

A Deep Learning Approach to Fake News Classification Using LSTM

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ABSTRACT

The rapid spread of misinformation on digital platforms poses a major significant challenge today. The ability to detect false information is essential to mitigate the crucial in mitigating its associated harmful consequences. This research presents a deep learning approach for detecting fake news using a Long Short-Term Memory (LSTM) model, which captures linguistic patterns and long-term dependencies in text. Our approach consists of involves optimizing the model through different various experiments based on hyperparameter tuning, using utilizing a pre-processed preprocessed dataset. The evaluation is performed using different metrics such as accuracy, precision, recall, and F1-score. Researchers evaluate the model using various metrics, including accuracy, precision, recall, and F1-score. Experimental results show that the LSTM model achieves a high accuracy of 0.9974, with an embedding dimension of 128 using, 100 LSTM units, a batch size of 64, and a dropout rate of 0.48. It is a substantial improvement over previous studies study. The application of cross-validation further confirms the model's reliability. This research demonstrates that the application of a fine-tuned LSTM network, combined with robust data preprocessing, can provide a powerful tool to combat for combating online misinformation.

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1. INTRODUCTION

People widely use social media platforms for entertainment, but also as a source of information. However, these online social media platforms very often expose consumers to misinformation and fake news. It can influence public opinion, political decisions, and financial markets among others, disrupting social and economic order [1]. Addressing this issue is therefore of paramount importance crucial. However, traditional checking methods are time-consuming and inefficient in addressing the volume of fake news generated daily. Therefore, a more efficient and accurate approach to fake news classification is necessary

Natural Language Processing (NLP) techniques can analyze text patterns and classify news as real or fake. Deep learning models, particularly LSTM networks, have shown promising results in capturing linguistic patterns and dependencies over time. Unlike traditional machine learning models, LSTMs can remember long-term dependencies, making them effective for text-based classification tasks [2]. Studies have demonstrated that hybrid models combining different networks, such as the Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) with LSTMs, achieve high accuracy in fake news detection [3][17][21]–[23][34]–[42]. However, challenges remain, including handling short news statements and improving early detection capabilities [4].

Fake Research on fake news detection research has grown quickly rapidly, as misinformation can spread rapidly quickly on social media [6][11]. Deep Learning (DL) models, especially particularly LSTM networks, show have shown promising results in solving addressing this challenge [7][8]. Several studies highlight different LSTM-based approaches that address specific issues in fake news detection. We group the studies in into hybrid CNN-RNN models, an ensemble of deep classifiers, and bidirectional LSTM and attention models.

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For hybrid CNN–RNN models, Ajao, Bhowmik, and Zargari [2] explored investigated fake news detection on the Twitter/X platform. They combined CNNs and RNNs with an LSTM layer. This design helped enabled the model to capture features from text data while remembering retaining important context. Their hybrid model reached an accuracy of 82%, similar to that of a simple LSTM model.

However, previous studies have noted that adding dropout to LSTM sometimes lowers their achieved accuracy. This finding suggests that dropout might not always help be beneficial in fake news classification, especially if when the model needs require a deeper contextual understanding of context. Another study highlighted how domain-specific datasets, such as COVID-19 news, can benefit from employing hybrid LSTM and CNN layers for improved accuracy [13]. As for Regarding an ensemble of deep classifiers, Ali et al. [3] built constructed an ensemble of different various classifiers, including standard LSTMs, deeper LSTMs, CNNs, and n-gram-based models. They introduced a Self-Adaptive Harmony Search (SAHS) algorithm to combine classifier outputs more effectively. After that, they discovered that short social media texts remained difficult to classify. Their work revealed that fake news often involves brief statements that are tricky to evaluate. The study also highlighted the need for better improved feature extraction methods, like such as n-grams, to capture subtle cues in short messages. In the category of Bidirectional LSTM and Attention, Padalko et al. [4] proposed using bidirectional LSTMs and attention mechanisms for better classification. They demonstrated how attention layers can help the model focus on the most important parts of the text. This approach outperformed earlier deep learning solutions [15]. Other studies incorporating weakly supervised data have shown encouraging performance, especially when the model combines Bi-LSTM layers with specialized classifiers for short social media text [12]. However, they underlined highlighted some limits limitations, such as not having enough a lack of diverse data or facing lower efficiency in real-time systems. Finally, they stressed emphasized the importance of advanced deep learning methods to handle in handling the evolving language use in the creation of fake news creation.

