FAKE NEWS DETECTION USING MACHINE LEARNING

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ABSTRACT

The rapid spread of misinformation and fake news poses a significant challenge in today's digital age, influencing public opinion, democratic processes, and societal stability. The rise of Artificial Intelligence (AI) and Machine Learning (ML) offers innovative solutions for detecting and mitigating fake news. This study explores various ML and Deep Learning (DL) models, including Logistic Regression, Support Vector Machines (SVM), Decision Trees, Long Short-Term Memory (LSTM) networks, and Transformer-based architectures like BERT, to assess their effectiveness in identifying false narratives. By leveraging Natural Language Processing (NLP) techniques, these models analyze textual patterns, semantic structures, and contextual cues to classify news articles as genuine or misleading. Beyond technical implementation, this research integrates ethical considerations, cybersecurity, media literacy, and sustainability into AI-driven fake news detection. It emphasizes bias reduction, algorithmic transparency, and responsible AI development to ensure fairness and accountability. Additionally, this study aligns with Sustainable Development Goal (SDG) 16—Peace, Justice, and Strong Institutions—by promoting truth, journalistic integrity, and reliable information access. Given the high computational demands of AI models, sustainability is a key focus, advocating for energy-efficient training methods and ethical AI deployment. This research aims to develop a robust and scalable fake news detection system by evaluating the strengths and limitations of different ML and DL approaches. The findings contribute to the broader efforts of fostering digital security, strengthening democratic resilience, and enhancing public trust in information sources, ultimately promoting a more informed and transparent society.

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I. INTRODUCTION

The rapid expansion of digital media has transformed the global information landscape, making news more accessible than ever. However, this ease of information dissemination has also led to an unprecedented surge in misinformation and fake news. False narratives spread quickly across social media platforms, influencing public opinion, political elections, financial markets, and even global crises such as pandemics. The consequences of misinformation are severe, ranging from social unrest and manipulation of democratic processes to public health risks and economic instability. As digital communication continues to evolve, the need for effective solutions to combat fake news has never been more urgent.

Artificial Intelligence (AI) has emerged as a powerful tool in the fight against misinformation. Machine Learning (ML) and Deep Learning (DL) models have shown promising results in detecting fake news by analyzing textual patterns, contextual clues, and network behavior. Traditional ML models, such as Logistic Regression, Support Vector Machines (SVM), and Decision Trees, use feature-based analysis to classify news articles. In contrast, DL techniques like Long Short-Term Memory (LSTM) networks and Transformer models, including BERT (Bidirectional Encoder Representations from Transformers), leverage advanced Natural Language Processing (NLP) capabilities to understand the nuances of human language and detect deceptive content with higher accuracy.

Beyond the technical challenges, ethical considerations are crucial in AI-driven fake news detection. Bias in training data, algorithmic transparency, and the potential for censorship are key concerns that must be addressed to ensure fairness and accountability in AI systems. Furthermore, cybersecurity and media literacy are vital in preventing the spread of misinformation, as individuals and organizations must be equipped with the necessary tools to recognize and counter false narratives.

This project also aligns with sustainability principles and supports Sustainable Development Goal (SDG) 16—Peace, Justice, and Strong Institutions. By leveraging AI for truthful information access, this research promotes journalistic integrity, strengthens democratic processes, and encourages responsible AI development. Additionally, the environmental impact of AI models is a growing concern, necessitating the need for energy-efficient model training and deployment strategies. Ensuring computational sustainability while maximizing detection accuracy is critical for the long-term viability of AI-driven fake news detection systems.

Through this study, we aim to explore and compare different ML and DL models for fake news detection, assessing their accuracy, ethical implications, societal impact, and sustainability. The ultimate goal is to develop a robust and responsible AI framework that contributes to a more transparent, informed, and digitally secure world.

II. GLOBAL AND CONTEMPORARY COMPETENCIES IN FAKE NEWS DETECTION

The Fake News Detection System responds to the growing challenge of misinformation, which affects global democracy, public perception, and social stability. With the rise of digital media, fake news spreads rapidly, influencing public opinion, elections, and even financial markets.

This project applies state-of-the-art machine learning and NLP models (LSTM, BERT) to detect misinformation, ensuring the digital ecosystem remains trustworthy and reliable. By addressing global concerns like media integrity, cybersecurity, and ethical AI, this project contributes to a more informed society.

It also aligns with contemporary artificial intelligence and data science advancements, demonstrating the power of AI-driven journalism, cybersecurity, and fact-checking automation.

