Deep Learning for Sentiment Analysis in Cryptocurrency Markets: An NLP Approach

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Abstract:

The cryptocurrencies are highly utilized in various financial and business ventures because they are highly volatile in terms of price. The development of the processing of natural language and analytics of the large data has led to the birth of automated systems that determine sentiments in online communities and which have of late played a vital role in enabling people to publish their views in this platform. Among the most popular known social media, Twitter has a number of tweets on cryptocurrencies. Using this information, we may forecast the movement of the bitcoin prices by applying deep learning (DL). By examining the sentiment on Twitter, the researchers will get to know more and examine an issue which is causing erratic price of cryptocurrencies. The main concern in this article is the absence of the standard model that can be addressed to the study of textual emotions, however, textual emotions are one of the justifications of the rise and fall of the cost of cryptocurrencies. This article is an attempt to categorize the sentiments concerning the expression into three groups. neutral, negative, and positive. The approaches which have been taken consist of Word embedding FastText model, recurrent neural networks (RNNs) and gated recurrent units (GRUs) and Long-short-term memory networks (LSTMs), one-dimensional convolutional neural networks (CONV1D) a bi-LSTM+CONV1D, Recurrent-Convolutional Neural Networks(RCNN), self-explaining neural networks (SENN), capsule networks (CapsNets), hierarchical attention network(HAN) (The Three different datasets which consist of different tweets on cryptocurren The best findings, in the terms of the major findings, were created within LSTM and HAN approach, which followed the DL method. The accuracy of the respective performances of the techniques could be recorded as 70.12, 97.15, 98.20, 96.00, 96.00, 95.10, 95.13, 95.15, and 97.30 percent. We therefore draw the conclusion that the LSTM strategy had performed better than the other strategies in the process of deducing the type of sentiment being portrayed in the text of the cryptocurrencies.

Keywords: sentiment analysis, deep learning, cryptocurrencies, natural language processing.

Introduction:

In the last couple of decades, consumers and business companies have embraced the digital currencies at an unforeseen pace. Due to this reason, cryptocurrencies become an essential part of society and alter its lifestyle. The use of social media has been welcomed by many businesses to advertise their products or seek product feedbacks as customers have changed minds with digital age. These are social networking sites such as WhatsApp, Instagram, LinkedIn, Google Plus, and twitter. People use such sites to communicate with others to exchange their thoughts and views.

Twitter is the popular social networking site, which provides an opportunity to everyone to send and receive short messages in text. Twitter allows strangers to interact and read the posts of the other person. Since investors frequently tweet to share their emotions, Twitter is a great source when beginning to learn emotional intelligence and gives up-to-date details of the bitcoin. It is possible to use deep learning (DL) technology to detect data sentiment.

This research got inspired by the fact that there was no reliable, accurate, and precise model to assess emotional content on social media. It is important to have an idea of the way the value of cryptocurrencies changes as it has a great influence on the chance of profit. Investors, who buy these guarded currencies ought to have a wise strategy of what they are to do with this. The positive results of deep learning have been achieved in many areas of study, so, deep learning was applied.

With the help of definitions, illustration, and the identification of the DL and its applications in the evaluation of how people exhibit their feelings through social media, readers of the presented post will become aware of the locus of person-environment correlations. This is remarkable since this study is imperative considering that the prices of bitcoins are volatile. The results of the experiment indicated that Deep Learning approach presented superior performance as compared to other old-fashioned machine learning algorithms. Moreover, the results can guide the traders to choose the various deep learning model to analyze the sentiment of the social media tweets and get the comments as neutral, positive, or negative.

Sentiment Analysis, or SA, is the process of inferring the polarity of the subjective opinions of people based on the simple natural language texts. SA consists in grouping literary terms into positive, negative and neutral. Each emotion is assigned a polarity score in the range between -1 and +1 which are floating point numbers. It is possible to identify the sentiments behind the statement. Polarity greater than zero represents positive emotions; polarity zero represents neutrality, and finally polarity that is less than zero represents negative emotions. Thus, we suggest improving the accuracy of sentiment analysis with the help of deep learning.

Gated recurrent units (GRUs), long-short-term memory networks (LSTMs), recurrent neural networks (RNNs), self-explanatory neural networks (SENN), capsule networks (CapsNets), hierarchical attention networks (HAN), one-dimensional convolutional neural networks (CONV1D), a bi-LSTM+CONV1D, and recurrent-convolutional neural networks (RCNN). The FastText approach categorizes the emotion labels of each tweet into three classes: neutral, positive, and negative. This, it does, by hurting semantic word vectors of the words in the input word of each tweet. As revealed in the examination, the LSTM and HAN model produces better sentiment classification outcomes.

The remaining seven sections of the article are as follows: Section 2 contains a review of the literature. Section 3 illustrates the background information. Section 4 introduces our proposed model. Section 5 contains the proposed model testing. Section 6 includes experimental results and discussion, and finally, Section 7 presents conclusions and future work.

Literature review:

With growing popularity and volatility of cryptocurrencies have drawn significant thoughts from banking industry, retailers and working professionals in finance areas. investors, researchers, and financial analysts. Use of machine learning techniques, natural language processing has been widely employed to extract sentiment from unstructured text, offering insights into investor behavior. Traditional techniques have been tested to understand cryptocurrency markets; but the deployment of intelligent techniques such as deep learning have shown superior performance in handling complex language patterns. Deep neural networks, including architectures like CNNs, RNNs, and Transformers, have proven particularly effective in understanding the social media text. This section details the existing research that combines sentiment analysis, deep learning, and NLP to understand and forecast trends in the cryptocurrency ecosystem.

