IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

Deep Learning Techniques for Fake News Detection

Varsha Negi[1], Priynka[2]

Department of Computer Science, Shayam Lal College Evening, Shahdara, Delhi University, Delhi – 110032, India[1]

Shah Satnam Ji Girls, College, Sirsa – 125055, India[2]

Abstract: In this study, we explore the application of DNN algorithm for detection of fake-news, focusing on the role of attention mechanisms in improving performance. Four Algorithms were developed and assessed CNN, Bi-LSTM, Attention Convolutional Neural Network (ACNN), & Attention Bidirectional LSTM (ABiLSTM) to investigate their ability to accurately identified faked news by appropriate capturing context and semantic information in text. The LIAR database was applied to comprehensively assess the performing of such algorithm across training, validation, and test sets. Our results show that deep learning technique could improved the ability of deep models to focus on key components of the text, thereby improving such abilities to distinguish fake from true news. Among the models, the two attention-based methods, ACNN and ABiLSTM, demonstrated higher test accuracy of 0.56, reflecting a slight improvement over their non-attention counterparts. Furthermore, these models maintained a desirable balance between precision and recall, which underscores their robustness and ability to perform well across different evaluation criteria.

Additionally, the F1-scores of the attention models were notably higher. Specifically, the ACNN and ABi-LSTM technique achieved F1-scores of 0.748 and 0.77 on the test set, outperforming the non-attention variants (CNN and BiLSTM). On the validation set, the F1-scores were 0.66 and 0.67, further validating their improved ability to extract and leverage important context-dependent features in the text. Among the two, ABiLSTM performed slightly better, suggesting that combining bidirectional LSTM with an attention mechanism is particularly effective for detecting fakes-news.

Overall, this studies highlights the potential of attention mechanisms to enhance deep neural network models by focusing on the most informative components of text. The results underscore the importance of integrating attention into deep architectures to achieve greater robustness, accuracy, and generalization in detecting fakes news tasks.

Keywords: Bi-LSTM, Hybrid Model, Fake News

I. INTRODUCTION

The detection of fake news has emerged as a critical research area as it has a profound influence on public opinion and democracy. Research is being conducted to improve the accuracy and effectiveness of fake news detection models using advanced AI techniques, specifically attention mechanisms. It has shown considerable promise in this area that the attention mechanism can enhance neural network performance by focusing on crucial parts of the input.

A simple attention mechanism enables models to concentrate on the most important parts of the text. This ability to highlight relevant words or phrases can help in better understanding context and nuances that are often vital in distinguishing fake news from the real news. Attention mechanism requires less computation than a complex architecture such as a transformer. Their limited computational resources make them suitable for applications with limited resources. Due to their reduced complexity, simple attention mechanisms typically result in faster training and inference times. This is beneficial for scenarios like real-time fake news detection systems when quick model development and deployment are necessary. Comparing these mechanisms to more complex models, their simplicity makes them less prone to overfitting. For fake news detection models to continue to be reliable, this feature aids in improving generalisation on unseen data.

Attention methods allow models to filter out unnecessary or misleading information, making them more resilient to noisy data. This is especially crucial in social media environments where there is a lot of fake news and wide variations in data quality. Various types of models, such as Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and even more basic feed-forward networks, can be equipped with simple attention processes. They are an appropriate choice for improving a variety of false news detection systems due to their flexibility.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⩩ Peer-reviewed & Refereed journal ⩩ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

The author has highlighted some possible future directions and unresolved challenges in the detection of false news. In the context of fake news detection, the terms ‘data-oriented’, ‘feature-oriented’, ‘model-oriented’ and ‘application-oriented’ refer to different perspectives or approaches depicted in figure 1 considered when designing and implementing methods or techniques to identify fake news.