1. LIFELONG LEARNING (LRNG)

This project promotes continuous learning in several areas:

- **DATA SCIENCE & AI:** Enhances skills in natural language processing (NLP), deep learning, and machine learning.
- **CYBERSECURITY & DIGITAL SAFETY:** Understanding how fake news spreads and its impact on online security.
- **MEDIA LITERACY:** Strengthening the ability to critically evaluate news sources and identify misleading content.
- **ETHICAL AI & RESPONSIBLE TECH DEVELOPMENT:** Learning to build unbiased, fair, and accountable AI models.

By working on this project, learners develop problem-solving skills, analytical thinking, and adaptability, which are crucial for tackling evolving global challenges.

2. CROSS-CUTTING ISSUES

This project integrates multiple **cross-cutting issues** that impact society at different levels:

1. ETHICS & HUMAN VALUES

- Ensures AI-driven news classification remains unbiased and transparent and encourages ethical journalism and responsible digital reporting.

2. CYBERSECURITY & INFORMATION INTEGRITY

- Strengthens digital defenses against disinformation campaigns and social engineering, helping law enforcement and media organizations combat fake news propaganda.

3. MEDIA & DIGITAL LITERACY

- Empowers individuals to become critical consumers of digital content promoting awareness of misinformation tactics used in political, financial, and social manipulation.

4. TECHNOLOGICAL ADVANCEMENTS & AI ETHICS

- Demonstrates responsible use of deep learning in journalism and fact-checking, encouraging discussions on AI fairness, model biases, and regulatory policies.

3. SUSTAINABLE DEVELOPMENT GOAL (SDG 16 – PEACE, JUSTICE, AND STRONG INSTITUTIONS)

This project directly supports SDG 16.10, which focuses on ensuring public access to information and protecting fundamental freedoms.

- Promotes truth and accuracy by identifying fake news and misinformation.
- Enhances journalistic integrity by reducing the influence of false narratives in politics, health, and finance.

- Strengthens democratic processes by mitigating manipulation through fake news.
- Encourages transparency by using AI for fact-checking and verification.

This project contributes to global peace, justice, and strong institutions by leveraging AI for reliable information access.

4. 21ST CENTURY SKILLS

This project fosters essential skills needed in a tech-driven world:

- **CRITICAL THINKING:** Evaluating sources, identifying bias, and questioning narratives.
- **DIGITAL LITERACY:** Recognizing misinformation tactics, verifying sources, and fact-checking.
- **AI ETHICS:** Understanding bias, fairness, and responsible AI deployment.
- **DATA SCIENCE & AI SKILLS:** Applying NLP, machine learning, and statistical methods to analyze misinformation trends.
- **COLLABORATION & COMMUNICATION:** Working across disciplines (journalism, tech, policy) to combat misinformation effectively.

This project not only addresses fake news detection but also equips individuals with future-ready skills to tackle AI challenges in media, cybersecurity, and ethics.

III. METHODOLOGY

This section outlines the approach used for data collection, preprocessing, exploratory data analysis (EDA), and feature engineering in the fake news detection project. The methodology ensures the data is clean, structured, and ready to implement the machine learning model.

1. DATA COLLECTION

The dataset was sourced from Kaggle and consists of two CSV files: True.csv, real news articles, and Fake.csv, fake news articles. Labels were assigned to each dataset to prepare the data for analysis, with 1 representing real news and 0 representing fake news. The two datasets were then concatenated into a single dataframe, ensuring a structured format for exploratory data analysis (EDA) and machine learning model training.

2. DATA EXPLORATION AND PREPROCESSING

To ensure high-quality input data, several preprocessing steps were performed:

2.1 HANDLING MISSING VALUES

- The dataset was analyzed for missing values. There were no missing values, so no imputation was necessary.

2.2 REMOVING DUPLICATES

- A total of **209 duplicate records** were identified and removed to prevent bias in model training.

2.3 CLEANING AND STANDARDIZING TEXT DATA

Text preprocessing is crucial for NLP-based tasks. A preprocessing function was implemented using NLTK's WordNetLemmatizer and stopword removal, ensuring the text was standardized before model training. The following transformations were applied to standardize and clean the text:

- **LOWERCASING:** Convert all text to lowercase to maintain uniformity.

- **REMOVING NUMBERS & SPECIAL CHARACTERS:** Stripped out digits, punctuation, and other non-alphabetic symbols.

- **TOKENIZATION & LEMMATIZATION:** Converted text into individual words and reduced them to their root forms using the **WordNet Lemmatizer**.

