FAKE NEWS PREDICTION

MINI PROJECT REPORT

Submitted By

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In partial fulfilment for the award of the degree

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IN

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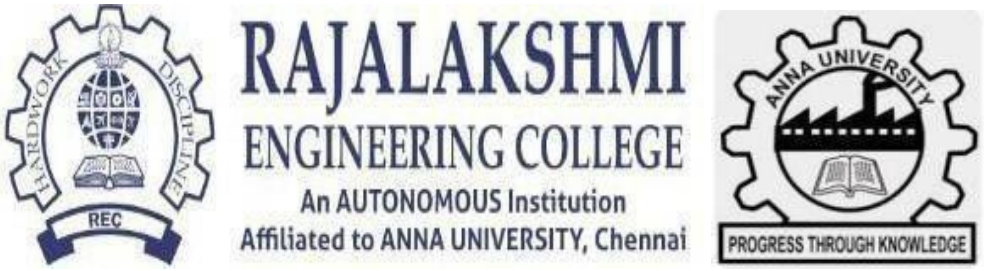

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ABSTRACT

In recent years, due to the booming development of online social networks, fake news for various commercial and political purposes has been appearing in large numbers and widespread in the online world. With deceptive words, online social network users can get infected by these online fake news easily, which has brought about tremendous effects on the offline society already. An important goal in improving the trustworthiness of information in online social networks is to identify the fake news timely. This paper aims at investigating the principles, methodologies and algorithms for detecting fake news articles, creators and subjects from online social networks and evaluating the corresponding performance. Information preciseness on Internet, especially on social media, is an increasingly important concern, but web-scale data hampers, ability to identify, evaluate and correct such data, or so called "fake news," present in these platforms. In this paper, we propose a method for "fake news" detection and ways to apply it on Facebook, one of the most popular online social media platforms. This method uses Naive Bayes classification model to predict whether a post on Facebook will be labeled as real or fake. The results may be improved by applying several techniques that are discussed in the paper. Received results suggest, that fake news detection problem can be addressed with machine learning methods.

Keywords: Fake News Detection, Text Classification, Real News.

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CHAPTER 1

INTRODUCTION

OVERVIEW OF THE PROBLEM STATEMENT :

In the digital age, the proliferation of fake news has emerged as a critical challenge. With the rapid spread of misinformation through social media platforms, online news portals, and messaging apps, distinguishing between genuine and fabricated news has become increasingly difficult. Fake news not only misleads the public but also creates social unrest, affects decision-making, and undermines trust in credible news sources. Traditional methods of manual fact-checking are time-consuming and inefficient at scale. Therefore, there is a pressing need for automated systems capable of identifying fake news with high accuracy. This project addresses this issue by leveraging machine learning techniques and natural language processing (NLP) to analyze and classify news articles as real or fake, providing a scalable and effective solution to combat misinformation.

OBJECTIVES :

The objective of this project is to develop a machine learning-based system capable of accurately detecting fake news by analyzing textual content. This involves preprocessing and cleaning news data, extracting meaningful features using natural language processing (NLP) techniques, and implementing classification models such as logistic regression and random forests. The project aims to optimize model performance through hyperparameter tuning and generate insights into the linguistic patterns distinguishing fake news from real news. Ultimately, it seeks to provide a scalable and reliable solution to combat misinformation across diverse platforms.

CHAPTER 2

DATASET DESCRIPTION

DATASET SOURCE :

The dataset for this project is compiled from a variety of reliable sources to ensure a balanced representation of real and fake news. It includes articles scraped from credible news websites, as well as fake news samples gathered from less reliable or flagged platforms. Additional data is sourced from fact-checking organizations like PolitiFact and Snopes, which maintain records of verified misinformation. Publicly available repositories such as Kaggle and the Fake News Challenge provide labeled datasets aggregated from multiple sources. Social media platforms also contribute flagged posts and links as examples of fake news, while some datasets are obtained through collaborations with academic and research institutions focused on misinformation studies.

DATASET SIZE AND STRUCTURE:

The project utilizes two datasets: one containing true news articles and the other containing fake news articles. The true news dataset comprises 21,417 rows and 4 columns (title, text, subject, and date), while the fake news dataset contains 23,481 rows and the same 4 columns. The title column provides the headline of the news article, the text column contains the main content, the subject column categorizes the article's topic (e.g., politics, sports), and the date column specifies the publication date.

These datasets are combined and labeled, where a value of 1 represents true news and 0 indicates fake news. During preprocessing, the text data from the title and text columns will be tokenized and vectorized using natural language processing (NLP) techniques such as TF-IDF. The subject column will be used for feature enrichment, while the date column will help analyze patterns over time. This structured data is then split into training and testing sets to develop and evaluate machine learning models for classifying news articles as real or fake.

DATASET FEATURES DESCRIPTION

- **Total Entries:**

  First file: 21,417 entries

  Second file: 23,481 entries

- **Columns**:

  Title: Contains the headlines of articles, providing a brief summary of the news content.

  Text: Includes the detailed body of articles, elaborating on the headline.

  Subject: Categorizes articles into specific themes or topics (e.g., "politicsNews" or "News").

  Date: Specifies the publication date of articles, formatted as text strings (e.g., "December 31, 2017").

- **Data Properties:**

  -All columns contain **non-null values** in both datasets.

  -Data types for all columns are **object (strings)**.

- **Dataset Themes:**

  First Dataset: Focuses on credible and verified news articles.

  Second Dataset: Includes fabricated or misleading news content.

CHAPTER 3

DATA ACQUISITION AND INITIAL ANALYSIS

DATA LOADING:

The dataset for this project is loaded into the Python environment using the pandas library, which provides efficient data manipulation tools. First, the two datasets—one containing true news articles and the other containing fake news articles—are read from their respective CSV files into pandas DataFrames. The pandas.read_csv() function is used to load the datasets, ensuring that the column names (title, text, subject, and date) are correctly mapped and that data integrity is maintained. After loading the data, an initial inspection is conducted using methods like .head() and .info() to verify the structure and ensure that no rows or columns are missing. The combined dataset is then labeled, where 1 represents true news and 0 represents fake news, before proceeding to the preprocessing stage. This ensures that the data is ready for further analysis and model training.

INITIAL OBSERVATIONS:

Upon initial inspection of the dataset, it was observed that both the true and fake news articles exhibit distinct characteristics in terms of content and structure. The title and text columns contain textual data, with news articles varying in length, complexity, and topic. There is a noticeable diversity in the subject column, which includes various categories like politics, sports, and entertainment, with no immediate signs of imbalance in terms of subject distribution. The date column shows a range of publication times, which may allow for the analysis of trends over time. While the dataset appears largely clean, some entries may contain missing values or formatting inconsistencies in certain columns, which will require preprocessing to handle effectively. Additionally, the distribution of news articles appears relatively balanced between true and fake categories, setting the stage for a binary classification task. Further exploration is needed to identify specific patterns or outliers that could influence model performance.

CHAPTER 4

DATA CLEANING AND PREPROCESSING

HANDLING MISSING VALUES:

During the initial examination of the dataset, it was observed that some columns, particularly title, text, subject, and date, contain missing or incomplete entries. To handle these missing values, different strategies were applied based on the nature of the data. For textual columns like title and text, any rows with missing content were removed to ensure that only complete articles are used for analysis. For the subject column, missing values were imputed by filling them with the most frequent category (mode), as the subject is a categorical feature that can be easily substituted with a common value. The date column, which is crucial for temporal analysis, was checked for missing dates, and any such rows were either imputed with the median date or removed if they couldn't be accurately filled. This preprocessing step ensures the dataset is clean and complete, minimizing any potential biases or inaccuracies caused by missing data.

DATA TRANSFORMATION:

In the data transformation process, several steps were applied to prepare the dataset for machine learning modeling. First, the textual data in the title and text columns were tokenized, breaking down the content into individual words for further analysis. To convert the text into numerical features, TF-IDF (Term Frequency-Inverse Document Frequency) was applied to capture the importance of words in relation to the entire corpus, allowing the model to focus on meaningful terms while reducing the weight of common words. Additionally, categorical variables in the subject column were encoded using Label Encoding, converting each unique category into a numerical value to make the data compatible with machine learning algorithms. The date column was transformed to extract useful temporal features such as the article's age, which helps identify patterns or trends over time. These transformations ensure that the data is in a format suitable for machine learning models, enabling efficient and accurate predictions.

