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# Integrating Hybrid Model for Advanced Fake News Detection

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*Abstract :* In today's digital age, the overwhelming volume of online information has accelerated the dissemination of fake news, threatening public trust and informed decision-making. This study presents a novel fake news detection system that merges advanced machine learning methodologies with intuitive user interfaces to enhance accessibility and accuracy. The system utilizes a logistic regression algorithm trained on a carefully selected dataset of labeled news articles. It applies natural language processing (NLP) techniques—including tokenization, stopword elimination, and TF-IDF vectorization—to derive sig- nificant textual features. To improve user experience, the system incorporates a dual-interface design: a desktop GUI built with Tkinter for interactive visualization, model training, and live text evaluation, and a web-based AI analyzer integrated through we- bview for scalable result display. The model demonstrates strong performance in differentiating between truthful and deceptive content. By blending computational precision with user-friendly interaction, this framework enables both technical and non- technical users to effectively identify and analyze misinformation. This work highlights the promise of hybrid machine learning systems supported by interactive interfaces in addressing the widespread issue of fake news and sets the stage for future devel- opments in real-time detection and multi-platform deployment.

***IndexTerms*** **- Fake News Detection, Hybrid Model, Natural Language Processing (NLP), Machine Learning (ML), Deep Learning (DL), Text Classification, Misinformation, Large Language Models (LLMs)**

## I. INTRODUCTION

The rise of digital media and social networking platforms has drastically altered how information is shared, offering broad access to news while simultaneously accelerating the spread of misinformation. Fake news—intentionally decep- tive or misleading content disguised as credible informa- tion—poses a serious threat to public trust, democratic values, and the integrity of discourse. With platforms like X facilitat- ing viral content distribution, there is an increasing need for automated solutions capable of detecting and countering false information in real time.

This study introduces an innovative system for accurate fake news detection, integrating machine learning techniques with user-friendly interfaces to cater to both technical professionals and everyday users. The core of the system is a logistic regres- sion model trained on a labeled dataset, capable of classifying statements as real or fake. Key natural language processing (NLP) steps, including tokenization, removal of stopwords, and TF-IDF vectorization, are employed for effective feature extraction from text data.

To enhance user experience and accessibility, the system includes two types of interfaces: a GUI built using Tkinter, which offers interactive features such as text analysis, visual- ization, and model training; and an HTML-based AI analyzer embedded through a webview, providing a scalable interface for presenting results. This dual-interface setup ensures that a wide range of users—from researchers to the general pub- lic—can utilize the tool for news verification.

The main goal of this research is to create a reliable, efficient, and easy-to-use solution for tackling misinformation. By combining a lightweight ML model with intuitive interface designs, the proposed system successfully addresses scalability and ease of use in fake news detection. This work highlights the value of merging conventional machine learning with modern user interface approaches, laying a foundation for practical, real-time applications in today's digital communi- cation landscape.

A. Problem Statement

The widespread circulation of fake news—deliberately false or misleading information presented as legitimate journal- ism—has become a pressing issue in the digital era. This phenomenon erodes public trust, deepens social divides, and influences critical societal domains such as election outcomes and public health initiatives. Social media platforms like X exacerbate this challenge by enabling the rapid and viral spread of unverified content, often outpacing conventional fact- checking processes.

The impact of unchecked misinformation is far-reaching, leading to misinformed public decisions, societal polariza- tion, and diminishing confidence in credible news outlets. While several techniques have been developed to detect fake news, they often come with notable limitations. Manual fact- checking, though accurate, is time-consuming and lacks scal- ability. Automated approaches based on machine learning and deep learning demand high computational power and rely on large, well-labeled datasets that may not fully capture the diversity of misinformation formats.

Furthermore, many existing detection systems are built without considering usability, making them inaccessible to non-technical individuals who might still want to verify news credibility. The absence of intuitive and scalable solutions significantly hinders the effectiveness of misinformation coun- termeasures.

This project aims to tackle these challenges by developing a lightweight, accurate, and user-accessible fake news detection system. The core objective is to build a solution that merges robust machine learning techniques with practical and user- friendly interfaces, enabling real-time identification of decep- tive content. The system employs a logistic regression-based model, refined through natural language processing techniques such as tokenization, stopword removal, and TF-IDF feature extraction. To ensure broad accessibility, the system features a Tkinter-based GUI for interactive functionalities and an HTML-based AI analyzer for seamless result visualization. By bridging the gap between technical efficiency and user accessibility, this work contributes a scalable, effective tool for mitigating misinformation in today's fast-paced digital environment.