This study proposes an LSTM-DL LSTM-based deep learning approach for classifying fake news. The model is trained and evaluated on a publicly available dataset. Additionally, the results are compared with existing research to highlight the effectiveness of the proposed approach. The main primary objectives of this research are (1) to explore investigate the effectiveness of LSTMs in classifying fake news classification. 2) To evaluate model performance using key classification metrics. 3) To compare the results with previous studies and discuss improvements. The main contribution of this work is that our proposed LSTM approach achieves a substantial improvement in classifying fake and real news.

This study is structured as follows: Section 2 explains the adopted methodology, based on an empirical approach. It describes the dataset, data preparation steps, model selection, and experiment design. Section 3 presents the results and compares them to existing works, and Section 4 presents the conclusion concludes with a discussion of the limitations and future work.

2. METHOD

2.1. Dataset Selection and Preprocessing Steps

The Fake and Real News dataset [16] contains comprises both fake and real honest news articles on covering a diverse range of topics. It consists of around 23,000 entries labeled as “fake” and around 21,000 entries labeled as “real.” Each entry typically includes a title, a brief summary denoted as text, a subject which that represents the topic category, and finally a date which that indicates the publication dates date, as shown in Table 1. The dataset accurately reflects real-world news content, with varied featuring a diverse range of writing styles. It also captures differences between short headlines and longer text. These characteristics help the model learn patterns in language usage, topic bias, and sensational wording. The balanced distribution of classes supports better training outcomes. Both the fake and true accurate labels have been merged and shuffled to ensure randomness in the training process.

Table 1. Dataset with Fake and Real/True Entries

Title	Text (partial)	Subject	Date	Label
Breaking: Cop Finally Gets His Due, Walter Scott's Killer Sentenced To Prison	In America, we have been having a conversation about police brutality against black Americans. Despite the countless black people murdered unjustly by police, there is usually no justice. Sandra Bland, Philando Castile, Keith Lamont Scott, Michael Brown, Freddie Gray, too many to mention here, really. All of those people were senselessly murdered by cops. Cops senselessly murdered all of those people.	News	December 31, 2017	Fake
Virginia officials postpone lottery drawing to decide tied statehouse election	(Reuters). Officials indefinitely postponed a lottery drawing to settle a tied Virginia legislative race that could shift the statehouse balance of power, state election officials said on Tuesday, after the Democratic candidate mounted a legal fight.	Politics-News	December 27, 2017	True

This dataset is suitable for developing and evaluating LSTM-based fake news detection. The Exploratory Data Analysis (EDA) shows reveals a balanced set of datasets comprising both real and fake articles, with minimal missing data. After removing duplicates and irrelevant entries, the dataset offers a rich source for understanding how false information differs from factual reports.

The dataset has a fairly balanced distribution with almost 50% labeled as "fake" and the other 50% as "real." This balance is crucial for training the model effectively by reducing as it reduces the risk of bias toward one class, leading and leads to more accurate and fair predictions. As far as text length and word frequency is concerned, the articles have a similar average length compared to real ones. This indicates that text length alone may not be a reliable feature for distinguishing between fake and real news. Text length alone may not reliably indicate fake or real news. Common words across both real and fake news suggest that these words are more related to the topic than to the authenticity of the news. However, some fake news articles use employ more sensational language, although while many also adopt neutral wording, making it challenging to identify fake news based solely based on word choice.

The text data is cleaned by converting all the text to lowercase, which ensures ensuring consistency. The system removes special characters and punctuation, eliminating noise and irrelevant symbols [43]. The system then splits the text into individual words, known as tokenization. Stop-words like "the", "is", which carry little meaning on their own, are removed. The application of lemmatization reduces words to their root form. For example, "running" and "ran" become "run." Splitting the text into individual words helps the model understand the core meaning of words. After cleaning, the text is converted into numerical sequences, ensuring that all input sequences have the same length. This makes the data compatible with the model. The model uses an embedding layer to represent words as dense vectors, which assists the learning of semantic relationships between words.

