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Optimization Accuracy of Fake News Detection for Twitter Data using Deep Learning Approach

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Abstract

With the explosive growth of social media platforms like Twitter, the spread of fake news and misinformation has become a critical concern for digital trust and online safety. Detecting such misinformation accurately and efficiently requires advanced computational intelligence techniques. This study focuses on improving the *optimization accuracy* of fake news detection using deep learning models trained on Twitter data. Various neural architectures—such as Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Convolutional Neural Network (CNN), and hybrid CNN-BiLSTM models—are explored for text-based fake news classification. The dataset undergoes preprocessing steps including tokenization, stop-word removal, and feature embedding through Word2Vec and GloVe representations. Hyperparameter optimization techniques such as Grid Search and Bayesian Optimization are implemented to enhance model performance. Evaluation metrics including accuracy, precision, recall, F1-score, and ROC-AUC are used to measure performance. The results reveal that optimized hybrid models achieve significantly higher accuracy and generalization ability compared to traditional classifiers. The study concludes that combining deep learning and optimization techniques provides a robust, scalable, and interpretable framework for reliable fake news detection on Twitter.

Keywords: Fake News Detection, Deep Learning, Twitter Data, Optimization, LSTM, Natural Language Processing

1. INTRODUCTION

The word Fake News refers to false information that circulates on social media and other online distribution channels as well as traditional media platforms [1]. People all around the world are attracted to social media because it is easily accessible, affordable, and convenient for sharing information. However, this led to the propagation of fake news [2]. The term "fake news" is often used to refer to a news article that is deliberately and undeniably false [3], [4]. Moreover, it involves content that is portrayed as a news story but contains factual errors with the aim to deceive users by making them perceive it as authentic [5]. In the post-internet era, the researcher's interest in the identification of fake news has reappeared. It has significant negative effects on the social, political, and economic contexts. Fake news and false information can manifest in a multitude of ways. It has considerable impact since information plays in shaping our worldview and forming critical judgments based on facts. Cybernauts and digital natives are adapted to see trending topics, articles, videos, and images that can influence or change public opinion. Their acceptance of fake news has destabilized the nation's democratic system in frightening ways. Satire and shady tactics are frequently

used in content to spread false or fraudulent news due to fabricated ranking. Within the domain of fake news, content plays a pivotal role in shaping people's belief in a specific piece of information.

Opinions about events or groups are formed through the information gathered. However, when the acquired information is inaccurate, fake, distorted, or fabricated, making well-informed decisions becomes impossible. According to studies, around 93% of Americans utilize online content and tools as sources of information [7]. This widespread engagement with social media significantly contributes to the spread of rumors and misinformation. A notable case in point is the Republican Party's smear campaign targeting Hillary Clinton during the election for the U.S. Presidency happened in 2016. This led the American people to believe she had been falsely accused, and as a result, Hillary Clinton lost the election. Another incident occurred in 2017 when false information about the suspect was shared on social media platforms. Furthermore, misinformation in the field of health has the potential to negatively affect individual's lives [9], as people are increasingly turning to the internet to find health related news. Consequently, the dissemination of false information has yielded a significant and adverse impact on society. Also, the economy is vulnerable to the dissemination of fake news.

2. PROPOSED METHODOLOGY

An early ensemble learning strategy called bagging classifier, also known as bootstrap aggregation is primarily used to reduce overfitting (variance) over the training sample. Intuitively, the bagging model is used to reduce overall variance. The subset of data from the training sample is chosen using random sampling with the replacement for each tree, and the class is chosen using the average of all predictions from the different numbers of trees i.e., for regression problem, the bagging model is the mean of multiple estimates. For the classification problem, the majority voting mechanism is taken into account.

LSTM, a popular ensemble method, is utilized to enhance the capabilities of weak models, making them proficient learners. The work introduced involves sequential trees, typically drawn from random samples, where the objective at each stage is to correct the cumulative error from the preceding trees. This approach enables less proficient learners to progressively rectify misclassifications in the data points. LSTM are a type of RNN that can better retain long term dependencies in the data.

The LSTM has an information-controlling cell in the memory known as a "gated" cell which decides what memory information is to keep or discard. The LSTM model identifies which information is valuable enough to keep or reject.

Afterward, dropout is employed to mitigate overfitting, following which they are transmitted produce the final result. The overall process is depicted in Figure 1. For each LSTM neuron output, a ReLU activation function is applied, and subsequently, a dense layer follows this step. The benefit of utilizing this activation function is its ability to deactivate negative neurons, leading them to produce zero output and introducing.