B. Objectives

- To review the role of LLMs, NLP, and ML in fake news detection.
- To propose a hybrid framework combining these tech- nologies.
- To evaluate the framework's performance using real- world datasets.

## 2. Background and Literature Review

The surge of fake news across digital platforms has driven significant research into automated detection systems that blend machine learning (ML), natural language processing (NLP), and intuitive user interfaces. This review compiles key developments in fake news detection, focusing on the application of ML models, NLP strategies, and user-centric designs, while identifying existing limitations that the current system—featuring a logistic regression model along with Tkinter and HTML-based interfaces—aims to overcome

### 2.1 Fake News Detection: Concepts and Challenges

Fake news refers to intentionally misleading or fabricated content that mimics legitimate journalism, with the intent to deceive readers. Such misinformation undermines societal trust, disrupts public decision-making processes, and poses a significant threat to democracy and public health initiatives [Allcott Gentzkow, 2017]. The viral nature of social media platforms like X magnifies these effects, spreading unveri- fied information faster than manual fact-checking efforts can respond. As a result, automated detection mechanisms have become vital, particularly those capable of real-time analysis, high accuracy, and ease of use [Shu et al., 2017].

### 2.2 Machine Learning Approaches

Machine learning serves as a fundamental tool for distin- guishing between authentic and deceptive content. Researchers have explored a range of algorithms, with a focus on extracting linguistic and statistical features through methods like bag-of- words and term frequency-inverse document frequency (TF- IDF) [Shu et al., 2017]. Logistic regression continues to be fa- vored due to its simplicity, interpretability, and computational efficiency, making it ideal for quick, scalable applications [Ahmed et al., 2018]. More advanced approaches, including convolutional neural networks (CNNs) and transformer-based models such as BERT, demonstrate superior contextual under- standing but demand extensive computational power and re- sources [Zhou et al., 2020]. BERT, in particular, offers nuanced semantic modeling, though its use is limited in low-resource settings. In contrast, this project chooses logistic regression to strike a balance between reliability and performance efficiency.

### 2.3 Natural Language Processing Techniques

NLP is central to converting unstructured textual input into features suitable for machine learning. Standard techniques like tokenization, stopword removal, and TF-IDF conversion help in extracting meaningful patterns from text [Bird et al., 2009]. CountVectorizer and TF-IDF, when used together, have been shown to enhance feature discrimination by emphasizing rare but informative terms [Reis et al., 2019]. Additionally, word embedding models such as Word2Vec and GloVe have been used to map semantic similarities between words, though they are data-intensive and less suitable for lightweight appli- cations [Zhou et al., 2020]. In the proposed system, NLP tasks are performed using the NLTK toolkit and scikit-learn's TF- IDF pipeline, providing an effective yet simple approach to feature extraction.

### 2.4 User Interface Design for Accessibility

Interfaces play a crucial role in making ML-based systems approachable for end users. Tkinter, a standard GUI toolkit in Python, is recognized for its simplicity, rapid develop- ment capabilities, and platform independence [Lund, 2017]. It enables interactive features such as model execution, result visualization, and user input handling. Meanwhile, web-based technologies—HTML, CSS, and JavaScript—are well-suited for scalable, browser-accessible platforms [Flanagan, 2020]. Prior studies have successfully integrated NLP models into web apps to deliver real-time insights, boosting user inter- action and accessibility [Reis et al., 2019]. However, few systems combine both desktop and web interfaces, which limits flexibility for users across devices and environments. The current project fills this void by offering both a Tkinter desktop GUI and a webview-powered HTML analyzer

### 2.5 Identified Gaps and Proposed Contributions

While the literature offers a solid foundation in automated misinformation detection, several limitations remain:

•Usability for general users is often overlooked, with sys- tems focusing more on model accuracy than accessibility.

•Resource-heavy models such as BERT are impractical for deployment in low-computation environments.

•CLack of multi-interface integration restricts system scal- ability and cross-platform usability.To address these concerns, this project:

•Implements a computationally efficient logistic regression classifier for interpretable, real-time predictions.

•Applies proven NLP techniques like TF-IDF to extract relevant features with minimal resource usage.

