Bitcoin Tweets Sentiment Analysis by Leveraging Transfer Learning with BERT

Abstract
Over the past several years, the cryptocurrency industry has grown at an unparalleled rate. Similar to traditional cash, virtual payments for goods and services are made with the help of no centralized authority using cryptocurrency. Although using cryptographic techniques, cryptocurrency assures authentic and one-of-a-kind transactions, this business is still in its infancy, and substantial concerns have been expressed concerning its use. To get an overall picture of how people feel about cryptocurrencies, sentiment analysis is particularly desired. Considering this, the suggested research attempts to make use of BERT, a cutting-edge transformer-based model, for sentiment analysis on a dataset of Bitcoin tweets. The suggested technique includes many crucial phases for preprocessing the data, enhancing the BERT model, and assessing the effectiveness of the model. We want to create a sentiment analysis model that can properly categorize the sentiment of tweets about Bitcoin by putting this suggested technique into practice. The study's findings will help people better comprehend sentiment analysis methods used on social media data pertaining to cryptocurrencies.

Introduction
The current world has many intriguing themes, and cryptocurrency has altered how people see money. It is virtual money that is managed through a Blockchain-based cryptography mechanism (Chohan, 2022). Its broad use and ongoing adoption have significantly increased the value of its real-world applications. The first cryptocurrency was created in 2009, and its name is Bitcoin (Nakamoto, n.d.). It is a decentralized kind of electronic money that may be used for digital transactions. Bitcoin is an extremely volatile currency, and socially created perceptions have an impact on its value. Previous research found that some of the rapid fluctuations in Bitcoin's price were related to significant occurrences in China (Kristoufek, 2015). With the development of Internet technology, consumers are sharing more ideas and feelings via textual or multimedia data on platforms such as social media and e-commerce than ever before (Behera et al., 2020), (Gupta & Gupta, 2018), (Wang et al., 2020), and (Z. Zhang et al., 2017). This phenomenon has produced and generated a wide range of data, which may be examined to determine attitudes. Given the huge amount of data being produced, both individuals and businesses may benefit from sentiment analysis (Liu, 2020).

For a number of reasons, it is critical to comprehend the sentiment of Bitcoin tweets. First of all, sentiment analysis may offer insightful information about popular opinion, assisting investors in determining the general attitude toward Bitcoin and informing their judgments. Second, traders might modify their strategies as a result of emerging trends and probable market shifts identified by sentiment analysis. The influence of public mood on the bitcoin market may also be evaluated by financial experts with the use of sentiment analysis, allowing for more precise market predictions and risk evaluations.

A thorough study of the literature on sentiment analysis and cryptocurrencies finds that sentiment analysis has been broadly used in different contexts, including news articles, social media posts, and consumer evaluations. However, there isn't a lot of work that specifically applies sentiment analysis to tweets on Bitcoin. This knowledge gap emphasizes the importance of investigating sentiment analysis techniques designed especially for tweets on Bitcoin. Despite the development of numerous approaches for sentiment analysis including machine learning, lexicon-based and hybrid approaches, supervised machine learning methods have been proven more accurate compared to other methods. However, this method requires labelled data (Sebastiani, 2002), which may be time-consuming, costly, and error-prone (Zhu, 2005). This data is needed to create and test a classifier model. This can be troublesome for systems like Twitter that use microblogging and often have vast amounts of data with few labels.

Moreover, Microblogging messages can be more chaotic, random, and ambiguous than texts in traditional media (Feng & Kirkley, 2021), (Saif et al., 2012), making it challenging for supervised classification using machine learning to draw conclusions from them. Due to the large scale of the dataset and vocabulary, text representation methods, such as term frequency-inverse document frequency ("TF-IDF") or "n-gram," frequently result in a high-dimensional feature space. The data representation is also quite sparse due to the short and noisy sentences. The development of an understandable model with a high prediction accuracy is significantly challenging by this high-dimension sparse representation. On the other hand, the huge scale of microblogging can offer more unprocessed information for extracting features for the complexity of the model, which strengthens and improves the machine learning model (Da Silva et al., 2016). Only a few research have examined this aspect in sentiment analysis, despite the fact that the size of the dataset can influence the performance of the model during the training process and influence deciding the values of model parameters. Due to the time-consuming nature of labelling and processing all raw data, the appropriate dataset size to capture all required features to build an effective classification model when raw data are huge is another crucial aspect of sentiment analysis.

