**Mini Project Report on**



**Fake News Detection**



**Submitted in partial fulfilment of the requirement for the award of the degree of**

**BACHELOR OF TECHNOLOGY**

**IN**

**COMPUTER SCIENCE & ENGINEERING**

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**Dehradun, Uttarakhand**

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**CANDIDATE’S DECLARATION**

I hereby certify that the work which is being presented in the project report entitled **“Title of the project”** in partial fulfillment of the requirements for the award of the Degree of

Bachelor of Technology in Computer Science and Engineering of the Graphic Era (Deemed to be University), Dehradun shall be carried out by the under the mentorship of **Mr. Mohd. Rehan Ghazi**, Department of Computer Science and Engineering, Graphic Era (Deemed tobe University), Dehradun.

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**Chapter 1**

**Introduction**

**1.1 Background**

The advent of the internet and the rise of social media platforms have dramatically transformed how information is disseminated and consumed. While these developments have facilitated rapid information sharing, they have also enabled the spread of misinformation and fake news. Fake news is defined as false or misleading information presented as news, often with the intent to deceive. This phenomenon has far-reaching implications, affecting political landscapes, public opinion, and social stability.

The 2016 US presidential election and the COVID-19 pandemic are notable examples where fake news has had significant impacts. In the former, fake news was used to manipulate voter perceptions, while in the latter, misinformation about the virus, treatments, and vaccines led to public confusion and health risks. Given these concerns, the need for effective fake news detection systems has become increasingly urgent.

**1.2 Objectives**

The primary objective of this project is to develop a machine learning model capable of accurately classifying news articles as real or fake. The specific goals are:

1. Utilize textual data from news articles, including titles and author names, for classification.
2. Implement and compare the performance of Logistic Regression and Naive Bayes models.
3. Evaluate the models using accuracy, precision, and F1 score metrics to determine their effectiveness.
4. Provide insights into the strengths and limitations of each model.

**1.3 Scope**

This project focuses on implementing and evaluating two machine learning algorithms for fake news detection using a dataset obtained from Kaggle. The dataset comprises 20,800 news articles labeled as real or fake. The scope includes data preprocessing, feature extraction, model training, evaluation, and comparison. The models are evaluated on their ability to classify news articles based on the provided textual data.

**Chapter 2**

**Literature Survey**

### 2.1 Overview of Fake News Detection

Fake news detection is an interdisciplinary field that combines natural language processing (NLP), machine learning, and information retrieval. Researchers have explored various approaches to tackle this problem, ranging from linguistic analysis to network-based methods. These approaches can be broadly categorized into content-based and context-based methods.

### 2.2 Related Work

#### 2.2.1 Text Classification

Text classification involves converting textual data into a format that machine learning models can process. Techniques such as Term Frequency-Inverse Document Frequency (TF-IDF) and word embeddings (e.g., Word2Vec, GloVe) are commonly used for feature extraction. TF-IDF captures the importance of words in a document relative to a corpus, while word embeddings provide dense vector representations of words, capturing semantic relationships.

#### 2.2.2 Machine Learning Algorithms

Several machine learning algorithms have been applied to fake news detection:

* **Naive Bayes**: A probabilistic classifier based on Bayes' Theorem, assuming feature independence. It is known for its simplicity and efficiency.
* **Logistic Regression**: A discriminative model that predicts the probability of a binary outcome. It is widely used for binary classification problems due to its robustness.
* **Support Vector Machines (SVM)**: A powerful classifier that finds the optimal hyperplane separating different classes. It is effective in high-dimensional spaces.
* **Neural Networks**: Deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown promising results in text classification tasks.

#### 2.2.3 Performance Metrics

Evaluating the performance of fake news detection models requires appropriate metrics:

* **Accuracy**: The ratio of correctly predicted instances to the total instances. It provides an overall measure of the model's performance.
* **Precision**: The ratio of correctly predicted positive instances to the total predicted positive instances. It indicates the model's ability to avoid false positives.
* **Recall**: The ratio of correctly predicted positive instances to the total actual positive instances. It measures the model's ability to capture true positives.
* **F1 Score**: The harmonic mean of precision and recall. It provides a balanced measure of the model's performance, particularly useful in the presence of class imbalances.

**Chapter 3**

**Methodology**

### 3.1 Data Collection

The dataset used in this project is sourced from Kaggle and consists of 20,800 news articles labeled as real or fake. Each entry includes the title and author of the news article. The dataset is well-suited for binary classification tasks and provides a sufficient volume of data for training and evaluating machine learning models.

### 3.2 Data Preprocessing

#### 3.2.1 Handling Missing Values

Missing values in the dataset are handled by replacing them with empty strings. This ensures that the data is complete and can be processed without errors.

#### 3.2.2 Text Cleaning

The text data is cleaned by:

* Removing non-alphabetic characters to eliminate noise.
* Converting text to lowercase to standardize the data.
* Removing stopwords (common words that do not contribute to the meaning of the text) to reduce dimensionality.

#### 3.2.3 Stemming

Stemming involves reducing words to their root forms using the Porter Stemmer algorithm. For example, "running," "runner," and "ran" are reduced to "run." This helps in consolidating different forms of the same word, improving the consistency of the data.

#### 3.2.4 Feature Engineering

The author and title of each news article are merged to form a single feature for classification. This combines the available information, potentially enhancing the model's ability to distinguish between real and fake news.

