SURVEY ON SENTIMENT ANALYSIS-DRIVEN MACHINE LEARNING APPROACH TO CRYPTO PRICE PREDICTION.

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Abstract -This study looks at how people express feelings in tweets about cryptocurrency.Understanding these feelings is crucial for predicting cryptocurrency pricesaccurately. We gathered tweets from Twitter and used different tools to figure out theemotions and sentiments in them. We tried out various computer models to seewhich ones work best for this task. We even combined different models to make asupermodel for better results. We also used different techniques to pull out important features from the data, likeBag of Words and others. What we found is that some models perform better whenwe use certain techniques. Our best model got a really high score for understandingsentiments in tweets, reaching 99 out of 100. It also did well in terms of precision andrecall, which are ways to measure how accurate and complete our predictions are

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

1. INTRODUCTION

The rapid evolution of the cryptocurrency market has been remarkable since its inception. Functioning as decentralized digital currency, cryptocurrencies operate without the control of any central authority, relying on system ledger entries known as 'tokens' for online transactions. Employing elliptical curve encryption, public-private key pairs, and cryptographic algorithms, the security of transactions is ensured through hashing functions.

Bitcoin, introduced in 2009 as the pioneer blockchain-based cryptocurrency, continues to dominate the market. However, a multitude of cryptocurrencies has emerged over time, each offering distinct features and specifications. Investors in the cryptocurrency realm navigate a volatile market with tools designed to forecast price fluctuations.[1],[2] Notably, sentiment analysis has gained prominence, reflecting the impact of public opinion and governmental policies on the demand for cryptocurrencies.

This research addresses the significance of sentiment analysis in predicting market trends. Investors increasingly rely on the analysis of public sentiment, particularly through platforms like TwitterTM, to inform their decisions.[3] The paper proposes an ensemble model that combines the strengths of long short-term memory (LSTM) and gated recurrent unit (GRU) for enhanced sentiment analysis accuracy.

In addition to sentiment analysis, the research delves into emotion analysis using Text Blob for sentiment annotation and Text2Emotion model for emotion annotation. Positive, negative, and neutral sentiments are considered alongside emotions categorized into happy, sad, surprise, angry, and fear.[4],[5] The study evaluates the performance of various feature engineering approaches, including term frequency-inverse document frequency (TF-IDF), bag of words (BoW), and Word2Vec.

The experimentation involves 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). Furthermore, the research scrutinizes the effectiveness of LSTM and GRU models.[7][8]

Despite numerous sentiment analysis approaches, challenges persist, including complex sentence structures and domain-specificity. This research endeavors to address these challenges, focusing on predicting sentiments and emotions in the cryptocurrency market through supervised machine learning models.[9] Leveraging a Twitter dataset, an ensemble model combining long short-term memory (LSTM) and gated recurrent unit (GRU) is proposed for high-accuracy sentiment analysis. Emotion analysis, using Text Blob for sentiments and Text2Emotion for emotions, further enriches the understanding of investor perspectives.

Building upon existing sentiment analysis approaches, this study acknowledges and addresses several challenges encountered in the field. An intrinsic challenge lies in the complexity of sentence structures, demanding simplified sentences for accurate sentiment annotation. Moreover, the paper emphasizes the domain-specific nature of sentiment analysis, highlighting the need for tailored approaches as what proves effective in one domain may not yield comparable results in another.[10][11]

Additionally, the study recognizes the pivotal role of feature extraction techniques, emphasizing the importance of understanding and optimizing specific techniques to enhance overall sentiment analysis accuracy.[12]

Structured methodically, the paper unfolds by discussing pertinent research papers in Section II, followed by the presentation of the proposed approach, dataset details, and machine learning algorithms in Section III. Section IV critically analyzes and discusses the experimental results. Finally, Section V encapsulates the paper with a comprehensive conclusion.

2. LITERATURESURVEY

2.1 Emotion Detection from Tweets using AIT-2018 Dataset.

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

Everyday communication involves the expression of emotions, which can be discerned throughfacial expressions, behavior, writing, speech, gestures, and physical actions. The interactionbetween individuals heavily relies on emotions. Detecting emotions in written text poses asignificant challenge for researchers, yet it holds practical value in various real-worldapplications. The goal of automatically identifying emotions in original text extends torecognizing emotions across digital mediums, utilizing natural language processing techniquesand diverse approaches.Equipping machines with the capability to perceive emotions within specific types of text, suchas tweets on Twitter, holds substantial significance in sentiment analysis and affectivecomputing. Our efforts have focused on the recently published gold dataset (AIT-2018). Wepropose a model that incorporates lexical-based strategies, employing WordNet-Affect and EmoSentic Net, along with supervised classifiers to detect emotions in tweet texts.

