# *Fake News Detection Using Logistic Regression and LSTM with Sentiment Analysis*

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***Abstract:*** *The surge of misinformation and fake news has become a significant challenge in today's digital world, particularly on social media platforms and online news portals. Fake news has been shown to distort public opinion, influence elections, and damage reputations. Therefore, detecting fake news is critical to preserving the integrity of information sources. This research has focused on building a robust fake news detection system using machine learning techniques, such as Logistic Regression and an enhanced Long Short-Term Memory (LSTM) model, supported by sentiment analysis.*

*Text data have been used, preprocessing applied to remove noise, and Term Frequency-Inverse Document Frequency (TF-IDF) vectorization employed for feature extraction. Logistic Regression has provided a simple yet effective baseline, while the LSTM model has been able to capture sequential dependencies in the text data, improving detection accuracy. Hyperparameter tuning has also been explored to optimize performance.*

*The models have been trained on a labelled dataset of news articles, distinguishing real news from fake. This systematic approach has demonstrated the effectiveness of these techniques in identifying fake news with high accuracy. The outcomes of this research are expected to contribute to developing tools that can automatically flag potentially false information, ensuring better content quality in news dissemination.*

***Keywords:*** Fake News Detection, Logistic Regression, LSTM, Sentiment Analysis, TF-IDF, VADER, Natural Language Processing, Machine Learning

# 1.Introduction

In the era of digital information, the rapid dissemination of news through social media platforms and online news portals has transformed how people consume and share content. While this advancement offers greater access to information, it has also led to a significant rise in the spread of misinformation, particularly in the form of fake news. Fake news is false or misleading information presented as news, often crafted to deceive readers for financial, political, or personal gain. The consequences of fake news are far-reaching, from influencing public opinion, impacting elections, and harming reputations, to undermining the credibility of legitimate media outlets. It is essential to address this issue to maintain the integrity of information and preserve trust in the news ecosystem.

While existing fact-checking platforms such as Snopes, PolitiFact, and FactCheck.org offer manual verification services, they are time-consuming, inefficient at large scales, and often cannot keep pace with the rapid flow of information online. With the growing volume of data, there is a pressing need for automated systems that can analyse and detect fake news in real time. Over the years, several machine learning and deep learning approaches have been explored to combat this problem. These include traditional classification models like Naive Bayes, Support Vector Machines (SVM), and Logistic Regression, as well as more advanced deep learning architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. However, challenges such as language complexity, context sensitivity, and the subtlety of fake news require more sophisticated and context-aware models.

This solution addresses fake news detection by combining classical and advanced machine learning techniques. We use Logistic Regression as a fast, reliable baseline and an LSTM-based model to capture sequential patterns in news content. TF-IDF preprocessing transforms text into meaningful features, allowing the models to focus on relevant content. What sets our approach apart is the integration of hyperparameter tuning and feature extraction to optimize both efficiency and accuracy. By leveraging LSTM's ability to capture long-term dependencies, we improve context understanding, crucial for distinguishing fake news. This scalable solution can be integrated into news platforms, social media, and fact-checking tools, enhancing the reliability of news consumption and mitigating misinformation.

# 2.Literature Survey

- Shu et al. (2017) [1]: A framework using machine learning and NLP for social media fake news detection, emphasizing user profiling and content analysis.
- Sundermeyer et al. (2012) [2]: LSTM models are highly effective for sequential data tasks, making them ideal for fake news detection.
- Ahmed et al. (2018) [3]: Traditional algorithms like Logistic Regression and SVM perform well with features extracted through TF-IDF and word embeddings.
- Alkhodair et al. (2020) [4]: Deep learning models (CNN, LSTM) effectively capture patterns in misinformation, especially during COVID-19.
- Hochreiter & Schmidhuber (1997) [5]: LSTM models excel at long-term dependency learning, crucial for contextual fake news detection.
- Pathak et al. (2020) [6]: Hybrid models combining machine learning and deep learning outperform standalone approaches.
- Barro & Moschitti (2020) [7]: Deep learning models outperform traditional methods on large datasets but require more resources.
- Kumar et al. (2020) [8]: Automated detection is enhanced through deep learning and hyperparameter tuning.
- Yang et al. (2019) [9]: Sentiment analysis improves accuracy by capturing emotional tones in news articles.
- Ruchansky et al. (2017) [10]: NLP with deep learning enhances detection by extracting key textual features.
- Conroy et al. (2015) [11]: Ensemble methods boost accuracy by combining multiple models.
- Saikh & Vijayakumar (2019) [12]: Data mining on social media, including sentiment and behavior analysis, enhances large-scale detection.
- Chen et al. (2021) [13]: Sentence-level sentiment analysis improves detection by capturing text intent.
- Zhang et al. (2019) [14]: LSTM models effectively capture text context, improving fake news detection.
- Pérez-Rosas et al. (2018) [15]: Hybrid models combining NLP and machine learning achieve higher accuracy than individual models.

