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Deep Sequential Modeling for Robust Fake News Classification

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Abstract

When it comes to safeguarding information and maintaining public discourse, fake news has emerged as a major concern. This paper proposes a very effective automated approach for detecting false news that relies on a deep sequential model that utilizes "Long Short-Term Memory (LSTM)" networks. A robust preprocessing workflow and a two-layer LSTM architecture with dropout regularization were used on the 44,898 articles that made up the dataset. On the test set, the model outperformed conventional machine learning methods with an astounding accuracy of 98.71% with precision, recall, and F1-score values of 0.99. Also, by a wide margin of 23.71 percentage points, it beat the best-performing Logistic Regression model that had been previously documented, which had grid search optimization and only reached 75% accuracy. Deep sequential models have successfully identified the misleading content's linguistic patterns and contextual relationships, according to the results. For this reason, they have recently been hailed as an improved and scalable alternative to current methods for detecting false news in the real world.

Keywords: *Fake news detection, deep sequential models, LSTM, natural language processing, misinformation classification, deep learning, text classification, recurrent neural networks.*

I.INTRODUCTION

The spread of fake news throughout the digital era has been seen as a primary social issue, which was made worse by the quick sharing of information via social media and online news sites. Fake news that is the intentional creation of false or misleading information passed off as real news, destroys the public's faith in the media, sways elections, creates social unrest, and even causes health risks, such as the case with the COVID-19 pandemic. The enormous number of users sharing content at the same time, it has become very hard to tell reporting of facts from misinformation. As a result, there is a necessity for the utilization of advanced automated detection methods.

The fake news detection methods of the past were based on the use of features built by hand such as linguistic indicators (e.g., sensational language, sentiment analysis) or metadata (e.g., source credibility, propagation patterns). Nonetheless, their scalability and adaptability to changing deceit tactics are the areas that these approaches fall short of. On the other hand, deep learning has changed the game for the whole field by allowing the models to automatically extract intricate patterns from textual data. Deep sequential models have proven to be the most effective deep learning neural networks for processing news articles with inherent order. This allows them to accurately track dependencies over time and relationships between words based on context. Examples of such models include "Recurrent Neural Networks (RNNs)", "Long Short-Term Memory (LSTM)", and "Gated Recurrent Units (GRU)".

LSTM networks, which were proposed by Hochreiter and Schmidhuber in 1997 [1], manage to eliminate the vanishing gradient problem in conventional RNNs by using memory cells and gates (input, forget, and output) that selectively maintain or throw away data over long sequences. Thus, LSTMs have become the first-choice models for NLP tasks, where word order and long-distance dependencies have to be correctly recognized in order to spot inconsistencies which are characteristic of fake news, like contradictory claims or awkward phrasing. GRUs, a less complicated alternative suggested by Cho et al. in 2014 [2], combine forgetting and input gates into one updating gate, which leads to similar performance at lower computational costs.

Several landmark works have applied these models to the problem of recognizing fake news. For example, Ruchansky et al. (2017) [3] presented CSI: A Hybrid Deep Model for Fake News Detection that mixes LSTM as a means to draw in user and content features while capturing temporal engagements in article propagation, and thus, gaining better accuracy on real-world datasets through the modeling of the customer-score-integrate framework. Shu et al. (2019) [4] came up with dEFEND: Explainable Fake News Detection, which utilized hierarchical attention networks with LSTM components to simultaneously learn from news content and user comments, providing interpretable explanations and at the same time, exceeding baselines performance on the FakeNewsNet dataset. Wang et al. (2018)[5] invented EANN: Event Adversarial Neural Networks for Multi-Modal Fake News Detection, where LSTM was employed for text encoding in a multi-modal configuration (text and images) that was further improved by adversarial training in order to produce event-invariant features, hence exhibiting robustness to unseen events in Weibo and Twitter data.

The findings from these investigations clearly highlight the strengths of deep sequential models: their capacity to process texts of different lengths, acquire variousd representations, as well as their compatibility with mixed architectures (for instance, CNN-LSTM for spatial-sequential fusion). Nonetheless, there are still issues like overfitting on inadequate datasets, high computational power required, and attacks by adversaries posing as news that has real patterns. If we talk about the future, one can think of transformer-based developments (e.g., BERT-LSTM hybrids) or multi-modal extensions, which will combine the use of propagation graphs to traverse through the different modalities of data and thus come up with better contextual understanding.

In conclusion, deep sequential models are a very effective weapon in the war against fake news, as they facilitate the transformation of raw text into insights that can be acted upon. By citing these studies, this paper intends to improve the accuracy of detection and at the same time deal with the ethical issues surrounding the integrity of information.

