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Survey On Crypto Sentiment Analysis With The Help Of Machine Learning

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Abstract - This study explores cryptocurrency sentiment using tweets, employing a deep learning ensemble (LSTM-GRU) model. Analyzing emotions with Text Blob and Text2Emotion, it reveals predominant positive sentiments, especially happiness. Utilizing term frequency-inverse document frequency, word2vec, and bag of words features, the LSTM-GRU ensemble achieves high accuracy (0.99). Notably, machine learning models excel with bag of words features. The cryptocurrency market's rapid evolution prompts sentiment analysis, shedding light on public perceptions and emotions, crucial for predicting market trends.

Keywords – Cryptocurrency, Sentiment analysis, Machine learning, Deep learning & LSTM-GRU ensemble.

1. INTRODUCTION

Cryptocurrency market has been developed at an exceptional pace since its emergence. Cryptocurrency is a digital currency however it is not controlled by any central authority to make online payments. It uses system ledger entries called ‘tokens’ to make online payments for goods and services. Elliptical curve encryption and public-private key pairs are used as

The associate editor coordinating the review of this manuscript and approving it for publication was Seifedine Kadry. cryptographic algorithms. Similarly, hashing functions are utilized to protect online payments and ensure legitimate and unique transactions. Bitcoin was the first blockchain-based cryptocurrency introduced in 2009 and it remains important and leading the market today. In addition to Bitcoin, a large number of cryptocurrencies have been introduced over time, each with its opportunities and functions to provide different features and specifications. Such cryptocurrencies include Bitcoin clones, as well as, entirely new currencies with additional features.

Cryptocurrency investors expect both profit and loss due to ups and downs in the crypto market. For this purpose, many tools are available which can forecast the crypto market and occasionally investors invest based on such forecasts. The rise and fall in the demand for cryptocurrencies are also affected by general public opinion or Governmental policies. In this regard, peoples’ sentiments and emotions can help in determining the up and down of cryptocurrency market value, especially, sentiment analysis is trendy nowadays for investment in cryptocurrency [1], [2]. Investors first perform an analysis of peoples’ sentiment for a specific currency and then make investments according to the sentiments [3]. Because of that, sentiment analysis on cryptocurrency markets has become a task of great importance [4]. Studies show that tweets containing positive sentiments have a substantial impact on the demand for cryptocurrencies and vice versa [5], [6].

Despite the proposal of several sentiment analysis approaches, several challenges require further research efforts. For example, sentiment annotation is challenging when the sentence structure is complex. Often, simple sentences are needed to produce high-accuracy annotations. Similarly, a single approach cannot be generalized and applicable to all the corpus. An approach designed for sentiment analysis in one domain does not necessarily produce good results in another domain. In addition, the role of a specific feature extraction technique cannot be ignored fully. From this perspective, this study is specially designed for predicting people’s sentiments and emotions on the cryptocurrency market using supervised machine learning models. Owing to the wide use of Twitter TM for expressing opinions and thoughts on specific topics, this study leverages a tweets dataset for this purpose. This study makes the following contributions

- An ensemble model is proposed to perform sentiment analysis with high accuracy. For this purpose, the advantages of long short-term memory (LSTM) and gated recurrent unit (GRU) are combined.
- Sentiment analysis and emotion analysis are performed. Text Blob is used for annotating the sentiments data while emotions are annotated using the Text2Emotion model. Positive, negative, and neutral sentiments are used while emotions are classified into happy, sad, surprise, angry, and fear.
- The suitability and performance of three feature engineering approaches are studied including term frequency-inverse document frequency (TF-IDF), bag of words (BoW), and Word2Vec. Experiments are performed using several well-known machine learning models such as support vector machine (SVM), logistic

regression (LR), Gaussian Naive Bayes (GNB), extra tree classifier (ETC), decision tree (DT), and k nearest neighbor (KNN). Additionally, the performance of LSTM and GRU models is also analyzed.

The rest of the paper is structured as follows. Important research papers related to the current study are discussed in Section II. The proposed approach, the dataset used for experiments, and machine learning algorithms are presented in Section III. Section IV provides the analysis and discussion of results. In the end, the conclusion is given in Section V.

