Optimized Deep Learning Techniques for the Detection and Identification of Fake News in Digital Media

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Abstract: The exponential expansion of social media has greatly accelerated the dissemination of disinformation, endangering public safety and undermining faith in news outlets and government agencies. The authors of this work suggest using deep learning to identify false news posts on Twitter. The methodology involves pre-processing raw data through stop word removal, stemming using Porter's Algorithm, and tokenization with the N-gram model. The detection model employs Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and AdaBoost algorithms. Results indicate that LSTM outperforms CNN and AdaBoost, achieving an accuracy of 99.24%, specificity of 99.2%, and sensitivity of 98.67% in fake news detection.

1 INTRODUCTION

Fake news spreads misinformation, misleading people and impacting society, businesses, and individuals. It harms reputations, leaving lasting damage even after corrections. By reinforcing biases, it deepens divisions, fosters distrust, and fuels conflicts. Politically, misinformation manipulates public opinion to serve specific agendas. Additionally, the rise of fake news erodes trust in journalism, weakening democracy and accountability. Greater emphasis has been placed on identifying and removing disingenuous material due to the spread of false information on social media platforms like Twitter and Facebook. Misleading information spreads rapidly, often diverting attention from critical issues, with many users trusting social media over traditional sources despite scepticism about reliability (t'Serstevens,et al, 2022). Confirmation bias further reinforces misinformation, making deception harder to recognize. False news appears in various formats, including articles, images, and videos, contributing to widespread confusion. Rumours can disrupt social harmony and cause significant societal impact. Additionally, fake websites mimic credible sources to manipulate public perception, influencing opinions and advancing political or financial agendas (Igwebuike, E. E., & Chimuanya, L. 2021). A complicated process for false information detection is depicted in Figure 1.

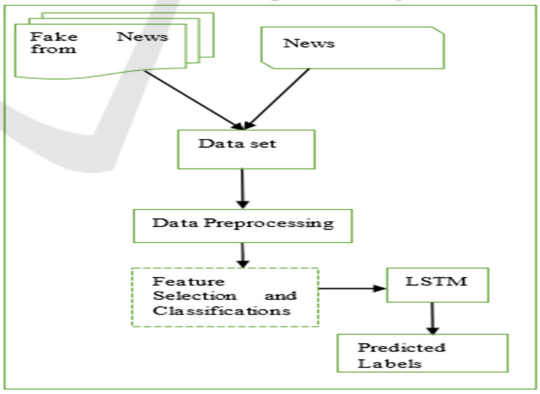

Figure 1: Block diagram of fake news detection.

The original data is preprocessed by gathering tweets from Twitter using aggregation. The dataset is passed through a preprocessing phase, which includes the removal of stop words, stemming, and tokenization. Features for the classification model are identified to make it more efficient. Machine learning and deep learning methods are then used to classify tokenized data. As a result, techniques from deep

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learning and machine learning are used to identify rumours and false news.

The advent of online and social media has enabled the incorporation of false information with real or verified information. This situation can be utilized to influence people's opinions, thus impacting their perceptions, thoughts, and behavior. As a result, disseminating links, messages, photos, videos, and audio files over several social media platforms has become very simple for those who propagate fake news. People who spread these fakes usually have a political or social agenda. Therefore, the development of an efficient system to detect misinformation is of utmost importance (Kaliyar, R. K., et al, 2021). An approach to detecting false news stories using deep learning is presented in this research. There are input datasets that make up methodology. Information culled from the microblogging service Twitter is the source of this dataset. Input data that is in its raw form undergoes data preparation initially. Remove Stop Words, Stemming, and Tokenization are the main components of data preparation. Use the NTLK library to remove stop words. Stemming is done using Porters Algorithm. Tokenization is completed by N-gram model. Model is developed using LSTM, CNN and AdaBoost algorithms. Results have shown that LSTM's Compared to CNN and AdaBoost methods, the accuracy, specificity, and sensitivity are higher.