2.2. NLP Framework and Model Selection

An LSTM network remembers important context over time [17]. Therefore, it helps is helpful when analyzing articles with varying lengths and styles. Traditional models often struggle to retain this long-range information. The model architecture contains an Embedding Layer to convert words to numerical vectors, an LSTM Layer to capture sequential dependencies in text, a Dropout Layer to prevent overfitting, and a Dense Layer for final classification.

The architecture of an LSTM is based relies on a memory unit. This unit, also known as an LSTM unit, is made up consists of four feedforward neural networks, each with an input and output layer [44]. The input neurons are connected to all output neurons. The forget gate (F_t), the input gate (I_t), and the output gate (O_t) from the feedforward network handle the selection of information. The candidate memory (C_t), which is the fourth gate memory, creates new candidate information to be inserted into the memory is where the network creates new candidate information to insert into the memory. The corresponding functions are listed below, with input state X_t , hidden state H_t , at and time stamp t . W represents the weights, and the bias term is b . Using a combination of I_t and F_t with the element-wise operator, the memory cell is given by Eq. 5. For the hidden state to remain between -1 and 1, the tanh function is applied to the memory cell internal state, followed by the element-wise product with the output gate [17][38][39][42].

$$I_t = \sigma(X_t W_{xi} + H_{t-1} W_{hi} + b_i) \quad (1)$$

$$F_t = \sigma(X_t W_{xf} + H_{t-1} W_{hf} + b_f) \quad (2)$$

$$O_t = \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o) \quad (3)$$

$$\tilde{C}_t = \tanh(X_t W_{xc} + H_{t-1} W_{hc} + b_c) \quad (4)$$

$$C_t = F_t \odot C_{t-1} + I_t \odot \tilde{C}_t \quad (5)$$

$$H_t = O_t \odot \tanh(C_t) \quad (6)$$

2.3. Experiment Design

The dataset was randomly split into training and testing subsets, respectively, using the `train_test_split` function from Scikit-learn [19]. 80% of the original dataset was considered for the training subset, and 20% for the testing subset. The experiment uses 80% of the original dataset for training and 20% for testing. The LSTM model was built using the Keras library [20] Library on top of the TensorFlow machine learning

platform [21]. The model was trained using the Adam optimizer and the binary cross-entropy loss function for binary classification during training. The training has been experimented with different numbers of epochs and batch sizes. The performance is evaluated. The study evaluates performance using the following metrics: Accuracy, Precision, Recall, and F1-score. We performed further evaluation with cross-validation, using stratified K-Fold cross-validation with 5 five splits ($K = 5$) to ensure model reliability and generalization [46]. The model is trained and validated on each fold. The study calculates the average accuracy across all folds to provide a robust estimate of performance. The computer used for the training has the following configurations: an Apple M3 Pro chip with an 11-core CPU, a 14-core GPU, and a 16-core Neural Engine. The Main Memory available was 18 GB.

3. RESULTS AND DISCUSSION

3.1. Classification Results

The results show that the LSTM model is correctly classifying fake and real news. Before hyperparameter tuning, the model achieved an accuracy of 0.9903, a precision of 0.99, a recall of 0.99, and an F1-score of 0.99. After hyperparameter tuning, the model achieved a slight increase in accuracy of 0.9974 with the hyperparameters configurations as shown in Table 2. The Accuracy refers to the predictions made by the model model's predictions compared to the real actual values. The embedding dimension (dim) defines to the size of the continuous vector space into which discrete input elements, the words, are mapped. The LSTM unit acts functions as a specialized memory cell, capable of remembering retaining information over long extended sequences and selectively forgetting discarding irrelevant data through internal gates that control the flow of information. The dropout rate is a regularization technique where a random selection of neuron connections is temporarily ignored during training, forcing the network to learn more robust and independent features, thereby reducing overfitting. Recurrent dropout applies dropout masks to the recurrent connections (i.e., the hidden state) at each time step, further controlling overfitting. Batch size refers to the number of samples during training. The learning rate defines determines the step size at by which the parameters of the model model's parameters are updated during training.