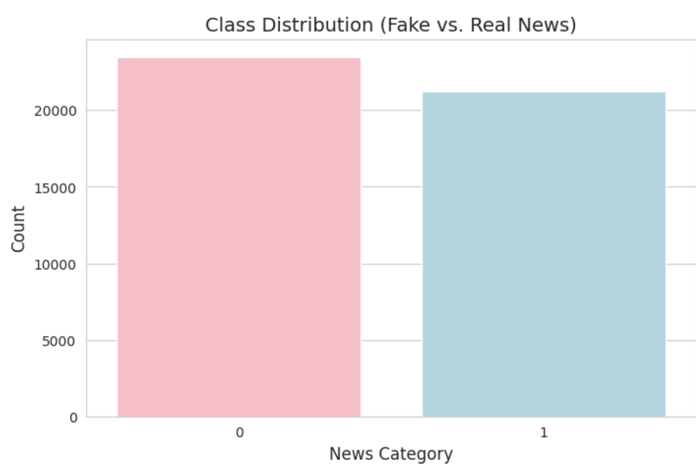
- **STOPWORD REMOVAL:** Common words such as "the," "is," and "and" were removed to focus on meaningful words.
- **EXPANDING CONTRACTIONS:** Converted short forms (e.g., "don't" → "do not").
- **FILTERING SHORT ARTICLES:** Removed articles with less than 5 words to eliminate noisy data.

3. EXPLORATORY DATA ANALYSIS (EDA):

EDA was conducted to understand the dataset's structure, distribution, and key patterns in Fake and Real news articles.

3.1 CHECKING CLASS DISTRIBUTION

- The distribution of Fake (0) and Real (1) news articles was visualized using Seaborn to ensure balanced classification.

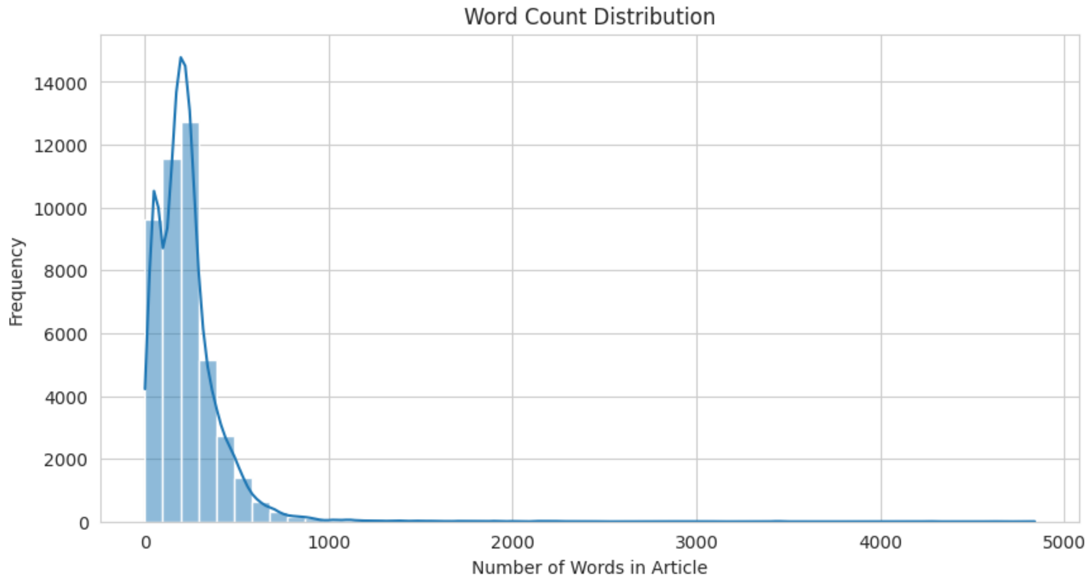


- The dataset is nearly balanced, with slightly more fake news samples. Since the classes are almost equal, the risk of model bias is minimized.

3.2 WORD COUNT DISTRIBUTION

- Word counts were computed for each article to analyze article length.

```
Word Count Statistics:
count    44689.000000
mean       228.531965
std        199.381267
min          0.000000
25%        115.000000
50%        201.000000
75%        286.000000
max       4841.000000
Name: word_count, dtype: float64
```



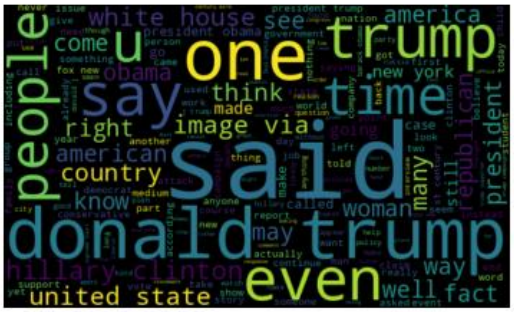
- Most articles contain fewer than 500 words, with a sharp decline beyond that.