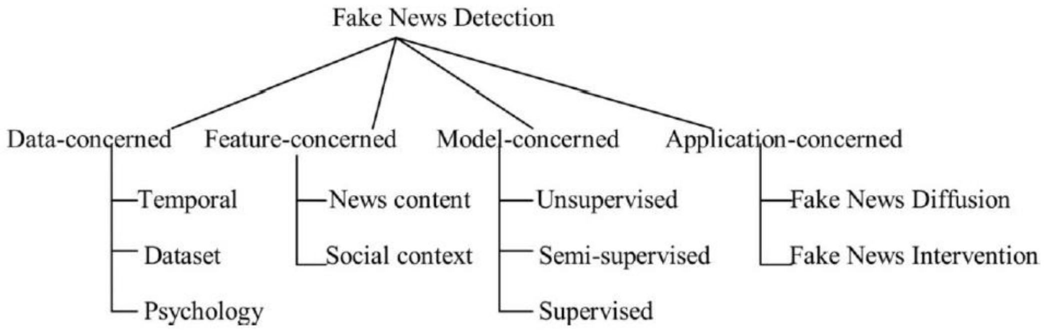

Fig. 1. Different Methodologies for Fake News Detection

Data-oriented: In the context of a fake news detection system, a data-oriented model emphasises the importance of understanding and effectively utilising the data used for training and testing a model. Temporal is a time-related aspect of data, such as how news and information change over time. Dataset relates to the collection of data and their compilation and use in the process of identifying false news. Psychology involves understanding the psychological aspects that affect the creation and distribution of misleading information.

Feature-oriented: In the framework of a false news detection system, a feature-oriented approach concentrates on the recognition, extraction, and application of pertinent features that aid in accurately classifying news articles as real or fake. News content includes both textual and visual content. A social context includes the social dynamics surrounding the news, including the behavior and structure of users who spread it, as well as readers' engagement patterns.

Model-oriented: A model-oriented approach in fake news detection stresses the choice and architecture of the machine learning or deep learning model used for classifying news articles as genuine or fake. The primary focus is on selecting and designing a model that effectively learns and generalises from the features extracted from any given data. Unsupervised models do not depend on labeled data while semi supervised models use both labeled and unlabeled data. Supervised model relies exclusively on labeled data to detect fake news.

Application-oriented: The application-oriented approach includes research on false news identification, fake news diffusion and intervention. Building an application oriented model for a false news detection system involves tailoring the solution to effectively address the needs of users and deploying the model in real-world scenarios. Fake news diffusion entails modelling and analysing the propagation of misleading information on social media and other websites. Fake news intervention refers to techniques and tools that use public awareness campaigns, real-time detection systems, and debunking efforts to moderate the impact of fake news.

II. RELATED WORK

News articles in the form of textual data is created in massive quantities every day in online surveys, and social media are automatically classified based on their credibility and reliability using text classification techniques and deep learning models.

Yang (2017) introduced a distinctive dataset called LIAR, comprising 12.8K manually annotated claims sourced from politifact.com. He focused on identifying fake news in online news sources automatically. He employed word2vec embeddings for extracting features.

Abdullah *et al.* (2019) introduced a framework that leverages feature engineering. They extracted various features from a Twitter dataset, including counts of words, individual word vectors, sequences of words (n-grams), and even character-level vectors. To enhance the reliability of their models, the authors utilized five well-established machine learning algorithms: Support Vector Machines (SVM), Naive Bayes, Logistic Regression, and Recurrent Neural Networks.

The approach proposed by Aljabri *et al.* (2022) utilizes Natural Language Processing (NLP) to analyze the news's main text and categorize it as either true or fake. The Random Forest (RF) and SVM models, each with a unique feature extraction method, were used in their experiments. The model is capable of detecting fake news with high reliability in the real world. Ahmed *et al.* (2020) employed various ensemble methods like bagging and boosting and integrated them with the Linguistic Inquiry and Word Count (LIWC) feature set. The authors used ensemble classifiers like bagging, boosting, voting, and random forest and demonstrated that the ensemble models outperformed the individual models.

Khan *et al.* (2021) explored various machine learning algorithms for fake news detection, including Support Vector Machines (SVM), Logistic Regression (LR), Decision Trees, and Nearest Neighbors. Their model utilized pre-trained word embeddings (GloVe) with a dimensionality of 100. The architecture included 128 filters and employed the Adam optimizer with a learning rate of 0.01. They trained the model with batch sizes of 64 and 512 over ten epochs. The authors observed that neural network-based model experienced overfitting issues with smaller datasets.

Reddy *et al.* (2019) proposed hybrid ensemble voting algorithms that combine Naïve Bayes, SVM, KNN, Decision Trees, and Random Forest machine learning algorithms. Their findings demonstrated that the ensemble algorithm outperformed individual models and yielded higher accuracy.

Prasad *et al.* (2023) designed a stacked ensemble of classifiers, including Naïve Bayes, Random Forest, and SVM, with Logistic Regression as the meta-learner. They asserted that the ensemble model produced better results compared to the individual models.

Hakak *et al.* (2021) established an ensemble model that incorporated three machine learning algorithms, namely decision tree, random forest, and extra tree classifiers.

Alghamdi *et al.* (2022) conducted both classical and advanced machine learning classifiers, using various word embedding methods and transformer-based models. To create a robust model, they combined LR, SVM, MNB, DT, RF, and XGB as base classifiers, which resulted in an F1-score of 0.70, exceeding the performance of individual classifiers.

