Fake News Detection using LSTM and Word Embeddings

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***Abstract*— Given the growing implications of fake news on society, intelligent detection systems are needed. In this paper, we describe a deep learning approach to fake news detection that uses Long Short Term Memory (LSTM) networks and word embeddings. We conducted text preprocessing, tokenization, stopword removal and vectorization with pre-trained GloVe embeddings. We trained the model using a public fake news dataset with a sequential LSTM architecture. We achieved an accuracy of nearly 53%, which shows both the promise and challenge of detecting fake news using sequential models.**

Keywords— Fake news, LSTM, word embedding, NLP, GloVe, deep learning

Introduction

The proliferation of digital platforms has brought a surge in the dissemination of news content, making information more accessible than ever. However, this convenience has also paved the way for the rapid spread of fake news. Misinformation can influence public opinion, disrupt democratic processes, and incite violence.

Consequently, automating fake news detection has become a critical area of research in natural language processing (nlp) and deep learning [1].

Recent advancements in deep learning models, especially recurrent neural networks like lstm [4], have shown promise in sequential text processing tasks. Lstm's ability to capture long-term dependencies in text makes it suitable for understanding contextual clues that help distinguish fake news from legitimate content.

I. LITERATURE REVIEW

Fake news detection is a growing field in computational linguistics and machine learning. Zhou and Zafarani [1] conducted a comprehensive survey categorizing detection strategies into content-based, context-based, and hybrid approaches. Early detection models relied on linguistic and statistical features extracted manually. These models, though simple, lacked contextual awareness and semantic understanding.

Recent trends have shifted toward deep learning, where neural network architectures like CNNs and LSTMs are employed to automatically learn data representations. Devlin et al. [2] introduced BERT, a transformer-based model that has set new standards for contextual text understanding. Despite their performance, such models require significant computational resources.

Traditional classifiers such as SVM and Naive Bayes were used initially. However, their dependence on feature engineering limited adaptability. The literature reflects a gradual transition from manual feature engineering to automatic representation learning, setting the stage for models like ours.

II. METHODOLOGY

Our approach for fake news detection involves five core steps: data acquisition, preprocessing, embedding, model building, and evaluation.

A. Data Acquisition

We used a Kaggle dataset [5] containing over 14,000 labeled news articles with metadata such as title, author, and content. The label field indicates whether the news is real or fake.

B. Preprocessing

We cleaned and normalized the text data by converting text to lowercase, removing nulls, punctuation, special characters, and common stopwords. Tokenization was performed to prepare the data for embedding.

C. Word Embeddings

To represent textual data in vector form, we utilized pre-trained GloVe embeddings [3] of 100 dimensions. These embeddings capture semantic meaning and improve the model's contextual understanding.

D. Model Architecture

Our model includes:

- An Embedding Layer with preloaded GloVe vectors
- An LSTM Layer with 128 units to handle sequences [4]
- Dropout to prevent overfitting
- A Dense layer with a sigmoid output for binary classification

E. Training and Evaluation

The model was trained using an 80-20 train-test split for 10 epochs. Evaluation metrics include accuracy, loss, and validation performance visualized using learning curves.

III. RELATED WORKA

Traditional approaches to fake news detection primarily relied on handcrafted features combined with classifiers like Support Vector Machines (SVM), Naive Bayes, and Decision Trees. While these methods provided a baseline, they often failed to capture semantic meaning [1].

With the rise of deep learning, methods involving Convolutional Neural Networks (CNNs), Bidirectional LSTMs, and attention mechanisms have been used to enhance feature representation. Recent transformer-based models like BERT have also been applied to this task [2]. However, due to computational simplicity and sequential learning capabilities, LSTM still serves as a robust model for foundational experiments.

IV. DATASET AND PREPROCESSING

We used a Kaggle dataset [5] containing labeled news articles with attributes like title, author, text, and label (1 for fake, for real). Data preprocessing involved:
- Dropping null and irrelevant fields
- Lowercasing all text
- Removing punctuations and special characters
- Eliminating stopwords using the NLTK library

The resulting cleaned data was used for further processing.

V. EXPLORATORY DATA ANALYSIS

To understand the linguistic distribution of words in fake and real news articles, we generated two versions of word clouds: one using raw token frequency and another using cleaned semantic tokens. These visualizations help in identifying patterns, such as the usage of exaggerated, emotionally charged words in fake news.