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

Author–Daniel Haryadi, Gede Putra Kusuma

Humans possess the ability to experience a diverse range of emotions as life is replete withvarious emotional states. Theexpression of human emotions can be conveyed through thecreation or interpretation of text. Recent years have witnessed the development of studiesfocused on detecting emotions through textual content, with a predominant reliance on machinelearning techniques.In this paper, we employ deep learning techniques, specifically LongShort-Term Memory (LSTM) and Nested Long Short-Term Memory (Nested LSTM), tocategorize seven emotions—anger, fear, joy, love, sadness, surprise, and thankfulness. Acomparative analysis with Support Vector Machine (SVM) is conducted. The models are trainedon 980,549 instances of training data and evaluated on 144,160 instances of testing data.Ourexperiments reveal that both Nested LSTM and LSTM outperform SVM in the detection ofemotions in text. Nested LSTM achieves the highest accuracy at 99.167%, while LSTM excelsin terms of average precision (99.22%), average recall (98.86%), and f1-score (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 within online social networks (OSNs) holds potential for various applications, including personalized advertisement services and recommendation systems. Traditionally, emotion analysis has concentrated on predicting sentence-level polarity or classifying a single emotion label. This approach, however, tends to overlook the possibility that users may experience multiple emotions simultaneously.In this study, we tackle the challenge of detecting multiple emotions in OSNs from a user-level perspective, framing the issue as a multi-label learning problem. Initially, we identify correlations among emotion labels, social connections, and temporal factors using an annotated Twitter dataset. Subsequently, leveraging these findings, we employ a factor graph-based emotion recognition model to integrate emotion label correlations, social connections, and temporal correlations into a unified framework. The goal is to detect multiple emotions using a multi label learning approach.Performance assessment indicates that the factor graph-based emotion detection model surpasses existing baselines in its ability to effectively identify multiple emotions within OSNs.

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 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 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 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

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data publicly Numerous traders rely on Twitter tweets as a guiding force for their day-to-day cryptocurrency trading activities. This project delves into the feasibility of automating sentiment analysis for cryptocurrencies, focusing specifically on the altcoin NEO. Our investigation involved the targeted collection of relevant data, with a paramount emphasis on data collection and cleaning. Initially, we acquired the last five years' worth of daily tweets containing NEO hashtags from Twitter. Subsequently, we refined the collected tweets to exclusively include mentions or references to NEO. A subset of these tweets was manually labeled with positive, negative, and neutral sentiment classifications. Using this labeled dataset, we trained and tested a Random Forest classifier, achieving a test set accuracy of 77%.In the project's second phase, we explored whether the daily sentiment expressed in tweets correlated with the NEO price. Positive correlations emerged between the volume of tweets and daily prices, as well as between the prices of different cryptocurrencies. It is noteworthy that we have made the data publicly accessible for broader utilization.

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 global spread of Covid-19 has raised significant health concerns worldwide. Social media has become an increasingly prevalent platform for sharing news and opinions related to the pandemic. A realistic understanding of the situation is crucial for the optimal and appropriate allocation of resources. This research focuses on conducting sentiment analysis of Covid-19 tweets using a supervised machine learning approach. Analyzing sentiments expressed in tweets about Covid-19 enables informed decision-making for managing the ongoing pandemic effectively.The dataset utilized in this study is sourced from Twitter, extracted using IDs provided by the IEEE data port. Tweet extraction is carried out by a custom-built crawler utilizing the Tweepy library. To prepare the dataset for analysis, preprocessing techniques are applied, and sentiments are extracted using the Text Blob library. The novelty of this work lies in evaluating the performance of various machine learning classifiers using our proposed feature set. This set is created by concatenating the bag-of-words and term frequency-inverse document frequency. Tweets are categorized as positive, neutral, or negative, and classifier performance is assessed based on accuracy, precision, recall, and F1 score.For comprehensive analysis, further exploration of the dataset is conducted using the Long Short-Term Memory (LSTM) architecture of the deep learning model. Results indicate that Extra Trees Classifiers outperform other models, achieving a 0.93 accuracy score with our proposed concatenated feature set. Notably, LSTM exhibits lower accuracy compared to machine learning classifiers. To underscore the effectiveness of our proposed feature set, 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

