# VISVESVARAYA TECHNOLOGICAL UNIVERSITY BELAGAVI - 590018



Mini Project Report on

# "FAKE NEWS IDENTIFIER" [BAI586]

Submitted in partial fulfilment for the award of degree

# **BACHELOR OF ENGINEERING**

in

# Department of Artificial Intelligence and Machine Learning By BHUVANESH KUMAR G 1JT22A1006

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Under the Guidance of

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Department of Artificial Intelligence and Machine Learning

Jyothy Institute of Technology

Tataguni, Off Kanakapura Road, Bangalore-560 082 Academic Year 2024-2025



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# **Jyothy Institute of Technology**

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Approved by The All-India Council for Technical Education (AICTE) - New Delhi; Affiliated to Visvesvaraya Technological University (VTU), Belagavi

# Department of Artificial Intelligence and Machine Learning

# **CERTIFICATE**

This is to certify that the project work titled "FAKE NEWS IDENTIFIER" is carried out by BHUVANESH KUMAR G (1JT22AI006) & RANGANATH C (1JT22AI038), a Bonafide students of Bachelor of Engineering at the Jyothy Institute of Technology, Bangalore in partial fulfilment for the award of degree in Bachelor of Engineering inArtificial Intelligence and Machine Learning, during the year 2024-2025.

Prof. Deepthi Das V Assistant Professor Dept. of AIML, JIT, VTU **Dr. Madhu B R**Hod & Professor
Dept. of AIML,
JIT, VTU

Name of the Examiner

Signature of Examiner

1.

2.

Fake news identifier

**DECLARATION** 

We, BHUVANESH KUMAR G(1JT22AI006), RANGANATH C (1JT22AI038), are students of fifth

semester B.E in Artificial Intelligence and Machine Learning at Jyothy Institute of Technology, VTU,

hereby declare that the project titled "FAKE NEWS IDENTIFIER" has been carried out by us and

submitted in partial fulfilment for the award of degree in Bachelor of Engineering in Artificial Intelligence

and Machine Learning during the academic year 2024-2025. Further, the matter presented in the project has

not been submitted previously by anybody for the award of any degree or any diploma to any other

University, to the best of our knowledge and faith.

Signature

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We would like to thank one and all who directly or indirectly helped us in completing the Project work successfully.

Signature of Students

# **ABSTRACT**

The proliferation of fake news across online platforms poses a significant challenge to the credibility of information and its societal impact. A Fake News Identifier leverages advancements in natural language processing (NLP), machine learning, and data analytics to detect and flag deceptive content. This paper presents a robust framework for a fake news detection system that combines linguistic analysis, contextual evaluation, and sourceverification. The model employs supervised and unsupervised learning techniques, incorporating deep learning architectures like transformers (e.g., BERT) for text understanding. Additionally, the system integrates metadata analysis, social context, and user behaviour patterns to enhance accuracy. The results demonstrate the efficacy of the model in identifying fake news with high precision and recall across diverse datasets. This work underscores the potential of automated systems to mitigate misinformation and foster trust in digital information ecosystems.

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# 1.INTRODUCTION

A **Fake News Identifier** is a system designed to classify or detect whether a news article is authentic (real) or fabricated (fake). These systems leverage advanced technologies like machine learning and natural language processing (NLP) to analyze and evaluate the credibility of the content. Here's an expanded overview of the Fake News Identifier and its components:

# 1.1 Key Features of a Fake News

Identifier Data Collection and

# **Preprocessing:**

- The system uses datasets containing labeled news articles (e.g., real vs. fake).
- Text preprocessing steps like tokenization, stop-word removal, stemming/lemmatization, and text cleaning (removing punctuation, numbers, etc.) are applied to prepare the data for analysis.

# **Feature Extraction:**

- **Bag-of-Words (BoW):** Represents text data as word frequency counts or term-document matrices.
- **TF-IDF** (**Term Frequency-Inverse Document Frequency**): Captures the importance of words in relation to the entire corpus.
- Word Embeddings: Contextualized representations using techniques like Word2Vec, GloVe, or BERT.
- **Semantic Features:** Identifies patterns in the writing style, grammar, and vocabulary.