2 LITERATURE REVIEW

In order to identify false news, researchers use n-gram analysis and TF-IDF for feature extraction. After that, they use decision trees, SGD, Linear SVM, Logistic Regression, SVM, and KNN as machine learning classifiers (Lahby, M.,et al, 2022). Pennycook & Rand (Pennycook, G., & Rand, D. G. 2021). developed an SVM-based satire detection model with 90% accuracy. Bahad et al. showed RNNs outperform manual rumor detection, while Ruchansky et al. introduced the CSI model, integrating content, user comments, and sources for improved accuracy. For fake images, Hsu et al. developed CFFN, using GANs and DenseNet to classify manipulated images. Bird et al. developed NLTK, a comprehensive Python toolkit that facilitates various NLP tasks such as tokenization, parsing, stemming, and classification, making text analysis more accessible and efficient. Huan et alsuggested a deep learning strategy for text classification that effectively captures both sentiment and semantic context, improving accuracy in emotionally charged text analysis (Bird, S., Klein, E., & Loper, E. 2009). Umer et al. demonstrated that combining convolutional neural networks (CNNs) with Fast Text embeddings enhances text classification by efficiently extracting contextual and syntactic features (Umer, M.,et al, 2023). Optimized deep learning methods for spotting rumors and misleading information in online social networks were presented by Zamani et al, leveraging advanced neural architectures to enhance misinformation identification and content credibility assessment (Abu Sarwar Zamani, et al, 2025).

3 RESEARCH METHODOLOGY

3.1 Deep Learning for Fake News Detection

This technique involves collecting data from Twitter in order to utilize deep learning to identify false news. Pre-processing involves stop word removal (NLTK), stemming (Porter's Algorithm), and tokenization (N-gram model). Tokenization applies unigrams, bigrams, and trigrams to structure text. The model integrates LSTM, CNN, and AdaBoost for classification. LSTM, an RNN variant, is effective in pattern recognition due to its input (I/P), forget (f), and output (O/P) gates, along with a memory cell. These gates regulate information flow, ensuring data integrity and sequence retention, improving accuracy while preventing gradient descent issues. Figure 2 and 3 illustrate the LSTM network, providing A schematic illustration of its composition. The network takes an embedding xi as input at each time step and calculates its output hi by adding the output h i-1 together with the latest embedding xi to the latest cell state h i-1. It is possible to insert or remove data from the cell, depending on its present state

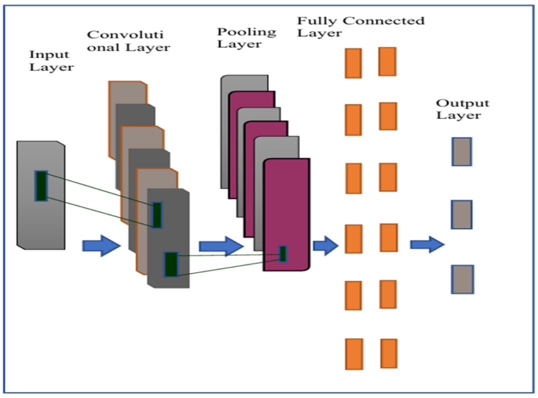

Figure 2: LSTM architecture.

$$ft = \sigma(wf.[yt - 1, xt] + b) \quad (1)$$

$$it = \sigma(wi.[yt - 1, xt] + b) \quad (2)$$

A Convolutional Neural Network (CNN) comprises key components like convolution and pooling layers. While CNNs are well-known for image processing, they also identify data interdependencies. Feature extraction from input data is made possible by the convolution layer, which allows operations on the embedding matrix for word embeddings. The pooling layer then reduces dimensionality and selects important features using methods like max, min, or average pooling. Finally, the extracted features are processed by a fully connected neural network. A CNN applies activation functions to generate the final output, typically consisting of convolutional, pooling, activation, and fully connected layers. Deep CNNs enhance learning by stacking multiple convolutional layers, which act as filters, processing small pixel sections at a time (e.g., 3×3 filters). Researchers at the University of Michigan developed AdaBoost, an advanced gradient-boosting method for binary classification. It starts with an initial decision tree, evaluates its accuracy, and integrates multiple classifiers to build a robust model.

The first model is built with the training data and is then enhanced by including other models to address its shortcomings. This process continues until all training data is accurately predicted or the model limit is reached. To enhance accuracy, multiple classifiers are combined into a single optimized model. AdaBoost is widely used for pedestrian detection, where images are cropped into sections, and marking windows help identify pedestrians. The same method is applied iteratively with different selection sequences. Figure 3 shows Convolutional Neural Network. A window is classified as containing a pedestrian if no models reject it, refining the classification process further.

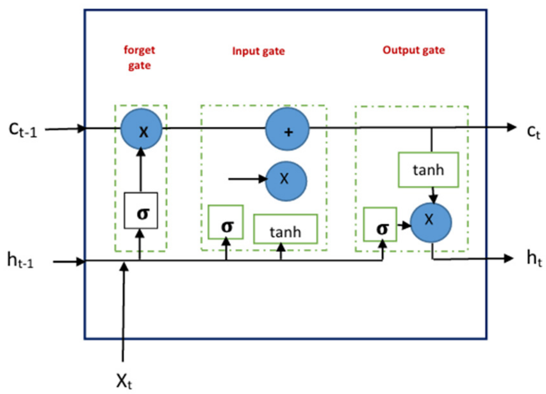

Figure 3: Convolutional neural network.

