leftarrow \varnothing$
  $\kappa \leftarrow append(X_{out1 \rightarrow LastValue})$
  DELETE $(\kappa, (X_{out1 \rightarrow FirstValue})$
  $\kappa \rightarrow append(X_{out2 \rightarrow LastValue})$
  for $\eta = 1, 2, 3, \ldots$ to $\mathscr{P}_{values}$ **do**
    $\mathscr{P}_{values} \rightarrow append(\mathscr{R}.\mathscr{P}_{\kappa})$
    DELETE $(\kappa, X_{out1 \rightarrow FirstValue})$
    $\eta \rightarrow append(\mathscr{P}_{values}.X_{out2 \rightarrow LastValue})$
  end for
  $\mathscr{R}(\mathscr{P}_{values})$
end procedure=0

are combined and run through a dense layer, the result is determined. A GRU layer with 30 neurons makes up the GRU network. To prevent overfitting, the layer is followed by a dropout layer. In a dense layer, the dropout's output is fed. In contrast, the Bi-LSTM network contains a 30-neuron Bi-LSTM layer. A dropout layer is placed after the Bi-LSTM layer as well to prevent an over-fitting issue. ReLU is the chosen activation function, while Adam is the chosen optimizer. The model has undergone 100 epochs.

The most recent n observations are used as input for prediction, where n is the model's input sequence length. The following value is anticipated using this. Once this value has been obtained, the following input, which consists of the most recent n-1 values and the forecast value, is created. This procedure is repeated t times, where t is the size of the prediction window. The algorithm 2 has been used to describe this procedure. The other models used for competitive comparison are LSTM, CNN, LR and MLP. These models are trained for the same number of epochs (100) as the proposed hybrid model is trained with.

2) LSTM

The LSTM model's capacity to handle sequential data and learn temporal connections has shown it to be extremely relevant and successful in predicting cryptocurrency prices. Its ability to overcome the drawbacks of conventional machine learning models when working with time series data is what makes it so effective, especially considering how dynamic and intricate digital currency markets are. LSTM easily captures long-term dependencies in time series data, which helps it identify and learn from patterns that develop over long time horizons. When projecting future prices, the memory cells' ability to retain and retrieve information during time delays guarantees that previous occurrences are considered.

Additionally, it effectively manages the intricate nonlinear interactions between price fluctuations and basic components. The model can learn from price variation patterns that enable it to drop short-term fluctuations and consider only meaningful trends. One of the best features of this model is its ability to simultaneously incorporate multiple fundamental factors, having a wide range of data for prediction. Moreover, it continuously updates itself for real-time input data. Furthermore, it confirms the novelty of the suggested model and provides insightful information about how LSTM may be used to identify patterns in pricing data. This comparison strengthens the study's validity and advances our knowledge of efficient modeling approaches in the cryptocurrency space.

Including an LSTM in the comparison analysis gives us a standard by which to measure the performance of our suggested models. If our GRU and Bi-LSTM models outperform the LSTM across pertinent evaluation metrics, this not only confirms the creativity and superior predictive abilities of our approaches but also shows that our models are well-suited for the unique complexities and nuances of cryptocurrency price data. Furthermore, we may learn more about each design's relative advantages and disadvantages by the comparison study using an LSTM model.

In the context of projecting the value of cryptocurrencies, it offers a chance to evaluate how each model manages long-term relationships, catches subtle patterns, and generalizes to unobserved data. Last but not least, using an LSTM model in our analysis broadens the scope of our study and improves its usefulness to both researchers and practitioners. It provides a thorough overview of the modeling strategies available for predicting cryptocurrency prices, assisting current and future academics and stakeholders in selecting the right models for comparable tasks. In summary, including an LSTM model in our comparison study is a wise and strategic decision. Our suggested GRU and Bi-LSTM models offer the possibility of giving higher predictive performance. It gives our study context, validation, and insights and broadens its application, ensuring a full assessment of our cutting-edge methods in the field of BTC price prediction.

3) CNN

Price predictions for cryptocurrencies may be made with great accuracy using the Convolutional Neural Network (CNN) model. Because of its unique characteristics, it can efficiently handle sequential data, which makes it ideal for the volatile and fast-moving cryptocurrency markets. Some of the main benefits are adaptability to irregular time series, automated feature extraction, local pattern identification, time-invariant feature recognition, and effective multivariate data processing. CNNs may also acquire hierarchical representations and gain from transfer learning, improving their market sentiment comprehension.

We have narrowed down the CNN model as a competitive benchmark for predicting cryptocurrency prices because it has been employed in most earlier research. It offers a reliable benchmark against which the effectiveness of the suggested model may be evaluated. In addition to ensuring impartiality in evaluation, this comparison study also aids in highlighting the advantages and disadvantages of other competing strategies. Furthermore, it confirms the novelty of the suggested model and provides insightful information about how CNNs may be used to identify patterns in pricing data. Ultimately, this comparison strengthens the study's validity and advances our knowledge of efficient modeling approaches in the cryptocurrency space.

4) LINEAR REGRESSION

By creating a link between the predictor variables (fundamental elements) and the target variable (cryptocurrency price), a linear regression model may be used to forecast cryptocurrency values. The strategy entails gathering historical data for important fundamental variables such as commodity prices, volatility indices, stock indices, bond yields, currency exchange rates, risk-free rate proxies, and cryptocurrency price data.

Data preparation, which includes cleansing, controlling outliers, and assuring regular time intervals, is a subsequent stage. It is important to select relevant basic elements, standardise their scales, and separate the data for model training and testing. Analysis of the coefficients for each factor's influence on pricing is required for interpretation. Predictions are created using the trained model on new data to help with future price forecasts based on basic characteristics. Regular revisions and updates take into account shifting market dynamics. Although linear regression presumes linearity, it is observed that the complexity of cryptocurrency markets reveals possible limits, promoting the investigation of more sophisticated approaches like polynomial regression, support vector regression, or machine learning for increased forecast accuracy.

Using the LR model in the comparison analysis serves some beneficial objectives. First off, LR is one of the most extensively used modeling approaches that are both straightforward and easy to understand for regression applications, including predictive modeling. Adding an LR model provides a visible baseline, making it easier to compare with our more intricate suggested models. This offers a simple benchmark for assessing the potency and sophistication of our unique strategies. Including an LR model in the comparison analysis also adds a critical viewpoint to the work that needs to be done.

If our GRU and Bi-LSTM models do indeed outperform the LR model according to the pertinent evaluation metrics, this not only confirms the creativity and sophistication of our methods but also highlights how well-suited they are to capture the complex dependencies and patterns present in cryptocurrency price data. Additionally, the comparison with an LR model enables us to evaluate the relative benefits and drawbacks of each modeling strategy. An LR model offers insights into how well linear associations may explain the changes in BTC values, but deep learning models like GRU and Bi-LSTM are skilled at capturing complicated nonlinear interactions in data. This can reveal if deep learning models' higher level of complexity is necessary for the particular forecasting objective.

For practitioners and stakeholders looking for simpler, easier-to-understand models for digital currency price prediction, including an LR model in our research can be very instructive. It illustrates model complexity and performance trade-offs, assisting decision-making when choosing the best models for various settings and resource constraints. In summary, including an LR model in our comparison study is both wise and instructive. It provides context, validation, and insights into model complexity and allows for transparent comparisons, providing a thorough assessment of our cutting-edge methods for predicting the price of cryptocurrencies.

5) MLP

An MLP model can handle complicated non-linear connections and interpret multivariate data. It may be used to forecast cryptocurrency values with fundamental elements. Multilayer neural networks, or MLPs for short, are an excellent tool for identifying complex relationships and patterns between the core elements that drive the pricing of cryptocurrencies.

The capacity to capture non-linear correlations, analyze multivariate data, automatically learn pertinent features, scale with big datasets, flexibility in model design, interpretability, and real-time prediction capabilities are just a few advantages of utilizing an MLP model. Despite their advantages, MLP models could not always outperform LSTM, CNN, or LR models. The prediction goal and the properties of the data determine which model is optimal. MLPs work well with tabular data and basic relationships, which makes them appropriate for non-sequential data with clear-cut patterns. They provide real-time forecasts and interoperability. MLP is a well-known and often used neural network design for regression and forecasting, among other machine learning applications.

