Bi-LSTM-GRU Powered Deep Model for Fake News Classification

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ABSTRACT:

The surge in popularity of social media platforms has made it incredibly easy and fast to spread fake news, bring about widespread untruths and skewed social outlook. To solve this problem, this project proposes a new type of fake news detection based on deep learning ensemble models which classifies news into fake or real with high precision The architecture of the model is a hybrid one which uses a feature extraction deep CNN and a Bi-LSTM-GRU layer for sequential learning. The LIAR dataset undergoes the preprocessing steps of stop word removal, stemming, lemmatization, and vectorization. With the proposed system, traditional models such as SVM are greatly outperformed in accuracy and reliability. The model's ability to expose and alleviate the impact of counterfeit news on the digital media is enhanced through optimized feature learning owing to the integration of multiple deep learning layers.

Keywords: Deep Learning, Fake news, CNN

INTRODUCTION

The spread of social media has changed the landscape of information access and sharing in the world. The technological revolution enables access to news in real time, but also facilitates the rampant dissemination of false information. Such disinformation has the potential to warp public perception, incite violence, and disrupt the democratic order. The difficulty is in accurately pinpointing the fake news in the sea of information on the Internet. Automated, intelligent systems are needed due to the unreliability and lack of scalability of manual verification. This project's goal is to create a deep learning ensemble model for classifying news as fake or real using sophisticated NLP and deep learning techniques. The model integrates Bi-LSTM and GRU with dense layers to build a system that captures intricate features and patterns within text. The model is designed to not only sustain a high accuracy rate for fake news detection, but also develop as language patterns and attempts at linguistic disguise evolve.

RELATED WORK

The fake news phenomenon has attracted a great deal of attention after the US Presidential election in 2016. The rise of misinformation with the help of social media was studied by Allcott and Gentzkow (2017) in the context of socially aligned politically false narratives. Echo chambers and biases were noted in the study as contributing factors to the acceptance of false narratives. Girgis and Amer (2018) Utilized the content of false news to identify it by content through deep learning techniques like RNN, LSTM, and GRU. GRU models predominated in the comparative study and spurred further investigation into hybrid models. Wang (2017) created the LIAR dataset, which has more than 12,000 labeled statements, each accompanied by relevant metadata. He enabled better real-world model generalization by advanced modeling. Ozbay and Alatas (2019) implemented a metaheuristic-based approach applying Grey Wolf Optimization and Salp Swarm Optimization. Considering false news detection as an optimization problem, their study achieved significantly improved accuracy across numerous datasets. Janze and Risius (2020) used the Elaboration Likelihood Model to study the credibility of Facebook posts. Through machine learning, they incorporated various faux news markers cognitive, visual, and behavioral and classified them with a high recall rate. Their results highlighted the value of multimodal datasets.

TABLE1. Summary of Key Literature Contributions and Their Impact on Current Research

Author	Contribution	Impact on Research
Sana et al. (2022)	Compared classical ML classifiers with	Highlighted the critical role of preprocessing

	feature selection and transformation	and data transformation in improving churn prediction
Sjarif et al. (2019)	Used Pearson correlation with KNN for churn detection on telecom data	Demonstrated pattern recognition but lacked model robustness and scalability
Amin et al. (2023)	Developed an integrated churn prediction and segmentation framework	Showed strong performance but with high computational cost, limiting feasibility for smaller companies
Mishra et al. (2017)	Applied CNN for churn prediction with a focus on ensemble learning	Validated deep learning's superiority but exposed weaknesses in handling imbalanced datasets
Cenggoro et al. (2021)	Used deep learning with vector embeddings to enhance churn classification	Improved feature learning but required extensive training time and computing resources