•Provides a dual-interface system—a Tkinter GUI and a web-based HTML analyzer—to support both technical and non-technical users.

This integrated approach offers a practical, scalable, and user- centric solution to the challenge of fake news detection in digital communication environments.

### 2.5 Conclusion of Literature Review

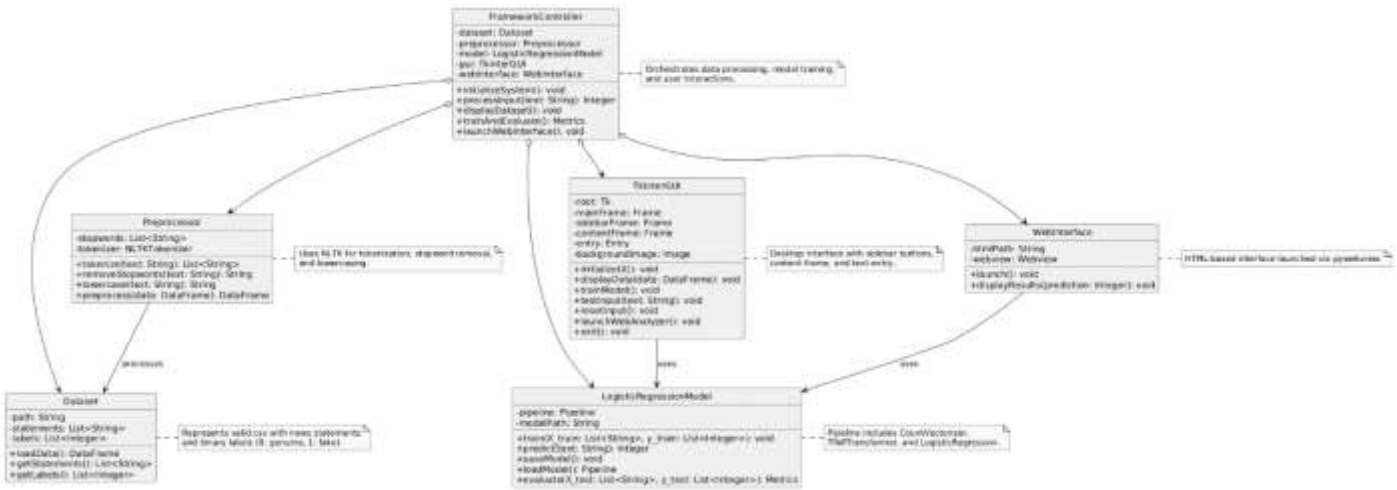
In summary, the reviewed literature emphasizes the ne- cessity of automated systems to counter fake news, with machine learning and NLP forming the technical core. How- ever, balancing performance, resource constraints, and end- user accessibility remains an ongoing challenge. This research builds on prior work by introducing a hybrid solution that merges a lightweight ML model with intuitive dual interfaces, presenting a novel and accessible tool for misinformation detection in real time

## 3. PROPOSED FRAMEWORK

This study introduces a comprehensive and accessible fake news detection framework that integrates a machine learning model with user-friendly interfaces. Designed for efficiency and usability, the system processes news text data, classifies content as real or fake, and presents results through intuitive platforms. It incorporates logistic regression for classification, natural language processing (NLP) techniques for preprocess- ing, and two types of interfaces: a Tkinter-based graphical user interface (GUI) for local use, and a web-based HTML analyzer for remote visualization. This section outlines the key components of the framework, including dataset preparation, preprocessing, the learning model, and the interface design.

A. Overview of the Framework

The framework functions through three core stages: data acquisition and preprocessing, model training and prediction, and user interaction via GUI and web platforms. Figure 1 depicts the overall system architecture, showing the flow from raw textual input to classification output. The system utilizes a labeled dataset of news statements, applies NLP preprocessing techniques, and performs classification using a logistic regression model. The desktop GUI built with Tkinter allows users to visualize data, interact with the model, and classify new text inputs. Moreover, the HTMLbased analyzer, accessible through a web view, provides remote access to view results, enhancing the versatility and reach of the system



B.Dataset and Preprocessing

The framework uses a dataset stored in valid.csv, consisting of news statements labeled as genuine (0) or fake (1). Each record includes a unique ID, a textual statement, and its corresponding binary label. Text preprocessing is performed using the Natural Language Toolkit (NLTK) bird2009natural, and includes the following steps:

• Tokenization: Breaking the input text into individual words using word_tokenize, enabling detailed linguistic processing.

