A Multi-Model Intelligent Approach for Rumor Detection in Social Networks

Nikita Mariam Santhosh*, Jo Cheriyan‡, (Sr. Member-IEEE), Lekshmi S Nair†, (Member-IEEE)
*‡Department of Computer Science and Engineering, Saintgits College of Engineering, Kerala, India
†Department of Computer Science and Engineering, Amrita Vishwa Vidyapeetham, Amritapuri, India
*nikita.css2022@saintgits.org, ‡jo.cheriyan@saintgits.org,†lekshmisn@am.amrita.edu

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***Abstract*—The impact of social media on public opinion has far-reaching repercussions across society. Even though social media give outlets to share news and opinions, the sheer number of posts on Twitter and Facebook makes it challenging to maintain quality control. These platforms have many users and offer various services, such as content creation and distribution. Not all information disseminated via the internet is accurate and reliable. Many people try to spread false and misleading information to influence public opinion. This paper reviews different algorithms for rumor identification, particularly fake news detection. It also proposes detection and classifications of fake news and its corresponding classification. Misinformation, commonly known as rumors, can cause serious harm due to unverified information. Despite their widespread use, the uncontrollable nature of social media platforms frequently results in the spread of rumors. One of the most sought after study areas in social media analytics is automatically recognizing rumors from tweets and posts.**

***Index Terms*—Social media, rumor, fake news, minimization**

I. Introduction

Information spreading or propagation is made easy with the help of social media [1]. Many users worldwide widely use social media platforms like Facebook or Twitter. Because of the Internet and social media, getting news has become much easier and more convenient. On the Internet, users can frequently follow events of interest. This process is made more accessible by the growing use of mobile devices. However, significant potential comes with a great deal of responsibility. The media has a significant impact on society. As is often the case, someone wants to take advantage of that fact. The media can manipulate information in various ways to reach specific goals. As a result, news stories that are not wholly true are published if not entirely false. A handful of websites are dedicated almost solely to spreading false information. They purposefully produce hoaxes, misinformation, and disinformation masquerading as actual news, and they typically use social media to increase traffic and influence. Fake news websites are primarily used to alter public opinion on specific problems. As a result, fake news is both a global problem and a global challenge.

Many scientists believe that artificial intelligence and machine learning can assist solve the problem of fake news. Because hardware is less expensive and more extensive datasets are more readily available. Artificial intelligence algorithms have recently begun to outer- form humans on a range of categorization tasks like picture recognition, voice detection. Because information impacts our perceptions of the universe, fake news and other misleading facts can take various forms. According to intelligence research, misinformation posted on social media has a long-lasting effect on less intelligent people, preventing them from making the best decisions. False news is used to instill fear in individuals, promote racist ideologies, and encourage bullying and violence against innocent people. Because of the growing number of customers in web-based living, anyone can instantly transmit news, jeopardizing its reliability. Because false news is published intended to deceive the listener, it is not easy to detect based just on the content of the news.

The majority of the strategies are intend to identify rumors threat, problem as a classification task, assigning labels such as fake or real, true or false, to specific texts [2]. The details are explained in the literature. Deep learning and machine learning approaches yield promising results in specific situations [3]. SVMs outperformed most supervised machine learning (SML) algorithms for deception recognition in texts, according to research, by utilizing content-based features like visual and linguistic features. Detecting fake news leads to various applications, especially through social media such as online marketing, recommender system [4]. We propose numerous categories of rumors in this research and detection of rumors using various machine learning approaches [5].

The major contributions of this paper include,

- Categorization of the suspicious information into rumor and non-rumor using machine learning algorithms, classifiers.
- Recommending the most effective machine learning classifier.

The remaining part of the artile is organized as follows, Section II discusses the literature on various rumor detection systems by machine learning approach. The proposed rumor detection method explained in Section III and its validation procedure and results are dipcted in Secion IV. Finally, we conclude the article in Section V.