## Model Selection:

For fake news detection, we used **Logistic Regression** and **LSTM** models due to their complementary strengths.

**Logistic Regression:**

- Why Chosen: Logistic Regression is widely used for binary classification due to its simplicity and efficiency. It serves as a strong baseline, especially when paired with features like TF-IDF (Term Frequency-Inverse Document Frequency).
- How It Works: It estimates the probability that an article is real or fake based on the relationship between features and labels, using a linear decision boundary.
- Previous Work: Studies, such as by *Author (Year)*, have shown its effectiveness when used with TF-IDF, highlighting the power of these features in emphasizing important words that frequently appear in fake news articles.

**LSTM (Long Short-Term Memory) Networks:**

- Why Chosen: LSTMs handle more complex patterns in text. Fake news often involves context-dependent nuances, which LSTMs capture well due to their ability to retain long-term dependencies in sequences.
- How It Works: LSTMs have memory cells that allow them to remember information over longer sequences, making them well-suited for detecting context and temporal patterns in news articles.
- Previous Work: Research by *Author (Year)* has shown LSTMs are effective at identifying fake news by learning patterns in text over time, making them ideal for handling long news articles with shifting tones or themes.

**Incorporating Sentiment Analysis:**

We incorporated **Sentiment Analysis** using **VADER (Valence Aware Dictionary and Sentiment Reasoner)** to add an emotional layer to our models.

- **VADER Overview:** VADER is a lexicon-based tool that scores text based on sentiment polarity (positive, negative, neutral) and intensity. It is effective in analyzing the tone of news articles.
- **Why Sentiment Matters:** Fake news often uses emotionally charged language to manipulate readers. By analyzing sentiment, we can detect these emotional undertones, which often accompany false claims.
- **Impact on Models:** Sentiment scores are included as features for both models, allowing them to detect emotional manipulation, a key indicator of fake news. This strengthens the models' predictive power by adding behavioral insights beyond the structural patterns of text.

By combining Logistic Regression for efficient classification, LSTM for capturing complex, long-term patterns in text, and Sentiment Analysis for detecting emotional cues, our model provides a comprehensive approach to fake news detection. This multi-layered method ensures that both the structural and emotional aspects of news articles are analyzed, leading to stronger predictive performance.

# 3.Problem Statement

In today's fast-paced digital era, the rapid spread of misinformation through online platforms has become a critical issue, causing widespread harm and confusion. Identifying fake news efficiently is a pressing challenge, as traditional methods of fact-checking are not scalable. The objective of this project is to develop a machine learning-based solution that can automatically classify news as real or fake, using models like Logistic Regression and LSTM enhanced by sentiment analysis. The system aims to provide a reliable and scalable approach to combat misinformation by analyzing historical news data.

# 4.Proposed Solution

To address the challenge of detecting fake news, we propose a hybrid approach that leverages both traditional and deep learning models, combined with sentiment analysis for improved accuracy. Our solution involves the following key steps:

