Forecasting the Early Market Movement in Bitcoin Using Twitter's Sentiment Analysis: An Ensemble-based Prediction Model

Ahmed Ibrahim
University of Waterloo
Computer Science Department
Waterloo, Ontario, Canada
a24ibrah@uwaterloo.ca

2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS) | 978-1-6654-4067-7/21/$31.00 ©2021 IEEE | DOI: 10.1109/IEMTRONICS52119.2021.9422647

Abstract—**Data collected from social media such as tweets, posts, and blogs can assist in an early indication of market sentiment in the financial field. This has frequently been conducted on Twitter data in particular. Using data mining techniques, opinion mining, machine learning, natural language processing (NLP), and knowledge management, the underlying public mood states and sentiment can be uncovered. As cryptocurrencies play an increasingly significant role in global economies, there is an evident relationship between Twitter sentiment and future price fluctuations in Bitcoin. This paper assesses Tweets' collection, manipulation, and interpretation to predict early market movements of cryptocurrency. More specifically, sentiment analysis and text mining methods, including Logistic Regressions, Binary Classified Vector Prediction, Support Vector Mechanism, and Naïve Bayes, were considered. Each model was evaluated on their ability to predict public mood states as measured by 'tweets' from Twitter during the era of covid-19. An XGBoost-Composite ensemble model is constructed, which achieved higher performance than the state-of-the-art prediction models.**

Keywords—Bitcoin, Sentiment Analysis, Market Movement, prediction Models, Ensemble Modeling, Validation Measures.

I. Introduction

Cryptocurrencies, such as Bitcoin, Ethereum, and Litecoin, are an alternative class of digital assets primarily used as a medium of exchange [1]-[5]. Public key cryptography and blockchain technology are utilized to facilitate decentralized peer-to-peer transactions. Bitcoin, created in 2009, is widely regarded as the world's first cryptocurrency. Following Bitcoin's success, numerous other cryptocurrencies, dubbed 'altcoins' have been developed. The rise of Bitcoin and altcoins has produced a deluge of data on social media platforms, blogs, forums, and countless other online mediums. There have been quite a few researchers trying to predict Bitcoin prices' behavior based on its emotions on social media platforms, such as Twitter, using various machine learning algorithms [6]-[8]. Researchers have been known to get some significant prediction results. However, very few focus on using ensemble modeling to achieve better prediction results.

XGBoost is an ensemble classifier that provides benefits such as no need for normalized data, scalability to larger data sets, and rule-based behavior that is easier for people to interpret. Thus, this paper aims to propose a Composite Ensemble Prediction Model (CEPM) using the notion of sentiment analysis. The CEPM framework is comprised of five stages, 1) text preprocessing, 2) Sentiment Scoring, 3) individual XGBoost classifications, 4) composite ensemble aggregation, and 5) model validation. In stage1, various preprocessing steps are performed, including word quantization, text stemming, and stop word removal. The second stage includes converting tweet text into a sentiment score as a representative of its emotion. Such a task is suited to VADER, a lexicon and rule-based sentiment analysis tool that can deal with the syntax usually used on social media. In the third stage, various instances of the XGBoost classifiers are used. The ensemble modeling is designed to maximize the model performance by utilizing a stacking of ensembles using a majority vote of XGBoost ensembles. Finally, the composite ensemble model is validated using accuracy, recall, precision, and F-scores quality measure. Experimental analysis on Twitter datasets collected during the era of COVID-19 shows that the CEPM model outperforms the individual models. It can be effectively used as an efficient (Bitcoin) BTC predictor to forecast the early market movement of Bitcoin even after the COVID-19 pandemic.

The rest of this paper is organized as follows: Section 2 provided a literature review. In section 3, the text preprocessing is discussed. Vader scoring is presented in section 3. Section 4 presents the adopted classifiers. In section 5, the proposed staking ensemble is introduced. Experimental results and analysis are discussed in section 6. Finally, section 7 concludes the paper and highlights future directions.