How can we create a personalized sentiment analysis model to precisely categorize Bitcoin tweets into positive, negative, and neutral sentiment classes? is the main research topic driving this work? How else may the performance of the classification model be impacted by the amount of data or the extracted features? We suggest using a modified BERT or Transformer model with transfer learning strategies to answer this query. The performance of BERT and Transformer models in sentiment analysis and other natural language processing applications has been exemplary. We want to create a strong sentiment analysis model that can capture the distinctive qualities and feelings conveyed in tweets about Bitcoin by utilizing these models and applying transfer learning.

The suggested study makes numerous contributions to the field of sentiment analysis. First off, it adds to the body of research by applying sentiment analysis exclusively to tweets about Bitcoin, which stand out for their importance and influence on the cryptocurrency market. Second, the study makes use of cutting-edge preprocessing techniques to guarantee the accuracy and dependability of the sentiment analysis model. To improve the precision of sentiment categorization, this entails deleting abnormalities, irrelevant data, and noisy language. Finally, by using transfer learning techniques with a tailored BERT or Transformer model, the model is able to learn from a vast corpus of text data and adapt particularly to sentiment analysis connected to Bitcoin, resulting in better accuracy and performance. The planned study will also look at how the performance of the classification model is impacted by the amount of data.

Literature Review

The diffusion of knowledge about cryptocurrencies through social media and online media has expanded as their popularity has grown (Kim et al., 2016). Social media may be used to forecast upcoming events and developments by examining feelings on socioeconomic issues and public attitudes (Schoen et al., 2013). Previous research (Garcia & Schweitzer, 2015), (Phillips & Gorse, 2018) has supported the relationship between Twitter and the forecast of bitcoin prices. Hybrid sentiment analysis, which combines supervised machine learning with a semantic lexicon, has received more attention in recent years (D, 2019), (Fan et al., 2017), and (Tanesab, 2017). VADER is one of the most often used lexical semantic methods for calculating sentiment polarity ratings. In order to determine the sentiment score, the 2014-introduced VADER lexicon and rule-based sentiment analysis model determines the polarities (positive/negative) and intensities (strong) of emotions. The following are some of VADER's benefits: In addition to being an open-source tool and using a human-centric approach, it is also specifically made for social media content (Valencia et al., 2019). The most often used methods for sentiment analysis, whether alone or in combination with VADER, are supervised machine learning techniques like support vector machines (SVM) and Naïve Bayes (NB). Sentiment lexicons and unsupervised learning have both been demonstrated to provide less accurate sentiment analysis (Bermingham & Smeaton, 2010).

Because there are so many uncommon terms included in tweets, Saif et al. (Saif et al., 2012) have shown that Twitter tweets text is sparser than other forms of data (such as movie review data). Grammar mistakes and the use of slang terms might cause such a characteristic. Additionally, there is a lot of noisy data on Twitter, including URLs, emojis, punctuation, stopwords and special characters. Therefore, as outliers to the text in focus, unrelated words and data that are just there by random events or have no impact on the current text may change the polarity or entropy of the tweet text. Due to the vast amount of raw data, it is essential to automatically identify pertinent information from these data, which has led several researchers (C. Huang et al., 2019; Kübler et al., 2018; Kumar & Khorwal, 2017; Tommasel & Godoy, 2018) to investigate different feature selection techniques and classifier models. Due to its ease of use and processing effectiveness, the bag-of-words model represents the sentence and document as a list of words with their frequency using the document-term matrix (Aggarwal & Zhai, 2012). Based on their relative distances, the words in the matrix are grouped together. Information retrieval, text grouping, and categorization of texts have all benefited from the application of this strategy. Due to the fact that each document will only include a small portion of the unique phrases that are present across the corpus, most DTMs are high dimensional and sparse (Buenaño-Fernández et al., 2017). Any matching document row will have zeros for phrases that were not used in that document as a result of this condition. Consequently, we want a strategy to lessen dimensionality. A common technique for determining the word weight value in a group of texts is the TF-IDF (Havrlant & Kreinovich, 2017), (Spärck Jones, 2004). It displays how each word in a text or corpus is distributed over the whole document.

