Machine Learning Technique for Fake News Detection Using Text-Based Word Vector Representation

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Abstract. In the modern era, social media has taken off, and more individuals may now utilise it to communicate and learn about current events. Although people get much of their information online, some of the Internet news is questionable and even deceptively presented. It is harder to distinguish fake news from the real news as it is sent about in order to trick readers into believing fabricated information, making it increasingly difficult for detection algorithms to identify fake news based on the material that is shared. As a result, an urgent demand for machine learning (ML), deep learning, and artificial intelligence models that can recognize fake news arises. The linguistic characteristics of the news provide a simple method for detecting false news, which the reader does not need to have any additional knowledge to make use of. We discovered that NLP techniques and text-based word vector representation may successfully predict fabricated news using a machine learning approach. In this paper, on datasets containing false and genuine news, we assessed the performance of six machine learning models. We evaluated model performance using accuracy, precision, recall, and F1-score.

Keywords: Machine learning · NLP · LR · SVM · Linear regression · Fake news

1 Introduction

Due to the fast growth of the Internet, social networks have become a significant vehicle for the dissemination of false news, distorted information, fraudulent

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reviews, rumours, and satires [12,19]. Many people believe that false news played a role in the United States' 2016 presidential election campaign; as a result of this election, the phrase has entered the popular lexicon [10,24]. Therefore, academia and industry are collaborating to study and create methods for analysing and identifying false news. In addition, the battle against fake news is closely linked to social networks and data consumption issues. By distributing harmful information, a user wastes the network and processing resources, while also jeopardising the service's reputation. Deceptive news leads to an increase in distrust, which is reflected in the Quality of Trust metric [13,20,21,27].

Fake news is disseminated on social media to trick readers or start rumours. The proliferation of social media platforms has accelerated the transmission of rumors and incorrect information, resulting in an increase in the distribution of fake news [9,13]. Due to the widespread mistrust of conventional media, social network users often depend on false news, which is frequently shared by friends or confirms previous information. Additionally, when consumers are constantly bombarded with false information, it becomes difficult to tell the difference between real and fake news. In terms of 3 V [16], as shown in Fig. 1, it also posed a danger to many communities and had a profoundly detrimental effect on people through widespread advertising, online purchasing, and social messaging.

Several academics have been working on developing effective and automated frameworks for detecting online fake news in recent years in order to distinguish spurious news from legitimate news [1,3,10,23]. Numerous researchers presented their models through the use of machine learning and deep learning methods [7,25]. However, finding false news on social networks is difficult. To begin with, collecting statistics on false news is challenging. Additionally, manually identifying false news is a challenge. Due to their intent to mislead readers, they are difficult to identify just on the basis of the news substance [2,18]. It is difficult to evaluate the validity of newly released and time-bound news, since they provide an insufficient training dataset for the application. Significant methods for recognizing trustworthy individuals, extracting valuable news characteristics, and developing an authentic information distribution system are only a few of the critical study areas that need further exploration [18]. However, the suggested techniques have significant limits in terms of accuracy. A new technique is required to address these problems and efficiently identify false news.

We used many classification algorithms, including the Multinomial NB Algorithm, Logical Regression, Gradient Boosting classifier, Random forest, and support vector machine to see if they might be used to detect fake news in this research. To increase the overall performance of each model, the stacking approach was used. Kaggle dataset was used in our study. To tokenize the text and title features of these two datasets, we employed counter-vectorization methods. Performance is frequently measured using the following four categories: accuracy, recall, f1 score, and precision. New experimental findings were compared with results from previous literature to assess the effectiveness of the suggested stacking approach. All experimental data have been gathered in separate tables

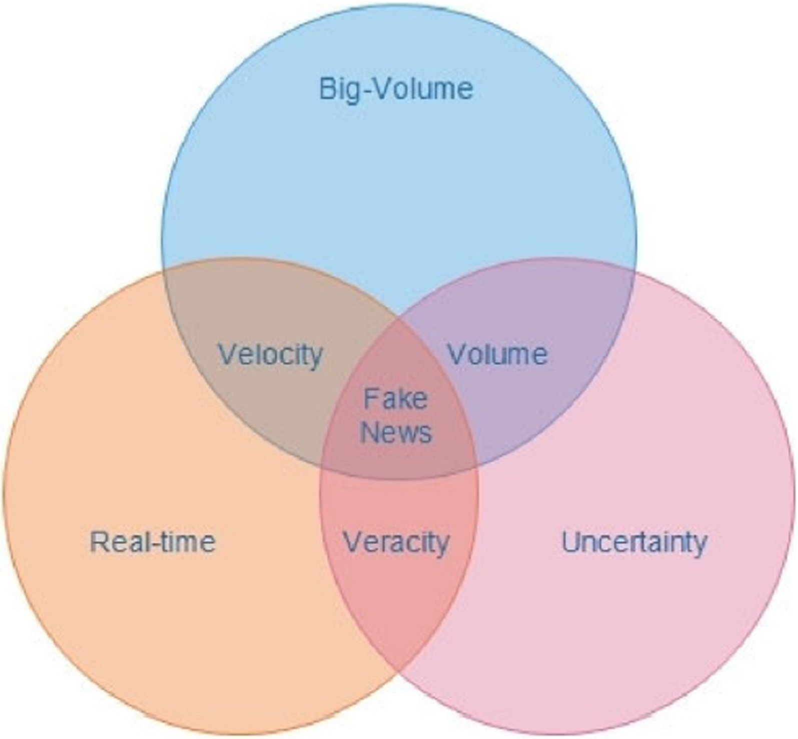


Fig. 1. 3 V's of fake news [16]

and are shown graphically in various figures, with the intention of facilitating comprehension.