2. LITERATURE SURVEY

2.1 Emotion Detection from Tweets using AIT-2018 Dataset.

Author – Faisal Muhammad Shah, Abdus Sayef Reyadh, Asif Imtiaz Shaafi, Sifat Ahmed

People show emotions for everyday communication. Emotions are identified by facial expressions, behavior, writing, speaking, gestures and physical actions. Emotion plays a vital role in the interaction between two people. The detection of emotions through text is a challenge for researchers. Emotion detection from the text can be useful for real-world application. Automatic emotion detection in the original text aims to recognize emotions in any digital medium by using natural language processing techniques and different approaches. Enabling machines with the ability to recognize emotions in a particular kind of text such as twitter's tweet has important applications in sentiment analysis and affective computing. We have worked on the newly published gold dataset (AIT-2018) and propose a model consisting of lexical based using WordNet-Affect and Emo Sentic Net with supervised classifiers for detecting emotions in a tweet text.

2.2 Emotion Detection in Text using Nested Long Short-Term Memory.

Author – Daniel Haryadi, Gede Putra Kusuma

Humans have the power to feel different types of emotions because human life is filled with many emotions. Human's emotion can be reflected through reading or writing a text. In recent years, studies on emotion detection through text has been developed. Most of the study is using a machine learning technique. In this paper, we classified 7 emotions such as anger, fear, joy, love, sadness, surprise, and thankfulness using deep learning technique that is Long Short-Term Memory (LSTM) and Nested Long Short-Term Memory (Nested LSTM). We have compared our results with Support Vector Machine (SVM). We have trained each model with 980,549 training data and tested with 144,160 testing data. Our experiments showed that Nested LSTM and LSTM give better performance than SVM to detect emotions in text. Nested LSTM gets the best accuracy of 99.167%, while LSTM gets the best performance in term of average precision at 99.22%, average recall at 98.86%, and f1-score at 99.04%.

2.3 Emotion Detection in Online Social Networks: A Multi-label Learning Approach.

Author – Xiao Zhang, Wenzhong Li, Haochao Ying, Feng Li

Emotion detection in online social networks (OSNs) can benefit kinds of applications, such as personalized advertisement services, recommendation systems, etc. Conventionally, emotion analysis mainly focuses on the sentence level polarity prediction or single emotion label classification, however, ignoring the fact that emotions might coexist from users' perspective. To this end, in this work, we address the multiple emotions detection in OSNs from user-level view, and formulate this problem as a multilabel learning problem. First, we discover emotion labels correlations, social correlations, and temporal correlations from an annotated Twitter data set. Second, based on the above observations, we adopt a factor graph-based emotion recognition model to incorporate emotion labels correlations, social correlations, and temporal correlations into a general framework, and detect the multiple emotions based on the multilabel learning approach. Performance evaluation demonstrates that the factor graph-based emotion detection model can outperform the existing baselines.

2.4 Tweet Sentiment Analysis for Cryptocurrencies.

Author – Emre Sasmaz, F. Boray Tek

Many traders believe in and use Twitter tweets to guide their daily cryptocurrency trading. In this project, we investigated the feasibility of automated sentiment analysis for cryptocurrencies. For the study, we targeted one cryptocurrency (NEO) altcoin and collected related data. The data collection and cleaning were essential components of the study. First, the last five years of daily tweets with NEO hashtags were obtained from Twitter. The collected tweets were then filtered to contain or mention only NEO. We manually tagged a subset of the tweets with positive, negative, and neutral sentiment labels. We trained and tested a Random Forest classifier on the labeled data where the test set accuracy reached 77%. In the second phase of the study, we investigated whether the daily sentiment of the tweets was correlated with the NEO price. We found positive correlations between the number of tweets and the daily prices, and between the prices of different crypto coins. We share the data publicly

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2.5 A performance comparison of supervised machine learning models for Covid-19 tweets sentiment analysis.

Author – Furqan Rustam, Madiha Khalid, Waqar Aslam, Vaibhav Rupapara, Arif Mehmood, Gyu Sang Choi.

