

# **Fake News Detection Using Various Machine Learning Approaches**

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**Abstract:** Fake news is spreading quickly on social media and other platforms, which is quite concerning since it may have serious negative effects on both the national and societal levels. Extensive research efforts are currently underway to detect and combat this issue. This study surveys the existing research on fake news identification and studies the efficacy of traditional ML (Machine Learning) models to develop a supervised ML method that can accurately identify fake news as either true or false. To achieve this, tools such as NLP and Python sci-kit-learn for textual analysis will be utilized. The process will involve feature extraction and tokenization of text data. This library provides valuable devices including Count Vectorizer and Tiff Vectorizer. Additionally, feature selection methods will be employed to test and detect the most suitable features that yield the greatest precision, as examined by the confusion matrix results.

Keywords: Fake News, Naive Bayes, Linear Regression, K-Nearest Neighbour

# 1. Introduction

In the present era of information, the rapid spread of news and information is facilitated by the accessibility and immediacy of digital platforms. Nevertheless, within this vast amount of information, a significant issue has arisen: the general dissemination of fake news. The phrase "fake news" has become an integral part of our conversations, symbolizing the dissemination of false or deceptive information disguised as authentic news. The widespread existence of false information presents considerable obstacles to individuals, societies, and institutions across the globe. Its consequences go beyond spreading misinformation, as it also has the power to sway public sentiment, mold political storylines, and even disrupt economic equilibrium. As a result, understanding the complexities of fake news, such as its sources, means of spreading, and societal effects, has become more and more crucial to establishing robust systems for identifying and reducing risks.

This work presents an approach for building a model that analyzes the words, phrases, sources, and titles of articles to determine which ones are real and which ones are fraudulent. This method entails applying supervised machine learning algorithms to a manually validated and classified dataset. The confusion matrix results also show that feature selection techniques are used to identify the best characteristics that yield the maximum precision. Our suggestion is to use different categorization methods to build the model. After that, the generated model will be assessed using fresh data, and the outcomes will be shown graphically. In the end, there will be a strong model that can recognize and classify fake articles. This model can be readily included in any system for later usage.

## 2. Literature review

In [1], the objective of the present paper is to identify fake news by analyzing it through two phases: disclosure and characterization. The fundamental ideas and precepts of fake news are emphasized on social media during the first phase. Using several supervised learning algorithms, the existing techniques for detecting fake news are examined during the discovery stage. With XGBoost, the author achieved over 75% accuracy, surpassing that of SVM and RF (Random Forest), which yielded about 73% accuracy. To identify fake news detection, the author [2] tested five ML (SGD: "Stochastic Gradient Descent", LR: "Logistic Regression", NB: "Naïve Bayes") and DL (LSTM: "Long Short-Term Memory", ASGD Weight-Dropped LSTM, or AWD-LSTM) models. In the end, our research has shown that the Naive Bayes Classifier is the most successful model for classifying bogus news, with an F1-macro mean of 32 percent on the most recent test outcomes. NBC has the highest F1-macro average (32%), making it the strongest model for classifying fake news. This author [3] has presented a comprehensive overview of the automated fact-checking study by combining the task formulations and methodology from several study projects into a single framework that includes the development of justifications, claim identification, evidence retrieval, and verdict prediction.



[4] The author conducted a comprehensive study of 118 datasets pertaining to research on fake news, examining the data from three angles: (1) fact verification, (2) false news identification, and (3) other tasks, such as analyzing fake news and satire detection. It uses 42 datasets for additional tasks, 25 datasets for fact-checking, and 51 datasets for detecting fake news. [5] Experts have verified 21,152 of the statements in the dataset. There are six categories in which all the statements are placed: true, mostly true, half true, false, mostly false, as well as pants on fire. Furthermore, to provide different information about fact-checking, [5] also lists the sources from which the statement was taken, which may be important to derive different conclusions regarding fact-checking. [6] This paper presents a comprehensive review of different ML methods employed for the identification of fake news. [6] analyzes a wide range of methodologies, including supervised, unsupervised, and deep learning algorithms, discussing their strengths and limitations. [7] This study examined the issue of employing ensemble methods and ML models to categorize fake news stories. Rather than categorizing news, particularly political news, the data utilized in [7] is gathered from the WWW ("World Wide Web") and comprises news pieces from multiple domains to cover the majority of the news. The main purpose of the current study is to determine textual patterns that differentiate real news from bogus pieces [7]. [8] This research proposes a KNN-based detection system using GEFeS for feature selection, achieving 91.3% accuracy. Exploring quantum KNN with 84.4% accuracy shows potential for future applications. In [9], the study showed that training a classifier on 1876 news items using NLP and various ML/DL algorithms (Naive Bayes, SGD, LR, LSTM, AWD-LSTM). The best model, Naive Bayes, achieved 56% accuracy and 32% F1-macro score. [10] boosts detection by first training on easier tasks like identifying common parts (bolts, nuts), then applying that knowledge to pinpoint actual issues. This doubles the recall rate without overwhelming inspectors with false positives. In [11], it discusses the work that tackles automated news categorization as real or fake using ensembles of various machine learning algorithms trained on different textual features. The proposed approach outperforms individual algorithms, paving the way for more accurate news classification. Studies [12] explore automated detection of this "misinformation zoo" (fake news, rumors, spam) using advanced, data-hungry techniques like deep learning.