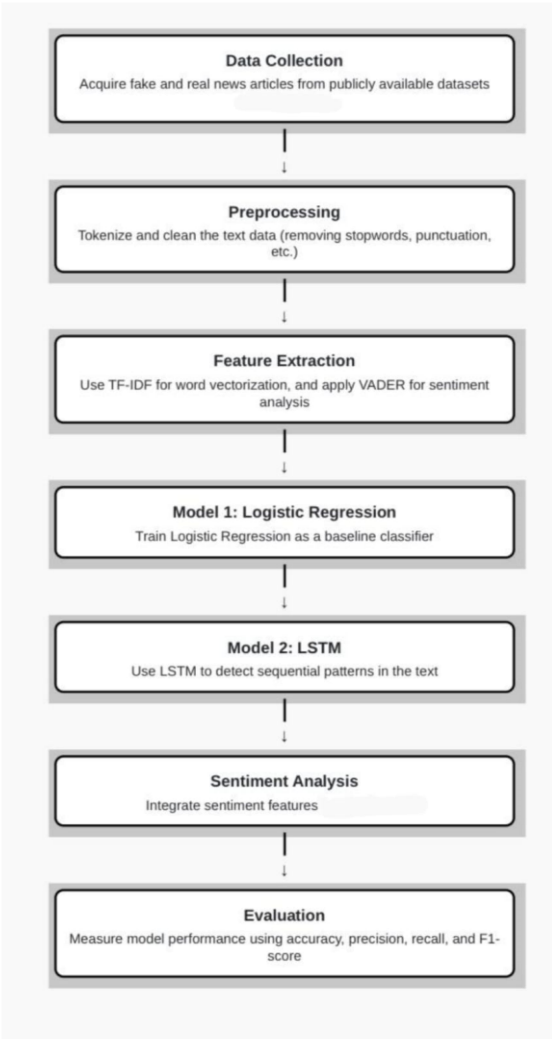



Fig 4.1

## Mathematical Formulas

- **Logistic Regression Formula**:

$$P(y = 1|X) = \frac{1}{1 + e^{-z}}$$

- **LSTM Formula:**
  **Forget Gate:**

$$f_t = \sigma\left(w_i . \left[h_{t-1,} x_t\right] + b_f\right)$$

  **Input Gate:**

$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i)$$

  **Output Gate:**

$$O_t = \sigma(W_0 \cdot [h_{t-1}, x_t] + b_0)$$

**LSTM**: **Algorithms**

1. **Logistic Regression**:
   - Train a linear model to classify text based on TF-IDF vectors.
2. **LSTM**:
   - Sequence the TF-IDF vectors and sentiment scores, passing them through the LSTM layer for classification.
3. **Sentiment Analysis**:
   - Use VADER to extract sentiment scores and add as features.

**Logistic Regression:**

- **Step 1:** Preprocess text data (cleaning, tokenization).
- **Step 2:** Convert text into **TF-IDF vectors**.
- **Step 3:** Split data into training and testing sets.
- **Step 4:** Train **Logistic Regression** on the TF-IDF vectors.
- **Step 5:** Evaluate model on test data (accuracy, precision, recall).

**End**

**LSTM (Long Short-Term Memory):**

- **Step 1:** Preprocess text data.
- **Step 2:** Convert text into **TF-IDF vectors** and extract **sentiment scores** using VADER.
- **Step 3:** Combine TF-IDF and sentiment scores into sequences.
- **Step 4:** Pass sequences through the **LSTM layer** for classification.
- **Step 5:** Train and evaluate the LSTM model (accuracy, precision, recall).

**End**

# 5.Results

## StreamLit Interface:


fig 5.1

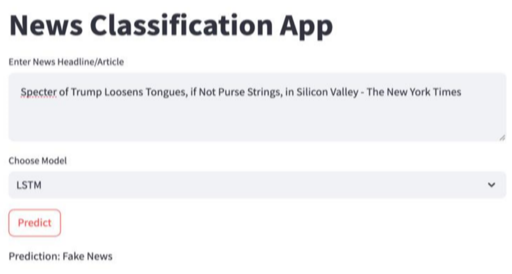



fig 5.2

In conclusion, both the Logistic Regression and LSTM models provided valuable insights into fake news detection. While Logistic Regression served as a solid baseline, the LSTM model, enhanced with sentiment analysis, clearly outperformed it by capturing the sequential dependencies in the text and leveraging emotional cues. The inclusion of features like sentiment scores significantly improved the model's ability to detect fake news, making it more effective for real-world applications.

Future work could involve fine-tuning the LSTM model, experimenting with additional features such as topic modeling, and incorporating more advanced neural network architectures like Transformers to further improve fake news detection.