This paper delves into two pivotal facets of organizational theory: the dynamics of organizational communication during crises and the influence of emotions conveyed through social media on the stock prices of companies. Extracting emotional content from 189,303 tweets, we gathered financial data spanning six quarters for 105 companies listed on the New York Stock Exchange, drawn from the Fortune 1000 list. To quantify emotion in organizational tweets, we operationalized a set of metrics. Our analysis revealed that these operationalized metrics, measuring emotion in organizational tweets, served as significant predictors of firms' stock prices. Further scrutiny demonstrated a moderation effect of the crisis on the relationship between emotion expressed in organizational tweets and stock prices, accounting for control variables.This study conducts a comprehensive examination of constituent positive emotions (happiness) and negative emotions (anger, fear, and sadness) in organizational tweets and their correlation with firms' stock prices. The findings offer valuable insights for practitioners and regulators, enabling them to assess organizational communication effectively and harness Twitter more strategically for crisis response

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

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

aspects of our daily lives, sparking a growing interest in research. However, traditional deep learning approaches like deep belief networks (DBN), restricted Boltzmann machines (RBM), and convolutional neural networks (CNN) encounter challenges in their time-consuming training processes. This is primarily attributed to the intricate fine-tuning of a large number of parameters and the complex hierarchical structure they entail. Moreover, the intricacies involved make it challenging to theoretically analyze and establish the universal approximation capabilities of these conventional deep learning approaches.To address these issues, the introduction of multilayer extreme learning machines (ML-ELM) has significantly advanced the field of deep learning. ML-ELMs stand out for their non-iterative and rapid nature, facilitated by a random feature mapping mechanism. In this paper, we conduct a comprehensive examination of the evolution of ML-ELMs, encompassing stacked ELM autoencoder (ELM-AE), residual ELM, and local receptive field-based ELM (ELM-LRF), while exploring their applications. Additionally, we delve into the correlation between random neural networks and traditional deep learning methods.

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

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

The landscape of wireless localization is undergoing a transformation with the advent of Device-free Localization (DFL), which eliminates the necessity of attached electronic devices on the target. Traditional methods used to characterize the impact of targets on wireless links are time-consuming. This paper presents a groundbreaking approach: a hierarchical Extreme Learning Machine (ELM) rooted in deep learning, termed as the Multilayer Probability ELM (MP-ELM). By integrating ELM autoencoders into a stacked architecture, MP-ELM ensuresswift learning and provides probabilistic estimations, effectively addressing uncertainty and redundant links within DFL. Assessment in both indoor and outdoor environments reveals the superior performance of MP-ELM when compared to classic ELM, multilayer ELM, hierarchical ELM, deep belief networks, and deep Boltzmann machines.

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

Author – Wendong Xiao, Jie Zhang,
Yanjiao Li.

The extreme learning machine (ELM) has gained considerable attention for its accelerated speed and superior generalization performance, proving to be an effective learning approach. However, conventional ELM approaches often overlook strategies for handling imbalanced data distributions, a common occurrence in various fields. Existing methods for imbalanced learning primarily focus on the number of class samples, disregarding the data's dispersion degree, potentially resulting in suboptimal learning outcomes.This paper introduces a novel ELM variant, the class-specific cost regulation extreme learning machine (CCR-ELM), along with its kernel-based extension. Designed for binary and multiclass classification problems with imbalanced data distributions, CCR-ELM incorporates class-specific regulation costs for misclassification in the performance index. This serves as a tradeoff between structural risk and empirical risk. The efficacy of CCR-ELM is demonstrated using benchmark datasets and a real blast furnace status diagnosis problem.Experimental results underscore that CCR-ELM outperforms the original ELM and existing ELM imbalance learning approaches in classification problems with imbalanced data distributions. Moreover, the kernel-based CCR-ELM demonstrates further improvement in performance.

