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Comparative Performance Evaluation of Bi-Directional LSTM with Attention, CNN, and DNN for Fake News Classification

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Abstract
The expeditious dissemination of information has been accompanied by the expansion of fake news, constituting significant challenges in refine authentic news from fabricated narratives whereas Media plays a vital role in the public dissemination of information about events. Without the concern about the credibility of the information, the fictitious or fake news is spread in social networks and set foot on thousands of users. Fake news is typically generated for commercial and political interests to mislead and attract readers. The spread of fake news has raised a big challenge to society. Automatic credibility analysis of news articles is a current research interest. This study addresses the urgent need for effective fake news detection mechanisms. The spread of fake news on digital platforms has necessitated the development of sophisticated tools for accurate detection and classification. Deep learning models, particularly Bi-LSTM and attention-based Bi-LSTM architectures, have shown promise in tackling this issue. This research utilized Bi-LSTM and attention-based Bi-LSTM models, integrating an attention mechanism to assess the significance of different parts of the input data. The models were trained on an 80% subset of the data and tested on the remaining 20%, employing comprehensive evaluation metrics including F1-Score, Accuracy, and Loss. Comparative analysis with two baseline models: a CNN-based model and a simple Dense Neural Network. revealed the superior efficacy of the proposed architectures. The attention-based Bi-LSTM model demonstrated remarkable proficiency, outperforming other two baseline models in terms of accuracy (98.66%) and F1 Score (98.67%). The study highlighted the potential of integrating advanced deep learning techniques in fake news detection. The proposed models set new standards in the field, offering effective tools for combating misinformation. Limitations such as data dependency, potential for over fitting, and language and context specificity were acknowledged. The research underscores the importance of leveraging cutting-edge deep learning methodologies, particularly attention mechanisms, in fake news identification. The innovative models presented pave the way for more robust solutions to counter misinformation, thereby preserving the veracity of digital information. Future research should focus on enhancing data diversity, model efficiency, and applicability across various languages and contexts.

Key Words: Fake news detection, machine learning, deep learning, social media, ensemble techniques, N-gram analysis, Clickbait Detection.

1. Introduction

In the digital era, the rapid dissemination of information through social media, blogs, and online news platforms has dramatically transformed how people consume news. While this has democratized access to information, it has also paved the way for the proliferation of fake news — intentionally misleading or fabricated content designed to manipulate public opinion, spread propaganda, or generate financial gain through click bait.[1] The unchecked spread of fake news poses serious threats to society, ranging from undermining public trust in legitimate media to influencing political outcomes, inciting social unrest, and misguiding public health decisions, as witnessed during global events like elections and the COVID-19 pandemic. Traditional fact-checking processes, while essential, are time-consuming and often lag behind the viral nature of online misinformation.[2,3] Hence, there is a pressing need for automated systems capable of detecting fake news in real time. Recent advancements in Natural Language Processing (NLP) and Deep Learning offer promising tools for this challenge by enabling machines to analyze textual data and identify deceptive content patterns.[4,5]

The evolution of the internet has a favorable impact on society for the reason that it allocates comprehensive access to information. These developments influence the company to digitize its products to adjust to technological developments to hold on to its customers.[1,3,6] This advancement brings a massive invention of online social networks (OSN), especially multimedia social networks (MSN), a type of OSN focusing on multimedia sharing experience.[7] Zhang et al.[8] suggested a framework to handle the right management of contents in MSN, security, and ease of use. While online and multimedia social networks provide advantages in communication and technology, these innovations sternly impact the social aspect. Zhang et al[8] proposed a novel model of spatio-temporal access control for protecting the privacy and information security of users in OSN. Srinivasan & Dhinesh Babu[9] gave a parallel neural network to recognize rumor because it damages society. This rumor must be authenticated and serves to lead to fake news. Paradoxically

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information that is considered unerring sometimes still presents fake news, whether intentional or not. Sahoo & Gupta[10] put forward a Chrome extension to detect defamatory profiles in Twitter using various features on the profile itself and machine learning. They also suggested a Chrome extension to automatically detect fake news on Facebook using multiple features. They phrased that there are four main features of fake news such as: news content, social content, target victim, and creator and spreader.