### 3.3 Model Implementation

#### 3.3.1 Logistic Regression

Logistic Regression is a discriminative model that uses a logistic function to predict the probability of a news article being real or fake. It is chosen for its effectiveness in binary classification problems. The model is implemented using the following steps:

1. **Feature Extraction**: Convert the textual data into numerical representations using TF-IDF.
2. **Model Training**: Train the Logistic Regression model on the training data.
3. **Model Evaluation**: Evaluate the model using accuracy, precision, and F1 score metrics.

#### 3.3.2 Naive Bayes

Naive Bayes is a generative model that applies Bayes' Theorem with the assumption of feature independence. It is known for its simplicity and efficiency. The model is implemented using the following steps:

1. **Feature Extraction**: Convert the textual data into numerical representations using TF-IDF.
2. **Model Training**: Train the Naive Bayes model on the training data.
3. **Model Evaluation**: Evaluate the model using accuracy, precision, and F1 score metrics.

### 3.4 Evaluation Metrics

The models are evaluated using the following metrics:

* **Accuracy**: Measures the overall correctness of the model's predictions.
* **Precision**: Indicates the proportion of positive predictions that are actually positive.
* **F1 Score**: Provides a balanced measure of the model's performance by combining precision and recall.

**Chapter 4**

**Result and Discussion**

**4.1 Model Performance**

The performance of both models is compared based on the evaluation metrics.

* **Logistic Regression**:
  + Accuracy: 0.9766
  + Precision: 0.9694
  + F1 Score: 0.9767
* **Naive Bayes**:
  + Accuracy: 0.9591
  + Precision: 0.9959
  + F1 Score: 0.9594

**4.2 Discussion**

The Logistic Regression model outperforms the Naive Bayes model in terms of accuracy and F1 score, indicating that it is more effective in classifying news articles accurately. However, the Naive Bayes model demonstrates higher precision, suggesting it has fewer false positives. This difference can be attributed to the inherent characteristics of the algorithms:

* **Logistic Regression**: Handles correlated features well and can capture complex relationships in the data. It uses a sigmoid function to model the probability of the binary outcome and can adapt to different data distributions.
* **Naive Bayes**: Assumes feature independence, which might not hold true in real-world data, leading to lower accuracy but higher precision. It is computationally efficient and can handle large datasets with ease.

**4.3 Interpretation**

* **Logistic Regression** is better suited for this task due to its ability to handle correlated features and capture complex relationships in the data. It provides a robust and reliable solution for fake news detection.
* **Naive Bayes** is computationally efficient and performs well in scenarios where the feature independence assumption holds. It is also less likely to produce false positives, making it a good choice when precision is crucial.

**4.4 Error Analysis**

An analysis of the misclassified instances reveals that:

* **Logistic Regression**: Some misclassifications occur in articles with ambiguous or sensational titles that do not clearly indicate the veracity of the news. The model may also struggle with titles that are grammatically correct but semantically misleading.
* **Naive Bayes**: Misclassifications are more frequent in articles where the independence assumption of features is violated. For example, certain combinations of words that are strongly indicative of fake news might not be captured effectively due to the feature independence assumption.

**4.5 Insights and Recommendations**

Based on the performance and error analysis, the following insights and recommendations can be made:

* **Feature Enhancement**: Incorporating additional features such as the full text of the article, source credibility, and publication date could improve the model's performance.
* **Hybrid Models**: Combining the strengths of different models, such as Logistic Regression and Naive Bayes, could lead to better performance. Ensemble methods like Random Forest or Gradient Boosting could be explored.
* **Domain Adaptation**: Testing the models on cross-domain datasets could help in building more generalizable models that perform well across different types of news sources.

**Chapter 5**

**Conclusion and Future Work**

### 5.1 Conclusion

The project successfully implemented and compared two machine learning models for fake news detection. Logistic Regression proved to be more accurate and reliable in classifying news articles as real or fake, while Naive Bayes showed higher precision. The results highlight the importance of choosing the right model based on the specific requirements of the task.

### 5.2 Future Work

Future work could explore the following directions:

* **Incorporate More Features**: Use the full text of the articles for a more comprehensive analysis. Additional features such as publication date, source credibility, and social media engagement could also be considered.
* **Advanced Models**: Experiment with more advanced models like Support Vector Machines, Random Forests, or Neural Networks. Deep learning models such as LSTM or BERT could also be explored for better performance.
* **Real-Time Detection**: Develop a system that can process and classify news articles in real-time, enabling immediate detection of fake news.
* **Robustness**: Test the models on a more diverse dataset to ensure robustness across different types of news sources. Incorporating cross-domain datasets could help in building more generalizable models.
* **Explainability**: Enhance the explainability of the models by identifying key features and patterns that contribute to the classification decision. This can help in building trust and transparency in the system.
* **User Interface**: Developing a user-friendly interface that allows users to input news articles and receive immediate feedback on their authenticity. This can increase the accessibility and usability of the system for a broader audience.
* **Integration with Fact-Checking Organizations**: Collaborating with fact-checking organizations to validate the model's predictions and improve its accuracy. This can also help in continuously updating the model with new data and patterns.
* **Ethical Considerations**: Addressing ethical considerations related to automated fake news detection, such as potential biases in the data and ensuring that the system respects user privacy.

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