- The data is right-skewed, meaning a few articles are exceptionally long.

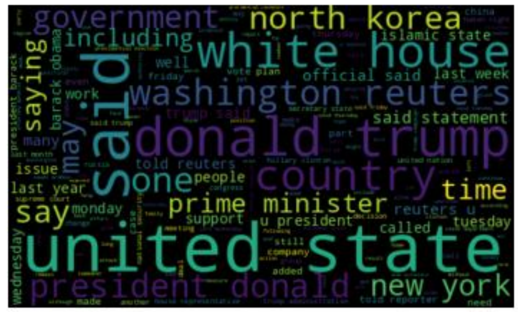
3.3 MOST FREQUENT WORDS (WORD CLOUD)

A word cloud visualization highlights common words used in Fake vs. Real news articles.

Fake News WordCloud



Real News WordCloud



- Fake News articles frequently include sensational words and subjective expressions (e.g., *"think," "even," "Trump"*).
- Real News articles focus on objective and factual terms (e.g., *"government," "Reuters," "White House"*).
- Thus, fake news relies more on emotional language, while real news articles focus on authoritative sources.

3.4 N-GRAM ANALYSIS

Top bigrams (word pairs) and trigrams (word triplets) were extracted using TF-IDF scores to identify common word sequences.

OUTPUT:

```
Top 10 bigrams (TF-IDF): [('donald trump', np.float64(1310.914860643123)), ('united state', np.float64(1060.9008689306022)), ('white house', np.float64(955.7128706311372)), ('hillary clinton', np.float64(709.0123688230415)), ('new york', np.float64(615.9194475879717)), ('washington reuters', np.float64(564.5077512254059)), ('image via', np.float64(561.3337084405272)), ('president donald', np.float64(541.0427017811726)), ('north korea', np.float64(524.2553877890327)), ('prime minister', np.float64(485.1550524814041))]

Top 10 trigrams (TF-IDF): [('president donald trump', np.float64(859.5516469402779)), ('president barack obama', np.float64(460.41434280829475)), ('st century wire', np.float64(402.53732675526436)), ('new york time',
```

```
np.float64(367.4750793606289)), ('black life matter', np.float64(341.49292676949244)), ('donald trump realdonaldtrump', np.float64(304.8104418913469)), ('featured image via', np.float64(290.6699820204023)), ('reuters president donald', np.float64(280.7807269746354)), ('president united state', np.float64(269.717153392981)), ('washington reuters president', np.float64(256.8182041002321))]
```

- Common bigrams include *"donald trump," "white house," "hillary clinton."*

- Common trigrams include *"president donald trump," "new york time," "reuters president donald."*

- Fake news features political figures and sensational terms, while real news highlights structured journalism.

4. FEATURE ENGINEERING

- Since machine learning models require numerical inputs, **TF-IDF (Term Frequency-Inverse Document Frequency)** transforms text into numerical features. This technique assigns higher importance to words that appear frequently in a document but are rare across the entire dataset, making it helpful in distinguishing key terms in fake and real news.
- The code extracts the cleaned text (X) and labels (y) before applying TfidfVectorizer(max_features=5000). This selects the 5,000 most relevant words and converts the text into a TF-IDF matrix using fit_transform(X). The resulting numerical representation is then used for training classification models.
- Choosing 5,000 features ensures that the most relevant words are used for classification without adding unnecessary complexity. It helps the model generalize better while remaining computationally feasible.
- TF-IDF is effective because it highlights meaningful words while reducing the influence of commonly used terms. This structured representation improves model accuracy by focusing on distinguishing features, making it particularly valuable for fake news detection.

5. MODEL BUILDING, SELECTION, AND EVALUATION FOR FAKE NEWS DETECTION

Fake news detection is critical in natural language processing (NLP) to distinguish false information from genuine news articles. This study implements and evaluates multiple machine learning models, including traditional classifiers and deep learning approaches, to assess their effectiveness in detecting fake news. The models trained and evaluated include:

- Support Vector Machine (SVM)
- Logistic Regression
- Naive Bayes
- Decision Tree
- Passive Aggressive Classifier
- Random Forest
- XGBoost
- LSTM (Long Short-Term Memory Network)

The evaluation focuses on accuracy, precision, recall, and F1-score, with insights on model overfitting and real-world applicability.