The spread of Covid-19 has resulted in worldwide health concerns. Social media is increasingly used to share news and opinions about it. A realistic assessment of the situation is necessary to utilize resources optimally and appropriately. In this research, we perform Covid-19 tweets sentiment analysis using a supervised machine learning approach. Identification of Covid-19 sentiments from tweets would allow informed decisions for better handling the current pandemic situation. The used dataset is extracted from Twitter using IDs as provided by the IEEE data port. Tweets are extracted by an in-house built crawler that uses the Tweepy library. The dataset is cleaned using the preprocessing techniques and sentiments are extracted using the Text Blob library. The contribution of this work is the performance evaluation of various machine learning classifiers using our proposed feature set. This set is formed by concatenating the bag-of-words and the term frequency-inverse document frequency. Tweets are classified as positive, neutral, or negative. Performance of classifiers is evaluated on the accuracy, precision, recall, and F_1 score. For completeness, further investigation is made on the dataset using the Long Short-Term Memory (LSTM) architecture of the deep learning model. The results show that Extra Trees Classifiers outperform all other models by achieving a 0.93 accuracy score using our proposed concatenated features set. The LSTM achieves low accuracy as compared to machine learning classifiers. To demonstrate the effectiveness of our proposed feature set, the results are compared with the Vader sentiment analysis technique based on the GloVe feature extraction approach.

2.6 Emotions in Twitter communication and stock prices of firms: the impact of Covid-19 pandemic.

Author – Suparna Dhar , Indranil Bose

In this paper, we explored two key aspects of organization theory—organizational communication in the face of crisis and the influence of emotions expressed in social media communication and their impact on stock prices of firms. We extracted emotional content from 189,303 tweets and collected financial data for six quarters for 105 companies listed on the New York Stock Exchange from the Fortune 1000 list of companies. We operationalized a set of metrics to measure emotion in organizational tweets. Our analysis showed that the operationalized metrics to measure emotion expressed in organizational tweets were significant predictors of stock prices of firms. Further analysis showed a moderation effect of the crisis on the association between emotion expressed in organizational tweets and stock prices in the presence of control variables. The study provides a detailed analysis of constituent positive (happiness) and negative (anger, fear, and sadness) emotions in organizational tweets and their association with stock prices of firms. Practitioners and regulators may use the analysis and the metrics to assess organizational communication and better leverage Twitter for crisis response. This paper showcases organizational crisis response of Twitter and its financial impact.

2.7 Non-iterative and Fast Deep Learning: Multilayer Extreme Learning Machines.

Author – Zhang, J, Li, Y, Xiao, W et al

In the past decade, deep learning techniques have powered many aspects of our daily life, and drawn ever-increasing research interests. However, conventional deep learning approaches, such as deep belief network (DBN), restricted Boltzmann machine (RBM), and convolutional neural network (CNN), suffer from time-consuming training process due to fine-tuning of a large number of parameters and the complicated hierarchical structure. Furthermore, the above complication makes it difficult to theoretically analyze and prove the universal approximation of those conventional deep learning approaches. In order to tackle the issues, multilayer extreme learning machines (ML-ELM) were proposed, which accelerate the development of deep learning. Compared with conventional deep learning, ML-ELMs are non-iterative and fast due to the random feature mapping mechanism. In this paper, we perform a thorough review on the development of ML-ELMs, including stacked ELM autoencoder (ELM-AE), residual ELM, and local receptive field-based ELM (ELM-LRF), as well as address their applications. In addition, we also discuss the connection between random neural networks and conventional deep learning.

2.8 Multilayer probability extreme learning machine for device-free localization.

Author – Zhang, J, Xiao, W, Li, Y et al.

Device-free localization (DFL) is revolutionizing wireless localization by eliminating the need for attached electronic devices on the target. Traditional methods for characterizing target influence on wireless links are labor-intensive. This paper introduces a novel hierarchical Extreme Learning Machine (ELM) based on deep learning, named multilayer probability ELM (MP-ELM). MP-ELM, stacked with ELM autoencoders, ensures rapid learning and outputs probabilistic estimations, addressing uncertainty and redundant links in DFL. Evaluation in indoor and outdoor settings demonstrates superior performance over classic ELM, multilayer ELM, hierarchical ELM, deep belief network, and deep Boltzmann machine, making MP-ELM an efficient solution for fast and accurate DFL.

2.9 Class-Specific Cost Regulation Extreme Learning Machine for Imbalanced Classification.

Author – Wendong Xiao, Jie Zhang, Yanjiao Li.

