

# **Fake News Detection Using Machine Learning Techniques**

**A Comprehensive Analysis of Multiple Machine Learning Models for Identifying Fake News Articles**

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## **Abstract**

The prevalence of fake news has become a critical issue in the digital age, leading to the spread of misinformation and negatively impacting public discourse. This study aims to tackle the problem of fake news detection by utilizing various machine learning techniques. A comprehensive analysis of multiple machine learning models is conducted to identify the most effective approach for distinguishing fake news articles from legitimate ones. The research includes the evaluation of traditional algorithms, such as Logistic Regression and Naive Bayes, as well as more complex methods, such as Support Vector Machines and Neural Networks. The dataset used in this study comprises a large collection of news articles from diverse sources, with both true and fake labels. The data undergo preprocessing, feature engineering, and model input preparation to optimize the performance of the machine learning models. The models are then trained, evaluated, and optimized through hyperparameter tuning. The results and discussion section presents a comparative analysis of the performance of different models, shedding light on their strengths and weaknesses. The conclusion highlights the most effective models for fake news detection and suggests future research directions to further improve the accuracy and efficiency of these models.

The complete project code and resources can be found at:

[https://colab.research.google.com/drive/1MeuU8PteBX\\_phCP-eO0KtHoRIyKrS9Cs](https://colab.research.google.com/drive/1MeuU8PteBX_phCP-eO0KtHoRIyKrS9Cs)

## **Introduction**

The rapid growth of the internet and social media platforms has revolutionized the way information is disseminated and consumed. While this has led to increased access to news and knowledge, it has also resulted in the widespread distribution of fake news. Fake news, defined as deliberately fabricated information that mimics the style of legitimate news articles, has the potential to manipulate public opinion, influence elections, and undermine trust in media institutions. The detection of fake news has thus become a pressing issue that requires innovative solutions.

Machine learning, a subfield of artificial intelligence, offers a promising avenue for addressing the challenge of fake news detection. By employing algorithms that can learn from data, machine learning models can automatically identify patterns and make predictions based on those patterns. This study aims to investigate the effectiveness of various machine learning techniques for detecting fake news, with the goal of identifying the most accurate and efficient models for this task.

The research begins with a review of existing literature on fake news detection, focusing on the methods and models that have been previously proposed. Next, the study presents the dataset used for model evaluation, along with the preprocessing techniques employed to clean and prepare the data. This is followed by a discussion of feature engineering and model input

preparation, which are crucial steps in ensuring the optimal performance of the machine learning models.

The core of the study involves the selection, training, and evaluation of different machine learning models, including traditional algorithms such as Logistic Regression and Naive Bayes, as well as more advanced techniques like Support Vector Machines and Neural Networks. Model optimization and hyperparameter tuning are then explored to further enhance the performance of the selected models. Finally, the results and discussion section provides a comparative analysis of the models' performance, leading to the conclusion that outlines the most effective models for fake news detection and suggests future research directions.

## **Literature Review**

The challenge of fake news detection has attracted considerable attention from the research community in recent years. Various approaches have been proposed to tackle this problem, ranging from traditional machine learning techniques to more advanced deep learning models. This literature review provides an overview of the most relevant and influential studies on fake news detection, highlighting the key methodologies and findings.

### **1. Feature-based approaches:**

Feature-based approaches involve the extraction of relevant features from the text, which are then used as input to machine learning models. Some common features used in fake news detection include:

- a. Linguistic features: Researchers have explored the use of linguistic features, such as sentiment analysis, readability scores, and part-of-speech tags, to distinguish between fake and real news (Pérez-Rosas et al., 2018; Horne & Adali, 2017).
- b. Content-based features: Content-based features, such as the presence of specific keywords, article length, and n-grams, have also been used to identify fake news (Zhang et al., 2018; Chen et al., 2015).
- c. Source-based features: The credibility of news sources has been found to be an effective feature for fake news detection (Castillo et al., 2011; Gupta et al., 2013).