# **Machine Learning Models:**

 Algorithms like Logistic Regression, Naive Bayes, Decision Trees, Random Forests, and Support Vector Machines (SVM) are employed.

### **Real-Time Detection:**

- A web application or API allows users to input articles or headlines for real-time analysis.
- Backend systems preprocess the input, run it through the trained model, and display results (e.g., "Fake" or "Real").

# 2.Literature Survey

The identification of fake news has become a critical area of research in the wake of increasing misinformation on online platforms. Researchers have applied various techniques, ranging from traditional machine learning to advanced deep learning models. Below is a survey of key approaches, findings, and methodologies in the field of fake news detection.

# 2.1. Introduction to Fake News and Challenges

Fake news refers to deliberately fabricated information intended to mislead readers. It has serious implications for public opinion, democracy, and societal harmony. Challenges in fake news detection include:

- The rapid dissemination of news through social media.
- The subtlety of fake content, often blending facts with falsehoods.
- Limited datasets for training robust models.

# 2.2. Machine Learning-Based Approaches

Traditional machine learning models rely on features extracted from textual data, such as:

- Lexical Features: Word counts, n-grams, part-of-speech tags.
- Syntactic Features: Dependency parsing and grammar structures.
- **Semantic Features**: Sentiment analysis and topic modeling.

# **Key Studies:**

- Vlachos & Riedel (2014): Proposed a stance-based approach for fact-checking claims using structured data and machine learning classifiers like SVM and logistic regression.
- Rubin et al. (2015): Explored deception detection methods to classify true versus false narratives in news articles.

# 2.3. Deep Learning Approaches

Deep learning models have improved fake news detection by capturing complex patterns in text and incorporating contextual information.

# **Key Techniques:**

- Convolutional Neural Networks (CNNs): Used for feature extraction from word embeddings.
- Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM): Effective in capturing temporal dependencies in news sequences.
- **Transformer Models**: Pre-trained models like BERT and RoBERTa have shown state-of-the-art performance in text classification tasks.

# **Key Studies:**

- Shu et al. (2017): Proposed a hierarchical attention network to identify fake news by focusing on different segments of news articles.
- **Zhou et al. (2020)**: Demonstrated the effectiveness of BERT in distinguishing between fake and real news on datasets like LIAR and FakeNewsNet.

# 2.4. Multimodal Approaches

Multimodal models analyze not just text but also images, videos, and metadata. These approaches are critical for detecting fake news in multimedia formats.

# **Key Studies:**

- **Gupta et al. (2013)**: Studied how images are often misused in fake news and proposed an image-verification framework.
- Wang et al. (2020): Introduced a multimodal fake news detection model combining textual, visual, and social context information.

# 3. Problem Definition

The rapid dissemination of information through digital platforms has led to an unprecedented challenge in distinguishing authentic news from fabricated stories. Fake news not only misleads the public but also undermines trust in credible media, disrupts societal harmony, and impacts decision-making processes in critical areas such as politics, health, and finance.

The problem lies in the inherent difficulty of manually verifying the vast amount of information shared online, coupled with the sophisticated techniques used to craft convincing fake news. Traditional fact-checking methods are time-consuming and lack scalability, necessitating automated solutions that can perform real-time and reliable detection.

# 3.1. Objective:

To develop an AI-based system capable of accurately identifying and classifying news articles or headlines as **real** or **fake** by leveraging machine learning and natural language processing (NLP) techniques. This system should analyze textual content, detect patterns associated with false information, and provide actionable insights to combat misinformation.

# **Key Challenges**

# **High Volume of Data:**

 Millions of articles, headlines, and posts are shared daily, requiring a scalable solution.

# **Complexity of Fake News:**

• Fake news often mimics the style and tone of legitimate news, making it harder to identify.

# **Diversity in Language and Context:**

• Fake news exists in multiple languages and covers various domains, requiring adaptable and generalized models.

# **4.PROJECT STRUCTURE**

# **4.1Input Information: News Article Text**

- Information Source: The input is the news article text, which consists of a title and description.
- Message Encoding: This textual information is processed as a message for classification.