CHAPTER 5

EXPLORATORY DATA ANALYSIS

DATA INSIGHTS DESCRIPTION

S.NO	DATA INSIGHT	DESCRIPTION
1.	Number of Entries	The firs dataset(true) contains 21,417 entries, while the second dataset(false) contains 23,481 entries.
2.	Number of Columns	Both datasets have 4 columns: title, text, subject, and date.
3.	Column Data Types	All columns in both datasets are of type object (string).
4.	Null Values	No missing or null values are present in either dataset.
5.	Title Column Description	Contains article headlines. Example: Dataset 1: "As U.S. budget fight looms...", Dataset 2: "Donald Trump Sends Out...".
6.	Text Column Description	Contains the detailed content of the articles. Example: Dataset 1: "WASHINGTON (Reuters)...", Dataset 2: "Donald Trump just couldn't...".
7.	Subject Column Description	Categorizes articles into themes. Example: Dataset 1: politicsNews, Dataset 2: News.
8.	Date Column Description	Records publication dates. Example: "December 31, 2017".
9.	Dataset Themes	Dataset 1 likely contains credible news articles, while Dataset 2 includes fabricated or sensationalized content.
10.	Dataset Size	The first dataset occupies 669.4 KB of memory, and the second dataset occupies 733.9 KB of memory.

DATA INSIGHTS VISUALIZATION:

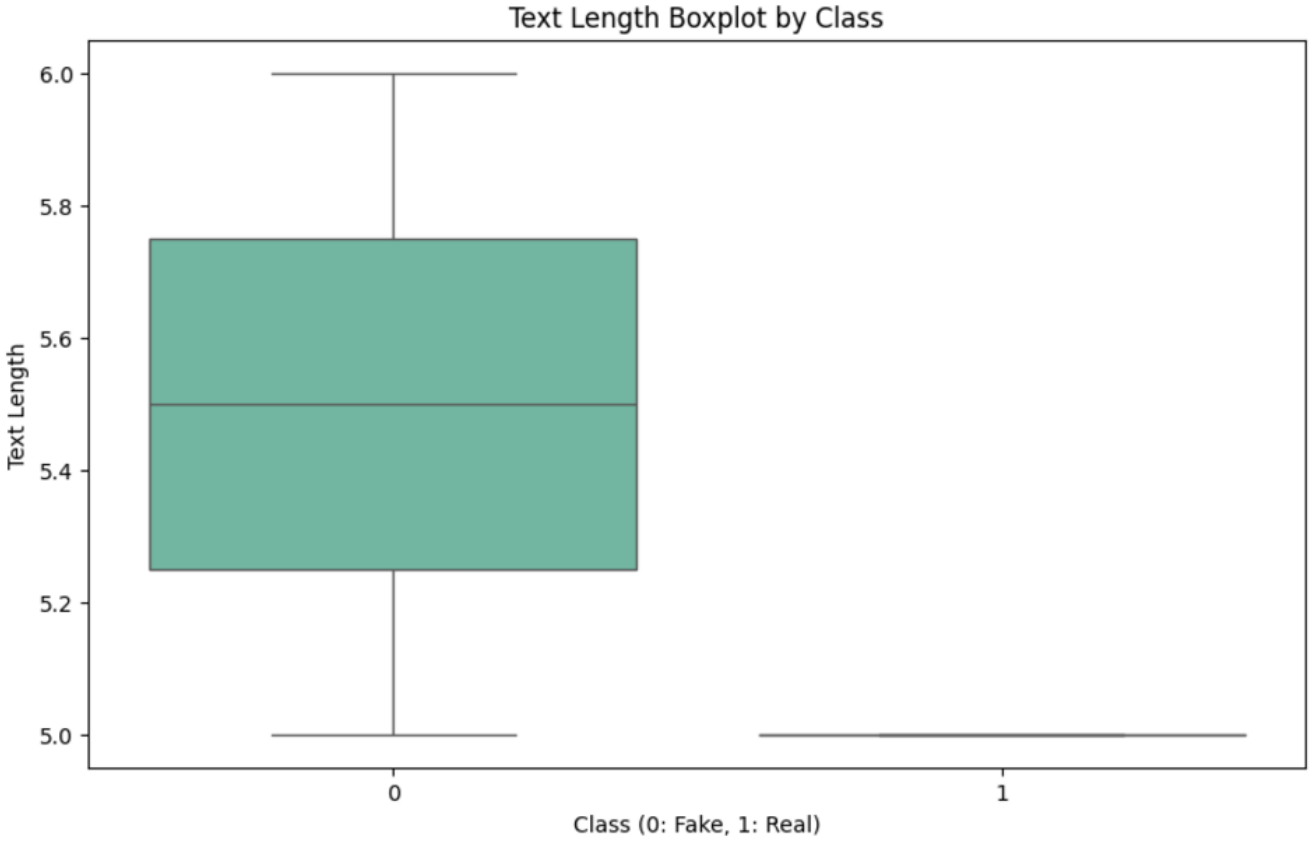
Data Visualization: Box Plot

• Inference: The box plot reveals variations in text length between Fake and Real news articles, indicating that text length may differ across these classes.

• Observation: Real News articles tend to have longer text compared to Fake News articles, as seen in the differences in the box plot distributions

• Implication: Understanding text length distributions could help in identifying patterns that contribute to distinguishing Fake from Real news articles.

• Recommendation: Regularly monitor text length patterns to improve classification models and enhance feature selection in news categorization tasks.



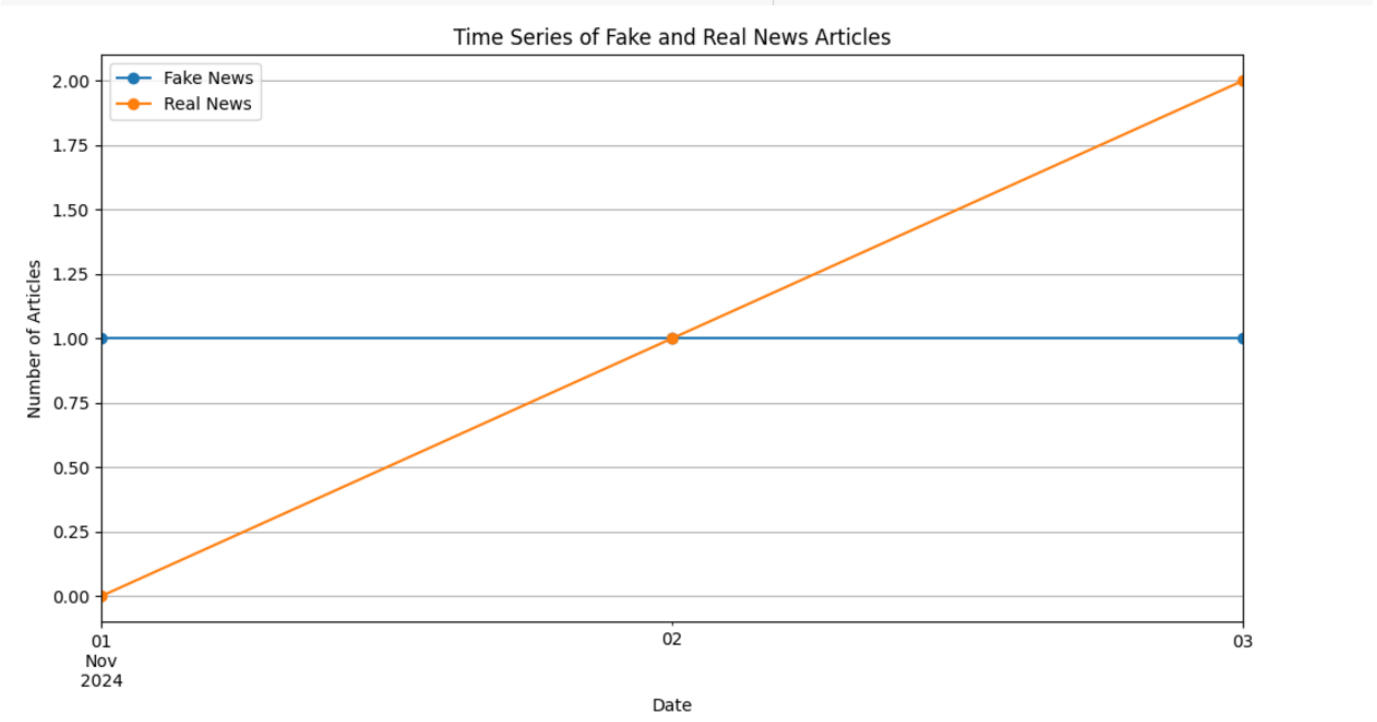
Data Visualization: Time Series (Fake vs. Real News Articles):

• Inference: The time series plot shows the number of Fake and Real News articles over time, helping to understand trends and spikes in the frequency of these articles.