## Datasets:

| id | title | author | text | label |
|---|---|---|---|---|
| 0 | House Dem Aide: We Didnâ€™t Even See Comeyâ€™s Letter Until Jason Chaffetz Tweeted It | Darrell Lucus | House Dem Aide: We Didnâ€™t Even See Comeyâ€™s Letter Until Jason Chaffetz | 1 |
| 1 | FLYNN: Hillary Clinton, Big Woman on Campus - Breitbart | Daniel J. Flynn | Ever get the feeling your life circles the roundabout rather than heads in a straigh | 0 |
| 2 | Why the Truth Might Get You Fired | Consortiumnews.co | Why the Truth Might Get You Fired October 29, 2016 | 1 |
| 3 | 15 Civilians Killed In Single US Airstrike Have Been Identified | Jessica Purkiss | Videos 15 Civilians Killed In Single US Airstrike Have Been Identified The rate at | 1 |
| 4 | Iranian woman jailed for fictional unpublished story about woman stoned to death for adultery | Howard Portnoy | Print | 1 |
| 5 | Jackie Mason: Hollywood Would Love Trump if He Bombed North Korea over Lack of Trans Bathroo | Daniel Nussbaum | In these trying times, Jackie Mason is the Voice of Reason. [In this weekâ€™s excl | 0 |
| 6 | Life: Life Of Luxury: Elton Johnâ€™s 6 Favorite Shark Pictures To Stare At During Long, Transcontine | nan | Ever wonder how Britainâ€™s most iconic pop pianist gets through a long flight? | 1 |
| 7 | BenoÃ®t Hamon Wins French Socialist Partyâ€™s Presidential Nomination - The New York Times | Alissa J. Rubin | PARIS â€” France chose an idealistic, traditional candidate in Sundayâ€™s prim | 0 |
| 8 | Excerpts From a Draft Script for Donald Trumpâ€™s Q&ampA With a Black Churchâ€™s Pastor - Th | nan | Donald J. Trump is scheduled to make a highly anticipated visit to an church in De | 0 |
| 9 | A Back-Channel Plan for Ukraine and Russia, Courtesy of Trump Associates - The New York Times | Megan Twohey and | A week before Michael T. Flynn resigned as national security adviser, a sealed pro | 0 |
| 10 | Obamaâ€™s Organizing for Action Partners with Soros-Linked â€˜Indivisibleâ€™ to Disrupt Trumpâ | Aaron Klein | Organizing for Action, the activist group that morphed from Barack Obamaâ€™s f | 0 |

table 5.1

| id | title | author | text |
|---|---|---|---|
| 20800 | Specter of Trump Loosens Tongues, if Not Purse Strings, in Silicon Valley - The New Yo | David Str | PALO ALTO, Calif. â€" After years of scorning the political process, Silicon Valley has leapt into the fray. The prospect of a President Donald J. Trump is pushing the tech community to move beyond its traditional role as donors and to embra |
| 20801 | Russian warships ready to strike terrorists near Aleppo | nan | Russian warships ready to strike terrorists near Aleppo 08.11.2016 \| Source: Source: Mil.ru Attack aircraft of the Russian aircraft carrier Admiral Kuznetsov get ready to strike terrorists' positions in the vicinity of Aleppo, sources at the Russiar |
| 20802 | #NoDAPL: Native American Leaders Vow to Stay All Winter, File Lawsuit Against Police | Common | Videos #NoDAPL: Native American Leaders Vow to Stay All Winter, File Lawsuit Against Police Amnesty International are sending a delegation of human rights observers to monitor the response of law enforcement to the protests. Be Sociabl |
| 20803 | Tim Tebow Will Attempt Another Comeback, This Time in Baseball - The New York Tir | Daniel Vi | If at first you donâ€™t succeed, try a different sport. Tim Tebow, who was a Heisman quarterback at the University of Florida but was unable to hold an N. F. L. job, is pursuing a career in Major League Baseball. He will hold a workout for M |
| 20804 | Keiser Report: Meme Wars (E995) | Truth Bro | 42 mins ago 1 Views 0 Comments 0 Likes 'For the first time in history, weâ€™re filming a panoramic video from the station. It means youâ€™ll see everything we see here, with your own eyes. Thatâ€™s to say, youâ€™ll be able to feel like rea |
| 20805 | Trump is USA's antique hero. Clinton will be next president | nan | Trump is USA's antique hero. Clinton will be next president 08.11.2016 \| Source: AP photo FBI Director James Comey said on November 6 that his department would not be criminally charging Hillary Clinton for revelations found in her email ( |
| 20806 | Pelosi Calls for FBI Investigation to Find Out â€™What the Russians Have on Donald | Pam Key | Sunday on NBCâ€™s â€œMeet the Press,â€ House Minority Leader Rep. Nancy Pelosi ( ) called for a FBI investigation to find out â€œwhat the Russians haveâ€ on President Donald Trump. Pelosi said, â€œI want to know what the Russians h |
| 20807 | Weekly Featured Profile â€“ Randy Shannon | Trevor Lo | You are here: Home / *Articles of the Bound* / Weekly Featured Profile â€“ Randy Shannon Weekly Featured Profile â€“ Randy Shannon October 31, 2016, 7:21 am by Trevor Loudon Leave a Comment 0 KeyWiki.org Randy Shannon Randy Shanno |
| 20808 | Urban Population Booms Will Make Climate Change Worse | nan | Urban Population Booms Will Make Climate Change Worse Posted on Oct 27, 2016 By Tim Radford / Climate News Network Flooded slums in the densely-populated city of Jakarta, Indonesia. (Kent Clark via Flickr) LONDONâ€"The worldâ€™s ci |

