Text Mining Based Rumor Detection on Twitter data

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Received 16.03.2022**, received in revised form** 22.04.2022**, accepted** 09.05.2022
DOI: 10.47904/IJSKIT.12.1.2022.18-23

Abstract- Rumors are misleading information that is not sustained at the time of circulation and are not true at the time of verification. In other words, Rumors are a set of linguistic, symbolic or tactile propositions whose veracity is not quickly or ever confirmed. As the popularity of social networking sites has increased, in recent years, incorrect information and rumors have circulated widely causing a significant influence on people's lives. Microblogging platforms are an excellent way to spread rumors and automatically disprove them in critical situations. Existing approaches to detecting rumors have depended on hand-crafted features for utilizing machine learning algorithms, which necessitates a significant amount of manual effort. In this work, we have used stylometric and word vector features and put them into machine learning models. These features are extracted from the twitter-16 dataset and by applying SVM, we have attained the highest accuracy in comparison to existing newest studies.

Keywords– Rumors, Machine Learning, Twitter

1. INTRODUCTION

The notion of rumor existed long before the Internet and other computer technologies." Rumors can disseminate misinformation or disinformation, both of which are types of misleading information." There are several outlets for accessing rumors, such as social media, blogs, comments, and so on. Anyone who uses these sites has the ability to generate and distribute false news or rumors. Microblogging websites like Twitter, Instagram, Facebook, Telegram, etc., may quickly spread news, rumor, and authentic information. Moreover, rumors may not be safe for anyone [1–4]. False or unconfirmed information travels on the internet the same way that truthful information does, potentially going viral and affecting public opinion and choices. Researching on rumors. Fact-checking websites like snopes.com and factcheck.org which report on rumors are examples of collaborative endeavors. Nevertheless, because such initiatives entail manual verification phases, these websites do not cover all topics and might take a long time to debunk [5, 6].

The majority of users on social media do not check material before spreading it. Manually spotting bogus news is a huge challenge for everyone. As a result, there is a need for an automated system that can recognize phony news or rumors quickly. After changing the text, image, audio, and video, publish misleading material on social media platforms to deceive people. Rumors study on multimedia content is an important area due to the following reasons:

- People spread wrong information and create controversies about that wrong information.
- Some users submit material on a blog, but the information does not verify the title or facts, degrading user experiences.

False information emotionally stymies the public [7] emotions.

One of the newest areas of research is detecting misleading information on social media. Rumor and fake news are two common examples of incorrect information. Figure 1 shows a trend study of people's web searches on fake news and rumors over the previous seven years [17].

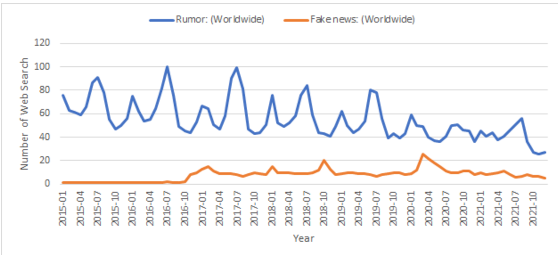

Figure 1: The amount of times a person has searched for rumor and fake news in previous years.

In recent years, a slew of new studies on the issue of rumor detection has been published. This examination, on the other hand, includes several well-known works in the domain. Figure 2 illustrates the proportion of publications from the preceding seven years that were examined for the research Identification of rumors, we apply machine learning approaches to datasets and identify how many rumors are in a dataset. Rumor is defined as an unconfirmed remark spread over multiple networks that originates from single or multiple sources [8, 9].

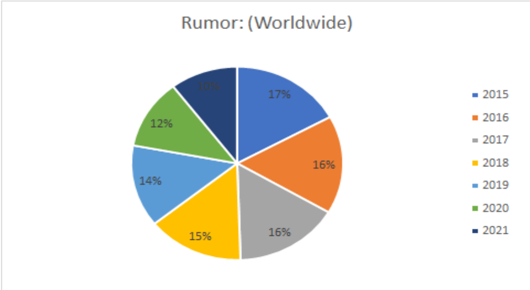

Figure 2: Percentage of rumor analysis over last 7 years.

Because of the omnipresence of online platforms and social networks, a large amount of multimedia data is produced. The flexibility and simplicity with which information on social media platforms may be disseminated stimulate the spread of information across the network, regardless of its veracity. This sort of disinformation is typically disseminated in the event of an exclusive piece of news [34, 35]. As a result of unconfirmed information, such information, sometimes referred to as rumors, has the potential to do catastrophic damage. Despite their popularity, the chaotic nature of social media platforms usually leads to the propagation of rumors [2, 3]. Using supervised and unsupervised machine learning algorithms, we may identify rumors. Some machine learning methods are defined for rumor detection, such as classification, regression, clustering, and decision making. Machine Learning models may apply to the datasets, and these data sets are available on the internet [32, 33].