## 3. Dataset and Data Preprocessing

This dataset contains high-quality fact-checking information gathered from the well-known PolitiFact website. Experts have verified 21,152 of the statements in the dataset. Six categories comprise all of the statements: false, mostly false, half true, true, mostly true, and pants on fire. This dataset contains sources where the statement appears in addition to numerous fact-checking-related facts. These sources may be important for deriving different insights regarding fact-checking. Furthermore, it provides links to the fact-check article published on PolitiFact so that extra text can be extracted regarding the published fact-check story if needed. Each record consists of 8 attributes:

- **Verdict**: The results of fact tests are classified into 6 groups: true, half true, mostly true, false, mostly false, as well as pants-on-fire.
- Statement originator: The person whose statement is undergoing fact-checking.
- **Statement**: The fact-checking of a statement.
- Statement date: The date when the statement being fact-checked was made.
- **Statement source**: The source in which the statement was made. It is one of 13 categories: blog, news, television, speech, social media, advertisement, campaign, meeting, radio, email, testimony, statement, and other.
- Fact-checker: Name of the individual who verified the information.
- FactCheck date: Date of publication of the fact-checked article.
- FactCheck analysis link: URL for the article on fact-checked analysis.



	verdict	statement_originator	statement	statement_date	statement_source	factchecker	factcheck_date	factcheck_analysis_link
0	true	Barack Obama	John McCain opposed bankruptcy protections for	6/11/2008	speech	Adriel Bettelheim	6/16/2008	https://www.politifact.com/factchecks/2008/jun
1	false	Matt Gaetz	"Bennie Thompson actively cheer-led riots in t	6/7/2022	television	Yacob Reyes	6/13/2022	https://www.politifact.com/factchecks/2022/jun
2	mostly- true	Kelly Ayotte	Says Maggie Hassan was "out of state on 30 day	5/18/2016	news	Clay Wirestone	5/27/2016	https://www.politifact.com/factchecks/2016/may
3	false	Bloggers	"BUSTED: CDC Inflated COVID Numbers, Accused o	2/1/2021	blog	Madison Czopek	2/5/2021	https://www.politifact.com/factchecks/2021/feb
4	half- true	Bobby Jindal	Tm the only (Republican) candidate that has	8/30/2015	television	Linda Qiu	8/30/2015	https://www.politifact.com/factchecks/2015/aug
4								

# **Figure-1 DataSet snippet**

## 3.1 CLASSES DEFINITIONS

There are six classes in our verdict column. Below is a summary along with the count class figure for these classes.

- **True**: Nothing is substantially missing, and the statement is accurate.
- Mostly true: The statement is correct, but further details or explanation are needed.
- Half true: The statement is true in part, but it neglects crucial information or presents ideas out of context.
- **Mostly false**: Although there is some truth to the statement, it misses important details that could cast doubt on it.
- **False**: The assertion is inaccurate.
- **Pants-fire**: The assertion is false and contains a preposterous claim, alternatively known as "Liar, Liar, Pants on Fire!"





# **3.2 PREPROCESSING OF DATA**

By filtering and cleansing data, the model can be fitted. For instance, remove any email, tag, URL, or non-ASCII characters, convert to lemmatize, end words, punctuation, lowercase, or substitute a blank string for a nan value. Constant characters such as numbers, punctuation, and word length of one to two characters have been eliminated. Python regular expressions, the text-hammer from an external library, and natural language toolkit (NLTK) utilities were utilized to accomplish this. Altering the values of the verdict column from false, mostly false, and pants-fire to zero, and from true, mostly true, and half-true to one. Following that, concatenate the title and the content text column. The below illustrates the phase that follows preprocessing.