A clear and understandable comparison with our hybrid model is largely made feasible by including an MLP model in the comparative study. Recurrent models are particularly good at capturing sequential dependencies, but MLPs are notable for their capacity to simulate complicated nonlinear interactions. This investigation can shed light on the best kind of architecture to predict the price of cryptocurrencies. Including an MLP model provides a thorough assessment of our cutting-edge methods for forecasting cryptocurrency prices.

B. SENTIMENTAL ANALYSIS

Unstructured text data, such as that found in tweets, online articles, text messages, emails, and other formats, makes up a large portion of that online data. The emergence of natural language processing (NLP) as a field of study or research results from the enormous amount of unstructured data. NLP is a collection of techniques for text analysis and comprehension by computers. Sentiment analysis identifies and quantifies the irrational feelings or views represented in the text. The ultimate objective is to use sentiment analysis to gather cryptocurrency-related data from the internet (blogs, posts, tweets, google trends, etc.) to assess whether they positively or negatively impact cryptocurrency values.

Text preprocessing, classification, and sentiment analysis are the three main steps in the process breakdown. Text preprocessing, the initial step, entails cleaning and standardizing the text data. Finding pertinent features in the text, like keywords and phrases, is the second step in the feature extraction process. Lastly, the text is classified according to its sentiment in this step.

In the domain of sentiment analysis, two important methodologies have emerged as the cutting-edge of sentiment classification: VADER, a rule-based sentiment analyzer, and BERT, a transformer-based model. Each of these techniques offers its particular benefits and limitations. In this study, we propose a unique hybrid model that blends the qualities of both BERT and VADER to develop a more robust and accurate sentiment analysis technique. To offer a thorough understanding of our method, it is crucial to first delve into the merits and drawbacks of each BERT and VADER model, which will serve as a solid framework for the ensuing explanation and discussion of our hybrid model.

1) VADER

VADER is a tool for sentiment analysis based on rules. The tool is particularly helpful for sentiment analysis on social media because of a few features [43]. It offers a vocabulary and rule-based sentiment analysis tool for social media text. The semantic orientation of the lexicon categorizes the user's data or reviews as favorable, unfavorable, or neutral. The VADER model computes a compound score by adding up all of the lexical ratings. The lexical techniques do not require labeled data to train a model. The reviews or ratings are accessed through the average total ratings for each word rather than through a single word. Context, circumstances, human assessments, mood, and emotions all play a role.

The input text determines the semantic score, associating lexical properties with intensity. VADER excels at using acronyms, slang, and emoticons in conversations. By adding together the different token scores, determine the total sentiment score for each document (post, article, tweet, etc.). Each token is given a sentiment polarity score from VADER, indicating whether it is positive, negative, or neutral. The sentiment ratings should align with the associated timestamps of cryptocurrency price data. In short, VADER excels in swiftly analyzing sentiment in text data, making it appropriate for real-time applications and large-scale social media monitoring. Its rule-based design enables it to catch emotional subtleties to some level, but it may struggle with recognizing context and irony, leading in occasional mistakes.

VADER produces three scores: "Positive," "Negative," and "Neutral," which indicate the percentages of text that fall into each category. The analysis also produces a fourth output, the "Compound" score. It is a normalized value that ranges from +1 (most extreme positive) to -1 (most extreme negative), combining the three outputs. This weighted, normalized composite score is a commonly used indicator of sentiment. The daily sentiment scores are calculated by averaging the daily compound score. A threshold is defined for compound score accordingly, and the sentiment is classified as positive, neutral or negative. For example, If the compound score is greater than or equal to 0.05 it is considered positive sentiment. If the compound score is less than or equal to -0.05 it is classified as negative. It is in the neutral class if it is less than 0.05 and greater than -0.05.

2) BERT

The BERT model, contrary to convolutional and RNN, is a pre-trained model that employs the encoder component of the Transformer as the model's foundation. The BERT model may be extended to very deep depths thanks to the strength of the transformer encoder, completely using the characteristics of deep neural network models and enhancing model accuracy. After the pre-training phase, the model can easily capture the deep abstract features of the statements because of the excellent word vector expression and model parameters. As a result, the fine-tuning phase of the model mainly entails training the output layer's parameters and slightly modifying the pre-trained model, which guarantees the fine-tuning phase's convergence speed and classification accuracy.

As a transformer-based approach, BERT has revolutionized natural language processing applications, including sentiment analysis. It demonstrates extraordinary contextual comprehension, making it particularly proficient at recognizing complicated sentiment patterns, sarcasm, and context-dependent sentiment alterations. However, the computational complexity of BERT models might be negative, making them less appropriate for real-time or resource-constrained applications. Moreover, fine-tuning BERT models for particular sentiment analysis tasks requires a large quantity of labeled data.

By merging the contextual knowledge of BERT with the efficiency of VADER, we intend to produce a sentiment analysis technique that excels in accuracy, context awareness, and efficiency. Our hybrid model tries to alleviate the limits of separate models while maximizing their respective benefits, giving a more adaptable solution for sentiment analysis.

3) PROPOSED HYBRID MODEL

We propose a BERT and VADER hybrid model, as shown in Figure 7, which combines the advantages of the BERT and VADER models to examine sentiment trends about the present cryptocurrency offerings on the market. This methodology integrates deep learning methods with sophisticated lexical rule-based procedures to provide a thorough understanding of sentiment dynamics. Initially, the gathered data was cleaned by removing noise. The data may contain unnecessary information like hashtags, URLs, and emotions. This cast of personalities makes sentiment analysis a difficult task. Data preprocessing is a crucial stage in sentiment analysis since it affects how well the subsequent processes work.

The common preprocessing steps include changing words to lowercase, stemming from getting rid of tense differences, and using regular expressions for pattern-based cleaning. By guaranteeing consistent word representation, this technique supports sentiment analysis. We eliminated hashtags, quotations, question marks, and https links, which might create bias in the findings of sentiment analysis using preprocessing programs and regular expressions that were readily accessible. Regular expressions were extremely helpful to find and clean up certain text patterns and improve the quality of the data for analysis.

The lexicon-based models VADER and TextBlob were weighted averaged in our hybrid ensemble model, yielding the following weights: VADER 0.45 + TextBlob 0.55. TextBlob was given a greater weight of 0.55 because it had better positive sentiment classification accuracy than VADER [44]. The averaged output was merged with the BERT deep learning model using rule-based constructs. The lexical models fared better for positive feelings, whereas the BERT model performed better for neutral and negative attitudes. To combine them, IF-ELSE rule-based programming constructs were used. The IF-ELSE criteria picked a positive output as the final output of the ensemble if the result of the lexicon-based weighted averaging was positive; otherwise, for neutral and negative emotions, the output of the BERT model was favored as the final ensemble output sentiment as illustrated in Figure 7 and mentioned in the Pseudocode 3.

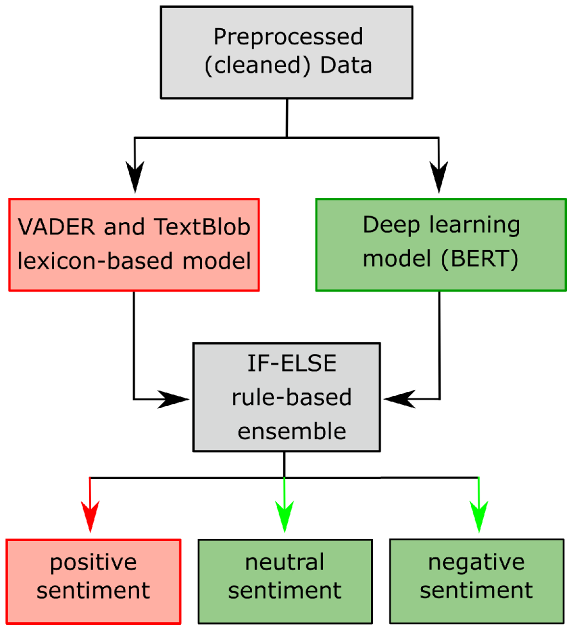

FIGURE 7. A BERT and VADER-based hybrid model for sentiment analysi.