Following the ReLU activation function, there is a 1-D Global max-pooling layer. This layer generates a new output by taking the input's maximum value. By employing this practice, the possibility of overfitting is reduced as the input representation is down-sampled or its dimensionality is reduced before being passed to the next layer. Since the dropout layer is set to 0.1 for the entire model, it aids in mitigating overfitting by removing input values that are below the specified dropout rate. LSTM is an expert at handling sequential data.

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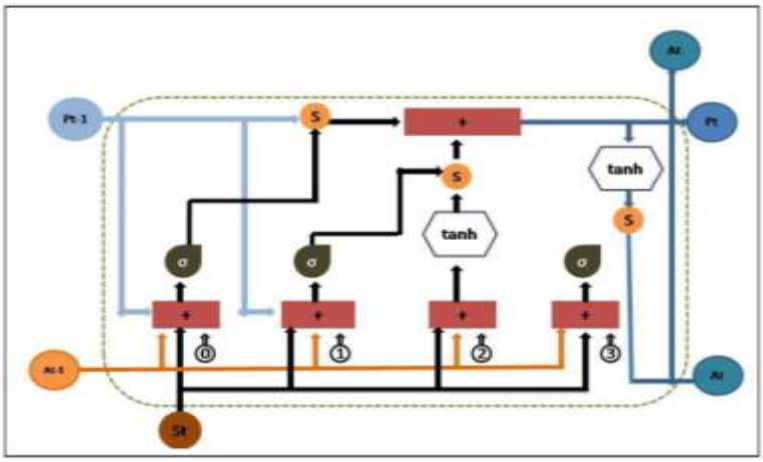

Fig. 1: Working of LSTM

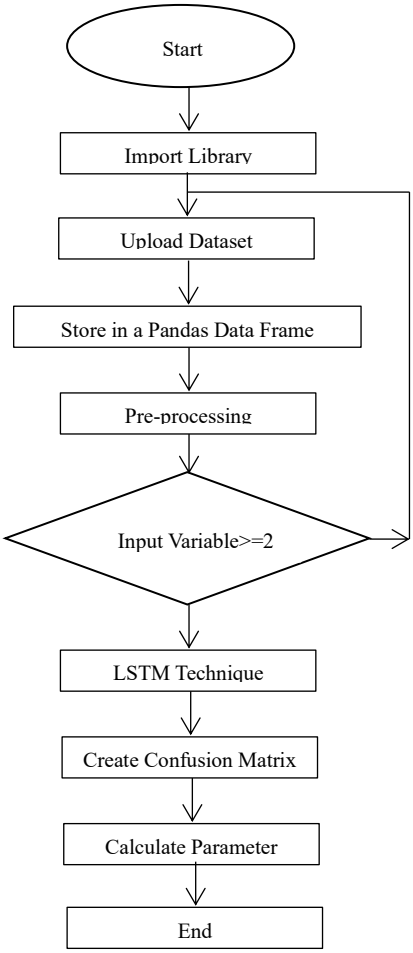

Fig. 2: Flow Chart of Proposed Methodology

A series of structured data is organized in a sequential manner, preserving the information from previous inputs in a chain-like sequence. Depending on the dropout value, should be

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retained and which should be removed. Furthermore, collectively, these gates regulate the process of updating the current memory cm and the hidden state ht. Ultimately, the final layer comprises while binary classification tasks utilize the Sigmoid activation function. During the testing phase on both datasets, the Adam optimizer is employed.

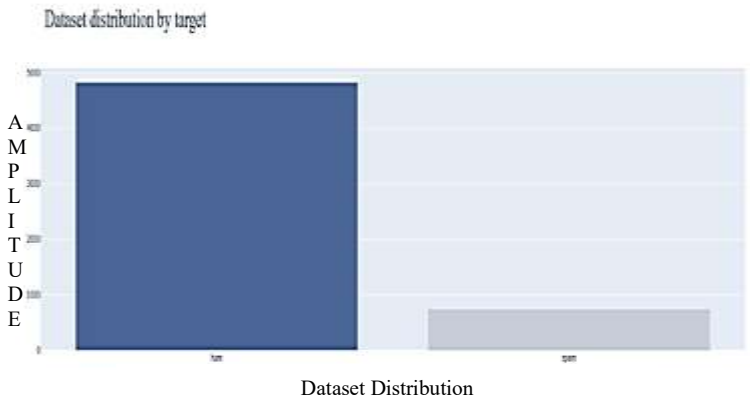
Algorithm for LSTM

All the processing is applied Python software and colab platform and all result are shown in below:

1. Load library and dataset: During a challenge at the MediaEval2015 event, verified multimedia users provided a Twitter Dataset in order to identify fake content on social media.
2. Process data with pandas data frame: All twitter dataset is arrange labeled axes i.e. row and columns.

	target	message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

3. Perform EDA: exploratory data analysis (EDA) with python involves summarizing data to gain insights and analyzing.



Dataset Distribution

Fig. 3: Dataset Distribution

As you can see, the classes are not evenly distributed, so resampling might be an option more on this later but in any case, it doesn't seem necessary.

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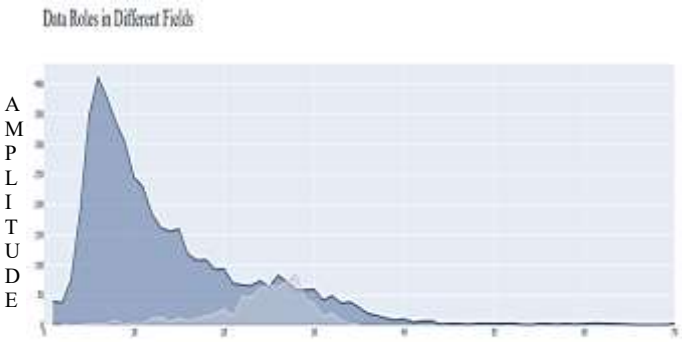

Dataset in different field

Fig. 4: Dataset in different field

4. Make text lowercase, remove text in square sections, remove connections, remove accents, remove words with numbers

	target	message	message_len	message_clean
0	ham	Go until jurong point, crazy.. Available only ...	20	go until jurong point crazy available only in ...
1	ham	Ok lar... Joking wif u oni...	6	ok lar joking wif u oni
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	28	free entry in a wkly comp to win fa cup final...
3	ham	U dun say so early hor... U c already then say...	11	u dun say so early hor u c already then say
4	ham	Nah I don't think he goes to usf, he lives aro...	13	nah i dont think he goes to usf he lives aroun...

5.Apply stopwords: Stopwords are removed in NLP to focus on the more meaningful and informative words in a text.

	target	message	message_len	message_clean
0	ham	Go until jurong point, crazy.. Available only ...	20	go jurong point crazy available bugis n great ...
1	ham	Ok lar... Joking wif u oni...	6	ok lar joking wif oni
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	28	free entry wkly comp win fa cup final tkts m...
3	ham	U dun say so early hor... U c already then say...	11	dun say early hor already say
4	ham	Nah I don't think he goes to usf, he lives aro...	13	nah dont think goes usf lives around though

6.Stemming and Lemmatization: The stemming approach is much faster than lemmatization but it's more crude and can occasionally lead to un-meaningful common base roots.

	target	message	message_len	message_clean
0	ham	Go until jurong point, crazy.. Available only ...	20	go jurong point crazi avail bugi n great world...
1	ham	Ok lar... Joking wif u oni...	6	ok lar joke wif oni
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	28	free entri wkli comp win fa cup final tkts m...
3	ham	U dun say so early hor... U c already then say...	11	dun say earli hor alreadi say
4	ham	Nah I don't think he goes to usf, he lives aro...	13	nah dont think goe usf live around though

7.Tokens visualization: A token is the smallest unit of a Python program. All statements and instructions in a program are processed using tokens.

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3. SIMULATION ESULTS

a. Simulation Parameter

Accuracy is a measure that define the overall progress of the model. It measures the frequency at which the algorithm assigns the correct classification to a data point. So, the accuracy can be measured according to Eq. 1

$$Accurancy = \frac{TN + TP}{TN + TP + FN + FP} \quad (1)$$

For a diabetes classification problem, its measures include Precision-Recall and accuracy. The formula to derive these measures is given in Eq. 2 and Eq. 3.

$$\text{Pr}ecision = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Re}call = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - Score = \frac{2 * (\text{Pr}ecision * \text{Re}call)}{\text{Pr}ecision + \text{Re}call)} \quad (4)$$

Table I represents the method of LSTM. LSTM method shows a accuracy of 96.48%, a precision of 99.45%, a recall of 99.32% and a F1-score of 95.78%. Fig. 5 and 6 shows the graphical representation of the comparison result.