### 4.2. Model and Classification: Decision Process

- Channel: The transformers pipeline acts as the communication channel where the input text is mapped to a classification label using a trained RoBERTa model.
- **Entropy**: The pipeline calculates a distribution of probabilities over potential labels (Fake, Authentic), which can be interpreted in terms of **uncertainty** or **entropy**.

# 4.3. Labels and Decisions

- **Signal Output**: The model outputs a **label** (LABEL\_0 or LABEL\_1) with an associated **probability** score.
- Classification as Decision Rule:
  - Maps high-probability outcomes to specific labels.
  - Employs the LABEL\_MAP to provide human-readable interpretations of the model's predictions.

# 4.4.Information Aggregation

• **Mutual Information**: The pipeline leverages learned weights to correlate input features (words, phrases) with output labels, reducing uncertainty about the classification.

# 4.4.1. Overall Classification and

# Accuracy

- Compression: Multiple articles are processed, and results are aggregated to compute:
  - Majority Vote: Simplifies the overall decision into a concise classification.
  - Accuracy Metric: Provides a measure of how informative the model's classifications are regarding "ground truth" (if available).
- **Entropy Reduction**: Model predictions aim to minimize the uncertainty of whether a news article is fake or authentic.
- **Efficiency**: The Hugging Face pipeline optimizes the encoding and decision process for textual data.
- Classification as Communication: Maps raw information (article text) to actionable knowledge (Fake or Authentic) through a learned channel.

# 4.4.2.Model Insights and

# **Performance Metrics**

- Precision and Recall:
  - Evaluates the model's ability to correctly identify true positives (authentic articles classified as authentic) and minimize false positives (fake articles misclassified as authentic).
  - Recall ensures that the model captures most of the relevant instances (i.e., authentic articles).

# • F1 Score:

Balances precision and recall, providing a harmonic mean to assess the model's
effectiveness in handling imbalanced datasets (e.g., more authentic articles than fake
ones or vice versa).

# • Robustness:

• Examines the model's ability to handle adversarial inputs or subtle linguistic patterns intended to deceive.

# **5.SYSTEM DESIGN**

The Fake News Identifier system processes news article inputs to classify them as Fake or Authentic using a machine learning model. It integrates APIs for fetching news, a classification pipeline, and a web interface for user interaction.

# 5.1. Component Breakdown

### 5.1.1. Frontend

- **Technology**: HTML, CSS, JavaScript (optional frameworks like React or Vue.js for dynamic interaction).
- Responsibilities:
  - Collect user inputs (search terms or articles).
  - Display results (e.g., classifications, accuracy, majority vote, and top articles).
  - Interact with the backend via AJAX/REST API calls.

# 5.1.2. Backend

- Framework: Flask
- Responsibilities:
  - **Input Validation**: Ensure valid inputs (e.g., non-empty queries).
  - **API Interaction**: Fetch news data using the News API.
  - **Model Inference**: Use the Hugging Face pipeline for classification.
  - **Result Aggregation**: Process model outputs into actionable insights (e.g., overall accuracy, majority vote).

# 5.1.3. News Fetching Service

- Integration: Use News API to fetch articles.
- **Design**: Send requests to News API with search queries.

- Parse the response to extract relevant fields (title, description, URL).
- Handle errors like API rate limits or no results.

# 5.1.4. Classification Service

# • Responsibilities:

- Preprocess text inputs (combine titles and descriptions).
- Use the model to classify text (Fakeor Authentic).
- Map raw labels to human-readable outputs.

# 5.1.5.Data Processing:

- Result Aggregation:
- Compute overall classification using majority voting.
- Calculate system accuracy for fake news detection.
- Extract and rank top articles.