II. Literature Review

Several attempts have been made that uses sentiment analysis to predict the early market movement of cryptocurrencies using tweets sentiment [9]-[17]. In [9], authors compared the causality of tweet sentiments, tweet volume, and buyers' ratio to sellers on Twitter with the price returns and daily trading volumes of cryptocurrencies. It has been speculated that sentiments expressed on Twitter could help in predicting cryptocurrency price changes. Li et al. [10] have attempted to demonstrate this concept by training an Extreme Gradient Boosting Regression tree model (XGBoost) with Twitter sentiments to predict ZClassic price changes. The research in [10] provided the KryptoOracle to predict the Bitcoin price for the next minute

978-1-6654-4067-7/21/$31.00 ©2021 IEEE

using current and historical data from Twitter sentiments and Bitcoin closing prices. XGBoost, a regression tree model, was used because of its performance, speed, and retraining simplicity. In [13], Jain et al. attempted to predict the prices of Bitcoin and Litecoin two hours in advance based on the sentiments expressed in current tweets. They wanted to investigate if social factors could predict the prices of cryptocurrencies. So they used a Multiple Linear Regression (MLR) model to predict a bihourly average price from the number of positive, neutral, and negative tweets accumulated every two hours. Authors in [14] compared the significance of different preprocessing techniques for tweets' sentiment analysis. They used four different machine learning algorithms to classify tweets, and they tested 16 different preprocessing methods. Based on their results, it was recommended to use lemmatization, replacing repeated punctuation, replacing contractions, or removing numbers. The research work in [17] attempted to characterize Twitter users who use controversial terms when mentioning COVID-19 on Twitter and trained various machine learning algorithms for classifying such users. The machine learning algorithms trained on these attributes included Logistic Regression, Random Forest, Support Vector Machine, Stochastic Gradient Descent, Multi-Layer Perceptron, and XGBoost. Random Forest had the highest AUC-ROC score out of all algorithms when trained on the baseline, demographic, and geolocation data.

III. TEXT DATA PREPROCESSING METHODS

To categorize a large data set as Twitter, the data be appropriately cleaned to save computational time and increase the data manipulation's overall accuracy. In heavily text-based datasets, stemming and stop word analysis are crucial in the proper analysis [19]-[22].

A. *Text Stemming*

Stemming is a pre-processing method utilized in text mining, natural language processing, and information retrieval applications. It is an effective approach to reduce grammatical and word conjunctions to essentially extract the root form or "stem" to improve searching by automatic sorting of word endings at the time of indexing and searching. Since certain words have similar semantic meanings but different word forms, stemming allows for a reduction in the number of distinct terms in a document and increases the number of retrieved documents. The decrease in overall variability of the text, thus shortening the final output processing time for an Information Retrieval System. In stemming, converting a word to its stem assumes each is semantically related, leaving separate words with different meanings. Two main errors occur with stemming: Over-stemming and under-stemming. In over-stemming, words with different stems are stemmed from the wrong root (false positive), and under-stemming is when words that should be stemmed to a specific root are not (false negative). Porter's stemming is an example of a truncating method that removes suffixes or prefixes of a word. It consists of five steps, where within each step, rules are applied until a condition is met. The suffix is removed if the condition is completed and the subsequent step is performed. The result at the end of the 5th step is the resulting stem. The rules follow the syntax: Porter Stemming usually provides a much better output compared to other stemmers, has less stemming error rates, and also the Porter Snowball stemmer framework is independent of the language being used. A drawback of using the porter stemming algorithm is that the stems produced are not always real words, and the five steps in the algorithm make it a time-consuming process.

B. *Stop Word Removal*

Stop words in documents occur frequently but are effectively insignificant as they are used to join words in sentences. These words do not contribute to the context, and due to their frequency, they hinder information comprehension. Therefore, they are removed because they increase the amount of text in data slowing down information retrieval effectiveness in text mining. Stop words include words like "and", "are", "because" etc.

IV. SENTIMENT ANALYSIS USING VADER SCORING

To categorize tweets, the words must be assigned a positive or negative relative to cryptocurrency markets. A predefined value was assigned to the tweet's specific words to predict cryptocurrencies' probability of increasing or decreasing based on tweet sentiment. These words were cross-referenced with programming libraries containing lexicons of words that were assigned positive and negative values. The text used in early market predictors for cryptocurrencies using tweets was weighted positively or negatively based on these predetermined values.