Algorithm 3 :Steps of Hybrid Algorithm

Input: input text (TEXT)
Output: Classified sentiment
1: Initialization:
Lexicon weight VADER = 0.45,
Lexicon weight TEXTBLOB = 0.55
2: Use VADER and TEXTBLOB to calculate weighted average sentiment scores for input (TEXT):
Avg sentiment score = (lexicon weight VADER * VADER score) + (lexicon weight TEXTBLOB * TEXTBLOB score)
3: **if** (Avg sentiment score >= 0:) **then**
4: Set lexicon output = "positive
5: **else**
6: Set lexicon output = "neutral/negative"
7: **end if**
8: Use BERT deep learning model to predict (TEXT) sentiment:
Set BERT output = BERT model(TEXT)
9: **if** (lexicon output == "positive") **then**
10: Set ensemble output = lexicon output
11: **else if** (BERT output == "neutral" OR BERT output == "negative") **then**
12: Set ensemble output = BERT output
13: **end if**

IV. MATERIALS AND EVALUATION METRICS

This section describes the data used by the proposed models in detail. It also includes information about the evaluation metrics that have been used to evaluate the framework in the result section afterwards.

A. DATA DESCRIPTION

The input data and its technical and sentiment analysis processing are provided below.

1) DATA FOR TECHNICAL ANALYSIS

The historical data is fetched from the Binance website (https://www.binance.com/). Our customized code fetches the original cryptocurrency price values by calling the "get_binance_data" function with a provided cryptocurrency symbol, start date, end date, and interval (symbol, start_date, end_date, interval). This function requests an API to Binance using the method client.get_historical_klines(...), which retrieves historical price data for the specified date range and interval. After fetching the raw data, the function processes it by iterating through each entry and extracting the timestamp and opening price. The timestamp is converted to a readable date format and is stored in the formatted_data list. Once this function completes its execution, the original values (opening prices) are then extracted and stored in the original_values list using the line: original_values = [float(entry['price']) for entry in historical_data].

2) DATA FOR SENTIMENT ANALYSIS

The data sources for sentiment analyzers are Twitter, CoinDesk, and CoinMarketCap. Our customized written program fetches recent news (past hour) from CoinDesk and CoinMarketCap using their APIs. From Twitter, news was fetched from top-profile investors in Binance, ETH and BTC. For Twitter data collection, we used the tweepy library to fetch recent tweets from specific users. First, we import datetime from datetime, timedelta using tweepy. To fetch from "CoinDesk Data Collection", import requests were made by the command: COINDESK_API_URL = "https://api.coindesk.com/v1/bpi/currentprice.json". For "CoinMarketCap" data collection, the following API is used: COINMARKETCAP_API_URL: "https://pro-api.coinmarketcap.com/v1/cryptocurrency/listings".

B. EVALUATION METRICS

The evaluation of the trained models entails a thorough analysis using various performance criteria. These parameters are essential gauges of how well the models predict the digital currency values. The important metrics listed below are used for thorough evaluation:

- Mean Absolute Percentage Error (MAPE) measures the typical percentage difference between the predicted and observed values, offering information about the forecasting accuracy of the models. The equation 9 presents the formula for MAPE.
- Mean Absolute Error (MAE) measures the accuracy of the models by expressing the average absolute difference between predicted and actual values. The equation 10 presents the formula for MAE.
- Root Mean Squared Error (RMSE), which gives more weight to larger errors and provides a thorough picture of predictive ability, computes the square root of the average squared disparities between projected and actual values. The equation 11 presents the formula for RMSE.
- Mean Squared Error (MSE) measures how well a model can account for fluctuations in the data by averaging the squared discrepancies between anticipated and actual values. The equation 12 presents the formula for MSE.

$$MAPE = \frac{1}{N}\sum_{x=1}^{N}\frac{|v_x - \hat{v}_x|}{|v_x|} * 100 \tag{9}$$

$$MAE = \frac{1}{N}\sum_{x=1}^{N}|v_x - \hat{v}_x| \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{x=1}^{N}\left(v_x - \hat{v}_x\right)^2} \tag{11}$$

$$MSE = \frac{1}{N}\sum_{x=1}^{N}(v_x - \hat{v}_x)^2 \tag{12}$$

where, v_x and $\hat{v}_x$ are the actual and predicted values, respectively.

V. RESULTS

A. TECHNICAL ANALYSIS

With a focus on sharp volatility, the goal is to use machine learning to anticipate cryptocurrency prices in real-time. We use machine learning models to anticipate cryptocurrency prices at short intervals after they have been well-trained for the historical data. Our experimental investigation used four other prediction models, including LSTM, CNN, MLP, and LR, to evaluate our proposed hybrid model and its predictive abilities. We have shown our results for three top-10 cryptocurrencies: BTC, ETH, and Dogecoin. We thoroughly analysed our prediction models under various training time situations to identify the best training dataset for producing the most accurate prediction outcomes. Our models were specifically trained using historical trend data for cryptocurrencies covering 2, 4, 12, and 48 weeks.

There is an inherent risk when retraining the model on predicted values, which could result in compounding errors and an increased error rate in subsequent predictions. The robustness of the model is preserved by sticking to the use of a pre-trained model based on real values. Additionally, a cautious approach to data integrity drives the decision to use historical data with actual values rather than predicted values for model training. The supplemental material (S10 - S13) offers a thorough analysis showing that improving model performance solely by adding training data points is not guaranteed.

The findings of these training situations and their accompanying evaluation metrics are discussed in the following sections, providing readers with an in-depth understanding of how effectively our models perform when trained for different periods.

1) 1ST SCENARIO: (2 WEEK'S TRAINING DATA)

Using a 2-week historical dataset with 4032 data points covering the period from June 15, 2023, to June 30, 2023, we trained our models to forecast prices for the subsequent hour. The subsequent 24-hour prediction prices were created at 5-minute intervals, yielding 288 displayed data points in total. Figure 8 (a) shows the results of this modeling work for BTC. Even though the graph shows that the prediction trend and the actual price trend are closely related, it is noteworthy that the error rate is substantially higher. An error calculation was performed using the evaluation metrics values for all five models, as shown in Table 1. This indicates our proposed model error rate is lowest compared to other models.

The computation of the training data points is performed as follows:

Total hours in a day × Number of days × data points per hour

The training data points from 2 weeks or 14 days with 12 data points from every hour results in a total of 4032 training data points.

2) 2ND SCENARIO: (4 WEEK'S TRAINING DATA)

In this scenario, we estimate the price of a cryptocurrency for the next day by training our models leveraging a 4-week historical dataset that includes data from June 1, 2023, to June 30, 2023. The training data points from 4 weeks or 28 days with 12 data points from every hour results in a total of 8064 training data points. The subsequent three days' prediction prices were created at 15-minute intervals, yielding 288 displayed data points in total.

Prices were predicted for three cryptocurrencies: BTC, ETH, and Dogecoin. The outcomes as the forecast of our proposed model are shown in Figure 2 (b), (c), and (d), respectively. Additionally, we could compare the price prediction graph for BTC for the 2-week and 4-week training scenarios in Figure 2 (a) and (b), respectively, to highlight the impact of the training dataset time frame. This comparison readily indicates that, compared to the 2-week training dataset, the anticipated price graph generated from the 4-week training dataset closely resembles the actual values.

Furthermore, we computed error rates and recorded them in Tables 1 for the 2-week training dataset and Table 2 for the 4-week training dataset, concentrating on the proposed model to quantify this performance difference. The comparison reveals unequivocally that the model trained with a 4-week dataset performs better than the two-week training. Using the LSTM, CNN, MLP, and LR models, we expanded our analysis to include ETH and Dogecoin. Table 2 also shows the corresponding error rates for these two cryptocurrencies.

