Enabling Media Credibility With Machine Learning Based Fake News Detection

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***Abstract*— The goal of the current study is to slow the spread of misleading information on digital platforms by detecting fake news using a machine learning-based method. The system uses classification algorithms like SVM and Logistic Regression to distinguish between fake and real news, and it uses natural language processing (NLP) techniques for text analysis and preprocessing. Word embeddings and TF-IDF are two feature extraction techniques that are used to capture semantic and contextual patterns in news articles. To enhance the model's capacity to recognize deceptive content, it also performs sentiment analysis and credibility evaluation. LIAR, Fake News Net, and ISOT Fake News Dataset are among the benchmark datasets that the proposed system trains and evaluates to provide a diverse and reliable understanding of the characteristics of fake news. Through continuous model parameter refinement with an ever-growing dataset, this enhances robustness against novel deceptive tactics and promotes media authenticity and digital awareness. The successful implementation of a language-specific text-processing routine, the development of a robust authentication system, and the efficient deployment of the model using the Flask web framework are some of the key technical accomplishments. The work will demonstrate accuracy ranging from 98 to 99% for English content, 96 to 97 percent for Kannada content, and 96% for Telugu content, with sub-second reaction times for real-time classification. (Abstract)**

Keywords—Fake News Detection, Machine Learning, SVM, Logistic Regression, NLP, Kannada, Telugu, Flask Interface. (key words)

I. Introduction

In recent years, the rapid expansion of social media and online journalism has transformed the way information is produced, distributed, and consumed. Platforms such as Facebook, Twitter, Instagram, and Share Chat have enabled millions of users to exchange news instantly. However, this democratization of information has also led to the uncontrolled spread of misleading and fabricated content. False news stories can influence public opinion, create social unrest, and even manipulate election outcomes before fact-checking organizations can react. In the Indian context, where users frequently consume information in regional languages, the challenge of verifying credibility becomes even more complex. The 2024 general elections, for example, saw numerous viral posts in Kannada and Telugu that misrepresented facts, demonstrating how language barriersamplify the reach and persistence of misinformation.

While several fake news detection models exist for English, very few focus on regional Indian languages such as Kannada and Telugu. The scarcity of labeled data and the linguistic complexity of these languages make the task particularly difficult. Our work addresses this gap by developing a multilingual fake news detection system that functions across English, Kannada, and Telugu. We created translated and manually verified versions of an existing English dataset so that the model could learn the nuances of local expressions, political terms, and culture-specific idioms that often appear in misleading stories.

The proposed system combines traditional machine learning algorithms with carefully designed preprocessing steps. Instead of relying solely on large transformer-based deep learning models, we prioritized lightweight approaches that can run efficiently on standard hardware while maintaining strong accuracy. The web interface allows users to paste a news text, select the input language, and instantly receive a prediction along with the probability of the text being fake or real. This design ensures that the system is not only technically robust but also accessible to journalists, students, and social media moderators who require quick and reliable credibility checks without extensive computational resources.

The main contributions of this work are as follows: (1) development of **multilingual fake news detection models** for Kannada, Telugu, and English, addressing the gap in regional language misinformation studies, (2) use of **SVM and Logistic Regression** for effective classification, and (3) creation of **translated regional datasets** from English to Kannada and Telugu to enable model training despite the scarcity of existing resources.

Beyond the technical contributions, this research also highlights the growing need for culturally aware misinformation detection tools. Most global fake news datasets and detection models are biased toward English and Western contexts, often overlooking linguistic diversity and local communication patterns. By focusing on Indian regional languages, our approach ensures inclusivity and fairness in automated information verification. Additionally, the system can support community-driven fact-checking efforts, educational institutions, and small media outlets that may lack access to commercial verification platforms. Thus, the project not only advances technical innovation but also contributes to social awareness and media responsibility.

