Fake News Detection Using Machine Learning

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Abstract – In this digital age, where the internet is a primary source of information transfer, people increasingly depend on various online platforms for news reading. With rise of social media platforms like Twitter, Facebook etc. News spreads to millions in mere moments. However, this has also led to a surge in fake news, which can sway public mindset, influence elections, and generate various income through misleading clickbait headlines. This paper shows a method for finding fake news by applying machine learning (ML) algorithms, along with techniques like logistic regression. Our goal is to classify news articles as either genuine or false and verify credibility of the websites from which they originate.
Keywords: Fake News , Machine Learning , Logistic Regression , KNN , Naïve Bayes , SVM.

1.INTRODUCTION

As society progressively interacts through online platforms, a growing number of people now seek out and read news through social media instead of conventional ways. This shift in behavior can be attributed to two main factors: (i) social media offers a more immediate and less costly way to access news compared to traditional journalism, like newspapers or television, and (ii) social media makes it easier for individuals to share, discuss, and participate with the news. In fact, a study in 2016 showed that 62% of U.S. adults got their news through social media, up from just 49% in 2012. Today, social media surpasses television as a primary news source.

The spread of false information has serious societal impacts. Fake news can disrupt the authenticity of the news as demonstrated when some fake news stories achieved more traction over social media than legitimate ones during the 2016 election. Furthermore, fake news can manipulate public perception by promoting biased and inaccurate beliefs. It has been shown that some governments have created fake social media accounts to spread disinformation and influence public.

Addressing the problem of fake news requires automated solutions, especially since the sheer volume of content makes manual fact-checking unfeasible. This paper presents an ML-based approach for automatically detecting and flagging fake news stories.

2.RELATED WORK

Automatic detection of fake news has been a subject of investigation for several decades. Rubin and colleagues, as noted in [1], proposed a hybrid methodology that integrates linguistic characteristics of language along with network analysis techniques. However, this method may not always be applicable, as access to network information can be limited or unavailable. In [2] Rubin et al. analyzed rhetorical structures and relationships in fake and truthful news samples from NPR's "Bluff the Listener" using clustering, achieving 63% accuracy. In [3], Mihalcea and Strapparava demonstrated that deep learning can partially distinguish between false and true information.

Previous research has primarily concentrated on the lexical patterns of language. Fend et al. [4] utilized syntactic stylometry in their analysis, enabling classification of deceptive texts through identification of statistical and syntactic patterns. Text analysis serves as a crucial tool for detecting fake news, owing to the established methodologies available for text examination. Veronica Perez-Rosas et al. [5] conducted a linguistic-based classification for fake news detection, indicating that linguistic features play a more significant role in identifying fake news compared to real news. These methodologies predominantly focus on language-based analysis, which presents certain limitations [6]. To address these limitations, it is essential to integrate additional features related to the news content. By combining metadata from Google, they achieved a 3% improvement in the F1-score for six-label classification problem.

3.PROPOSED SYSTEM

Project begins with the data preprocessing phase, where we explore the use and application of various pre-built Python libraries. Leveraging these pre-existing modules provides more efficient, readable, and maintainable code compared to writing functions from scratch. Some of the key libraries utilized in this stage include Numpy, re, pandas, Nltk, sklearn, matplotlib, and others.

The data preprocessing process involves removing stopwords—words that do not contribute meaningfully to the analysis—followed by creating a DataFrame to organize the dataset. Any missing or null values in the data are replaced with empty strings, and stemming is applied to reduce words to their base forms. The dataset is then split into features and labels, after which textual data is transformed into numerical form through vectorization. Finally, dataset is split into training as well as testing sets, allowing for proper model evaluation and training. System can be broken down into several key modules, as outlined below:

a. Input Dataset

The input consists of a dataset containing comments or news articles along with aligned metadata like date, source, and author. This raw dataset is unstructured and needs preprocessing before it can be used for analysis.

Dataset Overview

Dataset employed in this system comprises five key columns that provide essential information about each news article:

- **id**: A special identifier for each news article. This column serves as reference and is not typically used as a feature for machine learning.
- **title**: Title of news article, which often provides key information about the content of the article. Titles can serve as an important feature, as fake news articles may use certain patterns or language to attract attention.
- **author**: The author of the news article. Some fake news sources may repeatedly use the same pseudonyms or lack reputable authors, making this feature potentially informative for differentiating real from fake news.