### **2. Traditional machine learning models:**

Various machine learning models have been applied to the problem of fake news detection, including Logistic Regression, Naive Bayes, Decision Trees, and Support Vector Machines. These models have shown promising results, with some studies reporting accuracy rates of over 80% (Zhang et al., 2018; Shu et al., 2017).

### **3. Deep learning models:**

Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated their effectiveness in various natural language processing tasks, including fake news detection. Researchers have applied these models to both textual and visual content to identify patterns that indicate fake news (Wang, 2017; Ruchansky et al., 2017).

### **4. Ensemble methods and model combinations:**

To improve the accuracy of fake news detection, researchers have explored the use of ensemble methods and model combinations. For instance, Zhou and Zafarani (2018) proposed an ensemble of different machine learning models, including SVM, CNN, and RNN, to detect fake news, achieving better results than individual models.

### **5. Social context and propagation patterns:**

In addition to textual and visual features, researchers have also investigated the use of social context and propagation patterns in fake news detection. Studies have shown that fake news often exhibits distinct sharing patterns on social media, which can be leveraged to improve detection accuracy (Vosoughi et al., 2018; Wu et al., 2015).

In conclusion, the existing literature on fake news detection offers a rich set of methodologies and models that can be used to tackle this problem. The present study aims to build on these findings by exploring various machine learning techniques and identifying the most effective models for detecting fake news in a large-scale dataset.

## **Feature Engineering and Model Input Preparation**

In this study, we utilized multiple datasets to create a comprehensive dataset for fake news detection. The datasets used in this study are:

1. Fake and real news dataset from Kaggle [13].
2. All the news dataset from Kaggle [14].
3. Additional fake news dataset from Kaggle [15].
4. LIAR dataset [16].
5. FakeNewsNet dataset from GitHub [17].

First, we loaded and preprocessed each dataset individually. For the first dataset, we labeled real news as 1 and fake news as 0, then combined them into a single DataFrame. We also parsed the date strings into datetime objects using the dateutil library. For the second dataset, we dropped

unwanted columns, changed the 'date' column to datetime dtype, and assumed that all the articles were legitimate by labeling them as 1. The same process was applied to the third dataset, keeping only the relevant columns, renaming them to match the existing data, and labeling the dataset as fake news (0). We also converted the string dates to datetime objects with timezone information and converted them to UTC timezone.

For the LIAR dataset, we combined the train, test, and valid datasets and assigned column names. We then renamed the columns to match the existing data and created empty columns for 'title' and 'date' with None values. We converted the labels to binary values, with true statements labeled as 1 and false statements labeled as 0. Finally, we merged the LIAR dataset with the existing data.

For the FakeNewsNet dataset, we loaded the gossipcop and politifact datasets, renamed the 'news\_url' column to 'url', and assigned the appropriate labels. We then selected the relevant columns and combined all datasets into a single DataFrame. We also shuffled the combined data to ensure randomness.

We filled the missing values in the 'text' and 'title' columns with an empty string and added sentiment analysis as a feature using the TextBlob library. We preprocessed the text using NLTK and regular expressions to remove non-word characters, extra spaces, and stopwords, and performed stemming on the remaining words.

We tokenized the text and split the dataset into training and testing sets using the Keras Tokenizer. We padded the sequences to have equal length and calculated the size of the dataset in megabytes. Finally, we saved the data DataFrame to a CSV file and the x\_train and x\_test arrays to numpy binary files for further analysis.

## **Model Optimization and Hyperparameter Tuning**

Optimizing the performance of a machine learning model involves finding the best combination of hyperparameters. In this study, Keras Tuner was used to perform hyperparameter tuning. The Keras Tuner library allows for an easy and efficient approach to finding the optimal configuration of a model by searching through the specified hyperparameter space.

The model's hyperparameters included the number of convolutional layers, filters, kernel size, number of dense layers, units in each dense layer, dropout rate, learning rate, and the number of units in the LSTM and GRU layers.

A random search strategy was employed for the hyperparameter tuning process. The search was conducted over 10 trials with the objective of maximizing the validation accuracy.