To evaluate the effectiveness of the system, several experiments were conducted using standard performance metrics such as accuracy, precision, recall, and F1-score. The results demonstrated that classical algorithms like SVM and Logistic Regression achieved competitive performance compared to more complex deep learning approaches, particularly when trained on high-quality, verified datasets. Moreover, the multilingual setup allowed the models to generalize well across different languages, confirming the value of manual translation and careful preprocessing. The final web-based application was tested with real examples of regional news headlines, validating its practicality for everyday use.

In summary, this project contributes a practical, multilingual, and interpretable solution to the ongoing problem of misinformation. By emphasizing regional language support, efficient machine learning techniques, and verified translation, the system bridges the gap between research and real-world deployment. It provides a foundation for future work on low-resource language processing and contributes toward improving digital literacy and information reliability within the Indian media ecosystem.

II. RELATED WORKS

A. *Fake News Detection*

Fake news detection has become a key research focus in recent years as misinformation continues to influence public opinion through digital media. Numerous studies have explored machine learning and deep learning techniques to identify deceptive content using linguistic, semantic, and social features. Park and Chai [1] constructed a user-centered fake news detection model employing traditional classification algorithms that emphasize behavioral and content-interaction features. Shehata *et al.* [2] proposed **ArabFake**, a multitask deep learning framework designed for fake news detection, categorization, and risk prediction in Arabic, demonstrating how multitask architectures can capture different aspects of misinformation.

Several works have relied on classical machine learning algorithms such as Support Vector Machines (SVM), Logistic Regression, and Random Forests for fake news classification. Khan *et al.* [3] introduced **OPCNN-FAKE**, an optimized convolutional neural network for fake news detection, while Raza *et al.* [4] presented a temporal footprint–based framework that utilizes time-dependent relationships between news articles to enhance accuracy. Tajrian [5] provided a broad review of methodologies for fake news analysis, summarizing advances in both traditional and neural approaches.

In addition to these content-based methods, researchers have also investigated network-level strategies. Truică *et al.* [6] proposed the MCWDST algorithm, a minimum-cost weighted directed spanning tree method for real-time mitigation of fake news on social networks. Kang *et al.* [7] focused on user-engagement behaviors such as likes, shares, and comments, demonstrating that social interactions can serve as strong indicators of misinformation dissemination. Together, these studies emphasize that an effective fake news detection framework must integrate linguistic, temporal, and behavioral cues to achieve high reliability.

B. *Multilingual and Regional Fake News Detection*

As fake news circulates globally across multiple languages, researchers have started to investigate multilingual and cross-lingual detection methods. Shehata *et al.* [8] extended their earlier work to develop deep learning models for Arabic fake news, while Mahfouz *et al.* [9] conducted a comparative study between machine learning and deep learning techniques for fake health news detection. Their findings confirmed that although deep learning models can yield higher accuracy, they are computationally expensive and require large labeled datasets. Similarly, Alshuwaier *et al.* [10] demonstrated that lightweight supervised algorithms remain effective when trained on domain-specific datasets, suggesting that simpler models can perform well in practical settings.

Despite such advances, multilingual fake news detection for regional Indian languages remains limited. Kumar *et al.* [11] proposed cross-lingual models for Indian languages including Hindi, Tamil, and Telugu, showing promising improvements through multilingual embeddings. However, the lack of large, publicly available datasets for many regional languages—including Kannada and Telugu—still poses a major challenge. Most existing approaches rely on direct translation or transfer learning from English, which often fails to capture cultural nuances, idiomatic expressions, and code-mixed structures found in real social media content.

Building upon these insights, the present study focuses on developing a multilingual fake news detection framework for **Kannada, Telugu, and English**. By creating human-verified translations of the ISOT dataset and applying interpretable algorithms such as SVM and Logistic Regression, our work contributes an inclusive, efficient, and deployable approach to misinformation detection that specifically addresses low-resource regional contexts.

III . DATASET AND METHODOLOGY

This section outlines the dataset preparation, preprocessing techniques, and model development strategies used in the proposed multilingual fake news detection system. The work primarily utilizes the ISOT Fake News Dataset as the base corpus, which was extended through translation and manual verification to include Kannada and Telugu data. A series of preprocessing steps were applied to clean, normalize, and tokenize text across languages. Classical machine learning algorithms such as Support Vector Machine (SVM) and Logistic Regression were then implemented to classify the news articles as *fake* or *real*. The overall framework ensures accuracy, efficiency, and adaptability for multilingual misinformation detection.