Surprisingly, the proposed hybrid model continuously displayed the lowest error rate across all three currencies, highlighting its efficacy in predicting cryptocurrency prices over various training times. For readers' interest, we plot the outcomes from all five models for BTC price prediction in supplementary **S1**. This comparison enables a comprehensive evaluation of model performance. We computed error rates for all currencies using all five models to quantify and compare the performance of our models. Moreover, the predicted plots for ETH and Dogecoin are plotted using all five models and shown in supplementary materials S2 and S3, respectively.

3) 3RD SCENARIO: (12 WEEK'S TRAINING DATA)

Our goal in this scenario is to forecast cryptocurrency prices for the next three days using a 12-week historical dataset. This dataset, which covers April 1, 2023, to June 30, 2023. The training data points from 12 weeks or 84 days with 4 data points from every hour results in a total of 8064 training data points. With 288 displayed data points, the projection prices for the following three days were calculated at 15-minute intervals. The graph in Figure 9 (a), (b), and (c) shows the results of proposed model-based price predictions for BTC, ETH, and Dogecoin, respectively. The findings are shown in Table 3. Notably, the Bi-LSTM model consistently produced the lowest error rates across all the currencies studied, suggesting its strong predictive skills for cryptocurrency values under the circumstances described in this scenario. The plots for BTC, ETH, and Dogecoin for all models are presented in supplementary materials S4, S5, and S6, respectively.

4) 4TH SCENARIO: (48 WEEK'S TRAINING DATA)

In this scenario, cryptocurrency price forecasts for the next 12 days were calculated using a rigorous training procedure on a large historical dataset covering 48 weeks. The training data points from 48 weeks or 336 days with 1 data point from every hour results in 8064 training data points. The data points were taken from August 1, 2023, to June 30, 2023. Hourly intervals were used to construct the price forecasts for the next 12 days, which resulted in 288 plotted data points. We used the Bi-LSTM model as our forecasting tool because it was specifically created for BTC, ETH, and Dogecoin price prediction. Figure 10 shows the outcomes of Bi-LSTM model-based BTC, ETH, and Dogecoin price forecasts, respectively.

The supplementary materials S7, S8, and S9 show the price prediction results from BTC, ETH, and Dogecoin models, respectively. This would help with a thorough comparison examination of BTC price forecasts. We computed error rates for all currencies using the five models under consideration to thoroughly assess and compare the performance of all models across all cryptocurrencies, and the results are shown in Table 4. Interestingly, the Bi-LSTM model continually showed the lowest error rates for all the currencies evaluated, highlighting its effectiveness and dependability in properly forecasting cryptocurrency prices, even in the challenging environment of this lengthy 48-week training scenario.

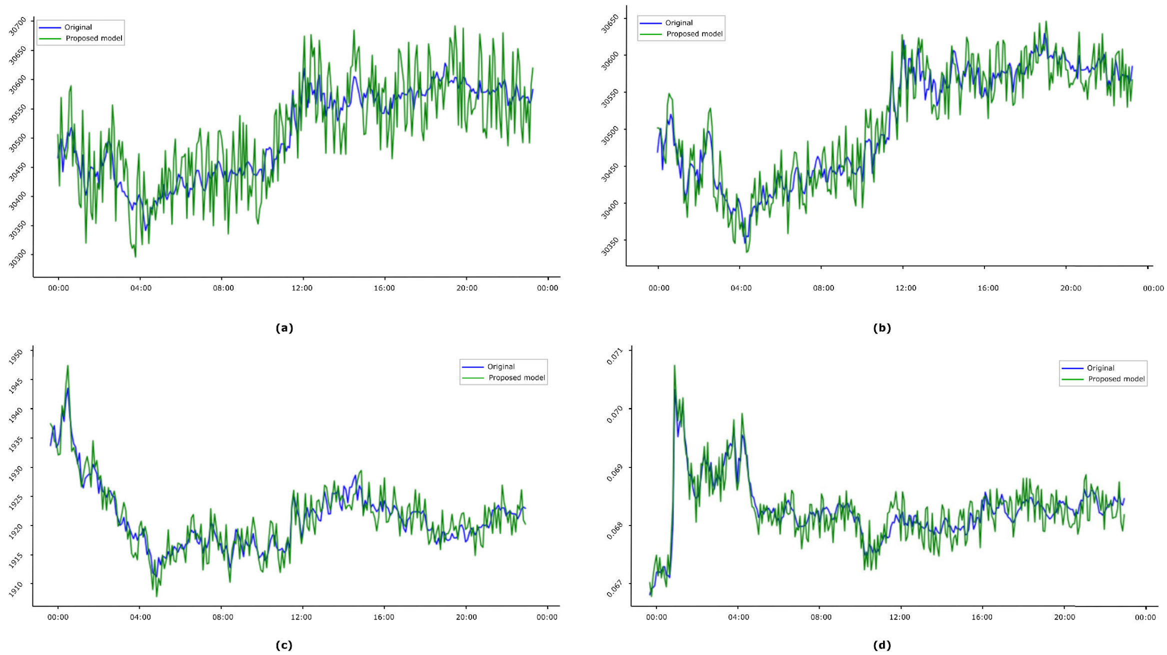

FIGURE 8. Price prediction by training the Bi-LSTM model with 2 weeks (only for BTC) and 4 weeks for (BTC, ETH and Dogecoin) prior data. The graphs display (actual and predicted) values at 5-minute intervals over 24 hours. (a) and (b) shows the graph with 2 and 4 weeks of training data for BTC, respectively. (c) and (d) shows the graphs with 4 weeks of training data for ETH and Dogecoin, respectively.

TABLE 1. Two weeks training data with 4032 data points.

Model	MAPE	MAE	RMSE	MSE
LSTM	0.7575	14.56	16.86	284.3
CNN	0.9803	18.84	21.92	480.4
LR	1.006	19.34	22.09	488.1
MLP	1.425	27.39	31.95	1021
Proposed model	**0.3847**	**0.7821**	**0.1349**	**0.0182**

The technological advantages provided by our model are found in its ability to provide accurate price forecasts in an incredibly brief duration. Our methodology enables users to make split-second, data-driven decisions, successfully capitalizing on lightning-fast market fluctuations by providing real-time insights and forecasts.

It is to be noted that the training data sample points were kept constant (a total of 8064 data points) while changing the historical data period. Notably, the proposed hybrid model shows the lowest error rate among the models tested in this scenario. We have introduced additional scenarios for assessing our suggested model to provide a better assessment. By constructing scenarios with varied quantities of training points and prediction windows, we acquire a more thorough picture of our model's performance. These expanded scenarios serve as useful testing grounds, allowing us to analyze the model's flexibility and resilience under varied settings. The specifics of these extended scenarios are explored below, boosting our insights' trustworthiness and the prediction model's adaptability.

5) EXTENDED SCENARIOS

We have proposed a hybrid model intended to maximize the prediction of cryptocurrency values, and its performance has been carefully verified across numerous training sessions to ensure optimum outcomes. In the aforementioned experimental situations, we applied our proposed hybrid model for cryptocurrency price prediction, utilizing varied training durations ranging from 2, 4, 12, to 48 weeks, all while keeping a consistent dataset size of 8064 data points. An important concern typically arises is whether the model's performance might be further boosted with increased training data points. To answer this issue thoroughly, we ran an extensive series of tests, expanded forth below.

TABLE 2. Four weeks training data with 8064 data points.

Model	Currency	MAPE	MAE	RMSE	MSE
LSTM	BTC	0.4946	9.506	10.99	120.7
	ETH	0.1517	2.915	3.343	11.17
	DOGE	0.2546	4.895	5.648	31.90
CNN	BTC	0.6851	13.17	15.42	237.6
	ETH	0.4978	9.568	11.02	121.5
	DOGE	1.0158	19.52	22.31	497.7
LR	BTC	1.007	19.36	22.37	500.8
	ETH	0.7775	14.94	16.91	286.2
	DOGE	0.4664	8.967	10.43	108.8
MLP	BTC	0.9412	18.09	21.26	452.1
	ETH	0.9531	18.32	21.42	458.9
	DOGE	0.9603	18.46	20.95	439.0
Proposed model	**BTC**	**0.0580**	**0.115**	**0.0265**	**0.0007**
	ETH	**0.0157**	**1.215**	**0.1667**	**0.0278**
	DOGE	**0.1260**	**0.535**	**0.1212**	**0.47**

In these trials, the suggested model underwent training for diverse periods, including variable amounts of data points, while ensuring that the training time remained constant.