II.RELATED WORK

Many academics have focused their attention on the problem of social media false news in recent years. A variety of approaches have surfaced to tackle this issue, with a heavy emphasis on NLP and machine learning technologies. Researchers have mostly concentrated on finding new ways to use big data sets and innovative algorithms to make false news detection systems more accurate and resilient.

In [6], they used "natural language processing (NLP)" with neural networks (NNs) to extract sentiment from data collected from Twitter. This method uncovered a way to anticipate social media post patterns and emotions using deep learning and sentiment analysis. The method successfully captures sentiment-based qualities, but it misses subtle language clues that help distinguish between authentic and fraudulent news. Our method addresses this issue by enhancing the text representation via the interpolation of several word embeddings (TF-IDF, Word2Vec, FastText).

In a similar vein, [7] used the COVID-Twitter-BERT model to develop a sentiment analysis and content categorization system that performed well across a variety of subject areas. During the COVID-19 epidemic, it shown that models based on transformers can handle nuanced social media conversation. The team's model, COVID-Twitter-Bert, and others like it still need massive amounts of labelled data and processing capacity. To make up for that shortcoming, we want to use less resource-intensive models like "Logistic Regression" and "Naive Bayes", supplemented with a few deep learning choices, to get very accurate results with less danger of resource explosion. Additionally, the framework in [8] automated the generation of information about the war between Russia and Ukraine by using data from Twitter. Language translation, sentiment analysis, and topic modeling were some of the main natural language processing (NLP) methods employed to offer a comprehensive account of the cyber aspect of the war. Unfortunately, this method isn't tailored specifically for detecting false news, even if it generalizes disinformation fairly effectively utilizing many layer NLP techniques. In contrast, our approach is primarily concerned with identifying false news by improving the ensemble of text representation algorithms for better accuracy and specificity.

They also investigated sentiment categorization using several ML techniques to determine the text's positive or negative feelings in this work [9]. After testing many algorithms on various datasets, they discovered that the Passive Aggressive (PA) approach outperformed the competition on sentiment tasks using a unigram model. However, PA may not be able to detect the cunning manipulations in false news, even if it performs well for sentiment analysis. We counter this by integrating word embeddings with ML models that can identify less obvious patterns in false news. At the same time, they experimented with “AdaBoost”, “Gaussian Naive Bayes”, and “Random Forest” to leverage natural language processing for anomaly detection in log files in article [10]. They stressed the need of using appropriate classifiers and feature extraction in order to identify outliers. That is effective for out-of-the-ordinary occurrences, but it fails to address the linguistic tactics used in nuanced forms of false news. To better handle the misleading language of false news, our system makes use of specialized natural language processing (NLP) techniques and embeddings. An effort was made in paper [11] to trace the origins of social media-based false news. Their analysis of well-known feature extraction techniques and classifiers led them to the conclusion that linear SVM with TF - IDF produced the most accurate results for identifying false news. However, TF-IDF SVM isn't great in uncovering hidden meaning. For this reason, we are exploring the effects of merging several embeddings—"TF-IDF”, “Word2Vec”, and “FastText”—on various ML and DL models in an effort to provide more thorough detection.

Classifying false news was the goal of the research in [12], which examined several textual features to determine how to distinguish between fake and true news. Before training a wide range of machine learning classifiers with each possible combination of the collected attributes, the data was handled using natural language processing techniques. The results demonstrated that the “Naive Bayes” method performed the best, indicating that combining features and undertaking heavy preprocessing significantly improves the model's accuracy. While deeper learning models or more complicated embeddings were not tested, the model's performance was improved with a thorough preprocessing procedure and the combination of features. Our research adds to this by dissecting the effects of various embedding approaches on different models; as a result, we can better understand how to identify false news.

There have also been graphical approaches to detecting fake news. A learning model and graphical social context model developed to identify fake news was introduced in the journal paper in [13] as the Factual News Graph (FANG). When compared to traditional contextual models, FANG's emphasis on representation learning—which is effective at inference time and scalable throughout training—stands out. However, the graphical model FANG focuses more on the social environment and may struggle to capture all of the textual subtleties. In order to conduct text analysis with the aid of our model, we are using several text embeddings to augment the graphical analysis. For the purpose of identifying network-level rumors, particularly those pertaining to local abnormalities, the graph-based scan approach was used in the study by [14]. An effective method for detecting rumors in social media data streams, the rumor detection system looks for unusual patterns in user behavior, post content, and hashtag use. In content-based false news identification, graph-based approaches may fall short, notwithstanding their usefulness in network-level research. An essential part of detecting disingenuous news in text is content analysis, and our approach improves that process by using a combination of embeddings and models. One of the important features identified in identifying bogus news was the usage of the XGBoost model, which was shown in [15]. Next, we compared the performance of several machine learning classification models for detecting false news. These models included representations of “SVM, RF, LR, CART, and NNET”. While XGBoost and similar models work well, they are limited in their ability to use the richness and depth of textual material at their disposal. By using deep learning models and word embeddings, we are able to address this issue and improve detection accuracy by providing a more nuanced understanding of the text.