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 commonly manifests on social networking sites where individuals express negative sentiments, hatred, and opinions through positive language, posing a challenge for detection. While previous studies have explored sarcasm detection on basic datasets, this research marks the inaugural attempt to identify sarcasm within a multidomain dataset amalgamated from Twitter and News Headlines datasets. A hybrid methodology is proposed, employing Convolutional Neural Networks (CNN) for feature extraction, followed by training and testing using Long Short-Term Memory (LSTM). Performance analysis involves various machine learning algorithms, including random forest, support vector classifier, extra tree classifier, and decision tree.Both the proposed model and traditional machine learning algorithms undergo scrutiny using term frequency-inverse document frequency, bag of words approach, and global vectors for word reSentiment 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, andImran Ashraf.

Amid the COVID-19 pandemic, the widespread closure of educational institutions led to a surge in online learning. This research, leveraging a Twitter dataset containing 17,155 tweets related to e-learning, employs sentiment analysis tools such as Text Blob, VADER, and SentiWordNet. Machine learning models, including random forest and support vector machines with Bag of Words features, achieve a commendable accuracy of 0.95. A comprehensive comparison involves Text Blob, VADER, SentiWordNet, and deep learning models (CNN, LSTM, CNN-LSTM, Bi-LSTM). Through topic modeling, the study identifies key e-learning challenges, including uncertainty about campus reopening, difficulties faced by children in online education, and concerns regarding inadequate network infrastructure. The research highlights the effectiveness of machine learning in assessing sentiments towards e-learning.

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

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

Assessing classifiers poses a complex challenge, with various testing methods and performance estimation measures available. The majority of these measures are tailored for two-class problems, leading to a lack of consensus on their generalization for multiclass problems. This paper suggests extending the F-measure and G-mean similar to the approach taken with the AUC. Diverse datasets, encompassing different characteristics, are utilized to create fuzzy classifiers and C4.5 trees. The paper implements common evaluation metrics, comparing their output values where a higher response indicates a more optimistic measure. The results highlight two well-behaved measures playing opposing roles: one consistently optimistic and the other consistently pessimistic.

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

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

In recent years, the utilization of data from social networks, particularly Twitter, has witnessed a notable increase for enhancing political campaigns, product and service quality, sentiment analysis, and more. The collaborative and crucial task of classifying tweets based on user sentiments is addressed in this paper through the proposal of a voting classifier (VC). The VC leverages logistic regression (LR) and stochastic gradient descent classifier (SGDC), employing a soft voting mechanism for the final prediction. The sentiment categories for tweets include positive, negative, and neutral.Additionally, various machine learning classifiers undergo evaluation using accuracy, precision, recall, and F1 score as performance metrics. The impact of different feature extraction techniques, such as term frequency (TF), term frequency-inverse document frequency (TF-IDF), and word2vec, on classification accuracy is thoroughly investigated. Furthermore, the paper analyzes the performance of a deep long short-term memory (LSTM) network on the selected dataset.Results indicate that the proposed VC outperforms other classifiers, achieving an accuracy of 0.789 and 0.791 with TF and TF-IDF feature extraction, respectively. Ensemble classifiers consistently exhibit higher accuracy than their non-ensemble counterparts. Experiments confirm that machine learning classifiers perform better when TF-IDF is used as the feature extraction method, while word2vec feature extraction lags behind TF and TF-IDF. The LSTM, in comparison, achieves a lower accuracy than the machine learning classifiers.

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

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

The proliferation of manipulated media, encompassing fake videos, audios, and images, has witnessed a substantial increase in recent years. The availability of sophisticated digital manipulation tools has facilitated the creation and dissemination of deceptive content across social media platforms. Moreover, tweets featuring deep fake content often find their way into social platforms, making the analysis of their sentiment crucial in gauging public opinion about deep fakes. This paper introduces a deep learning model designed to predict the polarity of tweets containing deep fake content.To achieve this goal, a stacked bi-directional long short-term memory (SBi-LSTM) network is proposed for sentiment classification. Additionally, the study explores various well-known machine learning classifiers, such as support vector machine, logistic regression, Gaussian Naive Bayes, extra tree classifier, and AdaBoost classifier. These classifiers are employed with both term frequency-inverse document frequency and bag of words feature extraction methods. The performance of deep learning models, including long short-term memory network, gated recurrent unit, bi-directional LSTM, and convolutional neural network + LSTM, is also scrutinized. Experimental findings reveal that the proposed SBi-LSTM outperforms both machine and deep learning models, achieving an accuracy of 0.92

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

Author – Sakirin Tam, Rachid Ben Said.