As stated in the literature, both deep learning and big data can entirely disrupt several industries, including the financial one. One of the areas that these technologies could be of great interest in as far as understanding consumer behavior is concerned is sentiment analysis where text information is classified as neutral, negative and positive (C. Balaji et al. [1]).

A. Jahan et al. [2] Through literature review it has been pointed out that in social media and mainly in Twitter sentiment analysis plays an important role. It emphasizes the importance of the sentiment composition rules in the identification of the polarity and provides a list of the methods, such as rules and case-based reasoning. Prior research on investigating the proposed sentiment analysis techniques like fuzzy rule based, and contrast between the supervised and non-supervised learning systems has been done. Mohamed et al. [3] evaluates a series of publications on sentiment analysis (SA) methods applied to the Bitcoin (BTC) based on deep learning (DL) and machine learning (ML) concepts. It points out the less talked about limitations of the previous study findings like the limited size of the data, use of obsolete methods and inaccuracies.

A.Patil et al. [4] As applied to subjectivity and polarity, the sentiment analysis classified the tweets into three portions, which include subjective, negative, and positive. The full-optimization version of the BERT model demonstrated that it was clearly superior to the traditional machine learning models, i.e., the F1 score was equal to 0.99 (results). The findings illustrated the prospects of the existence of the dataset in the context of future research, namely, the detection of hate speech and fake tweets, and trends in the opinions of the people on the dispute. H. S. Jeon et al. [5] The paper titled Identifying Social Media Sentiment and Its Relationship with Fluctuations in the Price of Bitcoin addresses the increased application of social media platforms, especially Twitter, in forecasting the change in bitcoin price. It has been established in previous studies that there is a correlation between the sentiment of social media and any changes in the price of Bitcoin. To take one example, Stenqvist and Lonno (2017) examined some 2+ million tweets about Bitcoin and stated that sentiment analysis could be helpful in obtaining information about price changes.

M. G. Albino et al. [6] According to the literature analysis, sentiment analysis is increasingly being made available through numerous source such as Twitter and other social media. The authors use some techniques to understand the attitudes such as Kenya- Nearest Neighbors (KNN) and Support Vector Machines (SVM). The study says sentiment analysis is applicable in various contexts such as product opinion and political views and opinions relating to elections. V. K. Tayal et al. [7] Each of these works demonstrates the potential of using social media data to support financial analysis and represents the first step toward more advanced methods that can predict market developments based on crowd opinion relying on machine learning and natural language processing. Through the optimization of the RoBERTa model specifically to the financial tweets, the present work aims at enhancing the accuracy and valuable use of the sentiment analysis applications within the financial sector.

S. Ao et al. [8] As the study examines the developing importance of emotion study in the financial field, the methodology used in the research is based on how social media, especially Twitter, enables individuals to choose to share their opinion regarding the stock market. Besides the fact that the study reveals how much power the emotion of the investors can have on the volatility of the stock market, it also shows the extent to which there is a close correlation between the tone of the financial news and the stock market trends. N. Pitts et al. [9] Collectively, these studies illustrate the significance of research about sentiments as regards to better know the dynamics within the market and how to group and interpret the comments in social media, especially those concerning the trading of stocks. A. J. Oroh et al. [10] The literature review covers the study of social network analysis (SNA) and how it can be utilized in terms of identifying the key players involved in the information-dissemination process on the social networking sites especially Twitter. It refers to very diverse research that has had different orientations to the study on user behavior and community formations, like the Dynamically Socialized User Networking (DSUN) approach, which focuses on end-user behaviors and community learning that have been made on basis of topic-aware influence effects and relativities.

Sahana N B et al. [11] The article addresses the interest that has been garnered towards cryptocurrencies such as Bitcoin, their volatility and emergence of various prediction methods. Other studies used such interventions as Bayesian regression or deep reinforcement learning to ensure a high payoff, whereas the traditional one was based on the historical prices.

R. Srinivasan et al. [12] Movie comments are evaluated using Maximum Entropy, Naive Bayes (NB) and Support Vector Machines (SVM). The examination of tweets in the Egyptian presidential election used TF-IDF to compare SVM and NB classifiers and created real-time sentiment analysis algorithms applied to the tweeting of political actors with the addition of the political actors election outcome predictions. SVM along with Bag of Words (BOW) was discovered to have the highest accuracy. Cam et al. [13] The literature review assists in pointing out the increasing trends and popularity of the sentiment analysis particularly in the financial markets business. In practical sentiment classification in English, Arabic, and Turkish languages among others, deep learning (DL) and machine learning (ML) methods have been used in many studies. The review shows the utility of hybrid systems that are a combination of lexicon and machine learning.

D. A. Damaratih et al. [14] The literature review addresses the relevance and importance of sentiment analysis and more so what they are to social media networks such as twitter. It states that Twitter is increasingly being used as a source of news and popular opinion, especially in the COVID-19 crisis. The particularity of this review is that it demonstrates the importance of knowing the attitude of the people toward conducting online lectures because this can affect the creation of an educational policy and practice. F. Frasincar et al. [15] Sentiment analysis or SA has gained prominence in the financial sector. It is especially so when trading cryptocurrency since the social media influences the sentiments in the market in a big way. As previous studies point out, understanding of what people think can as well enable an individual to facilitate the effectiveness of trading models through presentation of market dynamics and characteristics of investors.

S. Bylaiah et al. [16] As per the literature review, sentiment analysis can be helpful to evaluate the views of people in the social media out there within Twitter and other forms of social media. Many studies have also revealed the extent to which machine learning systems can classify the expression relating to the feeling that tweets carry. As an example, some earlier studies have classified tweets based on selecting semantic analysis tool to identify in three categories such as positive, neutral and negative outlooks of tweets. Y. Arifin et al. [17] The literature study focuses on the development of sentiment analysis and its role in measuring the opinion of the masses in the social media. It surveys generous quantities of views on sentiment analysis algorithms and strategies, less so to Naive Bayes and other machine learning-hungry strategies, Bayesian networks, and Support Vector Machines. It means that sentiment analysis has the potential to offer important data regarding perspectives of the users and the issues in the society.