3.2 Dataset Overview and Preprocessing

The dataset, sourced from Kaggle, contains 40,000 articles 20,000 real and 20,000 fake. A pre-trained Glove Twitter dataset is also referenced.

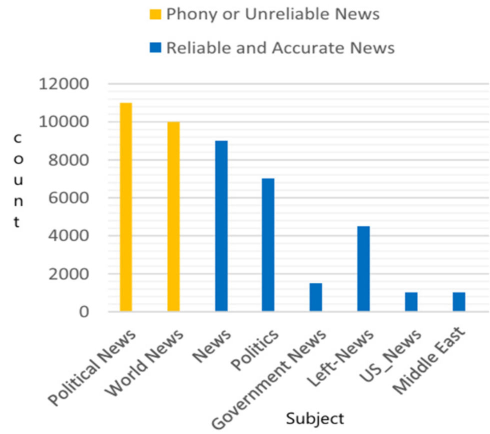

Figure 4: Present tendencies across different types of fake news and real news.

Data pre-processing is a crucial step to enhance efficiency, involving data transformation and cleaning before execution. The following section elaborates on these processes. A figure illustrates that balanced, indicating stability. In the visualization, the "0" class (orange bar) represents fake news, while the "1" class (blue bar) represents real news. Since topic contents vary between categories, only the main text is processed, while the subject, title, and date are removed. Figure 4 explains the topics that comprise the dataset, showing how news spreads in society. The count of each subject highlights its presence in the dataset—blue bars denote unreliable news, while orange bars indicate credible news. Real news covers global and political topics, whereas fake news is often found in categories like politics, general news, left-wing media, U.S. news, and Middle Eastern news.

3.3 Deep Learning LSTM Model

A sequential model has one input and one output tensor per layer, requiring a defined input shape. Sequence classification predicts categories based on sequential data, posing challenges due to varying lengths and complex patterns. To detect false information, an LSTM model is used, leveraging LSTM cells with input, forget, and output gates. Figure 2 shows how a tan layer regulates the combination of the previous output ht−1 with the value of the new sequence, xt in order to smooth inputs.

3.3.1 LSTM Cell Process

The LSTM model begins with a tanh layer that smooths the combined input. Next, the input gate, with sigmoid activation, filters relevant values by scaling the compressed input. The forget gate (st) determines which information to retain, while the previous state (st−1) is added to maintain long-term dependencies, reducing the risk of gradient disappearance. The forget gate further refines stored information, ensuring only necessary data is preserved. Finally, the output gate regulates the final output using a tanh function, determining which values from the cell (ht) are allowed as output.

The input is reduced to a range of -1 to 1 by using a tanh activation function. Shown below is one way to do it:

$$g = tanh(b^g + X_t\, U^g + h_{t-1}V^g) \tag{3}$$

where Vg stands for the input weight and bg for the preceding cell output, with bg representing the input bias.

The symbol for the forgotten gate is:

$$f = \sigma(b^f\ + x_tU^f + h_{t-1}V^f \tag{4}$$

The output is st−1, which is the element-wise sum of the prior state and the forget gate. It is possible, nonetheless, to represent output gates as

$$0 = \sigma(b^0 + x_tU^0 + h_{t-1}V^0) \tag{5}$$

As shown in Figure 2, the final output of the network is ht. To enhance performance, a stacked LSTM model is used with the return sequence set to true, allowing each neuron's hidden state to serve as input for the next LSTM layer. Two long short-term memory (LSTM) layers, one with 128 memory units and the other with 64, follow each word is represented as a 32-length vector in the embedding layer model. The first dense layer activates 32 memory units and uses Re LU, while the second layer uses a sigmoid function to train a single neuron for output. Neurons in a dense layer are completely connected, so data from all neurons in the layer below it may reach each one.

