AI BASED SYSTEM FOR DETECTING AND COMBINATING FAKE NEWS PROPOGATION

PROJECT REPORT

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In partial fulfilment for the award of the degree

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In

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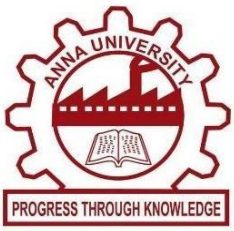

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BONAFIDE CERTIFICATE

This is to certify that the final year project entitled **"AI BASED SYSTEM FOR DETECTING AND COMBINATING FAKE NEWS PROPOGATION"** is the Bonafide work of "**MALARVIZHI R, DINESH BALAJI R, POOJA SHREE R"** who carried out the project work under my supervision.

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ABSTRACT

Fake news detection has become increasingly important as misinformation spreads rapidly across digital platforms, influencing public opinion and societal trust. This paper focuses on detecting fake news using logistic regression combined with natural language processing (NLP) techniques. By utilizing text classification and feature extraction methods, we aim to differentiate between authentic and fake news articles. The study highlights how NLP methods, including tokenization, stop word removal, and vectorization, are employed to transform textual data into a structured format suitable for machine learning algorithms.We explore the application of logistic regression, a widely used machine learning algorithm, to classify news articles as either real or fake. The simplicity and efficiency of logistic regression make it an attractive choice for fake news detection, especially when paired with effective feature selection from textual content. The paper also examines the role of different NLP techniques in improving classification accuracy, including sentiment analysis, keyword extraction, and topic modeling, to capture essential patterns within the text.Despite the potential of these methods, challenges such as data imbalance, the dynamic nature of language, and the need for high-quality labeled datasets remain. The study concludes by discussing future research directions, emphasizing the importance of enhancing model robustness and scalability to handle the ever- evolving landscape of online misinformation**.**

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LIST OF ABBREVIATION

S.NO	ABBEREVIATION	DESCRIPTION
1	NLP	Natural language processing
2	TF-IDF	Term Frequency Inverse Document Frequency
3	BOW	Bag-of-words
4	SVM	Support Vector Machine
5	RNN	Recurrent Neural Network
6	BERT	Bidirectional Encoder Representations Transformers
7	NGP	Non-Governmental Organization
8	APL	Application Programming Interface
9	GPU	Graphics Processing Unit
10	NLTK	Natural Language Toolkit
11	CSV	Comma-Separated Values

CHAPTER 1
INTRODUCTION

1.1 OBJECTIVE

This project's goal is to create an intelligent system that uses a Logistic Regression algorithm and Natural Language Processing (NLP) approaches to identify bogus news items. In the current digital age, a vast amount of information is shared via messaging applications, social media sites, and online news sources. Not all of this information, though, is reliable or accurate. False information that imitates news content in form but not in organizational process or intent is known as fake news, and it has grown to be a potent weapon for deceiving the public, causing fear, influencing political opinion, or furthering nefarious goals. This project uses natural language processing (NLP) to process and comprehend the structure and semantics of news material, extracting significant features from text data in order to tackle this expanding challenge.

After that, a supervised learning method called logistic regression is utilized to determine whether the input news is authentic or fraudulent. Based on patterns discovered after training, the system can evaluate a dataset of news headlines or bodies and forecast the probability that the news is fraudulent. The system's overarching objective is to assist individual users in confirming the veracity of news while also providing a basis for future integration into online browsers, news apps, and social media platforms. The project has a strong emphasis on using language models and machine learning to raise awareness, stop the spread of false information,and promote responsible information consumption in the digital sphere.

1.2 SCOPE

This project's scope encompasses the crucial field of digital communication misinformation detection. It is not feasible to manually verify the trustworthiness of news because millions of articles, headlines, and posts are released every day. As a result, an automated system that assesses news's veracity based on its textual content is absolutely necessary. The Fake News Detection system uses machine learning and natural language processing to automate this verification process. 'Fake' or 'Real' news stories are the main emphasis of this project. It is trained and evaluated using a pre-labeled dataset. To guarantee the model's generality and resilience, the dataset covers a wide range of linguistic structures, writing styles, and subjects.

Several components are supported by the system, including: NLP techniques for text preprocessing (tokenization, stemming, stop-word removal) Feature extraction with methods such as TF-IDF and Bag-of-Words Training a model with logistic regression Forecasting and categorizing fresh, undiscovered news information Future improvements could include the following, even if the current scope only includes news material in the English language:

Multilingual identification of bogus news Using computer vision to identify deceptive photos or movies Analysis of real-time news feeds using web crawlers and APIs Mobile apps or browser add-ons for immediate detection Journalists, news organizations, social networking sites, academic institutions, and even governmental organizations can use the system to confirm the accuracy of news before it is shared.

1.3 PROBLEM IDENTIFICATION

Defining the problem The line between factual reporting and fiction has become increasingly hazy due to the proliferation of digital media and the democratization

of information sharing. With serious social, political, and economic repercussions, fake news has spread widely. The dissemination of false information has the potential to permanently harm society, from swaying elections to inciting needless panic during public health emergencies. Conventional news verification techniques rely on human fact-checking, which takes a lot of time and effort and is not scalable to the speed at which news circulates. The problem is exacerbated by an increasing number of people who frequently distribute news pieces without checking the content or source.

The primary issue this project aims to solve is the absence of an intelligent, automated, and scalable system for real-time fake news detection. The solution must be able to recognize language patterns that are typical of fake news, comprehend the underlying semantics, and evaluate vast amounts of textual data. Important difficulties include: Recognizing linguistic subtleties and context Handling skewed or purposefully false information Managing unstructured or noisy data from several sources Cutting down on false negatives and false positives This research offers a workable approach that is scalable and efficient by using Natural Language Processing (NLP) techniques to process and extract features from news text and using Logistic Regression to classify the material.

1.4 OVERVIEW

This project offers a comprehensive pipeline that uses natural language processing and logistic regression to identify bogus news. It has multiple phases, all of which work toward the ultimate objective of precise classification. Information Gathering: Obtaining a dataset with labeled news articles is the initial stage. Fields like the news title, author, text body, and label indicating whether it is authentic or fraudulent are commonly included in the dataset. Commonly utilized public datasets include those from Kaggle. Preprocessing Data: To guarantee that the raw text is standardized and clean, preprocessing is essential. This comprises: Eliminating special characters and punctuation Text conversion to lowercase

Eliminating stopwords (such as "is," "the," and "and") Using lemmatization or stemming to simplify words to their most basic form.

Feature Extraction: The text is cleaned and then transformed into numerical representations using methods such as Words in a Bag (BoW): determines how frequently each word appears in the document. Term Frequency–Inverse Document Frequency, or TF-IDF: determines a word's significance by looking at how often it occurs in a document in comparison to the corpus as a whole. Model Training: Training and testing sets are created from the processed data. The training data is used to train a Logistic Regression model. The association between word patterns and their related labels—whether genuine or fraudulent—is something that this model learns to recognize. Prediction: After being trained, the model uses the textual content to determine whether recently published, unseen news stories are authentic or fraudulent.

Evaluation: The model's performance is assessed using accuracy, precision, recall, and F1-score. Visualizations of confusion matrices may also be used to explain the categorization outcomes.

1.5 PROJECT IMPACT

The implementation of a Fake News Detection system has significant implications for modern society. In an era where information travels at the speed of light, the ability to validate the authenticity of news is vital for maintaining societal trust, political stability, and public safety. Social Impact: Reduces the spread of false information Encourages responsible sharing and consumption of content Protects public from psychological manipulation, scams, and propaganda Technological Impact: Demonstrates the power of machine learning and NLP in solving real-world problems Sets a foundation for future AI-based journalism tools Encourages the integration of AI in content moderation and media platforms.Impact on Education: Offers an example of how to apply supervised machine learning methods to NLP issues. informs developers and students about

the risks of false information and how AI may combat it. Impact on the Economy: aids businesses in preventing losses brought on by erroneous information that damages stock markets or brand perception. helps NGOs and governments communicate during crises by removing false information. This initiative encourages digital literacy and protects the information ecosystem by providing a dependable, scalable, and affordable solution.

1.6 PROJECT OUTCOME

A strong and clever tool that can distinguish between authentic and fake news pieces has been developed as a result of the Fake News Detection system's successful deployment. A highly interpretable and effective method is produced when NLP is used for feature extraction and Logistic Regression is used for classification. Important results include: A functional classifier that can identify between fake and authentic news with a decent level of accuracy A neat and organized pipeline for data processing that can be used for upcoming projects An expandable and reusable codebase for use in real-world or educational settings A greater understanding among stakeholders of disinformation and how to spot it In addition to providing a technological answer, this effort spreads awareness of the value of double-checking information before sharing or relying on it.