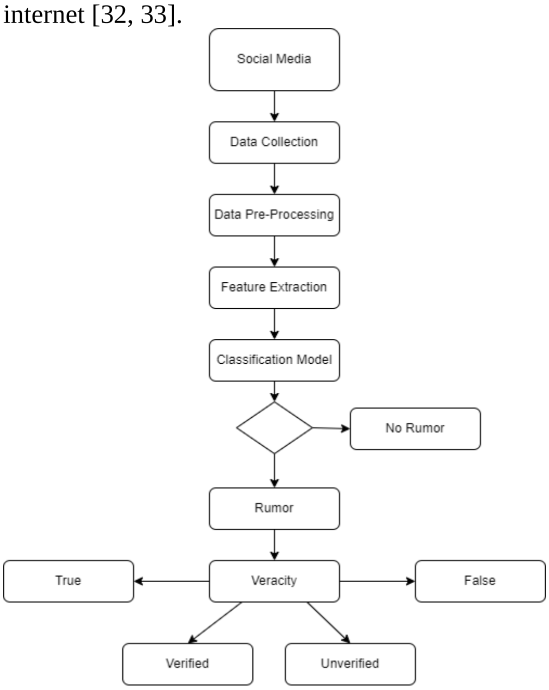

Figure 3: Process for social media rumor detection and veracity Assessment.

As shown in Figure 3, the first phase is data collecting, which can be done using two alternative methods: social networking sites (Twitter, Facebook, YouTube, Sina Weibo, etc.) or pre-existing datasets. To make the text more relevant, the next step is to apply data pre-processing. Additionally, characteristics are retrieved that will be used to train the model and categories the problem as a binary class classification to identify whether or not the given post/topic is a rumor. Finally, the content's veracity can be evaluated as true, false, verified, or unverified.

2. RELATED WORK

This specific section emphasizes delivering a rapid review of the literature which is in connection with our topic. The related works will be outlined is in the context of feature selection, rumor analysis, and collection of data.

Using Twitter to evaluate rumors, they demonstrate a specific classification method in order to reveal classification [18]. The approach took advantage of a new collection of distinct problem-specific features that could be identified automatically, considerably improving the classifier's quality. They employed two different data sets in their experiments: the rumor Eval dataset and the PHEME dataset.

The significance of the qualities is analyzed, as well as their impact on performance. The reasons for adopting the k-best technique to select the final feature set. Using the PHAME dataset, this paper provides a supervised machine learning approach for detecting false news [19].

Most of the work in the last several years, has been completed on rumors detection. Microblogging systems are perfect for propagating rumors, and automatically debunking myths is a critical issue [6, 10]. Existing methods for detecting rumors have relied on handmade features rather than machine learning algorithms. As shown in figure 4, access data from social media approaches, like APIs, scraping the web, and Selenium web driver.

In [11] authors recognize the rumor on Twitter data using propagation structure with kernel learning, where they achieve the accuracy of 75%. They also find the results on false rumors, true rumors, non-rumor, and verified rumors.

