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Research Article

Deep Learning and Machine Learning-Based Sentiment Analysis on BitCoin (BTC) Price Prediction

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ABSTRACT: Emotions form an essential and fundamental aspect of our lives. What we do and say reflects some of our feelings in some way, though not directly. We must examine these feelings using emotional data, also known as affect data, to comprehend a person's basic behavior. Text, voice, facial expressions, and other data types can be included. Since social networking websites have become so popular, many individuals have started reading the material on these numerous sites. Twitter is one of these social networking sites. People's feelings and thoughts about a subject reveal positive, negative, and neutral emotional values. Doing sentiment analysis on Twitter is a critical and challenging task. In this study, we aim to investigate the sentiments of Bitcoin and provide an overview of its effect on the value of Bitcoin by utilizing the power of deep learning architectures and machine learning methods. The study collected tweets in English shared on Twitter between December 12, 2021, and March 13, 2022. First, people's feelings about Bitcoin were assessed using TextBlob, a natural language processing (NLP) tool. Then, it was done using basic machine learning algorithms for sentiment classification and Convolutional neural network (CNN), Long short-term memory (LSTM), and Bidirected Long short-term memory (BiLSTM) deep learning architectures that we modeled. However, deep learning models were tested separately with the TF-IDF and Glove word embedding approaches. Experimental results prove the success of deep learning architectures using the Glove word embedding approach.

Keywords: BitCoin, Sentiment Analysis, Machine Learning, Deep Learning, Glove, TF-IDF, CNN, LSTM, BiLSTM.

1. INTRODUCTION

The general purpose web has increased with the Internet's rising popularity. As a result, many individuals communicate their views and opinions through various online resources. It will be used for users, who will be used automatically, to use the public's constant looking and use. The popularity of social networking sites has led to the emergence of several fields devoted to extracting vital information from social networks and their content.

Sentiment analysis is the process of determining a text's emotional meaning from its content. Given the long and well-known use of public opinion in decision-making, sentiment analysis is an area of NLP, and there must have been much early research on this topic. However, sentiment analysis is still being developed in the new millennium. Scholars, corporations, governments, and organizations have adopted sentiment analysis in recent years [1]. Sentiment analysis has grown in popularity among the research community in recent years. The phrase "Idea Analysis or Idea Mining"

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is another name for sentiment analysis. The sentiment analysis work has lately expanded. Twitter remains the best indicator of the world's broader pulse and what is happening within it. The data provided by Twitter and the insights we can gather from it can truly change the world in more ways than most people realize. Twitter data is now included in most stock analyst systems, including Bloomberg's.

In this study, the shares of Twitter users about BitCoin were initially automatically captured with the Twitter API application we designed [2]. In this process, the extracted data is not clean as it is a raw data set. For this reason, pre-processing steps were applied to the text. Many unnecessary special characters, expressions, links, tags, emojis, etc., are cleaned in this context. Thus, unnecessary characters are deleted. After the pre-processing step, meaningful information was extracted from the obtained quality dataset using the Glove data embedding approach. In the Glove-based BiLSTM approach we designed for this study, the data in the created corpus were classified into three classes positive, negative and neutral. The determination of the emotional tendencies in social media is directly proportional to the preferred topic and the popularity of the topic on social media. Therefore, detecting missing, incorrect, and false information about BitCoin will help control the sudden rise and fall of cryptocurrencies.

2. RELATED WORKS

Sentiment Analysis is analyzing data and classifying it according to the research needs. Sentiment analysis is a method that automatically scans natural language utterances, picks out important claims or opinions, and organizes them into groups according to emotional attitudes. These emotions can be used to gain a better understanding of various events and the effects they cause. Analyzing these emotions allows us to determine what people like, want, and their primary concerns. Sentiment analysis methods are explained under dictionary-based, Machine learning, and hybrid approaches.

Dictionaries are a set of tokens, each with a predetermined score reflecting the neutrality, positivity, or negativity of the text to which it is allocated [3]. The Dictionary-Based Approach adds the positive, negative, and neutral evaluations separately for each token to do a full-text analysis. The highest value of the individual scores is used to determine the text's general polarity in the final step. As a result, the text is first separated into symbols made up of single words, after which each symbol's polarity is determined and added. The dictionary-based approach is suitable for feature- and sentence-level sentiment analysis. Since no training data is needed, it can be referred to as an unsupervised technique.

Systems that use machine learning can classify emotions. The machine learning method takes on the problem of sentiment classification, which is a typical text classification problem, by using syntactic and/or linguistic components. The categorization model links the attributes of the underlying record to one of the class labels. The model then predicts the class label for a particular instance of an unknown class. We are given a difficult categorization task when a sample is given just one title. A soft classification problem is one in which the probabilistic value of the labels is assigned to a sample. Systems can learn new skills using machine learning without explicitly coding them. Algorithms for sentiment analysis, for instance, can be taught to read beyond simple definitions to recognize sarcasm, context, and phrases that aren't supposed to be used in that way. The hybrid method combines dictionary-based and machine-learning techniques. The term "hybrid" describes the fusion of sentiment analysis, machine learning, and dictionary-based methods. Emotional dictionaries play a crucial part in most systems in the modern hybrid approach, which mixes the two. Sensitivity analysis is a hybrid method for polarity recognition that combines statistical and knowledge-based techniques [4]. He suggested a hybrid approach to machine learning that combined two feature selection methods, “Multithreaded Optimizer and Relief Algorithms with SVM” [5]. A hybrid strategy using machine learning, incorporating RF and SVM, was developed for the sentiment analysis problem [6]. The hybrid model, which combines both methods, had a more accurate performance in the dataset of product reviews provided by amazon.com, which was close to 84 percent. Many researchers have proposed a hybrid architecture that blends dictionary-based and machine-learning techniques to improve the results. However, many studies are still being done on this topic, which is still quite popular.