## **3.3 DATA PROCESSING**

Raw data cannot be utilized directly in our models. The data is inefficient for our machine learning models. We must convert the unprocessed data into features that have been extracted. We have utilized TF-IDF, Count Vectorizer, and Word2vec in our efforts.



- 1. **TF-IDF**: We utilized this program from the sci-kit-learn v1.0.2 text module of the Python library for feature extraction.
- 2. **CountVectorizer**: A collection of text documents is converted to a document count metric utilizing this vectorizer. We transformed text into counter vectors utilizing the Python sci-kit-learn library.
- 3. **Word2vec**: To transform words into real integers, the word2vec function from the Gensim library was utilized. Word2vec is utilized to produce word embeddings.

	verdict	statement_originator	statement	content
0	1	Barack Obama	John McCain opposed bankruptcy protections for	Barack Obama John McCain opposed bankruptcy pr
1	0	Matt Gaetz	"Bennie Thompson actively cheer-led riots in t	Matt Gaetz "Bennie Thompson actively cheer-led
2	1	Kelly Ayotte	Says Maggie Hassan was "out of state on 30 day	Kelly Ayotte Says Maggie Hassan was "out of st
3	0	Bloggers	"BUSTED: CDC Inflated COVID Numbers, Accused o	Bloggers "BUSTED: CDC Inflated COVID Numbers,
4	1	Bobby Jindal	"I'm the only (Republican) candidate that has	Bobby Jindal "I'm the only (Republican) candid
21147	0	Donald Trump	Says the large trade deficit with Japan stems	Donald Trump Says the large trade deficit with
21148	0	Donald Trump Jr.	"Tens of thousands" of people leave New York e	Donald Trump Jr. "Tens of thousands" of people
21149	0	Chris Abele	"I have fought for our shared values without b	Chris Abele "I have fought for our shared valu
21150	0	Bloggers	"Germany halts all Covid-19 vaccines, says the	Bloggers "Germany halts all Covid-19 vaccines,
21151	0	Facebook posts	Says for otherwise healthy people "experiencin	Facebook posts Says for otherwise healthy peop

21152 rows × 4 columns

# **Figure-3 Processed dataset**

## 4. Research Models

We utilized the models outlined below to assess the veracity of news articles in this study. The following section contains research models.

# **Naive Bayes**

Naive Bayes is a powerful and easy-to-understand method for making predictions based on probability. It's widely used in various machine learning applications, particularly for tasks involving classification. Let's break down the theorem in simple terms:

You have an event (let's call it A) that could be caused by multiple factors (B, C, D). Bayes' theorem helps you calculate the probability of one of those factors (say, B) being the culprit, provided that event A has already occurred.

The Formula:

$$P(B|A) = (P(A|B) * P(B))/P(A)$$
 (1)

where:

- P(B|A) presents the posterior probability, which represents the probability of B being true given that A is true. This is what we're trying to find.
- P(A|B) is the likelihood, which indicates the probability of observing event A if factor B is true.
- P(B) indicates the prior likelihood, which represents the probability of B being true before considering any evidence (A).
- P(A) is the evidence, which represents the overall probability of observing event A, regardless of the cause.

Table-1	Naive	Bayes
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	Precision	recall	f1-score	Support
0	0.75	0.63	0.69	2352
1	0.61	0.74	0.67	1879
accuracy			0.68	4231
macro avg	0.68	0.68	0.68	4231
weight avg	0.68	0.68	0.68	4231

## **Decision Tree**

A DT is a simple, yet powerful ML method that can be applied to classify data. The algorithm operates by recursively dividing the dataset into progressively smaller subsets by specific decision criteria until each subset exclusively comprises data points that are members of the same class. In the context of fake news classification, a decision tree can be used to identify patterns in the text of news articles that differentiate between real and fake news.

	Precision	recall	f1-score	Support
0	0.68	0.67	0.67	2352
1	0.59	0.61	0.60	1879
accuracy			0.64	4231
macro avg	0.64	0.64	0.64	4231
weight avg	0.64	0.64	0.64	4231

**Table-2 Decision Tree** 

## Logistic Regression

This model utilizes supervised learning. This is a situation in which labeled data is utilized. It is a classification model as well. A "sigmoid function" is utilized where there are two possible categories for the outcome. Logistic regression, within the domain of false news classification, tasks to forecast the veracity or falsity of a given news article. This model was obtained using scikit-learn.