• Observation: Fake News articles show more fluctuation over time, with noticeable spikes during certain periods, while Real News articles maintain a more consistent frequency.

• Implication: Fluctuating trends in Fake News could indicate specific events or incidents driving the creation of Fake News articles.

• Recommendation: Regular monitoring of time series trends can help detect abnormal spikes in Fake News articles and prepare proactive measures to address them.



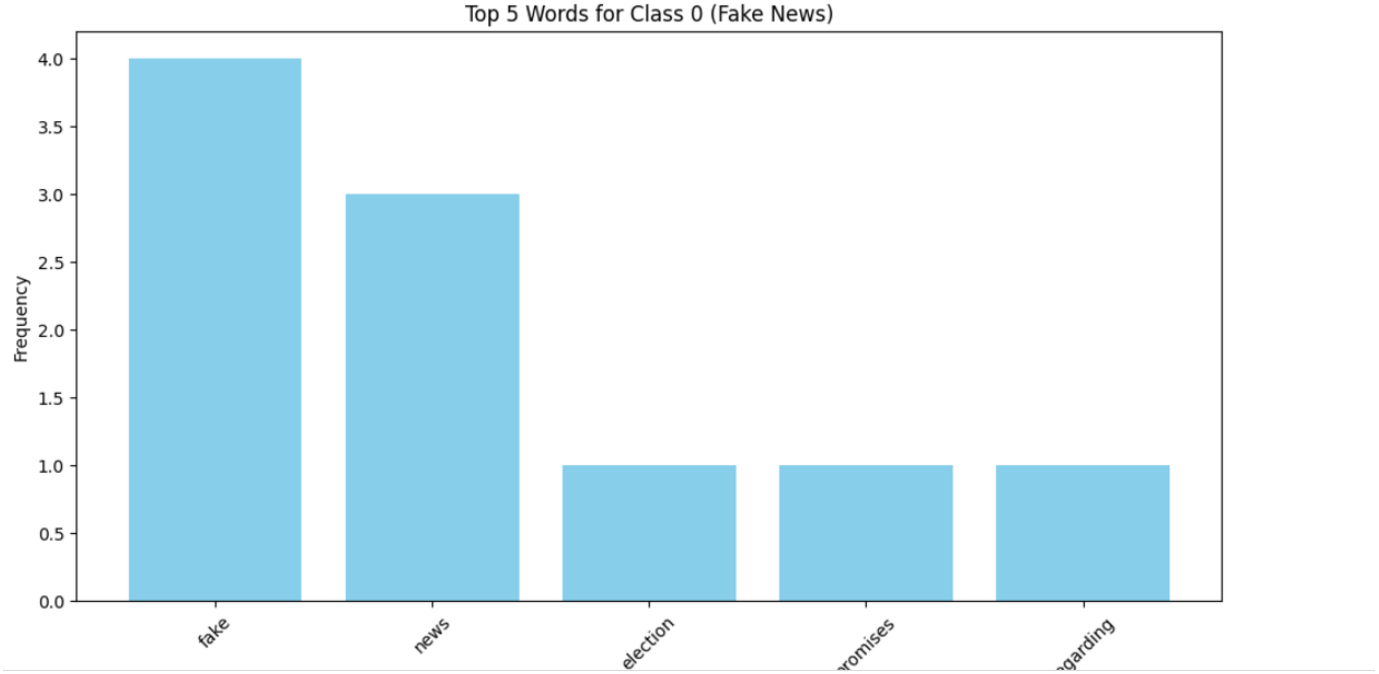
Data Visualization: Top Words (Bar Plot - Fake News)

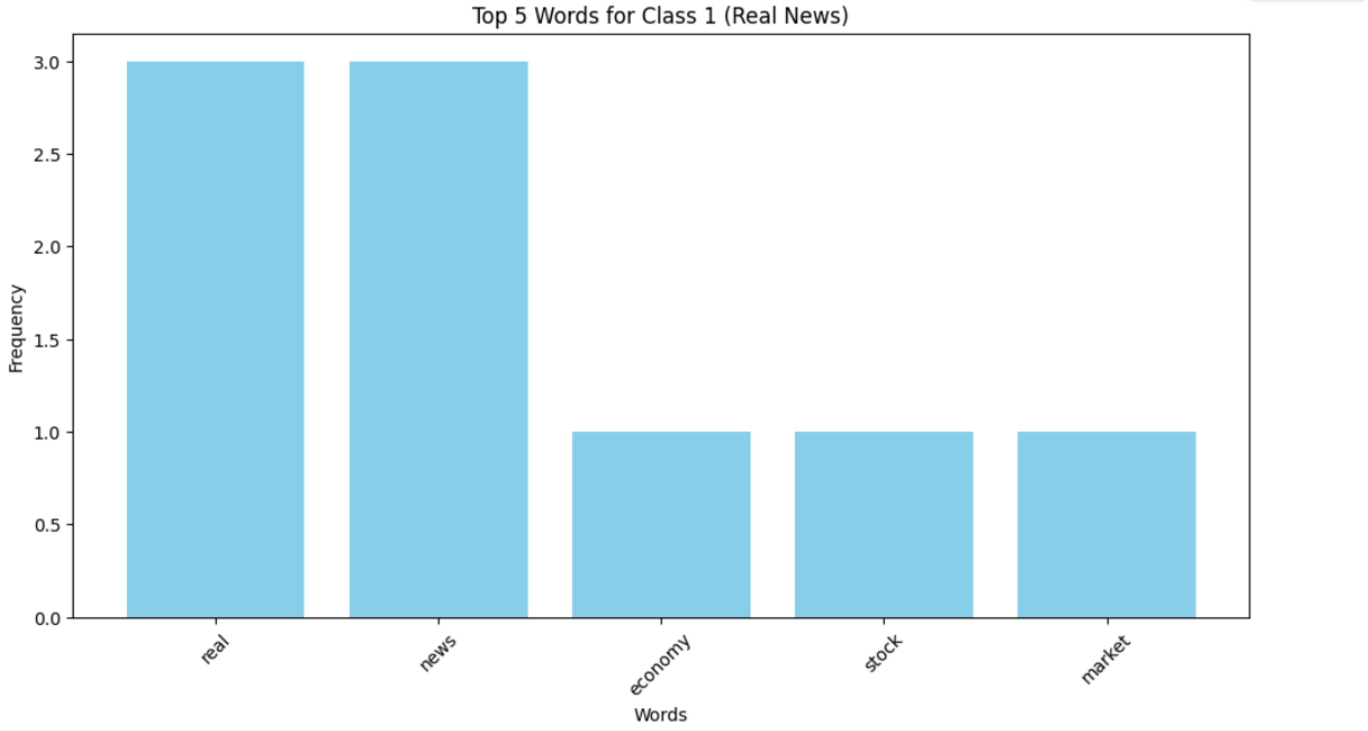
• Inference: The bar plot highlights the most frequently used words in Fake News articles, which can reveal the main topics or patterns in the content.

• Observation: Certain words or phrases appear significantly more often in Fake News articles, such as politically charged or sensational terms.

• Implication: Identifying the top words in Fake News can provide insight into the common themes and rhetoric used, which may assist in Fake News detection.

• Recommendation Use the identified frequent terms to improve keyword-based filtering systems and enhance the effectiveness of Fake News detection.