Table 2. Performance Comparison of Different Trials.

Trial	Accuracy	Embedding Dim	LSTM Units	Dropout Rate	Recurrent Dropout	Batch Size	Learning Rate
0	0.9909	64	100	0.40	0.21	64	0.0015
1	0.9793	64	150	0.26	0.20	128	0.0001
2	0.9944	256	50	0.32	0.24	128	0.0013
3	0.9952	64	100	0.29	0.23	64	0.0011
4	0.9974	128	100	0.48	0.39	64	0.0047

The high accuracy of 0.99 indicates that the model properly correctly identified almost all news articles. Precision and recall scores also being of 0.99 also show indicate that the model not only avoids false positives but also captured effectively captures true trustworthy fake news effectively. The balanced F1-score of 0.99 shows indicates that the model works performs well on different across various types of news articles. It can help media outlets and social media platforms reduce the spread of false information. To further refine its performance, we applied conducted a systematic hyperparameter search across various parameters, including embedding dimensions, number of LSTM units, dropout rates, batch sizes, and learning rates. After running multiple trials, the best hyperparameters emerged in Trial 4, leading to resulting in a slight increase in accuracy of to 0.9974 (99.74%) on the test set, along with an F1-score similarly near close to 0.997. The model achieved the training within 11 minutes and 45 seconds. These results highlight that relatively small minor adjustments, such as optimizing the dropout rate, or learning rate can yield significant gains in model performance.

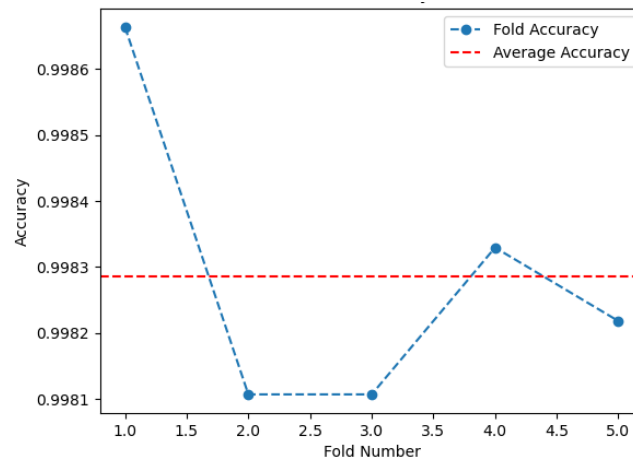


Figure 1. Accuracy achieved across different folds (y-axis) based on the number of Cross-Validation Folds (x-axis). The red dotted line also shows the Average Training Accuracy (y-axis).

To confirm consistency, we performed a stratified K-fold cross-validation with five folds on the training set. The results in Figure 1 shows show that the model maintained an average cross-validation accuracy exceeding 0.998, indicating strong generalizability to unseen data. The high precision and recall signify few misclassifications of either class. The approach also demonstrates training stability, as shown in Figure 2. The training loss converges, showing reduced signs of overfitting on the validation folds. However, further experiments are required to ensure that the model is not overfitting.

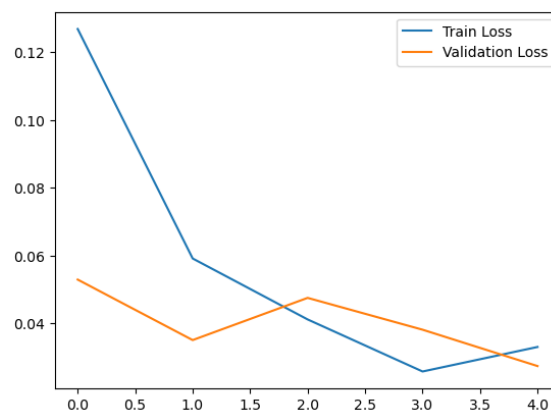


Figure 2. Training and Validation loss (y-axis) over the number of folds (x-axis)

3.1. Comparative Analysis

The accuracy from the previous studies considered in this research ranges between 90% and 98% [2]-[8]. Our model reached an accuracy of 99.74% through systematic tuning. This improvement indicates that our optimization pipeline can provide a higher prediction from the chosen dataset. While some previous studies have encountered imbalanced precision and recall, our LSTM model held achieved both metrics above 0.99, thereby reducing the classification of real news as fake or false positives, and fake news as real or false negatives. Unlike methods relying that rely on manual hyperparameter manipulation, we applied employed an automatic tuning approach. This method demonstrates its ability to identify the best values for dropout rate and learning ratio, making our approach more flexible to different and large datasets.