More intricate designs like LSTM or transformers, real-time detection systems, and the identification of visual or multimedia fraudulent content can all be added to the model in subsequent research.

CHAPTER 2

SYSTEM ANALYSIS

2.1 LITERATURE REVIEW

2.1.1 BIG DATA BASED FAKE NEWS DETECTION USING DISTRIBUTED LEARNING

This study presents a big data-oriented approach to fake news detection by leveraging distributed machine learning through Apache Spark. The authors emphasize the need for scalable systems capable of processing the immense and continuously growing volumes of data generated on social media platforms. By using Apache Spark, the model takes advantage of parallel processing, allowing for faster computation and the ability to handle large datasets efficiently. This scalability makes the approach particularly well-suited for real-time social media monitoring environments, where the volume of data can be overwhelming for traditional systems. One of the major strengths of this model is its capability to deal with massive amounts of unstructured text data using Spark's powerful processing engine. However, despite its technical robustness, the model is restricted by its reliance on batch processing. This means that it processes data in chunks rather than in real-time, making it ineffective in scenarios where fake news spreads rapidly and demands immediate attention. Thus, while highly efficient in large-scale data analysis, the model falls short in dynamic, time-sensitive fake news detection.

2.1.2 ADVANCING FAKE NEWS DETECTION: HYBRID DEEP LEARNING WITH FASTTEXT AND EXPLAINABLE AI

In this 2024 paper, the authors propose a hybrid deep learning model aimed at improving the performance of fake news detection systems. Their architecture combines Convolutional Neural Networks (CNNs) for local feature extraction,

Long Short-Term Memory (LSTM) networks for capturing sequential dependencies, and FastText embeddings for enhanced word representation. This combination allows the model to learn rich semantic relationships in text data, resulting in significantly higher accuracy in identifying fake news articles. Furthermore, the authors integrate Explainable AI (XAI) methods into their model, providing transparency and interpretability in the decision-making process—a critical factor in building trust among users and stakeholders. The use of FastText helps in understanding out-of-vocabulary and morphologically rich words, which enhances the model's performance across different domains and languages. Despite its strengths, the model's primary limitation lies in its focus on textual data alone. It does not process or analyze multimedia elements such as images, videos, or memes, which are commonly used in the spread of fake news. As a result, the model's applicability is constrained in real-world environments where fake news often relies on non-textual elements for virality and impact.

2.1.3 SYSTEMATIC REVIEW OF FAKE NEWS, PROPAGANDA AND DISINFORMATION:

CONTENT AND SOCIAL IMPACT THROGH MACHINE LEARING

This comprehensive review paper provides a high-level examination of the various dimensions of fake news, propaganda, and disinformation, with a particular focus on their detection through machine learning methods. The authors systematically analyze existing literature, presenting a categorization of techniques based on their approach to identifying authorship, content structure, and the social impact of misinformation. The paper is notable for its broad scope, covering a wide range of methodologies including supervised, unsupervised, and hybrid machine learning models. Additionally, the authors highlight critical challenges in the field such as the lack of standard datasets, the dynamic nature of fake news content, and the ethical implications of automated detection systems.

The review also sheds light on under-researched areas, pointing to the need for interdisciplinary solutions that blend technical, psychological, and sociological insights. While the paper provides valuable theoretical insights and helps map out future research directions, its primary drawback is the lack of practical implementation. It does not present any experimental validation or propose a novel model, limiting its use for practitioners seeking to build or deploy real-world fake news detection systems. Thus, it serves more as a foundational guide than a directly applicable solution.

2.2 EXISTING SYSTEM: The majority of the current approaches for identifying false news are either rule-based or rely on fact-checkers' manual verification. These methods frequently take a long time, are ineffective, and cannot keep up with the enormous amount of news that is released every day. Nowadays, a lot of sites use third-party verification services or crowdsourcing to identify false information. Others employ blacklists of recognized false news sources or simple keyword identification. These systems are vulnerable to mistakes and manipulation, nevertheless, because they do not examine the linguistic patterns and textual structure.

Drawbacks of Current Systems: Manual Intervention: Takes a lot of time because it needs human verification. Keyword-Based Only: Simple keyword-based detection is useless. Lack of Scalability: Unable to manage massive amounts of news data. Not appropriate for real-time detection is the delayed response. Static databases devoid of adaptive learning are known as "no learning mechanisms." Limited Language Support: Regional languages are not supported by the majority of tools, which only function in English.

DISADVANTAGES

1. No real-time detection (batch mode only).
2. Requires high computational resources.

3. Only supports text-based fake news.
4. Doesn’t handle multimedia content.
5. Language limitations in detection.
6. Explainability still complex.
7. No practical implementation in review study.
8. Lack of experimental validation.

2.3 PROPOSED SYSTEM

The suggested approach employs Logistic Regression, a small yet effective machine learning technique, for classification and Natural Language Processing for preprocessing and vectorizing news information. It offers an automatic, scalable, and real-time solution to the problems caused by disinformation. Important Elements: NLP Feature Extraction for Text Preprocessing (TF-IDF, Bag-of-Words) Training a Logistic Regression Model Accuracy assessment of prediction engines in real time and model optimization. This system can classify news as "Fake" or "Real" with a high degree of accuracy and low latency. It works well with browser extensions, online news sources, educational institutions, and more.

ADVANTAGES

- **Quick and Efficient:** Training and prediction are made quickly with logistic regression.
- **Automatic Detection:** Classification doesn't require human input.
- **Real-Time Capable:** Fit for watching live news streams.
- **Cost-effective:** Makes use of common computer power and open-source libraries.
- **Adaptable:** Able to be included into web apps or APIs.
- **Lightweight:** Doesn't require sophisticated infrastructure or GPUs.

2.4 FEASIBILITY STUDY: The feasibility study looks at the system's actual implementation from a number of angles

2.4.1 TECHNICAL FEASIBILTY: The project builds the application using popular technologies like Flask, NLTK, Python, and Scikit-learn. Because these libraries are popular and well-supported for machine learning and text processing, the system may be constructed using the resources and techniques that are currently accessible.

2.4.2 ECONOMICAL FEASIBILITY

The idea is financially feasible because it makes use of open-source software and doesn't require expensive hardware. Any common personal computer or cloud-based notebook, such as Google Colab, can be used for development. Because there are no license or subscription costs, it is affordable for both schools and students.

2.4.3 OPERATIONAL FEASIBILITY

The system can be made available as a web-based or desktop application. Predictions are shown clearly, and the UI is easy to use. It delivers binary categorization results and only requires the most minimal user intervention, which is the input of news material.

2.4.4 LEGAL FEASIBILITY

Since the system does not gather personal information and makes use of publicly available datasets, there are no legal issues. The project respects copyright laws and digital rights while adhering to ethical norms.

2.4.5 ETHICAL FEASIBILITY: The system seeks to uphold the truth and dissuade false information, which is consistent with moral journalism and technology practices. Instead of encouraging censorship, it gives people factual analysis based on data patterns.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 SOFTWARE REQUIREMENTS

The set of tools, languages, libraries, and platforms necessary for the creation, testing, and implementation of the Fake News Detection system utilizing Python, Django, HTML, CSS, and JavaScript are specified in the software requirements.

3.1.1 PROGRAMMING LANGUAGES

- **PYTHON 3.8+ -** Utilized for constructing machine learning models, preparing data, back-end development, and Django framework integration. Additionally, Python libraries are utilized for model validation, NLP, and data visualization.
- **HTML5 and CSS3 –** Used to organize and design the web application's front interface. makes certain that the user interface is accessible, hygienic, and responsive.
- **JAVASCRIPT -** Used to bring interactive front-end elements, like dynamic result presentation, form validation, and improvements for user input.

3.1.2 FRAMEWORKS AND LIBRARIES

FRAME WORKS

DJANGO

- The machine learning model is integrated with a full-stack web application using a high-level Python web framework. It offers features such as:
    - Routing of URLs
    - Rendering a template
    - Handling backend logic
    - Safe management of user input

LIBRARIES

PYTHON

- **Pandas:** Used to import and work with True.csv and Fake.csv datasets
- **Scikit-learn:** For machine learning (accuracy scoring, train-test split, and logistic regression)
- **Nltk:** For activities involving Natural Language Processing, like text cleaning and stopword elimination
- **CountVectorizer:** For utilizing Bag-of-Words to convert text into numeric representation for training and forecasting models, logistic regression when exporting predictions, use openpyxl to save the results to Excel.