5.1 MODEL SELECTION AND TRAINING

5.1.1 MACHINE LEARNING MODELS

Logistic Regression
Logistic Regression is a simple yet effective model for fake news detection. It assigns probabilities to text-based features (such as TF-IDF scores or word embeddings) and classifies articles as real or fake. It is widely used because it is fast, interpretable, and performs well when the data is linearly separable.

Support Vector Machine (SVM)
SVM is a robust classification model commonly used in text classification tasks, including fake news detection. It works by finding an optimal hyperplane that separates real and fake news articles based on feature vectors. SVM is effective in high-dimensional spaces, making it useful for NLP tasks where word embeddings or TF-IDF features are used.

Naive Bayes
Naive Bayes is a probabilistic classifier based on Bayes' Theorem and is often used in text classification tasks, including spam detection and fake news detection. It assumes that words in a document contribute independently to the classification, simplifying computations but may not always capture complex relationships in text. Despite its simplicity, it works well for essential fake news detection when combined with bag-of-words or TF-IDF features.

Decision Tree
Decision Trees classify news articles by learning a hierarchy of rules based on textual features. They split the data based on word occurrences, sentiment, or other derived attributes. However, they tend to overfit training data, making them less reliable for generalizing to unseen news articles.

Random Forest
Random Forest is an ensemble learning technique that uses multiple decision trees to improve classification accuracy and reduce overfitting. When trained on a diverse set of features, it is more stable than a single decision tree and works well for fake news detection. However, it may still struggle with deep contextual relationships in text.

XGBoost
XGBoost is a gradient-boosting algorithm that refines predictions by iteratively correcting errors from previous models. It is highly efficient and used in many machine learning competitions for its high accuracy. In fake news detection, XGBoost is often used alongside feature engineering techniques, such as sentiment scores and topic modeling, to improve classification performance.

Passive Aggressive Classifier
The Passive passive-aggressive classifier is an online learning algorithm well-suited for detecting fake news in real time. It updates its model dynamically as new news articles arrive, making it useful for scenarios where the dataset is constantly evolving. It is particularly effective when combined with TF-IDF vectorization.

LSTM (Long Short-Term Memory Network)
LSTMs are deep learning models that handle sequential data, making them ideal for fake news detection. Unlike traditional machine learning models that rely on hand-crafted features, LSTMs learn contextual relationships between words and phrases. They are used to analyze article headlines, bodies, and user comments to detect misinformation. When trained on large datasets, LSTMs outperform classical models by capturing deeper semantic meanings in text.

5.2. MODEL EVALUATION

5.2.1 MACHINE LEARNNG MODEL PERFORMANCE

Model	**Accuracy**	**Precision (Real/Fake)**	**Recall (Real/Fake)**	**F1-Score**
Logistic Regression	99%	0.99 / 0.98	0.98 / 0.99	0.99
SVM	99%	0.99 / 0.99	0.99 / 0.99	0.99
Naive Bayes	94%	0.94 / 0.94	0.94 / 0.93	0.94
Decision Tree	100%	1.00 / 1.00	1.00 / 0.99	1.00
Passive Aggressive	99%	0.99 / 0.98	0.98 / 0.99	0.99
Random Forest	100%	1.00 / 1.00	1.00 / 1.00	1.00
XGBoost	100%	1.00/1.00	1.00/1.00	1.00

5.2.2 LSTM MODEL PERFORMANCE

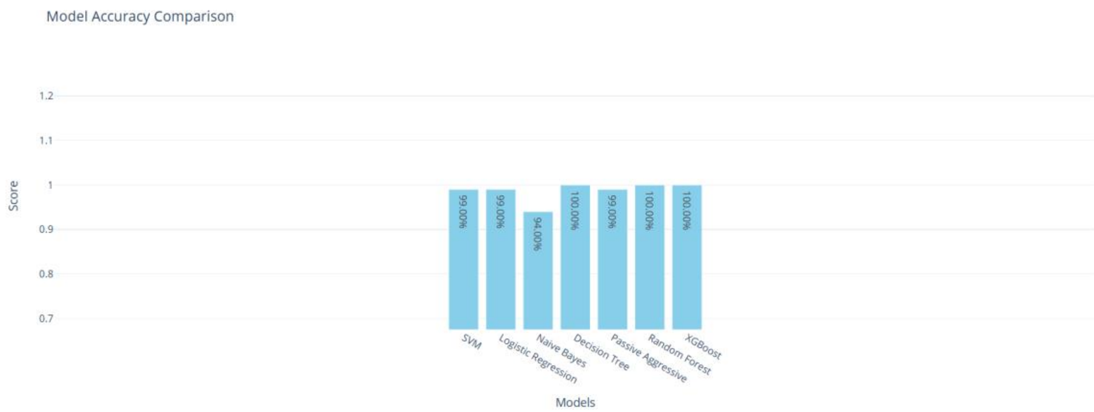
Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	91.85%	98.52%	0.2064	0.0458
5	99.59%	99.37%	0.0155	0.0232