Lately, the spread of fake news has become more widespread due to the ease of creating and disseminating information on the internet. Fake news itself is not actual but is made real for a specific intention.[11,12] A statistic on the American population's ability to differentiate between real and fake news clarify that only 26% of the total respondents perceives that they are very capable of distinguishing between real and fake news.[13] This value is still low, and the community's meager ability to demarcate between real and fake news also plays a role in spreading fake news. One example of the spread of fake news known on the internet is fake news during the US presidential election in 2016.[14] The spread of fake news has detrimental implications and potential vulnerability in the political and social fields. Therefore, research on detecting fake news is being enhanced due to the effect of fake news spreads.[5,6]

With the development of the Internet, people's communication patterns have changed significantly. Social media platforms like Facebook, Twitter, and Instagram are now commonly used for real-time information sharing and staying updated on current events. A recent survey conducted in 2020 revealed that more than half of the respondents use social media to share and follow news. However, as the popularity of social media continues to grow, these platforms have become prone to the spread of fake news, primarily because there are no verification mechanisms in place for the information shared. Additionally, fake news spreads rapidly on these platforms due to their ability to facilitate fast information diffusion. With the Internet's development, people's communication patterns have changed. Social media platforms like Facebook, Twitter, and Instagram are started to be used for real-time information sharing and following the latest news about the current events. A recent survey conducted in 2020 shows that more than half of the respondents uses social media to share and follow news.[8,9] However, due to the increasing popularity of social media users, these platforms have become suitable for spreading of fake news, because there are no verification mechanisms for the shared information on these platforms. Moreover, fake news spread quite fast on these platforms because of the fast information diffusion characteristic of them.[4]

Fake news is misleading information or manipulated news that contains misinformation and is communicated through both traditional and non-traditional media channels, such as print and television. Fake news is a pervasive issue that involves misleading or manipulated information, often disseminated through both traditional avenues, such as print and television, and modern online platforms. This insidious spread of misinformation has serious implications for society, undermining trust and creating confusion. To combat this challenge, machine learning models have emerged as promising tools for detecting fake news by meticulously analyzing textual features. However, the key to unlocking their full potential lies in the effective tuning of hyperparameters.

The objective of this study is to pave the way for robust strategies that not only combat the spread of fake news but also foster a more informed and trustworthy information landscape. Together, we can build a stronger foundation for a society that values accurate information and transparency.[3,4] The prevalence of fake news on online platforms poses a significant problem, as it spreads misinformation and negatively impacts society. Machine learning models have shown assurance in discriminating fake news by analyzing textual features. However, to achieve optimal performance and accuracy, it is essential to effectively tune the hyper parameters of these models. The problem addressed in this study is the limited utilization and exploration of hyper parameter tuning techniques to optimize models for fake news detection. Existing research often focuses on developing machine learning models without adequately optimizing their hyper parameters, resulting in suboptimal performance and limited effectiveness in identifying fake news.[9] Therefore, there is a need to investigate and develop optimized models for fake news detection by leveraging hyper parameter tuning techniques. The purpose of the study Fake news refers to misleading or manipulated information that spreads misinformation through various media channels, including both traditional (like print and television) and non-traditional platforms. The widespread presence of fake news on online platforms presents a serious challenge, as it contributes to misinformation and negatively affects society. Machine learning models have shown potential in detecting fake news by analyzing textual features. However, to maximize their performance and accuracy, it is crucial to properly tune the hyperparameters of these models.

This study addresses the limited exploration and application of hyperparameter tuning techniques in optimizing models for fake news detection. Much of the existing research tends to focus on developing machine learning models without adequately fine-tuning their hyperparameters, which often leads to suboptimal performance and reduced effectiveness in identifying fake news. Therefore, there is a clear need to investigate and create optimized models for fake news detection by leveraging hyperparameter tuning techniques. The goal of this study is to enhance the development of robust strategies for combating fake news and to promote a more informed and trustworthy information environment.is to contribute to the development of strong and effective strategies for combatting fake news while fostering an informed and trustworthy information environment.