In addition to sentiment analysis, some works anticipate emotional analysis by utilizing Bitcoin-related tweets. Generally, the positive emotion reflects the positive sentiment and vice versa. For NLP and sentiment analysis (SA) experts, Twitter sentiment analysis has emerged as a popular study subject. However, it is hard for people to do sentiment analysis due to the diversity and volume of the data on social media. This issue required the automated system for the sentiment analysis of Bitcoin tweets. As a result, there is substantial material of literature on sentiment and emotion analysis. For instance, a study (Hasan et al., 2019) suggests a machine-learning method for automatically identifying emotions from material uploaded on social media. By doing the text categorization, sentiments are found. The study examines a number of issues, such as the semantic complexity of messages, the informal tone of microblogs, the presence of many feelings in text, and various emotional states. To discriminate between tweets with and without emotions, binary classifiers are utilized. The method's two primary tasks are offline training and online classification tasks. Emotex, a developed emotion categorization system, can classify texts with an accuracy of 90%.

Similar to (Hasan et al., 2019), (Sharifirad et al., 2019) predicts the degree of emotion intensity and emotion detection. Natural language processing (NLP) technologies are used for sexist tweets, which are divided into three categories: indirect harassment, physical harassment, and sexual harassment, for this purpose. In addition, low, medium, and high-intensity feelings of joy, sadness, and fear are studied. Word2Vec, global vector (Glove), and FastText are used with SVM, Naive Bayes (NB), KNN, Multi-layer Perceptron (MLP), LSTM, and convolutional neural network (CNN) to achieve excellent classification accuracy for multilabel classification. The study also looks at three kinds of speech that contain sexist comments to determine the strength of each emotion. Results indicate a direct relationship between happiness and indirect harassment, and when intensity is taken into account, anger is linked to sexual harassment. Similar to how sentiments of rage, happiness, and grief are connected to physical abuse.

Using the AIT-2018 dataset, the study (Shah et al., 2019) does tests to identify the emotions expressed in tweets. The authors suggest a brand-new methodology for identifying emotions that makes use of

WordNetAffect and EmoSenticNet. Results indicate that the short dataset and issues with linguistic ambiguity have an impact on performance. Because the material contains many emotions, accuracy is diminished. In (X. Zhang et al., 2020), the authors use lexicon-based and machine-learning techniques to do sentiment analysis on online social networks. For this, a multilabel learning algorithm is shown. The suggested method uses machine learning techniques to create a multilabel emotion detection system with the goal of multiple-level emotion detection regarding user perspective. In addition to emotion label association, the authors also find social and temporal correlation. The suggested technique, while its potential, is constrained by the use of a tiny dataset and poor accuracy. In (Haryadi & Putra Kusuma, 2019), a stacked LSTM model for emotion detection is introduced. It is based on deep learning. The authors want to improve how accurately Ekman's emotions are classified. The studies make use of a sizable dataset that includes 144,160 testing samples and 980,549 training samples. With a 99.16% accuracy rating, nested LSTM is the most accurate approach. The findings are not noticeably different from other models, which is a flaw that needs to be fixed.

