

Original Article

# A Study on Fake News Detection Techniques using Machine Learning

Rohan Prasad<sup>1</sup>, Ambar Dutta<sup>2</sup>

<sup>1,2</sup>Amity Institute of Information Technology, Amity University, Kolkata, West Bengal, India.

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**Abstract** - Fake news has been emerging often and in great quantity online in recent years due to the explosive growth of online social networks for political and economic goals. Online social network users can easily become infected by these fake news stories using misleading language, which has already had a significant impact on offline culture. Natural Language Processing cannot be used in isolation to solve the problems associated with fake news detection. Without additional fact-checking, even a human would struggle to determine an article's veracity. Promptly detecting fake news is a key objective in enhancing the credibility of information in online social networks. This paper aims to evaluate the performance of various machine learning algorithms for detecting fake news with the help of various performance measures. Gradient boosting and random forest algorithms performed better than decision tree and logistic regression algorithms.

**Keywords** - Classification, Comparative analysis, Fake news, Machine learning, Performance measures.

## 1. Introduction

Fake news is a false or misleading piece of information that targets damaging the reputation of a particular community, person, or entity. The main motive of fake news is making money. Fake news can reduce the impact of real news by competing with it. The prevalence of fake news has increased quite with the rise of social media. For example, Facebook, Instagram, etc., these social media platforms are a major career of fake news as people spend most of their time in social media scrolling feeds. People use social media not solely to connect with people but conjointly to assemble news and data. With the increased number of people on these platforms, there is a probability that a piece of news published can be fake. Fake news is viewed as one of the greatest threats to democracy, humanity, and freedom of expression. Fake news not only spreads from social media but from one person who reads a fake news to another who does not.

There are different types of fake news available in the literature. Targeted misinformation is a piece of false information disseminated for personal gain. Misinformation is frequently targeted at individuals who are most sensitive to it, such as those who embrace and spread contentious content without verifying its veracity. Fake headlines are made-up headlines designed to attract attention. These are frequently used by less respected magazines, such as tabloid newspapers. The content of the article frequently does not match the headline, which is known as "clickbait headlines." Viral posts are new stories and materials are flooding social media networks. Users rarely take the trouble to validate their posts as a result. Because large social networks value shares,

likes, and followers - even if the content is bogus news - popular postings appear more frequently in a user's threat. Satire is when current events and news stories are incorporated into fictitious, often absurd, circumstances in satirical news. Satire is commonly used to create societal awareness or to criticize government misconduct. However, there is always the possibility that the satirical components may go unnoticed, and the pieces will be misinterpreted.

If a piece of fake news is not detected, it can cause tremendous chaos and even cause wars between different persons, communities, or entities. Any person can publish/print whatever fake news they desire, and it can spread like a huge wave.

Machine learning algorithms have shown to be incredibly effective in the field of information engineering for a variety of applications. Since the first efforts focusing on social media reliability and computer fake news detection, machine learning approaches have been used in a number of studies on the subject of false information detection on the web, and mediated communication has shown promising outcomes.

The majority of machine learning algorithms for detecting fake news and rumors have used a supervised learning paradigm. It also helps in the detection of fake news by using classifiers. Training data set (which is a data set) is first used to train the classifiers. After that, these classifiers can automatically detect fake news based on the learning from the training data set.



## 2. Related Works

Z. Khanam's [1] research focuses on detecting fake news through two levels of review: characterization and disclosure. The essential concepts and principles of fake news are addressed in the first stage on social media. The current strategies for detecting false news utilizing different supervised learning algorithms are discussed during the discovery stage. They utilized the Naive Bayes classifier to detect fake news from different sources, with results of an accuracy of 74%. The aforementioned study summary and system analysis show that most research articles employed the Naive Bayes algorithm, with a prediction precision of 70-76%, and that they generally used qualitative analysis based on sentiment analysis, titles, and word frequency repetition.

Pritika Bahad, Preeti Saxena, and Raj Kamal[2] research used deep learning models to predict bogus news articles. GloVe word embedding is used in the proposed model to measure the link between the headline and body of the news story. GloVe handles the variance of high-dimensional news stories well. Bi-directional LSTM-RNN model accuracy with CNN, vanilla RNN, and unidirectional LSTM-RNN are examined and compared. The studies reveal that the adaptive learning rate significantly impacts the output when dealing with the vanishing gradient problem in RNNs.

