



AUTOMATED DETECTION OF FAKE NEWS USING MACHINE LEARNING

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ABSTRACT:

The internet has developed into a vital global network that makes connection and information sharing possible quickly everywhere. The digital era's mainstay, social media platforms, offer a host of benefits, such as better communication, a wealth of educational materials, and numerous business opportunities. Social media has benefits, but it also encourages the spread of false information, particularly fake news. Within moments of going viral, fake news weakens the facts, skews public perception, and affects policy discussions. The visual similarity between fake and authentic news in the digital era makes it even more difficult to distinguish between the two. The application of machine learning techniques to the identification of fake news is examined in this research. A subfield of computer science called machine learning (ML) is concerned with using data and algorithms to enable artificial intelligence. Using labelled data sets, supervised learning is a machine learning technique that trains algorithms to identify patterns and forecast results. In order to identify fake news, we use a binary logistic regression model in this study. There are two datasets: one with real news and the other with false information. After these datasets are combined, the data is pre-processed to get rid of noise like stopwords and punctuation. Using vectorization techniques, the cleaned text is subsequently converted into numerical representations. The model is then trained, and its accuracy is evaluated by looking at how well it performs. After training, the model can be used to predict the authenticity of new, unknown news articles. The new dataset is then updated with these predictions, offering a quick and easy method of categorizing news items as true or false. This pipeline offers a simple method for creating a binary classification model in order to tackle the increasingly difficult problem of detecting fake news.

Keywords: Fake news detection, Machine Learning, Supervised learning techniques, Logistic Regression, social media.

1. Introduction:

The internet has developed into a huge and essential worldwide network in recent years, promoting connectivity among many populations and enabling the quick flow of information^[1]. Social media platforms have grown to be vital parts of the digital world, giving users access to channels of contact and information never before possible. Social media's widespread use has made information more accessible to all, but it has also made it more difficult to distinguish reliable sources from fraudulent content, or "fake news"^[2]. Public discourse, political processes, and social trust may all suffer as a result of this pervasive transmission of false information. People's ability to identify fact from fiction is made more difficult by the visual indistinguishability of real and fake news stories^[3]. Fake news is being automatically identified using machine learning and artificial intelligence approaches. The application of machine learning (ML) to the problem of detecting fake news is examined in this research. A subfield of computer science called machine learning (ML) is concerned with using data and techniques to help AI mimic human learning processes and progressively increase its accuracy^[4]. Machine learning (ML) enables computers to learn on their own from data and historical experiences, finding patterns to generate predictions with little assistance from humans. A subset of machine learning known as "supervised learning" trains algorithms to identify patterns and forecast outcomes using labelled information. Using a dataset of labelled news stories, this study uses machine learning techniques—specifically, binary logistic regression—to identify false news. A data analysis method called logistic regression use mathematics to determine the connections between two data elements^[5]. The value of one of those parameters is then predicted depending on the other using this relationship. The data is trained using a logistic regression model, and the model's ability to differentiate between authentic and fraudulent news stories is assessed using a range of sample sizes. Next, news articles from a fresh dataset are analyzed using the trained model to evaluate if they are authentic or fraudulent. This study adds to the continuing fight against disinformation by offering a reliable and scalable method for identifying bogus news that may be successfully incorporated into practical applications.

2. Literature Review:

Jones and Li (2024) suggest a graph-based propagation model to improve the detection of false information^[6]. Their approach allows for early detection by modelling the unique ways that fake news spreads on social networks. The study demonstrates that by capturing the structural propagation properties

of the data, graph-based algorithms perform better than traditional text-based methods. Improved accuracy and resilience in identifying fake news are demonstrated by the results, underscoring the model's potential for widespread use.

Noor, M., Ibrahim, M., and Ibrahim, N. (2024): This study uses transfer learning with pre-trained multilingual BERT models to detect fake news in low-resource languages including Tamil, Malayalam, and Kannada. This strategy performs noticeably better than conventional techniques, attaining high classification accuracy while successfully resolving issues with linguistic diversity and data scarcity^[7]. The research identifies cross-lingual transfer as a strong tactic and comes to the conclusion that transfer learning holds promise for improving the identification of fake news in underrepresented languages, opening the door for further advances in this field.

Sharma, M., and Singh, R. (2023): The study offers a methodology for early false news identification that makes use of deep learning and big data analytics^[8]. The program effectively detects fake news by analyzing massive datasets to find patterns in content and social dissemination. The outcomes illustrate the system's scalability for real-time applications by demonstrating excellent accuracy and quick detection capability. The authors come to the conclusion that early detection is greatly improved by combining big data processing with advanced deep learning techniques. They recommend additional advancements through feature engineering and larger datasets.

Rashid et al. (2020) provide a hybrid strategy that uses machine learning approaches to detect fake news, improving accuracy and lowering false positives. Their research emphasizes the necessity of a diversified strategy to counteract false information in diverse contexts^[9]. The effectiveness of the suggested approach as a detection platform suggests that bigger datasets and more sophisticated feature engineering techniques can lead to even greater advancements. This study emphasizes how effective hybrid approaches may be in detecting fake news.