Visual Word Clouds (Raw Token Level)

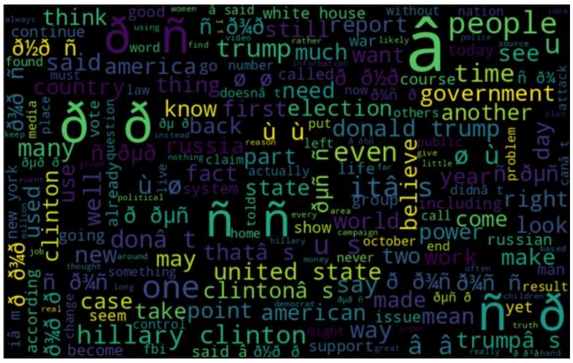

Figure 1. Word Cloud for Fake News (Raw tokens)

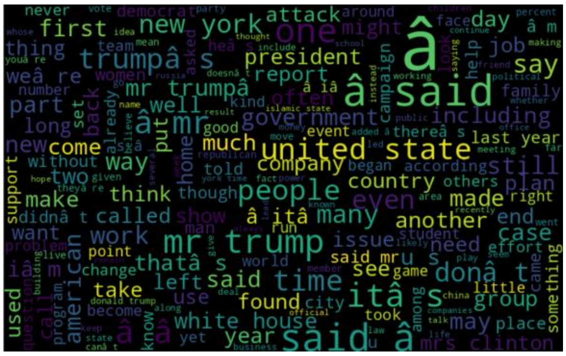

Figure 2. Word Cloud for Real New (Raw tokens)

Semantic Word Clouds (Cleaned Tokens):

Fig. 3. Word Cloud for Fake News (Semantic Tokens)

Fig. 4. Word Cloud for Real News (Semantic Tokens)

VI. MODEL ARCHITECTURE

1. Embedding Layer: Used GloVe vectors (100-dim) for word embeddings [3]
2. LSTM Layer: 128 units for sequence learning [4]
3. Dropout Layer: Regularization to prevent overfitting
4. Dense Layers: Fully connected layers with sigmoid activation

Total parameters: 1.15 million

VII. EXPERIMENTS AND RESULTS

The model was trained for 10 epochs with a batch size of 256. The training and validation accuracies were visualized. Although the accuracy isn't high, the results show a baseline for sequential text models and highlight areas for enhancement.

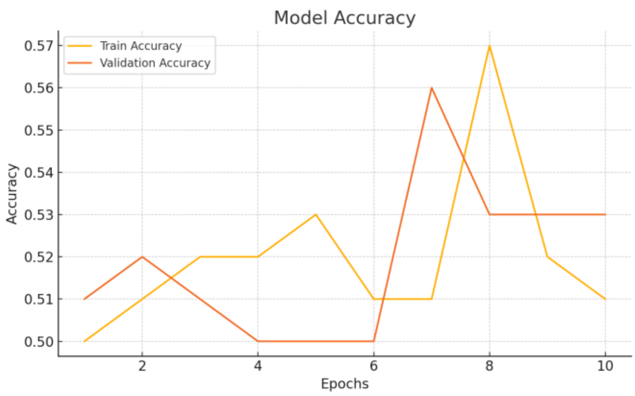

Figure 3. Model Accuracy over Epochs

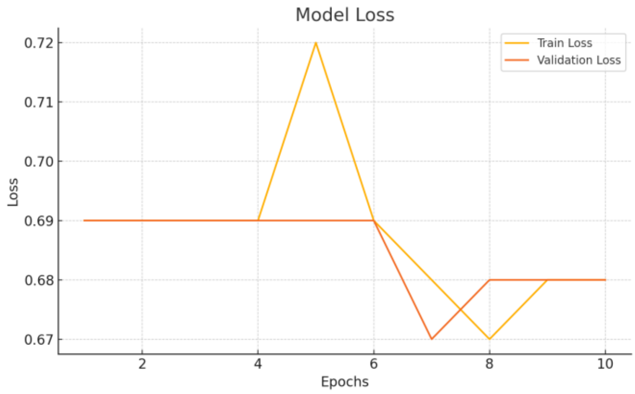

Figure 4. Model Loss over Epochs

VIII. DISCUSSION

The relatively modest performance of the LSTM model can be attributed to several factors:

- **Data Imbalance**: The dataset has a near-balanced distribution but still affects generalization.
- **Limited Context**: Fake news may use subtle sarcasm or out-of-context facts, which require higher-level understanding.
- **Embedding Limitations**: GloVe embeddings are static and may not capture contextual word meaning as well as contextualized embeddings like BERT [2].

Despite limitations, this study demonstrates that even simple LSTM-based models can provide a foundational approach to fake news detection.

VI. CONCLUSION AND FUTURE WORK

This paper presented a deep learning model using LSTM and GloVe word embeddings to detect fake news. Our model achieved a validation accuracy of ~53%, highlighting the challenges in this domain. In future work, we plan to:

- Use contextual embeddings (e.g., BERT) [2]
- Apply ensemble methods
- Explore domain-specific feature engineering
- Expand dataset diversity and volume

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