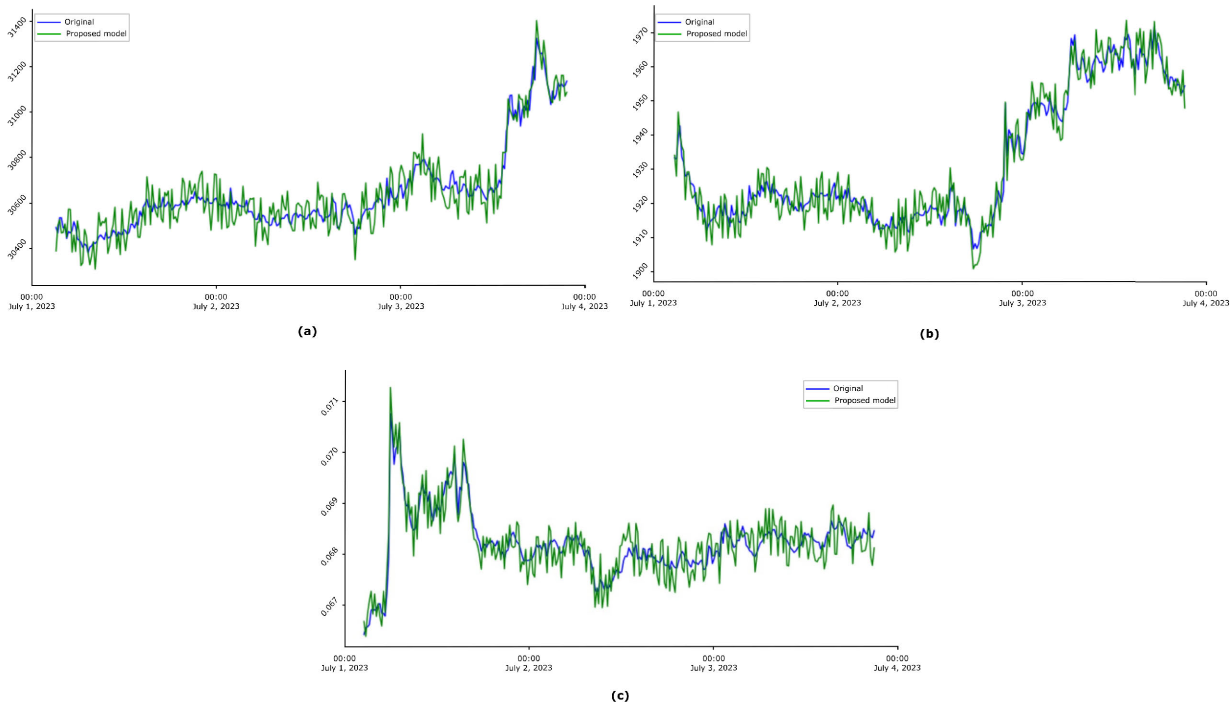

FIGURE 9. Graphs generated as a result of 12 weeks of training data points. The predicted and actual values are plotted at 15-minute intervals over 3 days. (a), (b) and (c) show the BTC, ETH, and Dogecoin graphs, respectively.

TABLE 3. 12 weeks training data with 8064 data points.

Model	Currency	MAPE	MAE	RMSE	MSE
LSTM	BTC	0.4990	9.593	11.11	123.4
	ETH	0.2009	3.862	4.396	19.33
	DOGE	0.3566	6.854	7.908	62.54
CNN	BTC	0.5764	11.08	12.96	167.9
	ETH	0.6372	12.25	14.29	204.2
	DOGE	0.9588	18.43	21.39	457.7
LR	BTC	0.5342	10.27	11.99	143.7
	ETH	0.8193	15.75	18.29	334.6
	DOGE	1.445	27.77	32.06	1028
MLP	BTC	0.6258	12.03	13.92	193.7
	ETH	0.6536	12.56	14.41	207.6
	DOGE	1.251	24.04	27.32	746.5
Proposed model	**BTC**	**0.0642**	**0.221**	**0.0361**	**0.0013**
	ETH	**0.0214**	**0.1685**	**0.0284**	**0.0021**
	DOGE	**0.0148**	**0.417**	**0.1330**	**0.0177**

TABLE 4. 48 weeks training data with 8064 data points.

Model	Currency	MAPE	MAE	RMSE	MSE
LSTM	BTC	0.7295	14.02	16.47	271.2
	ETH	0.3670	7.056	8.231	67.74
	DOGE	0.9789	19.207	18.86	118.1
CNN	BTC	0.6372	12.25	14.28	204.2
	ETH	0.9944	19.11	22.23	494.3
	DOGE	1.125	21.64	24.88	619.2
LR	BTC	1.204	23.15	26.70	713.1
	ETH	56.57	20.65	22.64	512.8
	DOGE	1.589	30.55	35.31	1247.3
MLP	BTC	1.532	29.45	33.56	1126
	ETH	0.9145	17.57	19.85	394.0
	DOGE	1.185	22.78	26.19	685.8
Proposed model	**BTC**	**0.0574**	**1.054**	**0.0458**	**0.0021**
	ETH	**0.0290**	**0.1787**	**0.0374**	**0.0014**
	DOGE	**0.0247**	**0.5105**	**0.1217**	**0.0148**

The next part thoroughly explains the output outcomes acquired from these varied settings. Our study involves a comprehensive investigation of training period modifications and dataset sizes, finally giving information on the model's flexibility and resilience. The insights gathered from these lengthy studies testify to the adaptability and usefulness of our hybrid model in forecasting cryptocurrency values across diverse scenarios.

4 week's training (14400 data points):

In this specific scenario, our suggested model undergoes training on a dataset including BTC, ETH, and Dogecoin data over four weeks in June 2023. The dataset used for training is robust, consisting of 14,400 data points recorded at regular intervals of every 3rd-minute. The training data points from 4 weeks, including 1 day before and after or 30 days in total, with 20 data points from every hour results in 14,400 training data points. Subsequently, after the successful training of our model, a prediction graph is generated for BTC, ETH, and Dogecoin to analyse the model performance, as shown in supplementary material S10. These summarize the model's one-day estimates for July 1, 2023. The graph exhibits 288 prediction values corresponding