Ashwin Nair et al. [18] The basis of the study is the use of the sentiment analysis and machine learning classification to determine the existence of spam accounts in Twitter. It examines the various existing approaches to the detection of spam accounts and the usefulness of several classification algorithms such as AdaBoost, Random Forests, XGBoost and Decision Trees. M. Ramzan et al. [19] The review of literature has elicited the importance of sentiment analysis (SA) in many disciplines especially on politics and businesses. It explains how Twitter can be used as a market of public opinion research where scholars can identify opinions dealing with elections and problems of political nature.

J. Agbaje et al. [20] By using such feature extraction procedure as the Term Frequency Inverse Document Frequency (TF-IDF) to a set of data, one may derive the most relevant terms contained therein and used in numerous studies. To achieve improved classification, this approach has been applied with different machine learning algorithms, which include support vector machines (SVM) and deep learning algorithms.

DATASET:

1. Cryptocurrency Tweets Dataset:

In this dataset, there are ten thousand cryptocurrency-related tweets sourced in Kaggle. It is intended to be used in the area of sentiment analysis or trend tracking and natural language processing (NLP) applications as part of bitcoin conversations. The tweets are used to give details about sentiment and opinion in the cryptocurrency industry, thus referring to a particular number of the most famous cryptocurrencies, such as Dogecoin, Ethereum, Bitcoin, and others. tweet_id: Unique to each tweet; username: Twitter username of the user who tweeted; timestamp: Time and date a tweet was published; text: All text of the tweet; Retweets: Number of retweets a tweet received; likes: Number of likes on a tweet; hashtags: Hashtags used in a tweet.

2. Merged Twitter data:

The dataset provides an in-depth insight into Twitter discussions on cryptocurrencies because it aggregates tweets on various cryptocurrencies in multiple places. It suits well research and machine learning projects involving social media mining, the analysis of sentiment, the analysis of market trends, and natural language processing (NLP). The process of cleaning and aggregating the data has generated a rich and diverse set of tweet contents, such as user information, timestamps and measures of engagement, in the form of likes and retweets.

3. Bitcoin Tweets Data Set 2:

We gathered Bitcoin Tweets as a variant in the Kaggle site between February 10 of 2021 and January 28 of 2022. This data could be found at https://www.kaggle.com/datasets/kaushiksuresh147/bitcoin-tweets. The data that is found in this is founded on more than 174439 tweets, which were developed through application of a few algorithms on the complete assembly. The study aimed at ascertaining the attitude of the masses towards the use of Bitcoin and therefore SA of the tweets was the focus. The data includes thousands of columns such as '$user', 'userlocation', and '[count of followers of available user] userid, namely the total number of the followers along with the name of the user, their location, and other features other than the text of the tweet and the rating of the user. In them, the study of the text of the tweet is discussed. The data was not labeled to give information of the polarity of the sentiment, positive and negative or neutral and this is why the study used VADER classifier to classify the polarity of the sentence."

Proposed Methodology:

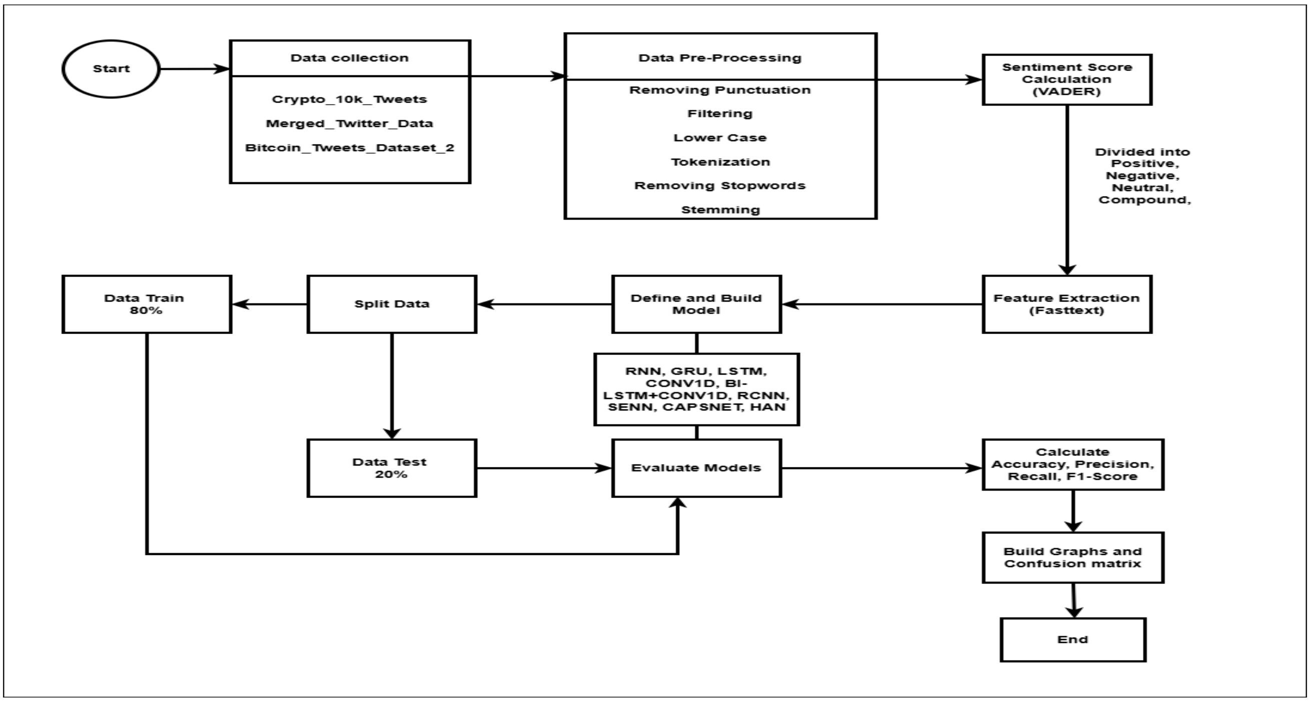


Fig. 1. Twitter data sentiment analysis architecture

The Fig.1 It can be seen in the processing that the entire pipeline is shown to examine the sentiments expressed regarding the cryptocurrencies on tweets. It begins with the collection of data set like Crypto_10k_Tweets, Merged_ Twitter_ Data, and Bitcoin_ Tweets_Data Set_2 and followed by valid data cleaning processes like removal of punctuation marks, lower conversion, tokenization and stemming. In the calculation of sentiments there is the VADER tool which is applied and the sentiments are scored between positive, negative, neutral or combined tweets. The process that extracts the features is FastText, which uses textual data in order to get features in the form of numerical vectors. The various deep learning models (RNN, GRU, LSTM, Bi-LSTM+Conv1D, RCNN, SENN, CapsNet, HAN) are built and are trained based on the processed data whose 80 per cent is taken as training data and 20 per cent as testing data. Finally the accuracy, precision, recall, and F1-score is used to assess the models and graph and also the confusion matrices are used to determine which model is better.

Deep Learning Models:

1. RNN:

Introduction to RNNs:

Recurrent neural networks RNNs are one of the types of the deep learning model that is employed in the process of sequential data processing. Unlike other feedforward neural networks, RNNs possess the recurrent connection, thanks to which they can keep in mind the data of the prior steps. It implies that they are the best fit those cases, when sentiment analysis is based on words, as the word order is important to produce sentiment and meaning.

How to work RNN Model:

Embedding Layer offers the provided words in dense vector form. Saved in the embedding_matrix are pre-trained embedding matrices (e.g. Word2Vec and GloVe). Use of trainable=False saves the meaning sense of the embeddings. Once the input sequence is fed to the first layer, SimpleRNN(300, return_sequences=True), which would have generated the sequence output, the other successive levels can deal with the sequential dependency. The sequence is sent to the second SimpleRNN (64) after which dimension is reduced but contextual information is again retained. The Dense(32, activation='relu') layer is applied to extract features of the high level of the sentiment. Dense(1, activation='sigmoid'): It makes a binary sentiment prediction (positive or negative).

2. GRU:

Introduction to GRU:

In order to partly resolve some of the weaknesses of canonical RNNs (vanishing gradient problem), a special sub-type of RNN was invented- a gated recurrent unit (GRU). GRUs presented by Cho et al. (2014) are efficient and effective in managing long-range dependency data in the form of text because of resorting to gates to manage the information flow. Since the GRUs can effectively capture long-range dependencies and causative relationships within the text, it appears in sentiment analysis rather frequently. This makes them fit to be utilized in the research on twitter cryptocurrency activity in whose indicators of market signals are rampant sentimental expressions.

How to work GRU Model:

Embedding Layer creates compact bases of vector description of the words used. This procedurally enhances understanding of the words when there is the assistance of an embedding matrix, which it has already been learned (e.g. a Word2Vec, or the GloVe). Trainable=False will cause the embeddings to not change during the training because it will bind them by making them constant. GRU(200, return_sequences=True): Processes the word by word analysis of the word twit based of the given previous context. The returns following sequential outputs are linked to next GRU layer to come back. The exertion of any country by individual Caribbean countries cannot be considered different from others. In the year 1998 the European Union started a programme of supervising the internal market by using the juridical control which enables members take legal action in cases of violation of internal market. Other process the sequence and produces the results in the form of the final hidden state which is a summary of sentiment of the tweet. Dense(32, activation='relu'): Decodes the features of the higher levels of sentiment. Dense(1, activation='sigmoid'): produces a 2 class sentiment expert (positive or negative).

3. LSTM:

Introduction to LSTMs:

To resolve the vanishing gradient problem which is a major drawback of the conventional RNN a certain type of RNN namely long short-term memory or LSTM was developed. LSTMs, which had first been proposed by Hochreiter & Schmidhuber (1997), constrain the flow of information through the incorporation of a memory cell and three gates; input, forget, and output gates. As LSTMs are able to find long-term coherence from text, they are also rather helpful for sentiment analysis with respect to cryptocurrencies. LSTMs can remember previous sentiment clues of a tweet irrespective of a large number of words separating them unlike regular RNNs that have the challenge of remembering important sequence when the sequence is long.

How to work LSTM Model:

Embedding Layer creates dense structures of words. The applications of trained word embeddings (e.g. Word2Vec,ne Words2Vec and GloVe) that were stored in embedding_matrix. trainable=False, give us a way of making the embeddings fixed, based on the knowledge learned concurrently about the meanings of the words. LSTM(300, return_sequences=True): It takes as input and input sequence and provides a sequence output to be passed to other layers of LSTM to gain information. LSTM(100): Produces the last temporal dependencies, and outputs the hidden state that summarizes the input. Dense(32, activation='relu'): Obtains high level sentiment features. Dense(1, activation='sigmoid'): Gives a two part categorization (negative/positive sentiment).