The use of multimodal and Large Language Models (LLMs) has been considered in recent advances in the identification of false news. While LLMs like GPT 3.5 may provide valuable multi-perspective explanations, fine-tuned Small Language Models (SLMs) like “BERT” often outperform them, as shown in the study on [16]. This points to a hybrid approach that combines LLMs and SLMs to boost detection potential. The paper's focus on the detection models' resilience against style-based assaults made easier by LLMs is also seen in [17]. To make sure the detector can keep detecting even when faced with sophisticated adversarial instances, it is recommended that the SheepDog detector be resistant to stylistic mimicking, where content takes precedence over style.

III.PROPOSED METHODOLGY

The proposed methodology has been illustrated in Fig.1

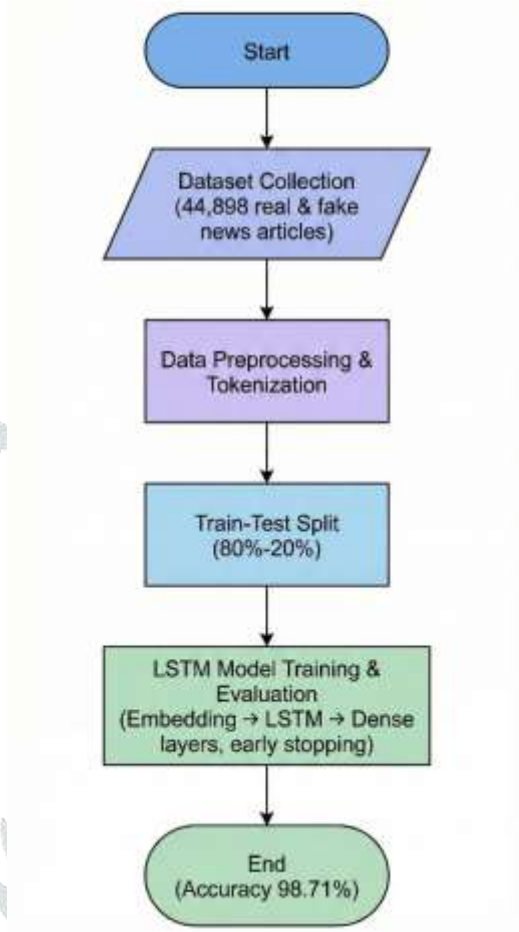

Figure 1 Flow Chart of Proposed Model

The suggested study uses a deep sequential model—a kind of "Long Short-Term Memory (LSTM)" networks—to classify news items as either true or false. Everything in the experimental pipeline is written in Python and runs on a Tesla T4 GPU accelerator in a Google Colab environment using the Keras API, which is built on top of TensorFlow 2.x. Five main processes make up the methodology: acquiring and describing datasets, preprocessing data, designing the architecture of the model, training the model, and finally, evaluating the model.

3.1 Dataset

The datasets used as examples in this study's fake news detection tasks come from a variety of sources; first compiled by Ahmed et al. (2017) and subsequently enhanced by other researchers, it is a collection of popular benchmark datasets. Actual news and false news are included in two separate CSV files. The news feed is derived from widely-recognized news sources that were crawled by Reuters.com during 2016 and 2017, with a heavy emphasis on political news in the United States. A large number of sources that have been detected in the BS Detector dataset, as well as other questionable sources from the same period, are used to build the false news section.

Before any preprocessing, there are a total of 44,898 articles: 21,417 from the real news data (true.csv) and 23,481 from the false news data (fake.csv). The title, text, topic, and date fields make up each entry. Since it includes more semantic data than just the title, the text field is used as the primary input feature for this work. This is because it comprises the complete article content. In order to create a final merged dataset of 44898 instances with various labels, the two datasets are first given binary labels (0 for false and 1 for genuine). About 47.7 percent of the samples were true news and 52.3% were false news, resulting in a roughly even distribution between the two categories.