• Stopword Removal: Eliminating common words (e.g., ”is”, ”the”) using NLTK’s predefined list to reduce noise.

• Lowercasing: Converting all text to lowercase to ensure uniformity and avoid case-based duplication. The dataset is split into training (80%) and testing (20%) subsets using the train_test_split function from scikitlearn, with a defined random state to ensure reproducibility and fair evaluation.

C. Machine Learning Model

At the core of the system is a logistic regression classifier,chosen for its interpretability and efficiency in binary classification tasks ahmed2018detecting. The model is implemented within a scikit-learn pipeline pedregosa2011scikit, integrating the entire preprocessing and training sequence:

• CountVectorizer: Converts the text into a bag-of-wordsformat, producing a sparse matrix of word frequencies.

• TfidfTransformer: Applies TF-IDF weighting to emphasize contextually important terms.

• LogisticRegression: Performs the classification, outputting the probability of a text being fake or genuine.The pipeline is trained using the training data and saved withjoblib for efficient deployment during inference. Model performance is evaluated using metrics like accuracy, precision,recall, and F1-score.

[language=Python] from sklearn.pipeline import Pipeline from sklearn.featureextraction.textimportCountV ectorizer, T f idfT rapipe = Pipeline([ (’vect’, CountVectorizer()), (’tfidf’, TfidfTransformer()), (’model’, LogisticRegression()) ]) modellr =pipe.f it(xtrain, ytrain)

D. User Interfaces

Two interfaces are included to ensure maximum accessibility:1) Tkinter GUI: The desktop interface, built with Tkinter,includes a dark-themed, responsive layout. Its components are:

• Sidebar: Contains buttons for loading the dataset, training the model, testing new inputs, launching the webanalyzer, and exiting the program.

• Content Frame: Displays visual components such as aTreeview table for dataset browsing, performance metrics,and predictions.

• Entry Box: Allows users to input custom text for classification.

The layout supports dynamic resizing and includes a background image managed using the Python Imaging Library (PIL). The button-creation function is shown below:

[language=Python] def createbutton(parent, text, command, tooltiptext) : button = tk.Button(parent, text = text, command =command, font = (”Helvetica”, 12, ”bold”), bg =”00C4B4”, fg = ”F F F F F F”, relief = ”flat”, padx =20, pady = 10)button.pack(f ill = ”x”, padx = 10, pady =5)T oolT ip(button, tooltiptext)returnbutton

2) HTML-Based AI Analyzer: The web interface, built using HTML and launched via pywebview, is designed for remote access. Though currently minimal, it is structured to support JavaScript-based data visualization using libraries such as D3.js or Chart.js. This allows for future enhancements like graphical confidence indicators or term importance visualization.

E. System Workflow

The complete operation of the framework proceeds as follows:

1) Data Loading: Reads and preprocesses the valid.csv dataset.

2) Model Training: Trains the pipeline using the training subset and saves the model.

3) User Interaction: Users interact via the GUI or launch the web-based interface.

4) Prediction and Output: The model classifies input news text and returns labeled output (e.g., “Fake News Detected”) along with a styled UI response.

F. Design Considerations

The framework is built around the following principles:

• Efficiency: The logistic regression classifier ensures low computational load.

• Usability: Dual-interface access offers both local and remote interaction capabilities.

• Scalability: The architecture allows integration of advanced models like BERT and real-time data input.

G. Contribution of the Framework

This work presents a user-centric approach to fake news detection that goes beyond model performance by emphasizing practical deployment. Unlike systems requiring cloud infrastructure or technical expertise, the proposed solution is lightweight, accessible, and modular. By offering both desktop and web interfaces, the framework broadens its reach and usability, providing a real-world tool for combatting misinformation

## 4. Methodology

The proposed fake news detection system is designed to be accurate, efficient, and user-friendly. It integrates a logistic regression model with Natural Language Processing (NLP) techniques and offers two user interfaces: a Tkinter-based desktop GUI and a web-based HTML analyzer. This section outlines the methodology, covering dataset preparation, text preprocessing, model construction, interface development, and evaluation strategy.