II. Literature Study

Some relevant research is offered in the area of rumor detection. In [6], the authors employ machine learning techniques such as Bayesian networks, lazy learners, Support Vector Machines, Logistic Regression, Decision trees, and

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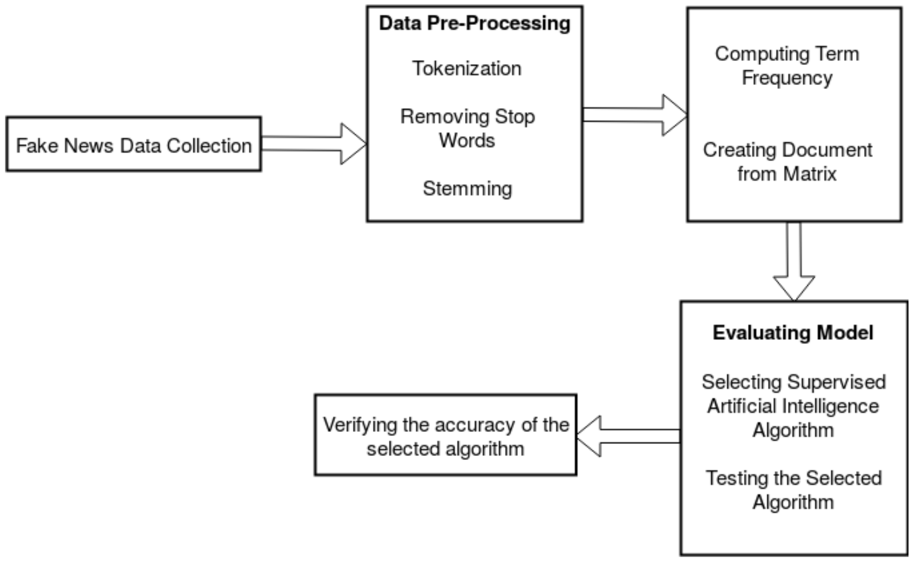

Fig. 1. Rumor Detection and Classification Process

Rule learners to detect fake financial statements. According to the findings, the decision tree surpasses the other models in terms of classification accuracy. The accuracy rate could be increased by supplementing the input vector with qualitative data.

The authors in [7] detect financial rumors over a large data platform. The authors also proposed architecture that allows the successful detection of financial rumors. Multiple case studies can be used to investigate the rumor detection framework further. This research aims to use context for rumor detection on social media. Rumor detection is done using Nave Bayesian and Support Vector Classifier algorithms. Experimentation has revealed that the proposed model has improved inaccuracy. For accuracy, different categorization algorithms might be used.

In [8], the authors focus on rumor identification and classification utilizing a supervised approach, namely, the J48 classifier, which is implemented in the WEKA platform under a single-step Rumor Detection Classification (SRDC) and two-step RDC (TRDC). For the MIX dataset, the results demonstrate that TRDC has a better F-measure than SRDC. The limitation in the model restricts the pre-processing activity due to tool limitations.

The authors in [9] propose a new model called Propagation Kernel Tree (PKT), which incorporates the SVM classifier into a supervised learning framework. On the Twitter dataset. The suggested approach outperforms the current state-of-the-art baseline for both broad and early rumor detection.

To detect health-related rumors on Twitter, the authors in [10] employed three machine learning algorithms: Nave-Bayes, Random Forest, and Random Decision Tree. Experiments demonstrate that the Random forest has the best precision and recall of the three classifiers, with a precision of 0.946 and a recall of 0.944.

A novel framework called Cross-topic Emerging Rumor Detection (CERT) based sparse representation model is suggested to detect emerging rumors in social media [11]. Experiments reveal that CERT outperforms previous techniques for spotting rising rumors. The system can be enhanced by including cross-modal data. An automatic rumor detection system based on hot topic detection and Rumor Identification with various features. Many tests are carried out to compare random forest, Nave Bayes, and logistic regression in the rumor categorization task. Experiments show that random forest works best and that investigating a more extensive collection of features and better probabilistic models can improve the models efficacy.

In [12], the authors suggested an efficient algorithm for detecting fake news and misinformation using crowd wisdom. On specified datasets, the propagation of misinformation can be effectively curtailed, according to the results. On the other hand, adding aggressive behavior can help progress even more. The authors in [13] developed a content representation strategy for microblog rumor detection using a bag of words and a neural network model. The results demonstrate that the neural model has a 60% accuracy rate, while the bag of words model has a 90% accuracy rate. However, by looking at other features and settings, the models performance can be improved even more.