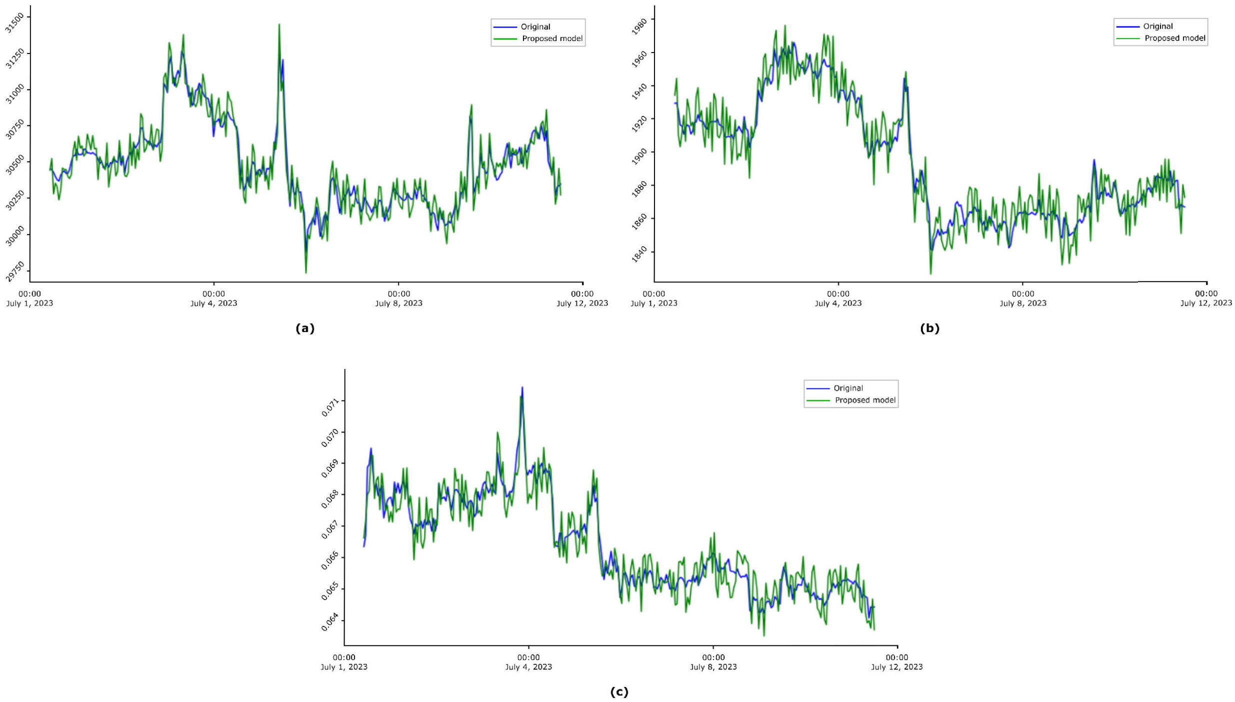

FIGURE 10. Graphs generated as a result of 48 weeks of training data points. The predicted and actual values are plotted at 60-minute intervals over 12 days. (a), (b), and (c) show the graphs for BTC, ETH, and Dogecoin, respectively.

to each 3rd-minute interval inside the specified prediction window. Moreover, the assessment metrics computation is described in supplementary material T1.

4 week's training (43200 data points):
In this scenario, the model training on 4 weeks of data from June with 43200 points was performed. The training data points from 4 weeks, including 1 day before and after or 30 days in total, with 60 data points from every hour results in 43,200 training data points. The core of this technique resides in the thorough separation of the training process for each cryptocurrency, enabling the model to capture the particular subtleties and patterns associated with each digital asset. The predictive values of this extended training approach are illustrated as a graph in the supplementary material S11, which exhibits the prediction graphs for each cryptocurrency. The evaluation performance measures are calculated and provided in the supplementary material T2, presenting a detailed assessment of the model's predictive capabilities and emphasizing its strengths and areas of development.

8 week's training (17280 data points):
The training procedure includes an extended eight weeks of historical data, notably encompassing the month of May and June 2023. The model is trained on 17,280 training points, with data collected at regular 5-minute intervals. The training data points from 8 weeks including 2 days before and after or 60 days in total with 12 data points from every hour results in 17,280 training data points. This intentional selection of data frequency guarantees that the model is exposed to a constant supply of cryptocurrency market data, boosting its potential to catch real-time patterns and changes in cryptocurrency values with heightened accuracy. The predicted price graph for July 1, 2023, comprising 288 prediction points, is shown in supplementary material S12. The evaluation metrics for this scenario are mentioned in supplementary material T3.

12 week's training (25920 data points):
In this scenario, a 12-week training session includes data from April, May, and June 2023. With a dataset of 25,920 training points gathered at 5-minute intervals, the model develops the capacity to capture real-time patterns and market changes properly. The training data points from 12 weeks including 3 days before and after or 90 days in total with 12 data points from every hour results in 25,920 training data points. The training concludes on July 1, 2023, with a prediction graph comprising 288 forecast points at accurate 5-minute intervals. Supplementary material S13 illustrates this graph, presenting a visual picture of the model's predictive capabilities. In addition to showing predictions, we assess the model's performance using extensive measures in supplementary material T4.

In analysing these extended situations, a clear tendency emerges: the incremental addition of training data points does not generate substantial gains in predicting accuracy. While the projections often track the original price trend, they demonstrate a larger error rate. This problem may be related to a possible issue of data overfitting, where the model becomes too customized to the training data, making it less adaptive to larger market changes.

6) RELATIVE COMPARISON OF THE PROPOSED MODEL

In analyzing the importance of our work within the cryptocurrency price prediction area, we refer to Table 5, which serves as a clear benchmark for our model's performance in contrast to current competitive methodologies. What makes this comparison analysis helpful is that it goes beyond a basic listing of methodology and gives insight into the assessment metrics supplied by this research. Across a variety of cryptocurrencies and prediction approaches, our suggested model outperformed. It exceeds previous methodologies regarding predicted accuracy, resilience, and flexibility. These results emphasize the usefulness of our technique in navigating the complexity of the digital currency market, proving its relevance and application as a valuable prediction tool.

B. SENTIMENT ANALYSIS

This section shows the results of our suggested BERT-VADER ensemble model for sentiment analysis. Table 6 presents instances of sentiments categorized by our model, demonstrating its efficacy in encapsulating various sentiments. Table 7 shows how VADER computes positive sentiments. The threshold value used for compound score is the same as mentioned in the previous section, "Proposed hybrid model". A real-time example is also provided to support the findings, showing how positive sentiments are associated with increases in BTC price and negative sentiments with price decreases.

The candlestick chart in Figure 11 illustrates a full visual picture of the dynamic interaction between feelings and the price changes of BTC. Crypto candlestick charts serve as a condensed information source, offering essential facts about the asset's trading activities over time. This chart, particularly, summarizes the performance of BTC over a set period, displaying its starting and closing prices and the highest and lowest values within this window, making it important for traders and analysts. Initially, the chart depicts a reasonably steady time for BTC, with values bouncing within a band of 25,000 to 29,000. However, a key crossroads emerged before June 15, 2023, when the influence of multiple positive sentiment news spike became undeniably obvious.

Following are some sentiments that were classified as positive by the VADER model. A quote by R. F. Kennedy: "Potential biases in traditional banking, emphasizing BTC's decentralized nature." Another positive sentiment identified at this time arrives from the U.S. Secretary: "Crypto regulatory scrutiny, possibly making BTC a preferred 'safe' asset". These sentiments ignited a huge upsurge in BTC's value, marking a "Bullish" condition, which ended after a short time on June 23, 2023. During this time, BTC's price soared to 31,500, which is represented by the green arrow. Following the bullish phase, the chart illustrates a continuous but more confined price volatility within the region of 29,400 to 31,500.

However, a noticeable change happens when a surge of negative sentiment news materializes. Following are a couple of negative sentiments classified by BERT. "The exhaustion of US household excess savings indicates a reduced potential for retail investment into assets like BTC." Moreover, another negative sentiment, "UST 10-year yield hitting 4.42%, its highest level since 2011, suggests a shift of investor preference towards traditional safe-haven assets, possibly diverting funds away from riskier investments like cryptocurrencies." is identified at the same time.

This combination of diminished discretionary income and a shifting interest rate environment undoubtedly led to the downward pressure on BTC prices. This indicates the commencement of a "Bearish" condition, ushering in a visible downward trend in BTC's worth. The red arrow represents This downward track, demonstrating BTC's drop from 29,400 to 25,600. This negative phase remains until the blue arrow signifies the conclusion of the downturn.

In short, this candlestick chart is a great tool for understanding the intricate link between mood and cryptocurrency price changes. This illustration clearly demonstrates the responsiveness of BTC's value to both positive and negative feelings, giving it an important tool for traders and analysts dealing with the unpredictable nature of the cryptocurrency market. The merging of sentiment analysis with technical analysis signifies an unprecedented achievement. As seen in the preceding instance, real-time sentiment may tremendously affect the market. Data will inject volatility and uncertainty into the forecasting system depending entirely on technical analysis. Consequently, sentiment analysis emerges as a crucial component of our proposed model, providing depth and durability to its predictive capabilities.

Positive or negative sentiments could significantly impact cryptocurrency prices as shown in Figure 11, marked by swings between bullish and bearish states. By incorporating market trends, regulatory frameworks, and economic policies into our analysis, we hope to understand better the dynamics affecting cryptocurrency prices during transition periods. This will offer insightful information about the interaction between sentiment and underlying market variables.