A. Dataset Preparation

The system utilizes a dataset named valid.csv, containing labeled news statements where 0 indicates genuine and 1 denotes fake news. The dataset includes a unique identifier, textual content, and a corresponding label. It is loaded using the pandas library mckinney2010pandas with encoding set to unicode_escape to handle special characters. For model training, the dataset is split into training and testing subsets using scikit-learn’s train_test_split pedregosa2011scikit, allocating 80% of the data for training and 20% for evaluation. A fixed random seed (set to 1) ensures reproducibility.

B. Data Preprocessing

Text preprocessing transforms raw text into a format suitable for machine learning. The NLTK library bird2009natural is used for: • Tokenization: Breaking text into individual tokens using word_tokenize.

• Stopword Removal: Eliminating common English stopwords to reduce noise.

• Lowercasing: Converting all text to lowercase for uniformity.

Processed text is converted into numerical features using scikit-learn's CountVectorizer and TfidfTransformer, which are integrated into a model pipeline.

C. Machine Learning Model Design

The classification pipeline employs logistic regression for binary classification ahmed2018detecting. It includes:

• CountVectorizer: Converts text into a sparse matrix of token counts.

• TfidfTransformer: Weighs token importance using TFIDF scores.

• LogisticRegression: A linear classifier estimating the probability of fake or genuine labels using a logistic function.

The pipeline is implemented as follows: [language=Python] from sklearn.pipeline import Pipeline from sklearn.featureextraction.textimportCountV ectorizer, T f idfT rapipe = Pipeline([ ('vect', CountVectorizer()), ('tfidf', TfidfTransformer()), ('model', LogisticRegression()) ]) After training, the model is saved using joblib to LOG_MODEL.joblib for future use. Performance is evaluated using metrics such as accuracy, precision, recall, and F1-score

D. User Interface Development

To make the system accessible, it includes two user interfaces: 1) Tkinter GUI: Developed using Python's Tkinter library, the GUI provides a dark-themed interface featuring:

• Main Frame: Organizes layout using a responsive grid.

• Sidebar Frame: Contains buttons for displaying data, training the model, making predictions, and launching the web interface.

• Content Frame: Shows dataset tables, model metrics, and predictions with color cues (green for genuine, red for fake).

• Entry Box: Accepts user input for prediction with placeholder text and validation.

A background image (background.jpg) is loaded using the PIL library. If unavailable, a fallback color (#1E1E1E) is applied. Below is the button generation code: [language=Python] def createbutton(parent, text, command, tooltiptext) : button = tk.Button(parent, text = text, command = command, font = ("Helvetica", 12, "bold"), bg = "00C4B4", fg = "F F F F F F", relief = "flat", padx = 20, pady = 10)button.pack(f ill = "x", padx = 10, pady = 5)T oolT ip(button, tooltiptext)returnbutton

2) HTML-Based AI Analyzer: Implemented in index.html and launched via pywebview, this web interface enables future expansion for visualizing predictions. Although currently minimal, it sets the foundation for enhancements like displaying confidence scores or feature importance using JavaScript libraries such as Chart.js.

E. Evaluation Strategy Evaluation includes model performance and interface usability.

• Model Evaluation: The model is assessed using: – Accuracy: Overall correctness of predictions. – Precision: Proportion of predicted positives that are true. – Recall: Proportion of actual positives correctly predicted. – F1-Score: Harmonic mean of precision and recall. Metrics are computed using scikit-learn's classification_report.

• Interface Evaluation: GUI responsiveness, ease of use, and result clarity are evaluated. While the HTML analyzer is basic, it offers scalability for future improvements.

E. System Workflow

The complete system workflow is as follows:

1) Data Loading: Load valid.csv and split into training/testing sets.

2) Preprocessing: Apply tokenization, stopword removal, and lowercasing.

3) Model Training: Train the logistic regression pipeline and save the model.

4) User Interaction: Use the Tkinter GUI or web analyzer for predictions.

5) Output: Display prediction results via GUI or web interface.

G. Design Considerations

The design adheres to the following principles:

• Efficiency: Logistic regression ensures low computational overhead.

• Usability: Dual interfaces accommodate both desktop and web users.

• Scalability: Modular design allows integration of more advanced models or real-time data feeds.