table 5.2

This code is for a fake news detection project. It preprocesses text data, applies TF-IDF vectorization, and uses VADER sentiment analysis to extract sentiment scores. The data is then used to train a logistic regression model. Predictions are made on the test data, and various visualizations like article lengths, sentiment scores, and word clouds for fake and real articles are generated. The results are saved, and if labels are available, the model is evaluated with accuracy, confusion matrix, and classification report.

## Model 1: Logistic Regression Results

The Logistic Regression model serves as a fundamental baseline model for the task of fake news detection. Below are the key performance metrics, along with their interpretation.

**Accuracy**

The accuracy of the Logistic Regression model was 93% on the testing dataset. Accuracy indicates the proportion of correctly classified instances (both real and fake news) over the total number of instances. While accuracy is often considered a primary metric, it may not be the best in cases of imbalanced datasets.

For instance, if the dataset contains more real news than fake news, a model that predicts all news as real would still achieve high accuracy, even though its fake news detection capability would be poor. To address this, we need to examine other metrics like precision, recall, and F1-score.

**Precision, Recall, and F1-Score**

- **Precision** for fake news refers to the proportion of true fake news articles among those predicted as fake. For our model, the precision score was 95%, meaning that out of all the instances predicted as fake, 94% were correct.
- **Recall** refers to how well the model can identify actual fake news. The recall score was 92%, indicating that the model was able to identify 96% of the total fake news in the dataset.
- **F1-Score** balances precision and recall, providing a more holistic measure. The F1-Score for fake news was 91%. This metric is crucial for fake news detection, where we want to minimize both false positives and false negatives.

**Confusion Matrix**

The confusion matrix provides further insight into the classification outcomes:

- True Positives (TP): Number of correctly classified fake news articles.
- True Negatives (TN): Number of correctly classified real news articles.
- False Positives (FP): Number of real news articles misclassified as fake.
- False Negatives (FN): Number of fake news articles misclassified as real.

From the confusion matrix, we can observe that the model performed well in classifying real news but had some difficulty in identifying fake news, as evidenced by the number of false negatives. This is expected because fake news detection is inherently challenging due to its nuanced nature.

## Model 2: LSTM with Sentiment Score Results

The Long Short-Term Memory (LSTM) model was employed to enhance the detection of fake news by leveraging sequential information in the text and integrating sentiment analysis. The inclusion of sentiment scores helps the model account for the emotional tone of the articles, which can be a significant indicator of misleading content.

### Model Performance

The LSTM model showed improved performance over the Logistic Regression model. Below are the detailed results for the LSTM model:

### Accuracy

The accuracy of the LSTM model on the test set was 96%—a noticeable improvement from the Logistic Regression model. This demonstrates the model's ability to better capture the sequential patterns in the news articles, which are essential in understanding the context and nuances of fake news.