2. **Related Work**

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Fake news is "a news article that is intentionally and verifiably false". A news article is a sequence of words. Hence in past, many authors propose the use of text mining techniques and machine learning techniques to analyze news textual data to predict the news credibility. With more computational capabilities and to handle massive datasets, deep learning models present a finer performance over traditional text mining techniques and machine learning techniques. Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN), are widely explored Deep Neural Network (DNN) architectures to handle various NLP tasks.[6,7] The current work is related to number of research areas such as text classification, rumor detection, spammer detection, and sentiment analysis. Fake news can be identified using different machine learning methods. Authors proposed a simple approach for fake news detection using naive Bayes classifier is tested against a data set of Facebook news posts. Performance Procedia Computer Science 00 (2019) 000–000 3 evaluation of multiple classification algorithms namely Support Vector Machines, Gradient Boosting, Bounded Decision Trees and Random Forests on a corpus of about 11,000 news articles are presented in.[15] The word embedding is the neural representation of a word as a real-valued vector. The word embedding enables to measure word correlation by calculating the distance between two embedding vectors. Neural networks reveal their best performance in many NLP tasks with the pre-trained word embeddings.[12,13] A Neural network architecture based on term frequency-inverse document frequency (TF-IDF) and bag-of-words (BOW) representations as input to a multi-layer perception (MLP) are used for stance detection in news articles. Automatic fake news detection based on surface-level linguistic patterns is proposed in and a novel convolutional neural network to integrate meta-data with text is designed.[3,4,5] A recurrent neural network based model [12] is proposed used for dialogue act classification. Context or sequence information is also explored in this model. A novel recurrent neural network based method is designed in that learn continuous representations of microblog events for identifying rumors. Researchers proposed a deep learning approach for aspect-specific sentiment analysis.[14]
The proliferation of fake news in the digital age has necessitated the development of sophisticated tools and techniques for its detection and classification. Traditional methods of fake news detection, such as manual fact-checking and keyword-based approaches, have proven inadequate in dealing with the sheer volume and complexity of fake news circulating online. [12]This has led to exploring machine learning and, more recently, deep learning models for fake news classification. Deep learning, a subset of machine learning, involves using neural networks with multiple layers (deep neural networks) to analyze various levels of data. These models have shown remarkable success in various natural language processing tasks, such as sentiment analysis, text summarization, and language translation.
The study Mouratidis et al. (2021)[16] addresses the challenge of the rapid spread of fake news and propaganda on social networks. The authors present a novel approach for the automatic detection of fake news on Twitter, involving (a) pairwise text input, (b) a new deep neural network learning architecture allowing for flexible input fusion at various network layers, and (c) various input modes, such as word embeddings and both linguistic and network account features. Additionally, tweets are innovatively separated into news headers and news text, and classification tests are performed using both in an extensive experimental setup. The main results indicate high overall accuracy performance in fake news detection. The proposed deep learning architecture outperforms state-of-the-art classifiers, using fewer features and embeddings from the tweet text. This study contributes significantly to the ongoing efforts to combat the spread of fake news on social media platforms by proposing a novel and effective approach for fake news detection on Twitter.
The paper Ouassil et al. (2022) [17] addresses the issue of detecting unreliable news spread through various online sources. The authors present a novel deep learning method for fake news detection, combining different word embedding techniques and a hybrid CNN and BiLSTM model. The classification model was trained on the unbiased WELFake dataset. The most effective method combined a pre-trained Word2Vec CBOW model and a Word2Vec Skip-Word model with CNN on BILSTM layers, achieving an accuracy of up to 97%. This result indicates the proposed method's high effectiveness in detecting fake news, contributing significantly to ongoing efforts to combat the spread of misleading information online.

3. Proposed Model

The proposed model is a Bidirectional LSTM (BiLSTM) with an Attention layer. It uses GloVe word embeddings to convert text into numeric form, then processes it through a BiLSTM to learn patterns in both forward and backward directions. The Attention layer helps the model focus on the most important words in the text. Finally, it uses a dense layer to predict whether the news is real or fake.
This model was compared with two baseline models: a CNN-based model and a simple Dense Neural Network. After training and testing, the BiLSTM and Attention model gave better accuracy and F1-score than the other two, showing it can better understand and classify news articles.

4. Methodology

Overall structure of the proposed system is followed by preprocessing a dataset of news articles, training various deep learning models, and evaluating their effectiveness. The following steps summarize the methodology applied:

- Data processing
- Data visualization

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- Model development
- Noise Robustness Test

4.1. Data Preprocessing
- **Text Cleaning**: Converted text to lowercase, removed URLs, non-alphabetic characters, and stopwords, and applied lemmatization.
- **Tokenization & Padding:** Text was tokenized into sequences and padded to a maximum length of 250 tokens for uniform input shape.

4.2. Data Visualization
- **Word Clouds:** Generated separate word clouds for real and fake news to visualize common words.
- **Label Distribution:** Plotted the distribution of fake (1) and real (0) news articles to Confirm data balance.