3. CRYPTO CURRENCY, TWITTER AND SENTIMENT ANALYSIS

Bitcoin: A Peer-to-Peer Electronic Cash System, written by "Satoshi Nakamoto" in 2009, describes a peer-to-peer payment system employing electronic cash (cryptocurrencies) that may be delivered directly from someone [7]. Bitcoin is the first cryptocurrency, which came to life using cryptography, that is, encryption technology, using the name "Satoshi Nakamoto" and was invented in 2009 by an unknown person or group. However, peer-to-peer payment systems are one use case for blockchain technology and many more. They are suitable for IoT applications, distributed storage systems, healthcare, and more since they give the other side security, anonymity, and a distributed ledger without using a third party to validate the transaction [8].

Information gathered through social media networks is referred to as social data. There are social media platforms where people interact with each other on many issues and share their feelings on certain issues. One of these platforms is Twitter. The tweets individuals write about specific topics enable Twitter, a social media tool, to be used as a dynamic data source. The tweets written about the topics on the agenda can give information about the direction of the comments on that topic. Researchers can collect tweets on hot topics and reveal positive, negative, or neutral feelings about those topics [3] and use Twitter data for training to reveal the success of hybrid models in sentiment analysis. The Twitter API was used to retrieve up to 6900 tweets for educational purposes. According to the data, their model outperformed most models, which indicated a 96% reduction in features. Additionally, they highlighted hybrid models' advantages and concluded that they might surpass all others with exemplary architecture and careful hyperparameter selection [5].

One of the hot topics is the digital currency Bitcoin. The thirteen years since Bitcoin launched have seen much growth and controversy. Recently, cryptocurrency has gained much attention, partly because of its destructive potential and claims of unheard-of profits [9] [10]. Additionally, scholars are becoming more aware of Twitter's ability to predict various events, particularly those related to financial markets. This subject is widely discussed in tweets and has grown in popularity, especially in recent years. Bitcoin and altcoins are the currencies that are invested in and evaluated as financial resources. People, especially investors, are effective in encouraging investments in those coins by sharing tweets about the coins they invest in. This study collected tweets about Bitcoin and the most popular coins daily. In our work with the collected tweets, we will analyze the effect of Twitter on bitcoin with a deep learning-based model. The forecasting capability of Twitter sentiment in various cryptocurrency ecosystems is the topic of this study.

Twitter Sentiment Analysis [11] has become a trendy research topic for researchers working on NLP and Sentiment Analysis (SA). However, the diversity and size of the data in social media make it impossible for people to conduct sentiment analysis. This situation necessitated an automated sentiment analysis system.

NLP, a set of techniques allowing computers to analyze and understand text, has emerged as a subject of study or development due to the proliferation of unstructured data [12]. This study used a set of NLP tools called "sensitivity analysis". Whitelaw et al. [13] defined sentiment analysis as “labeling documents as positive or negative according to the target”. Sentiment analysis approaches generally classify emotions as positive, negative, or neutral. Sentiment analysis is not a new field of research; many researchers have put forward many studies on sentiment analysis over the years.

4. MATERIALS AND METHODS

4.1. Data Collection

Twitter, the world's largest social media platform, was chosen as the data source in the study. The data were collected from tweet data shared publicly on Twitter. For this data set, only tweets shared in English were collected in tweets shared publicly by area. The study used the MAXQDA [14] qualitative data analysis tool to collect Twitter data. First, after the "Twitter API Key" entries were made using the Twitter Developer Account, 256502 Tweets about Bitcoin and sub-coins published between December 12, 2021, and March 13, 2022, were collected in English. Then, to reach the target tweets, the search terms "BTC OR ETH OR XRP OR BCH OR EOS OR LTC OR ADA OR XLM OR TRX" were used after identifying the most tweeted hashtags about Bitcoin on Twitter. Finally, the collected data was converted to a CSV file in the pre-processing and emotion classification steps. As a result, a dataset of 256502 English tweets was collected between December 12 and March 13, 2022. To ensure the accuracy of this data set, the pre-processing stage, whose details are given in the next stage, was carried out. After the pre-processing steps, the size of the dataset consisting of English tweets was reduced to 152398 tweets.