Jamal Abdul Nasir, Osama Subhani Khan, and Iraklis Varlamis[3] paper introduces a novel hybrid deep learning model that blends convolutional and recurrent neural networks. The model was successfully verified on two fake news datasets (ISO and FA-KES), with detection results that outperformed non-hybrid baseline approaches. Further testing of the suggested model's generalization over other datasets yielded promising outcomes. The suggested hybrid technique, which combines a CNN network that learns the spatial, therefore conceptual, properties of text with an LSTM that captures the sequential flow of text, overcomes the limitation of neural networks to handle one problem at a time. The key hypothesis has been proven empirically that a hybrid Convolutional Neural Networks (CNN) Recurrent Neural Networks (RNN) model may outperform state-of-the-art baselines for fake news detection. Experiments on two real-world fake news datasets (100% accuracy on the ISOT dataset, 45000 articles; 60% accuracy on the FAKES dataset, 804 articles) show that hybrid approaches outperform non-hybrid baseline methods. In this paper, such models function well on a given dataset but do not generalize well. Consideration of generalization of false news detection methods can open up new opportunities.

Jiawei Zhang, Bowen Dong, and Philip S. Yu[4] have discussed the unknown properties of fake news and the numerous linkages across news stories, creators, and subjects, providing issues in this work. This paper introduces FAKEDETECTOR, a new automatic fake news credibility inference methodology. FAKEDETECTOR creates a deep

diffusive network model based on a set of explicit and latent properties collected from textual material to simultaneously learn the representations of news articles, producers, and subjects. This model has provided 40% accuracy, and they investigated the topic of detecting false news articles, creators, and subjects in this research. A collection of explicit and latent qualities can be retrieved from the textual information of news articles, producers, and subjects based on the news-enhanced heterogeneous social network. A deep diffusive network model has been proposed to incorporate the network structure information into model learning.

In this article, Kai Shu, Ahmed Hassan Awadallah, Susan Dumais, and Huan Liu [5] have discussed how many components of social media might be used as weak social monitoring. They specifically exploited current research on fake news detection as a use case, where social engagements are many but annotated instances are limited, to demonstrate that weak social supervision is successful in the face of labelled data scarcity. When labelled data is insufficient, this work opens the way to learning with weak social supervision for similar emergent tasks. Labeled data is rare in many machine-learning applications, and collecting more labels is costly. They concentrated on the application of detecting bogus news on social media. They showed that weak social supervision can provide a new representation to describe social information that is only available when a better warning is sought, which has promising results and great potential in detecting fake news, including challenging settings of effective fake news detection and explainable fake news detection.

Mohammad Hadi Goldani, Saeedeh Momtazi, and Reza Safabakhsh[6] implemented capsule networks to detect fake news in this paper. For varied lengths of news statements, they offered two structures. They used two methodologies to increase the capsule networks' performance for the task. Firstly, they implemented four parallel capsule networks to extract distinct n-gram features from the input texts to detect medium or lengthy news pieces. Secondly, they have adopted non-static embedding, which means that during the training phase, the word embedding model has incrementally uptrained and updated. The results are based on two different datasets. The ISOT dataset is used for medium or lengthy news stories, whereas the LIAR dataset is used for short stories. The experimental results on these two well-known datasets revealed a 7.8% boost in accuracy on the ISOT dataset, 3.1% on the validation set, and 1% on the test set of the LIAR dataset.

Monther Aldwairi and Ali Alwahedi[7] goal of the project was to provide a system that consumers can use to detect and filter out websites that contain inaccurate or misleading information. The logistic classifier achieved a 99.4% accuracy in the experiments. The logistic classifier provides the best classification quality, with a precision of

99.4%. The best recall, or sensitivity, was 99.3% for the Logistic and Random Tree classifiers. The Logistic and Random Tree classifiers surpassed others at 99.3% using the f-measure, which combines precision and recall. Finally, the best area under the ROC curve was achieved by Bayes Net and Naïve Bayes.