	Precision	recall	f1-score	support
0	0.70	0.69	0.70	2352
1	0.62	0.63	0.63	1879
accuracy			0.67	4231
macro avg	0.66	0.66	0.66	4231
weight avg	0.67	0.67	0.67	4231

**Table-3 Logistic Regression** 

## **Random Forest**

It is a supervised learning algorithm that operates by constructing a multitude of DTs, each built with a different random subset of features and data points. Predictions are made by aggregating the individual predictions of each tree, leading to a more accurate and robust outcome compared to a single DT. This ensemble approach effectively addresses the overfitting issue often encountered with decision trees, making them reliable for real-world applications.

	Precision	recall	f1-score	Support
0	0.73	0.68	0.71	2352
1	0.63	0.69	0.66	1879
accuracy			0.69	4231
macro avg	0.68	0.69	0.68	4231
weight avg	0.69	0.69	0.69	4231

# **Table-4 Random forest**

## **Support Vector Machines**

SVMs are powerful ML methods commonly utilized for classification tasks, including fake news detection. They operate by locating a hyperplane where the margin between two classes of data elements is maximized. This hyperplane is the decision boundary that separates real news from fake news.

	Precision	recall	f1-score	Support
0	0.70	0.67	0.68	2352
1	0.61	0.63	0.62	1879
accuracy			0.65	4231
macro avg	0.65	0.65	0.65	4231
weight avg	0.66	0.65	0.65	4231

#### Table-5 SVM

#### **KNN: K-Nearest Neighbors**

The KNN method is a simple yet effective ML technique that is well-suited for classification as well as regression tasks. The algorithm functions by initially determining the k data points that are in the nearest proximity to the new data point and then employing the labels of those k data points to estimate the label of the new data point.

## Table-6 KNN

	precision	recall	f1-score	support
0	0.67	0.74	0.70	2352
1	0.62	0.54	0.58	1879
accuracy			0.65	4231
macro avg	0.64	0.64	0.64	4231
weight avg	0.65	0.65	0.65	4231

## **Stochastic Gradient Descent**

Iterative optimization is the operation of the SGD algorithm. It is highly compatible with the optimization of neural networks. The algorithm in question was obtained from the scikit-learn Python library.

	precision	recall	f1-score	support
0	0.70	0.70	0.70	2352
1	0.63	0.62	0.63	1879
accuracy			0.67	4231
macro avg	0.66	0.66	0.66	4231
weight avg	0.67	0.67	0.67	4231

## Table-7 SGD



## 5. Results

The present work aims to cover the new data contained within a PolitiFact dataset, which consists of expertevaluated news classified as either false or trustworthy. An analysis has been conducted on the "PolitiFact" dataset. Utilizing the perplexity matrix, the outcomes of the dataset analysis conducted with the seven algorithms are illustrated. Here, the following seven algorithms are employed for detection:

- NB
- DT
- LR
- RF
- SVM
- KNN
- SGD



Fig. 4 Comparison result

**Random Forest:** Random Forest demonstrated the highest accuracy among the assessed models, achieving an accuracy score of 69%. It also displayed a balanced pre-decision and recall for both classes, indicating a well-rounded performance in classifying both fake and real news articles.

**Naive Bayes:** Naive Bayes showed promising results with an accuracy score of 68%. It portrayed a better precision for identifying real news but slightly lagged in recall compared to Random Forest.

**LR and SGD:** Both LR and SGD exhibited an accuracy of 67%. While their accuracies were comparable to Naive Bayes, their precision and recall rates were also similar.

**SVM and K-Nearest Neighbours (KNN):** SVM and KNN performed slightly lower than the aforementioned models with an accuracy of 65%. They showcased relatively balanced precision and recall but were outperformed by Random Forest, Naive Bayes, and the other models in overall accuracy.

**Decision Tree:** Decision Tree yielded an accuracy score of 64% and displayed a balanced yet slightly lower precision and recall in comparison to other models.

#### 6. Conclusion

In conclusion, among the assessed models for fake news detection, Random Forest emerged as the most effective with the highest accuracy. Nevertheless, it's vital to consider other metrics alongside accuracies, such as recall, precision, and the specific requirements of deployment, to make an informed choice regarding the most suitable model for practical application in identifying fake news articles.

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