Leveraging Twitter as a crucial source of information, sentiment analysis becomes pivotal in understanding people's attitudes. Traditional algorithms exhibit limitations, prompting the adoption of deep learning models such as Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM). While CNN excels in local feature extraction, it lacks sequential correlation learning. Conversely, Bi-LSTM enhances context but struggles with parallel local feature extraction. This study introduces Conv BiL STM, a novel model that seamlessly integrates CNN and Bi-LSTM. Tweets are numerically represented through word embedding, with CNN extracting features and Bi-LSTM facilitating classification. The impact of Word2Vec and GloVe on the model is analyzed.Applied to both Tweets and SST-2 datasets, Conv BiL STM, particularly with Word2Vec on Tweets, achieves an impressive accuracy of 91.13%, surpassing other models. This integrated approach effectively addresses the challenges of sentiment analysis in Twitter data, providing an optimal solution.

3. SYSTEM ARCHITECTURE

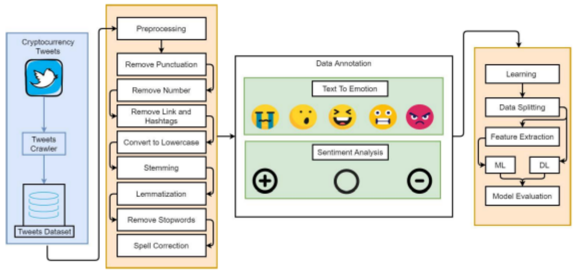

Fig.3.1. Architecture of the proposed methodology.

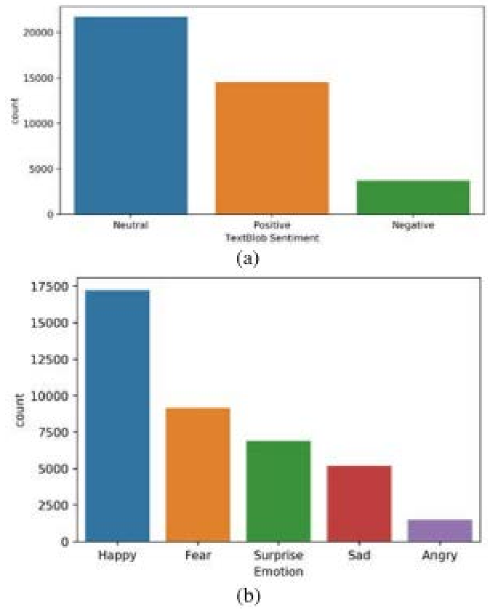

Fig.3.2.Number of samples, (a) Each class in the dataset, (b) Emotions found in the dataset.

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 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*, *Etherrum*, 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 research conducts an analysis of sentiments and emotions in tweets pertainingto cryptocurrency. Evaluating sentiment in cryptocurrency is particularly significant,given its widespread use in predicting market prices. Accurate sentimentclassification is essential for this purpose. To carry out experiments, tweets aresourced from Twitter and the dataset is annotated using Text Blob and Text2Emotionfor sentiments and emotions, respectively. The study employs various machinelearning and deep learning models for classification, incorporating recurrent neuralnetworks like LSTM and GRU to create an ensemble model that enhancesclassification performance.Additionally, feature extraction techniques such as Bag of Words (BoW), TF-IDF, andWord2Vec are utilized for machine learning models. The results reveal that machinelearning models exhibit superior performance with BoW features compared toTF-IDF and Word2Vec. The proposed model achieves outstanding sentimentanalysis results with a 0.99 accuracy score, along with the highest precision (0.99)and recall (0.98). Similarly, LSTM-GRU surpasses other models in terms of bothcorrect and incorrect predictions for sentiment analysis and emotion detection.The study notes that dataset balancing through random under-sampling indicates adecrease in LSTM-GRU performance due to a reduction in training data. While theprimary focus is on sentiment analysis for cryptocurrency-related tweets, theresearch outlines an intention to leverage the analyzed sentiments for futurecryptocurrency market price predictions.

5. REFERENCES

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