4.2. Data Cleaning and Pre-processing

The unstructured nature and high noise levels of Twitter data are well recognized. Therefore, to be effective in sentiment analysis, the gathered Twitter data must undergo a lengthy preparation process. Text cleaning is one of the text mining operations to clean up words or other components that are difficult to deduce or analyze the meaning of the text. During the analysis phase, many unnecessary special characters, expressions, links, tags, emojis, etc. These characters are challenging to analyze for sentiment because they don't provide a lot of information. These characters are challenging to analyze for sentiment because they don't offer much information. That may adversely affect the experimental results includes. At this stage, pre-processing was performed on the data set by applying the following procedures:

- Duplicate tweets are removed from the dataset.
- Numbers are removed.
- Punctuation marks are removed.
- Twitter RT, @, and links in sentences are cleared.
- The text is converted to lowercase, so words like “bitcoin” and “Bitcoin” are considered the same for analysis.

- Special characters and facial expressions (emojis) used to express emotions are removed after being detected in the text using their special codes.
- Tokenization is applied for each tweet. Tokenization is separating the words in the text according to the spaces.
- Then, stopwords are removed from the tweets.
- The words in each tweet are separated into their roots. Lemmatization uses morphological analysis of words.
- Finally, the sentiment of tweets was evaluated using TextBlob [15], an NLP tool.

The purpose of pre-processing is to reduce the number of words in the text without disturbing the basic meaning of the text. In the raw data set collected, some unnecessary words and expressions will not be used in the sentiment analysis phase. Therefore, pre-processing must be performed before performing any data analysis.

4.3. Word Representation Approaches

TF-IDF

The usefulness of a word to a document in a collection of documents is evaluated using a statistical method called TF-IDF [12]. This is accomplished by multiplying the frequency of a word within a document and the reverse document frequency over a set of documents. The most significant benefit is that it has a variety of uses for automated text analysis, including word scoring in machine learning algorithms for NLP.

TF-IDF was created for document search and information retrieval. It works by increasing a term's frequency in a document, but this is offset by the number of papers in which it appears. Because they are not particularly pertinent to that document, words like this, what, and if, often used throughout all documents, rank poorly. A word vector is a set of numbers for each potential sentence word in a document. By taking a document's text and turning it into one of these vectors, the text's content is somehow represented by the vectors' numbers. We can use TF-IDF to link each word in a document to a number representing its importance to that content. We then use a machine learning technique to hunt for documents with similar vectors and similar, related terms.

GLOVE

Spherical Vectors for Word Representations is the abbreviation for GloVe. The GloVe [16] is an unsupervised learning technique for discovering word placement for various words in vector representation. The global word-to-word co-occurrence matrix, which tracks how frequently words occur together in a given whole, provides nonzero inputs that the GloVe model is trained with. One pass across the full corpus obtains the information needed to fill this matrix. Large businesses may find this shift computationally expensive, but there is only one upfront expense. Subsequent training iterations are completed much quicker since nonzero matrix entries often make up a smaller proportion of the corpus than words.

4.4. Machine Learning Models

SVM

The Support Vector Machine (SVM) [17] uses classification methods to address two-group classification issues. After providing tagged training data sets to an SVM model for each category, they can classify the new text.

Compared to more contemporary algorithms like neural networks, it offers two major advantages: faster processing and better performance with fewer data (in thousands). Therefore, the method is ideally suited for text classification problems where access to a dataset with up to several thousand labeled samples is common.

Karasu et al., in the study conducted by [18], LR and SVM, two machine learning algorithms, were used to predict the price of bitcoin using a time series of daily closing prices from 2012 to 2018. It has been seen that the proposed SVM model gives more successful results than the LR model.

RF

Machine learning models called Random Forest (RF) models [19] combine the output predictions of some regression decision trees. A random vector generated from the input data is used to create each tree independently, ensuring that all the trees in the forest have the same distribution. Bootstrapping and random feature selection are used to average predictions from forests. RF models are reliable predictors for high-dimensional and small-sample data [20]. Wimala Gunaratne et al. [21] used ANN, SVM, RF, and NB algorithms for cryptocurrency price prediction. The success percentage of studies conducted on Twitter heavily depends on the correctness of the data.

A classifier that develops from decision trees is called a random forest. There are numerous decision trees in it. Each decision tree classifies a fresh sample by assigning a classification to the incoming data. Each tree receives sampled data from the original dataset as input. After gathering the categories, the random forest chooses the forecast with the highest votes.

Additionally, to develop the tree at each node, a random selection of features from the optional characteristics is selected. Finally, no tree gets pruned as it grows. The random forest technique enables a strong classifier to be formed from multiple weak or weakly connected classifiers.

LR

The supervised learning classification procedure known as logistic regression (LR) is utilized to calculate the likelihood of a target variable. Due to the binary nature of the target or dependent variable, only two viable classes exist. Data in a logistic regression model are recorded as 1 (representing success/yes) or 0 (meaning failure/no), depending on the binary nature of the dependent variable. A logistic regression model makes mathematical predictions about P(Y=1) as a function of X. Detecting spam, predicting diabetes, finding cancer, etc. It is one of the most straightforward ML techniques that may be applied to many categorization issues.