3.1.3 TOOLS AND PLATFORMS

- **IDE/Code Editors:** PyCharm and Visual Studio Code used to write and maintain front-end and back-end programs.
- **Web browser:** To launch and test the Django web application, use Chrome, Firefox, or Edge.
- **Database:** SQLite (the standard Django database)—used to store logs, forecasts, and user input history.
- **Git and GitHub:** are two tools for version control that are used to manage code versions and facilitate team collaboration.

3.1.4 ENVIRONMENT

- **Operating System:** Linux, macOS, and Windows 10 Version 3.8 or higher of Python
- **Manager of Packages:** pip
- **Web Server:** The Python manage.py runserver, which is Django's integrated development server
- **Supported browsers:** the most recent versions of Firefox and Chrome

3.2 HARDWARE REQUIREMENTS

High-end computing is not required because the system makes use of a lightweight algorithm called logistic regression. Standard desktops and laptops can run it effectively.

MINIMUM PREREQUISITES:

- **Processor:** AMD Ryzen 3 or Intel i3 or similar
- **RAM:** 4 GB; 8 GB is advised for efficient dataset management.
- **Storage:** 10 GB available
- **Display:** Any common monitor can be used to show web interfaces.
- **Internet:** necessary for testing APIs and installing packages

CHAPTER 4

SYSTEM DESIGN

4.1 SYSTEM ARCITECTURE

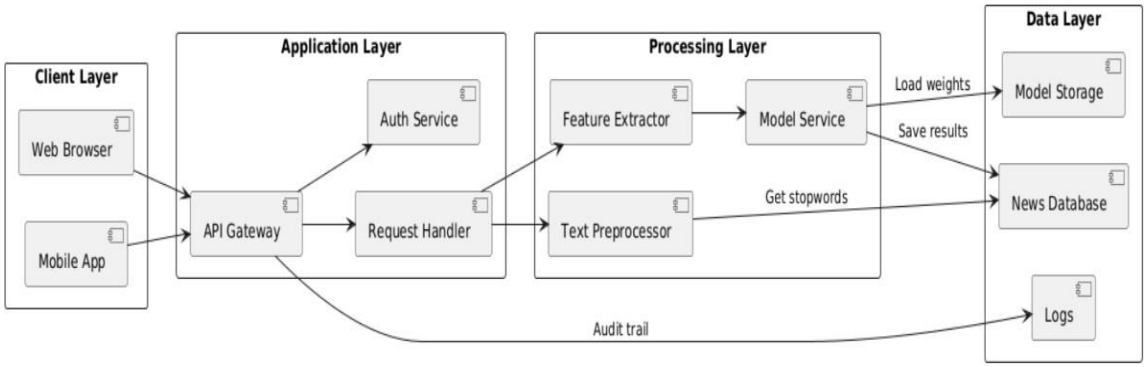


Figure 4.1.0

System Architecture

4.2 USECASE DIAGRAM

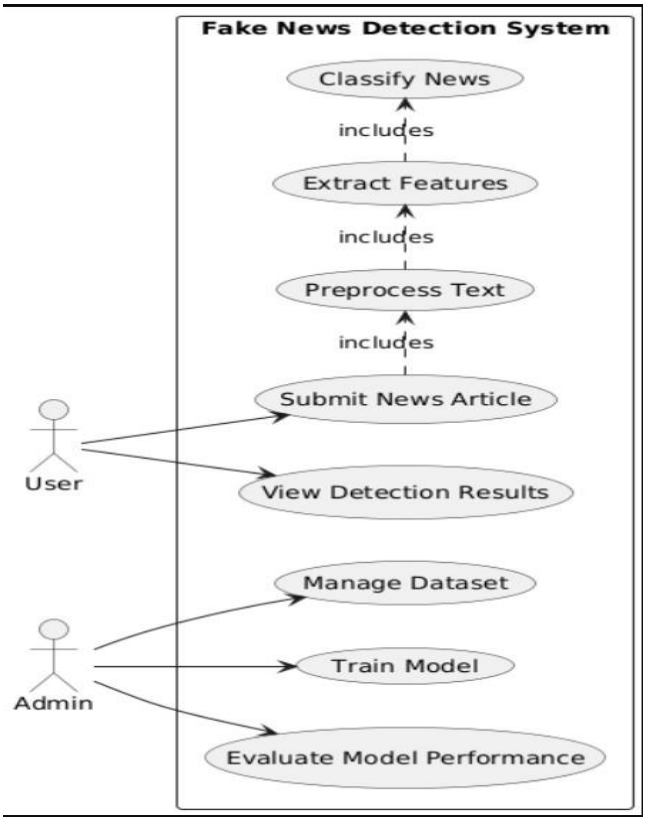


Figure 4.0.1

Usecase Diagram

4.3 CLASS DIAGRAM

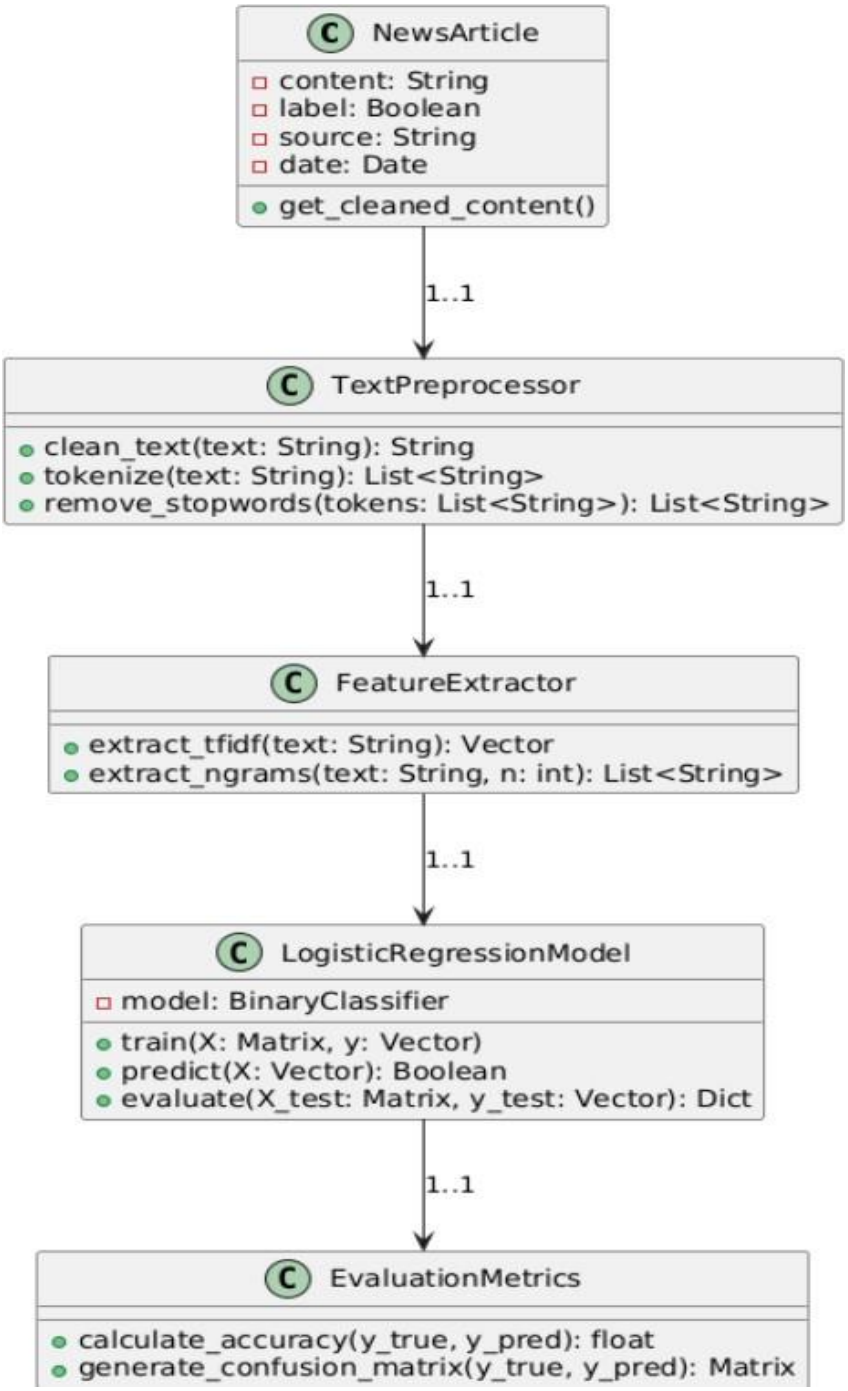


Figure 4.3.0

Class Diagram

4.4 SEQUENCE DIAGRAM

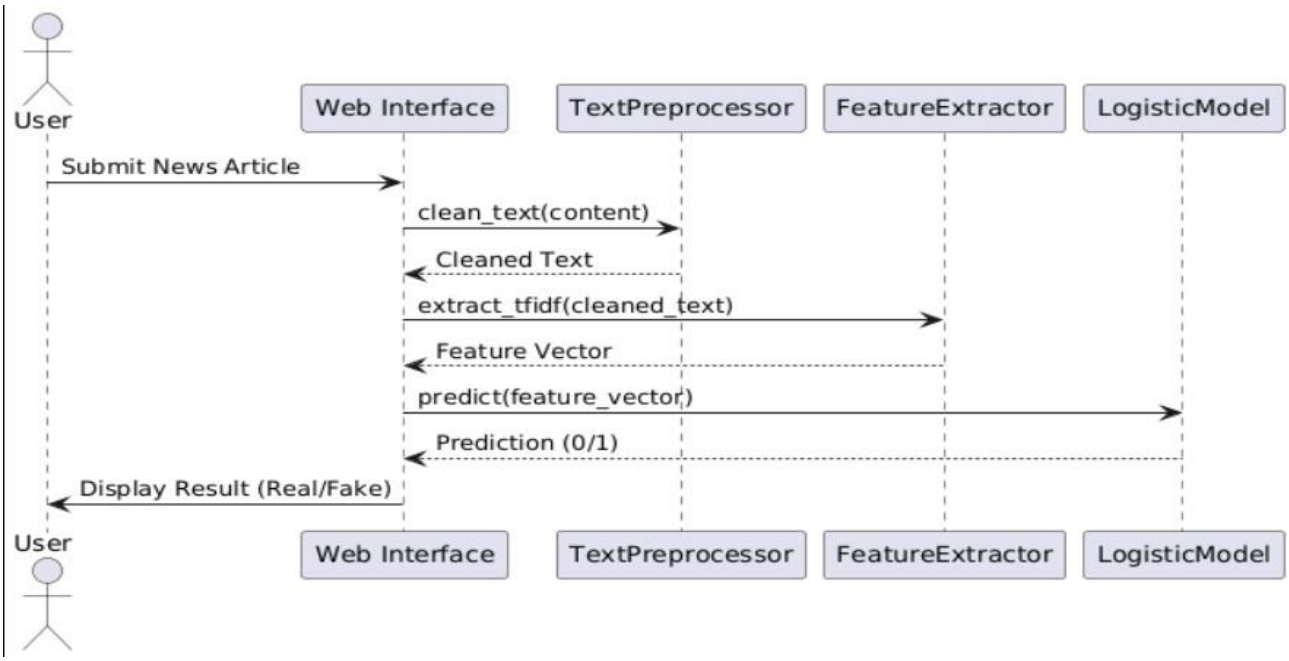


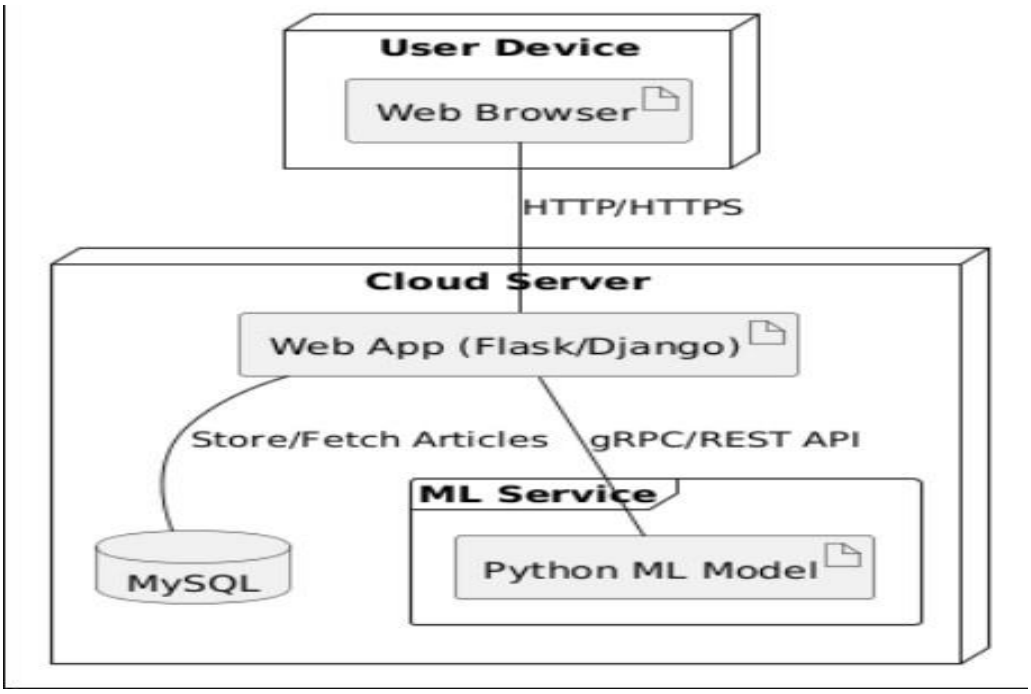
Figure 4.4.0

Sequence Diagram

4.5 DEPLOYMENT DIAGRAM

Figure 4.5.0

Deployment Diagram



4.5 ACTIVITY DIAGRAM

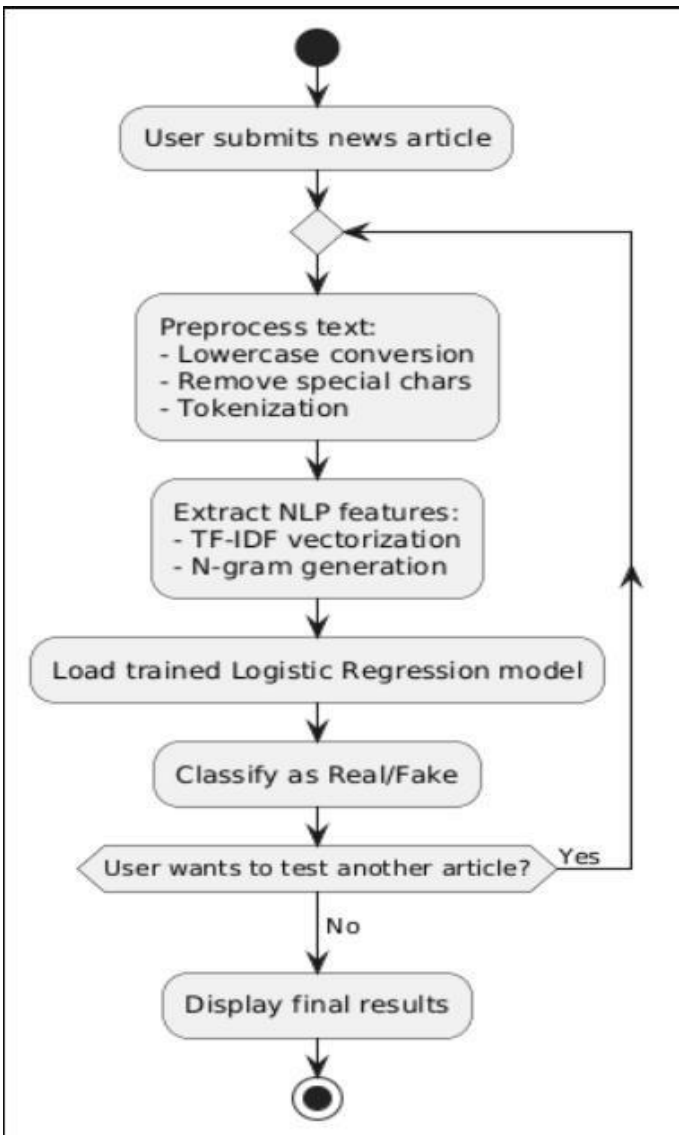


Figure 4.5.0

Activity Diagram

CHAPTER 5

SYSTEM IMPLEMENTATION

5.1 MODULES OVERVIEW: The implementation of the Fake News Detection system is described in detail in this chapter. The system classifies news stories as either authentic or fraudulent using Natural Language Processing (NLP) and machine learning techniques, particularly Logistic Regression. Python was used for the implementation, and to guarantee peak performance, the data was processed, trained, and assessed.