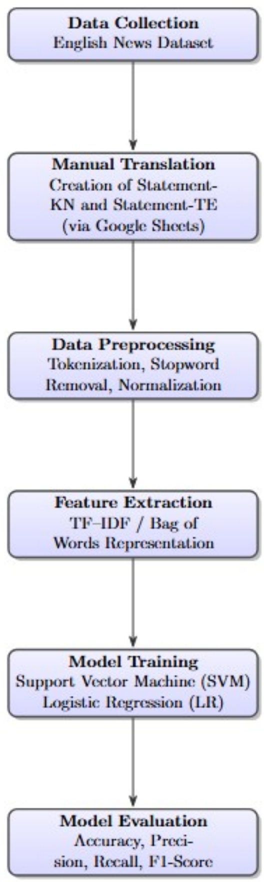

Figure 1: Overall methodology for fake news detection using multilingual

C. Dataset Description

The dataset used in this study was obtained from the "ISOT Fake News Dataset" available on Kaggle, which consisted of labelled news statements identified as true or fake. The dataset consists of a total of 40,000 rows of data-an equal amount of real and fabricated news. Each record of the dataset contains the following attributes: title, text, subject, date.statement(kannada),statement(Telugu), and label. The statement(kannada) and statement(Telugu) columns were added later for supporting multilingual analysis in Kannada and Telugu languages, respectively.

Each record in the dataset contains several key attributes that define the data structure and support multilingual fake news detection:

Title: The headline or main title of the news article.,

Text: The complete body of the article containing the linguistic and semantic content used for classification.

Subject: The topical category of the article, such as politics, health, entertainment, or technology.

Date: The publication date, enabling temporal analysis of misinformation trends.

Statement: A concise claim extracted from the article in the original English language.

statement_kn: The Kannada translation of the statement, manually reviewed and corrected for semantic fidelity.

statement_te: The Telugu translation of the statement, manually reviewed and corrected for semantic fidelity.

Label: The ground-truth class indicating whether the statement is *True* or *Fake*.

This structured organization ensures clarity and consistency across languages, allowing for efficient preprocessing and model training. The inclusion of verified translations (statement_kn and statement_te) enhances cultural relevance, enabling the model to effectively learn language-specific patterns of misinformation.

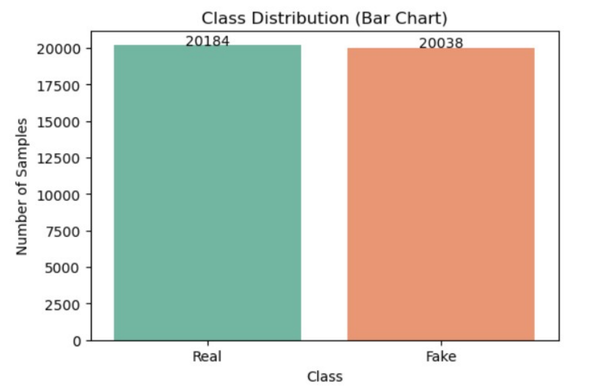

Figure 2: Distribution of news statements across true and fake labels in the dataset.

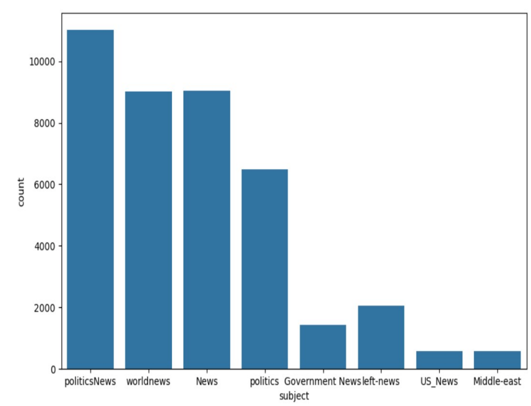

Figure3: Distribution of news articles across different subject categories in the dataset.