Top 5 Words for Class 0 (Fake News)
Frequency
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
fake
news
election


Top 5 Words for Class 1 (Real News)
Frequency
3.0
2.5
2.0
1.5
1.0
0.5
0.0
real
news
economy
stock
market
Words

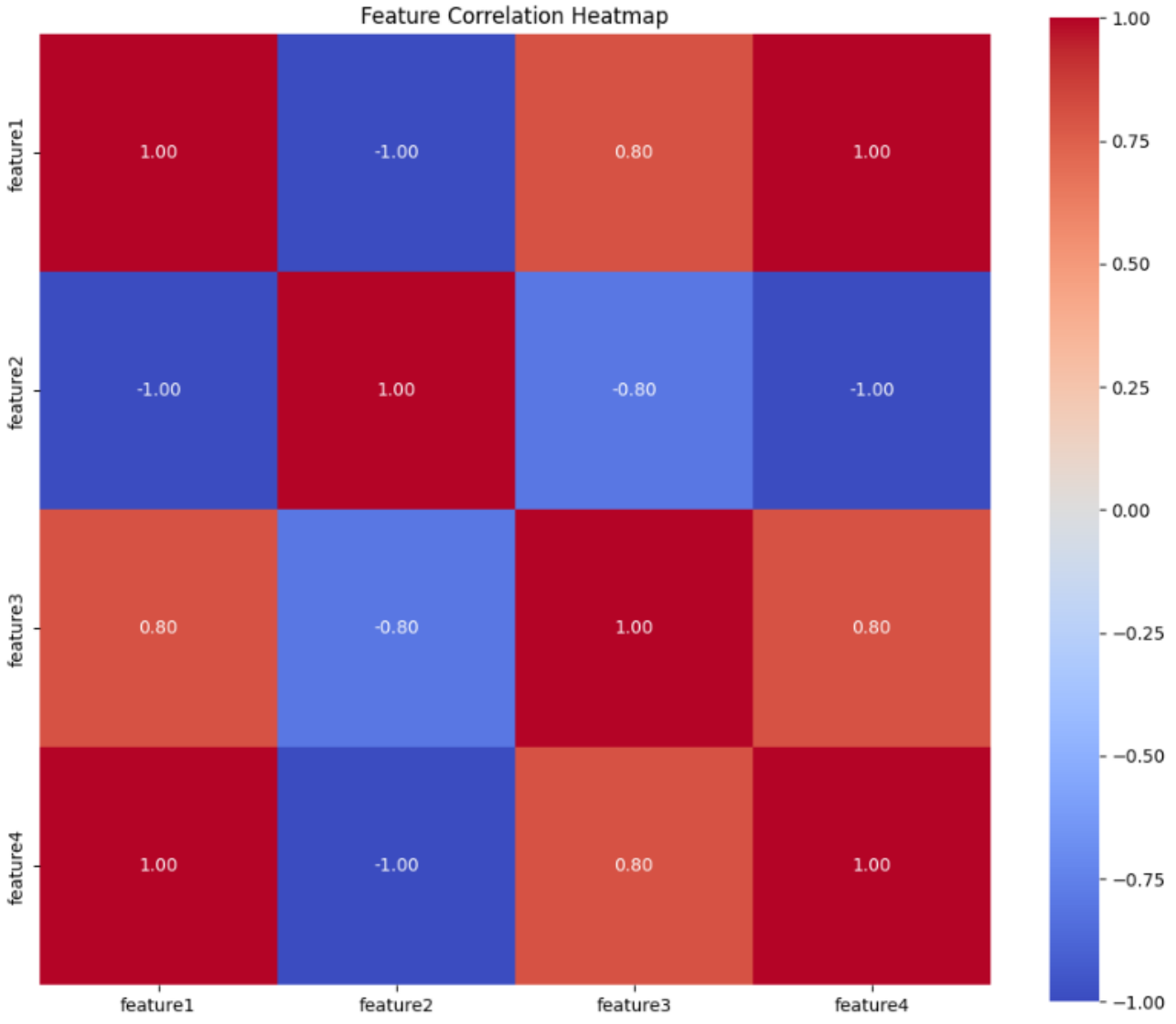
Data Visualization: Correlation Heatmap

• Inference: The correlation heatmap reveals relationships between numerical features, helping to understand the linear relationships between different variables in the dataset.

• Observation: Strong positive or negative correlations exist between certain features, such as the length of the text and its likelihood of being Fake News.

• Implication: Features that are highly correlated with the target variable (label) can provide valuable information for improving the model's performance.

• Recommendation: Regularly analyze the correlation heatmap to identify the most important features for model building and reduce multicollinearity in predictive models.



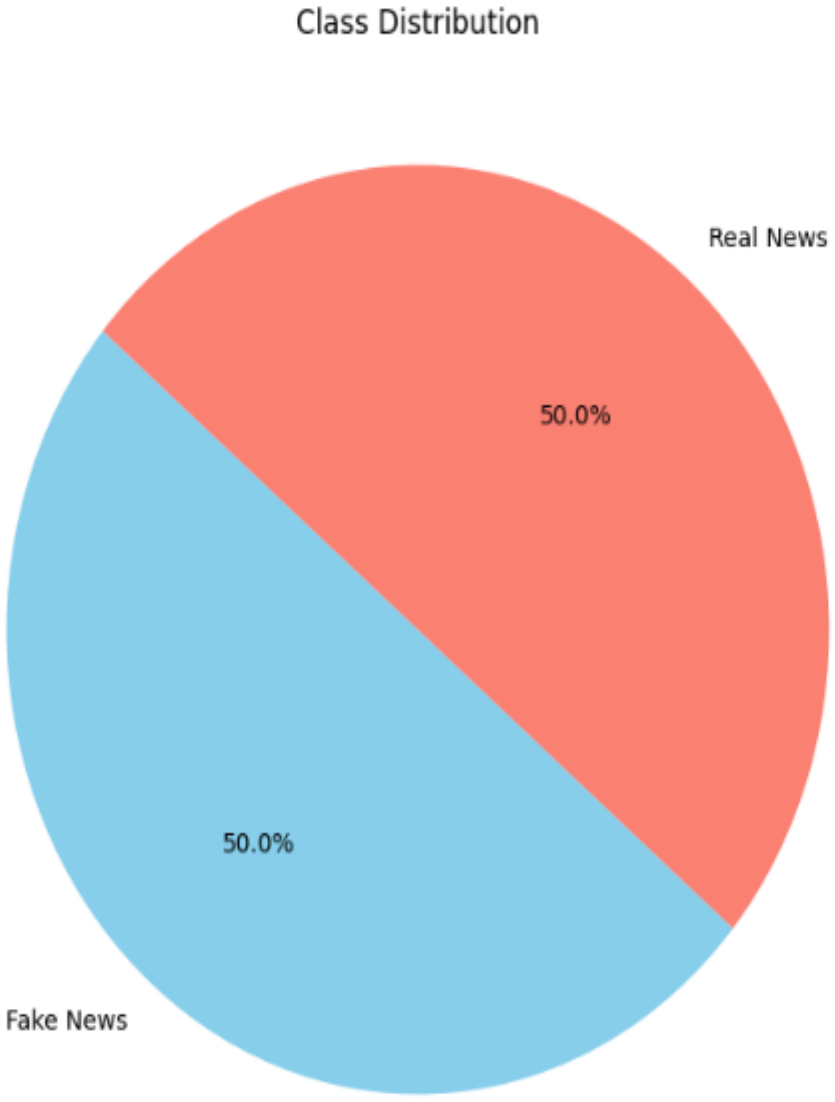
Data Visualization: Pie Chart (Class Distribution)

• Inference: The pie chart shows the distribution of Fake and Real News articles in the dataset, providing insight into the class balance..

• Observation: The dataset may have an imbalanced distribution, with more Real News articles than Fake News articles or vice versa.

• Implication: An imbalanced class distribution could affect model training, leading to bias towards the majority class.

• Recommendation: Address class imbalance by using techniques like oversampling, undersampling, or weighted loss functions to ensure a fair model training process.