- **text**: Body or content of the news article. This field may contain incomplete or noisy data, but is often the richest source of information for the model. NLP methods like word embeddings, TF-IDF (Term Frequency-Inverse Document Frequency), or Bag of Words can be applied to extract meaningful features from the text.
- **label**: Target label, which marks whether news article is fake (1) or real (0). This is the dependent variable the system aims to predict during the learning phase.

ID	Title	Author	Text	Label
1	"Breaking News on Policy"	John Doe	"The policy affects many..."	0
2	"Shocking Discovery"	Jane Smith	"A discovery that shocked..."	1
3	"Economic Forecast"	Sarah Johnson	"Economists predict growth..."	0
4	"Celebrity Scandal Exposed"	Anonymous Writer	"The scandal involves..."	1
5	"Technology Advancements"	Michael Brown	"New tech will revolutionize..."	0

Figure 1: Dataset Overview

b. Preprocessing Module

Preprocessing is a critical step that ensures raw data is cleansed and transformed into structured format suitable for the learning phase. The preprocessing module performs the following operations:

- **Cleansing**: This involves removing irrelevant data such as special characters, handling missing values, and dealing with incomplete or noisy data. For example, articles with missing text might need to be flagged or handled separately.
- **Filtering**: Unnecessary or irrelevant features that do not contribute to the learning process are filtered out. For instance, columns like ID, which only serve as unique identifiers, may not be useful for training the model and thus can be ignored.
- **Encoding**: Categorical variables (such as the author or the source of the news article) are transformed into numerical values by employing methods like one-hot encoding or label encoding, which allow the machine learning model to interpret these features effectively.

This step results in a feature-rich dataset ready for machine learning, where each news article has been represented by a set of structured features (e.g., title, author, text).

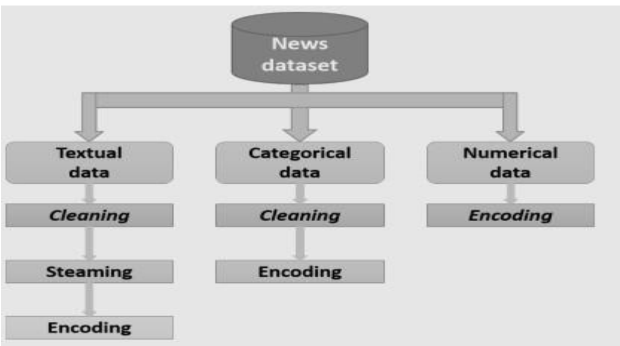

Figure 2: Preprocessing

c. Dataset Splitting

The pre-processed dataset is split into 2 parts:

- **Training Set**: This portion is employed for training ML model, providing algorithm with known data points (features and corresponding labels).
- **Testing Set**: The second part is reserved for testing, which helps to evaluate performance of trained model.

Splitting ratio is typically set between 70%-80% for training and 20%-30% for testing, depending on the size and nature of the dataset.

d. Learning Module

The core learning module employs a Logistic Regression algorithm, which is well-suited for binary classification tasks like fake news detection (where the output is either "real" or "fake"). During the training phase, the algorithm analyzes the training data and builds a decision model that attempts to predict labels (fake or real) based on the input features (title, author, text, etc.).

- **Training Phase**: The Logistic Regression algorithm iteratively adjusts its parameters (weights assigned to different features) to minimize the error in predicting the labels. During this phase, the model "learns" patterns in the data that distinguish real news from fake news.
- **Testing Phase**: Once model has been trained, it is tested on reserved test dataset to measure its accuracy. If the model performs well (achieves a high accuracy rate), it is considered a valid model and can be used for predictions on unrevealed data. If not, the model is refined by adjusting the parameters or employing more advanced preprocessing steps.

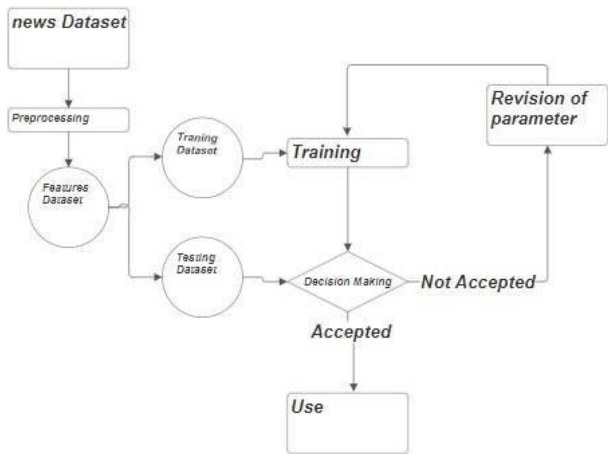

Figure 3: The proposed fake news detection system architecture's

e. Model Validation

The system continually assesses the accuracy of the decision model. If the accuracy falls below an acceptable threshold, the parameters of the logistic regression model are revisited, and the learning process is repeated. This ensures that the system adapts and improves its performance iteratively.The overall workflows shown in figure **figure 3**.