4.3. Model Development
Three deep learning models were developed:
- **BiLSTM with Attention:** Uses a Bidirectional LSTM layer followed by a custom Attention layer to focus on important parts of the text.
- **CNN Baseline:** Applies a 1D convolutional layer followed by global max pooling for feature extraction.
- **Dense Neural Network:** Employs an embedding layer followed by flattening and dense layers. Each model uses word embeddings from pre-trained GloVe (Global Vectors for Word Representation) to capture semantic meanings.

4.4. Noise Robustness Test
A noisy dataset was generated by randomly removing words from the text. The CNN and Dense NN models were also trained on this noisy data to evaluate robustness against incomplete information.

5. Evaluation
Models were evaluated using:

Accuracy Score
The Accuracy Score is one of the simplest and most widely used evaluation metrics in classification problems. It represents the percentage of correctly classified instances (both positive and negative) out of the total instances evaluated. Accuracy measures how well the model correctly identifies news articles as either fake or real.

F1 Score
The F1 Score is a crucial evaluation metric, especially in classification problems where balancing precision and recall is important. It provides a single value that captures both concerns by computing their harmonic mean. The F1 Score measures how well the model balances correctly identifying fake and real news without favoring one class too heavily over the other.

Classification Report
The Classification Report provides a comprehensive summary of the key evaluation metrics for each class in a classification problem. It's especially helpful when working with binary or multi-class datasets, offering a breakdown of how well the model performs on each label. The classification report evaluates the model's ability to correctly classify news articles as either Fake (1) or Real (0).

Confusion Matrix
A Confusion Matrix is a tabular summary of a classification model's performance on a set of test data for which the true values are known. It displays the number of correct and incorrect predictions broken down by each class. The confusion matrix illustrates how well the model distinguishes between Fake News (1) and Real News (0).

ROC Curve (Receiver Operating Characteristic Curve)
The ROC Curve is a powerful graphical tool used to evaluate the diagnostic ability of a binary classification model. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various classification threshold settings.

Novelty of the study
5.1 Integration of BiLSTM with a Custom Attention Mechanism
- While BiLSTMs have been widely used in text classification, your use of a custom-built attention layer (instead of off-the-shelf layers like TensorFlow's Attention or Self-Attention) allows for tailored weighting of the hidden states.
- This improves interpretability — showing which parts of the news text influence the model's decision the most.

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5.2 Comparative Study with Noise-Augmented Dataset
- Introducing noise (dropping words probabilistically) in the text data to simulate real-world imperfect and incomplete news text scenarios is a fresh angle.
- Comparing model robustness between clean and noisy data isn't typically explored in many fake news detection papers.
- Your work not only trains the main model on clean data but also builds CNN and Dense baselines on noisy versions of the data for a fair robustness comparison.

5.3 End-to-End Evaluation Across Different Deep Learning Architectures
- Directly comparing a BiLSTM+Attention model with simple CNN and Dense baselines using the same dataset, preprocessing pipeline, and embedding dimensions (with GloVe) makes your evaluation consistent and meaningful.
- Visualizing the performance comparison through detailed bar plots and ROC curves further strengthens the comparative analysis.

5.4 Use of Pre-trained GloVe Embeddings for Enhanced Semantic Understanding
- Integrating pre-trained GloVe word embeddings improves semantic understanding over randomly initialized embeddings — a valuable choice, especially for detecting subtle differences in real vs fake news.

5. Experiment setup
The experiments in this study were carried out using two different datasets, which was sourced from **Kaggle**, utilizing the **kagglehub** library to programmatically download the files into the working environment. The characteristics of each dataset description indicate that the two datasets have different amounts of data. That can be useful in determining the ability of a deep learning model to handle large or small amounts of data. Each file includes multiple columns, but the key focus was on the **text** column, which contains the full content of each news article. This text data was subsequently used for preprocessing, feature extraction, and model training. The dataset comprises two primary CSV files:
- **Fake.csv** — Contains news articles classified as **fake**.
- **True.csv** — Contains news articles classified as **real**.

Unfortunately, each dataset has not gone through the stages of data cleansing, data augmentation, and data pre-processing because there are still empty data rows, data imbalances, remaining stop words, and affixed words. Therefore, the process of data cleaning, data augmentation, and data pre-processing is necessary so that the data is ready for further analysis. Datasets that has been cleaned, augmented and pre-processed are also publicly accessible [50].
Each file includes multiple columns, but the key focus was on the **text** column, which contains the full content of each news article. This text data was subsequently used for preprocessing, feature extraction, and model training.