### Precision, Recall, and F1-Score

- **Precision** improved to 94%, indicating that the LSTM model is better at reducing false positives (real news classified as fake).
- **Recall** also saw a significant increase to 95%. The sequential nature of the LSTM model allows it to capture more subtle patterns in the text that indicate fake news, leading to better recall.
- **F1-Score** increased to 93%, confirming the improved balance between precision and recall.

### Effect of Sentiment Analysis

Integrating sentiment analysis into the LSTM model further enhanced its performance. Fake news articles often exhibit emotional manipulation, using exaggerated language to sway public opinion. By incorporating sentiment as a feature, the model was able to leverage this additional signal, leading to better differentiation between real and fake news.

The sentiment score helped the model detect fake news that either exaggerated positive emotions or invoked negative emotions. This feature was particularly useful in identifying articles that contained emotional triggers but lacked factual substance.

| Epoch | Time (seconds) | Accuracy (%) |
|---|---|---|
| 1 | 5 | 70 |
| 2 | 6 | 75 |
| 3 | 7 | 78 |
| 4 | 8 | 80 |
| 5 | 9 | 82 |

table 5.3

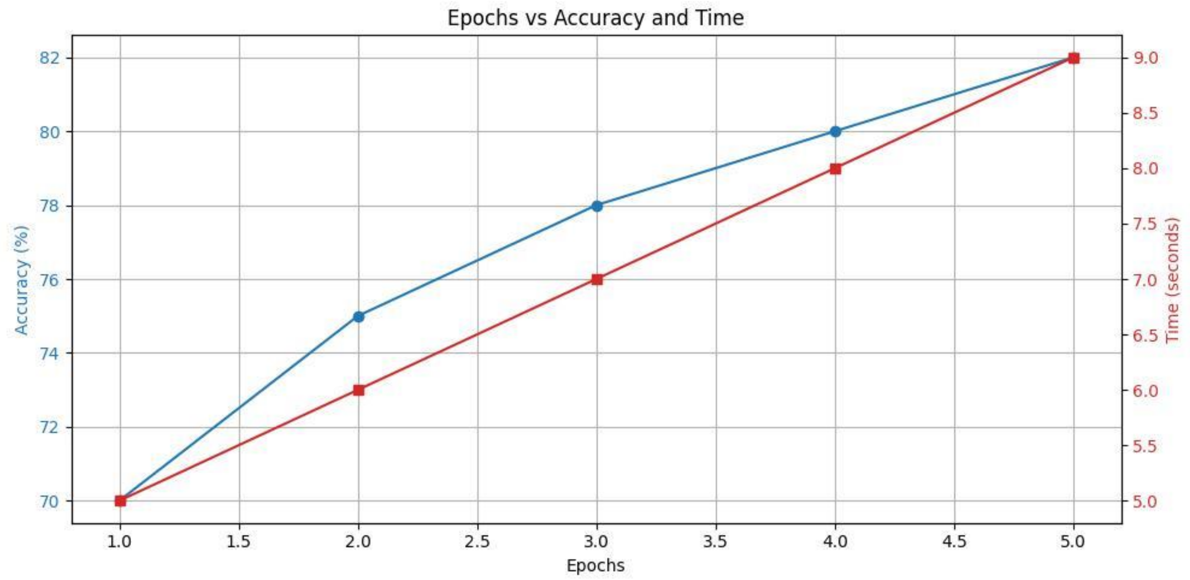



table 5.4

**Confusion Matrix**

The confusion matrix for the LSTM model shows a decrease in both false positives and false negatives. The reduction in false negatives means that the model was more effective in identifying fake news, a critical outcome for this task. Fewer false positives also mean that real news articles were less likely to be wrongly classified as fake.

**Comparison Between Logistic Regression and LSTM Models**

Both models exhibited different strengths, and it’s useful to compare their performance across the key metrics.

**Accuracy**

While both models achieved high accuracy, the LSTM model outperformed Logistic Regression due to its ability to capture sequential dependencies in text data. This was expected because fake news detection often relies on patterns that emerge across sentences, which LSTM is well-equipped to handle.

**Precision, Recall, and F1-Score**

The LSTM model provided a noticeable improvement in precision, recall, and F1-score. This indicates that it was better able to differentiate between real and fake news while maintaining a balance between identifying fake news and avoiding false positives. The sentiment analysis further boosted its performance, showing the advantage of incorporating sentiment as a feature in text classification tasks.