The sentiments that could potentially affect the crypto prices are evaluated by our proposed model on the publicly available dataset namely "First GOP Debate Twitter Sentiment" available on Kaggle. The dataset comprises 13,907 entries with 2247 positive, 3148 neutral, and 8512 negative sentiments. The true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values were 2134, 11105, 241, and 427, respectively. These values were used to compute the evaluation metrics, including sensitivity, specificity, accuracy, and F1-score as mentioned in equation 13, 14, 15, and 16, respectively.

$$Sens. = \frac{TP}{TP + FN} \tag{13}$$

$$Spec. = \frac{TN}{TN + FP} \tag{14}$$

$$Acc. = \frac{TP + TN}{TP + TN + FP + FN} \tag{15}$$

TABLE 5. Relative comparison of the proposed model with competitive existing techniques for cryptocurrency price prediction.

Study	Methodology	Objective	Targeted currency	Forecast duration	Evaulation metrics
[38]	AR, LSTM	Forecasting BTC price while improving the input variables for LSTM	BTC	71 days	RMSE: 247.33
[45]	ARIMA	Prediction using ARIMA	BTC	10 days	AR: 98.25%, MA: 87.58%, ARIMA: 90.31%
[46]	LSTM, ARIMA, GRU	Use LSTM, ARIMA, and GRU for time series prediction	BTC	492 days	RMSE LSTM:603.68%, ARIMA: 305.53, GRU:381.3%
[47]	PSO with SVM	Optimized SVM with particle swarm optimization	BTC, Litecoin, Ripple, ETH, Nem	360 days	Accuracy BTC: 90.4, Litecoin 92.1, Ripple 82.8, ETH 97, Nem 57.8
[41]	PSO with SVM	Use Artificial NN and LSTM predict the crypto price	BTC, ETH, Ripple, Stellar, Litecoin, Monero	1, 10, 20, 30 days	RMSE for BTC: 53.30, 67.99, 91.41, 45.71, for 1, 10, 20, and 30 days, respectively.
[48]	LSTM, HMM, GA	BTC dynamics understanding to optimize the prediction mechanism	BTC	3 days	RMSE for LSTM-HMM: 7.006, LSTM-HMM: 5.82, respectively.
[8]	SVM, RF, LSTM	A Use set of high-dimension features for BTC daily price prediction	BTC	1 days	Accuracy/Precision: 0.549/0.765, 0.648/0.731, and 0.672/0.722 for SVM, RF, and LSTM, respectively.
[49]	ANN, LSTM	Use ANN and LSTM to predict price fluctuations	BTC, ETH, Ripple	1, 3, 5, 7, 14 days	MSE: 2.0 (1 day) and 66 (7 days) as lowest and highest for ETH.
[9]	GRU	Use GRU with dropout for better results	BTC	15, 45, 60 days	RMSE: 0.019, 0.017, and 0.034 for GRU, GRU-dropout, and GRU-dropout-GRU, respectively.
[11]	GRU and LSTM		BTC	1, 3, 5, 7, 15 days	RMSE for LSTM/GRU 0.092/0.075, 0.079/0.065, 0.081/0.087, 0.045/0.051, and 0.067/0.067 for 1, 2, 5, 7, and 15 days, respectively.
[12]	MLP and LSTM	Stochastic model that is input with market statistics and reactions	BTC, ETH	180 days	RMSE: 0.0691 and 0.0608, 0.0469 and 0.0557, and 0.0570 and 0.0547 using MLP and LSTM models, respectively, for BTC, ETH, and LSTM price prediction.
[50]	ANN and SVM	Stochastic model that is input with market statistics and reactions	ETH	1 day	RMSE: 0.068 and 1.306 for ANN and SVM, respectively.
[51]	NN and LSTM with Bayesian optimization,	A hybrid ANN model using LSTM and Bayesian optimization	BTC	-	MAE: 2300.24
[52]	RL	Reinforcement Learning algorithm to predict crypto prices	Litecoin, Monero	3, 7, 30 days	RMSE: 4.0048/5.1838, 3.1692/7.3865, and 5.9518/20.4594 for Litecoin/Monero for 3, 7, and 30 days of prediction, respectively.
Proposed model	Bi-LSTM with GRU,	A Bi-LSTM and GRU hybrid model	BTC, ETH, Dogecoin	1, 3 days	Avg. RMSE 0.0361, 0.0775, and 0.1253 for BTC, ETH, and Dogecoin, respectively.

$$F1 = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{16}$$

For a concise overview of the sentiment model's evaluation performance, Figure 12 presents a confusion matrix. As indicated by the following metrics, the suggested sentiment analysis model has performed exceptionally well: sensitivity (83.33%), specificity (97.88%), accuracy (95.20%), and F1 score (86.57%). The model's accuracy of more than 95% highlights its dependability and potential as a reliable tool for putting in place a strong cautionary mechanism in the unstable cryptocurrency market.

The performance of our suggested model is rigorously compared with a recent competitive study. Table 8 demonstrates the promising outcomes of our proposed model. Moreover, in the dataset context, our model outperforms

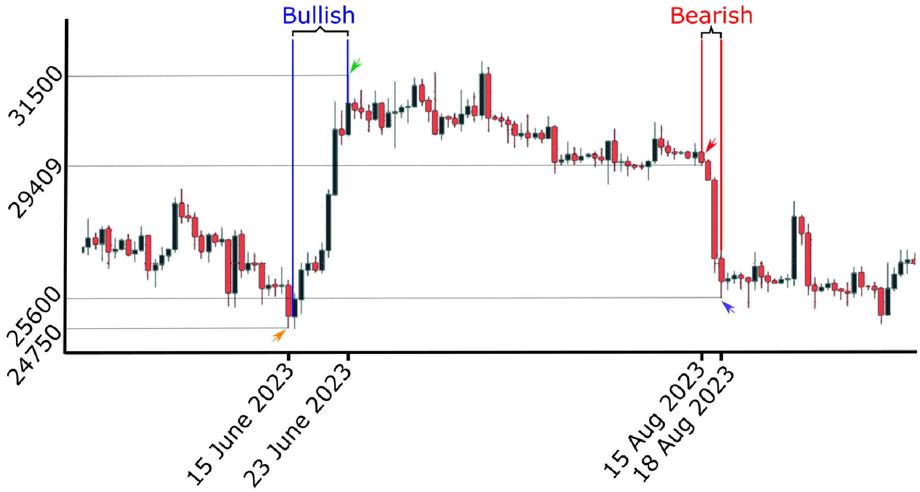

FIGURE 11. Trend of BTC showing bullish and bearish condition. The orange arrow shows the BTC's lowest price before a bullish state. The green arrow shows the maximum price reach. The red and blue arrows show the start and end of the bearish state, respectively.

TABLE 6. Examples of positive, neutral and negative sentiment classification by our proposed model.

Class	Sentiment statements
Positive	One should buy BTC these days.
	Great project with huge potential heading to the moon #Ethereum.
Neutral	Nigeria is unique; the young people there were enthusiastic about it and said, "Bring in the BTC, screw everything else, let's do this.
	Investors are cautious, and the market is stable with no significant positive or negative factors.
Negative	BTC no longer worth the mining cost
	Reality is very bad for #ETH.

TABLE 7. Examples of VADER positive (Pos), neutral (Neu), negative (Neg), and compound sentiment scoring.

Statement	Pos	Neu	Neg	Compound
One should buy BTC these days	0.32	0.58	0.00	0.39
Great project with huge potential heading to the moon #Ethereum	0.42	0.67	0.00	0.73

TABLE 8. Performance comparison of the proposed sentiment analysis model with the competitive study on First GOP Debate Twitter Sentiment dataset. GS stands for Gold standard. ([In %].).

Study	Model	Sens.	Spec.	F1	Acc.
[53]	TextBlob	-	-	-	60.63
	VADER	-	-	-	61.08
	Naïve Bayes	-	-	-	86.21
	TextBlob with GS	-	-	-	73.93
	VADER with GS	-	-	-	74.68
	Naïve Bayes with GS	-	-	-	91.72
Proposed	BERT-VADER	**83.33**	**97.88**	**86.57**	**95.20**

existing methods, demonstrating its efficacy and potential as a sophisticated and dependable tool for sentiment analysis.