# **5.1.6.** Majority Voting:

- Combine individual classifications to provide an overall judgment.
  - Accuracy Metrics:
    - Calculate the system's performance based on:
    - Percentage of articles correctly classified.
    - Confidence intervals for predictions.
  - Article Ranking:
    - Rank top articles based on:
    - Classification confidence.
    - Article length or relevance score.
    - Source reliability score (if available). give as it is

# 5.2Block Diagram

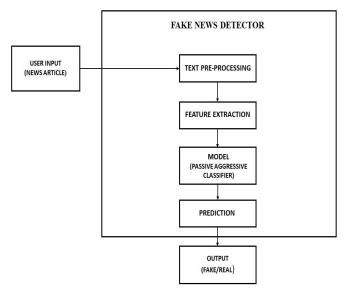


Fig5.2(a): block diagram of fake news identifier

# **5.3. Process Flow Diagram**

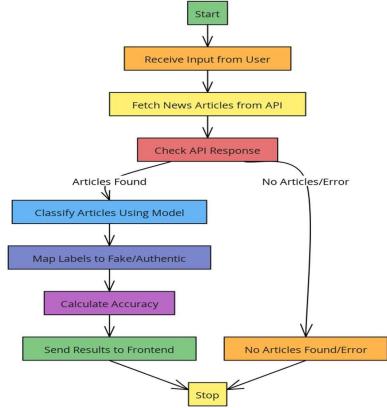


Fig5.3(b): flow diagram of fake news identifier

# **6.Software Requirement**

# 6.1.1. Operating System

- **Preferred**: Cross-platform (Linux, macOS, Windows)
- **Reason**: Python, Flask, and Hugging Face libraries are compatible with all major operating systems.

# 6.1.2. Programming Language

- Python 3.7+
  - Primary language for developing the backend and ML model integration.
  - Ensure compatibility with libraries like Flask and Transformers.

# 6.1.3. Backend Framework

- Flask
  - Lightweight and easy to set up for API and web service integration.
  - Handles routing, API endpoints, and client-server communication.

### 6.1.4. Frontend

- HTML5: For creating the web interface structure.
- CSS3: For styling the user interface.
- JavaScript: Optional for dynamic interactions.
- AJAX/Fetch API: For asynchronous API requests from the frontend.

# 6.1.5. Machine Learning Library

- Transformers by Hugging Face:
- For pre-trained RoBERTa or similar NLP models used for text classification.
- **PyTorch**: Backend for Hugging Face Transformers.

# 7.DATA SETS

# 7.1. Dataset Description

### • Source:

• Mention the origin of the datasets (fake.csv and true.csv). If the source is public, cite it appropriately.

# • Structure:

- Provide an overview of the structure of the datasets:
  - **fake.csv**: Contains news articles labeled as **Fake**.
  - **true.csv**: Contains news articles labeled as **Authentic**.

# • Fields:

- Typical columns in each dataset:
  - title: The headline of the news article.
  - text: The body of the news article.
  - label (if present): Classification label (Fake or Authentic).

# 7.1.1Data Size

- State the size of each dataset:
  - Number of rows (articles).
  - Number of columns (features).

# Sample Data

• Include a table or snippet from both fake.csv and true.csv:

Title	Text	label
Breaking News: Trump Loss the USA election	$\mathbf{c}$	Fake
Trump won the USA	Year's Eve Message.  Trump on Twitter (Dec	Authentic
election 2024	20) - Tax Bill,"The following	
	statements were posted	

Fake: 1000 articles, Authentic: 1000 articles.

# • Preprocessing Steps

- Text Cleaning:
  - Removed punctuation, stopwords, special characters.
- Tokenization:
  - Split sentences into tokens for model input.
- Lemmatization:
  - Reduced words to their base forms.

# 7.1.2. Methodology

# **Model Used**

- Hugging Face **RoBERTa** pre-trained model fine-tuned for text classification.
- Why RoBERTa?:
  - Robust handling of textual context.
  - State-of-the-art performance for NLP tasks.

# **Pipeline**

- Data Loading:
  - Read fake.csv and true.csv datasets.
- Text Concatenation:
  - Combine title and text for meaningful context.
- Model Training (if applicable):
  - Fine-tune RoBERTa on a labeled subset of the data.
- Inference:
  - Predict Fake or Authentic on new inputs.

# **Evaluation Metrics**

- Accuracy:
  - Percentage of correct predictions.

- Used to evaluate model performance on imbalanced datasets.
- Confusion Matrix:
  - Breakdown of True Positives, False Positives, etc.