4. conv1d:

Introduction to Conv1D for Text Processing:

Despite being conventionally associated with image processing, convolutional neural networks (CNNs) have also proven themselves useful in such natural language processing (NLP) tasks as sentiment analysis. Conv1D applies the convolutional filters for identifying the local patterns and characteristics of the text information rather than traditional deep learning models such as Recurrent Neural Networks (RNNs), and LSTM networks that are sequential in analyzing the text. Conv1D is valuable for cryptocurrency sentiment analysis on Twitter because it can pick out the significant words/word combinations which are used for describing the positive and/or the negative sentiment.

How to work CONV1D Model:

Has been taking words and building dense vectors of numbers to them. Leaves pre trained embeddings (Word2Vec, GloVe), so as to fish out semantic meaning. Word- embedding scan with filters(also called kernels). Such patterns as price increase, “market down” or bullish trend are found by the filter. The kernel size determines how many words will be covered by a single convolution. The kernel size. facilitates the process of choosing the most significant features among the output of the convolutional. Minimizing the length of the sequence by half using the MaxPooling1D (pool_size=2) keeps the best information. The most effective of the functions chosen in the sequence, the GlobalMaxPooling1D() has the advantage that it makes the model more efficient. During the training, it can avoid overfit because randomly deactivating the neurons. Dense(32, activation='relu') acquires abstract sentiment attributes. Due to Dense(1, activation=”sigmoid) a binary output (positive or negative sentiment) is produced.

5. bi-lstm+conv1d:

Introduction to Bi-LSTM + Conv1D:

The Bi-LSTM + Conv1D is a combination of two deep learning models, to a sentiment analysis hybrid model, which seeks to capitalise on the advantages of Bi-LSTM and Conv1D simultaneously. The architecture has been find it handy when conducting sentiment analysis in Twitter cryptocurrency given that it can be used to extract both sequential dependencies and a local tendency in the text data. Conv1D, as a feature extractor, identifies important n-grams distributions, including "bullish trend" and a "Bitcoin surge”. Bi-LSTM will enable the model to comprehend the context and the text long-term dependency of the text by processing each set of the extracted features in a forward and a backward direction.

How Bi-LSTM + Conv1D Works:

represents the words into dense numerical vectors which are pre-trained with embedding such as Word2Vec and GloVe. trainable=False makes the embeddings as they were so that the meanings of the words that have been learnt stay the same. exploits n-gram features of the text with the 1D convolutional filters. tracks the regional trends, like market down or Ethereum boom. detects the sentiment patterns in a window of five words with a kernel length of 5. uses the most pertinent features, which have been previously retrieved by Conv1D performing dimensionality reduction. Does not overfit and is quicker. The Bi-LSTM has the capability of reading forward and backward unlike the ordinary LSTM which reads the text left to right. This will guarantee that long-term past and future dependencies will be represented. Case: in the case of, “Bitcoin is going down yesterday, whereas today it is recovering”, both the negative and positive sentiment depend on each other. Such relationships are well learnt by the Bi-LSTM. In training, random neurons are switched off to avoid overfitting. The high level representation of sentiment is learned by dense(32, activation=relu). The result of Dense(1, activation=sigmoid) is a positive or negative sentiment.

6. Rcnn:

Introduction to RCNN:

RCNNs are a combined type of deep model, using the functionalities of CNNs and RNNs, in categorizing text, like conducting sentiment analysis using Twitter on cryptocurrency. CNNs (Conv1D) extract major phrases and local patterns in text, as well as find sentiment-heavy words in it (e.g. a bullish trend, market crash). The RNNs (SimpleRNN) are able to capture long-term dependencies within the text that have to be processed sequentially.

How RCNN Works for Sentiment Analysis:

converts words into dense numerical vectors using pre-trained word embeddings (like word2vec and Glove). Maintains the meaning content of words in tweet. Applies 1D convolutional filters to get useful n-gram features (e.g. "Bitcoin drop", "Ethereum rising"). Establishes kernel contents of 5 (i.e. it searches on five words at once to identify phrases with sentiments). Same padding keeps the position of the output the same. Diminishes dimensions and maintains most important aspects of sentiments. Improves efficiency of computing by choosing the most powerful features. Sequentializes data in order to embrace dependencies in context. The second RNN layer can receive sequential features by the first SimpleRNN (300 units, return_sequences=True). The second SimpleRNN (64 units) is used to extract the last high-level-level sentiment information. It does not overfit by random deactivation of neurons during the training process. Dense (32, activation= relu) decodes high-level features of sentiments. The dense(1, activation='sigmoid') model hands over a binary classification of output (opinion or negative sentiment).

7. Senn:

Introduction to SENN:

Self-Explaining Neural Network (SENN) is a deep learning model that is made to be transparent and explainable to make sentiment analysis more simple. Compared to the classical models of deep learning, which essentially work as black boxes, SENN breaks its decision- making mechanism into three main aspects: Explanation Module- Derives meaningful features of the text provided, Coefficient Module- Projects significance (weights) on the acquired characteristics, Combination Module of the Features- Multiplies the features and their coefficients and the multiple to form a prediction. In the context of tweet based cryptocurrency sentiment analysis, SENN is able to perform correct sentiment classification as well as provide explanations concerning the classification, giving the trader or analyst an answer on why a tweet is defined as good or negative.

How SENN Works for Sentiment Analysis:

it applies pre-trained embeddings (ex: Word2Vec, GloVe) to map words to dense numerical vectors. Extracts linguistic meaning of words on cryptocurrency tweets. A dense(64, activation='relu') layer is used to identify important sentiment features of the text. Recognizes the most common words like BTC crash, bullish momentum, or Ethereum pumping. There is another Dense(64, activation=softmax) layer that gives importance weights to the features that have been extracted. ensures that terms with high relevance to the sentiments form a bigger part of the end classifications. In the sentence of example, i.e. Bitcoin is recovering after a market dip, the words recovering and after will be more significant. The Mulitply() layer mixes the features that were extracted and the assigned coefficients. Represents noteworthy characteristics that bear heavily on sentiment. generates a 1D feature by taking concatenated representation of features. A binary sentiment classification layer that uses a Dense(1, activation='sigmoid') is done. Decides the sentiment of the tweet whether it is a positive or a negative tweet with respect to cryptocurrency.