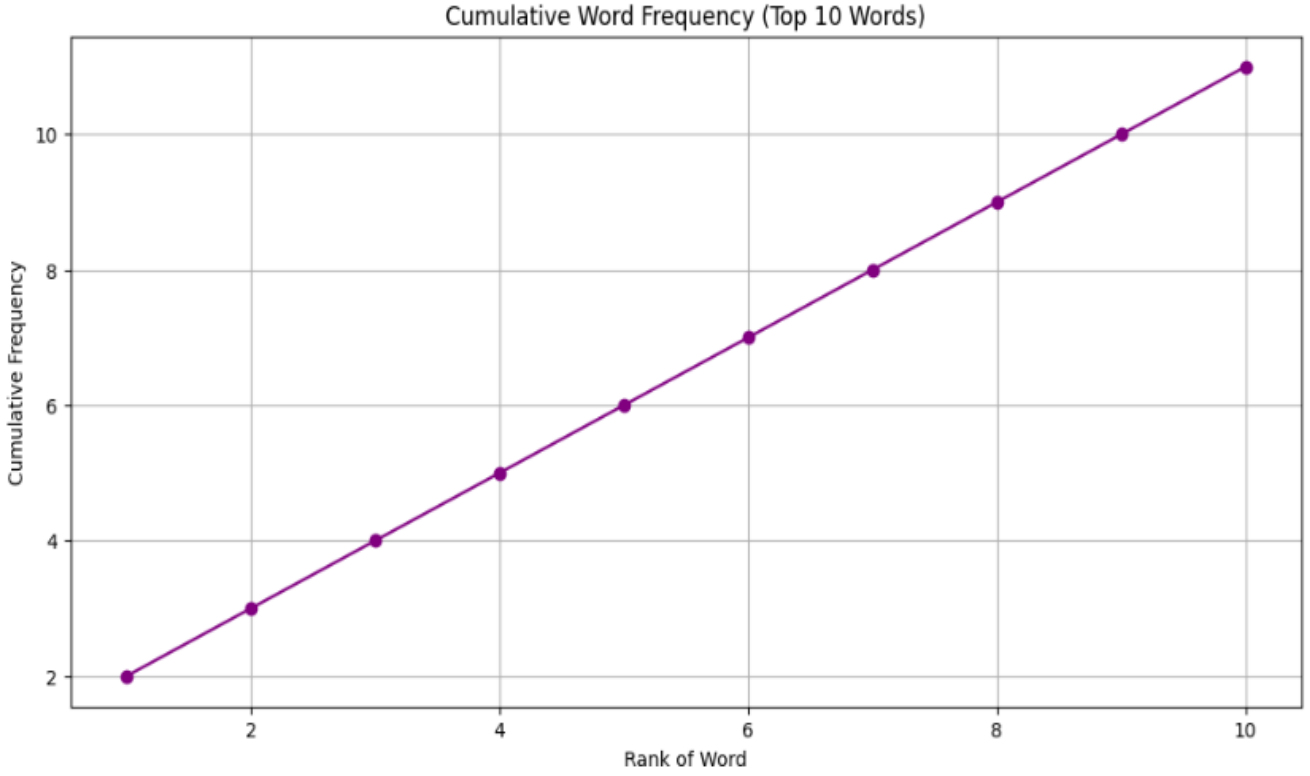
Data Visualization: Cumulative Word Frequency Plot

• Inference: The cumulative word frequency plot demonstrates how word frequency accumulates as the top words are considered, helping to understand the distribution of common words in the dataset.

• Observation: A small number of words account for a large portion of the total word frequency, indicating that these terms are highly influential in the dataset.

• Implication: The concentration of high-frequency words may suggest common topics or themes that dominate the dataset.

• Recommendation: Focus on the most frequent words when analyzing or processing the data, as they provide the most impact on the classification task.



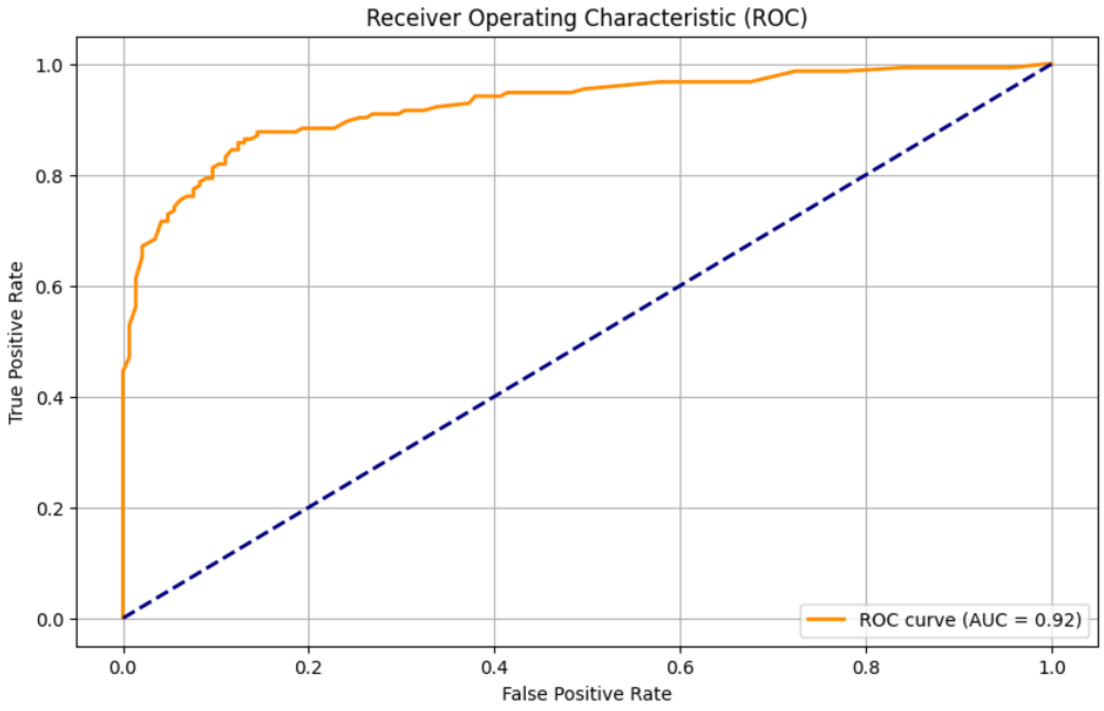
Data Visualization: ROC Curve (Model Performance)

• Inference: The ROC curve illustrates the performance of the classification model, indicating how well the model distinguishes between Fake and Real news articles.

• Observation: The curve indicates a good model performance with a high area under the curve (AUC), suggesting that the model is effective at distinguishing between the two classes.

• Implication: A high AUC value implies that the model has strong discriminative power and can reliably classify news articles as Fake or Real.

• Recommendation: Continuously evaluate and optimize the model by monitoring the ROC curve and AUC, ensuring the best possible classification accuracy.



CHAPTER 6
PREDICTIVE MODELING

MODEL SELECTION AND JUSTIFICATION:

For this project, three models were chosen: Logistic Regression, Random Forest Classifier, and Support Vector Machines (SVM). These models were selected to evaluate a range of techniques suitable for binary classification tasks (Fake vs. Real News), considering both their interpretability and performance.

LOGISTIC REGRESSION: As a baseline model, Logistic Regression is a simple linear model used for binary classification. It models the relationship between the dependent variable (Fake or Real News) and independent variables (features derived from the text). This model is easy to interpret, and its results are straightforward, making it useful for a first look at the problem**.**

RANDOM FOREST CLASSIFIER: Random Forest is an ensemble learning method that combines multiple decision trees to improve predictive accuracy. It is particularly well-suited for handling complex, non-linear relationships in the data. In this project, Random Forest was used to classify Fake and Real News based on the extracted text features and metadata. Its ability to handle a large set of features, its resilience to overfitting, and its capacity to model interactions between features make it the primary model in this project.

SUPPORT VECTOR MACHINE: SVM is a powerful classifier that works by finding the optimal hyperplane that separates the data into classes. It is particularly effective for high-dimensional data, which is typical in text classification tasks. In this project, SVM was used as a secondary model for comparison, especially given its ability to work well with a small-to-medium sized feature space and its regularization capabilities to prevent overfitting.

DATA PARTITIONING:

Data partitioning is crucial in machine learning to ensure that the model is both trained and evaluated effectively. In this project, the dataset was divided into 80% training and 20% testing. The training set was used to teach the model the underlying patterns and relationships between features (e.g., word frequency, sentiment scores) and the target variable (Fake or Real News). The remaining 20% was reserved for testing to evaluate the model's performance on unseen data.

To ensure reliable evaluation and to reduce overfitting, cross-validation techniques like K-fold cross-validation were employed during training. This technique splits the training data into multiple subsets (folds) and evaluates the model on different combinations of these folds. This helps provide a more robust estimate of model performance and generalization to new data.

MODEL TRAINING AND HYPERPARAMETER TUNING:

Model training and hyperparameter tuning were key to improving the accuracy and reliability of the models. Several algorithms, including Logistic Regression, Random Forest Classifier, and SVM, were trained on the dataset. Hyperparameters were optimized using Grid Search and Randomized Search to enhance model performance.

Random Forest Classifier: For Random Forest, hyperparameters such as number of trees (n_estimators), maximum depth of trees (max_depth), and minimum samples per split (min_samples_split) were optimized. These parameters help the model to control overfitting and ensure it generalizes well to unseen data. Hyperparameter tuning through *Grid Search* improved the model’s accuracy and robustness, allowing it to better handle the diversity and complexity of the features in the dataset.