III. The Proposed System

We propose an ensemble technique with distinct linguistic feature sets to identify authentic or fake news articles from multiple areas, building on previous work. The framework suggested ensembling the techniques with the Linguistic Inquiry and Word Count (LIWC) feature set. There is a slew of reputable websites that publish reliable news content that can be used for fact-checking. Furthermore, researchers maintain open repositories to retain an up-to-date list of currently available datasets and linkages to possible fact-checking sites that may aid in the fight against the spread of false news. However, for the studies, we chose three datasets that contained news from various domains (such as politics, entertainment, technology, and sports) and contained a mix of both true and false stories, and we merged the three datasets into one colossal dataset. The datasets were retrieved from Kaggle.

As the use of social media has grown, research into the evolution of rumor detection and verification systems has grown in popularity. A fact-checking procedure for a specific claim is a complex multi-step procedure that usually entails the following steps:

- obtaining possibly relevant documents as evidence for the claim
- predicting the position of each document concerning the claim
- rating the documents' trustworthiness.
- rendering a conclusion based on the sum of previous steps.

Rumor detection, rumor tracking, rumor stance classification, and rumor veracity classification are the four components of a rumor classification system. When developing a rumor classification system, temporal aspects, such as fresh rumors that appear during breaking news, are a major determining factor. Rumors that surface as a result of breaking news are usually ones that have never been heard before. As a result, rumors must be automatically discovered, and a rumor classification system must be able to deal with fresh, unheard rumors, given that the system's training data may differ from what it will later see. A stream of messages must be evaluated in real-time in these circumstances when early detection and resolution of rumors are critical. Long-standing rumors have been talked about for a long time. Some rumors might circulate long before their reality is proven with confidence. Despite the difficulties in determining the truth, these rumors pique people's interest. Furthermore, the system may categorize ongoing discussions about the rumor using past discussions about the rumor, where the vocabulary is less likely to alter, and so the classifier developed on old data can still be used for new data. Unlike newly emerging murmurs, long-standing rumors are frequently processed retrospectively; therefore, posts do not need to be processed in real-time.

The four-step procedure proposed here for rumor identification starts with gathering information from the various social media sites under consideration. This information must be organized consistently so that relevant features may be extracted. Consolidation, cleansing, transformation, and reduction are part of the pre-processing process. The essential features (content-based, pragmatic, and network-specific) are extracted. Each data is identified as a rumor or not a rumor using a variety of machine learning approaches such as Naive Bayesian, Support Vector Machines, Decision Tree, Random Forest, and Logistic Regression.

A. Date Pre Processing

The data collection for classifying fake news detecion is a difficult task, and labeling is challenging. The information and its natural label is as expected, if the information with counterfeit labels are very hard to detect during classification. There are many records explicity with errors. norder to finetune the records, we do the following steps,

- Clear all null records.
- All the duplicate records are to be removed and keep keep one record, then label it 1 (positive).
- Convert numeric data to standard records, and any unknown records (if any) to 0.

After the data is gathered, we follow the sequence of steps to pre-process:

- Data Consolidation: the acquired data is combined into a single data source. Converting all acquired data into a single format is also part of the process.
- Data-Cleaning: There is a lot of noise (data that is useless to us) in the data that needs to be removed. Noise, inconsistencies, and missing data are all removed during data cleaning.
- Data Transformation involves adding specific attributes to the data, aggregating it, and normalizing it.
- Data Reduction: the number of variables and cases is minimized. In this stage, the skewed data is also balanced.
- The data is shaped correctly after pre-processing and is acceptable for feature extraction.

Later the models are trained and tuned using SVM, Logistic Regression, Naive Bayes, and random forest. The Voting Classifiers are implemented to combine all aforementioned models. They form an ensemble classifier that uses all these classifiers to predict the label and class probability and use the soft voting method to make the final prediction.

Count Vectorizer

The English stopwords are removed from all the datasets, and then they are tokenized using spaces and punctuation marks as the delimiter. Once the headlines are tokenized, a sparse matrix is returned containing all the news headlines as rows and the tokens as columns. Several n-grams are returned to make the tokens represent the context in which they are used in addition to their morphological use.