8. Capsnet:

Introduction to Capsule Networks:

A superior deep learning structure to overcome the limitations of conventional CNN obtained a superior deep learning framework called Capsule Networks (CapsNet). CapsNet actually preserves spatial hierarchies because it memorizes the location and pose of features, as opposed to observations that are marked in Convolutional Neural Networks (CNNs) that focus on local features. Due to this property, CapsNet can perform complex text-based classification tasks that depend on word relationships and context such as sentiment analysis on Twitter of cryptocurrencies. To analyze the sentiment of the cryptocurrency, CapsNet would help get a refined sentiment-level of the tweets wherein the connection between words could be identified based not just on frequency, as shown in simple tweet sentiment analysis.

How CapsNet Works for Sentiment Analysis:

One undertakes pre-trained embeddings (Word2Vec, GloVe, FastText) to convert words into dense numerical vectors. Brings semantics into the words that already exist regarding cryptocurrencies like, bullish, HODL, FOMO, etc. According to the text, important features are spotted with a 1D Convolutional Layer (Conv1D), that captures local word dependencies through 128 filters of kernel size 9. The features got are transformed into small vector capsules which consist of 8 dimensions per capsule. Custom squash activation function makes sure that outputs of the capsules lie within a normalized scale. A feature presence in its pose (orientation) in each capsule is coded. The Capsule Layer is composed of ten capsules (each sixteen-dimensional) and is adapted to capture rich representations of sentiment. Capsule Layer makes use of dynamic routing an iterative agreement procedure which updates the importance of features using communication among capsules. CapsNet won?t lose information because the spatial hierarchies are preserved unlike CNNs that are using max-pooling. Capsule outputs are softened to one dimensional (1D) vector to facilitate classification. A Dense(1, activation='sigmoid') layer is used to perform binary sentiment classification as to whether the emotion in the tweet regarding cryptocurrencies is either good or negative.

9. HAN:

Introduction to Hierarchical Attention Networks (HAN):

Hierarchical Attention Networks (HAN), a complicated deep learning model was devised to handle the needs of text categorization like the analysis of sentiment in the case of cryptocurrencies on Twitter. HAN is actually a hierarchical model which allows word and sentence-level understanding of documents in a way that is similar to the human way of understanding language rather than the traditional distributed models in which text is viewed as a linear structure of words. HAN effectively detects contextual sentiment in cryptocurrency discussions, by the provision of varying attention to different words. This will enable the model to disregard less significant words and focus on significant ones such as, bullish, dumping, and moon.

How HAN Works for Sentiment Analysis:

The input layer is given a word string, like a tweet on cryptocurrencies. Embedding Layer: It is similar to embedding Layer, only that it applies the pre-trained embeddings (Word2Vec, GloVe, FastText) to enhance Word translation to the numerical vectors. A bidirectional GRU (100 units) is used to process every word, in both forwards and backwards directions, and maintains a history of contextual dependencies. This will enable HAN to interpret phrases such as the difference between Bitcoin is pumping and pumping Bitcoin which could be of different meanings. Words do not have total contribution to sentiment. The attention layer will give greater weights to the crucial words and then disregard other insignificant ones. Evidence: In Bitcoin is mooning! Huge gains ahead!, the words in this phrase are scored higher in the focus when it comes to the words mooning and gains. The model is an amalgamation of the weighted word characterizations to crank out one sentence representation. The Dense(1, activation='sigmoid') layer labels a sentiment as either negative or positive. Loss Function: Binary Cross-Entropy (as it is a binary classification).

Conversion of Sentiment Scores into binary:

Firstly, the sentiment score is calculated in 4 classes i.e. Positive, Negative, Neutral and Compound. And mainly focus is on compound part because it is combination of above three. But it very complicated to calculate the sentiment based on multiple classes so, we have converted the scores into binary. After conversion the sentence will be either positive or negative only and that also based on compound score.

```
        if (compound_score > 0)
positive
else
        negative
```

Experimental results and analysis:

In this section, results of all the nine models are shown. How all the nine models have performed on all three datasets. And further the graphs and confusion matrices are being showed for the models which have performed best among all for all the three datasets. The graphs contain model accuracy vs epochs and model loss vs epoch showing how the model had behaved from time to time.

1. Crypto_10k_Tweets:

Table 1. Calculated Metrics for Crypt_10k_Tweets Dataset

MODELS	ACCURACY	PRECISION	RECALL	F1-SCORE
RNN	0.84	0.74	0.72	0.73
GRU	0.91	0.84	0.87	0.85
LSTM	0.91	0.85	0.86	0.86
CONV1D	0.88	0.81	0.78	0.80
Bi-LSTM+CONV1D	0.87	0.77	0.82	0.79
RCNN	0.83	0.75	0.69	0.72
SENN	0.86	0.80	0.70	0.75
CAPSNET	0.87	0.80	0.77	0.78
HAN	0.91	0.87	0.82	0.85

The table above Table 1. shows the computed metrics of each model in the form of Accuracy, Precision, Recall and F1-Score. As we can observe, GRU, LSTM and HAN share 91 percent accuracy, and the rest of the metrics are different. Also, LSTM had performed better than the other measures.