Also Additionally, several previous solutions perform evaluation evaluate performance using only training and test sets. We further performed a stratified k-fold cross-validation, ensuring the that F1 score is consistent remained consistently above 0.99. This strategy provides stronger more substantial evidence of the model's resilience to data fluctuations. As opposed In contrast to studies that work with biased datasets or require a rebalancing technique, our data is balanced. Compared to resource-intensive methods, our lightweight LSTM design provides an effective architecture.

Overall, our experiments indicate suggest that a systematic hyperparameter search, combined with a well-structured LSTM architecture, can accurately effectively detect fake news articles. This effective performance is consistent with the recent literature, according to which suggests that deeper or hybrid models systematically

outperform basic classifiers. The high F1 scores suggest that data preprocessing steps, particularly tokenization and text cleansing, play a critical role in mitigating noise and improving classification boundaries. Moreover, the resilience of our model to overfitting underscores the importance of dropout and stratified cross-validation. In many other studies, performance gains often came at the expense of increased complexity or the risk of overfitting.

On the other hand, our method strikes a balance, preserving computational feasibility while obtaining achieving results close comparable to those of the best result best-performing method. However, the current approach may face domain changes, for instance, the emergence of social media jargon or multilingual datasets, if the underlying linguistic representations differ significantly from our training corpus. Therefore, continuous retraining or fine-tuning in new areas can be essential to maintain comparable performance over time.

4. CONCLUSION

The LSTM approach presented in this study shows demonstrates a strong ability to identify fake news on different across various topics. This capability is reinforced by a strategy of careful tuning of hyperparameters. A strategy of careful tuning of hyperparameters reinforces this capability. By comparing with existing studies, the approach reached good reasonable levels of performance. This indicates suggests that using utilizing a well-balanced dataset, a clear architecture, and advanced optimization techniques can significantly improves enhance detection accuracy. While the model demonstrates effective performance, researchers should consider several limitations. First, the model's performance intrinsically depends on the quality and diversity of the training dataset. If the dataset does not cover encompass a wide broad range of news topics and styles, the model might may not perform well in real-world scenarios. Second, while the model achieved high accuracy, precision, and recall, it may still struggle with highly ambiguous or contextually complex articles. These cases could lead to misclassifications, especially mainly if the news contains subtle cues that are hard to detect through standard text processing methods. Another limitation is that the model only considers the textual content of news articles. It does not incorporate other important factors, such as the credibility of the news source, the historical behavior of the source, or metadata like the date and authorship. Including such information could improve the model's robustness.

Future works can focus on using more advanced architectures such as Transformer-based models like BERT or GPT [26][48]-[50]. Researchers recognize these more recent approaches for their ability to handle context more effectively. Expanding the dataset to include multilingual and cross-domain news articles can help generalize the model to different contexts. Additionally, incorporating metadata and source credibility analysis into the model could enhance its ability to detect fake news more accurately. Exploring ensemble methods by combining the LSTM with other models might also improve performance. Exploring ensemble methods by combining the LSTM with other models also improves performance. Effective fake news detection offers significant benefits, but it also requires careful consideration of potential ethical implications, particularly concerning journalistic integrity and freedom of speech. One main major problem is the occurrence of false positives, which can harm journalism by unfairly suppressing or discrediting true accurate reports, bringing down thereby eroding both journalistic integrity and public trust. Moreover, if detection systems are too aggressive, they can unintentionally restrict freedom of speech. Therefore, future efforts in this field need to should focus not just only on making improving detection more accuracy but also on creating developing systems that are transparent, auditable, and involve incorporate human oversight to reduce minimize false positives and protect safeguard core democratic values.

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