B. Ensemble Method

The ensemble method is multi-model system which helps to minimize the error rate and increasing the performance, which leads to increased accuracy for the ensemble learners. The ensemble model is very similar to the model which already used. The procedure is suc that the numerous expert opinions are gathered before making a decision. Which help to reduce confusion towards finalizing or an unfavorable outcome. A classification algorithm produce a decision boundary that fits data. Such algorithms work on specific dataset by considering different parameters. The outputs are purely depends on the parameters selections, the machine learning model and tarining dataset. The training model overfit or underfit depends on data used, also generate some biased findings over unseen data. Overfitting issue can be reduced by corss validation. Models

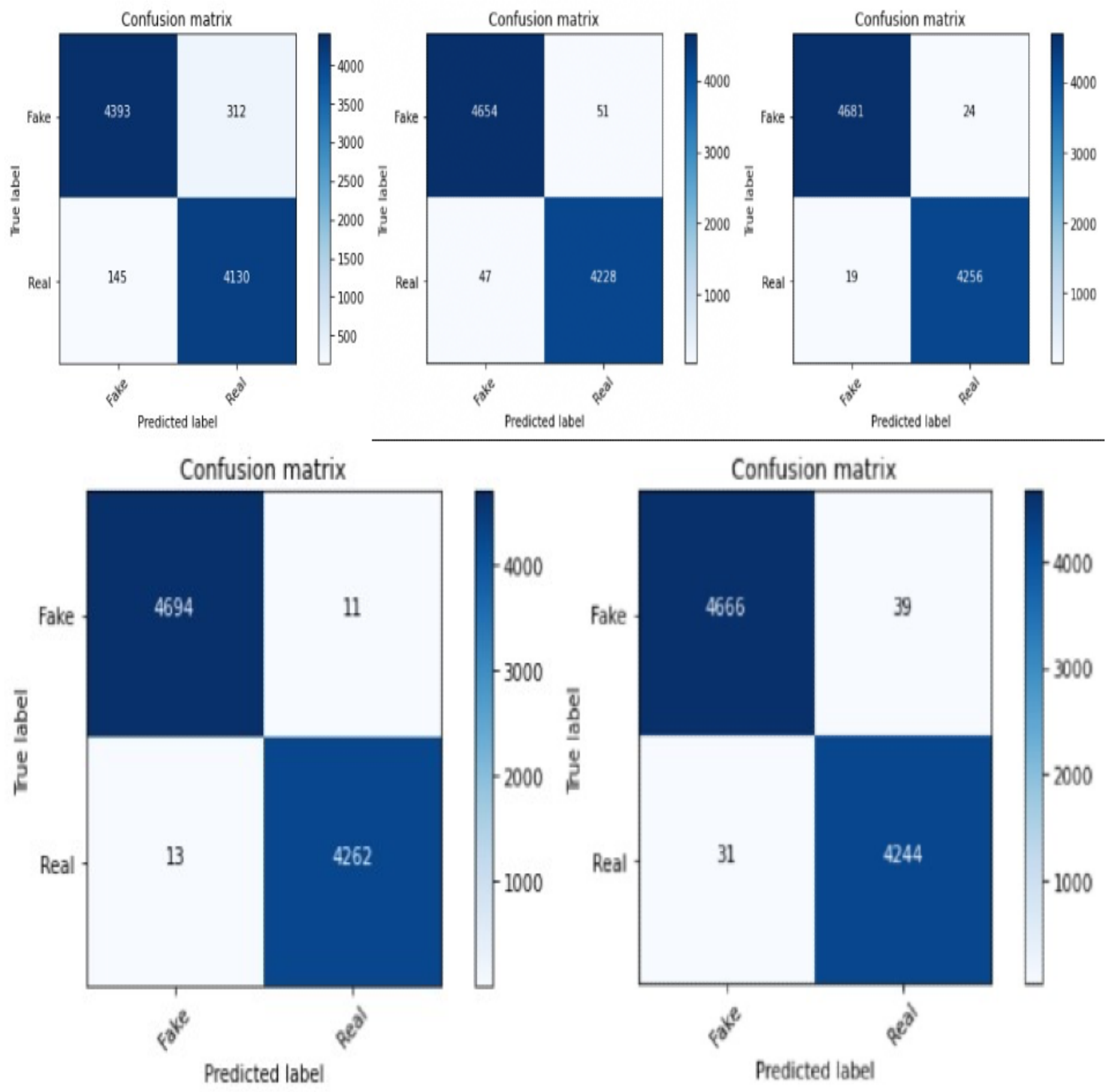

Fig. 2. Prediction Labels using Ensemble model

selection based on experience by training different dataset with respect to different parameters. As a result, appropriate model can be used for classification with pre defined decision and limits. Hence, ensemble learning approaches can be used for solving issues raised in the classification and produce the optimal output. The final classification depends on how many votes has received by the models by training different algorithms. Voting classifiers are one such example for the classification with respect to result of training algorithms.

1) Random Forest: The given model trained based on different parameters and fine tuned to find an optimal model which are accurately predict the outcome. The decision tree based algorithms performs better and works based on regression or classification problem. Variety of algoritms are come under this catagory and using data in the form of tree. The cost estimation method process the tree dataset and do classification efficiently. The Gini index is act as the cost function and found to be some classification issues, which works by subtracting the given dtata from sum of each class's squared probability.

2) Bagging Ensemble Classifier: One of the early ensemble methods used for avoiding overfitting are bagging classifier. The bagging classifier works based on selected class and solve the classification problem based on votes. It works on dataset by choosing data tree model. The model sometimes called as bootstrao aggregation. The random forest model is an example of bagging classifier.