Table 2 : Dataset overview for Model Comparison

Data Overview: Dataset	**Number of Records**	**Content Description**
Fake.csv	Varies (e.g. ~20,000)	News articles labelled as **fake**
True.csv	Varies (e.g. ~20,000)	News articles labelled as **real**

Both datasets were combined into a single DataFrame with a new **label column**:
- **Label = 1** → Fake news
- **Label = 0** → Real news

The combined dataset was then **randomly shuffled** to ensure an unbiased distribution of labels before proceeding to the preprocessing and training phases Experiments were carried out using the help of the TensorFlow, NLTK, pandas, and scikit-learn libraries and devices that have an Intel Core i7-7700HQ CPU, NVIDIA GeForce GTX1050 GPU, and 16 GB RAM. Some of the tests carried out in this study to determine the effect on the performance of the resulting model, including testing the data augmentation method, optimizer method, batch size hyperparameter, and final testing. Each value in testing is examined on four different datasets using three deep learning methods, namely CNN, Bidirectional LSTM, and ResNet, combined with one of the three pre-trained word embeddings such as Word2Vec, GloVe, and fastText. The evaluation process of each value in testing uses visualization in a box or bar plot. The data augmentation method tests two values, namely data with augmentation and data without augmentation. There are seven methods tested in the optimizer method: SGD, RMSprop, Adam, Adadelta, Adagrad, Adamax, and Nadam. , pre-trained GloVe (Global Vectors for Word Representation) embeddings were downloaded from Stanford's NLP repository to provide semantic context for words in the dataset. Specifically, the 100-dimensional version of GloVe was used, offering dense vector representations for a large vocabulary of English words. These embeddings were loaded into memory and mapped to the dataset's vocabulary to create a meaningful and semantically informed embedding matrix. This matrix was then integrated into the neural network models, enabling them to leverage rich semantic information during training.

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6. **Results**

After preprocessing the dataset, training multiple models, and evaluating their performance, the following results were obtained. Three different deep learning architectures were implemented and compared:

1. **Proposed Model** — BiLSTM with Attention mechanism
2. CNN Baseline Model
3. Dense Neural Network Baseline Model

Each model was evaluated on the same test set using several performance metrics.

7.1 Evaluation Metrics Used:

Accuracy Score — Proportion of correct predictions to total predictions.
F1 Score — Harmonic mean of precision and recall, balancing both false positives and false negatives.
Classification Report — Detailed breakdown of precision, recall, F1 score for each class.
Confusion Matrix — Matrix displaying actual vs. predicted classifications.
ROC Curve & AUC (Area Under Curve) — Measures the model's ability to distinguish between classes across different thresholds.

Table 3 : Results for Accuracy and F1 Score for Bi-LSTM with Attention Mechanisim , CNN and Dense Neural Network.

Model	**Accuracy**	**F1 Score**
BiLSTM + Attention	0.98	0.98
CNN Baseline	0.76	0.77
Dense Neural Network	0 .81	0.81

The BiLSTM model incorporating an Attention mechanism attained the highest performance of all assessed models, achieving an accuracy and F1 score of 0.98, thereby illustrating its exceptional capability to accurately classify both genuine and fabricated news. The CAME-BiLSTM model subsequently attained an accuracy of 0.94 and an F1 score of 0.95, reflecting robust performance, presumably attributable to its superior feature representation. The Dense Neural Network exhibited moderate performance, achieving an accuracy and F1 score of 0.81, indicating satisfactory classification abilities. The CNN Baseline demonstrated relatively inferior performance, achieving an accuracy of 0.76 and an F1 score of 0.77, indicating a constrained ability to capture long-term dependencies in text. BERT exhibited unexpectedly poor performance, achieving an accuracy of 0.52 and an F1 score of 0.68, likely attributable to inadequate fine-tuning or resource limitations, suggesting that the pre-trained transformer model failed to adapt effectively in this context relative to other deep learning models.