Girgis *et al.* (2018) introduced a comprehensive method for detecting fake news in online text. To classify fake news, they developed several classifiers, including Vanilla RNN, GRU, and LSTM. Lee *et al.* (2019) designed a fake news detection model that combined Shallow-and-Wide CNN with the fastest word embedding. Their work assessed the accuracy of 100,000 articles obtained from various businesses. This model resolved the issues for only Korean language.

Dong *et al.* (2020) used a deep neural network for fake news detection called two-path deep semi-supervised learning. Their model is quite useful for making fast decisions in situations involving the real-time detection of fake news, despite their moderate accuracy performance.

A false news detection and deep convolutional neural network was proposed by Kaliyar *et al.* (2020) and used predefined GloVe word embedding. The authors used both automatic and conventional feature engineering. They made use of a false news dataset and employed a categorical cross-entropy loss function.

Yang *et al.* (2018) integrated the explicit and latent features of the image and text data into their TI-CNN model. The RMS (Root Mean Square) prop optimization technique was utilized for the study. Agarwal and Dixit (2020) focused exclusively on text processing, without the metadata features. Word embeddings improved the CNN and Recurrent Neural Network (RNN)-based model, enabling them to achieve their results.

Fang *et al.* (2019) developed a model called Self Multi-Head Attention based Convolutional Neural Networks (SMHA-CNN), which relies solely on content. They utilized Reduce LR On Plateau to monitor the validation loss of the optimizer. The authors did not prioritize the semantics of fake news.

Vaishnavi and Anitha (2020) conducted experiments with RNN-LSTM neural networks. They employed GloVe embeddings in their work, utilized the Adam optimizer to update the weights, and implemented categorical cross-entropy loss. They experimented using a standard benchmark dataset. The model obtained an average accuracy of 70%.
Drif *et al.* (2019) focused on text-related features and proposed a combine CNN and LSTM framework. This hybrid approach allows the model to extract informative features from text data and understand the relationships between words across longer distances, potentially leading to more accurate fake news detection. The authors utilized the GloVe Vector representation approach, which is known to suffer from high dimensionality.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 14, Issue 6, June 2025
DOI: 10.17148/IJARCCE.2025.14681

Jaybhaye *et al.* (2023) used an LSTM-based model for identifying false news. Their work demonstrated the ability of the LSTM-based neural network model to detect fake news and provided a vital tool in the fight against misinformation. The authors showed their experimental results for their own dataset.

Mehta *et al.* (2021) presented a model that implemented several BERT layer neural networks and achieved 74% accuracy in identifying fake news. The model relied on Natural Language Processing and Bidirectional Encoder Representations from Transformers (BERT). They fine-tuned BERT for specific domain datasets and incorporated human judgments and metadata to improve the performance of their models.

Mina *et al.* (2021) designed an automatic fake news detection system with pre-trained transformer models. They used a content-based approach and experimented with various transform models like BERT, RoBERTa, ALBERT, DistilBERT and XLNET. They preprocessed the dataset and utilized the features from body text, titles, and combinations of both. They compared the obtained results with those obtained using baseline models like Naïve Bayes, SVM, and LR. They proved that RoBERTa produced accuracy of 0.84 than the other models.

Qazi *et al.* (2020) introduced a model for detecting real and fake news utilizing transformer models. They employed a well-balanced LIAR dataset and an Adam optimizer with a batch size of 128. For the hybrid CNN, the batch size was set to 64. Comparing the performance of their model with that of the hybrid CNN, they observed that the transformer model yielded better results.

Farokhian *et al.* (2023) designed MWPBERT-MaxWorth Parallel BERT. Only the BERT network encoded the headline, and another BERT encoded the body text using the MaxWorth algorithm.

These two encoded outputs were fed into a dropout layer. Then, the output is entered into the dense layer, where the news is classified as fake or real. The effectiveness of the proposed model was evaluated using the Fake News Net dataset.

Word embedding techniques can be divided into four main categories: traditional, frequency-based, static, and contextualized embeddings (Selva Birunda and Kanniga Devi, 2021). Within frequency-based embeddings, there are further subdivisions including Bag of Words (BoW), TF-IDF, and Count Vectorizer. Static word embeddings include methods like Word2Vec, GloVe, and FastText. Contextualized word embeddings encompass techniques such as ELMo, GPT, and BERT.