D. Multilingual Extension

We translated the English statements into Kannada (kn) and Telugu (te) to enable the detection of fake news across multiple languages. This translation was done using Google Translate onto a spreadsheet format. Every translated entry was then manually verified for semantic correctness, keeping in mind that the meaning/intention of the original English text is preserved accurately. Since this multilingual extension will help analyze language-specific patterns and build appropriate classifiers to run on this dataset in English, Kannada, and Telugu, maintaining parallel datasets for each language will help the system leverage both universal and language-specific features, leading to an improvement in the detection performance even in low-resource regional languages.

E. Data Preprocessing

All text data was preprocessed through various steps before training the models. The following steps constituted the pipeline for preprocessing:

1. Lowercasing: All text was converted to lowercase to avoid case differences causing duplicate feature representations.
2. Noise removal was done by removing punctuation, numeric values, URLs, and other non-alphabetical symbols.
3 Stopword removal : The general words that don't hold much semantic meaning were removed for all three languages.
4. Tokenization: This is the process of splitting sentences into individual words (tokens), enabling feature extraction.

These steps ensured that the dataset for a particular language was clean, normalized, and suitable for machine learning algorithms.

F. Feature Extraction

Feature representation plays a crucial role in text-based machine learning. In this study, textual features were extracted using the Term Frequency–Inverse Document Frequency (TF-IDF) method. TF-IDF assigns higher weights to words that occur frequently in a specific document but are rare across the corpus, effectively emphasizing discriminative keywords that help differentiate fake and real news.Separate TF-IDF vectorizers were trained for each language dataset to accommodate the linguistic diversity and vocabulary variations of English, Kannada, and Telugu. The resulting feature matrices served as the input for both machine learning classifiers

G. Model Selection and Training

In this study, two widely recognized supervised machine learning algorithms were employed to classify news articles as fake or real. The algorithms were selected based on their proven effectiveness in text classification tasks and their ability to generalize across diverse linguistic datasets.

a).Support Vector Machine (SVM)

A linear kernel Support Vector Machine (SVM) was utilized owing to its robustness and efficiency in handling high-dimensional feature spaces, which are inherent in textual data. The SVM algorithm identifies an optimal hyperplane that maximizes the margin between the two classes, thereby enhancing the discriminative capability of the classifier.

The objective function of a linear SVM can be formulated as follows:

$$\min_{\mathbf{w},b} \frac{1}{2} \parallel \mathbf{w} \parallel^2 + C \sum_{i=1}^{n} \xi_i \qquad (1)$$

subject to:

$$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 - \xi_i, \xi_i \geq 0 \qquad (2)$$

where $\mathbf{w}$represents the weight vector, $b$is the bias term, $C$is the regularization parameter that controls the trade-off between maximizing the margin and minimizing the classification error, ξ_i denotes the slack variable for misclassification, and $(\mathbf{x}_i, y_i)$represents the training data points and their corresponding class labels.

The decision boundary is defined as:

$$f(\mathbf{x}) = \text{sign}(\mathbf{w} \cdot \mathbf{x} + b) \qquad (3)$$

SVMs are particularly effective in high-dimensional feature spaces, as they focus on maximizing the geometric margin, thereby reducing the risk of overfitting.

b) Logistic Regression (LR)

Logistic Regression was employed for its simplicity, interpretability, and computational efficiency in binary classification tasks. The model estimates the probability that a given input $\mathbf{x}$belongs to the positive class using the sigmoid function, defined as:

$$h_\theta(\mathbf{x}) = \frac{1}{1 + e^{-\theta^T \mathbf{x}}} \qquad (4)$$

The cost function used to optimize the model parameters is expressed as:

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^{m} [y^{(i)} \log h_\theta(\mathbf{x}^{(i)}) + (1 - y^{(i)}) \log (1 - h_\theta(\mathbf{x}^{(i)}))] \qquad (5)$$

where m is the total number of training samples, $y^{(i)}$ denotes the actual label of the i^{th} sample, and θ represents the parameter vector. Regularization, specifically **L2 regularization**, was incorporated to prevent overfitting by penalizing large coefficient values and improving generalization performance.