Due to its much faster speed and better generalization performance, extreme learning machine (ELM) has attracted much attention as an effective learning approach. However, ELM rarely involves strategies for imbalanced data distributions which may exist in many fields. Existing approaches for imbalance learning only consider the effect of the number of the class samples ignoring the dispersion degree of the data, and may lead to the suboptimal learning results. In this paper, we will propose a novel ELM, class-specific cost regulation extreme learning machine (CCR-ELM), together with its kernel-based extension, for binary and multiclass classification problems with imbalanced data distributions. CCR-ELM introduces class-specific regulation cost for misclassification of each class in the performance index as the tradeoff of structural risk and empirical risk. The performance of CCR-ELM is verified using a number of benchmark datasets and the real blast furnace status diagnosis problem. Experimental results show that CCR-ELM can achieve better performance for classification problems with imbalanced data distributions than the original ELM and existing ELM imbalance learning approach, and the kernel based CCR-ELM can improve the performance further.

2.10 Detecting sarcasm in multi-domain datasets using convolutional neural networks and long short-term memory network model.

Author – Ramish Jamil, Imran Ashraf, Furqan Rustam, Eysha Saad, Arif Mehmood, Gyu Sang Choi

Sarcasm emerges as a common phenomenon across social networking sites because people express their negative thoughts, hatred and opinions using positive vocabulary which makes it a challenging task to detect sarcasm. Although various studies have investigated the sarcasm detection on baseline datasets, this work is the first to detect sarcasm from a multi-domain dataset that is constructed by combining Twitter and News Headlines datasets. This study proposes a hybrid approach where the convolutional neural networks (CNN) are used for feature extraction while the long short-term memory (LSTM) is trained and tested on those features. For performance analysis, several machine learning algorithms such as random forest, support vector classifier, extra tree classifier and decision tree are used. The performance of both the proposed model and machine learning algorithms is analyzed using the term frequency-inverse document frequency, bag of words approach, and global vectors for word representations. Experimental results indicate that the proposed model surpasses the performance of the traditional machine learning algorithms with an accuracy of 91.60%. Several state-of-the-art approaches for sarcasm detection are compared with the proposed model and results suggest that the proposed model outperforms these approaches concerning the precision, recall and F1 scores. The proposed model is accurate, robust, and performs sarcasm detection on a multi-domain dataset.

2.11 Sentiment Analysis and Topic Modeling on Tweets about Online Education during COVID-19.

Author– Muhammad Mujahid, Ernesto Lee, Furqan Rustam, Patrick Bernard Washington, Saleem Ullah, Aijaz Ahmad Reshi, and Imran Ashraf.

During the COVID-19 pandemic, widespread closures of educational institutions prompted a surge in online learning. This study, using a Twitter dataset of 17,155 e-learning-related tweets, employs Text Blob, VADER, and Senti WordNet for sentiment analysis. Machine learning models, including random forest and support vector machine with Bag of Words features, achieve a high accuracy of 0.95. Comparison involves Text Blob, VADER, Senti WordNet, and deep learning models (CNN, LSTM, CNN-LSTM, Bi-LSTM). Topic modeling identifies key e-learning challenges: uncertainty about campus reopening, difficulties for children in online education, and inadequate network infrastructure. The study underscores the efficacy of machine learning in assessing sentiments towards e-learning.

2.12 On extending F-measure and G-mean metrics to multi-class problems.

Author – R. P. Espíndola, N. F. F. Ebecken

The evaluation of classifiers is not an easy task. There are various ways of testing them and measures to estimate their performance. The great majority of these measures were defined for two-class problems and there is not a consensus about how to generalize them to multiclass problems. This paper proposes the extension of the F-measure and G-mean in the same fashion as carried out with the AUC. Some datasets with diverse characteristics are used to generate fuzzy classifiers and C4.5 trees. The most common evaluation metrics are implemented and they are compared in terms of their output values: the greater the response the more optimistic the measure. The results suggest that there are two well-behaved measures in opposite roles: one is always optimistic and the other always pessimistic.

2.13 Tweets Classification on the Base of Sentiments for US Airline Companies.

Author – Furqan Rustam, Imran Ashraf, Arif Mehmood, Saleem Ullah, Gyu Sang Choi .