To prevent overfitting, recommended networks use one or two dense layers. ReLU, a widely used activation function, prevents simultaneous neuron activation and offers advantages over sigmoid and tanh in convolutional neural networks. ReLu is represented by:

$$\sigma = max(0, z) \tag{6}$$

If Qij is sigmoid, then the likelihood of the word j occurring in connection to the term i is this. This is how we may express the inferred global objective function:

$$J = -\sum \text{LogOiji} \in \text{corpus}, \text{j} \in \text{context(i)} \tag{7}$$

A Dense output layer may be used to classify false news as either legitimate news (with a value of 0) or fake news (with a value of 1). Utilizing the optimizer, metrics, and loss function during model construction is essential. Ten iterations of training the model using the Binary Cross-Entropy loss function and a learning rate of 0.01 are implemented using the Adam optimizer. Decreased batch size, set at 256, has improved accuracy. The size of the embedding is 100. A random sample strategy was used in the execution of the investigation. From one of Bhutan's Colleges of Education, 22 first-year in-service postgraduate science teachers made up the sample. Males made up 13 (or 59% of the total) of these educators. Because of this, picking the right hyperparameters for a model is crucial for fast and accurate training. Internal operations of the cells that make up the LSTM network are the main point of differentiation.

Table 1: LSTM Layered Architecture.

Layer (type)	Output size	Param Number
Embedding_1 (embedding)	300 x 100	10,00,000
Lstm_1 (LSTM)	300 x 128	1,17,248
Lstm_2 (LSTM)	64	49,408
Dense_1 (Dense)	32	2080
Dense_2 (Dense)	1	33

Table 2: Hyperparameters for proposed model.

Hyperparameters	Value
Layer for embedding	1
LSTM layer	2
Layer with high concentration	2
Loss Function	Binary cross entropy
Function for activation	ReLu
Optimizer	Adam
Learning rate	0.01
Epoch count	10
Size of embedding	100
Group quantity	256

Tables 1 and 2 provide a comprehensive list of all the necessary hyperparameters for an LSTM model to improve performance, as well as the recommended settings considered best practices.

4 RESULT AND DISCUSSION

The dataset includes four attributes title, main text, topic, and date and is derived from Twitter. It includes pre-trained word vectors, with 20,000 features used for analysis 16,000 for training, 2,000 for testing, and 2,000 for validation. Vectorization is based on word frequency. Figure 5 shows for a comparison of classifier results in detecting false news in social media datasets. Data pre-processing involves removing stop words using the NLTK library, stemming words with Porter's Algorithm, and tokenizing with an N-gram model. Convolutional neural networks (CNNs), boosted by AdaBoost and LSTM, form the basis of the model. LSTM achieved 99.24% accuracy, outperforming CNN by 1.68% and AdaBoost by 5.02%. Its specificity is 99.2%, exceeding CNN by 2.04% and AdaBoost by 4.99%, while its sensitivity is 98.67%. LSTM is the most effective for fake news detection.

Table 3: Accuracy, specificity and sensitivity comparison of different classifiers.

Algorithm/Metric	Accuracy (%)	Sensitivity (%)	Specificity (%)
AdaBoost	94.22	96.55	94.21
CNN	97.56	96.33	97.16
LSTM	99.24	98.67	99.2

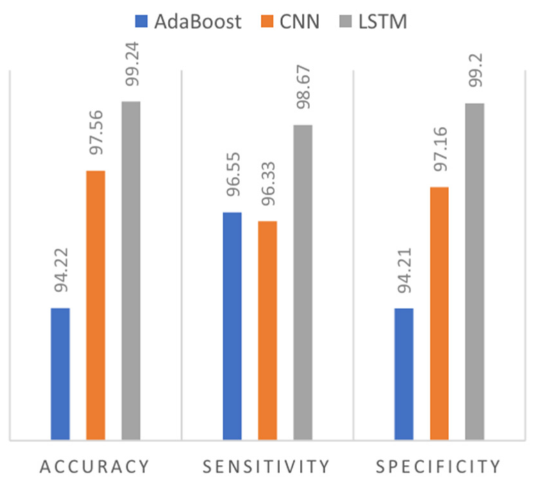

Figure 5: Comparison of classifier results in detecting false news in social media datasets.

Additionally, rhetoric plays a key role in English writing by enhancing persuasive abilities. Table 3 shows accuracy, specificity and sensitivity comparison of different classifiers. Understanding rhetorical devices like contrast and exaggeration helps writers improve their skills and grasp rhetorical concepts more effectively.

5 CONCLUSIONS

This research presents a method for detecting false news stories using Twitter data that is based on deep learning. Tokenization, stemming, and stop word removal are all part of the pre-processing. When compared to CNN and AdaBoost, LSTM achieves the highest accuracy rate of 99.24%. Future work aims to enhance automation, particularly for e-commerce platforms, where detecting false information is crucial.

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