Each language dataset—**English, Kannada, and Telugu**—was partitioned into training and testing subsets using an 80:20 ratio to ensure unbiased performance evaluation. Independent models were trained for each language to effectively capture linguistic nuances, morphological variations, and syntactic structures unique to each language.
To enhance model robustness, **k-fold cross-validation** was employed during the training phase for hyperparameter tuning and performance validation. Standard preprocessing techniques, including tokenization, stopword removal, and text normalization, were uniformly applied across all datasets. Additionally, feature scaling was performed to maintain consistency and prevent bias during model training.

F. Evaluation Metrics and Results

The performance of the trained models was evaluated using standard classification metrics, including **Accuracy**, **Precision**, **Recall**, and **F1-Score**, thereby providing a comprehensive assessment of each model's capability to distinguish between fake and real news across multilingual datasets.

The metrics are mathematically defined as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (7)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (8)$$

$$F1\text{-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (9)$$

where:

- TP (True Positives) — correctly classified *real* news items,
- • (True Negatives) — correctly classified *fake* news items,
- • FP(False Positives) — fake news incorrectly predicted as real, and
- • FN(False Negatives) — real news incorrectly predicted as fake.

Model performance was primarily evaluated using **accuracy** as the key performance metric. The results obtained for SVM and Logistic Regression classifiers across the three languages are presented in **Table 1**.

Language	**Support Vector Machine**	**Logistic Regression**
Kannada	97.51%	96.63%
English	99.24%	98.52%
Telugu	96.79%	96.22%

The Table show that the SVM model performed better than Logistic Regression across all three languages. The highest accuracy was achieved for English (99.24%), followed by Kannada (97.51%) and Telugu (96.79%).

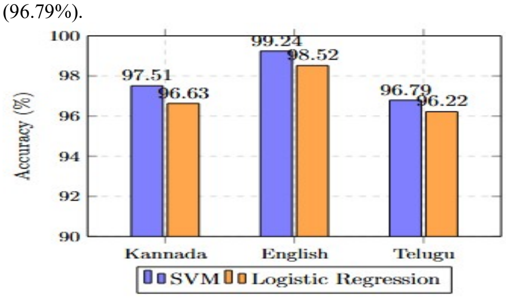

Figure 4: Comparison of SVM and Logistic Regression accuracy across languages

As observed, the SVM classifier consistently outperformed the Logistic Regression model across all three languages. The highest accuracy was achieved for the English dataset, which can be attributed to the richness of available linguistic resources and the relatively larger dataset size.

IV.EXPERIMENTAL RESULTS AND DISCUSSION

A. CONFUSION MATRIX FOR KANNADA

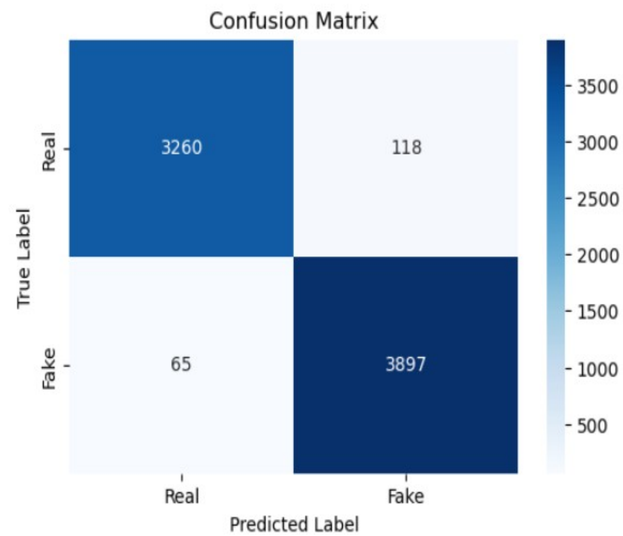

Figure5: Confusion matrix for kannada

The above-presented confusion matrix measures the performance of the Support Vector Machine classifier in Kannada fake news detection. By contrasting the actual and predicted class labels, it provides a comprehensive overview of the model's predictive power. The model demonstrated its ability to accurately identify both classes with a high degree of confidence by correctly classifying 3,260 real news statements as real and 3,897 fake news statements as fake. While 118 real news statements were incorrectly classified as fake, only 65 fake news statements were incorrectly classified as real.