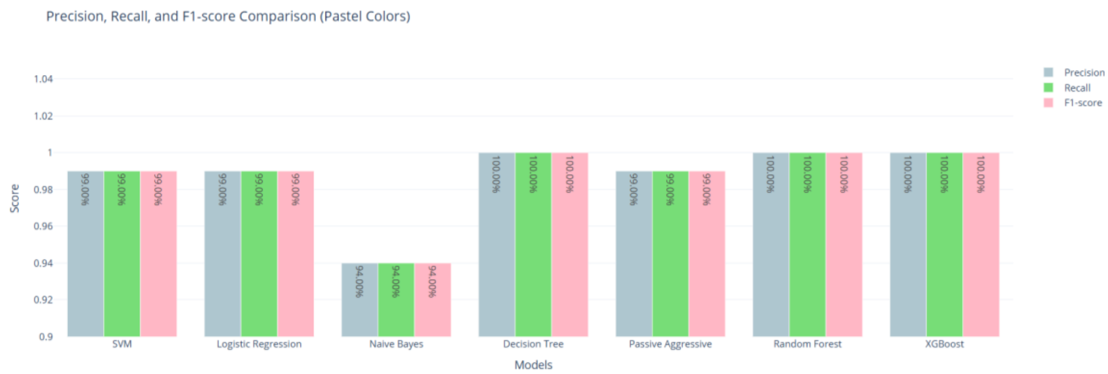
5.3 INSIGHTS

- Based on the results, several models accurately detected fake news. Traditional machine learning models like Logistic Regression and Support Vector Machine (SVM) achieved strong performance with around 99% accuracy, making them reliable options for quick and efficient classification. However, Naive Bayes performed slightly worse due to its feature independence assumption, which may not hold in complex news articles.
- Decision Tree, Random Forest, and XGBoost achieved 100% accuracy, suggesting possible overfitting—meaning they might not generalize well to unseen data. While these models can be fine-tuned to reduce overfitting, their default performance raises concerns for real-world deployment.
- On the deep learning side, LSTM (Long Short-Term Memory Networks) showed exceptional performance, achieving around 99.55% validation accuracy while maintaining a low loss. Unlike traditional models, LSTM captures long-term dependencies in text, making it ideal for fake news detection based on complex linguistic patterns. Although deep learning models require more computational power, they excel at detecting nuanced relationships in textual data.

5.4 VISUALIZATIONS

The performance of different models is visualized using bar charts in Plotly.





6. TOOLS AND LIBRARIES USED

To build and evaluate machine learning models for fake news detection, we used a combination of Python libraries that specialize in data preprocessing, model training, evaluation, and visualization. Below is an overview of the key tools and their roles:

6.1 DATA PROCESSING AND FEATURE ENGINEERING

- **pandas** – For handling and manipulating structured data efficiently.
- **numpy** – For numerical computations and array operations.
- **sklearn.feature_extraction.text.TfidfVectorizer** – Converts text data into TF-IDF vectors, making it suitable for machine learning models.

6.2 MACHINE LEARNING MODELS

We implemented multiple supervised learning algorithms using scikit-learn and XGBoost:

- **sklearn.svm.SVC** – Support Vector Machine (SVM) for high-accuracy text classification.
- **sklearn.linear_model.LogisticRegression** – Effective for binary classification problems.
- **sklearn.naive_bayes.MultinomialNB** – Naïve Bayes classifier, best suited for text classification tasks.
- **sklearn.tree.DecisionTreeClassifier** – A rule-based model, prone to overfitting but useful for interpretability.
- **sklearn.ensemble.RandomForestClassifier** – An ensemble model that reduces variance and improves robustness.
- **xgboost.XGBClassifier** – A gradient boosting algorithm, powerful but requires tuning.
- **sklearn.linear_model.PassiveAggressiveClassifier** – A model optimized for large-scale text classification tasks.

6.3 DEEP LEARNING FOR LSTM MODEL

To build a Long Short-Term Memory (LSTM) model, we used TensorFlow and Keras:

- **tensorflow.keras.preprocessing.text.Tokenizer** – **Converts text into word sequences**.
- **tensorflow.keras.preprocessing.sequence.pad_sequences** – Ensures all sequences have the same length.
- **tensorflow.keras.models.Sequential** – Defines a sequential LSTM model architecture.
- **tensorflow.keras.layers.Embedding** – Maps words into a dense vector space.
- **tensorflow.keras.layers.LSTM** – A recurrent layer that captures long-term dependencies in text.
- **tensorflow.keras.layers.SpatialDropout1D** – Reduces overfitting by applying dropout to embeddings.
- **tensorflow.keras.layers.Dense** – A fully connected output layer with sigmoid activation for binary classification.