The use of data from social networks such as Twitter has been increased during the last few years to improve political campaigns, quality of products and services, sentiment analysis, etc. Tweets classification based on user sentiments is a collaborative and important task for many organizations. This paper proposes a voting classifier (VC) to help sentiment analysis for such organizations. The VC is based on logistic regression (LR) and stochastic gradient descent classifier (SGDC) and uses a soft voting mechanism to make the final prediction. Tweets were classified into positive, negative and neutral classes based on the sentiments they contain. In addition, a variety of machine learning classifiers were evaluated using accuracy, precision, recall and F1 score as the performance metrics. The impact of feature extraction techniques, including term frequency (TF), term frequency-inverse document frequency (TF-IDF), and word2vec, on classification accuracy was investigated as well. Moreover, the performance of a deep long short-term memory (LSTM) network was analyzed on the selected dataset. The results show that the proposed VC performs better than that of other classifiers. The VC is able to achieve an accuracy of 0.789, and 0.791 with TF and TF-IDF feature extraction, respectively. The results demonstrate that ensemble classifiers achieve higher accuracy than non-ensemble classifiers. Experiments further proved that the performance of machine learning classifiers is better when TF-IDF is used as the feature extraction method. Word2vec feature extraction performs worse than TF and TF-IDF feature extraction. The LSTM achieves a lower accuracy than machine learning classifiers.

2.14 Deepfake tweets classification using stacked Bi-LSTM and words embedding.

Author – Rupapara V, Rustam F, Amaar A, Washington PB, Lee E, Ashraf

The spread of altered media in the form of fake videos, audios, and images, has been largely increased over the past few years. Advanced digital manipulation tools and techniques make it easier to generate fake content and post it on social media. In addition, tweets with deep fake content make their way to social platforms. The polarity of such tweets is significant to determine the sentiment of people about deep fakes. This paper presents a deep learning model to predict the polarity of deep fake tweets. For this purpose, a stacked bi-directional long short-term memory (SBi-LSTM) network is proposed to classify the sentiment of deep fake tweets. Several well-known machine learning classifiers are investigated as well such as support vector machine, logistic regression, Gaussian Naive Bayes, extra tree classifier, and AdaBoost classifier. These classifiers are utilized with term frequency-inverse document frequency and a bag of words feature extraction approaches. Besides, the performance of deep learning models is analyzed including long short-term memory network, gated recurrent unit, bi-direction LSTM, and convolutional neural network + LSTM. Experimental results indicate that the proposed SBi - LSTM outperforms both machine and deep learning models and achieves an accuracy of 0.92.

2.15 A Conv BiL STM Deep Learning Model Based Approach for Teitter Sentiment Classification.

Author – Sakirin Tam, Rachid Ben Said.

Twitter, a vital information source, is harnessed for sentiment analysis, gauging people's attitudes. Traditional algorithms fall short, motivating the adoption of deep learning models like Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM). While CNN excels at local feature extraction, it lacks sequential correlation learning. Bi-LSTM enhances context but struggles with parallel local feature extraction. This study introduces Conv BiL STM, integrating CNN and Bi-LSTM. Word embedding transforms tweets into numerical values, with CNN extracting features and Bi-LSTM providing the classification. Word2Vec and GloVe impact the model differently. Applied to Tweets and SST-2 datasets, Conv BiL STM, especially with Word2Vec on Tweets, achieves a notable 91.13% accuracy, surpassing other models. This integrated approach optimally addresses sentiment analysis challenges in Twitter data