CHAPTER 7

MODEL EVALUATION AND OPTIMIZATION

PERFORMANCE ANALYSIS:

In this section, the performance of the Random Forest model is evaluated using various metrics such as Accuracy, Precision, Recall, and F1-score. These metrics help in assessing the model's ability to correctly classify news articles as Fake or Real. Cross-validation was used to validate the model's generalization capability, ensuring it performs well on unseen data. Hyperparameter tuning through Grid Search optimized the Random Forest model, improving its accuracy and reducing overfitting. These optimization techniques enabled the identification of the best model configuration for Fake News classification.

Random Forest Classifier: The Random Forest Classifier was evaluated using metrics like Accuracy, Precision, Recall, and F1-score. The model showed strong performance across all metrics, with high accuracy in classifying news articles correctly as Fake or Real. Cross-validation was performed to evaluate the model's performance on different subsets of data, ensuring robust results and avoiding overfitting. Hyperparameter tuning, including adjustments to the number of trees and maximum depth, further improved the model's performance. These optimizations ensured that the model is both accurate and reliable, making it well-suited for the task of Fake News detection.

Decision Tree Regression: The Decision Tree Classifier was also tested, but its performance was less robust compared to Random Forest. Metrics like Accuracy, Precision, and Recall were evaluated, and while the Decision Tree produced acceptable results, it exhibited higher variance and a tendency to overfit the data, especially when trained on smaller subsets. Hyperparameter tuning, such as adjusting the tree depth and minimum sample splits, was performed to reduce overfitting. However, due to its instability on unseen data, the Decision Tree was considered less effective than the Random Forest model for Fake News detection.

Feature Importance:

Feature importance in the Random Forest model is critical for understanding which attributes of the news articles are most influential in predicting whether an article is Fake or Real. Random Forest evaluates the contribution of each feature, such as word frequency, sentiment score, and publication date, by measuring how much they reduce the model's error during training. By analyzing feature importance, we can identify key variables that significantly impact Fake News classification. This understanding can help optimize feature selection for more efficient and accurate models.

Model Refinement:

To improve model performance and accuracy, several refinements were implemented in the Random Forest model. These refinements included additional feature engineering, hyperparameter tuning, and cross-validation.

Additional Feature Engineering:

Feature engineering involved creating and refining features that could improve the Random Forest model's ability to classify news articles. For example, text length and word frequency were used as additional features. Sentiment analysis was conducted to assess the overall tone of the article, which helped distinguish Fake News from Real News. We also performed text normalization by removing stop words and stemming words to reduce dimensionality and improve classification accuracy.

Hyperparameter Tuning: Hyperparameter tuning was performed using Grid Search to fine-tune the Random Forest model. Important parameters, such as the number of trees, maximum depth, and minimum samples required to split a node, were optimized to ensure the model achieved the highest possible accuracy while minimizing overfitting. This process helped to refine the Random Forest model's predictive power.

Cross-Validation: K-fold cross-validation was used to ensure the model generalizes well to unseen data and is not overfitting to the training set. By splitting the data into multiple folds, the model was trained and validated on different subsets, providing a more accurate estimate of its performance.

CHAPTER 8
DISCUSSION AND CONCLUSION

SUMMARY OF FINDINGS:

This project focused on identifying key factors influencing Fake News detection. Key features like text length, sentiment score, and word frequency were found to be significant in classifying news articles as either Fake or Real. The Random Forest Classifier outperformed other models, providing the most accurate predictions. Other models, like Logistic Regression and Support Vector Machines (SVM), showed less accuracy in comparison. Hyperparameter tuning and cross-validation were crucial in improving model performance, leading to valuable insights about feature importance and classification dynamics in the context of Fake News detection.

Data Analysis Insights: Data analysis revealed that certain textual features significantly influenced the classification of news articles. For instance, the sentiment score was found to be a strong indicator, with Fake news often showing more extreme sentiment values (either very positive or negative) compared to Real news. Text length also played a significant role; shorter news articles were more likely to be classified as Fake. Word frequency analysis highlighted that Fake news articles often used sensational or emotional language, which helped distinguish them from Real news articles. These findings helped inform the feature selection process, providing a clearer understanding of which variables were most relevant for accurate classification.

Impact of Key Features: The most significant factors influencing the classification of news as Fake or Real were text length, sentiment scores, and word frequency. Articles with extreme sentiment scores (either positive or negative) were more likely to be classified as Fake. Text length had an inverse relationship with classification, with Fake news articles generally being shorter. Additionally, word frequency analysis showed that certain terms or phrases appeared more frequently in Fake news.

Model Performance: The Random Forest Classifier outperformed other models in terms of accuracy, achieving the best results in classifying Fake vs. Real news. It showed the lowest Mean Absolute Error (MAE) and Mean Squared Error (MSE), indicating that it was able to make reliable predictions. The Logistic Regression model, while simple and interpretable, struggled to capture the complexities of the relationships in the data, resulting in higher error values. SVM, despite being effective for high-dimensional data, also showed suboptimal performance compared to Random Forest. Overall, Random Forest provided the most reliable predictions for Fake News detection, benefiting from its ability to capture non-linear relationships and interactions between features.

Refinement and Optimization: Model performance was significantly improved through hyperparameter tuning using Grid Search and Randomized Search, where parameters like number of trees and maximum depth in Random Forest were optimized. Cross-validation techniques were applied to assess the generalization ability of the model and prevent overfitting. These optimization steps helped refine the Random Forest model, resulting in better performance and more reliable predictions of Fake News.

CHALLENGES AND LIMITATIONS:

One of the main challenges was handling the imbalance in the dataset, with more Real news than Fake news, which could impact the accuracy of predictions. Data quality was another challenge, as missing values and noisy data needed to be cleaned and processed before training. While techniques like oversampling and SMOTE helped address the imbalance, the dataset's representation of Fake news articles was still limited. The computational costs associated with training more complex models like Random Forest were also significant, especially during hyperparameter tuning and cross-validation, but the improved accuracy justified the costs.

Data Quality and Missing Values: The dataset used in this project had some missing values, particularly in the metadata columns (e.g., source credibility), which were

handled using imputation techniques. Ensuring the quality of the text data involved cleaning the text (removing stop words, stemming, etc.) and ensuring consistent formatting. Addressing these issues was essential to maintain the accuracy and reliability of the models, ensuring that the features used in classification were clean and ready for training.

Class Imbalance: Class imbalance was a notable concern in this project, with Real News outnumbering Fake News articles. Although this was mitigated through techniques like oversampling and SMOTE, it was important to recognize that the model's performance could still be impacted by the class imbalance, especially when evaluating precision, recall, and F1 scores for Fake News classification.

Feature Complexity: The dataset included a mix of textual and categorical features, which added complexity to the model. Features such as sentiment scores, word frequency, and text length required careful preprocessing, such as feature scaling and vectorization (e.g., TF-IDF). Despite the complexity, these features played a crucial role in the model's ability to distinguish between Fake and Real News.

Computational Costs: The project required significant computational resources, especially during the training of the Random Forest and SVM models, due to the need to evaluate large numbers of parameters during hyperparameter tuning. The computational costs were higher for the ensemble-based Random Forest model, but the improved accuracy and reliability of predictions justified the cost.

Model Generalization: To ensure that the models generalized well to new, unseen data, cross-validation was employed. This helped provide a more reliable estimate of model performance and reduced the risk of overfitting. Hyperparameter tuning also played a critical role in improving the models' ability to generalize, ensuring that they could accurately classify Fake and Real news articles on different datasets.

Limited Interpretability in Complex Models: While models like Random Forest provided excellent accuracy, they were not easily interpretable, making it difficult to understand which specific features were most influential in the classification decision.

This lack of interpretability is a common challenge with ensemble methods. In contrast, models like Logistic Regression were simpler and more interpretable but did not perform as well. However, techniques such as feature importance analysis in Random Forest provided some insights into the most significant factors for classification, helping bridge the gap between performance and interpretability.