Some studies use sentiment analysis of tweets related to cryptocurrencies in addition to emotion research to forecast cryptocurrency market values. Positive comments are frequently associated with rising Bitcoin market interest and vice versa. For instance, a study (X. Huang et al., 2021) suggests utilizing machine learning and sentiment analysis to estimate the value of cryptocurrencies. The Chinese social networking site Sina-Weibo is mined for cryptocurrency-related posts for examination. Both the proposed crypto-based sentiment dictionary and the LSTM model are used for prediction. The proposed technique outperforms the preceding methods by 18.5% and 15.4%, respectively, in terms of accuracy and recall. Similar sentiment research is carried out on particular bitcoin currencies by the authors in (Şaşmaz & Tek, 2021) utilizing the tweets dataset and machine learning methodology. The experiments were conducted on the NEO dataset and manually labelled dataset for sentiment analysis and got 77% classification accuracy. A summary of the state-of-the-art studies for sentiment analysis is presented in Table 1.

Table 1: Overview of State-of-the-art Studies

Reference	Year	Objective	Dataset	Model
(Hasan et al., 2019)	2019	Emotion Detection	Tweets Text	Machine Learning (SVM)
(Sharifirad et al., 2019)	2019	Emotion Detection of Sexist Tweets	Sexist Tweets Text	Machine Learning (SVM, KNN, NB, MLP, CNN and LSTM)
(Shah et al., 2019)	2019	Emotion Detection	AIT-2018	Machine Learning (DT, SVM, NB and proposed CNN)
(X. Zhang et al., 2020)	2020	Online Emotion Detection	Tweets Text	KNN and Proposed CNN for Multi-Label
(Haryadi & Putra Kusuma, 2019)	2019	Emotion Detection	Tweets Text	SVM, LSTM and Nested LSTM
(X. Huang et al., 2021)	2021	Emotion Detection for the Chinese Language	Chinese Text Data (Sina-Weibo Dataset)	LSTM
(Şaşmaz & Tek, 2021)	2021	Sentiment Analysis	Tweets Text	Machine Learning (Random Forest)
(Aslam et al., 2022)	2021	Sentiment Analysis	Tweets Text	Machine Learning and Deep Learning (LSTM and GRU)

Methodology

The suggested remedy involves using BERT, a cutting-edge transformer-based model, for sentiment assessment on a collection of Bitcoin tweets. Using the labelled Bitcoin Twitter dataset to fine-tune a pre-trained BERT model, we want to build a sentiment analysis model using a transfer learning technique that can precisely categorize the sentiment of tweets on Bitcoin.

Dataset

The dataset used for this proposed work is the BTC Tweets Sentiments dataset from the Data-world platform. This collection of tweets on Bitcoin from various individuals is accompanied by accompanying feelings. By gathering tweets that expressly reference Bitcoin, the dataset was created. The collection is made up of 50,852 distinct items, each of which represents a tweet about Bitcoin as shown in Table 2. There are rows separating these records. 10 more variables or columns in the dataset provide detailed information about the tweets and their feelings.

Table 2: Statistics of Selected Bitcoin Dataset

Dataset	**Number of Samples in Dataset:**	50852
	Number of Columns in Dataset:	10

According to the suggested technique, the dataset will be used to predict tweet sentiments using a deep learning model, especially a deep learning model based on BERT. The purpose of using this dataset to train and fine-tune the deep learning model is to create a model that can precisely predict the sentiment related to tweets regarding Bitcoin.

Preprocessing

Cleaning and converting the data is the first step in getting a dataset ready for machine learning models. We will use a range of data preparation techniques in this context, such as data cleansing, tokenization and lemmatization.

Tokenization: Tokenization is the separation of a text into discrete words (tokens). Tokenization, which divides the text into smaller pieces for simpler analysis and feature extraction, is a vital stage in the preparation of text. Take this declaration as an example: "I love Python programming". The text would be divided into the tokens ["I", "love", "Python ", "programming"] after tokenization.

There are several ways to accomplish tokenization, including using space as a delimiter, regular expressions, or specialized tools like NLTK or spaCy.

Lemmatization: Lemmatization is the process of condensing words to their root or basic form, or lemmas. It seeks to standardize words by condensing them into an analytically useful form. This helps manage word variants and condenses the lexicon. For instance, "running," "runs," and "ran" would all be reduced to "run."

To achieve correct lemmatization, each word's part of speech is taken into consideration. The lemma is determined through morphological analysis and language-specific dictionaries. Lemmatization functionality is offered by well-known libraries like NLTK and spaCy and may be used during the preprocessing stage.