Bagging classifier, or bootstrap aggregating, is an early ensemble method for reducing variance (overfitting) over a training set. One of the most popular bagging classifier variants is the random forest model. The bagging model selects the class for a classification problem based on primary votes measured by several trees, but the data for each tree is selected using random sampling with replacement from the entire dataset to reduce overall variance. On the other hand, the bagging model averages numerous estimates for regression issues.

3) Boosting Ensemble Classifier: This method uses an incremental approach to help learners accurately categorize data points that are frequently misclassified. For classifying a problem, identical weighted coefficients are utilized at first for all data points. In subsequent rounds, the weighted coefficients are reduced for correctly classified data points and increased for incorrectly classified data points. Each round's succeeding tree learns to reduce the previous round's faults and improve overall accuracy by correctly identifying data points that were misclassified in earlier rounds.

4) Voting Enssemble Classifier: The voting ensemble is more accessible to implement than bagging and boosting algorithms. Bagging algorithms construct several subsets of data by randomly picking and replacing data from the entire dataset, resulting in several datasets. Boosting involves training many models in a sequential fashion, with each model learning from the preceding by increasing weights for misclassified points, resulting in a generic model that can correctly categorize the problem. A voting ensemble is a collection of numerous independent models that produce classification results that contribute to the majority voting's total forecast. The prediction of fake news by enssemble method dipcted in Fig. 2.

IV. Experimentation and Result

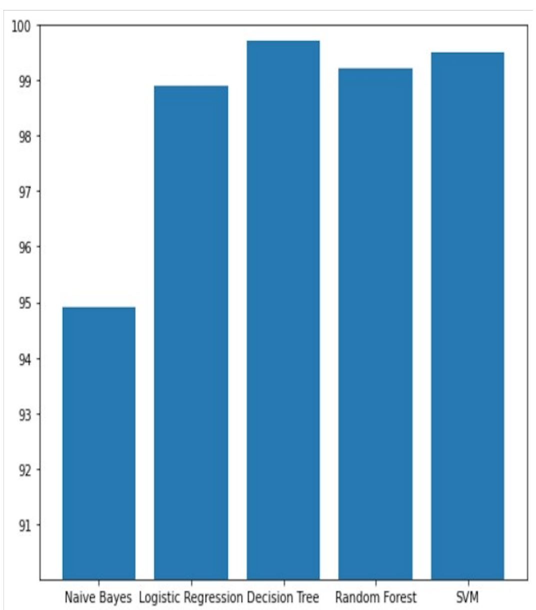

Fig. 3. Comparison of Ensemble model

The graph in Fig. 3 give a statistical relationship of different algorithms in terms of accuracy. The summary is picturized by considering the final dataset. It is found that 99.73% of accuracy is achieved while using decision tree, the maximum accuracy obtained. The support vector machine (SVM) shows the 99.52% accuracy, stands the second place. The third postion in terms of accuracy by random forest of 99.22%. The logic regression and naive bayes show the accuracy of 98.91% and 94.91% respectively. All the algoritms show almost inline with each other where decision tree show the highest accuracy and naive bayes shows the lowest in terms of accuracy of classifiction on the final dataset.