Sharma, M., and Singh, K. (2023): In order to effectively evaluate news material, the paper suggests a transformer-based architecture for fake news detection that makes use of models like BERT and RoBERTa^[10]. This approach performs better in terms of accuracy and robustness than conventional machine learning algorithms. The outcomes show how well the model generalizes across datasets, successfully tackling issues like linguistic variety and the spread of false information. The study finds that transformer-based techniques are quite successful at detecting fake news, and it suggests that these techniques be improved in the future by using better training data and fine-tuning strategies.

3. Methodology:

3.1 Dataset

The study's dataset includes two different types of news articles: "Fake news" and "True news." Kaggle offered two distinct CSV files, Fake.csv and True.csv^[11]. News articles with a variety of features, including their text content, are included within each file.

- Fake.csv: Contains news articles identified as fake.
- True.csv: Contains news articles identified as true.

Binary classification made it possible by categorizing each dataset, giving false news a value of 1 and true news a value of 0.

3.2 Data Preprocessing

Preprocessing enhanced the quality and applicability of the text data for subsequent analysis^[12]. The text was cleaned and preprocessed using the following procedures:

- **Lowercasing:** All text was converted to lowercase in order to standardize it.
- **Elimination of Punctuation:** To concentrate only on the words, all punctuation was removed from the text.
- **Stopword Removal:** To improve the text's signal and lower noise, common English stopwords were removed using the Natural Language Toolkit (NLTK) stopwords corpus.

By retaining only the significant words, the preprocessing stage simplifies the text data, improving feature extraction and reducing computing cost.

3.3 Feature Extraction

After preprocessing, the Term Frequency-Inverse Document Frequency (TF-IDF) approach was used to convert the text data into numerical features. This technique, which takes into account the frequency of terms in each document while reducing the influence of frequently occurring words across several documents, is frequently used to transform text into a format appropriate for machine learning models.

- To maximize computational performance, the TfidfVectorizer from the Scikit-learn library was used, with a feature count limit of 5000.
- The machine learning model uses the vectorized data as input features.

3.4 Model Training

For classification, a logistic regression model was selected since it is straightforward and effective for binary classification tasks. The dataset was divided using stratified sampling to ensure that the distribution of true and false news in the training and testing sets was proportionate. To investigate the effect of sample size on performance, the model was trained on increasingly larger subsamples, ranging from 100 to 2000 samples. Each subsample was split into two sets: one for testing (20%) and one for training (80%). The model was tested on the testing set and trained on the training set.

3.5 Evaluation Metrics

The model's performance was assessed using the metrics listed below:

- **Accuracy Score:** The proportion of news items in the test set that were properly classified out of all the articles.
- **Classification Report:** This comprises F1-score, recall, and precision for both fake and real news categories.

The accuracy results for several sample sizes were recorded and graphically depicted in order to examine the relationship between model accuracy and sample size, showing how performance improves as the volume of data increases.

3.5 Validation on a New Dataset

The trained model was further validated by uploading an unknown dataset and doing the same preprocessing and TF-IDF vectorization procedures. Using the information gathered from the previous training stage, the model then categorized the news articles in the dataset as either true or false. The new dataset was updated to include the generated predictions, and the total number of predictions was recorded.

3.6 Visualization

The accuracy of the model across different training sample sizes was displayed using a line plot. This graphic depiction made it easier to comprehend how the model learned and gave information about the sample size needed for best results.

4. Result and Analysis :

This study uses TF-IDF and logistic regression to examine an effective technique for identifying fake news. As seen in Figure 1e 1, the datasets were divided into two distinct categories: fake news (identified as 1) and authentic news (marked as 0). After being merged into a single dataset, the datasets were subjected to preprocessing procedures like lowercase conversion, punctuation removal, stopword removal, and text normalization.

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Package stopwords is already up-to-date!
Fake News Data:
                                title \
0 Donald Trump Sends Out Embarrassing New Year'...
1 Drunk Bragging Trump Staffer Started Russian ...
2 Sheriff David Clarke Becomes An Internet Joke...
3 Trump Is So Obsessed He Even Has Obama's Name...
4 Pope Francis Just Called Out Donald Trump Dur...

                                text subject \
0 Donald Trump just couldn t wish all Americans ... News
1 House Intelligence Committee Chairman Devin Nu... News
2 On Friday, it was revealed that former Milwauk... News
3 On Christmas day, Donald Trump announced that ... News
4 Pope Francis used his annual Christmas Day mes... News

                                date
0 December 31, 2017
1 December 31, 2017
2 December 30, 2017
3 December 29, 2017
4 December 25, 2017

True News Data:
                                title \
0 As U.S. budget fight looms, Republicans flip t...
1 U.S. military to accept transgender recruits o...
2 Senior U.S. Republican senator: 'Let Mr. Muell...
3 FBI Russia probe helped by Australian diplomat...
4 Trump wants Postal Service to charge 'much mor...