3. SYSTEM ARCHITECTURE

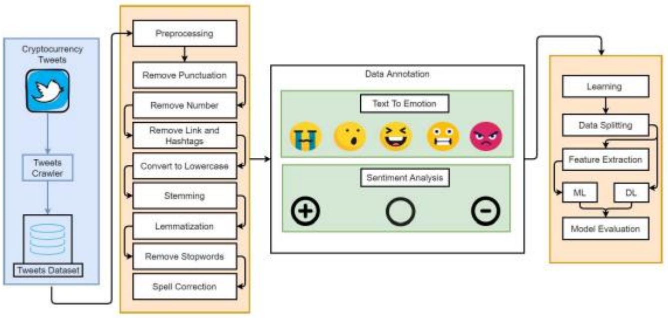
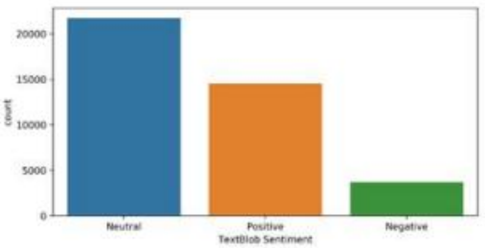
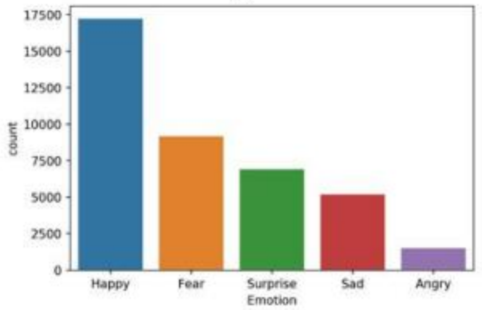


Fig.3.1. Architecture of the proposed methodology.



(a)



(b)

Fig.3.2. Number of samples, (a) Each class in the dataset, (b) Emotions found in the dataset.

TABLE 1. A summary of the discussed research works.

Ref.	Year	Model	Objective	Dataset
[9]	2017	SVM	Emotion detection from text	-
[10]	2018	K-means, Naive Bayes and SVM	Emotion Detection and Recognition from Text	Tweet data
[7]	2019	SVM	Text stream message emotion detection	Tweet data
[8]	2019	SVM, NB, KNN ,MLP,CNN, LSTM	detects emotions on sexist Tweet	Tweet data
[11]	2019	Naive Bayes, DT, SVM, Proposed Model Unifying WordNetAffect and EmoSenticNet	Tweet emotion detection	Tweet data AIT-2018
[12]	2019	Nested LSTM, LSTM,SVM	Emotion detection on text	Tweet data, 980,549 training data, 144,160 testing data
[13]	2019	DT,CNN, Doc2Vector	Text emotion detection	Facebook and tweet
[14]	2019	Naive Bayes Classifier	Text Classification into four different emotional classes	Social Media
[15]	2020	ML-KNN,Proposed model, Multi-label Learning Approach for Emotion Detection	Online Social Networks emotion detection	Tweet data
[16]	2020	Emotion Extraction Model	detect emotions	Dataset ('International Survey on Emotion Detection and Antecedents and Reactions' (ISEAR))
[17]	2020	LSTM	Bitcoin price prediction using sentiment analysis	Twitter™and Reddit
[18]	2021	LSTM	Cryptocurrency sentiment analysis for Chines language data	Chinese social media platform Sina-Weibo dataset
[19]	2021	RF	Cryptocurrency sentiment analysis	Tweets dataset

