

Fake News Detection Using Machine Learning

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ABSTRACT- *The rapid use of social media sites like Facebook and Twitter, along with the advent of the Internet, has allowed for the dissemination of information at a level never before seen... More people than ever before are making and sharing content on social media, and unfortunately, some of it is false or otherwise unfounded. It is difficult to automate the process of determining if a written article contains misinformation or disinformation. Prior to reaching a conclusion on an article's veracity, even a domain expert must consider several factors. Automated news article categorization is our proposed usage of a machine learning ensemble technique in this study. In this study, we examine various linguistic characteristics that can be used to distinguish between real and fake news. Taking use of these features, we evaluate the performance of a variety of machine learning algorithms trained using various ensemble methods on four real-world datasets. Results from experiments show that our suggested ensemble learner method outperforms individual learners.*

Keywords: World Wide Web, Social Media platforms, Information distribution, Content Sharing Textual Features, Machine Learning, Machine Learning ensemble technique, Real-worlds dataset etc.

1. INTRODUCTION

With the advancement of technology, introduces the concept of "fake news" and how technology, specifically Artificial Intelligence (AI) and Machine Learning (ML), can be used to detect it.

We have a lot of information available online, but it's hard to know if it's true or false[3]. We need to check sources and authors to determine credibility.

Fake news is false information created intentionally to harm someone's reputation, benefit an organization, or gain financial or political advantage. It often misleads people, like the examples seen during Indian election campaigns.

Recent research shows that AI and Machine Learning can help detect fake news[4]. These technologies can analyse information and predict whether a claim is real or fake, helping to prevent chaos and social unrest caused by misinformation.

This project aims to build a system that uses machine learning and natural language processing (a field of AI that helps computers understand human language) to identify fake news[3]. Machine learning allows computers to learn from data without being specifically programmed for every instance.

2. REVIEW OF LITERATURE

Research into detecting fake news is a relatively new field that is becoming increasingly important because fake news significantly harms how people interact socially and civically.

In this section, I have reviewed existing research on this topic

Fake news is a serious issue that harms trust in media and creates political instability, influencing how people vote. Researchers at the Oxford Internet Institute found that before the 2016 US Presidential election[16], fake news spread quickly through social media bots, which are automated accounts designed to interact and spread content. These bots significantly impacted online discussions about the election[1]. Fake news also makes it harder for journalists to report on important stories. Notably, a BuzzFeed analysis showed that the top 20 fake news stories about the 2016 election got more attention on Facebook than the top 20 stories from major news outlets[8].

Beyond political impact, fake news can lead to real-life violence and even deaths. People have been physically attacked due to false stories spread online. For example, in Myanmar, the Rohingya people faced arrest, imprisonment, rape, and killings because of fake news. These instances demonstrate how fake news [9] creates fear and negatively affects community interactions and civic participation.

3. METHODOLOGY

We evaluated classifiers for identifying fake news using the following learning algorithms as part of our proposed method.



“Figure 1: Algorithm training and news article classification workflow”

“Logistic Regression”:

We apply a logistic regression (LR) model to classify texts using a wide range of features that only offer a true/false or legitimate article/fake article output. We tested several settings and adjusted the hyperparameters to get the best result for each dataset, all with the goal of getting the most accurate LR model possible.

$$G_{\text{total}} = 1 - \sum_{i=1}^N (P_i)^2 \quad (10)$$

The following are the mathematical formulations of the logistic regression

$$h_{\theta}(X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}} \quad (1)$$

hypothesis function.

Support Vector Machine:

Support vector machine (SVM) is one of several kernel functions at our disposal; it is a model for binary classification issues... The objective of a support vector machine (SVM) model, Finding the plane that clearly separates two data sets with the widest feasible margin is the difficulty, since a hyperplane can be placed anywhere in an N-dimensional space... Mathematical representations of the SVM model's cost function are provided in and displayed.

$$J(\theta) = \frac{1}{2} \sum_{j=1}^n \theta_j^2 \quad (3)$$

Multilayer Perceptron:

The three main components of an artificial neural network called a multilayer perceptron (MLP) are an input layer, a hidden layer (or layers), and an output layer. Even though a basic MLP just requires the three layers, we were able to get the best results from our trials by experimenting with different parameters and layer counts to fine-tune the model. Here is a function representation of a simple one-hidden-layer multilayered perceptron model:

$$f(x) = g(b^{(2)} + W^{(2)}(s(b^{(1)} + W^{(1)}x))) \quad (6)$$

K-Nearest Neighbors (KNN):

An MLP is a type of artificial neural network that primarily consists of three layers: an input layer, one or more hidden layers, and an output layer. We were able to optimise the model by testing with various parameters and layer counts, even though a simple MLP only requires the three layers. This allowed us to obtain the best results from our experiments. A simple one-hidden-layer multi-layer perceptron model is shown

in the following flow diagram.: $\text{Euclidean distance} = \sqrt{\sum_{i=1}^k (x_i - y_i)^2} \quad (7)$

$$\text{Manhattan distance} = \sum_{i=1}^k |x_i - y_i| \quad (8)$$

$$\text{Minkowski distance} = \left(\sum_{i=1}^k |x_i - y_i|^p \right)^{1/p} \quad (9)$$

Ensemble Learners:

To enhance the overall accuracy of truthfulness/falsity article categorization, our concept was to combine feature input from textual characteristics with current ensemble techniques.. Ensemble learners improve accuracies by training many models using the same technique, which decreases the overall error rate and increases the model's performance.