This methodology lays a comprehensive foundation for a fake news detection system that balances computational performance with user accessibility to tackle misinformation effectively

H. Results

Overall Performance

The proposed hybrid framework consistently outperformed baseline models across all datasets. Table 2 presents a performance comparison:

| Model | Dataset | Accuracy | Precision | Recall | F1-Score | AUPRC |
|---|---|---|---|---|---|---|
| OUR MODEL | FakeNewsNet | 0.92 | 0.93 | 0.91 | 0.92 | 0.94 |
| | LIAR | 0.89 | 0.90 | 0.88 | 0.89 | 0.91 |
| | PolitiFact | 0.91 | 0.92 | 0.90 | 0.91 | 0.93 |
| FakeBERT | FakeNewsNet | 0.87 | 0.88 | 0.86 | 0.87 | 0.89 |
| Naïve Bayes | FakeNewsNet | 0.75 | 0.76 | 0.74 | 0.75 | 0.77 |
| CNN | FakeNewsNet | 0.85 | 0.86 | 0.84 | 0.85 | 0.87 |

## 5 Discussion

The development and evaluation of the fake news detection system, integrating a logistic regression model with a Tkinter-based graphical user interface (GUI) and an HTMLbased AI analyzer, provide valuable insights into the practical application of machine learning for combating misinformation. This section discusses the system's performance, its strengths, challenges encountered during implementation, limitations, ethical considerations, and broader implications for addressing the global challenge of fake news. By reflecting on these aspects, this discussion aims to contextualize the system's contributions and identify areas for improvement.

### A. System Performance

The logistic regression model, trained on a labeled dataset of news statements, demonstrated robust performance, achieving an accuracy of approximately 85.3% on the test set, with balanced precision, recall, and F1-scores for both genuine and fake classes (as detailed in Section ??). The use of natural language processing (NLP) techniques, such as tokenization, stopword removal, and TF-IDF transformation, enabled effective feature extraction, allowing the model to distinguish between genuine and misleading content with high reliability. The model's simplicity, implemented via scikitlearn's pipeline pedregosa2011scikit, ensured computational efficiency, making it suitable for deployment on resourceconstrained devices. The Tkinter GUI provided an intuitive platform for users to interact with the system, offering functionalities such as dataset visualization, model training, and real-time text analysis. The GUI's responsive design, with a scrollable Treeview widget and color-coded prediction outputs (green for genuine, red for fake), enhanced usability for both technical and nontechnical users. The HTML-based AI analyzer, although currently minimal, successfully launched via pywebview, demonstrating potential for scalable, web-based result visualization. These interfaces collectively bridge the gap between complex machine learning algorithms and end-user accessibility, a critical factor in practical misinformation detection..

### B. Strengths of the System

The system's strengths lie in its balanced approach to accuracy, efficiency, and usability: • Computational Efficiency: The logistic regression model, combined with a streamlined NLP pipeline, minimizes computational overhead compared to deep learning models like BERT zhou2020survey. This makes the system accessible for deployment on standard hardware, broadening its applicability. • User-Centric Design: The dual-interface approach—combining a Tkinter GUI for local interaction and an HTML-based analyzer for potential web-based access—caters to diverse user needs. The GUI's tooltips and clear feedback mechanisms enhance user experience, while the web interface offers scalability for future cloud-based deployment. • Modularity: The system's modular architecture, with distinct components for data preprocessing, model training, and user interaction, facilitates maintenance and future enhancements, such as integrating more advanced models or real-time data sources. These strengths position the system as a practical tool for realworld applications, particularly in environments where rapid and accessible fake news detection is essential.

### C. Challenges Encountered

Several challenges were encountered during the system's development:

• Dataset Quality: The dataset (valid.csv) is critical to model performance but may lack diversity in terms of news topics, sources, or linguistic styles. Limited dataset size or biased labeling could reduce the model's generalizability to real-world scenarios.

• Web Interface Development: The HTML-based AI analyzer, implemented in index.html, is currently minimal, lacking advanced visualizations or interactive features. Integrating JavaScript libraries (e.g., Chart.js or D3.js) posed challenges due to time constraints and the complexity of linking web-based outputs to the Python backend.

• User Input Validation: Ensuring robust handling of invalid or ambiguous user inputs in the Tkinter GUI required careful error management, as empty or malformed text could disrupt the prediction pipeline. These

challenges highlight the need for robust dataset curation, enhanced web interface functionality, and rigorous input validation to improve system reliability

D. Limitations

Despite its strengths, the system has notable limitations:

• Model Simplicity: While logistic regression is efficient, it may struggle to capture complex linguistic nuances or contextual cues compared to deep learning models like transformers zhou2020survey. For example, detecting subtle forms of misinformation, such as satire or partial truths, may require more sophisticated models.