In the study of Chen et al. [16], statistical methods for daily Bitcoin price prediction include Linear Regression (LR) and Linear Discriminant Analysis (LDA); machine learning algorithms utilized include Random Forest (RF), XGBoost (XGB), Second Order Discriminatory Analysis (QDA), SVM, and Long-Short-Term Memory Networks (LSTM). For daily Bitcoin price prediction, statistical methods had an accuracy of 66%, while machine learning algorithms had a success rate of 65.3%. Even the highest success rate was inadequate compared to previous research because of the study's numerous flaws. Other machine learning algorithms weren't employed either for the study's execution.

4.5. Deep Learning Models

CNN

This method, also referred to as CNN [22], allows us to analyze an image briefly. It is a deep learning algorithm that helps us distinguish various objects in the image from each other. As can be seen from Fig. 1, similar to a typical multilayer neural network, CNN has one or more convolutional layers, pooling layers, and one or more linked layers. With the same number of hidden units, CNNs have the advantage of requiring less training and fewer parameters than fully linked networks. CNN is an example of a feedforward neural network. CNN is ideal for image processing applications but can also be used in audio and NLP applications. A CNN model comprises three layers: the convolutional layer, the pooling layer, and the fully connected layer. Convolutional, pooling, and fully connected layers are included in the feature extraction phase; however, only the fully connected layer is included in the classification step. The feature map is extracted from the convolutional layer using filters. The input parameters are reduced in dimension by the pooling layer, which comes after the convolutional layer. One of the average pooling or maximum pooling approaches is typically selected for this technique. The filter moves along the input in the maximum pooling method and chooses the maximum values that will make up the output. In the average pooling method, the moving filter creates the output values by averaging the input values in the area. The flattened layer prepares the incoming input for the fully connected layer by converting it into a one-dimensional array. The layer where the qualities are categorized is the completely connected layer. Each neuron in a layer is linked to every neuron in the layer above it in a completely connected layer.

Roy and Ojha [23] stated that Twitter is a big gold mine where people share their instant feelings and thoughts, and based on this, they conducted a sentiment analysis on Twitter. Three deep-learning models were created and compared for sentiment analysis. Google BERT, LSTM, and CNN algorithms were used, and it was determined that the BERT model outperformed the others. The language of the study was English, which was an increasing factor in the accuracy rate.

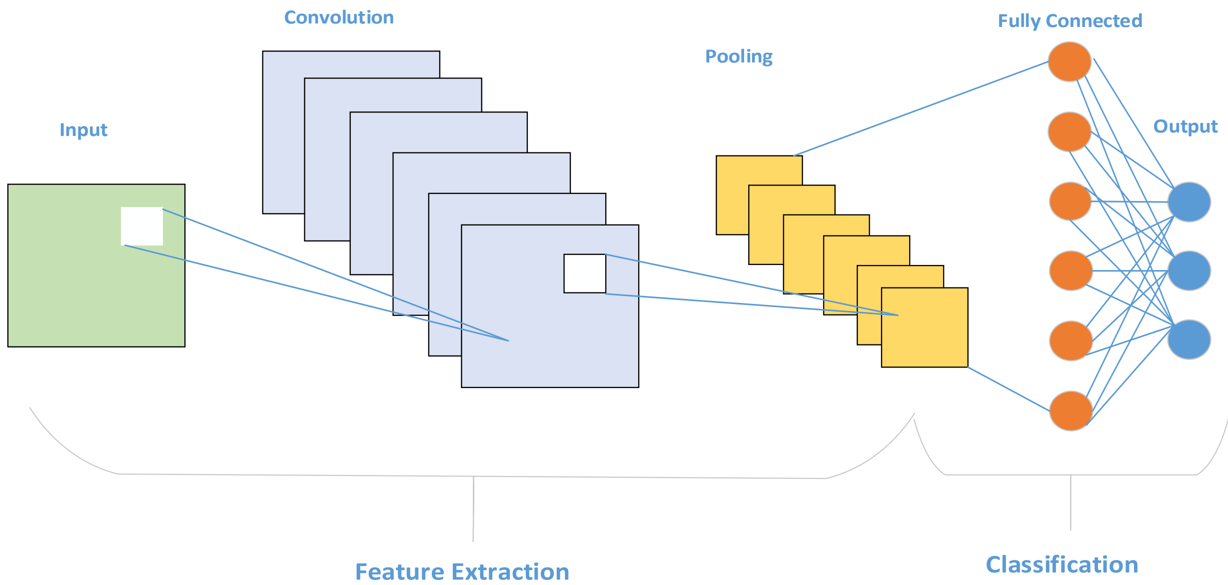

Figure 1. Basic Structure of the CNN Model

LSTM

LSTM is the most commonly used and successful RNN method in sentiment analysis. The method introduced by Hochreiter and Schmidhuber in 1997 is designed to avoid the problem of long-term addiction [24]. As seen from Fig. 2, an LSTM cell consists of an information flow line called the cell state and three interactive gates that form the decision mechanism. These gates are called forget gate (forget gate), the input gate (input gate), and the output gate (output gate). The LSTM operation first decides which information to keep or not in the cell state. The information obtained from the previously hidden layer and the information now being input are then transmitted to the forget gate. The sigmoid function is then used to construct the outcome. The result of the sigmoid function ranges from 0 to 1. 0 means forget information, 1 means retain information. The second stage involves selecting the new information that will be kept in the cell state. The input gate then selects which data to update using the sigmoid function. The cell state is then updated after evaluating the results and creating value vectors using the Tahn function. Which information from the cell state will be sent as a result is decided in the last phase. The Tahn layer organizes the information from the cell state, the output port completes the decision step, and the outcome is generated.