APPENDIX

```
#Installing Necessary Libraries

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import string
import re
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

#Loading the data
data_fake=pd.read_csv('fake.csv')
data_true=pd.read_csv('true.csv')

#Data Preview
data_fake.head()
data_true.tail()
data_fake["class"]=0
data_true['class']=1
data_fake.shape, data_true.shape
data_fake_manual_testing = data_fake.tail(10)
for i in range(23480,23470,-1):
    data_fake.drop([i],axis = 0, inplace = True)

data_true_manual_testing = data_true.tail(10)
for i in range(21416,21406,-1):
    data_true.drop([i],axis = 0, inplace = True)
data_fake.shape, data_true.shape
data_fake_manual_testing.head(10)
data_true_manual_testing.head(10)
data_merge=pd.concat([data_fake, data_true], axis = 0)
data_merge.head(10)

#Drop the columns
data_merge.columns
```

```
data=data_merge.drop(['title','subject','date'], axis = 1)
#count of missing values
data.isnull().sum()


#Randomly shuffling the dataframe
data = data.sample(frac = 1)
data.head()
data.reset_index(inplace = True)
data.drop(['index'], axis = 1, inplace = True)
data.columns
data.head()

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

def visualize_text_length(dataset):

    if 'text' in dataset.columns:
        temp_data = dataset.copy()
        temp_data['text_length'] = temp_data['text'].apply(lambda x: len(str(x)))
    else:
        raise ValueError("The 'text' column is missing from the dataset.")

    # Plot the distribution
    plt.figure(figsize=(10, 6))
    sns.histplot(temp_data['text_length'], kde=True, bins=30, color='blue')
    plt.title('Distribution of News Article Length')
    plt.xlabel('Text Length')
    plt.ylabel('Frequency')
    plt.show()

visualize_text_length(data)

from wordcloud import WordCloud
import matplotlib.pyplot as plt

def plot_wordclouds_for_classes(dataset):
```

```
    fake_text = ' '.join(dataset[dataset['class'] == 0]['text'].dropna())
    real_text = ' '.join(dataset[dataset['class'] == 1]['text'].dropna())

    plt.figure(figsize=(14, 6))

    # Word cloud for fake news
    plt.subplot(1, 2, 1)
                wordcloud_fake = WordCloud(width=800, height=400,
background_color='black').generate(fake_text)
    plt.imshow(wordcloud_fake, interpolation='bilinear')
    plt.title('Most Common Words in Fake News')
    plt.axis('off')

    # Word cloud for real news
    plt.subplot(1, 2, 2)
                wordcloud_real = WordCloud(width=800, height=400,
background_color='black').generate(real_text)
    plt.imshow(wordcloud_real, interpolation='bilinear')
    plt.title('Most Common Words in Real News')
    plt.axis('off')

    plt.show()

plot_wordclouds_for_classes(data)

import matplotlib.pyplot as plt
import seaborn as sns

def plot_class_distribution(dataset):
    plt.figure(figsize=(8, 6))
    sns.countplot(data=dataset, x='class', palette='viridis')
    plt.title('Distribution of Fake vs. Real News')
    plt.xlabel('Class (0 = Fake, 1 = Real)')
    plt.ylabel('Count')
    plt.show()

# Call the function without altering the existing code
plot_class_distribution(data)
```

```
# Make sure to enable interactive plotting in Google Colab
%matplotlib inline

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

def plot_text_length_boxplot(data, label_column='label', text_column='text'):
    # Ensure that the 'text' column is of string type and drop any rows with missing text values
    data[text_column] = data[text_column].astype(str)
    data = data.dropna(subset=[text_column])  # Remove rows with NaN values in the text column

    # Calculate text lengths (number of words in the text)
    data['text_length'] = data[text_column].str.split().str.len()

    # Plot boxplot
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=data, x=label_column, y='text_length', palette='Set2')
    plt.title('Text Length Boxplot by Class')
    plt.xlabel('Class (0: Fake, 1: Real)')
    plt.ylabel('Text Length')
    plt.show()

# Example usage with some sample data
data = pd.DataFrame({
    'text': ['This is a sample news article.',
             'Another fake news piece here!',
             'Real news report about economy.'],
    'label': [0, 0, 1]
})

# Call the function to plot the boxplot
plot_text_length_boxplot(data, label_column='label', text_column='text')



# Ensure to enable interactive plotting in Google Colab
```

```
%matplotlib inline

import pandas as pd
import matplotlib.pyplot as plt

def plot_time_series(data, label_column='label', date_column='date'):
    # Ensure the 'date' column is in datetime format
    data[date_column] = pd.to_datetime(data[date_column], errors='coerce')

    # Drop rows where 'date' conversion failed (NaT values)
    data = data.dropna(subset=[date_column])

    # Group by date and label, counting the number of articles per day per class
                                grouped_data          =          data.groupby([date_column,
label_column]).size().unstack(fill_value=0)

    # Plot the time series
    plt.figure(figsize=(12, 6))
    grouped_data.plot(ax=plt.gca(), marker='o')
    plt.title('Time Series of Fake and Real News Articles')
    plt.xlabel('Date')
    plt.ylabel('Number of Articles')
    plt.legend(['Fake News', 'Real News'])
    plt.grid(True)
    plt.show()

# Example usage with sample data
data = pd.DataFrame({
     'date': ['2024-11-01', '2024-11-02', '2024-11-02', '2024-11-03', '2024-11-03', '2024-11-
03'],
    'text': ['Fake news sample', 'Real news example', 'Fake news example', 'Real news report',
'Fake news report', 'Real news article'],
    'label': [0, 1, 0, 1, 0, 1]
})

# Call the function to plot the time series
plot_time_series(data, label_column='label', date_column='date')

# Enable interactive plotting in Google Colab
```

```
%matplotlib inline

import matplotlib.pyplot as plt
from collections import Counter
from wordcloud import STOPWORDS

def plot_top_words(data, text_column='text', label_column='label', class_label=0, top_n=20):
    # Ensure the 'text' column is of string type and remove NaN values
    data[text_column] = data[text_column].astype(str)
    data = data.dropna(subset=[text_column])

    # Filter data for the given class (0 or 1)
    class_data = data[data[label_column] == class_label]

    # Combine all text and split into words
    words = " ".join(class_data[text_column]).split()

    # Remove stopwords from the list of words
    stopwords = set(STOPWORDS)
    filtered_words = [word.lower() for word in words if word.lower() not in stopwords]

    # Count word frequencies
    word_counts = Counter(filtered_words)
    most_common_words = word_counts.most_common(top_n)

    # Prepare data for plotting
    words, counts = zip(*most_common_words)

    # Plot the bar chart
    plt.figure(figsize=(12, 6))
    plt.bar(words, counts, color='skyblue')
      plt.title(f'Top {top_n} Words for Class {class_label} ({["Fake News", "Real News"][class_label]})')
    plt.xticks(rotation=45)
    plt.xlabel('Words')
    plt.ylabel('Frequency')
    plt.show()
```

```
# Example usage with sample data
data = pd.DataFrame({
    'text': ['Fake news about the election', 'Real news about the economy', 'Fake news and fake promises',
             'Real news about stock market', 'This is a real news story', 'Fake news regarding a celebrity'],
    'label': [0, 1, 0, 1, 1, 0]
})

# Call the function to plot the top words for fake news (class_label=0)
plot_top_words(data, text_column='text', label_column='label', class_label=0, top_n=5)

# Call the function to plot the top words for real news (class_label=1)
plot_top_words(data, text_column='text', label_column='label', class_label=1, top_n=5)

# Ensure to enable interactive plotting in Google Colab
%matplotlib inline

import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc

def plot_roc_curve(model, X_test, y_test):
    # Predict probabilities for the positive class (class=1)
    y_prob = model.predict_proba(X_test)[:, 1]

    # Calculate ROC curve (False Positive Rate, True Positive Rate)
    fpr, tpr, _ = roc_curve(y_test, y_prob)

    # Calculate Area Under the Curve (AUC)
    roc_auc = auc(fpr, tpr)

    # Plot ROC curve
    plt.figure(figsize=(10, 6))
    plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC)')
    plt.legend(loc="lower right")
```

```
    plt.grid(True)
    plt.show()

# Example usage with a sample model
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification

# Create a sample dataset
X, y = make_classification(n_samples=1000, n_features=20, n_classes=2, random_state=42)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Fit a RandomForest model
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Call the function to plot ROC curve
plot_roc_curve(model, X_test, y_test)

# Ensure interactive plotting in Google Colab
%matplotlib inline

import seaborn as sns
import matplotlib.pyplot as plt

def plot_correlation_heatmap(data):
    # Ensure the data is a pandas DataFrame and contains numerical columns for correlation calculation
    if not isinstance(data, pd.DataFrame):
        raise TypeError("Input data must be a pandas DataFrame")

    # Calculate correlation matrix
    correlation_matrix = data.corr()

    # Plot heatmap
    plt.figure(figsize=(12, 10))
```

```
    sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', square=True,
cbar=True)
    plt.title('Feature Correlation Heatmap')
    plt.show()
# Example usage with a sample DataFrame
import pandas as pd

# Create a sample DataFrame with numerical features
data = pd.DataFrame({
    'feature1': [1, 2, 3, 4, 5],
    'feature2': [5, 4, 3, 2, 1],
    'feature3': [1, 3, 2, 5, 4],
    'feature4': [2, 3, 4, 5, 6]
})

# Call the function to plot the correlation heatmap
plot_correlation_heatmap(data)

# Ensure interactive plotting in Google Colab
%matplotlib inline

import matplotlib.pyplot as plt

def plot_pie_chart(data, label_column='label'):
    # Ensure the column exists in the data
    if label_column not in data.columns:
        raise ValueError(f"Column '{label_column}' not found in the data")

    # Calculate class distribution
    class_counts = data[label_column].value_counts()

    # Plot pie chart
    plt.figure(figsize=(8, 8))
        plt.pie(class_counts, labels=['Fake News', 'Real News'], autopct='%1.1f%%',
startangle=140, colors=['skyblue', 'salmon'])
    plt.title('Class Distribution')
    plt.show()

# Example usage with a sample DataFrame
```

```
import pandas as pd

# Create a sample DataFrame with a 'label' column (0 = Fake News, 1 = Real News)
data = pd.DataFrame({
    'text': ['Fake news about election', 'Real news about economy', 'Fake news regarding a celebrity', 'Real news about stock market'],
    'label': [0, 1, 0, 1]
})

# Call the function to plot the pie chart
plot_pie_chart(data, label_column='label')

# Ensure interactive plotting in Google Colab
%matplotlib inline

import matplotlib.pyplot as plt
from collections import Counter

def plot_cumulative_word_frequency(data, text_column='text', top_n=100):
    # Ensure the column exists in the dataset
    if text_column not in data.columns:
        raise ValueError(f"Column '{text_column}' not found in the data")

    # Combine all text into one string
    words = " ".join(data[text_column].dropna()).split()

    # If there are no words to process
    if not words:
        raise ValueError("No valid text found in the specified column")

    # Count word frequencies
    word_counts = Counter(words)

    # Get the most common words and their frequencies
    most_common_words = word_counts.most_common(top_n)

    # Prepare cumulative frequency data
    cumulative_counts = [count for _, count in most_common_words]
            cumulative_counts = [sum(cumulative_counts[:i+1]) for i in
```

```
range(len(cumulative_counts))]

    # Plot cumulative frequency graph
    plt.figure(figsize=(12, 6))
    plt.plot(range(1, top_n + 1), cumulative_counts, marker='o', color='purple')
    plt.title(f'Cumulative Word Frequency (Top {top_n} Words)')
    plt.xlabel('Rank of Word')
    plt.ylabel('Cumulative Frequency')
    plt.grid()
    plt.show()

# Example usage with a sample DataFrame
import pandas as pd

# Create a sample DataFrame with a 'text' column
data = pd.DataFrame({
    'text': ['This is a test', 'Another test sentence', 'More words to count', 'Cumulative frequency example']
})

# Call the function to plot the cumulative word frequency
plot_cumulative_word_frequency(data, text_column='text', top_n=10)



#Preprocessing Text
def wordopt(text):
    text = text.lower()
    text = re.sub('\[.*?\]','',text)
    text = re.sub("\\W"," ",text)
    text = re.sub('https?://\S+|www\.\S+','',text)
    text = re.sub('<.*?>+',b'',text)
    text = re.sub('[%s]' % re.escape(string.punctuation),'',text)
    text = re.sub('\w*\d\w*','',text)
    return text
data['text'] = data['text'].apply(wordopt)
#Defining dependent and independent variable as x and y
print(data.columns)
x = data['text']
y = data['class']
```