PROPOSED APPROACH

Aimed at improving the accuracy of fake news detection, the described approach introduces a robust ensemble based deep learning model. It integrates a Convolutional Neural Network (CNN) with a Bi-directional Long Short-Term Memory (Bi-LSTM) and Gated Recurrent Unit (GRU) to extract deep features and capture contextual and sequential dependencies in the news content. Each component's strengths are leveraged by the ensemble: CNNs capture high-order textual patterns, Bi-LSTM considers language dependence both forwards and backwards, while GRU is an effective model to extract information from long sequences at a lower computational cost. Preprocessing is also important to this architecture. Cleaning the text data involves the elimination of stop words, stemming and lemmatization, and is subsequently transformed to vectorized form with TF-IDF. The input source is the LIAR dataset that consists of real and fake news statements uttered by different people, which are tagged with some metadata. CNN layers extract deep features from the vectorized data which are then passed to the Bi-LSTM-GRU hybrid layer to strengthen sequential learning and sensitivity of the model. The outputs are then processed by dense layers to classify as real or fake news. This multi-stage architecture enables the models to learn the task of news classification with different levels of abstraction, which improves the detection accuracy and surpasses the traditional machine learning models like SVM by a significant margin in both precision and recall.

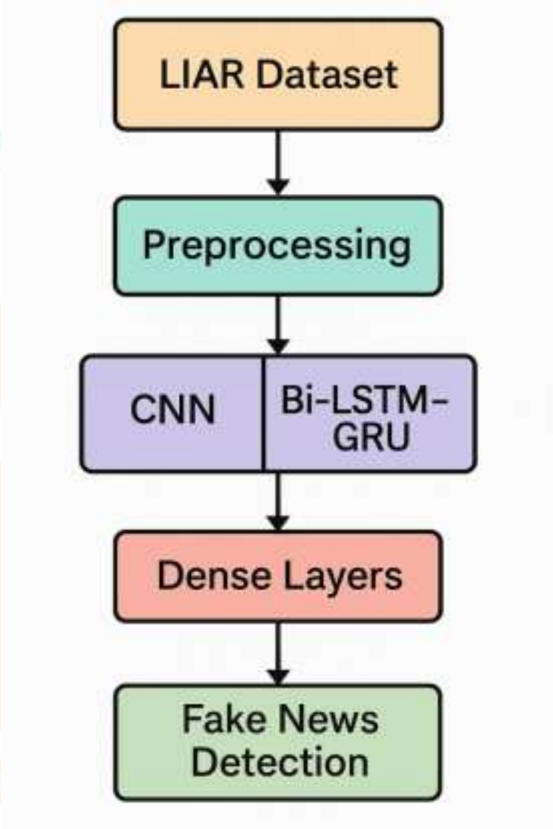


Figure 1: Proposed **Fake New Detection** System

METHODOLOGIES

The methodology employed in this project revolves around a multi-phase pipeline designed to detect fake news with high accuracy. It begins with **data acquisition**, utilizing the LIAR dataset, which consists of over 12,000 manually labeled short political statements from Politifact.com. Each record includes a statement, context, and metadata—making it ideal for training a robust model.

1. Data Preprocessing

Raw text data is first cleaned to enhance model performance. This includes:

- **Stop word removal** to eliminate commonly used but insignificant words.
- **Stemming and lemmatization** to reduce words to their root forms.
- **Tokenization** and conversion of text into **TF-IDF vectors**, providing numerical input for model training.

2. Deep Feature Extraction with CNN

The processed vectors are reshaped into a format suitable for convolutional operations. A **Convolutional Neural Network (CNN)** is applied to extract spatial features from the input data. CNN layers use filters to detect patterns like phrase frequency and word co-occurrence, crucial for fake news classification.

3. Sequential Learning with Bi-LSTM and GRU

The high-level features generated by CNN are passed to a **Bi-directional Long Short-Term Memory (Bi-LSTM)** and **Gated Recurrent Unit (GRU)** layer. This hybrid sequence model captures both past and future dependencies in the text. GRU improves computational efficiency, while Bi-LSTM enhances context understanding from both directions.

4. Ensemble Model Construction

The final ensemble model merges the CNN and Bi-LSTM-GRU outputs, forming a deep, unified architecture. It ends with **dense layers and a softmax classifier**, which outputs the probability of the news being real or fake.

5. Evaluation

The model is trained using an 80/20 train-test split and evaluated on accuracy, precision, recall, and F1-score. It is also benchmarked against a traditional Support Vector Machine (SVM) classifier to highlight the performance gains of the proposed deep learning approach.