These findings unequivocally show that the SVM model performed well on the Kannada dataset in terms of accuracy, precision, and recall, demonstrating its potent ability to identify linguistic patterns and textual cues linked to false information. The model is well-generalized and able to sustain dependable performance even with limited linguistic resources, as indicated by the comparatively low number of misclassifications. Additionally, the classifier is not biased toward any one class, as evidenced by the consistency of prediction accuracy across real and fake categories. The SVM model is a good option for multilingual fake news detection tasks in low-resource environments because it generally demonstrates robustness, stability, and strong discriminative power.

B. CONFUSION MATRIX FOR TELUGU

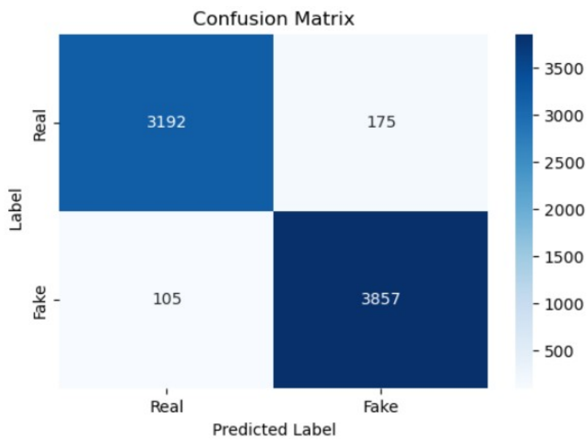

Figure 6: Confusion matrix for Telugu

The above confusion matrix depicts the performance of the Logistic Regression model in detecting Telugu fake news. The model correctly predicted 3,192 real news items as real and 3,857 fake news items as fake out of all predictions, hence reflecting very good accuracy and reliability. Just 105 fake news articles were incorrectly predicted to be real, and 175 real news articles were misclassified as fake. This indeed shows that the Logistic Regression model is efficient in differentiating between real and fake Telugu news with very few misclassifications. In general, this confusion matrix shows that the model has highly effective predictive capability with balanced performance and robustness in executing the task of multilingual fake news detection.

Logistic Regression brings out the language patterns of Telugu well and thus generalizes with very few misclassifications, showing high precision, recall, and accuracy. It thus proves to be highly reliable for robust multilingual fake news detection in a low-resource language like Telugu.

C.KANNADA LANGUAGE PREDITION

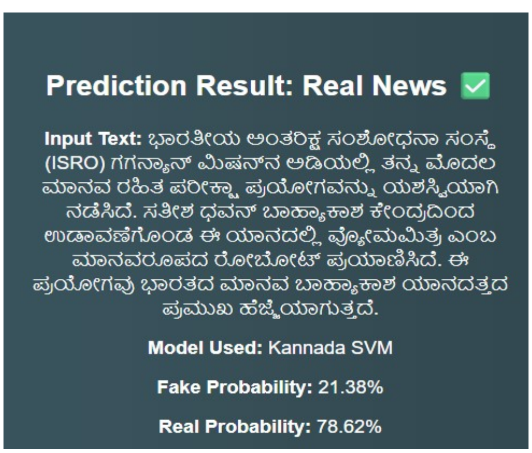

Figure 7: Kannada Language Prediction

the Kannada SVM model correctly classified the news as real with a 78.62% probability