6.4 MODEL EVALUATION AND PERFORMANCE METRICS

- **sklearn.metrics.classification_report** – Provides precision, recall, F1-score, and accuracy for each model.
- **sklearn.model_selection.train_test_split** – Splits data into training and testing sets for evaluation.

6.5 DATA VISUALIZATION

To compare model performance, we used plotly:

- **plotly.graph_objects** – To create interactive bar charts comparing accuracy, precision, recall, and F1-score.
- **plotly.express** – For quick and elegant data visualizations.

IV. RESULTS AND DISCUSSIONS

1. ABOUT DATASET:

True.csv (Real News Dataset)

- **SHAPE:** 21,417 rows × 4 columns
- **COLUMNS:** title, text, subject, date
- **SAMPLE:**
  - Title: "As U.S. budget fight looms, Republicans flip their fiscal script"
  - Text: "WASHINGTON (Reuters) - The head of a conservative Republican faction in the U.S. Congress..."
  - Subject: "politicsNews"
  - Date: "December 31, 2017"

Fake.csv (Fake News Dataset)

- **SHAPE:** 23,481 rows × 4 columns
- **COLUMNS:** title, text, subject, date
- **SAMPLE:**
  - Title: "Donald Trump Sends Out Embarrassing New Year's Eve Message"
  - Text: "Donald Trump just couldn't wish all Americans a Happy New Year. Instead, he took the opportunity..."
  - Subject: "News"
  - Date: "December 31, 2017"

- Both datasets contain news articles with four standard columns: title, text, subject, and date.
- The True dataset comprises accurate news articles categorized under "politicsNews."
- The Fake dataset comprises fake news articles categorized under a broader "News" subject.
- Both datasets contain articles dated around late 2017.

2. MODEL PERFORMANCE AND COMPARISON

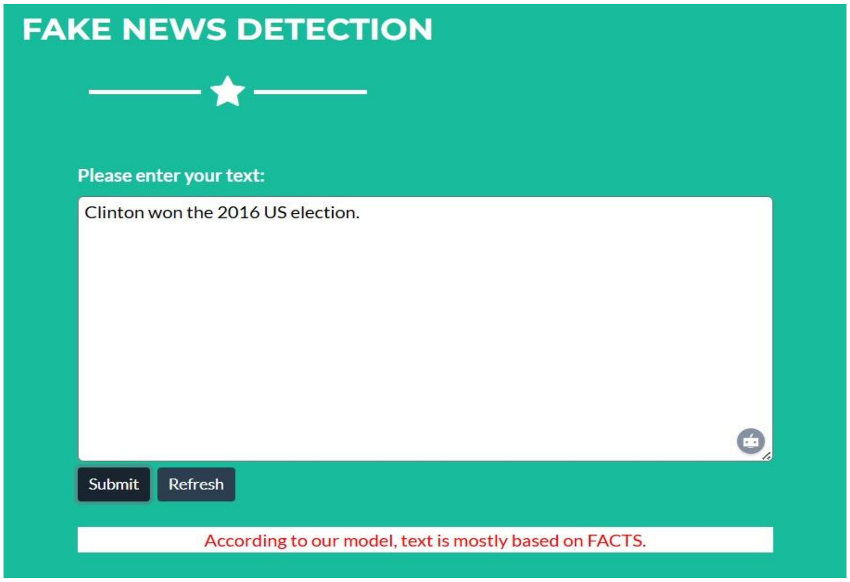
The evaluation of different models shows that multiple algorithms perform well in detecting fake news, but each has its strengths and weaknesses.