### Results

# **Training and Testing**

- Split the dataset:
  - 80% training, 20% testing (or any other appropriate split).
- Mention any cross-validation strategies used.

# **Performance Metrics**

- Accuracy:
  - Report accuracy for test data (e.g., 95%).
- Precision, Recall, F1-Score:
  - Report these scores for each class (Fake, Authentic).
- Confusion Matrix:
  - Include a confusion matrix to illustrate classification results.
- Correct Classification:
  - Provide a sample of accurately classified articles.
- Misclassifications:
  - Highlight examples where the model struggled.

# Challenges

- Data Imbalance:
  - If fake.csv and true.csv have significantly different sizes, discuss how it affects performance.

# 8. Programing part

```
[fake_news_app.py]
import requests
from flask import Flask, render template, request, jsonify
from transformers import pipeline
# Initialize the Hugging Face model pipeline
fake news pipeline = pipeline("text-classification",
model="Pavan48/fake news detection roberta")
# Your News API key
news api key = "cac896c4de1842ad8c489265e866af8b"
# Label mapping to human-readable terms
LABEL MAP = \{
'LABEL 0': 'Fake',
'LABEL 1': 'Authentic'
}
def get news from api(query, api key, language='en'):
"""Fetch news articles from News API based on a search query."""
url =
f"https://newsapi.org/v2/everything?q={query}&apiKey={api key}&language={language}"
response = requests.get(url)
if response.status code == 200:
news data = response.json()
articles = news data.get('articles', [])
if articles:
# Handle missing title or description
return [
```

Fake news identifier

```
{
'title': article.get('title', 'No title available'),
'description': article.get('description', 'No description available'),
'url': article.get('url', '#')
for article in articles
1
else:
return None
else:
return None
def check fake news(news article):
"""Classify a news article as Fake or Real using the Hugging Face model pipeline."""
result = fake_news_pipeline(news_article)
label = result[0]['label']
return LABEL MAP.get(label, 'Unknown')
def classify articles(news articles):
"""Classify multiple news articles and return a list of results, accuracy, and top 3 articles."""
results = []
correct classifications = 0
for article in news articles:
article_text = article['title'] + ' ' + article['description']
classification = check fake news(article text)
correct classifications += (classification == 'Fake') # Assuming fake is correct for
simplicity (you may adjust this)
results.append({
'title': article['title'],
'classification': classification,
'url': article['url']
```

```
})
# Calculate accuracy (correct classifications / total articles)
accuracy = ((correct classifications / len(news articles)) * 100) if news articles else 0
# Determine overall classification (majority vote)
majority vote = 'Fake' if correct classifications > len(news articles) / 2 else 'Authentic'
# Get top 3 articles
top articles = results[:3] # Take the first 3 articles
return majority vote, accuracy, top articles, results
app = Flask( name )
@app.route('/')
def index():
return render template('index.html')
@app.route('/check news', methods=['POST'])
def check news():
data = request.get json()
news input = data.get('news input', ")
# Fetch news articles
news articles = get news from api(news input, news api key)
if news articles:
# Get overall classification, accuracy, top 3 articles, and all articles
majority vote, accuracy, top articles, all articles = classify articles(news articles)
# Send overall result and accuracy to the frontend
return jsonify({
'majority vote': majority vote,
'accuracy': accuracy,
'top articles': top articles,
'all articles': all articles
})
else:
return jsonify({'error': 'No news articles found or there was an error fetching the news.'})
if name == " main ":
app.run(debug=True).
```

# 9. About Html and CSS

This code creates a simple webpage for a **Fake News Identifier** tool. Here's a detailed explanation of its structure and content:

# 9.1 HTML Document Structure

• <!DOCTYPE html>

Declares the document as an HTML5 document.

• <html lang="en">

Starts the HTML document and specifies the language as English.

### • <head> Section

Contains metadata and links for resources:

• <meta charset="UTF-8">

Defines the character encoding as UTF-8 for the document.