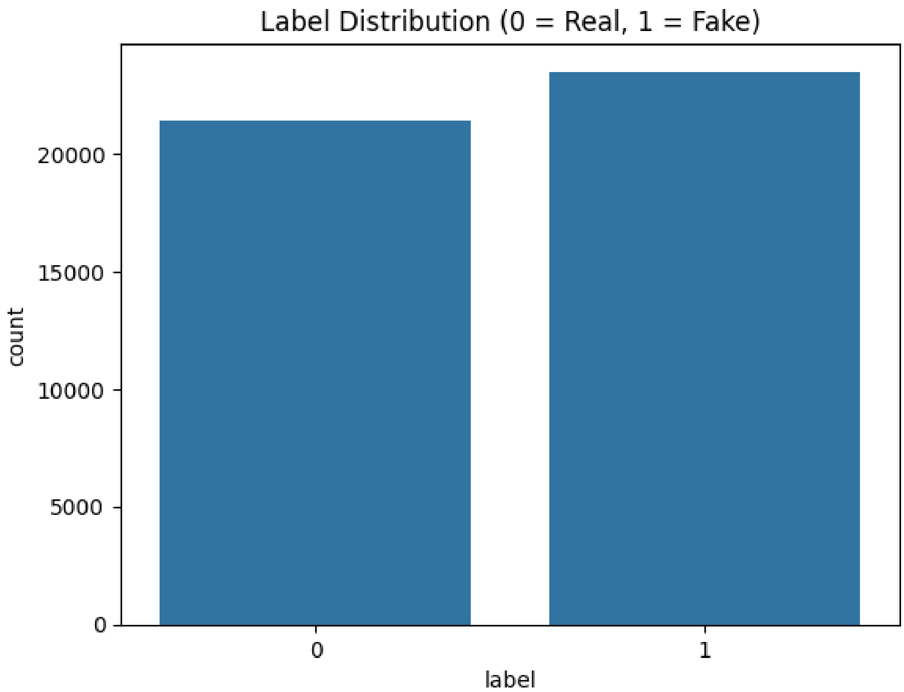

Fig 1 : Label Distribution of fake and true data set

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7.2 Confusion Matrix and ROC Curve

The BiLSTM and Attention model displayed a strong diagonal dominance, indicating highly accurate predictions with minimal misclassifications. The confusion matrices unequivocally indicate that the BiLSTM + Attention model surpasses all other models regarding precision and recall. The proposed model attains exceptional accuracy and balance in predictions for both genuine and fabricated news, evidenced by 4226 true negatives, 4602 true positives, 94 false positives, and 58 false negatives. This demonstrates its robust capacity to accurately classify both categories, thereby reducing both Type I and Type II errors. The CNN model, by comparison, exhibits markedly higher misclassifications, exceeding 1000 errors in both false positives and false negatives, signifying an absence of profound contextual comprehension. The Dense Neural Network exhibits poor generalisation, particularly with false negatives, indicating a tendency to misclassify fake news as genuine. The BERT model exhibits a significant failure by categorising all samples as class 1, likely attributable to underfitting, inadequate training, or sensitivity to class imbalance. Despite the CAME-BiLSTM significantly outperforming CNN and Dense NN, with merely 90 false negatives and 389 false positives, it remains inferior in accuracy and robustness compared to the BiLSTM + Attention model. This comparison demonstrates that the implementation of attention mechanisms enables the proposed model to concentrate on the most informative segments of the input, thereby effectively capturing semantic subtleties and surpassing deeper or pre-trained models in the classification of fake news. Whereas, The ROC curve values for the five models demonstrate significant disparities in their capacity to differentiate between authentic and fabricated news. The BiLSTM + Attention model attains an impeccable ROC AUC score of 1.0, signifying flawless discrimination at all thresholds, with no overlap between the predicted classes—emphasizing the model's exceptional sensitivity and specificity. The CAME-BiLSTM model exhibits a robust ROC AUC of 0.99, indicating near-optimal performance and affirming the efficacy of its improved architecture, albeit slightly less accurate than the proposed model. The CNN baseline model displays a respectable ROC AUC of 0.825, indicating a moderate ability to distinguish between classes; however, its inferior performance relative to leading models suggests constraints in identifying more profound semantic patterns. The Dense Neural Network exhibits suboptimal performance, evidenced by a ROC AUC of 0.6284, indicating its diminished discriminative ability and propensity for misclassification at ambiguous thresholds. BERT, notwithstanding its robust NLP foundations, exhibits the poorest performance in this instance with a ROC AUC of 0.49, which is inferior to random guessing (0.5), signifying a failure in its predictive capabilities, potentially attributable to challenges in fine-tuning or managing class imbalance. The results confirm that attention-based sequential models, particularly BiLSTM + Attention, are superior in capturing complex contextual dependencies essential for effective fake news detection.