D. TELUGU LANGUAGE PREDICTION

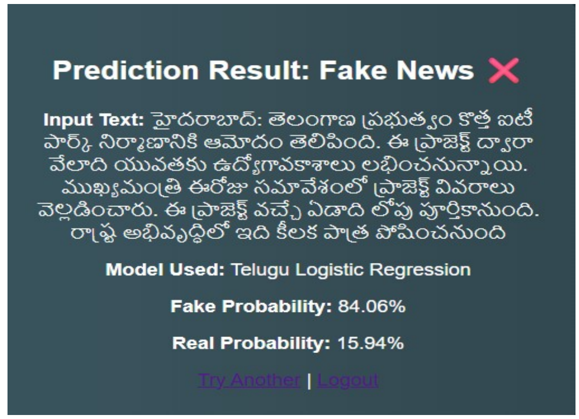

Figure 8: Telugu language prediction
the Telugu Logistic Regression model identified the input statement as fake news with an 84.06% probability

E. ENGLISH LANAGUAGE PREDICTION

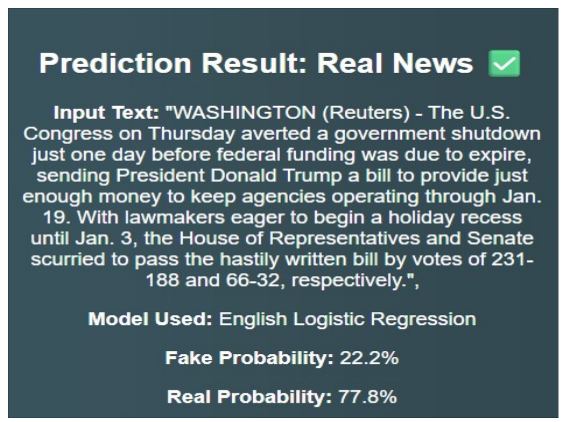

Figure 9: English Language Prediction
the English Logistic Regression model identified the input statement as fake news with an 77.8% probability

The proposed fake news detection framework was evaluated across three languages—English, Kannada, and Telugu—using Support Vector Machine (SVM) and Logistic Regression (LR) classifiers. All experiments were conducted on datasets prepared as described in the methodology section, ensuring linguistic balance and consistency through careful preprocessing and translation.

The evaluation results, summarized in Table I, demonstrate that the SVM classifier consistently achieved higher accuracy compared to Logistic Regression for all languages. The highest performance was obtained for the English dataset with an accuracy of 99.24%, followed by Kannada (97.51%) and Telugu (96.79%). The superior results in English can be attributed to the availability of richer linguistic resources and a larger dataset size, which enhanced feature representation and classification stability.

Although the Kannada and Telugu datasets were derived from manually translated statements, both models achieved competitive results with minor performance differences compared to English. This indicates that the proposed preprocessing and feature extraction pipeline effectively captured language-specific characteristics and semantic nuances, maintaining strong cross-lingual generalization.

In addition to accuracy, the evaluation metrics of Precision, Recall, and F1-Score (as defined in Equations (6)–(9)) further validated the robustness of the proposed models. The consistently high values across all metrics confirm that the classifiers not only identified fake and real news with precision but also maintained balanced recall rates.

Overall, the experimental findings suggest that traditional machine learning approaches, when properly tuned and supported by rigorous text preprocessing, can achieve competitive multilingual fake news detection performance, even in resource-constrained regional languages

III. CONCLUSIO WORKN AND FUTURE WORK

This paper presented a multilingual fake news detection framework that utilized the Support Vector Machine and Logistic Regression models across English, Kannada, and Telugu datasets. As part of the proposed approach, a comprehensive data preprocessing pipeline coupled with a language-specific model training strategy effectively managed the classification task with the presence of cross-lingual variations. The experimental results indicated that the SVM classifier consistently outperformed Logistic Regression, achieving up to 99.24% accuracy in the case of English, while Kannada and Telugu datasets showed accuracy above 96%.

In future work, this research can be extended in the following directions. First, the integration of deep learning architectures such as Bi-LSTM, CNN, or Transformer-based models-e.g., BERT or mBERT-will further improve feature representation and contextual understanding. Second, the dataset can be enriched by including social media posts and user-generated content, which will help improve the generalization of the model. Finally, the development of systems that allow for cross-lingual transfer learning and detect fake news in real time could result in more scalable, robust, and globally applicable solutions.

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