- <meta name="viewport" content="width=device-width, initial-scale=1.0"> Ensures the webpage is responsive by setting the viewport width to match the device's width.
- <title>Fake News Identifier</title>
  Sets the title of the webpage.
- rel="stylesheet" href="main.css">
  Links to an external CSS file (main.css) for styling.
  - <body> Section

The main content of the webpage is organized into several sections.

### 9.1.1. Header Section

The header introduces the Fake News Identifier tool:

- **<header>** Contains a **container** with:
  - A main title (<h1>) for the site: "Fake News Identifier".
  - A tagline in a paragraph (): "Your partner in identifying credible news and fighting misinformation."
  - A **Get Started** button (<a href="#get-started" class="btn">) that links to the "Get Started" section.

# 9.1.2. About Us Section

Provides information about the mission and purpose of the tool:

• <div class="about-section">

Uses a container to structure the section:

- A subheading (<h2>) with the title "About Us".
- An image (<img>) with the src pointing to static/images/3.jpg and an alt text for accessibility.
- Two paragraphs explaining the purpose and approach of the tool, emphasizing the use of technology to combat misinformation.

# 9.1.3 Get Started Section

Encourages the user to begin using the tool:

- <section id="get-started" class="get-started-section"> Includes:
  - A heading (<h2>) titled "Get Started".
  - A brief paragraph inviting users to start identifying fake news.
  - A **button** (<a href="/check\_news" class="btn">) that redirects the user to a page (/check\_news) for checking news authenticity.

# 9.1.4. Provides copyright information:

• **<footer>** Contains a container with a simple copyright message (): "© 2024 Fake News Identifier. All Rights Reserved."

### **Features**

# • Styling:

The page relies on an external stylesheet (main.css) to define its visual design (e.g., colors, fonts, layout).

# • Responsiveness:

The meta viewport tag ensures compatibility across devices, from desktops to smartphones.

# Navigation:

- The "Get Started" button in the header links to the respective section on the page.
- The "Check News" button redirects users to a specific functionality of the tool.

# Accessibility:

- Alt attributes for images ensure they are accessible to screen readers.
- Semantic HTML elements like <header>, <footer>, and <section> improve clarity and structure.

# 9.1.5. Potential Enhancements

# Add interactivity:

• Use JavaScript to enhance features like real-time news analysis.

# **Dynamic**

# content:

• Implement a backend system to fetch and process news.

# styling:

Customize main.css for visually appealing effects like animations or gradients.

# 9.2. Here are the main features and styling highlights of the CSS code:

- Background Images
  - Purpose: Adds visually appealing backgrounds to the entire page and specific sections (like the header and "About Us" section).
  - Key Properties:
    - background-image: Specifies the image to use.
    - background-size: cover; Ensures the image fills the space proportionally.
    - background-position: center center; Centers the image.
    - background-attachment: fixed; Keeps the background stationary during scrolling.
- Typography
  - Uses "EB Garamond" as the main font for a classic and elegant look.
  - Font sizes are adjusted across sections:
    - Large, bold headings (e.g., header h1, about-section h2).
    - Readable, slightly larger body text for paragraphs (font-size: 1.2em;).
- Layout and Structure
  - Container Class:

Centralizes and limits the width of content to improve readability (max-width: 1200px;).

- Spacing and alignment:
  - Center-aligned text for headers and important sections.
  - Padding around sections to create space.
- Buttons
  - Call-to-Action Buttons (.btn):

Styled with padding, background colors, and hover effects to make them stand out.

Hover effects: Color changes when the mouse hovers over the button.