After the search, the best model was selected and retrained with the full dataset. The final model achieved an accuracy of 89.73% on the test set. The confusion matrix and classification report

provided additional insights into the model's performance. The model achieved high precision and recall for the majority class (1), while the performance on the minority class (0) was lower. This suggests that further improvements might be possible by addressing the class imbalance or by employing more sophisticated techniques for hyperparameter tuning.

In addition to using Keras Tuner, other optimization methods, such as grid search and Bayesian optimization, can be employed for hyperparameter tuning. Furthermore, fine-tuning pre-trained language models, such as BERT, can also lead to improved performance in news classification tasks.

## **Results and Discussion**

Our study examined the performance of various machine learning models and approaches in classifying news articles. This section summarizes the results and discusses their implications.

We tested several models, including a custom deep learning model with pre-trained GloVe embeddings, LSTM, and hyperparameter tuning using Keras Tuner, as well as traditional machine learning models, such as Logistic Regression, Linear Support Vector Machine, and Random Forest, optimized with RandomizedSearchCV. We also experimented with fine-tuning pre-trained language models like BERT and RoBERTa.

### **1. Custom Deep Learning Model**

The custom deep learning model achieved an accuracy of 89.73% on the test set. The confusion matrix showed that the model performed better at classifying class 1 articles (true positives = 37343) than class 0 articles (true negatives = 5093). This result is also reflected in the classification report, with class 1 having higher precision, recall, and F1-score compared to class 0.

### **2. Traditional Machine Learning Models**

Traditional machine learning models, including Logistic Regression, Linear Support Vector Machine, and Random Forest, yielded similar test set accuracies of approximately 90%. All three models demonstrated a similar pattern as the custom deep learning model, with class 1 having higher precision, recall, and F1-score compared to class 0.

### **3. BERT and RoBERTa Fine-Tuning**

Comparing the two pre-trained language models, BERT showed better performance with a higher validation accuracy of 88.31% after 4 epochs, while RoBERTa achieved a validation accuracy of 79.89% after 3 epochs. It should be noted that the RoBERTa model's performance

plateaued after 3 epochs, which might indicate a need for further adjustments in the fine-tuning process, such as varying the learning rate or employing early stopping techniques.

In terms of training time, BERT took an average of 76ms/step, while RoBERTa took a longer average time of 121ms/step for the first epoch. This indicates that BERT was quicker to train, possibly due to the freezing of some layers during the fine-tuning process.

## **Conclusion**

In this study, we investigated various machine learning and deep learning models to classify news articles effectively. Our experiments included a custom deep learning model with pre-trained GloVe embeddings and LSTM layers, traditional machine learning models such as Logistic Regression, Linear Support Vector Machine, and Random Forest, and fine-tuning pre-trained language models like BERT and RoBERTa.

Our findings revealed that the custom deep learning model and traditional machine learning models achieved comparable accuracies of around 90%. BERT, after fine-tuning, showed a slightly lower accuracy of 88.31%. RoBERTa, on the other hand, had the lowest accuracy at 79.89%. However, it is important to note that further optimizations and adjustments could potentially enhance the performance of the RoBERTa model. The differences in performance between class 0 and class 1 across all models also indicate a possible need for further investigation into class imbalance or other factors affecting classification performance.

These results underscore the importance of selecting appropriate models and techniques based on the specific classification task at hand. Although deep learning models like BERT and RoBERTa have demonstrated impressive performance in various NLP tasks, traditional machine learning models should not be overlooked, as they can achieve similar results with lower computational requirements.

In future research, it would be beneficial to explore other pre-trained language models and fine-tuning strategies to identify the most effective approach for news article classification. Additionally, investigating techniques to address class imbalance and improve classification performance for underrepresented classes could lead to more robust and balanced models.

Overall, this study contributes to the growing body of knowledge on text classification and provides insights into the effectiveness of various models and approaches in the context of news article classification. The findings can be used to guide researchers and practitioners in developing accurate and efficient classification models for real-world applications.

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