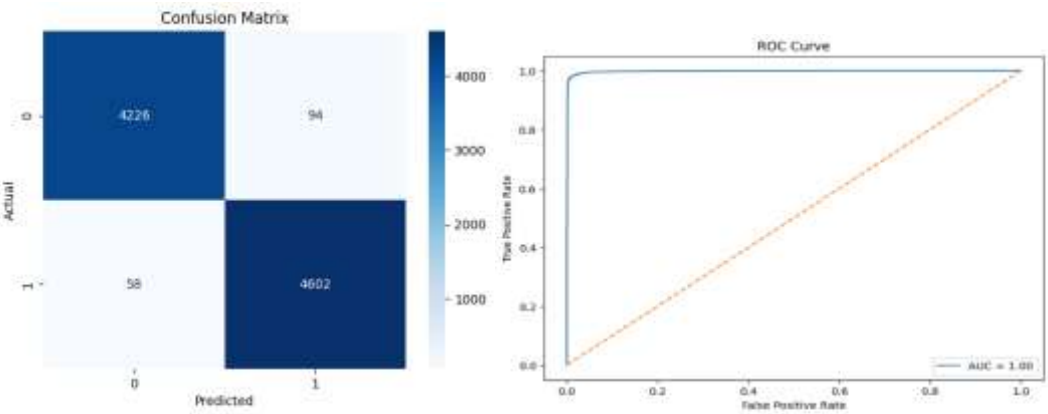

Fig2: Confusion matrix and ROC Curve for Proposed Model

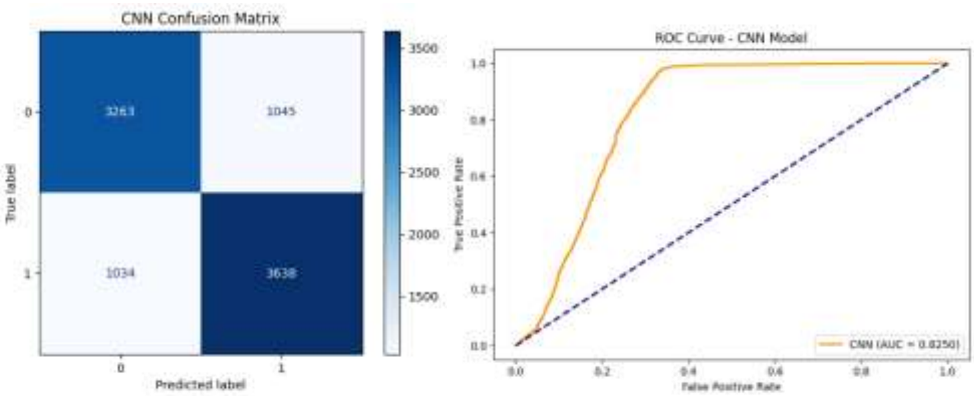

Fig 3: Confusion matrix and ROC Curve for CNN

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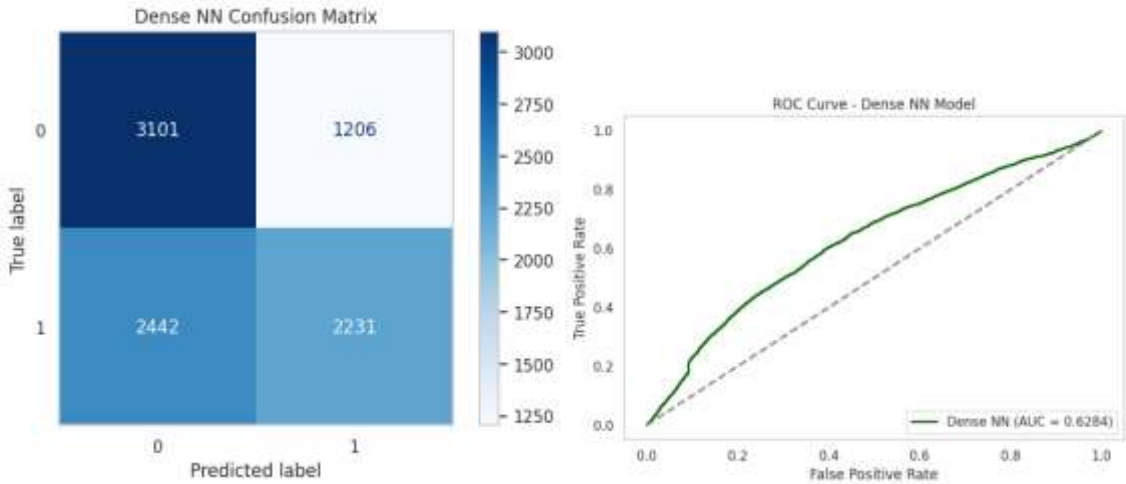