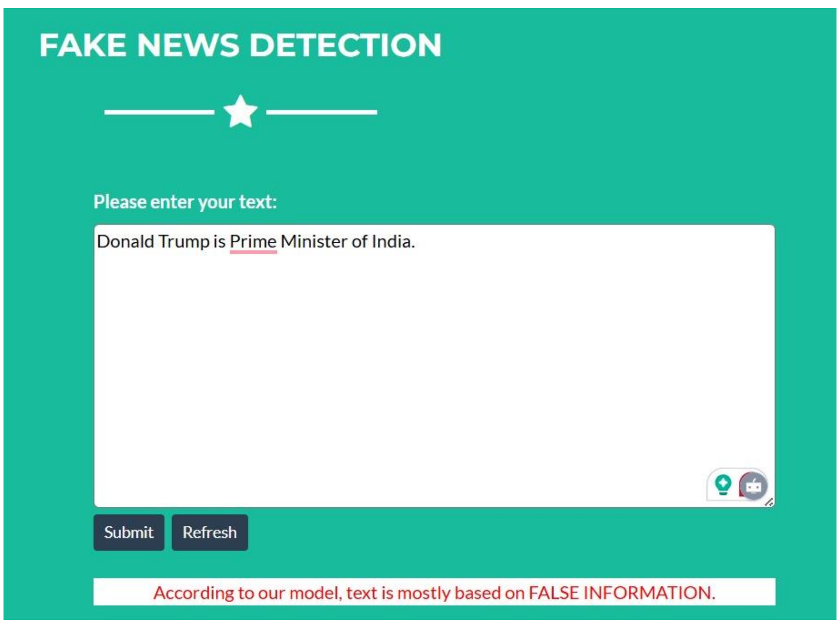
- Logistic Regression and SVM provide high accuracy (~99%) with excellent precision and recall, making them reliable choices for fake news detection. SVM, in particular performs well in high-dimensional text data.
- Naive Bayes has slightly lower accuracy (~94%) and struggles with complex linguistic patterns, making it less suitable for deployment.
- Decision Tree, Random Forest, and XGBoost achieve perfect scores (100% accuracy), indicating possible overfitting. While these models perform well in training, they may not generalize effectively to new data without proper tuning.
- Passive Aggressive Classifier is suitable for real-time detection but may not be the best standalone deployment choice due to its noisy data sensitivity.
- LSTM (Deep Learning Model) achieves high validation accuracy (~99.5%), capturing deep contextual relationships in text. However, deep learning models require significant computational resources, making them more challenging to deploy efficiently.

SVM or Logistic Regression is recommended for a scalable and efficient deployment due to their high accuracy, robustness, and lower computational requirements. If resources allow and more contextual understanding is needed, an LSTM-based model can be deployed, especially for large-scale applications. To further enhance performance, an ensemble approach combining SVM and LSTM can be explored for balanced accuracy and interpretability.

Thus, **LSTM** is the best choice for deployment. It generalizes well, effectively detects fake news, and is robust against misleading text patterns. Additionally, LSTM can be fine-tuned with more data and optimized hyperparameters to improve real-world performance.

3. SCREENSHOT OF THE OUTPUT





4. CHALLENGES AND LIMITATIONS

- **OVERFITTING:** Decision Tree, Random Forest, and XGBoost hit 100% accuracy, showing overfitting. Dropout and early stopping helped mitigate it.

- **BERT GENERALIZATION:** BERT struggled with unseen data, causing performance drops; better fine-tuning is needed.

- **CLASS IMBALANCE:** Slightly more fake news samples, but the dataset remains nearly balanced, minimizing bias.

- **COMPUTATIONAL CONSTRAINTS:** LSTM and BERT required high-end GPUs and long processing times, worsened by dataset size.

- **FEATURE Engineering:** Extracting meaningful text features was challenging; traditional NLP techniques had limitations.

5. DRIVE LINK OF THE DATASET AND CODE

https://drive.google.com/drive/folders/1Fic7PDPLcSVVOeS6ecz1O5Qn-DiZsILS?usp=drive_link

V. CONCLUSION

This project successfully implemented and evaluated multiple machine learning and deep learning models for fake news detection. The results indicate that while traditional machine learning models like Logistic Regression and SVM offer high accuracy and efficiency, deep learning models such as LSTM provide superior contextual understanding of text, making them highly effective for detecting misinformation.

Key insights from this study include:

- Traditional ML Models: Logistic Regression and SVM achieve ~99% accuracy, making them reliable choices for deployment due to their efficiency and interpretability.
- Ensemble Models (Random Forest, XGBoost): These models achieved 100% accuracy, but the risk of overfitting suggests they may not generalize well to unseen data.
- Deep Learning (LSTM): Achieved 99.5% validation accuracy, effectively capturing linguistic patterns in fake news. It is ideal for large-scale applications but requires more computational resources.

Given the trade-off between computational efficiency and model performance, LSTM emerges as the best choice for deployment, ensuring robustness against misleading text patterns while generalizing effectively. Future work can explore hybrid models combining ML and DL techniques for improved accuracy and real-time adaptability in detecting fake news. This projectstrengthens media integrity, promotes digital literacy, and mitigatesg misinformation in the digital ecosystem.

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