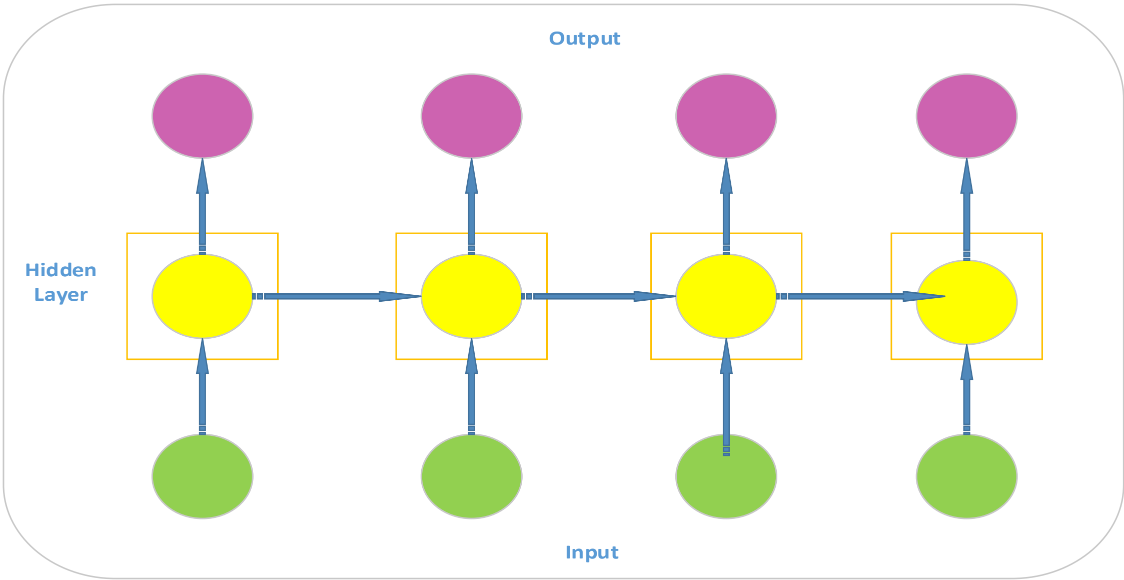

Figure 2. Basic Structure of the LSTM Model

BLSTM

A group of processing models called Bidirectional LSTM (BLSTM) [25] consists of two LSTMsThey have the ability to store data at any moment, including information from the past and the future. While the other receives input flowing backward, the former does the opposite. The network can access more data using BiLSTMs, which helps the context of the algorithm. You can run your inputs in two directions—from the present to the future and from the present to the future—by using bidirectional. This method combines two hidden states and is different from the unidirectional in that it uses backward working LSTM to safeguard information from the future.

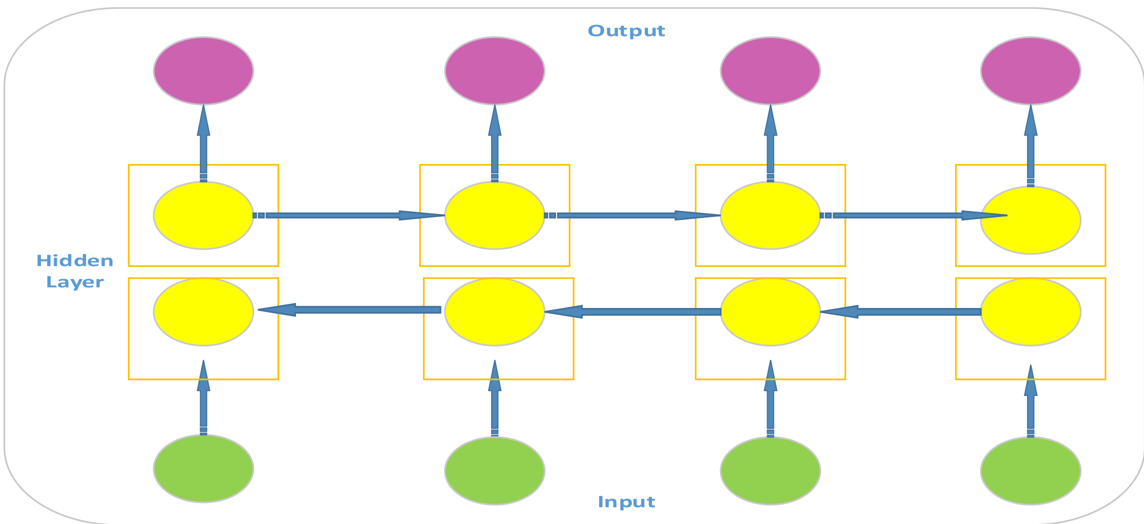

Figure 3. Basic Structure of the BiLSTM Model

4.6. Evaluation Metrics

We used four performance scales to evaluate the performance of deep learning and machine learning models. This study uses "Accuracy, Precision, Recall, and F1-score" [26], which are among the commonly used evaluation criteria.