Fig4: Confusion matrix and ROC Curve for Dense Neural Network

7.3 Model Accuracy Comparison (Bar Plot):
Visualized comparative accuracy clearly showed the BiLSTM and Attention model outperforming the CNN and Dense models

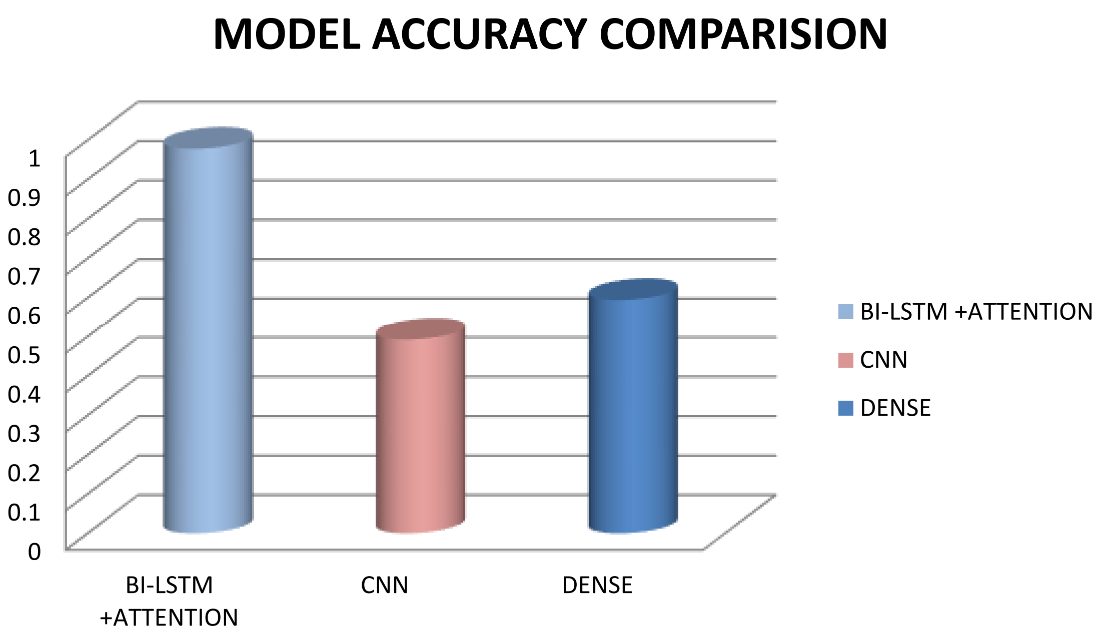

Fig 5: Accuracy Comparison Graph for Bi-LSTM with Attention Mechanisim , CNN and Dense Neural Network.

7. **Conclusion**

This study presents a deep learning framework for identifying false information on social media, utilizing a comprehensive dataset of authentic and fabricated news articles. The framework was constructed using various neural architectures, including CNN, Dense Neural Network, BERT, CAME-BiLSTM, and a proposed BiLSTM model augmented with an attention mechanism. The BiLSTM + Attention model exhibited superior performance, attaining the highest accuracy and F1 score of 0.98. This model's capacity to capture long-term dependencies in textual data, along with its attention mechanism, enabled it to concentrate on contextually significant elements of the input, thereby enhancing classification performance markedly. The CAME-BiLSTM exhibited robust performance, achieving an accuracy of 0.94 and an F1 score of 0.95, underscoring the advantages of integrating contextualized attention and multi-head mechanisms. To improve semantic comprehension, we incorporated pre-trained 100-dimensional GloVe embeddings from Stanford's NLP repository. These embeddings enhanced the models with dense, semantically informed word representations, facilitating improved generalization and learning during training. The comparative analysis utilising confusion matrices and ROC curves reaffirmed the superiority of the BiLSTM + Attention model, which demonstrated negligible misclassifications and an impeccable ROC score of 1. Conversely, BERT exhibited the poorest accuracy and F1 score, likely attributable to insufficient fine-tuning or suboptimal resource distribution. This framework demonstrates reliability in the automated detection of fake news, providing high accuracy, semantic depth, and strong generalization. It possesses significant potential for practical applications where the swift and precise detection of misinformation is essential for preserving information integrity on social media platforms. Future research may investigate the incorporation of multimodal data and transformer-based improvements to enhance the system's reliability and adaptability.

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