VADER is a lexicon and rule-based sentiment analysis tool that can handle words, abbreviations, slang, emoticons, and emojis commonly found in social media [23]. It is typically much faster than machine learning algorithms as it requires no training [23][24]. For each body of text, it produces a vector of sentiment scores with negative, neutral, positive, and compound polarities. The negative, neutral and positive polarities are normalized to be between 0 and 1. The compound polarity can be thought of as an aggregate measure of all the other sentiments, normalized to be between -1 (negative) and 1 (positive). VADER was introduced by C.J. Hutto and Eric Gilbert [24]. They found that it performed better than most other sentiment analysis tools and even surpassed some human judges.

V. FORECASTING MODELS

Several machine learning algorithms can be used to drill down the data to analyze how Twitter can be an early market indicator for cryptocurrency prices. Historical research indicates that the most commonly used Twitter Sentiment analysis tools include Vector Support Machines and Naïve Bayes to categorize the data into positive or negative reflections for cryptocurrencies in the market.

A. *Support Vector Machines (SVM)*

SVM is a supervised machine learning algorithm that can be used for classification. In this algorithm, each data item is plotted as a point in n-dimensional space (where n is the number of features), with the value of each feature is the value of a particular coordinate. For a binary categorization problem, the classification is performed by finding the hyperplane that differentiates the two classes, effectively separating the data

.

using an n-dimensional plane. In cryptocurrency Tweet predictors, the support vectors are positively or negatively valued words in tweets. SVM can be used to clearly and accurately predict an optimal threshold for positive or negative sentiment towards a cryptocurrency given a given tweet. In cases where there is no optimal solution utilizing a simple one-dimensional line, and data points have substantial outliers, the data needs to be graphed in a higher dimension. It is possible to create an n-dimensional hyperplane by transforming the data set that utilizes the same maximum distance characteristics as a two-dimensional hyperplane. By using kernel functions, mapping the data in higher dimensions is possible. For SVM, kernel functions can be represented in 3D space. These functions take low dimensional input space and transform them into a higher-dimensional space, therefore converting a non-separable problem to a separable problem. As the Logistic regressors do not optimize mislabeled data, we use SVM to minimize the classification error rather than solely rely on Naïve Bayes' likelihood. Therefore, the support vector machines model is chosen for the classification of mislabeled data. Using the hyperplane solution and mapping in the 3D plane, misplaced data can be encompassed in the proper classification. For applications in Twitter and cryptocurrencies, any Tweet related to cryptocurrencies is weighted with positive and negative values, then a hyperplane is placed to separate the data points. Once an initial hyperplane or line is determined and separates the data from each other, the ideal placement is determined. Maximizing the distances between the nearest data point and hyperplane determines the optimal solution. Once this best separating hyperplane is found, all data points added to the data set will be classified based on their position relative to the hyperplane.

B. *Naïve Bayes Classifier*

The Naïve Bayes classification is a simple model to apply to text mining. Naïve Bayes is practical as its assumptions include a feature vector and dependant variable Y. The optimal classification is determined through the maximum likelihood of the given function: While sentiment can have either a positive and negative meaning, for the sake of simplicity in this paper, a simple binary classification is used for Naïve Bayes classification. Thus or large amounts of data with a short 140-character document such as tweets, conditional-based probability can easily be used. There is little opportunity for varying thoughts in tweets about sentiments. This is based on the feature vector, words that are determined to be a positive or negative sentiment. Specifically, the frequency of these texts is collected for this specified model. In NB, targeted positive and negative words can be thought of as cues that direct each document being classified. Any words that appear multiple times with an insignificant or words that cannot be determined under any class can be removed from the documents to cleanse the data to ensure that probability calculations are more accurate. To account for negation, further manipulation of data with the addition of specific text to tag words with a negated meaning can then be counted as cues towards positive or negative sentiments accurately. The words are randomly grouped to determine the document's sentimental value, and each word's frequency is counted. Regardless of the word's position in a document, the words are placed to decrease frequency. This is based on the assumption that the word's position in the text does not affect how it is depicted in a document. The binary variable of each word is counted to determine the sentiment of the document. In this example, the tweet determines whether it is positive or negative or if the Bitcoin price increases or decreases. The maximum likelihood function is used using the prior class's probability with the likelihood that the document is given the class. Since we assume that the documents are independent of each other and do not affect the class, the maximum likelihood function becomes simpler to solve. Though the independence assumption is usually a constraint to using this model, tweets from individuals are unrelated to each other; thus, the independence assumption favorably works with the model.