5.2 MODULES IMPLEMENTATION

5.2.1 DATA LOADING MODULES: Two datasets, one with fake news and the other with real news, were added to the system during this phase. The entries in the false news dataset were classified appropriately, whereas every record in the real news dataset was labeled as authentic. For the machine learning model to be trained, this labeling is essential.

5.2.2 DATA COMBINATION & SHUFFLING: Both datasets were labeled before being merged into a single dataset. The entire dataset was randomly shuffled to stop the model from picking up any patterns depending on the data's order.

5.2.3 TEXT PRE-PROCESSING MODULE: Standard NLP approaches were used to clean the text of each news story. This involved changing the text to lowercase, deleting special letters and punctuation, and getting rid of frequent English stopwords. In order to focus on relevant material for analysis and eliminate noise in the data, this phase is crucial.

5.2.4 FEATURE EXTRACTION MODULE: Following preprocessing, a method known as vectorization was used to convert the textual data into numerical format. Text is transformed into a format that machine learning algorithms can comprehend and utilize for forecasting in this step.

5.2.5 MODEL TRAINING MODULE: Training and testing sets were then created using the cleaned and vectorized data. The model was trained using the training data and the Logistic Regression technique. The machine was able to learn the patterns that distinguish authentic news from fraudulent news thanks to this phase.

5.2.6 MODEL EVALUATION MODULE: The testing set was used to assess the model's performance once it had been trained. Accuracy, which measures how effectively the model can predict the proper label (genuine or fake) given unseen data, was the evaluation metric that was employed.

5.2.7 PREDICTION MODULE: Users can enter a bespoke news story into the system, and it will process it and run it through the trained model. Using the patterns it has learnt during training, the model makes predictions on the authenticity of the input.

5.2.8 RESULTS EXPORT MODULE: The final results were stored in external files like Excel and CSV to document the model's predictions. This makes it possible to analyze and validate the system's predictions in the future.

5.3 BACKEND AND FRONTEND CONNECTIVITY: Django was used to integrate the system with a web interface. User input is received by the frontend as a news article. Using the trained model, the backend analyzes this input and returns the prediction outcome. Because of this connectivity, people can engage with the model via an intuitive interface.

CHAPTER 6

SYSTEM TESTING

6.1 SYSTEM TESTING OVERVIEW

A crucial stage in the creation of every software project is system testing. It guarantees that the finished application functions as intended in a variety of scenarios. The accuracy, dependability, and functionality of every module of the Fake News Detection System—including the user interface, data handling, model predictions, and backend logic—were tested.

6.2 TYPES OF TESTING

6.2.1 UNIT TESTING: Individual system components, including data loading, prediction logic, and text preprocessing, were subjected to unit testing. To make sure it worked properly and handled both expected and unexpected inputs, each function was tested independently.

6.2.2 INTEGRATION TESTING: Integration testing was done after each module's independent functionality was verified. This was done to ensure smooth interaction between the modules. For instance, it was verified that the user input from the frontend was accurately transmitted to the backend model and that the user received the prediction results in a proper manner.

6.2.3 SYSTEM TESTING: To ensure that it satisfied all functional and non-functional requirements, the entire application was tested as a whole. This involved verifying that the system could load data files, export findings, handle user inputs via the web interface, and accurately distinguish between bogus and true news.

6.2.4 FUNCTIONAL TESTING: Functional testing made sure that every system feature operated in accordance with the requirements. The prediction feature, file upload, model training, and result generation were all tested.

6.2.5 PERFORMANCE TESTING: To see how the system responded to different loads, performance testing was done. This entailed evaluating the model's handling of larger datasets, response time to user input, and prediction time

6.2.6 USER ACCEPTANCE TESTING (UAT): Potential users were requested to submit news stories as part of a testing process to make sure the system is easy to use and meets practical needs. Their suggestions helped to improve the system's usability and interface.

6.3 TEST CASES

For various modules, a number of test cases were created and run:

TEST CASE 1: Enter an actual news story and anticipate a “Real” prediction.

TEST CASE 2: Enter a phony news story and anticipate that it will correctly identify it as “Fake”.

TEST CASE 3: To verify error handling, provide an empty input.

TEST CASE 4: Examine how the system reacts to unusual characters or unsupported formats in

TEST CASE 5: Make predictions based on articles that haven’t been seen before and confirm that the model is consistent.

6.4 RESULT AND ANALYSIS: Every significant test scenario was passed by the system. The usefulness of the Logistic Regression model was validated by the high prediction accuracy. Additionally, the system reacted in a reasonable amount of time and handled invalid inputs graciously.

CHAPTER 7

SYSTEM MAINTENANCE

7.1 INTRODUCTION

The system design serves as the blueprint for building the application as a whole. This project's Fake News Detection System uses a Logistic Regression model and Natural Language Processing (NLP) to determine if a news story is authentic or fraudulent. Both low-level interface and data flow designs as well as high-level architectural elements are included in the design phase. It guarantees the effective implementation of all functional and non-functional requirements.

7.2 SYSTEM ARCHITECTURE

USER INTERFACE LAYER: HTML, CSS, and JavaScript were used to create the user interface layer. Users can enter news stories and see the outcomes.

APPLICATION LOGIC LAYER: This layer serves as a link between the frontend and backend by processing inputs, maintaining routes, and calling the model. It is implemented using the Django Python framework.

MACHINE LEARNING MODEL LAYER: The trained Logistic Regression model, which uses Scikit-learn to determine whether the news is authentic or fraudulent, is part of the Machine Learning Model Layer.

DATA LAYER: The datasets (True.csv and Fake.csv) used for model evaluation and training are included in the data layer. enables storing forecasts in CSV or Excel as well.

DATA LAYER: Involves the datasets (True.csv and Fake.csv) used for training and evaluating the model. Also includes saving predictions to Excel or CSV

7.3 MODULE DESCRIPTION

1. DATA COLLECTION MODULE: Loading datasets of bogus and legitimate news from CSV files is the goal.

PROCEDURE: After being read and categorized, the false and actual news files are merged into a single dataset.

RELEVANCE: Offers the foundational data for model testing and training.

2. DATA PREPROCESSING MODULE: The goal is to prepare and clean the unprocessed text data.

FUNCTIONS: Text conversion to lowercase, Eliminating special characters and punctuation, Eliminating stopwords, or everyday terms that don't add meaning

SIGNIFICANCE: Guarantees that the model is provided with consistent and significant data for learning.

3. FEATURE EXTRACTION MODULE

GOAL: Provide numerical data from the cleaned text data.

METHOD: Count Scikit-Learn Vectorizer The model was trained using a sparse matrix of token counts as the output.

4. MODEL TRAINING MODULE

The goal is to use labeled data to train the logistic regression model.

30% of the dataset is for testing, while 70% is for training.

A trained model that is prepared to provide predictions is the output.

5. PREDICTION MODULE

GOAL: Determine if a given news input is authentic or fraudulent. User-typed headline or article as input**.** Labeled output with the words "Fake" or "Real"

6. RESULT HANDLING AND EXPORT MODULE

GOAL: Show the user the forecasts and provide the opportunity to save the outcomes.

QUALITIES: Results are output to a webpage. Export to Excel or CSV for documentation purposes

7.4 DATA FLOW DIAGRAM - DFD

DFD LEVEL 0 - Displays the system as a single process with a prediction result as the output and user input (news text).

DFD AT LEVEL 1 - Illustrates how the input passes through model prediction, vectorization, preprocessing, and output.

7.5 THE TECHNICAL STACK

- **FRONTEND:** JavaScript, HTML, and CSS
- **BACKEND:** Python's Django
- **MACHINE LEARNING:** Scikit-learn (Logistic Regression)
- **LIBRARIES:** sklearn, pandas, and nltk
- **TOOLS:** Visual Studio Code
- **STORAGE:** Excel or CSV file for output storage

7.7 DESIGN ADVANTAGES

- **MODULAR DESIGN:** Simple to update and maintain
- **SCALABLE:** Future additions of more models are possible.
- Interface that is easy to use
- Reliable forecasting with a trained machine learning model
- Safe processing of user input

CHAPTER 8

CONCLUSION

Fake news is a major hazard to both people and society at large in the current digital era. The goal of this research was to develop a phony News Detection system that uses machine learning techniques to accurately classify news articles as either authentic or phony. We successfully created a system that can accurately identify fake news by gathering trustworthy datasets, preparing the data, and using a logistic regression model.