Precision is called the precision of a classifier and indicates what percentage of all clusters are positively labeled and positive. It is calculated as follows:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Recall is often called a measure of completeness and indicates the percentage of true positive predictions labeled correctly. It is calculated as follows:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2}$$

Accuracy assessment may not be a good metric because there is no balanced data set. In such cases, the F1-score is used. Because the F1-score provides the results according to each target class, it is a statistical classification analysis criterion that considers both the precision of the classifier and the recall criteria. It is calculated as follows:

$$F1 - score = 2\frac{Precision\ x\ Recall}{Precision + Recall} \tag{3}$$

5. EXPERIMENTAL RESULTS

This section presents the results obtained with the machine and deep learning classifiers on the dataset we created by collecting tweets shared from Twitter about Bitcoin and altcoins through MAXQDA qualitative data analysis. Experiments were tested using the Python programming language on the Google Collaborate Pro platform. Pandas, Keras, Numpy, spaCy, and Sklearn python programming libraries were used in the experiments. All experiments were tested on a PC with an Intel Core i7 processor, 16 GB RAM, and Windows 10 operating system. The parameters of the deep models that were compared are shown in detail in Table 1.

CNN is good at capturing local invariant features but not at capturing word order information in a sentence. This greatly reduces a sentence's semantic representation. Therefore, the experimental results of the CNN model have lower performance for both word embedding approaches compared to other models.

For all the deep learning models compared, it is seen that the Glove word embedding approach outperforms the trained variations based on the TF-IDF word approach. TF-IDF identifies words that frequently occur in the given text and phrases that are not common in the remaining dataset. TF-IDF ignores the order of words and returns the mxn matrix (or mxn depending on the application, where n is the number of words in the vocabulary and m is the number of documents. TF-IDF cannot capture the order of words and semantic and syntactic information of words in a document because it is created with the word bag logic. On the other hand, Glove assigns each word a distinct vector based on the words that surround it. While TF-IDF is based on a sparse vector representation, Glove belongs to dense vector representations. For all these reasons, Glove was preferred as the word embedding approach in our proposed model. Glove and TF-IDF word embedding approaches were tested separately using CNN, LSTM, and BiLSTM deep learning architectures. As can be seen from Fig. 4 and Fig. 5, GloVe has achieved the best performance than TF-IDF for all compared deep models. Fig. 6, Fig. 7 and Fig. 8 represent the performance comparison of CNN, LSTM and BiLSTM using a different word embedding vectors, respectively. As can be seen from Fig. 6-7, GloVe has achieved the best performance than TF-IDF for all compared deep models. The glove method is computationally expensive, but it is a one-time upfront cost. Compared to TF-IDF, it performs better when training on datasets of similar or larger size. This is because it produces its best guess by learning the entire co-occurrence dataset once. It differs from the TF-IDF method, where additional sentences can be given for training and prediction.

Table 1. Hyperparameter setting.

	Hyperparameter	
Embedding and Input Layer	Optimizer	Adam
	Loss Function	Binary Cross Entropy
	Learning Rate	0.0001
	SpatialDropout1D	0,2
	Maximum Length	60
	Embedding size	200
	Batchsize	32
	Epoch	20
CNN	CNN filter size	100
	CNN kernel size	3
	CNN Activation	ReLu
	CNN Maxpooling size	2
	Dropout	0.25
LSTM	LSTM Node	128
	LSTM Activation	tanh
	LSTM Dropout	0.25
BiLSTM	BiLSTM Node	128
	BiLSTM Activation	ReLu
	BiLSTM Dropout	0.25
FC Layer	Dense 1	50
	Dense 1 Activation	ReLu
	Dense 2	1
	Dense 2 Activation	softmax