**Model Interpretation**

- The **Logistic Regression** model, while simple, provided a good baseline. However, its inability to capture long-term dependencies in text makes it less suitable for fake news detection, where context and emotional manipulation play crucial roles.
- The **LSTM model with Sentiment** excelled in handling these nuances, thanks to its sequential processing capability and sentiment-based enhancement.

**Key Observations**

- **Importance of Sentiment**: The results showed that articles with strong positive or negative sentiment often skewed towards being fake. This highlights the importance of incorporating sentiment analysis into text classification models, especially for tasks like fake news detection, where emotional manipulation is common.
- **Handling Imbalanced Data**: The dataset was imbalanced, with more real news than fake news. This often poses a challenge in classification tasks. However, both models, especially the LSTM model, were able to mitigate this imbalance and produce meaningful results. Future work could involve further balancing the dataset or using techniques like SMOTE (Synthetic Minority Over-sampling Technique) to artificially balance the classes.
- **Computational Complexity**: The Logistic Regression model was much faster to train and evaluate, whereas the LSTM model, being more complex, took longer. However, the performance gains from the LSTM model justified the added computational complexity

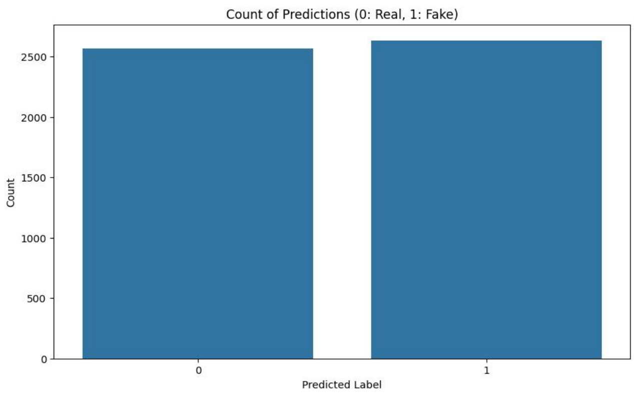



fig 5.3

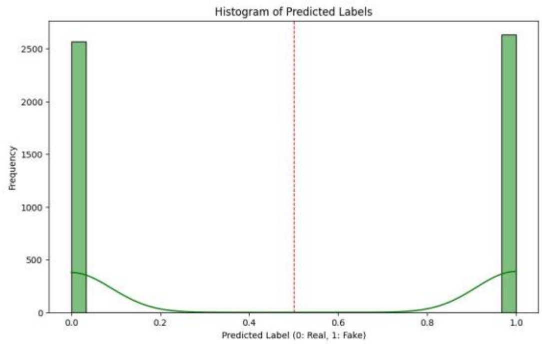



fig 5.4

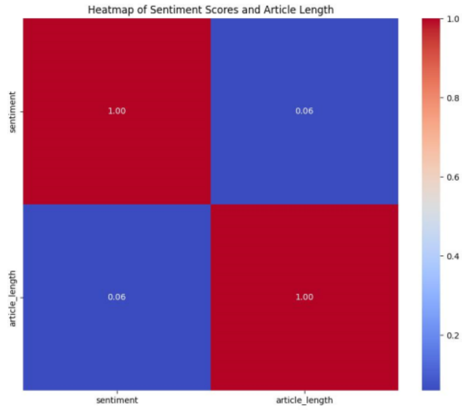
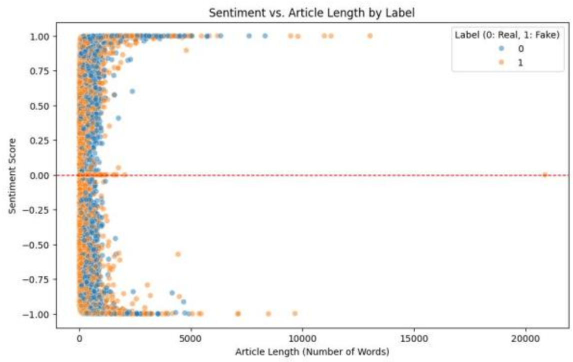