This paper is split into the following sections: The second part covers similar research in the field of false news detection. Section 3 describes the approach, while Sect. 4 summarizes the findings. Finally, Sect. 5 brings the paper to a conclusion.

2 Related Work

Numerous researchers have proposed a variety of approaches for detecting different cyber attacks [6,28,29] and fake news [5,26]. We presented some of the most widely used false news detection algorithms in this section.

The authors in [10] evaluated the performance of ML models and DL models on two different-sized fake and real news datasets. In order to build ML and DL models for text representation, the authors employed term frequency, term frequency-inverse document frequency techniques. Similarly, the authors in [14] tested twenty-three supervised AI systems on three datasets to determine the most effective approach for detecting false news. According to their findings, the decision tree technique outperformed all other algorithms in all assessment metrics except recall.

The authors in [16] provide an automated technique for detecting false news on Facebook using the Chrome browser. The authors utilize deep learning to evaluate a Facebook account's activity based on a range of account characteristics and some components of news content. The experimental examination of real-world data demonstrates that the proposed work intent was to distribute false information. The authors in [22] developed a novel approach termed 'Traceminor' to identify fake news broadcasts across a different network using deep learning classifiers. Additionally, it investigates how the material reacts when certain bits of information are omitted. In [11] authors proposes a novel hybrid deep learning model for classifying fake news that combines CNN and RNN. The model was successfully validated on two fake news datasets, providing detection results that were significantly superior to non-hybrid baseline approaches. To determine the trustworthiness of sources and, by extension, the news they publish or disseminate, the hybrid model of the author in [8] combines graph embeddings from the Twitter user follower network with individual attributes. The authors in [15] proposed a method involves creating more characteristics for NLP by using data storage mining; as a result, the efficiency of identifying fake news increases. Additionally, the authors compare the proposed approach's outcomes with those of existing machine learning methods, such as LSTM.

The authors in [17] proposed a model that illustrates how diverse methods of debunking falsehoods influence the distribution of misinformation among populations. We have confidence in this method since it is capable of locating and removing false news from OSNs. This suggested method establishes a key parameter known as the basic reproduction number (Rn) in the investigation of message propagation in OSNs. When Rn is smaller than one, it is possible to limit the distribution of fraudulent messages inside the OSN. Otherwise, the rumour will be unstoppable.

3 Methodology

Six fundamental machine learning algorithms are used in the proposed technique to detect false news. The suggested strategy begins with the elimination of superfluous characters, tokenization, and stop wording. Each ML technique's performance is evaluated using accuracy, precision, recall, and F-Measure. Figure 2 represents the flow diagram of the proposed technique.

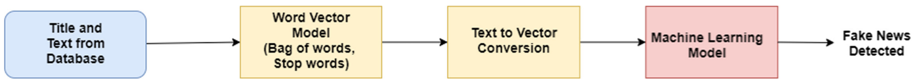


Fig. 2. Proposed approach

3.1 Dataset

Classifying a piece of news as "fake news" may be a time-consuming and complex task. As a consequence, a previously collected and recognized dataset of fake news was utilized. This project used data from the Kaggle dataset [4]. The dataset has a header and columns for title and content, as well as a flag indicating if the news item is fake or real.

3.2 Pre-processing of Dataset

Prior to incorporating text data into machine learning models, it must be preprocessed using techniques such as stop word removal, phrase segmentation, and punctuation removal. These approaches have the potential to significantly assist us in identifying the most pertinent keywords and optimizing model performance. Because our datasets are taken from real-world news stories, they contain a large amount of meaningless text and unusual characters. As a result, we eliminated duplication in our data collection by removing these unwanted characters. The next stage of preprocessing is to eliminate stop words. Stop words are frequently used in English sentences to complete the phrase structure, even if they serve no use in expressing specific concepts. As a result, we excluded them from all of our tests because of the possibility that they caused excessive noise.

3.3 Machine Learning Models

We preprocessed the data set using the machine learning models in the preceding part. However, because the utilized machine learning models can not accept text input, we transform the text information to machine-readable form using a counter vectorized. After converting the text to a vector format, we supplied the news headlines and body content to the machine learning model for training and testing purposes. Finally, statistical approaches are used to compare the performance of several machine learning models.