The system is robust and easy to use because it was constructed with Python, Django, HTML, CSS, and JavaScript. Before producing forecasts, inaccurate and irrelevant data were filtered out thanks to the incorporation of natural language processing. After evaluation, the final model demonstrated encouraging outcomes, effectively assisting consumers in differentiating between authentic and fraudulent news.

In addition to improving knowledge of text classification and machine learning, this research shows how technology can be applied to solve societal issues. It provides the framework for upcoming enhancements including adding other models, such as SVM or neural networks, incorporating real-time news feeds, and expanding the system's deployment.

In the end, the study makes a significant contribution to the battle against false information and demonstrates how artificial intelligence (AI) can help preserve the accuracy of information in the digital realm.

CHAPTER 9

FUTURE ENHANCEMENT

There is a lot of room for development and improvement even though the current system uses Logistic Regression and fundamental Natural Language Processing techniques to detect fake news successfully. Future developments could improve the system's intelligence, accuracy, and usability. Here are a few potential avenues for development:

1. INCORPORATION OF ADVANCED MACHINCE LEARNING MODELS

To improve the prediction accuracy, more sophisticated models like Support Vector Machines (SVM), Random Forest, or Gradient Boosting could be applied rather than only Logistic Regression. For improved handling of linguistic nuances, deep learning techniques like Recurrent Neural Networks (RNNs) or Transformers (like BERT) should be investigated.

2. REAL-TIME NEWS FEEDS ANALYSIS

Real-time false news detection can be made possible by integrating the system with APIs from social media platforms or live news websites. Users would be able to quickly confirm the legitimacy of popular posts or articles thanks to this.

3. MULTIPLE LANGUAGES SUPPORT

At the moment, the model only analyzes news in English. Future iterations may use multilingual NLP models to identify bogus news in regional or foreign languages.

4. USER FEEDBACK SYSTEM

By retraining the model on fresh, verified data, a feature that allows users to indicate whether they agree or disagree with the system's forecast can help it get better over time.

5. MOBILE APPLICATIONS INTEGRATION

The application could be made more widely available by creating a mobile version. Voice inputs, camera-based news clipping scanning, and intuitive user interfaces are a few examples of this.

6. FACT-CHECKING SOURCES INTEGRATION

Integrating the system with outside fact-checking databases can improve it and give its forecasts more legitimacy and support.

7. BIAS AND SECURITY REDUCTION

Enhancing the system to lessen bias and make sure it is impervious to hostile attacks will increase its robustness and credibility.

By putting these upcoming improvements into practice, the Fake News Detection system can develop into a more complete, flexible, and effective way to fight fals

CHAPTER 10
APPENDIX

10.1 SOURCE CODE

Index.html

```
{% load static %}
<!DOCTYPE html>
<html lang="en" data-theme="dark">
<head>
   <meta charset="UTF-8" />
   <title>Fake News Analyzer</title>
   <script src="https://cdn.tailwindcss.com"></script>
   <style>
      .toggle-dot { transition: transform 0.3s ease-in-out; }
      input:checked ~ .toggle-dot { transform: translateX(100%); }
   </style>
</head>
<body class="bg-black text-white flex flex-col min-h-screen">

<!-- Navbar -->
<nav class="flex justify-between items-center px-6 py-4 bg-gray-900 text-white
shadow-md">
   <div class="text-xl font-bold">Fake News Detection</div>
   <ul class="flex gap-6 items-center">
      <li><a href="{% url 'get_email' %}"
class="hover:underline">Home</a></li>
      <li><a href="#" class="hover:underline">Reports</a></li>
      <li><a href="#" class="hover:underline">Contact</a></li>
      <li>
         <label class="flex items-center cursor-pointer">
            <span class="mr-2 text-sm">Dark Mode</span>
            <input type="checkbox" id="themeToggle" class="hidden" />
            <div class="relative w-10 h-5 bg-gray-400 rounded-full">
               <div class="toggle-dot absolute top-0 left-0 w-5 h-5 bg-white
rounded-full"></div>
            </div>
         </label>
      </li>
   </ul>
</nav>
```

```
<!-- Main Container -->
<main class="flex-grow flex flex-col items-center justify-center px-4 py-10 relative">

  <!-- Error Alert -->
  {% if error %}
  <div class="fixed top-10 left-1/2 transform -translate-x-1/2 bg-red-700 text-white text-lg font-bold px-6 py-4 rounded-xl shadow-lg z-50 border border-red-300 max-w-xl w-full text-center">
    {{ error }}
  </div>
  <script>
    setTimeout(() => {
      const errorBox = document.querySelector('[class*="bg-red-700"]');
      if (errorBox) errorBox.style.display = 'none';
    }, 5000);
  </script>
  {% endif %}

  <!-- Result Popup -->
  {% if result %}
  <div id="popup" class="fixed inset-0 flex items-center justify-center bg-white bg-opacity-50 z-50 px-4">
    <div class="bg-gray-800 text-white border-2 border-blue-600 px-6 py-6 rounded-xl shadow-xl text-center max-w-md w-full">
      <h3 class="text-xl font-semibold mb-2">Analysis Result</h3>
      <p class="text-lg">
        This news is
        {% if result == "FAKE" %}
          <span class="text-red-500 font-bold">{{ result }}</span> ✗
        {% else %}
          <span class="text-green-400 font-bold">{{ result }}</span> ✅
        {% endif %}
      </p>
      <p class="text-sm mt-1">Based on our analysis this result is reliable</p>
      {% if result == "FAKE" %}
        <p class="mt-2 font-semibold text-red-400">
          ⚠ Warning! This article may contain false or misleading information. Potential misinformation detected — proceed with caution.
        </p>
      {% else %}
        <p class="mt-2 font-semibold text-green-400">
```

✅ This article appears to be trustworthy and legitimate. No indicators of misinformation found in this news piece.
</p>
{% endif %}

<!-- Sounds -->
<audio id="realSound" src="{% static 'sounds/clang_and_wobble.ogg' %}" preload="auto"></audio>
<audio id="fakeSound" src="{% static 'sounds/beep_short.ogg' %}" preload="auto"></

Views.py

```
import pandas as pd
from django.shortcuts import render, redirect
from django.core.mail import send_mail
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression

# Load dataset once at server start
data = pd.read_csv(r"C:\Users\LENOVO\Desktop\final project\dataset1.csv",
                   encoding='ISO-8859-1', header=None,
                   names=['text', 'label'])
data.dropna(subset=['text', 'label'], inplace=True)
data['text'] = data['text'].astype(str)

X = data['text']
y = data['label']
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                        test_size=0.2,
                                        random_state=42)

vectorizer = TfidfVectorizer(stop_words='english', max_df=0.7)
X_train_tfidf = vectorizer.fit_transform(X_train)

model = LogisticRegression(max_iter=1000)
model.fit(X_train_tfidf, y_train)
```

```
existing_news_set = set(data['text'].str.strip().str.lower())

def predict_news(text):
    tfidf = vectorizer.transform([text])
    prediction = model.predict(tfidf)[0]
    return "REAL" if prediction == 1 else "FAKE"

def get_email(request):
    message = None
    success = False

    if request.method == "POST":
        email = request.POST.get('email', '').strip()
        if email and '@' in email:
            # Save email to session
            request.session['user_email'] = email
            message = "Thank you for subscribing!"
            success = True
            # Redirect to analyze page after successful subscription
            return redirect('index')
        else:
            message = "Invalid email address, please try again."
            success = False

    return render(request, 'detectors/email_input.html',
                  {'message': message, 'success': success})

def index(request):
    result = None
    error = None

    if request.method == 'POST':
        news = request.POST.get('news', '').strip()
        user_email = request.session.get('user_email')

        if not user_email:
            error = "Please subscribe with your email first."
        elif not news:
            error = "Please enter some news text."
        elif news.lower() not in existing_news_set:
            error = "⃠ This news article is not found in the dataset. Invalid input!"
```

```
        else:
            result = predict_news(news)
            # Send email to user with result
            try:
                send_mail(
                    subject="Your Fake News Detection Result",
                    message=f"The news you submitted is classified as: {result}",
                    from_email=None,
                    recipient_list=[user_email],
                    fail_silently=False,
                )
            except Exception as e:
                error = f"Failed to send email: {str(e)}"

    return render(request, 'detectors/index.html', {'result': result, 'error': error})
```

Urls.py

```
from django.urls import path
from detectors import views

urlpatterns = [
    path('', views.get_email, name='get_email'),      # Email subscription page at /
    path('analyze/', views.index, name='index'),      # News analyze page at
/analyze/
]
```