In the paper of Deepak S. Bhadrachalam Chitturi[8], this model aimed to improve the identification of fake news by incorporating online data mining into the solution strategy. Different word vector representations were used to build deep learning models based on FNN and LSTM. The models were integrated with a live data mining section that collects

auxiliary information from the news article's content/title. These attributes, such as domain names and author information, are added to the original article before the word embedding step to give the data more context. The classification results show that they perform better when all models are integrated with data mining sections. Precision, recall, accuracy, and precision significantly improved using the proposed strategy. F1 score when LSTM was used in association with word2vec representation.

A summary of the papers studied is summarized in the following table (See Table 1).

**Table 1. Summary of the selected papers studied**

| Sl. No | Paper Title  | Purpose   | Technique Used                    | Performance   | Remark  |
|--------|--|---|-----------------------------------|---|---|
| 1.     | Comparison of Fake and Real News based on Morphological Analysis   | Analyzed the morphological tags and compared differences in their use in fake news and real news. | Tree Tagger                       | This has an accuracy of around 90%.   | Tree tagger can be implemented.                           |
| 2.     | Detecting fake News in Social Media Networks                       | Identifying solutions that could detect and filter sites containing fake news.                    | Random tree, Naïve Bayes.         | Random tree has an accuracy of 97.3%. Naïve Bayes has an accuracy of 100%.                          | Random tree and Naïve Bayes can both be implemented.      |
| 3.     | Analysis of Classifiers for Fake News Detection                    | A stacked model that fine-tunes the informational insight gained from data at each step.          | SVM                               | Recall: 0.62<br>Precision: 0.62<br>F1-score: 0.61   | SVM can be implemented.                                   |
| 4.     | A Survey on Fake News and Rumour Detection Techniques              | Different techniques to detect fake news and rumours.   | SVM                               | F1 accuracy of 0.79 and 0.81 for detecting rumours and non-rumours.                                 | SVM can be implemented.                                   |
| 5.     | A Deep Neural Approach to Fake News Identification                 | The live mining stage is used to fetch data from the internet and consider the validation.        | FNN, LSTM                         | FNN has achieved an accuracy of 82-84% and LSTM an accuracy of 91-94%.                              | LSTM can be implemented.                                  |
| 6.     | Fake News Detection using Machine Learning Approaches              | Detection of fake news using various algorithms.  | XGboost, SVM, Random Forest, KNN. | XGboost with the highest accuracy of 75%, followed by SVM (73%), random forest (73%) and KNN (70%). | XGboost can be better within the rest for implementation. |
| 7.     | Fake News Detection: A Hybrid CNN-RNN-based Deep Learning Approach | Detection of fake news with a hybrid CNN-RNN-based approach.                                      | Hybrid CNN-RNN approach.          | 82.19% accuracy was achieved.   | Hybrid CNN-RNN approach can be implemented.               |
| 8.     | Effective Fake News Detection with Deep Diffusive Neural Network   | Detecting fake news with deep diffusive network model learning.                                   | Deep diffusive unit model.        | 63% accuracy was achieved   | Deep diffusive unit model can be implemented.             |

### 3. Popular Machine Learning Algorithms

Some popular classifiers used by different people are K-nearest neighbor, Support Vector Machine (SVM), Decision Tree, Random Forest, Naïve Bayes, Logistics Regression, etc.

#### 3.1. K-Nearest Neighbor

It is a supervised algorithm used to solve classification problems. It stores the data in a classified manner and uses that data to classify new cases based on it. KNN works by calculating the distances between a query and all of the instances in the data, picking the K closest examples to the query, and then choosing the most frequent label (in the case of classification) or averaging the labels (in the case of regression).

#### 3.2. Support Vector Machine (SVM)

This classifier is mostly used for classification that learns from the labeled data set. Among every classifier, SVM has given the best result in detecting fake news. The goal of the SVM method is to discover the best line or decision boundary for categorizing n-dimensional space into classes so that subsequent data points can be easily placed in the right category. The ideal choice boundary is known as a hyperplane.

#### 3.3. Decision Tree

This is another classifier for the detection of fake news. It detects fake news by breaking the bigger group of data sets into smaller subsets. Decision trees employ various techniques to decide whether to break a node into two or more sub-nodes. The homogeneity of the ensuing sub-nodes rises as sub-nodes are created. To put it another way, the purity of the node improves as the target variable grows. The decision tree splits the nodes into sub-nodes based on all available variables and then chooses the split that produces the most homogeneous sub-nodes.