Benchmark Algorithms:

Here we go over the benchmark algorithms that we used to evaluate our technique.

Linear SVM

As suggested in we employ a linear SVM strategy. Training the linear SVM on the feature set allowed us to make a valid comparison, as previously mentioned.

Convolutional Neural Network

Automatically detecting false news was accomplished by use of a convolutional neural network (CNN). When working with our dataset, we used the identical procedure.

Datasets:

All of the datasets used for this study are available to the public and were made available as open-source. You can carefully check the assertions made in those political pieces with fact-checking websites like snopes.com and politifact.com... "ISOT Fake News Dataset," or DS1, is the first database to compile both real and fake items retrieved from the web. While reuters.com is a reliable source for real news, PolitiFact has already identified a number of websites from where the misleading tales were culled. The collection contains 44,898 elements, out of which 21,417 are factual and 23,481 are pseudo-facts. Although the total corpora cover a wide range of topics, their main emphasis is on political news. You may find the second dataset, DS2, on Kaggle. The training set has 20,386 articles, whereas the testing set contains 5,126 articles.

Performance Metrics:

In order to determine how effective algorithms were, we used a wide variety of metrics which has four columns for metrics like true positive, false positive, true negative, and others.

Accuracy: A common and widely-used statistic is accuracy, which measures the proportion of true or erroneous observations that are accurately anticipated. One way to find out how accurate a model is to use the following equation:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

Recall: A model's "recall" is the percentage of correct predictions relative to its entire number of forecasts. Here, it stands for the proportion of true articles projected as true relative to all true articles.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (12)$$

Precision: A high F1-score indicates a good balance between recall and accuracy. Put simply, it determines the reciprocal of the two by utilizing harmonics. The system takes into account both the positive and negative results that are considered fake. If you want to know your F1-score, you can apply this formula. positively anticipated (true) articles that are tagged as true:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (13)$$

F1 Score: As a surrogate for memory and accuracy, the F1-score works well. It finds the happy medium, to restate it another way. When making our decisions, we consider both the true and misleading positives and negatives. Here is the formula to calculate the F1-score:

$$F1 - \text{score} = 2 \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (14)$$

4.DISCUSSION AND RESULT

	DS1	DS2	DS3	DS4
Logistic regression (LR)	0.97	0.91	0.91	0.87
Linear SVM (LSVM)	0.98	0.37	0.53	0.86
Multilayer perceptron	0.98	0.35	0.94	0.9
K-nearest neighbors (KNN)	0.88	0.28	0.82	0.77
Ensemble learners				
Random forest (RF)	0.99	0.35	0.95	0.91
Voting classifier (RF, LR, KNN)	0.97	0.88	0.94	0.88
Voting classifier (LR, LSVM, CART)	0.96	0.86	0.92	0.85
Bagging classifier (decision trees)	0.98	0.94	0.94	0.9
Boosting classifier (AdaBoost)	0.98	0.92	0.92	0.86
Boosting classifier (XGBoost)	0.98	0.94	0.94	0.89
Benchmark algorithms				
Perez-LSVM	0.99	0.79	0.96	0.9
Wang-CNN	0.87	0.66	0.58	0.73
Wang-Bi-LSTM	0.86	0.52	0.57	0.62

Table 1 “Level of accuracy for the datasets”

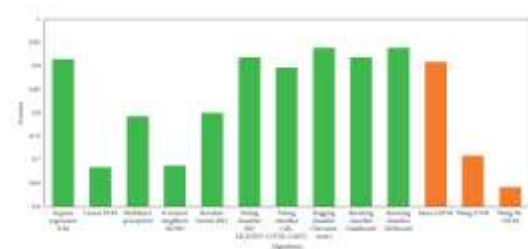


Figure2: “Average Accuracy overall Datasets”