2. Merged_Twitter_Data:

Table 2. Calculated Metrics for Merged_Twitter_Data Dataset

MODELS	ACCURACY	PRECISION	RECALL	F1-SCORE
RNN	0.79	0.78	0.83	0.80
GRU	0.96	0.95	0.97	0.96

LSTM	0.96	0.96	0.96	0.96
CONV1D	0.92	0.93	0.93	0.93
Bi-LSTM+CONV1D	0.93	0.92	0.94	0.93
RCNN	0.90	0.88	0.93	0.91
SENN	0.91	0.92	0.90	0.91
CAPSNET	0.91	0.92	0.90	0.91
HAN	0.95	0.95	0.95	0.95

The table Above Table 2., the results of each model according to the computed metrics, the Accuracy, Precision, Recall, and F1-Score are written. As one can observe, both GRU and LSTM demonstrate 96 percent accuracy, but they vary according to some other metrics. Moreover, in comparison to all other metrics, LSTM has also been at the top.

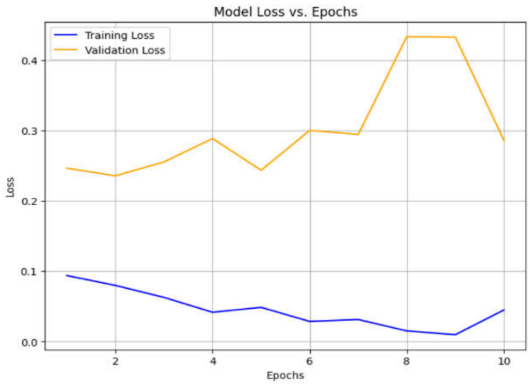
3. Bitcoin_ Tweets_Data Set_2:

Table 3. Calculated Metrics for Bitcoin_tweets_dataset_2 Dataset

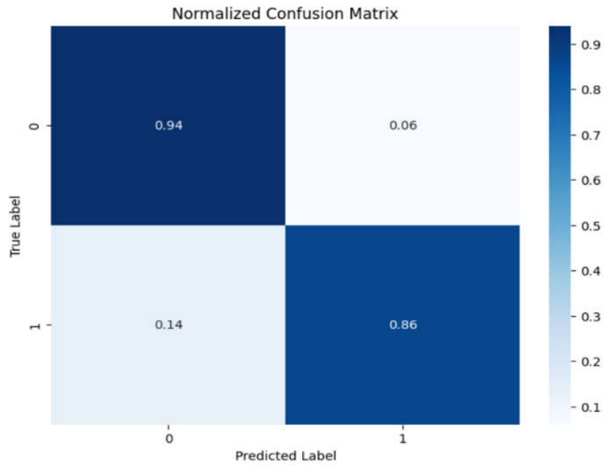
MODELS	ACCURACY	PRECISION	RECALL	F1-SCORE
RNN	0.70	0.56	0.65	0.60
GRU	0.98	0.98	0.95	0.97
LSTM	0.97	0.98	0.95	0.96
CONV1D	0.96	0.94	0.94	0.94
Bi-LSTM+CONV1D	0.96	0.96	0.94	0.95
RCNN	0.95	0.93	0.93	0.93
SENN	0.95	0.95	0.91	0.93
CAPSNET	0.94	0.93	0.91	0.92
HAN	0.97	0.96	0.96	0.96

Above Table 3. shows the metrics calculated for each model, together with Accuracy, Precision, Recall, and F1-Score. As could be observed, the accuracy rate of GRU is 98 percent. Also, GRU has even excelled in all the other criteria.

(a)



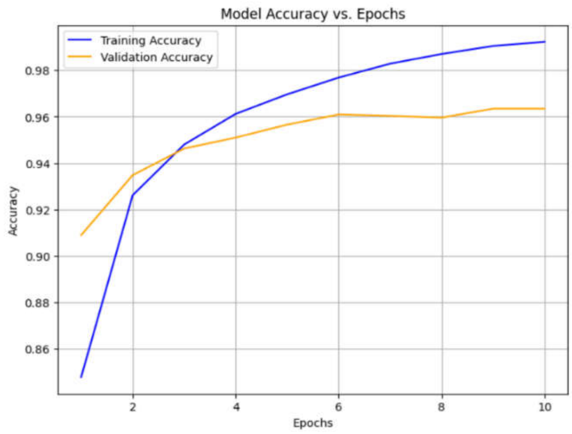
(b)



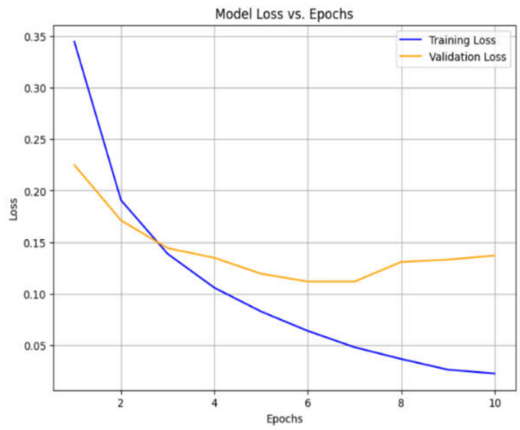
(c)

Fig. 2. Results of LSTM on Dataset Crypto_10k_Tweets

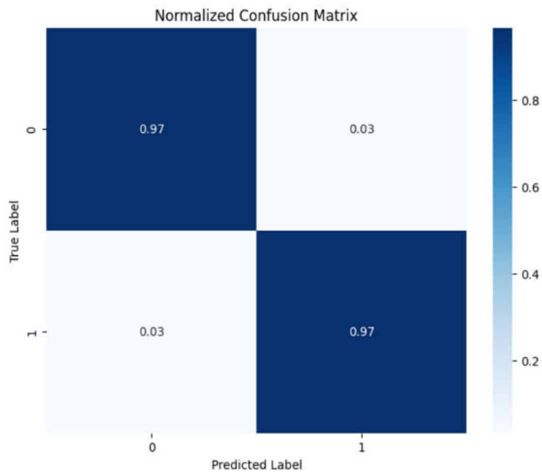
In the above Fig. 2., all results of LSTM are being showed on the dataset Crypto_10k_Tweets. LSTM is chosen because it is the model which have given best results for this dataset. In Fig. 2. (a), it shows a graph of model accuracy vs epochs means how the accuracy of model differs from time to time while training and validating. In Fig. 2. (b), it shows a graph of model loss vs epochs means how much loss have been made from time to time. And in Fig. 2. (c), it shows the confusion matrix of LSTM model on this dataset.