Noise Removal: Eliminating unneeded or extraneous text components that could not be helpful for analysis or sentiment categorization is known as noise reduction. Special characters, punctuation, URLs, usernames, and stopwords are typical examples of noise.

a. Special Characters and Punctuation: In sentiment analysis, special characters and punctuation marks like "@", "#", "$", and "?" are frequently deleted because of their lack of significance.
b. URLs and Usernames: Since they don't offer useful information for sentiment categorization, URLs and usernames are often eliminated.
c. Stopwords are typical words that pop up often in a language and don't add anything to the sentiment analysis assignment. Stopwords contain things like "and," "the," "is," etc. Stopwords are eliminated, which lowers noise and enhances the performance of sentiment analysis models.
d. Lowercasing: Treating terms with varying capitalizations as the same by changing all text to lowercase reduces repetition and broadens vocabulary.

To clean up the data, we will take out all stop words from tweets. Additionally, the removal of punctuations, special characters, symbols, integers and URLs will be a part of data cleaning. The hashtags and emoji icons were also removed from the tweets, and the rest of the text was altered to lowercase. Stemming, the last procedure in the preprocessing phase, converted words from their alternative forms to their traditional ones. To stem tweets, we will use the well-known Porter Stemmer Algorithm. Table 3 displays an example of a tweet after preprocessing.

Table 3: Examples of Raw and Processed Tweets.

Raw Tweet Text	Processed Tweet Text
@p0nd3ea Bitcoin wasn't built to live on exchanges.	Bitcoin, built, live, exchange
free coins https://t.co/DiuoePJdap	Free, coins

Tokenization, lemmatization, and noise reduction are some of the preprocessing techniques that aid in transforming unstructured, unstandardized text input into a format suited for sentiment analysis tasks. These methods allow the model to concentrate on the important information in the text while minimizing noise and pointless fluctuations.

Feature Extraction

After the tweets have been transformed into stem words, the necessary elements for categorization must be extracted, and the unnecessary words that have no particular effect on sentiment must be eliminated. Two other popular weighting methods for extracting features are Word2Vec and TF-IDF (Term Frequency Inverse Document Frequency).

A common technique for determining the word-weighted value in a collection of texts is the TF-IDF [29], [30]. It displays how each word in a text or corpus is distributed over the whole document. The TF-IDF score for each word is calculated by dividing the TF by the IDF. To obtain a TF-IDF score, follow these steps:

- compute the TF value using (1)
- determine the IDF value using (2)
- determine the TF-IDF weight value using (3)

$$tf(t,d) = \frac{f_d(t)}{\max_{\omega \epsilon d} f_d(\omega)} \qquad (1)$$

$$idf(t,d) = \ln\left(\frac{|D|}{|\{d \in D: t \in d\}|}\right) \qquad (2)$$

$$tfidf(t,d,D) = tf(t,d)\ x\ idf(t,d) \qquad (3)$$

In equ. 1 TF is the frequency of the words represents how many times a word appear in a document. While IDF in equ. 2 is the frequency of the document in which that word is appear. Finally, the TF-IDF is the natural log of all documents containing a specific word divided by the word document frequency. To count words and their frequencies for this study, we will convert the tweet texts into an integral representation using the scikit-learn Count Vectorizer class.

Train Test Split

The chosen dataset will be divided into three different groups for the proper training of the model labelled as training set, validation set and testing set. For this approach, a recommended split ratio of 70% for the training set, 10% for the validation set, and 20% for the test will be implemented. An explanation of the train-test split process is provided below:

1) Randomization: It is crucial to randomize the order of the records before dividing the dataset. This randomization eliminates any potential biases brought on by the dataset's initial order by ensuring that the data is dispersed equally throughout the training, validation, and test sets.
2) Train-Test Split: Using the chosen split ratios, the dataset will be split into the training, validation, and test sets:
   - Training Set: 35,597 records, or 70% of the dataset, will be used to train the model. This greater chunk of the dataset is utilized to supply the model with enough information to identify patterns and make precise predictions.
   - Validation Set: A separate validation set consisting of 10% of the dataset (5,085 records) will be employed. This collection is mostly used to evaluate how well the model performed during training. It aids in tracking the model's development, fine-tuning hyperparameters, and guarding against overfitting.
   - Test Set: The remaining 10,170 records, or 20% of the dataset, will serve as the test set. This set is used to assess the trained model's overall performance. It offers an unbiased evaluation of the model's capacity for generalization to unknown inputs.