The proposed benchmark Bi-LSTM-GRU model and its enhanced version Bi-LSTM-GRU with BERT-VADER model are evaluated. Evaluation metrics of both models have been

TABLE 9. Performance comparison of the integrated Bi-LSTM-GRU-BERT-VADER (BLGBV) model with the Bi-LSTM-GRU benchmark model.

Model	Targeted currency	RMSE
Bi-LSTM-GRU	BTC	0.0361
	ETH	0.0775
	Dogecoin	0.1253
BLGBV	BTC	0.0241
	ETH	0.0645
	Dogecoin	0.0978

carried out to determine the efficacy of this integration. Table 9 shows the result comparison of the Bi-LSTM-GRU model with the Bi-LSTM-GRU-BERT-VADER (BLGBV) model. It is noted that integrating the BERT-VADER model with the Bi-LSTM-GRU model improves the results by lowering the RMSE. The best results are achieved for BTC, where the RMSE value improves by 33.24%, then for dogecoin by 21.84% and finally ETC by 16.77%. The results show there is a significant contribution of the BERT-VADER model in the output predicted results.

VI. DISCUSSION

The system we have presented for cryptocurrency price prediction utilizes machine learning methods and historical data, delivering a helpful tool for investors seeking insights into the extremely dynamic and volatile crypto market. In addition to using a better hybrid machine learning model, what sets our approach distinct is the novel inclusion of a warning flag-raising mechanism, which plays a crucial role in alerting investors to possible sentiment-driven price changes. This method serves as a safety, prepared to inform investors when strong positive or negative feelings arise that might lead to major swings in the digital currency market. Incorporating the cautionary measure feature is a unique technique that fills a significant need in cryptocurrency prediction models.

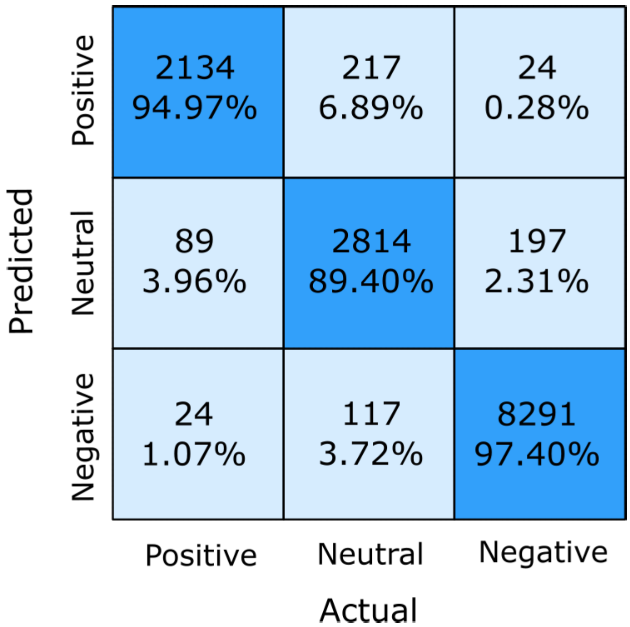

FIGURE 12. Confusion matrix of the proposed sentiment analysis model for the publically available dataset "First GOP Debate Twitter Sentiment".

While technical data analysis forms the cornerstone of our system, we know that cryptocurrencies are especially subject to external effects.

Factors such as news events, government regulations, and the social media presence of important personalities may influence cryptocurrency pricing. The framework recognises this reality and offers investors a useful resource for making educated judgments. Our system has two practical advantages. First off, it provides traders with trustworthy forecasts based on past performance and technical research. Second, it incorporates a surveillance function that signals when outside influences, such as news that affects people's emotions, have the potential to cause large market changes. With current and pertinent information at their disposal, investors are better equipped to navigate the complicated crypto world with security and confidence.

In summary, the warning flag-raising mechanism within our proposed framework acts as a cautious and proactive approach, allowing investors to make well-informed choices and preserve their assets. It bridges the gap between technical analysis and real-world occurrences, giving BTC a reasonably secure and trustworthy way to trading in a market where volatility and unpredictability are constants. By integrating both historical data and sentiment-driven elements, our approach attempts to boost investor resilience in the face of the ever-evolving digital currency ecosystem.

Past research in cryptocurrency price prediction has provided many studies applying machine learning approaches such as CNN and AI-based models. While some of this research has expanded into hybrid models, they have frequently struggled to lower prediction errors, suggesting a continuing area of progress. To solve this problem, our unique hybrid model outperforms previous algorithms, delivering impressively accurate cryptocurrency price forecasts with considerably reduced error rates. While several studies have aimed to forecast price fluctuations based on sentiment research, they typically confront constraints since sentiment alone may not give precise price predictions.

In response, we have implemented sentiment research as a critical component of our platform, using it as a cautionary signal system for investors. This new feature allows our proposed platform to proactively alert investors in the case of market turbulence, boosting cryptocurrency investments' security and trust. In conclusion, our work represents a leading achievement in cryptocurrency price prediction by drastically lowering forecast error and adding a unique feature that prioritizes investor protection via sentiment-based notifications. This complete method aims to transform the context of cryptocurrency investing techniques, delivering a more trustworthy and robust route for investors navigating the dynamic and turbulent crypto market.

VII. CONCLUSION AND FUTURE WORK

The challenges in the digital currency price prediction domain are multifarious, given the inherent volatility of cryptocurrencies driven by several variables, including economic, technical, market mood, and political aspects. This volatility leads to significant unpredictability in crypto values, underlining the need for more precise and dependable prediction models to assist investors.

This need is fulfilled by our research, by introducing a rigorous machine learning-driven framework that delivers near forecasts of cryptocurrency values and includes real-time market sentiment analysis to boost investment safety. The system is an intermediary for investors, notifying them to continue confidently in a neutral or positive market mood. In contrast, it is an alert mechanism when negative sentiments increase, allowing investors to exercise caution. The framework has shown excellent accuracy, exceeding the capabilities of its predecessors. This outcome coincides with our core research objective: to give superior digital currency price forecasts with lower error rates.

In the future, we aim to strengthen the prediction potential of our framework significantly by adding the fundamental analysis module. This module will account for the indirect factors that might impact cryptocurrency values, including variables such as oil prices, gold prices, currency exchange rates, and stock market performance. Combining fundamental analysis with our current technical and sentiment analysis modules will produce a holistic and multi-dimensional approach to cryptocurrency price prediction, providing more accurate predictions.

Moreover, we will also evaluate our model for other top-trend cryptocurrencies, including Litecoin, Monero, TRON, Solana, NEO, Binance Coin, etc. In context of sentiment module graphical sentiments will be incorporated to improve the sentimental analysis results. Future research on the study of graphical sentiments, especially those expressed by emojis, looks promising. We understand the significance of integrating graphical emotions into sentiment analysis frameworks, even as we acknowledge their difficulties, such as ambiguous meanings, multiple interpretations, connotations, contextual dependencies, mixed emotions, a lack of extensive training data, and platform-specific variations. The goal would be to develop strong models that can interpret the complex meanings associated with emojis, considering their context- and subject-dependent nature.

Future research endeavors will prioritize addressing the complex problem of sarcasm detection, a crucial aspect of sentiment analysis. A more profound comprehension of sentiment dynamics will result from creating models that recognize and analyze sarcastic expressions in textual content. By exploring the world of graphical sentiments, the future work section seeks to broaden sentiment analysis applications and open the door for more sophisticated and contextually aware sentiment prediction models.

We have plans to develop a user-friendly application designed for digital currency investors. This application will enable users to enter criteria such as their preferred cryptocurrency, investment amount, and desired investment duration. Leveraging our system's capabilities, the application will then deliver tailored recommendations on the ideal cryptocurrency for investment, helping users make educated and strategic investment choices in the changing cryptocurrency market.

SOURCE CODE AVAILABILITY

The source code for this study is available upon request from the corresponding author and is intended exclusively for research purposes.

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.

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