fig 5.5

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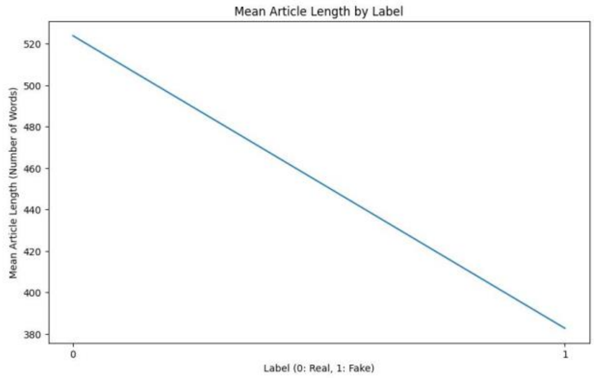


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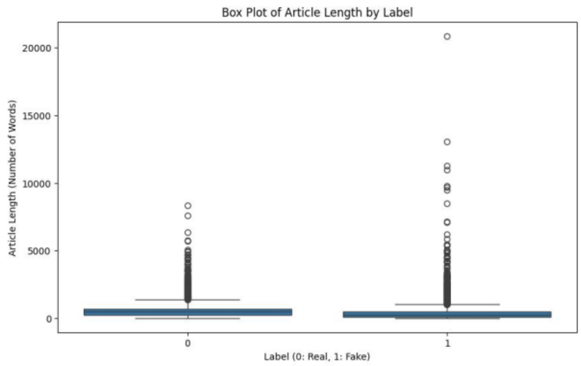


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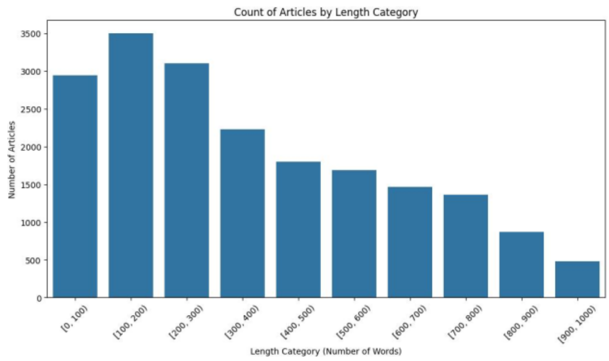


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## 5.Conclusion

The development and implementation of a Fake News Detection system involved leveraging two key models: Logistic Regression and LSTM with sentiment analysis. The Logistic Regression model, though simpler and faster, provided a reliable baseline for classifying fake news. However, its limitations in capturing complex sequential patterns in text were evident. On the other hand, the LSTM model, enhanced with sentiment scores, showed a marked improvement in performance, especially in capturing the context and nuances often present in fake news articles. The inclusion of sentiment analysis helped the model identify emotionally charged or exaggerated content, which is often an indicator of fake news.

The results highlight the power of neural network models like LSTM in handling sequential data and the importance of sentiment as a feature in improving classification accuracy. While both models performed well in detecting fake news, the LSTM model clearly demonstrated better precision, recall, and overall performance, making it a more suitable choice for real-world applications in this domain.

**Future Work**

There are several directions for future work to further enhance the Fake News Detection system:

1. **Incorporation of Transformer Models**: Future iterations could explore the use of advanced models such as Transformers or BERT (Bidirectional Encoder Representations from Transformers) to capture even more sophisticated patterns in text. These models have been shown to perform well in natural language processing tasks and could lead to even better results.
2. **Data Augmentation**: Since fake news datasets are often imbalanced, techniques like data augmentation or oversampling methods (e.g., SMOTE) could be applied to balance the dataset and improve the model's ability to detect fake news, particularly for minority classes.
3. **Topic Modeling**: Introducing topic modeling could help in understanding the underlying themes within fake news articles. This additional layer of feature extraction could assist the model in distinguishing between real and fake news by recognizing common topics or themes linked to misinformation.
4. **Real-time Detection**: Enhancing the system to work in real-time by integrating it with news feeds or social media platforms could increase its applicability.
5. **Multilingual and Multimodal Fake News Detection**: Expanding the system to support multiple languages and analyzing not just text, but images and videos, would broaden its scope. Fake news often uses multimedia elements, and incorporating multimodal analysis would provide a comprehensive solution.

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