VI. The Proposed Composite Ensemble Prediction model (CEPM)

We built a composite of the Extreme Gradient Boosting (XGBoost) using a majority vote over multiple cross-validations iterations. This composite is used to achieve a better overall prediction accuracy than baseline classifiers and individual boosting algorithms. XGBoost is a novel machine-learning algorithm that improves the gradient boosting decision tree (GBDT) and can be used for classification and regression problems [18]. XGBoost is a boosting-tree approach that integrates many weak classifiers to form a robust classifier. It uses the CART, classification, and regression tree model.

The CEPM framework is comprised of five stages, 1) text preprocessing, 2) Sentiment Scoring, 3) individual XGBoost classifications, 4) composite ensemble aggregation, and 5) model validation. In the initial stages, various preprocessing steps are performed, including text stemming and stop word removal. The second stage includes converting tweet text into a sentiment score using VADER. The VADER sentiment analysis algorithm was used to assign each tweet a compound sentiment score based on how positive, negative or neutral their words were. The final sentiment score is factored in the number of Twitter followers, likes, and retweets associated with each tweet. The closing price of Bitcoin, the final sentiment score, and the moving average of the last 100 data points were four input variables for our machine learning models. In the third stage, various instances of the XGBoost classifiers are used. The ensemble modeling is designed to maximize the model performance by utilizing a stacking of ensembles using a majority vote of XGBoost ensembles. In this paper, a 10-fold cross-validation method was employed. The dataset was divided into ten parts, 9 of which were taken in turn as the training set, one as the test set. The average value of the ten results was used as the evaluation value of the algorithm performance. Meanwhile, the experiment repeated the above process ten times, and ten evaluation values were obtained for each model, and their mean values and corresponding 95% confidence intervals were counted. The CEPM ensemble model is then validated using various quality measures.

VII. Experimental Analysis and Results

A. *Evaluation Metrics*

It was found that a confusion matrix is the most commonly used measure to determine the quality of the methods used in predicting the real-value cryptocurrency trading strategies. The confusion matrix provides a visual performance assessment of a classification algorithm as a matrix, which is then used to determine the quality of the results given the classification problem. For example, a confusion matrix can analyze models for understanding sentiments toward bitcoin in Tweets. Based on the words used in association with the term "bitcoin," each tweet is assigned to a negative or positive category. Positive tweets are indicators of upward movements in the bitcoin price. The most popular metrics used to evaluate the results presented in a confusion matrix include accuracy, precision, recall, and F-score. Each metric gives a value that can communicate whether the model is a good model or not [25]-[29] .

Accuracy is computed by determining the percentage of observations that were labeled correctly. This measure has been used as evidence to support the quality of some models used to predict bitcoin pricing. However, accuracy is not the most reliable metric since accuracy provides misleading results as the classes are not balanced, as is the bitcoin market. Accuracy is given as a percentage. The closer this value is to 100%, the better the model's predictive ability is. Precision measures the ratio of correct positive inputs. Recall, also known as the sensitivity, measures the ratio of the items present in the correctly identified input. These metrics focus on the true positives, making their results more reliable. If Precision is a higher ratio, it represents a robust predictive ability by the model. Lastly, the F-score; takes the weighted average of precision and recall, taking both false positives and false negatives. This metric is beneficial in evaluating cases with uneven class distributions [30]-[34].