Table I: Simulation Parameter

Algorithm	Accuracy	Precision	Recall	F1 Score
LSTM DL Model	96.48%	99.45%	99.32%	95.78%

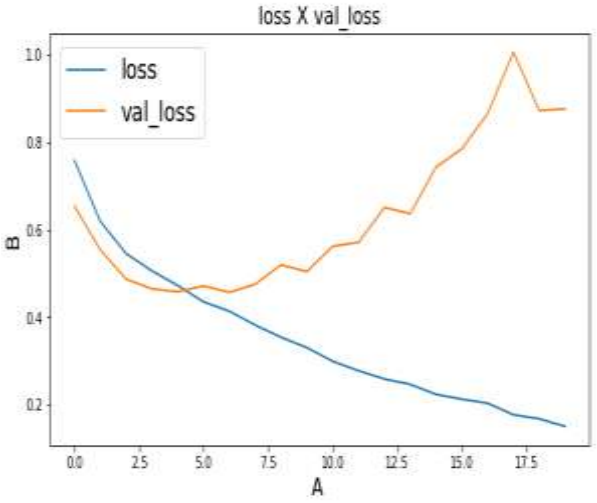

Fig. 5: Loss vs variable loss

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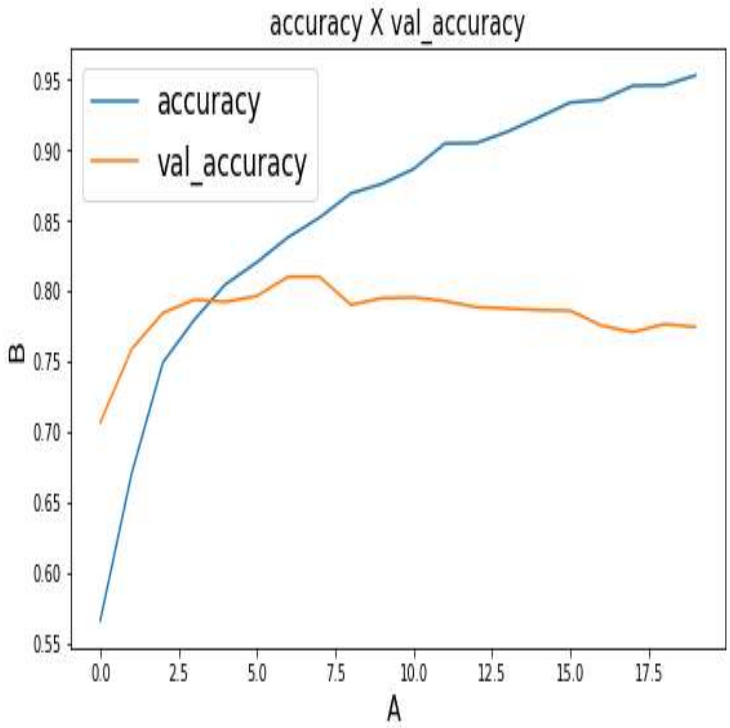

Fig. 6: Accuracy

4. CONCLUSIONS

This study concludes that optimizing deep learning models significantly enhances the accuracy and reliability of fake news detection for Twitter data. Deep learning architectures such as LSTM is capable of capturing the contextual, temporal, and semantic relationships present in short and informal tweet texts. Among these, hybrid models—particularly CNN-BiLSTM—exhibit superior performance by effectively combining spatial feature extraction with sequential dependency learning. The application of optimization techniques such as hyperparameter tuning and embedding selection further improves classification performance, achieving higher accuracy, precision, and recall compared to traditional machine learning approaches.

The findings demonstrate that optimized deep learning frameworks can accurately identify misleading or deceptive content in real time, thereby helping control the spread of misinformation on social media platforms. Moreover, these models can be scaled and adapted for multilingual and multimodal content to extend their real-world applicability. Future research can focus on integrating transformer-based architectures such as BERT or RoBERTa, incorporating user metadata and temporal features, and applying explainable AI (XAI) techniques to enhance transparency and interpretability. Overall, the optimization of deep learning approaches represents a robust and scalable pathway toward building trustworthy, automated fake news detection systems for dynamic environments like Twitter.

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