(a)



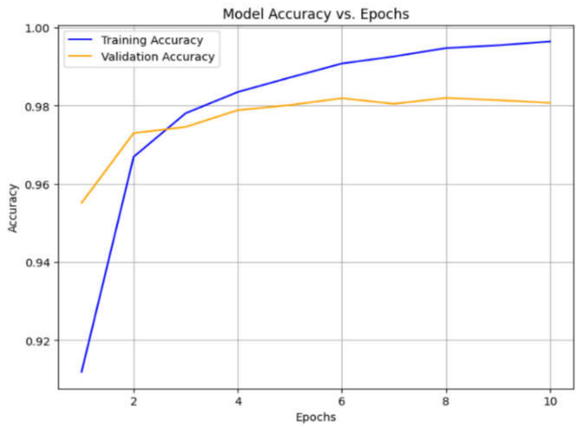
(b)



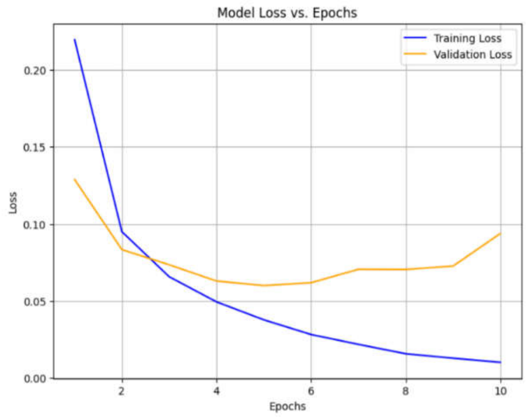
(c)

Fig. 3. Results of LSTM on Dataset Merged_Twitter_Data

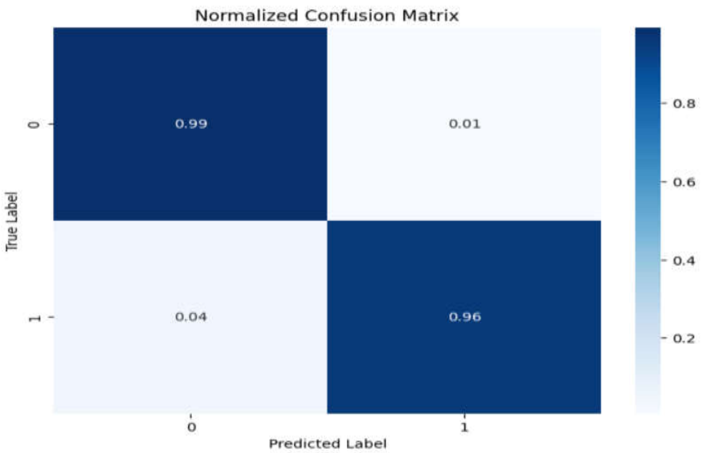
In the above Fig. 3., all results of LSTM are being showed on the dataset Merged_Twitter_Data. LSTM is chosen because it is the model which have given best results for this dataset. In Fig. 3. (a), it shows a graph of model accuracy vs epochs means how the accuracy of model differs from time to time while training and validating. In Fig. 3. (b), it shows a graph of model loss vs epochs means how much loss have been made from time to time. And in Fig. 3. (c), it shows the confusion matrix of LSTM model on this dataset.



(a)



(b)



(c)

Fig. 4. Results of GRU on Dataset Bitcoin_ Tweets_Data Set_2

In the above Fig. 4., all results of GRU are being showed on the dataset Bitcoin_Tweets_Dataset_2. GRU is chosen because it is the model which have given best results for this dataset. In Fig. 4. (a), it shows a graph of model accuracy vs epochs means how the accuracy of model differs from time to time while training and validating. In Fig. 4. (b), it shows a graph of model loss vs epochs means how much loss have been made from time to time. And in Fig. 4. (c), it shows the confusion matrix of GRU model on this dataset.

Conclusion and Future Scope:

In this paper, a detailed evaluation of several deep learning models to evaluate tweets on sentiment analysis of cryptocurrency would be given. We have tried to classify attitude in three categories namely positive, negative and neutral where we have used models like RNN, GRU, LSTM, Conv1D, Bi-LSTM+Conv1D, RCNN, SENN, CapsNet and HAN. All the results indicate that the LSTM and GRU models yield a higher accuracy, precision, recall and F1-score that are all higher than the other models with LSTM models performing barely better in the overall robustness and generali-zability. This explains the effectiveness of recurrent architectures to con-textual sentiment and long-term

dependencies within short informal social media texts. Also, the use of FastText in word embedding significantly improved the work of models and contributed to the improvement of semantics. Considering everything mentioned above, the proposed technique can serve as an effective starting point in the narrow characterization and analysis of market sentiment on Twitter and to deliver valuable information to cryp-tocurrency researchers and cryptocurrency investors.
Incorporation of multilingual data and live Twitter feed into the dataset can potentially improve the model to be used in global markets. It might also be improved with transformer-based systems BERT, RoBERTa, or DeBERTa, particularly when combined with financial text. In addition, The ability to predict the prices of the bitcoin could be improved by a hybrid model involving sentiment analysis merged with a price series.

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