B. Experimental Datasets

We used the Twitter dataset from [35][36]. The preprocessing steps over time with BTC's closing prices are computed per minute. As tweets are created much more frequently than once a minute, we aggregated all tweets' scores into a per-minute. The CEPM ensemble model is validated using accuracy, recall, precision, and F-scores quality measure. It can be shown from Table 1 that the XGBoost ensemble has the highest Precision, recall, and F-score as compared to Logistic regression, SVM, NB, and a single XGBoost. We have assessed the proposed CEPM model's performance using "accuracy" as another quality measure, as shown in Fig.1. It can be shown from Table 2 that the CEPM model has achieved an improvement of up to 21%, 16%, 18%, and 22%, in the Precision, Recall, F-score, and accuracy, respectively, as compared to the LR, SVM, NB, and XGBoost. In Fig.2, it can be illustrated that the proposed CEPM takes more iterations measured by the increase in the computational time as compared to other algorithms. Further adjustment to the number of iterations is considered future work to balance the trade-off between accuracy improvement and time overhead.

TABLE I. PRECISION, RECALL, F-SCORE (COVID-19 TWEETS)

	Precision	Recall	F-score
LR	0.6743	0.4532	0.54207141
SVM	0.64843	0.5543	0.59768152
NB	0.665732	0.65421	0.65992071
(XGBoost)	0.78953	0.809532	0.7994059
CEPM	0.8926	0.883474	0.88801355

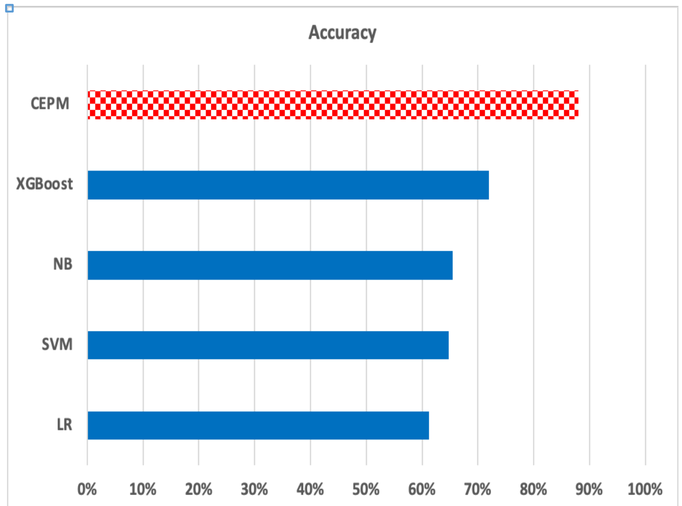

Fig. 1. Accuracy (COVID-19 Tweets)

TABLE II. % OF IMPROVEMENT IN PRECISION, RECALL, F-SCORE, ACCURACY (COVID-19 TWEETS)

Precision	Recall	F-score	Accuracy
21%	16%	18%	22%

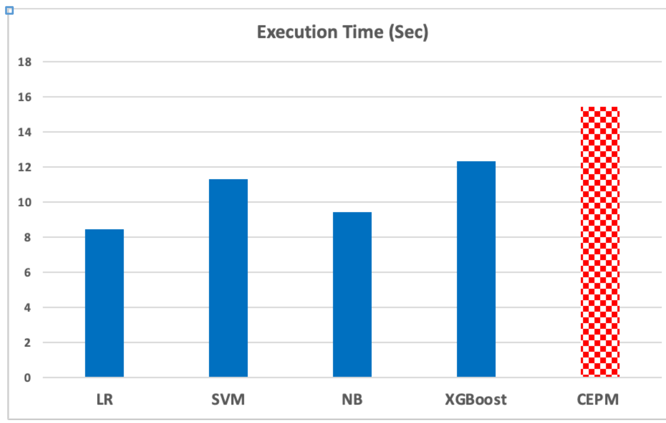

Fig. 2. Execution Time (COVID-19 Tweets)

VIII. CONCLUSION AND FUTURE DIRECTIONS

In this paper, we have developed a composite aggregate of the well-known XGBoost classifier to predict the BTC early market movement better. Experimental results show that the proposed CEPM outperforms other state-of-the-art techniques using Twitter datasets collected during the Era of COVID-19. The proposed model can be further adopted to forecast the BTC market even after the COV-19 pandemic to assess individuals and firms trading in future investments. Future research directions would include adjusting the number of incremental iterations of each XGBoost and incorporating various sentiment scoring schemes compared to VADER.

REFERENCES

[1] Tan, X., & Kashef, R. (2019, December). Predicting the closing price of cryptocurrencies: a comparative study. In *Proceedings of the Second International Conference on Data Science, E-Learning and Information Systems* (pp. 1-5).