It is essential to preserve the initial distribution of sentiment labels across the sets throughout the train-test split. This guarantees that each set fairly captures the attitudes found in the whole dataset. For instance, the train, validation, and test sets should keep a similar distribution if the original dataset contains 40% positive, 30% negative, and 30% neutral tweets. Programmatically implementing the train-test split is possible with a variety of modules and frameworks, including Python's scikit-learn. These libraries offer practical functions for dividing datasets while maintaining the label distribution and distributing the records randomly.

Model Training

We will use a variety of machine learning approaches, as well as a customized transformer-based Bert model, to categorize tweets that contain allusions to Bitcoin. We will employ a training set to educate well-known machine learning models including the SVM, RF, and KNN models. In addition, we'll train the BERT model using a set of tweets. The models will be trained on a train set of 6000 samples, and they will be tested on 1553 samples. All models were evaluated using the selected evaluation metrics.

Model Evaluation

An ablation study will be carried out to determine the ideal model for classifying the sentiment of tweets about Bitcoin. We will utilize a variety of assessment metrics, such as accuracy, precision, recall, and f1-score, to assess the trained models. Contrarily, precision or confidence refers to the percentage of predicted positive situations that are actually real positives. As a result, we may say that the accuracy is "how many are correctly classified among that class," and the recall is "how many of this class you find over the whole number of elements of this class." The harmonic mean of recall and accuracy is known as the f1-score. In eqs. 4-7, the formulas for determining accuracy, precision, recall, and f1-score are given.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{Eq. 4}$$

$$Precision = \frac{TP}{TP+FP} \qquad \text{Eq. 5}$$

$$Recall = \frac{TP}{TP+FN} \qquad \text{Eq. 6}$$

$$F1Score = \frac{2*(recall*Precision)}{Recall+Precision} \qquad \text{Eq. 7}$$

Tentative Schedule

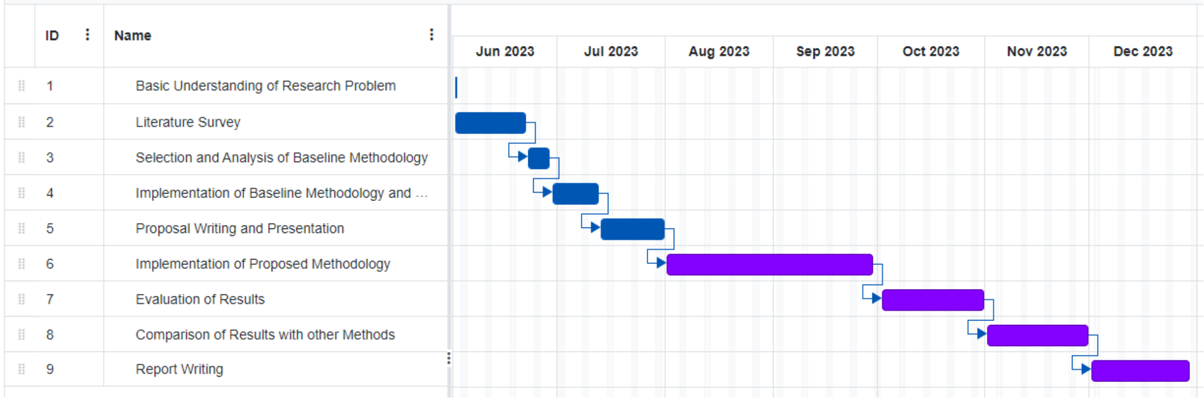

Figure 1: Timeline of the Proposed Work.

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