Settings.py

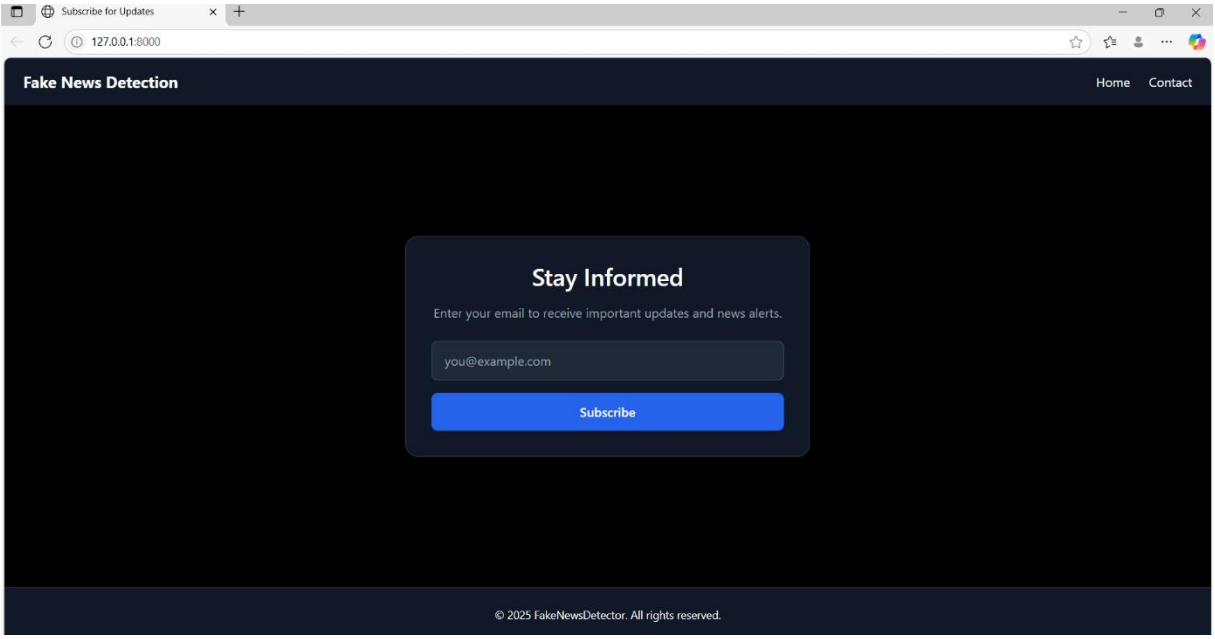
```
from pathlib import Path
import os

# Build paths inside the project like this: BASE_DIR / 'subdir'.
BASE_DIR = Path(__file__).resolve().parent.parent

# Quick-start development settings - unsuitable for production
# See https://docs.djangoproject.com/en/5.2/howto/deployment/checklist/

# SECURITY WARNING: keep the secret key used in production secret!
SECRET_KEY = 'django-insecure-
=rdoh@ouy_b2%nmy+zwjkp4mv*b*8wl%k)3v6mr#-ps$=-b%p_'
```

```
# SECURITY WARNING: don't run with debug turned on in production!
DEBUG = True

ALLOWED_HOSTS = []

# Application definition

INSTALLED_APPS = [
    'django.contrib.admin',
    'django.contrib.auth',
    'django.contrib.contenttypes',
    'django.contrib.sessions',
    'django.contrib.messages',
    'django.contrib.staticfiles',

    'detectors',
]

MIDDLEWARE = [
    'django.middleware.security.SecurityMiddleware',
    'django.contrib.sessions.middleware.SessionMiddleware',
    'django.middleware.common.CommonMiddleware',
    'django.middleware.csrf.CsrfViewMiddleware',
    'django.contrib.auth.middleware.AuthenticationMiddleware',
    'django.contrib.messages.middleware.MessageMiddleware',
    'django.middleware.clickjacking.XFrameOptionsMiddleware',
]

ROOT_URLCONF = 'fakenews_projects.urls'

TEMPLATES = [
    {
        'BACKEND': 'django.template.backends.django.DjangoTemplates',
        'DIRS': [os.path.join(BASE_DIR, 'detectors/templates')],
        'APP_DIRS': True,
        'OPTIONS': {
            'context_processors': [
                'django.template.context_processors.request',
                'django.template.context_processors.debug',
                'django.contrib.auth.context_processors.auth',
                'django.contrib.messages.context_processors.messages',
```

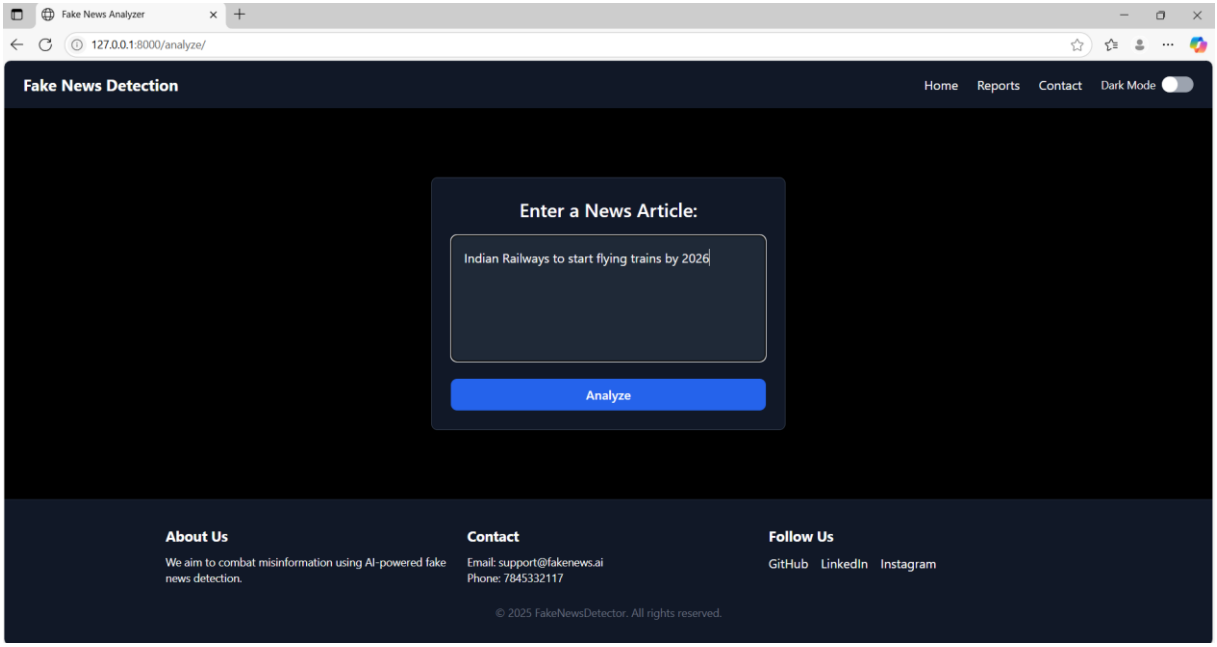
```
            ],
        },
    },
]



WSGI_APPLICATION = 'fakenews_projects.wsgi.application'

# Database
# https://docs.djangoproject.com/en/5.2/ref/settings/#databases

DATABASES = {
    'default': {
        'ENGINE': 'django.db.backends.sqlite3',
        'NAME': BASE_DIR / 'db.sqlite3',
    }
}

# Password validation
# https://docs.djangoproject.com/en/5.2/ref/settings/#auth-password-validators

AUTH_PASSWORD_VALIDATORS = [
    {
        'NAME':
'django.contrib.auth.password_validation.UserAttributeSimilarityValidator',
    },
    {
        'NAME':
'django.contrib.auth.password_validation.MinimumLengthValidator',
    },
    {
        'NAME':
'django.contrib.auth.password_validation.CommonPasswordValidator',
    },
    {
        'NAME':
'django.contrib.auth.password_validation.NumericPasswordValidator',
    },
]

# Internationalization
```

```
# https://docs.djangoproject.com/en/5.2/topics/i18n/

LANGUAGE_CODE = 'en-us'

TIME_ZONE = 'UTC'

USE_I18N = True

USE_TZ = True

# Static files (CSS, JavaScript, Images)
# https://docs.djangoproject.com/en/5.2/howto/static-files/

STATIC_URL = 'static/'

# Email configuration for sending emails via Gmail SMTP
EMAIL_BACKEND = 'django.core.mail.backends.smtp.EmailBackend'
EMAIL_HOST = 'smtp.gmail.com'
EMAIL_PORT = 587
EMAIL_USE_TLS = True
EMAIL_HOST_USER = 'malarvizhi1555@gmail.com'        # your Gmail
address
EMAIL_HOST_PASSWORD = 'yzacdgxarcymuoqj'     # your Gmail App
Password (16-char app password)


# Default primary key field type
# https://docs.djangoproject.com/en/5.2/ref/settings/#default-auto-field

DEFAULT_AUTO_FIELD = 'django.db.models.BigAutoField'
```