[2] Ibrahim, A., Kashef, R., Li, M., Valencia, E., & Huang, E. (2020). Bitcoin Network Mechanics: Forecasting the BTC Closing Price Using Vector Auto-Regression Models Based on Endogenous and Exogenous Feature Variables. *Journal of Risk and Financial Management*, *13*(9), 189.

[3] Ibrahim, A., Kashef, R., & Corrigan, L. Predicting market movement direction for bitcoin: A comparison of time series modeling methods. *Computers & Electrical Engineering*, *89*, 106905.

[4] Tobin, T., & Kashef, R. (2020, June). Efficient Prediction of Gold Prices Using Hybrid Deep Learning. In *International Conference on Image Analysis and Recognition* (pp. 118-129). Springer, Cham.

[5] A. F. Ibrahim, L. Corrigan and R. Kashef, "Predicting the Demand in Bitcoin Using Data Charts: A Convolutional Neural Networks Prediction Model," 2020 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), London, ON, Canada, 2020, pp. 1-4, doi: 10.1109/CCECE47787.2020.9255711.

[6] Kashef, R., & Kamel, M. S. (2010). Cooperative clustering. *Pattern Recognition*, *43*(6), 2315-2329.

[7] Kashef, R. (2008). Cooperative clustering model and its applications.

[8] Rasha Kashef, A boosted SVM classifier trained by incremental learning and decremental unlearning approach, Expert Systems with Applications, 2020, 114154, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2020.114154.

[9] O. Kraaijeveld and J. D. Smedt, "The predictive power of public Twitter sentiment for forecasting cryptocurrency prices," *Journal of International Financial Markets, Institutions, and Money*, p. 101188, Mar. 2020.

[10] T. R. Li, A. S. Chamrajnagar, X. R. Fong, N. R. Rizik, and F. Fu, "Sentiment-Based Prediction of Alternative Cryptocurrency Price Fluctuations Using Gradient Boosting Tree Model", *Frontiers in Physics*, vol. 7, Oct. 2019.

[11] S. Mohapatra, N. Ahmed, and P. Alencar, "KryptoOracle: A Real-Time Cryptocurrency Price Prediction Platform Using Twitter Sentiments", arXiv:2003.04967 [cs.CL], Feb. 2020.

[12] C. Kaplan, C. Aslan, and A. Bulbul, "Cryptocurrency Word-of-Mouth Analysis via Twitter", ResearchGate, 2018. [Online]. Available: https://www.researchgate.net/publication/327988035_Cryptocurrency_Word-of-Mouth_Analysis_viaTwitter

[13] A. Jain, S. Tripathi, H. D. Dwivedi and P. Saxena, "Forecasting Price of Cryptocurrencies Using Tweets Sentiment Analysis", 2018 Eleventh International Conference on Contemporary Computing (IC3), Noida, 2018, pp. 1-7, doi: 10.1109/IC3.2018.8530659.

[14] S. Symeonidis, D. Effrosynidis, and A. Arampatzis, "A comparative evaluation of pre-processing techniques and their interactions for twitter sentiment analysis," *Expert Systems with Applications*, vol. 110, no. Complete, pp. 298–310, Nov. 2018.

[15] K. Sailunaz and R. Alhajj, "Emotion and sentiment analysis from Twitter text," *Journal of Computational Science*, vol. 36, p. 101003, Sep. 2019, doi: 10.1016/j.jocs.2019.05.009

[16] A. Rosen, "Tweeting Made Easier," *Twitter*, 07-Nov-2017. [Online]. Available: https://blog.twitter.com/en_us/topics/product/2017/tweetingmadeeasier.html. [Accessed: 24-Jul-2020].

[17] H. Lyu, L. Chen, Y. Wang and J. Luo, "Sense and Sensibility: Characterizing Social Media Users Regarding the Use of Controversial Terms for COVID-19," in *IEEE Transactions on Big Data*, doi: 10.1109/TBDATA.2020.2996401.

[18] Wang, L., Wang, X., Chen, A., Jin, X., & Che, H. (2020, September). Prediction of Type 2 Diabetes Risk and Its Effect Evaluation Based on the XGBoost Model. In *Healthcare* (Vol. 8, No. 3, p. 247). Multidisciplinary Digital Publishing Institute.