#### 3.4. Random Forest

Different random forests produce a value in this classifier, and a value with more votes is the actual output of this classifier. Random Forest is a classifier that combines a number of decision trees on different subsets of a dataset and averages the results to increase the dataset's predicted accuracy.

#### 3.5. Naïve Bayes

The probability of the prior occurrence is compared to the chance of the current event in naive Bayes categorization. The total chance of the news as compared to the dataset is obtained after each probability of the event is calculated. The Bayes Theorem is used to create a Naïve Bayes classifier. It calculates membership probabilities for each class, such as the likelihood that a certain record or data point belongs to that class. The most likely class is defined as the one having

the highest probability. Maximum A Posteriori is another name for this (MAP).

#### 3.6. Logistics Regression

A categorical dependent variable's output is predicted using logistic regression. The outcome that is given is discrete or categorical. It can be Yes or No, 0 or 1, true or false, and so on; however, rather than exact values like 0 and 1, it provides probabilistic values between 0 and 1.

### 4. Results and Discussion

#### 4.1. Algorithm Used

- Step 1: Get the Datasets.
- Step 2: Combine a certain amount of data from both datasets.
- Step 3: Check the dataset for unimportant values.
- Step 4: Remove unnecessary columns from the dataset.
- Step 5: Cleaning the dataset, i.e., removing unnecessary links, special characters, etc.
- Step 6: Define the train and test variables and assign them with the percent of data to be trained with.
- Step 7: Vectorization of the train and test variable.
- Step 8: Putting the dataset on different classifications to get the complete analysis, i.e., accuracy, precision, recall and f1-score.
- Step 9: Create a function to give user input and show the result from all the algorithms used.

#### 4.2. Experimental Result

From the above experimentation, the result obtained can be interpreted first; the datasets we have are trimmed and concatenated into a single file, which is later trained and tested with different algorithms present in the Python library.

The result produced by that different algorithm gave us an idea of their accuracy along with their precision and recall values (see Figure 1). From the result that we have obtained, we can say that among the algorithms, the dataset we tested upon "Gradient Boosting" has the best accuracy. (see Table 2)

Table 2. Comparative results

| Algorithms          | Accuracy | Precision | Recall |
|---------------------|----------|-----------|--------|
| Logistic Regression | 0.977    | 0.968     | 0.971  |
| Decision Tree       | 0.973    | 0.962     | 0.972  |
| Gradient Boosting   | 0.989    | 0.981     | 0.978  |
| Random Forest       | 0.985    | 0.979     | 0.976  |

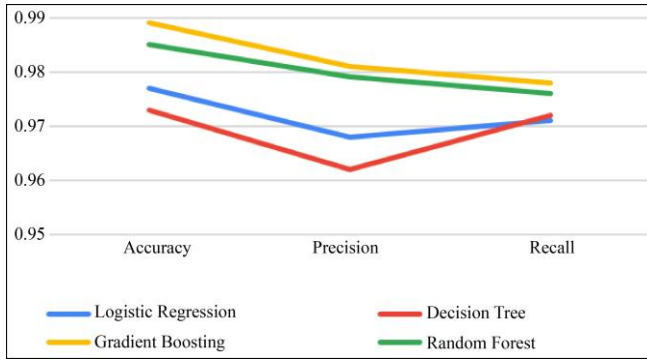


Fig. 1 Performance measures for different ML algorithms

## 5. Conclusion

Fake News Detection is a task that uses natural language processing to determine if news articles or other types of

material are real or fake. In order to combat false information and encourage the spread of accurate information, fake news detection aims to create algorithms that can automatically recognize and label fake news stories. In this paper, many machine learning algorithms have been implemented to identify fake news, and they are compared with respect to different performance measures.

It has been observed that Gradient Boosting and Random Forest algorithms performed better than Decision Tree and Logistic Regression algorithms. For future improvements, there can be further improved versions to approach the detection, achieving higher accuracy and less complexity. Moreover, we can add more machine learning algorithms, get a more detailed result, and even incorporate the whole model into a web or mobile-based application/software.

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