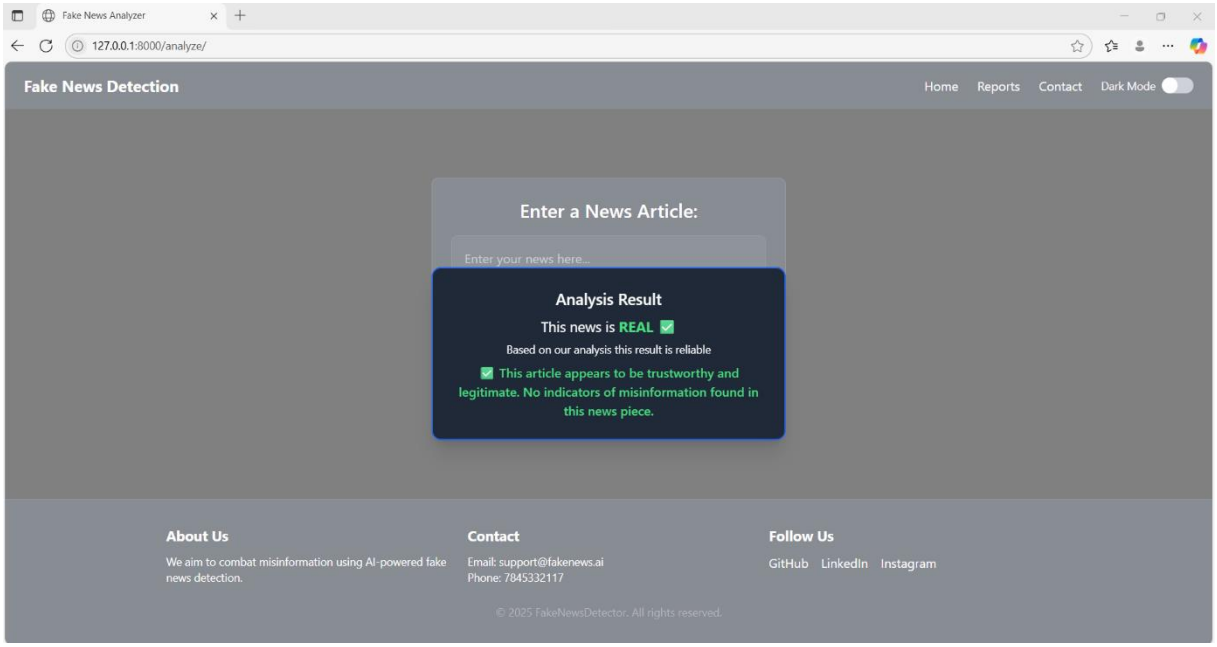
10.2 APPLICATION SCRENSHOTS:



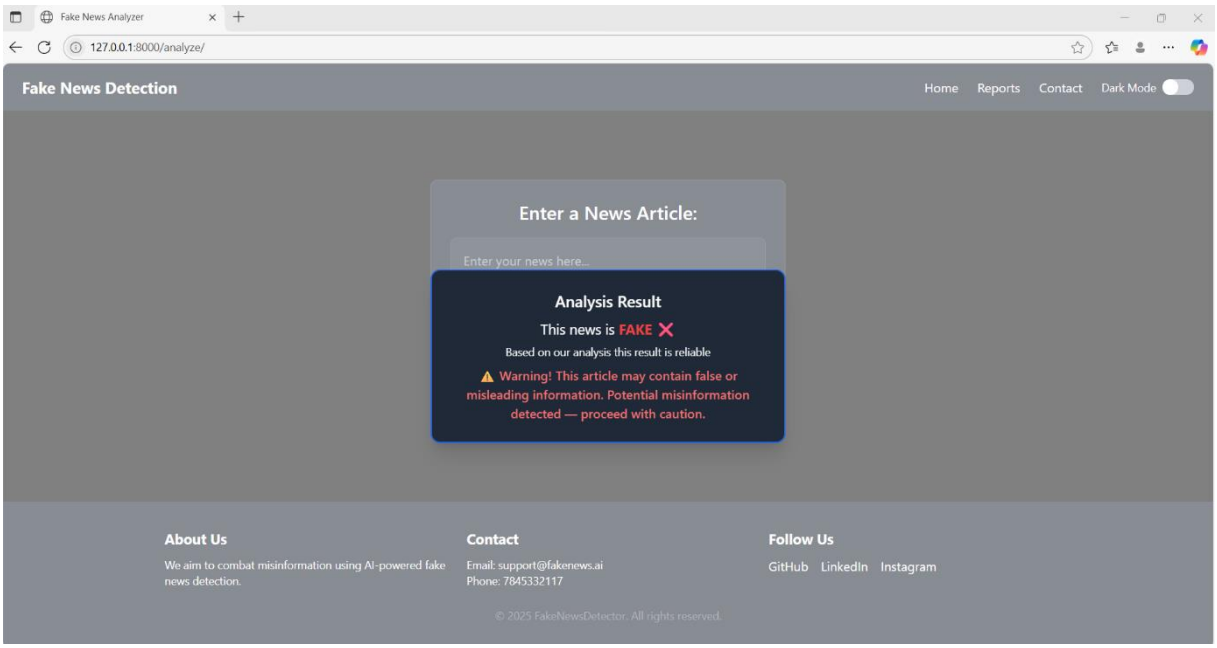
ENTER NEWS

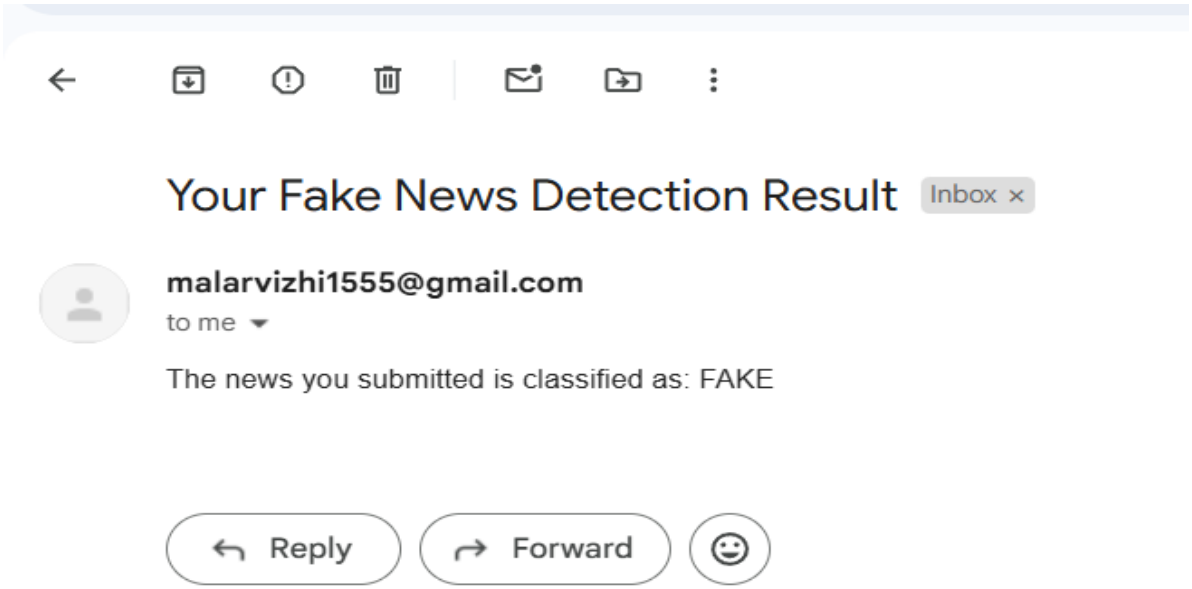


RESULT: REAL



RESULT:FAKE




Your Fake News Detection Result
Inbox ×
malarvizhi1555@gmail.com
to me
The news you submitted is classified as: FAKE
Reply
Forward

CHAPTER 11

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