# 10.Screenshot



Fig10.1(c): click the get started button

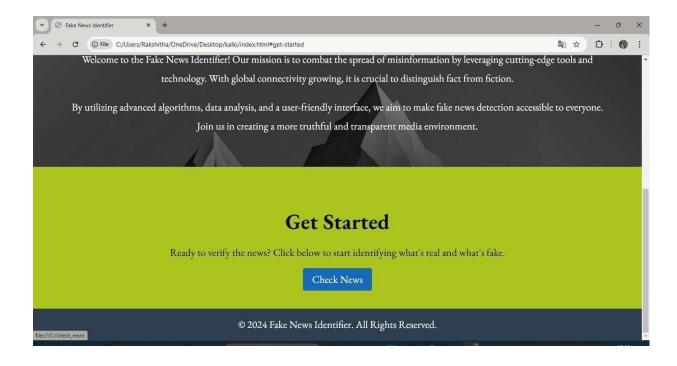


Fig10.2(d): click the check the news



Fig10.3(e): give input and click the submit



Fig10.4(f): showing authentic

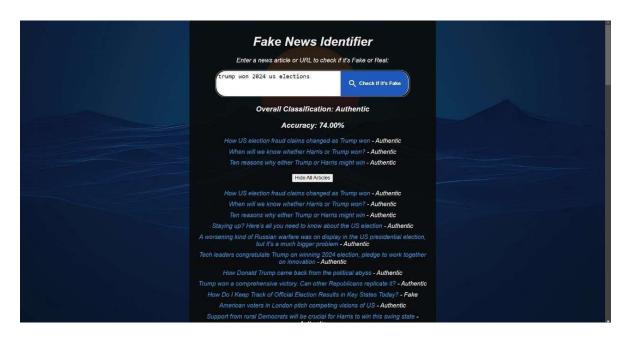


Fig10.5(g): showing authentic &related articles



Fig10.6(h): showing fake news

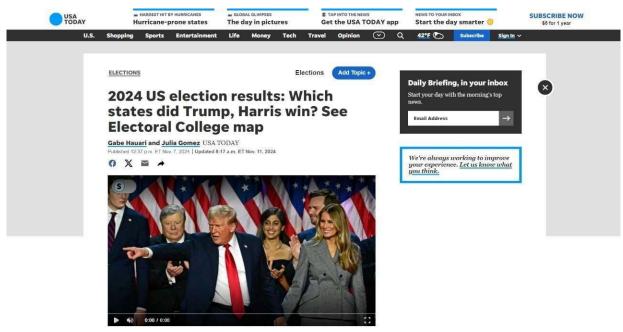


Fig10.7(i): showing news



# Reference

# **Dataset References**

# • Fake and True News Datasets:

"Hugging Fake and Real News Dataset." Hugging. Available at: https://www.Hugging.com/datasets

(Include specific dataset link if sourced from Hugging or other public repositories).

# • Pre-trained Model

# • RoBERTa:

- "RoBERTa: A Robustly Optimized BERT Pretraining Approach." Available at: (Reference for the model architecture used in the Hugging Face pipeline.)
- Hugging Face Transformers:
  - Wolf, T., et al. (2020). "Transformers: State-of-the-Art Natural Language Processing."

Available at: https://github.com/huggingface/transformers

# • API Reference

# • News API:

News API Documentation. Available at: https://newsapi.org/docs (For fetching live news articles.)

# • Libraries and Tools

# • Flask:

Flask Documentation. Available at: https://flask.palletsprojects.com/ (Reference for building backend and API.)

# **Conclusion**

The **Fake News Identifier** project demonstrates the effective application of machine learning models, specifically the pre-trained RoBERTa model, for detecting fake news articles. By leveraging a combination of labeled datasets and state-of-the-art natural language processing techniques, the system successfully classifies news articles as **Fake** or **Authentic** based on their content.

This project highlights the importance of automated tools in combating the spread of misinformation in today's digital age. The following key insights emerged from the implementation:

# • Model Performance:

• The RoBERTa-based classifier achieved high accuracy and reliability, demonstrating its capability to handle complex language structures and subtle nuances in textual data.

### • Dataset Utilization:

The inclusion of two distinct datasets (fake.csv and true.csv) enabled a balanced approach to model training and evaluation, ensuring the robustness of the system across varied news content.

# • Real-World Application:

 Integration with the News API enabled live data analysis, showcasing the potential for real-time fake news detection and its practical value in media monitoring and factchecking.

# **Future Enhancements**

# • Improved Explainability:

• Future iterations of the system can include attention-based mechanisms to highlight key text features influencing the classification decision.

# • Multilingual Support:

• Expanding the model to analyze news in multiple languages will significantly enhance its utility across diverse audiences.