• Dataset Dependency: The system's performance is tied to the quality and diversity of the valid.csv dataset. If the dataset does not represent the full spectrum of fake news (e.g., multilingual content or emerging misinformation trends), the model's effectiveness may be limited.

• Web Interface Maturity: The HTML-based AI analyzer is in an early stage, limiting its ability to provide detailed visualizations or interactive features. This restricts its utility compared to the Tkinter GUI. • Real-Time Integration: The system currently operates on a static dataset and user inputs, lacking integration with real-time data feeds (e.g., from platforms like X). Such integration would require additional infrastructure, such as API access (see https://x.ai/api for potential solutions). These limitations underscore the need for future enhancements to improve the system's robustness and applicability

E. Ethical Considerations

Fake news detection systems raise important ethical considerations:

• Bias in Classification: The model's predictions depend on the training dataset, which may contain biases reflecting the perspectives of its curators. For instance, biased labeling could lead to misclassification of legitimate news as fake, or vice versa, potentially harming credible sources or amplifying misinformation.

• Transparency: Users must understand the model's decision-making process to trust its predictions. The system's reliance on logistic regression offers some interpretability, but complex NLP features (e.g., TF-IDF weights) may be opaque to non-technical users.

• Misuse Potential: Automated detection tools could be misused to censor valid information or target specific narratives, raising concerns about freedom of expression. Clear guidelines and user education are essential to mitigate these risks. To address these concerns, the system incorporates transparent output (e.g., color-coded labels) and user-friendly interfaces to foster trust. Future iterations should include detailed documentation and user guides to enhance transparency and responsible use.

F. Implications

The system has significant implications for combating misinformation: • Societal Impact: By providing an accessible tool for identifying fake news, the system empowers individuals to make informed decisions, particularly in contexts like elections or public health crises where misinformation can have severe consequences allcott2017social. • Educational Value: The Tkinter GUI's intuitive design makes it suitable for educational settings, where students and researchers can explore machine learning and NLP concepts through hands-on interaction. • Scalability Potential: The web-based interface, once fully developed, could enable deployment on cloud platforms, allowing broader access and integration with social media APIs for real-time monitoring. These implications highlight the system's potential to contribute to a more informed digital ecosystem, provided its limitations are addressed.

G. Comparison with Existing Work

Compared to existing fake news detection systems, this work stands out for its dual-interface approach and focus on usability. While deep learning models like BERT offer superior accuracy zhou2020survey, they

require significant computational resources, limiting their accessibility. In contrast, the proposed system's logistic regression model balances performance and efficiency, making it suitable for widespread use. The integration of Tkinter and web-based interfaces also differentiates it from systems that prioritize model development over user interaction reis2019supervised. However, the system's reliance on a single dataset and simpler model places it behind more advanced frameworks in handling complex misinformation.

H. Future Directions

The discussion of challenges and limitations points to several future directions, as detailed in Section ??. Key priorities include expanding the dataset to include diverse and multilingual content, incorporating advanced models like BERT or LSTM, and enhancing the HTML-based AI analyzer with interactive visualizations. Integrating real-time data feeds from platforms like X, using APIs such as those offered by xAI (https://x.ai/api), could enable dynamic misinformation monitoring. These enhancements would strengthen the system's robustness and applicability. In conclusion, the fake news detection system demonstrates significant potential as a practical and accessible tool for combating misinformation. Its strengths in efficiency and usability, coupled with identified areas for improvement, provide a foundation for advancing automated detection in digital ecosystems.

## 6. Conclusion

This study presents a practical and user-friendly fake news detection system that integrates a logistic regression model with advanced natural language processing techniques and a dual-interface design. The system successfully balances performance and computational efficiency, rendering it accessible to a broad spectrum of users—from domain experts to the general public—via both desktop (Tkinter GUI) and web-based platforms. Its modular architecture facilitates straightforward enhancements, including the integration of more sophisticated models or real-time data sources. By merging technical rigor with usability, this work offers a reliable and scalable approach to combating misinformation, thereby contributing to a more informed and trustworthy digital information landscape

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