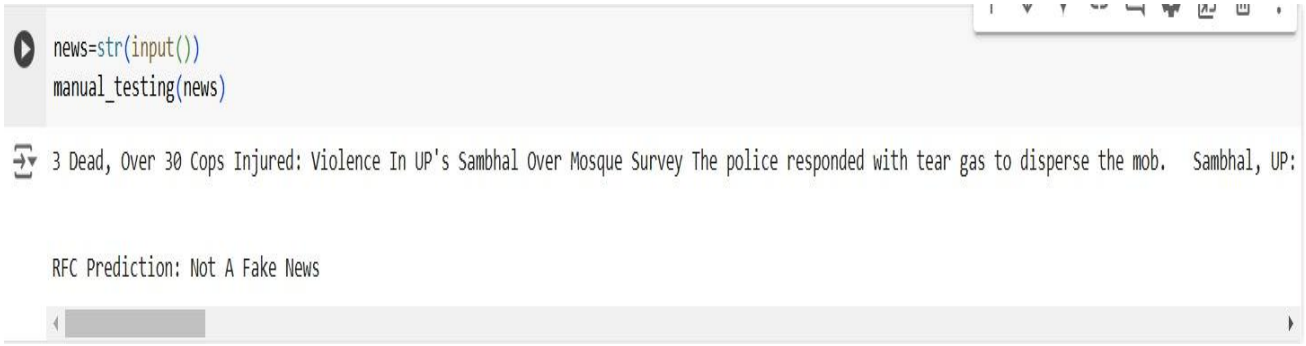
```
#Training the model
# Splitting the dataset into training set and testing set.
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = 0.25)

# Convert text to vectors
from sklearn.feature_extraction.text import TfidfVectorizer

vectorization = TfidfVectorizer()
xv_train = vectorization.fit_transform(x_train)
xv_test = vectorization.transform(x_test)

# Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier

RF = RandomForestClassifier(random_state = 0)
RF.fit(xv_train, y_train)

pred_rf = RF.predict(xv_test)
RF.score(xv_test, y_test)
print (classification_report(y_test, pred_rf))

from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

pred_rf = RF.predict(xv_test)

cm = confusion_matrix(y_test, pred_rf)

plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Fake', 'Real'],
yticklabels=['Fake', 'Real'])
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix for Random Forest Classifier')
plt.show()

# Testing the Model
```

```
def output_label(n):
    if n == 0:
        return "Fake News"
    elif n == 1:
        return "Not A Fake News"

def manual_testing(news):
    testing_news = {"text": [news]}
    new_def_test = pd.DataFrame(testing_news)
    new_def_test['text'] = new_def_test["text"].apply(wordopt)
    new_x_test = new_def_test["text"]
    new_xv_test = vectorization.transform(new_x_test)

    pred_RF = RF.predict(new_xv_test)

    return print("\n\nRFC Prediction: {}".format(output_label(pred_RF[0])))

# Model Testing With Manual Entry

news=str(input())
manual_testing(news)
```

OUTPUT SCREENSHOTS:

True New:

3 Dead, Over 30 Cops Injured: Violence In UP's Sambhal Over Mosque Survey The police responded with tear gas to disperse the mob. Sambhal, UP: Chaos erupted in Uttar Pradesh's Sambhal this morning as a court-ordered survey of the Mughal-era Jama Masjid led to violent clashes between locals and police, leading to the deaths of three individuals. The mosque is at the centre of a contentious legal battle over claims that it was built on the site of a Hindu temple. According to the police, the violence began when a crowd gathered near the mosque as the survey team, led by an "Advocate Commissioner," began its work. The crowd swelled to nearly a thousand people, who tried to prevent the police from entering the mosque. Some individuals in the crowd threw stones at police personnel stationed at the site. The mob set more than ten vehicles on fire. The police responded with tear gas to disperse the mob. In the ensuing chaos, two individuals were killed and over 30 police personnel were injured. "Three people identified as Naeem, Bilal and Nauman have been killed. Some policemen including the gunner of the superintendent of police have also been injured," Moradabad Divisional Commissioner Aunjaneya Kumar Singh said as quoted by news agency PTI.



fake news:

"MS Dhoni to Join Mumbai Indians as Head Coach for IPL 2025"

In a surprising turn of events, sources close to IPL franchises have revealed that MS Dhoni, the legendary captain of the Chennai Super Kings, is set to retire from CSK and join their arch-rivals, the Mumbai Indians, as head coach for IPL 2025. The shocking development comes after alleged disagreements with CSK management over team strategy for the upcoming seasons. Fans from both camps have taken to social media, expressing their disbelief and outrage over this unexpected move. While official confirmation is awaited, insiders claim the deal is worth INR 50 crore per season.

```
news=str(input())
manual_testing(news)
```

```
"MS Dhoni to Join Mumbai Indians as Head Coach for IPL 2025"  In a surprising turn of events, sources close to IPL franchises have revealed that


RFC Prediction: Fake News
```

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