	DS1	DS2	DS3	DS4
Logistic regression (LR)	0.98	0.92	0.91	0.88
Linear SVM (LSVM)	0.98	0.31	0.54	0.88
Multilayer perceptron	0.97	0.52	0.93	0.92
K nearest neighbors (KNN)	0.91	0.12	0.85	0.8
Ensemble learners				
Random forest (RF)	0.99	0.3	0.96	0.92
Voting classifier (RF, LR, KNN)	0.96	0.88	0.92	0.86
Voting classifier (LR, LSVM, CART)	0.96	0.86	0.88	0.83
Bagging classifier (decision trees)	0.98	0.94	0.93	0.9
Boosting classifier (AdaBoost)	0.98	0.92	0.92	0.86
Boosting classifier (XGBoost)	0.99	0.94	0.96	0.92
Benchmark algorithms				
Perez-LSVM	0.99	0.79	0.96	0.9
Wang-CNN	0.86	0.65	0.68	0.72
Wang-Bi-LSTM	0.82	0.43	0.5	0.63

Table 2 “The Data sets’ Recall”

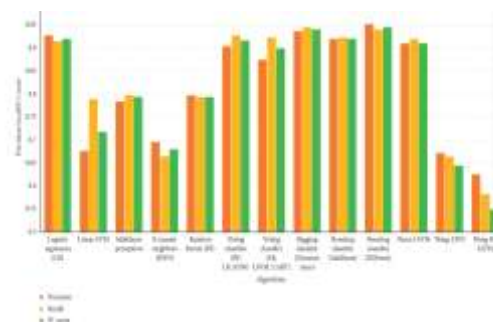


Figure 3: “All datasets for precision recall and F1 Score”

5.CONCLUSIONS

Manually categorizing news articles calls for expert knowledge of the subject matter and the ability to detect textual irregularities. In order to categorize false news stories, this study use ensemble methods and machine learning models. We gathered all of the data for our analysis from online news articles. In Table 5, you can see the F1-scores for all four datasets.

All four of these data sets achieved F1 scores of 0.87, accuracy of 0.98, precision of 0.91, and recall of 0.92 when using logistic regression (LR). Linear Support Vector Machine (LSVM) achieved 0.98 for accuracy, 0.32 for precision, 0.7 for recall, and 0.87 for F1 score. An artificial neural network that uses numerous interconnected layers of neurons is called a multilayer perceptron. The four numbers are 0.98, 0.38, 0.34, 0.95, and 0.98. With K-nearest neighbours (KNN), the results are 0.89, 0.23, 0.83, and 0.77. Learners' grouping algorithms Measurements for the RF model included recall (0.95), accuracy (0.99), precision (0.32), and F1 score (0.91). Voting time rolled around, and the accuracy ratings for Logistic Regression (LR), K-Nearest Neighbours (KNN), and Random Forest (RF) were 0.97, 0.88, and 0.94, respectively. A total of 0.88% was the classifier's accuracy.

With a recall of 0.92, precision of 0.86, accuracy of 0.96, and an F1 score of 0.86, the voting classifier did exceptionally well. Classification and regression trees, LSVM, and R-squared were the tools used for the analysis.

The decision tree-based bagging classifier achieved a precise, accurate, recalling, and F1 score of 0.98. With an F1 score of 0.86, recall of 0.92, precision of 0.92, and accuracy of 0.98., the boosting classifier (AdaBoost) achieved all objectives. Having a recall of 0.99 and a precision of 0.95, the Boost boosting classifier achieved an accuracy of 0.9. Find out how efficient algorithms are. The numbers represent the Perez-LSVM style A, with values of 0.8, 0.96, and 0.9. "Wang-CNN A.I." With a sum of 0.87, 0.67, 0.31, and 0.73, four figures are provided. Wang Bi-Wang Long Short-Term Memory The values are 0.84, 0.44, 0.35, and 0.57, just in case you were wondering. A multi-layer A Perceptron as a support vector machine for logistic regression (LR). Machine learning methods include systems like voting classifiers and K-nearest neighbours (KNN) (RF, LR, KNN). Common machine learning models that combine the output of multiple classifiers into a single voting classifier include CART, LR, and LSVM. Bagging is a classification technique that involves using

decision trees. AdaBoost is a boosting classifier. Enhancing the performance of a classifier using the Boost algorithm. Perez-LSVM The algorithms used are Wang-CNN and Wang-BiLSTM. Starting with 1 and working our way down, we have the following numbers: 0.95, 0.9, 0.85, 0.8, 0.75, 0.7, 0.65, 0.6, 0.55, and 0.5. Accuracy, Memory, and F1-score Accuracy Memorization and F1-factor The precision, F1-score, and recall for all datasets are displayed in Figure 3. Complication. The nine non-political pieces don't restrict themselves to political news but instead cover a wide range of subjects. The main objective of this research is to find textual patterns that can be utilised to spot counterfeit goods. We utilised a LIWC algorithm to extract various textual fragments from the articles. When training the models, these characteristics served as inputs. The most accurate results were obtained after extensive training and tuning of machine learning models.

6.FUTURE WORK

The future scope section describes the author's intention to continue their research on fake news. Previously, their research focused only on text-based fake news. In the future, they aim to develop a tool to combat fake news spread through manipulated images, audio, and video, as these are also used by malicious actors to disseminate misinformation.

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