4 Result and Discussions

We began by removing stopwords and special characters from our dataset in this research. Then, we utilised tokenization and counter vectorization algorithms to extract and transform the undesired text from the dataset. Following that, we trained individual models using five different machine learning techniques, including LR, DT, KNN, RF, and SVM. The performance of these machine learning models is evaluated using statistical metrics.

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{1}$$

$$Racall = \frac{T_P}{T_P + F_N} \tag{2}$$

$$Precision = \frac{T_P}{T_P + F_P} \tag{3}$$

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

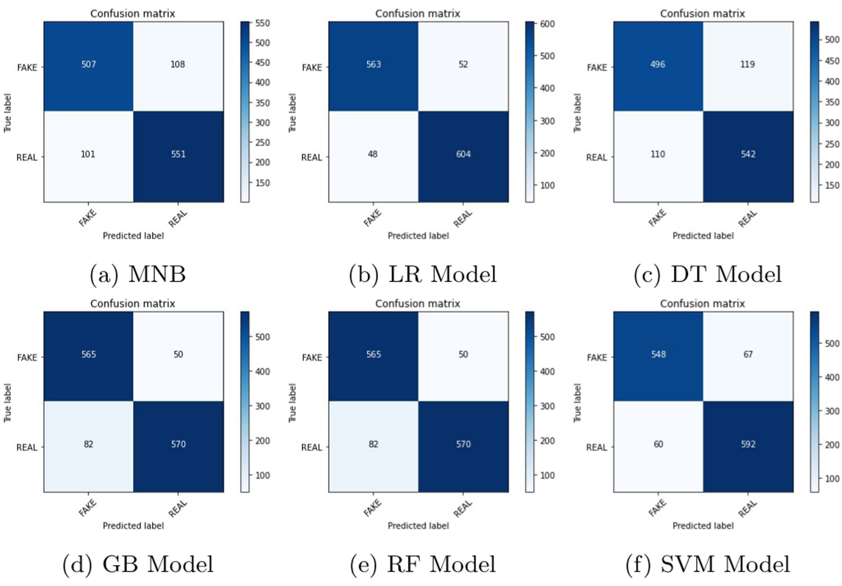
Where T_P is 'true positive', T_N is 'true negative', F_P is 'false positive', and F_N is 'false negative'.

4.1 Confusion Matrix Calculation

When evaluating the performance of a classification model, a confusion matrix is used. Actual target values are compared with the predictions made by the machine learning model in this matrix. The information provided by this gives us a complete view of how well our classification model is doing, as well as the kinds of errors it is making. Using a confusion matrix, it is straightforward to calculate precision, accuracy, recall, and the f-1 score.

4.2 Performance Comparison

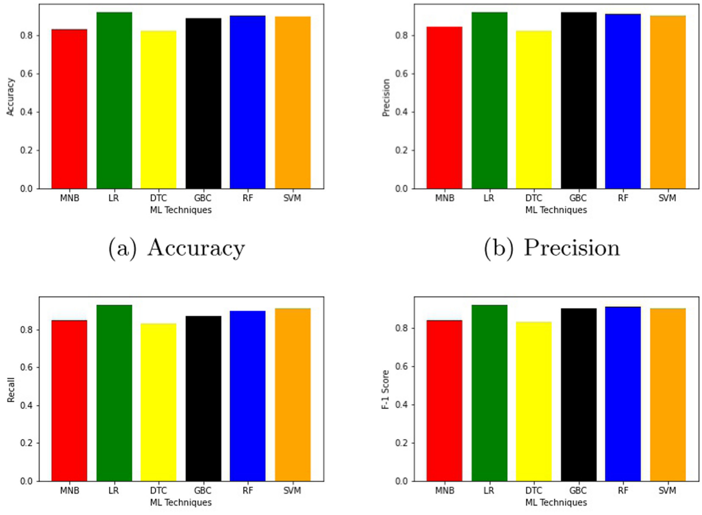
In this subsection, we assess the performance of six ML models based on their accuracy, precision, recall, and f-1 scores. All of these characteristics are derived from the confusion matrix and are shown graphically in Fig. 3 (Fig. 4).



(a) MNB (b) LR Model (c) DT Model

(d) GB Model (e) RF Model (f) SVM Model

Fig. 3. Confusion matrix for different ML models



(a) Accuracy (b) Precision

(c) Recall (d) F-1 Score

Fig. 4. Statistical parameters calculation

5 Conclusion

Fake news is a serious issue that is spreading like wildfire as information becomes more accessible to the general population in a variety of ways. In every country, fake news has the ability to have a major impact on people's political and social life. As a consequence, we evaluated the accuracy, precision, recall, and F1-score of five ML models on the kaggle fake news dataset in this paper. Certain models, such as LR, performed substantially better on the datasets than others, such as DT, SVM, LR, MNB, RF, and GB. We will do more testing in the future using a variety of data sets and languages. Additionally, we will try to detect fake news using a broader variety of machine learning and deep learning models. To assist in identifying fake news in different countries, we will also collect more data on fake and real news in numerous languages.

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