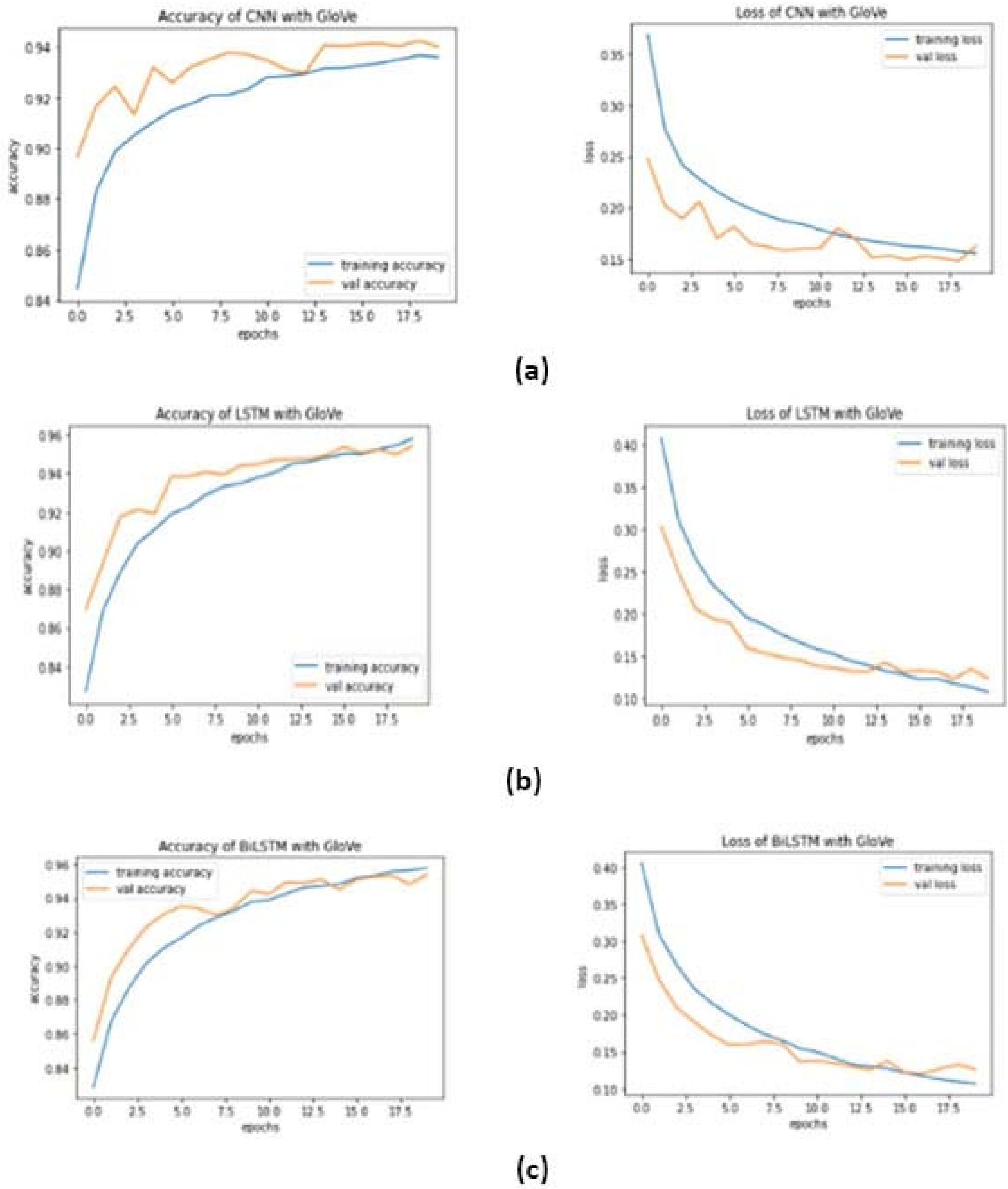

Figure 4. Comparison of (a) Glove-CNN, (b) Glove-LSTM, (c) Glove-BiLSTM Accuracy and Loss Curves