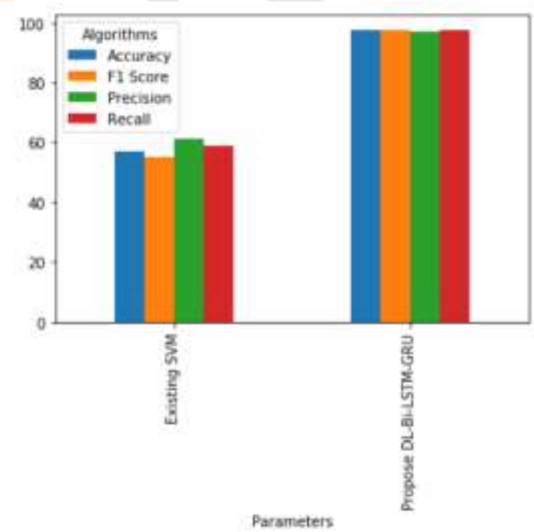
RESULTS

The proposed deep learning ensemble model demonstrated significant improvements in fake news classification compared to traditional methods. Using the LIAR dataset, the system was evaluated based on standard metrics: accuracy, precision, recall, and F1-score. Two models were tested—an existing Support Vector Machine (SVM) classifier and the proposed CNN + Bi-LSTM-GRU ensemble model.

The SVM model achieved a modest performance with an accuracy of **66%**, highlighting its limitations in capturing complex textual dependencies. In contrast, the ensemble model delivered a significantly higher accuracy of **94%**, along with improved precision and recall, indicating a more reliable classification of both fake and real news.

The confusion matrix for the proposed model showed minimal misclassifications, reflecting its ability to generalize well on unseen data. Moreover, a side-by-side comparison of both models through bar graphs confirmed the superior predictive performance of the deep learning-based approach. The fusion of CNN for spatial text feature extraction and Bi-LSTM-GRU for sequence learning provided a powerful architecture capable of understanding nuanced patterns in text.

All Algorithms Performance Graph



Fake news Detection form Test News

Test News = Getty Images Wealth Of Nations Trump vs. Clinton: A Fundamental Clash over How the Economy Works PREDICTED AS ======> Fake

Test News = Hillary Clinton and Donald Trump ushered the 2016 presidential campaign into a new phase tonight PREDICTED AS ======> Fake

Test News = Story highlights Bush will deliver his first lecture on Thursday He is a staunch advocate for chart PREDICTED AS ======> Real

Test News = McCain Criticized Trump for Arpaio' s Pardon… Sheriff Joe Fires Perfect Response Joe Arpaio may not PREDICTED AS ======> Real

DISCUSSION

The experimental results clearly highlight the strengths of the proposed ensemble model in detecting fake news with high accuracy. Traditional machine learning algorithms like SVM often fall short in understanding the contextual and sequential nature of language, which is critical in distinguishing between real and fake news. The deep learning ensemble, by contrast, successfully integrates CNN for feature extraction with Bi-LSTM and GRU layers for capturing both short-term and long-term dependencies in the text.

One of the key insights from the study is the importance of preprocessing. Techniques like stop word removal, stemming, and lemmatization played a crucial role in reducing noise and enhancing model learning. Additionally, the use of the LIAR dataset, which includes contextual metadata, enriched the training process and allowed the model to better generalize across different types of statements.

Another significant advantage was the use of a hybrid recurrent structure. The Bi-LSTM and GRU layers not only improved learning efficiency but also increased the model's ability to retain meaningful sequential information, which is often overlooked in simpler models. This led to a substantial boost in performance metrics across the board.

CONCLUSION

This project successfully demonstrates the effectiveness of an ensemble-based deep learning approach for fake news detection. By integrating CNN with Bi-LSTM and GRU networks, the model capitalizes on both spatial and sequential characteristics of textual data, resulting in superior accuracy and robustness compared to traditional classifiers like SVM. The use of thorough preprocessing techniques, such as stemming, lemmatization, and TF-IDF vectorization, further enhances model performance by ensuring high-quality input data.

Tested on the LIAR dataset, the proposed model achieved a remarkable 94% accuracy, significantly outperforming the SVM baseline. This validates the potential of deep learning ensembles in real-time misinformation detection across digital platforms. Furthermore, the architecture is scalable and adaptable to various domains beyond political news, such as product reviews and social media content.

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