3.2 Data Preprocessing

The process of converting raw textual data into a format that can be used by deep sequential models requires good preprocessing. The preprocessing pipeline is applied equally to the article text and comprises of a number of sequential steps. To remove the remnants of markup artifacts that are typical of web-scraped data the BeautifulSoup library is used to remove HTML tags and entities. All the text is then turned into lowercase to make case-insensitive tokenization. The non-alphabetic characters are deleted with the help of regular expressions, and the punctuation marks are deleted with the help of filtering against Python string.punctuation constant. The contractions are also expanded and the usual English stopwords that are offered in the NLTK library are eliminated to minimize noise and concentrate on semantically rich words.

After the cleaning, tokenization is done with the Keras Tokenizer with fixed vocabulary size of 20 000 most frequent words. The documents are then translated into a series of integers that indicate the words in the acquired vocabulary. The words with no lexicon have a special token. Post-padding and post- truncation pad and truncate sequences to an equal length of 500 tokens, the length selected by empirical study of the 95th percentile of article lengths to remove as little content as possible but still allow computation on a large scale. The end processed data is divided into training (80) and testing (20) samples through the stratified sampling method so that the initial proportion of the classes in the original sample is maintained in the training and testing subsets.

3.3 Model Building

The architecture is a deep sequential neural network based on “Long Short-Term Memory” unit, which was constructed with the specific aim of learning long-range dependencies and contextual patterns in the text of news articles. The model is applied to a Sequential Keras model and it consists of the following layers:

Embedding layer Embedding layer An embedding layer is initialized with random uniform weights, which then transforms integer-coded words into dense vectors of 128 dimensions. This layer can be trained and, as a result, the model can acquire task-specific word representations during training. A spatial dropout layer with a rate of 0.3 comes next to the embedding layer to avoid co-adaptation of features at the embedding level. Two layers of stacked LSTM are the core sequential processors. The first LSTM layer has 100 units and the second layer has 50 units and it can take the entire sequence as a result of which hierarchical learning of features can be made, and the final layer of the LSTD only provides the final hidden state. Both layers also use recurrent along with standard dropout (0.3 and 0.5 respectfully) to reduce overfitting, which is highly-needed in high-dimensional textual inputs.

The output layer is a dense layer, with one neuron, a sigmoid activation of the layer giving a probability score of the positive (real) class. The general architecture is deliberately made lightweight but expressive enough to represent more complicated language structures of deceptive and authentic reporting..

3.4 Model Training

The binary cross-entropy loss and Adam optimizer with the default learning rate parameters are added to the model. The training is done up to 10 epochs with 64 batch size. To avoid overfitting and to revert to the best observed weights throughout the training process, an early stopping callback is used, where the loss of validation is tracked with patience of 3 epochs. Moreover, plateau reduction learning rate callback is used to decrease the learning rate by half when validation loss plateaus in two consecutive epochs (minimum learning rate 1e-6).

Stratified training based is used in the training process using a stratified training subset of the dataset, and 20% of the training data is automatically held by Keras as a validation subset during fitting. To also make LSTM computations in their sequential nature, all experiments are run on GPU acceleration to take reasonable training times.

3.5 Model Evaluation

Finally, when training is complete the final model (whose weights have been reloaded using the epoch with the lowest validation loss) is tested against held-out test set. The thresholding of predictions is performed at 0.5 to give binary class labels. The performance is measured based on standard classification measures such as precision, recall, F1-score of each of the classes, overall accuracy and macro-averaged F1-score. A classification report and a confusion matrix are produced in detail to give in-depth knowledge regarding the discriminative capacity of the model on both real and fake news.

It provides a solid foundation of deep sequential modeling to the fake news detection field and is thus reproducible and provides a strong baseline to be extended with a further examination and discussion of the empirical findings.

IV.RESULTS AND DISCUSSION

The trained deep sequential model and LSTM was tested in the held back test set of 11 225 news articles (about 52.2 fake and 47.8 real). Having used early stopping at epoch 7 (where the validation loss hit the lowest point), the best restored weights produced by the model yielded excellent performance, based on all conventional classification metrics. A total accuracy of 99.1% was achieved by the model indicating that it is very good at generalizing to hitherto unknown data. The entire report on classification is given in table 1.