Fig : Algorithm Survey

Ref.	Year	Contribution	Expected result	Demerit
[6]	2017	Machine learning-based algorithms were used for price prediction of *Bitcoin*, *Litecoin*, and *Ethereum* with the sentiments of the news and social media.	Confusion matrix	Advanced models like LSTM and GRU were not explored. Data consideration was lesser in amount.
[7]	2018	ANN with its different variant was used for predicting the price of *Bitcoin*. There were 4 ANN methods used, and out of which the backpropagation neural network showed the best result.	MAPE	They only explored various types of ANN and did not explore sentiments and another deep learning-based model to find complex patterns.
[8]	2018	Different regression techniques had implemented for *Bitcoin* price prediction e.g.,theil-sen regression, huber regression, LSTM, and GRU	MSE = 0.00002, R2 = 0.992 (GRU)	Ignored impacting factors like sentiments and hybrid model also not explored.
[9]	2018	Machine learning-based algorithms like ANN, SVM, random forest and naive bayes were used for price prediction of different cryptocurrency.	Accuracy :- *Bitcoin* = 85%, *Ethereum* = 93.33%, *Bitcoin Cash* = 70%	Not considered deep learning based model to find complex patterns and sentiment of the cryptocurrency and hybrid model also not explored.
[10]	2019	They used hidden Markov models to show the historical data of cryptocurrencies and predicted future prices using the Long short-term memory model. This was the hybrid model-based approach.	MSE = 33.888 RMSE = 5.821 MAE = 2.510	They did not consider market sentiment as a feature, which can be used as means for prediction as it is important.
[11]	2019	Machine learning based algorithms were used with sentiments of the cryptocurrency for the prediction of price movment.	SVM Twitter and Market:- Accuracy = 0.66, Precision = 0.80, Recall = 0.67, F1 Score = 0.62	Not explored time-series-based models like LSTM and GRU.
[12]	2020	Introduced the novel big data platform for price prediction using sentiment and prices with classic machine learning models. Tweets from the twitter was collected in real-time.	RMSE	Deep learning models not considered for prediction such as RNN.
[13]	2020	LSTM-GRU's hybrid model was implemented for price prediction of *Litecoin* and *Monero* with different window sizes. The hybrid-based model helped to reduce the loss.	MSE RMSE MAE MAPE	Interdependence amongst cryptocurrency and sentiment as a feature not explored.
[14]	2020	ARIMAX and LSTM-based RNN experimented for price prediction of cryptocurrency.	MSE = 0.00030187	Hybrid models are not explored and feature fusion and sentiment were not considered.
[15]	2020	CNN-LSTM based hybrid model used for *Bitcoin's* price prediction with variations in the CNN models. Direction prediction and value prediction were also done.	MAE RMSE MAPE for value prediction, and precision recall F1 for direction prediction	Sentiment regarding cryptocurrencies in the market not considered.
[16]	2021	A hybrid LSTM and GRU-based deep learning model outperformed the state-of-the-art techniques, to predict the price of *Litecoin* and *Zcash* by the influence of the major coins like *Bitcoin*.	MSE	The sentiment of major crypto coins is not considered to predict the price of an influenced cryptocurrency.
[17]	2021	An ensemble model of LSTM, GRU, and TSN (Temporal Convolutional Networks) was used to predict the price of Ether based on its historical price data.	Accuracy:- 1-day = 84.2%, 1-week = 78.9%	Interdependence amongst cryptocurrency and sentiment is not considered as a feature for price prediction of Ether.
[18]	2021	To predict the price of *Bitcoin*, *Ethereum*, and *Litecoin*, the author proposed a system with LSTM and GRU. The price prediction was performed on two types of a data sample of *Bitcoin*, *Ethereum*, and *Litecoin*.	RMSE, MAE	One of the most important factors of market analysis is sentiment analysis, which is not considered, and interdependence among currencies is not considered.
Proposed	2022	Author proposed a new framework named DL-GuesS and it's performance evaluation was done by predicting prices of *Dash* and *Bitcoin Cash*. The price history of similar cryptocurrency i.e. Bitcoin and Litecoin, along with the twitter sentiments for each of them were used to predict the prices of *Dash* and *Bitcoin*	Dash MSE = 0.0185, MAE = 0.0805, MAPE = 4.7928 Bitcoin Cash MSE = 0.0011, MAE = 0.0196, MAPE = 4.4089	-

Fig : Live Survey

4. CONCLUSION

This study performs sentiment analysis and emotion detection on tweets related to cryptocurrency. Sentiment analysis of cryptocurrency holds potential significance as it is widely used for predicting the market price of the cryptocurrency which necessitates sentiments classification with high accuracy. For experiments, tweets are extracted from Twitter TM, and the dataset is annotated using Text Blob and Text2Emotion for sentiments and emotions, respectively. Besides the use of several machine learning and deep learning models for classification, this study leverages recurrent neural networks LSTM and GRU to form an ensemble model to enhance classification performance. In addition, BoW, TFIDF, and Word2Vec features are used as feature extraction techniques for the machine learning models. Results indicate that machine learning models perform well with BoW features compared with TF-IDF and Word2Vec. The proposed model achieves the highest performance for sentiment analysis with a 0.99 accuracy score and the highest precision and recall of 0.99 and 0.98, respectively. Similarly, LSTMGRU outperforms all other models in terms of correct and wrong predictions for both sentiment analysis and emotion detection. Dataset balancing using the random under sampling suggests that LSTM-GRU performance is decreased due to fewer training data. This study considers the sentiment analysis for cryptocurrency-related tweets, we intend to perform cryptocurrency market price prediction based on the analyzed sentiments in the future.

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