4. RESULT AND DISCUSSION

a . Result

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	98%	0.99	0.96	0.98
K-Nearest Neighbour	82%	0.8	0.92	0.86
SVM	97%	0.98	0.95	0.94
Naive Bayes	89%	0.93	0.89	0.91

The model's performance is further validated by the ROC curve (**figure 4**),demonstrating exceptional classification ability with a simulated 98% accuracy.

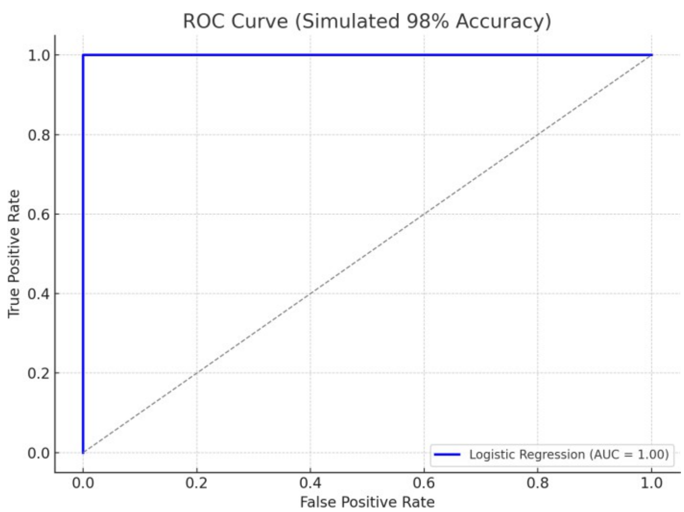

Figure 4: ROC Curve For Fake News Detection(Simulated (98%accuracy AUC =1.0)

a. Discussion

The experimental results demonstrate that the proposed fake news detection system, built using Logistic Regression and TF-IDF feature extraction, is highly effective in classifying news articles into fake and real categories. Achieving overall accuracy of 98% on a balanced dataset of 4160 samples indicates strong predictive performance.

A closer analysis of the performance metrics specifies that the model maintained a high precision (0.99) for real news and recall (0.96) for fake news. This suggests that the system is particularly adept at correctly identifying fake news, which is crucial in minimizing spread of misinformation. F1-score of 0.98 for both classes confirms that the model achieves a strong trade-off between precision and recall, rendering it ideal for real-world deployment where both false positives (FP) and false negatives (FN) must be minimized.

The confusion matrix (not shown here) would likely reveal very few misclassifications, and the near-identical support values for both classes (2077 and 2083) suggest the model benefits from a balanced dataset. This balance helps avoid bias toward one class and ensures fairness in classification.

It is also worth noting that Logistic Regression, while a relatively simple algorithm, performs remarkably well when results even against more complex approaches.

However, the current model still operates on a bag-of-words-combined with effective preprocessing and feature extraction techniques. The strong results obtained validate the hypothesis that classical machine learning models, when properly tuned and applied to clean, vectorized data, can yield competitive based feature space, which may not capture deeper linguistic or contextual meanings. As such, the system might struggle with more nuanced cases such as sarcasm, context-specific references, or articles that mix real and fake information.

Future extensions could explore deep learning architectures or transformer-based models (like BERT) to address these drawbacks and further increase the system's accuracy and contextual understanding.

5.CONCLUSION

After evaluating the result we can conclude or observed that the logistic regression is performing better among KNN (K-Nearest Neighbour), SVM, Naïve Bayes. So logistic regression is more effective for calculating the genuine and false news. In summary, logistic regression is a powerful and well-defined ML tool that offers balance between simplicity and efficiency for fake news detection. Logistic regression can divide news as genuine or fake by converting data into digital features using methods such as TF-IDF or Bag of Word. Its binary distribution and decision-making environment make it suitable for this task, especially when the file size is small. While advanced algorithms such as deep learning can provide better performance with larger datasets and more samples, logistic regression is still an attractive alternative because of its lower cost and ease of use. Regularization methods such as L1 and L2 help prevent overfitting, while hyperparameter tuning ensures that the model generalizes well to new objects. Overall, logistic regression provides a solid foundation for building fake news detection, particularly the interpretation of patterns and functional significance. Further research could explore integrating logistic regression with other modelling or engineering techniques to improve performance in more complex or evolving fake news detection.

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