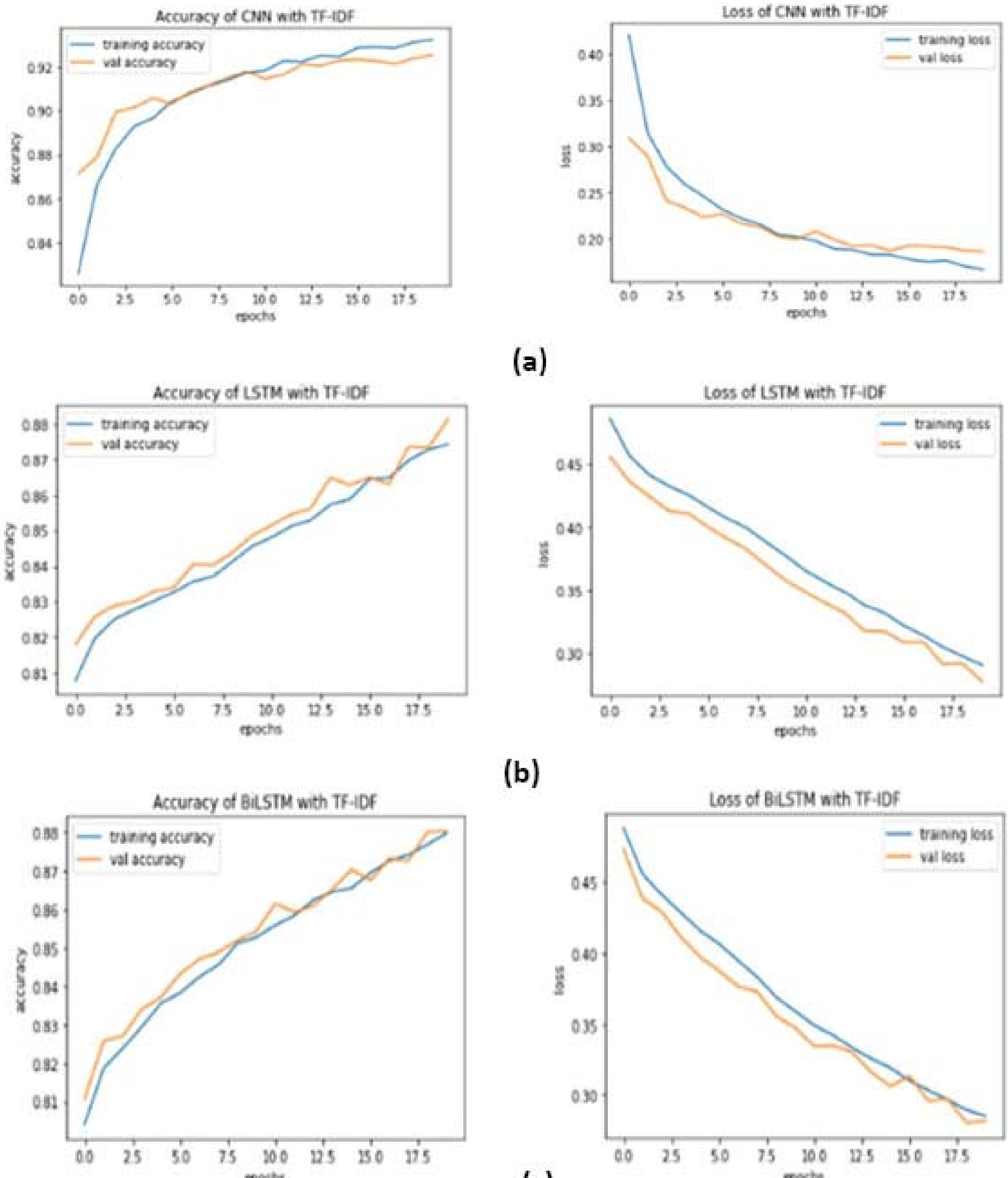

Figure 5. Comparison of (a) TF-IDF-CNN, (b) TF-IDF -LSTM, (c) TF-IDF -BiLSTM Accuracy and Loss Curves

Figure 6. Performance Comparison of CNN using Different Word Embedding Vectors

Figure 7. Performance Comparison of LSTM using Different Word Embedding Vectors

Figure 8. Performance Comparison of BiLSTM using Different Word Embedding Vectors

Fig. 9 shows the performance comparison of the RNN-based BiLSTM model with the basic machine learning algorithms, which achieved the best performance. However, as seen in Fig. 9, machine learning algorithms have a severe performance weakness compared to deep learning-based algorithms. The most important reason for this is that in machine learning methods, the learning process is divided into small steps, and the results of each step are combined into a single output. In contrast, in deep learning methods, the learning process is processed from end to end.

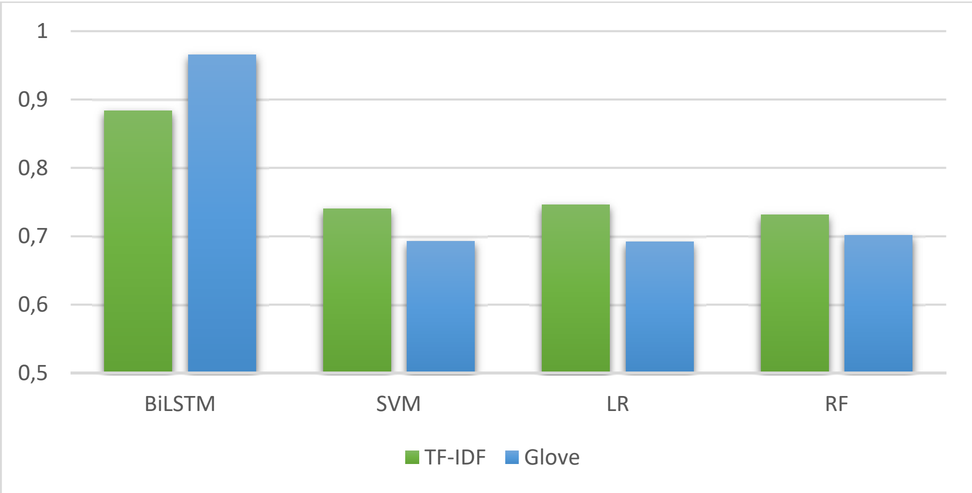

Figure 9. Comparison of the BiLSTM Deep Learning Model's Accuracy Performance with Other Machine Learning Models Using Different Word Embedding Vectors

6. CONCLUSION

Our study evaluated their feelings about Bitcoin using TextBlob, an NLP tool. Then, it was done using basic machine learning algorithms for emotion classification and CNN, LSTM, BiLSTM deep learning architectures that we modeled. Extensive experiments prove that the proposed model performs better. However, after the deep learning models were tested separately with the TF-IDF and Glove word embedding approaches, the experimental results prove the success of deep learning architectures using the Glove word embedding approach.

This study thoroughly investigated the English-language tweets that were shared between December 12, 2021, and March 13, 2022. For this analysis, 152398 shared tweets about Bitcoin and other currencies were used. The sentiment analysis results revealed that the overall sentiment polarity was positive and that there were around twice as many positive tweets as negative ones. The experimental findings of this study will make it easier to spot unreliable, inaccurate, and incomplete information on Bitcoin and other cryptocurrencies. In this way, individuals who experience Bitcoin investment indecision will be able to make the right choices in investment. Those who follow market investments can apply it efficiently in determining the valuation of Bitcoin investment. In the future, it is planned to develop an optimal deep learning-based system to detect fake accounts and false information and intervene in social media based on current work.

Acknowledgments

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declaration of Competing Interest
There is no conflict of interest.

Author Contribution
All authors contributed equally to every step of the article.

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