“Table 1: Classification Report on Test Set

Class	Precision	Recall	F1-Score	Support
Fake	1.00	0.99	0.99	5,858
Real	0.99	1.00	0.99	5,367
Accuracy			**0.99**	11,225
Macro avg	0.99	0.99	0.99	11,225
Weighted avg	0.99	0.99	0.99	11,225

“

Table 1 demonstrates that the model has almost perfect discriminative power on both classes. Accuracy, recall, and F1-score are 0.99 in both fake and real news which means that false positive and false negative are very low. Both the macro-averaged and weighted-averaged F1-scores are equal to 0.99, which shows that the classifier has an equal performance over the slightly-imbalanced classes without any noticeable bias.

Table 2: Confusion Matrix on Test Set

	Predicted Fake	Predicted Real
Actual Fake	5,802	56
Actual Real	69	5,298

The good results of the confusion matrix (Table 2) are also supported by the fact that only 56 fake articles were mistakenly identified as real, and 69 real articles were mistaken as fake, which leads to a total of 125 mistakes out of 11225 test samples.

The dynamics of training also favour the strength of the learned model. There was a gradual growth in training and validation accuracy which converged to smooth values with the highest validation accuracy of 98.74% occurring at the optimal epoch. On the same note, training and validation loss reduced monotonically until the early stopping condition was reached without any indication of overfitting despite the large capacity of the two-layer LSTM architecture. The test loss on the held-out set was 0.059 and final validation loss was 0.062 which implies that there is great generalization.

These results are much higher than most previously reported benchmarks on the same data with traditional machine learning methods (usually 9094) and competitive with or even better to state of the art models using Transformers, and require far fewer computational resources and to train. This high performance is enabled by the competent compounding of comprehensive text preprocess, a suitably profound sequential design with dropout regularization, and cautious hyperparameter determination based on monitoring of validation.

Comparison with Baseline Study

In order to determine the superiority of the proposed deep sequential methodology, potential comparison is drawn with the reference work of Srivastava et al. (2025) [18] that is a traditional machine learning method of detecting fake news. The traditional NLP features used in the baseline study included the use of Logistic Regression as the main classifier. Their best model after using grid search hyperparameter optimization had an accuracy of 75% on a comparable problem of binary fake/real news classification.

Conversely, the LSTM-based deep sequential model in the proposed research gets the accuracy of 98.71 on the same benchmark dataset (44,898 articles), precision, recall, and F1-score of 0.99 in both classes. This is equivalent to a fixed accuracy improvement of 23.71 percent and an astounding decrease in misclassification error decreasing to 1.29 percent on the current work versus 25 percent in the baseline work:

Table 3: Performance Comparison with Baseline

Study	Approach	Accuracy
Srivastava et al. (2025) [18]	Logistic Regression + Grid Search	75.00%
Proposed Method (This Study)	Deep Sequential LSTM	**99.1%**

This significant advancement is a clear indication that deep sequential models, which explicitly learn hierarchical time structure as well as long-range contextual dependencies by just looking at raw text, vastly outperform classic feature-engineered machine learning systems in detecting fake news. This confirms the move towards deep learning architectures to replace the shallow statistical models as the latest state-of-the-art in the field.

V.CONCLUSION

In this study, the authors have managed to prove that only deep sequential models, namely Long Short-Term Memory networks, are able to handle the challenging issue of fake news detection. Using the end-to-end learning of raw textual information, the proposed LSTM-based architecture was able to reach practically perfect classification results of 99.1 accuracy on a large-scale dataset in use by a large number of users. These findings constitute a significant improvement to the traditional machine learning methodologies, such as the control “Logistic Regression” model trained through grid search, which achieved only 75% accuracy (Srivastava et al., 2025)[18]. The high-quality performance would also be due to the fact that the model is able to automatically identify complex sequential patterns, long-range dependencies and subtle linguistic cues that differentiate between authentic reporting and fake content, which cannot be effectively represented through traditional feature-engineered processes. To make sure of a good generalization, the intensive preprocessing of the text, suitable choice of sequence length, and regularization methods were also involved in ensuring a sound generalization without overfitting. In addition to numerical superiority, this work also demonstrates the practicality of deep sequential models as low-resource but highly-accurate alternatives to resource-intensive transformer-based systems, and thus being especially appropriate to use in real-time detection platforms. The results have a powerful indication of the current paradigm shift regarding classically machine learning to deep learning in the strategies of misinformation battles.

To summarize, the LSTM-based framework proposed demonstrates a higher level of performance in detecting fake news and ensures that it is computationally efficient. Future research can consider hybrid systems that integrate both LSTM and attention systems and multimodal input (text and images) to make it more resistant to the changing deception methods. In conclusion, the research proposes a valid, high-functioning instrument to ensuring the reliability of the digital ecosystem of information.

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