V. Conclusion

Rumors spread hatred and fear, both of which are adverse to society. Hence rumors must be dispelled. The psychological research of rumors, existing methods to identify rumors, and the evaluation matrix used to evaluate method performance are all summarised in this work. As the use of social media grows in society, research into rumor detection grows as well. Because current approaches are incapable of efficiently processing stream data and automatically detecting new emerging rumors from social media, we require a comprehensive system to detect new developing rumors as soon as possible.

References

[1] E. Bakshy, I. Rosenn, C. Marlow, and L. Adamic, "The role of social networks in information diffusion," in *Proceedings of the 21st international conference on World Wide Web*, 2012, pp. 519–528.

[2] T. Takahashi and N. Igata, "Rumor detection on twitter," in *The 6th International Conference on Soft Computing and Intelligent Systems, and The 13th International Symposium on Advanced Intelligence Systems*. IEEE, 2012, pp. 452–457.

[3] A. Kumar and S. R. Sangwan, "Rumor detection using machine learning techniques on social media," in *International conference on innovative computing and communications*. Springer, 2019, pp. 213–221.

[4] N. M. Santhosh, J. Cheriyan, and M. Sindhu, "An intelligent exploratory approach for product recommendation using collaborative filtering," in *2021 2nd International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS)*, 2021, pp. 232–237.

[5] G. Liang, W. He, C. Xu, L. Chen, and J. Zeng, "Rumor identification in microblogging systems based on users behavior," *IEEE Transactions on Computational Social Systems*, vol. 2, no. 3, pp. 99–108, 2015.

[6] D. Wang, "Analysis and detection of low quality information in social networks," in *2014 IEEE 30th International Conference on Data Engineering Workshops*, 2014, pp. 350–354.

[7] X. Liu, A. Nourbakhsh, Q. Li, R. Fang, and S. Shah, "Real-time rumor debunking on twitter," in *Proceedings of the 24th ACM International on Conference on Information and Knowledge Management*, ser. CIKM '15. New York, NY, USA: Association for Computing Machinery, 2015, p. 18671870. [Online]. Available: https://doi.org/10.1145/2806416.2806651

[8] G. Cai, H. Wu, and R. Lv, "Rumors detection in chinese via crowd responses," in *2014 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2014)*, 2014, pp. 912–917.

[9] M. Lukasik, T. Cohn, and K. Bontcheva, "Estimating collective judgement of rumours in social media," *CoRR*, vol. abs/1506.00468, 2015. [Online]. Available: http://arxiv.org/abs/1506.00468

[10] S. Kwon, M. Cha, K. Jung, W. Chen, and Y. Wang, "Prominent features of rumor propagation in online social media," in *2013 IEEE 13th International Conference on Data Mining*, 2013, pp. 1103–1108.

[11] F. Yang, Y. Liu, X. Yu, and M. Yang, "Automatic detection of rumor on sina weibo," in *Proceedings of the ACM SIGKDD Workshop on Mining Data Semantics*, ser. MDS '12. New York, NY, USA: Association for Computing Machinery, 2012. [Online]. Available: https://doi.org/10.1145/2350190.2350203

[12] Z. Yang, C. Wang, F. Zhang, Y. Zhang, and H. Zhang, "Emerging rumor identification for social media with hot topic detection," in *2015 12th Web Information System and Application Conference (WISA)*, 2015, pp. 53–58.

[13] S. Wang and T. Terano, "Detecting rumor patterns in streaming social media," in *2015 IEEE International Conference on Big Data (Big Data)*, 2015, pp. 2709–2715.