[19] Kashef, R., & Kamel, M. S. (2009). Enhanced bisecting k-means clustering using intermediate cooperation. *Pattern Recognition*, *42*(11), 2557-2569.

[20] Kashef, R., & Kamel, M. (2006, November). Distributed cooperative hard-fuzzy document clustering. In *Proceedings of the Annual Scientific Conference of the LORNET Research Network*.

[21] Kashef, R., & Kamel, M. S. (2007, October). Hard-fuzzy clustering: a cooperative approach. In *2007 IEEE International Conference on Systems, Man and Cybernetics* (pp. 425-430). IEEE.

[22] Yeh, T. Y., & Kashef, R. (2020). Trust-Based Collaborative Filtering Recommendation Systems on the Blockchain. *Advances in Internet of Things*, *10*(4), 37-56.

[23] C. J. Hutto, "VADER-Sentiment-Analysis," *GitHub*. [Online]. Available: https://github.com/cjhutto/vaderSentiment. [Accessed: 24-Jul-2020].

[24] C. J. Hutto and E. Gilbert, "VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text," presented at the Eighth International AAAI Conference on Weblogs and Social Media, May 2014, Accessed: Jul. 24, 2020. [Online]. Available: https://www.aaai.org/ocs/index.php/ICWSM/ICWSM14/paper/view/8109.

[25] G. Hass, P. Simon and R. Kashef, "Business Applications for Current Developments in Big Data Clustering: An Overview," 2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, Singapore, 2020, pp. 195-199, doi: 10.1109/IEEM45057.2020.9309941.

[26] Close, L. and Kashef, R. (2020) Combining Artificial Immune System and Clustering Analysis: A Stock Market Anomaly Detection Model. Journal of Intelligent Learning Systems and Applications, 12, 83-108. doi: 10.4236/jilsa.2020.124005.

[27] Fayyaz, Z., Ebrahimian, M., Nawara, D., Ibrahim, A., & Kashef, R. (2020). Recommendation Systems: Algorithms, Challenges, Metrics, and Business Opportunities. Applied Sciences, 10(21), 7748.

[28] Kashef, R. F. (2018, January). Ensemble-Based Anomaly Detetction using Cooperative Learning. In *KDD 2017 Workshop on Anomaly Detection in Finance* (pp. 43-55). PMLR.

[29] M. Ebrahimian and R. Kashef, "Efficient Detection of Shilling's Attacks in Collaborative Filtering Recommendation Systems Using Deep Learning Models," *2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Singapore, Singapore, 2020, pp. 460-464, doi: 10.1109/IEEM45057.2020.9309965.

[30] Ebrahimian M, Kashef R. Detecting Shilling Attacks Using Hybrid Deep Learning Models. *Symmetry*. 2020; 12(11):1805. https://doi.org/10.3390/sym12111805

[31] Kashef, R. (2020). Enhancing the Role of Large-Scale Recommendation Systems in the IoT Context. *IEEE Access*, *8*, 178248-178257.

[32] Nawara, D., & Kashef, R. (2020, September). IoT-based Recommendation Systems–An Overview. In *2020 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)* (pp. 1-7). IEEE.

[33] Kashef, R., & Niranjan, A. (2017, December). Handling Large-Scale Data Using Two-Tier Hierarchical Super-Peer P2P Network. In *Proceedings of the International Conference on Big Data and Internet of Thing* (pp. 52-56).

[34] Li M, Kashef R, Ibrahim A. Multi-Level Clustering-Based Outlier's Detection (MCOD) Using Self-Organizing Maps. *Big Data and Cognitive Computing*. 2020; 4(4):24. https://doi.org/10.3390/bdcc4040024

[35] Pano, T., & Kashef, R. (2020, September). A Corpus of BTC Tweets in the Era of COVID-19. In *2020 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)* (pp. 1-4). IEEE.

[36] Pano, T., & Kashef, R. (2020). A Complete VADER-Based Sentiment Analysis of Bitcoin (BTC) Tweets during the Era of COVID-19. *Big Data and Cognitive Computing*, *4*(4), 33.