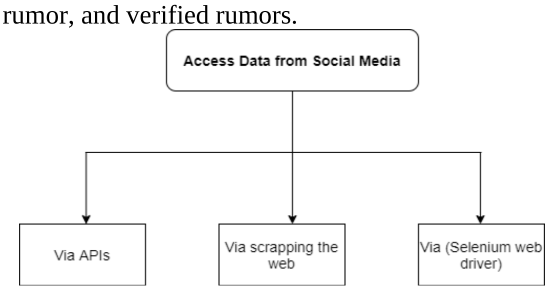

Figure 4: Access Data from social media

In [12] authors recognize the fake news on Twitter data used across several platforms and languages, where they achieve an accuracy of 79%. They also detect fake news in multiple languages (Latin, Germanic, and Slavic). In [13] authors recognize the rumor on Twitter data using dual convolutional neural networks, where they achieve approximately 80% accuracy. They also detect features like behavioral patterns and propagation tree patterns. In [14] authors recognize the rumor on Twitter data by employing a technique known as Bidirectional Long Short-Term Memory (BiLSTM) with Convolutional Neural Network, where they achieved 86.12% accuracy. They also find the results on non-rumor as well as a rumor. In [15] authors recognize the rumor on Twitter (PHEME dataset) data using deep learning, where they achieve 64.3% accuracy and they also find the results on rumor and non-rumor. In [9] authors recognize the rumor on Arabic Tweets by utilizing unsupervised as well as semi-supervised expectation-maximization (EM), where they achieved 78.6% accuracy using Gaussian Naive Bayes (NB). In [8] authors recognize the rumor on Twitter data using the one-class classification (OCC) approach, where they achieve 74% using the Zubiagaset approach and 93% using the Kwonset F-1 score without using non-Rumor. In [20] authors recognize the rumor on the Twitter data set using a structure that is a spatial-temporal neural network for rumor detection, known as STS-NN, where they achieve 80.9% accuracy on Twitter 15 and 82.1% accuracy on the Twitter 16 data set. In [21] authors get a 92.67 F1-score using XGA (namely XLNet – based Bidirectional Gated Recurrent Unit (BiGRU) network with Attention mechanism) model and it has been analyzed that the XLNet carried out better as compared to different word implant models in Cantonese rumor detection. In [22] authors work on false news using quality detection on Twitter News by using various methods of machine learning (NB, SVM, KNN, LR, RF, ME, and CRF) and they get 82.2% accuracy within aspects that are basically user-based and 83.4% using content features and user-based features. In [23] authors work on the application of a technique known as rumor detection on Twitter by using the SVM classification approach and get 78.71 % using TF-IDF features and detect rumors on Indonesian – language text. In [24] authors detect rumors using claim-guided hierarchical graph attention networks and get 85.9% accuracy in the PHEME twitter dataset and 84.7% accuracy in TWITTER-S and 83.5% accuracy using TWITTER-D datasets using the ClaHi-Gat method.

In [16] authors define examination by employing lingual aspects as well as word vector characteristics using machine learning. It has been analyzed that most of users do not justify information on the social media platform and also the manual determination of fake news is a terrible issue. Hence, the authors define a framework that deliberately separates fake news from a news article. From the fields of text, the data set pulls out stylometric or linguistic characteristics and also a base of words BOW TF-IDF and TF vector, and subsequently including bagging and boosting methods they apply a number of machine learning models (Support vector machine, Naive Bayes, KNN, Logistic regression) and get the best accuracy. In [25] authors define methods of machine learning for the examination of fake news. The data that is used by them is gathered from World Wide Web and consist of news from different – different fields in order to cover the majority of despite of particularly categorizing specific topic news. The research on various linguistic properties could be utilized to tell the variations between fake and authentic data. They extract a number of textual aspects from the article utilizing a LICWC method. They use different performance matrices in order to compare the consequences for all algorithms. They recall, F-1 score, calculate precession, as well as accuracy by using various models of machine learning such as– Linear SVM, random forest, Perez-LSVM, Wang-CNN etc. In [26, 27] authors examine news that is fake news by implementing different methods of machine learning. They use a particular tool known as python scikit-learn and also NLP tools for textual identifications. They use a library of python scikit-learn in order to perform tokenization along with the feature gathering of data using certain tools of library tools such as count vectorizer as well as tiff vectorizer. After this, they and then they execute methods of feature selection and obtain precision according to the confusion matrix.

As seen in figure 5, certain critical criteria were taken into account during the rumor data gathering procedure. They gather rumors from different sources and monitor them on reputable facts for examining websites (such as factcheck.org, and poynter.org) for full analysis [31]. They also gather online conversations from a platform like Twitter, which included a real-time conversation with certain tags. They track the updates of popular subjects using many related authorized accounts and tags (e.g., CNN, BBC News, ABC News, as well as Reuters) to obtain information from Twitter. They add extra information to the rumor sentences in their dataset, like the source website, authenticity, publication date, stance, and sentiment. They also involve speculations that have been reposted or retweeted, as well as their attitude designations [28, 29]. The rumors posted on Twitter are included in the Twitter dataset. The information is gathered from public accounts that use keywords that are related to the corona-virus pandemic such as corona-virus, COVID, COVID-19, and save it in. fakeID, release date, as well as full-text CSV files are available. Duplicate tweets are removed from the system. The emotion of each rumor is then classified based on a detailed study of the emotional content and context of the rumor. We also get metadata for each tweet, such as the content of reply/retweet comments, the reply number, the like number, the retweet number, and the date of publication. These metadata are recorded in separate files that are named after the fakeIDs of the tweets. The position of the retweet comments or responses is then manually labeled.