                                text subject \
0 WASHINGTON (Reuters) - The head of a conservat... politicsNews
1 WASHINGTON (Reuters) - Transgender people will... politicsNews
2 WASHINGTON (Reuters) - The special counsel inv... politicsNews
3 WASHINGTON (Reuters) - Trump campaign adviser ... politicsNews
4 SEATTLE/WASHINGTON (Reuters) - President Donal... politicsNews

                                date
0 December 31, 2017
1 December 29, 2017
2 December 31, 2017
3 December 30, 2017
4 December 29, 2017
```

Figure 1. True and fake news dataset

By employing TF-IDF to vectorize the extracted text, the feature space was constrained to 5000 words. To examine the effect of training data size on model performance, experiments were carried out with sample sizes of 100, 500, 1000, 1500, and 2000. As illustrated in Figure 2, the results showed that accuracy grew consistently with larger sample numbers, with the largest increases occurring at the smallest levels.

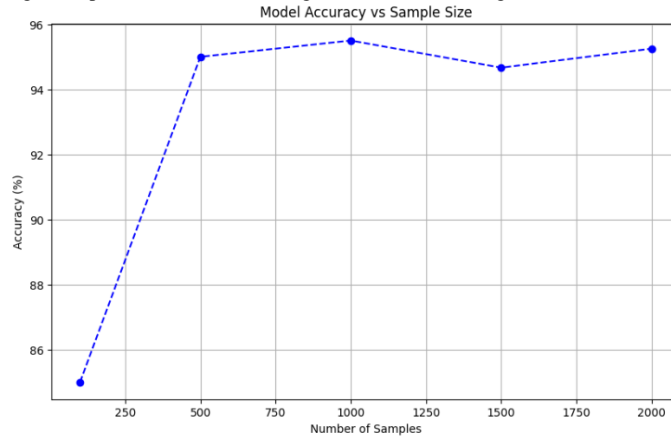


Figure 2. Accuracy graph

After 1500 samples, accuracy increases stabilized, demonstrating the adequacy of data. Table 1 illustrates how the Logistic Regression model proved to be reliable in binary classification tasks by attaining balanced performance, as indicated by the F1-scores, precision, and recall for the fake and true news classes. A different validation dataset was used to test the model's generalization capabilities.

Table 1. Model Performance Metrics

	Precision	Recall	F1-score	Support
0	0.93	0.96	0.95	176
1	0.97	0.95	0.96	224
Accuracy			0.95	400
Macro avg	0.95	0.95	0.95	400
Weighted avg	0.95	0.95	0.95	400

On the preprocessed validation data, the trained model showed excellent generalization performance, generating predictions that aligned with the patterns it had discovered in the training set. This illustrates the model's resilience and ability to function effectively on unknown datasets. Furthermore, a comparison of accuracy and sample size revealed that the model gains proficiency with relatively small datasets quickly, but that the returns decrease with bigger datasets, indicating that there is a suitable training size for this task. In summary, the suggested method successfully detects false information while exhibiting excellent performance and economical use of resources. The model is appropriate for real-world uses in fake news identification due to its capacity to generalize to fresh data.

5. Future Enhancement:

- Although Logistic Regression is a good place to start, exploring alternative classification methods such as Random Forest, Support Vector Machines, or Gradient Boosting may improve model performance.
- Instead of depending only on a straightforward train-test split, a more thorough assessment of the model's performance can be obtained by utilizing k-fold cross-validation.
- For real-world implementation, the model can be enhanced to do real-time news article classification as it is released.
- By utilizing multilingual models like mBERT or incorporating language translation APIs, the model might be modified to identify fake news in various languages, expanding the system's capabilities.
- By incorporating multimodal analysis, the system would be able to examine text, photos, videos, and infographics, ensuring a thorough method of identifying false information in a variety of content formats.
- By implementing detection systems on social media platforms, content may be monitored on a broad scale, which enables automated fact-checking and real-time identification of fake news to effectively stop its spread.

6. Conclusion:

In order to differentiate between fake and real news, this study employed a machine learning technique implementing logistic regression. Preprocessing methods like TF-IDF vectorization, stopword removal, and punctuation eradication were applied to the dataset, which consisted of labeled false and authentic news articles. The study's main goal was to assess the model's performance with different sample sizes and examine how well it predicted the veracity of news articles. The Logistic Regression model accurately classified news items as either authentic or fake. Accuracy showed consistent

performance throughout the data subsets and improved with increasing sample size. Notably, the model demonstrated its effectiveness in resource-constrained contexts by maintaining a respectable predictive performance even with less datasets. The model's accuracy was further confirmed by the classification report, which displayed excellent performance metrics for both the fake and real news categories. Additionally, an external validation dataset was used to evaluate the model, and it accurately determined new statements' authenticity. This illustrates how the model may be applied to actual situations, making it a useful instrument for halting the spread of false information.

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