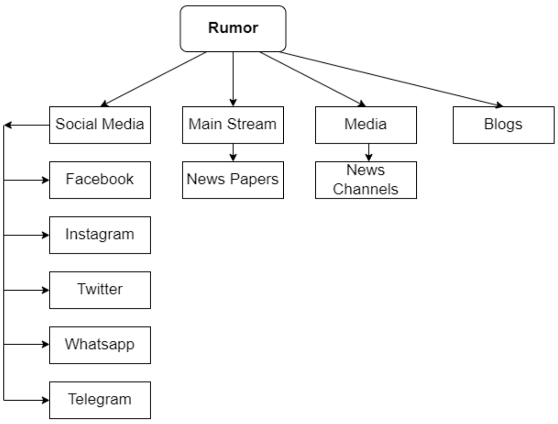

Figure 5: The factors about the rumor data collection.

Scientists come up with a response to the infodemic and fight rumors, conspiracies, misinformation, false information, and disinformation [30].

3. METHODOLOGY

It's a procedure that starts with data collection from social networking sites through API or an actual (Open Source) data set. To extract significant characteristics, the acquired data must be in a standard organized manner. Cleaning, transformation, consolidation, and reduction are all part of the pre-processing process. The dataset is then categorized as non-rumor or rumor using different machine learning approaches once relevant characteristics are extracted. The rumor detection process is shown in figure 6 as:

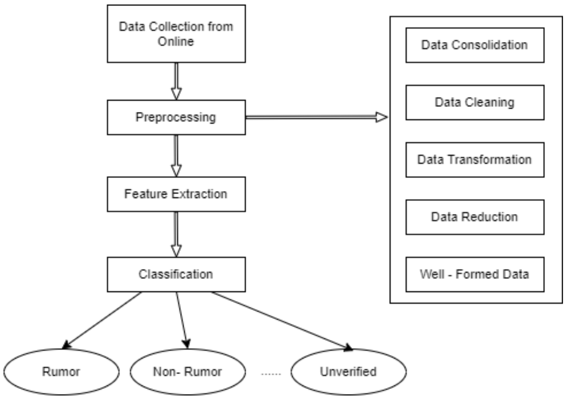

Figure 6: Rumor Detection Process

4. RESULT ANALYSIS

In this experiment, we take the help of word vectors and stylometric features to detect rumors. In Tables 1 we compare some machine learning classifiers like RF, DT, KNN, GBC, and SVM models on TF-IDF features with the highest accuracy of SVM 87.80%.

Table 1: Results of all machine learning classifiers on Content feature + TF-IDF

Classifier	Accuracy (%)	Precision	Recall	F-1 Score
Random Forest (RF)	82.31	.93	.95	.94
Gaussian Naive Bayes (GNB)	80.48	.86	.93	.99
Support Vector Machine (SVM)	87.80	1.0	.98	.99
K-Nearest Neighbors (KNN)	64.61	.62	.54	.58
Decision Tree (DT)	76.21	.86	.93	.89

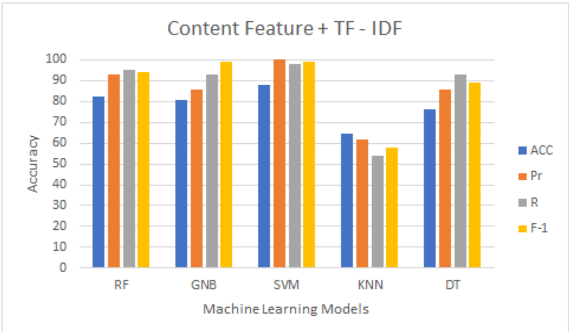

Figure 7: Graph of Content features + TF-IDF Results.

In figure 7 we show the graphical representation of machine learning models using Content Features + TF-IDF and we obtain the highest accuracy using the Random Forest model.
In this work, the data used is Twitter-16, and it is an open-source data set [11]. And using stylometric features and content features we analyze results. Using only 18 content features we achieve 87.80% highest accuracy using SVM. Although this novel approach has given good results but with some limitations, on which further work can be done to achieve results more efficiently. By including more content features and a large data set we will achieve more accuracy.

5. CONCLUSION AND FUTURE WORK

In this work, we have used only the text field of the tweet messages and drawn out the word vector as well as stylometric features to classify rumors. The result of these experiments is acquired in terms of precision, accuracy, recall as well as F-1 score. In this experiment, the aspects set contains 2909 features of content feature and word vector feature, and after that, these features are fed into various models of accuracy like RF, GNB, SVM, KNN, and DT. Using the highest developed machine learning model, we get the best result. And we compare our results with previous experiments. Using Term Frequency and content features we have attended 83.53% accuracy through SVM and we attained the maximum accuracy of 87.80% through SVM on content features and TF-IDF. Moreover, these results were more than the acceptable level compared with previous studies and research works.

Although this novel approach has given good results but with some limitations, on which further work can be done to achieve more results efficiently. In the future, we will integrate extended deep learning models for our proposed work and also include large datasets that contain rumors and non-rumors.

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