III. FAKE NEWS DETECTION USING HYBRID DEEP LEARNING MODEL

False news's semantics will nearly always be the same as that of real news. Therefore, in principle, it poses a challenge for a deep neural network to effectively focus on the specific elements of a news article that indicate its falseness. Attention based models amalgamate the advantages of CNN, LSTM, CLSTM, and BiLSTM architectures with the attention mechanism, thereby enhancing the robustness of the model for sequence classification tasks.

3.1 Attention-based CNN Model (ACNN)

This architecture utilizes a series of layers to process the data: an initial input layer, followed by an embedding layer, a convolutional layer, an attention layer, and finally, an output layer. Fake news detection relies on a crucial first step: text preprocessing. This involves applying a combination of techniques to clean and refine textual data before feeding it into machine learning models for classification. After the text content of the datasets has been pre-processed, the input texts are tokenized into words. Next, Glove embedding is used to turn the words into vectors. Figure 2 shows the proposed ACNN model for fake news detection.

DOI: 10.17148/IJARCCE.2025.14681

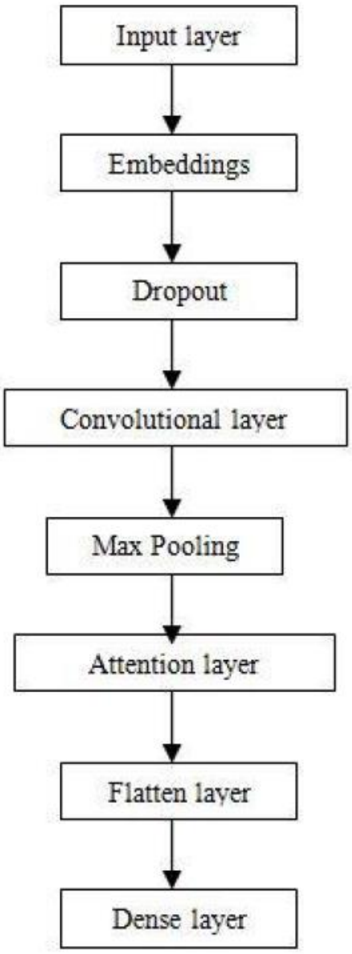

Fig. 2 Proposed ACNN model

A one-dimensional convolutional neural network can convert words in the sentence corpus into vectors in order to extract features and classify texts. GloVe embeddings that have been pre-trained in 100 dimensions are used to initialise the one-dimensional convolutional model. The model incorporates a max-pooling layer with a window size of two to reduce dimensionality. It also utilizes 128 filters of size three for feature extraction within the convolutional layer. To prevent overfitting, a dropout layer with a probability of 0.8 is employed.

3.2 ALSTM

The LSTM has 300 internal units (dimensions) and can process sequences of up to 300 time steps (words). To train the model effectively, the Adam optimizer is used with a learning rate of 0.001, which helps minimize the binary cross-entropy loss, a measure of how well the model performs. An attention layer is then added on top of the LSTM. This layer helps the model focus on the most important parts of the sequence by assigning weights to each element. These weights are calculated by a dense layer with a sigmoid activation function, which outputs values between 0 and 1.Finally, the weighted outputs from the LSTM layer are combined using a dot product operation. The entire model is trained in batches of 128 data points for 10 training epochs. The proposed ALSTM model for false news identification is depicted in Figure 3.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

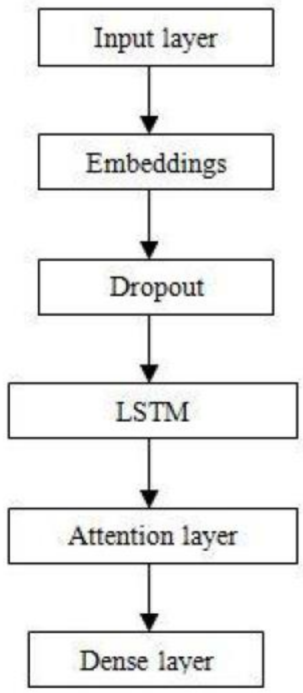

Fig. 3 Proposed ALSTM model

3.3 Attention-based BiLSTM Model (ABiLSTM)

To train the model effectively, the Adam optimizer is used. It acts like an automatic adjuster that minimizes a measure of error called binary cross-entropy loss. The learning rate, which controls how much the model adjusts with each training step, is initially set to 0.001.During training; the model processes data in batches of 128 examples at a time. A mechanism (callback) is used to monitor the loss after each training epoch. After ten epochs, the learning rate is automatically reduced to 0.0001 by the Adam optimizer to fine-tune the model and potentially improve its performance.

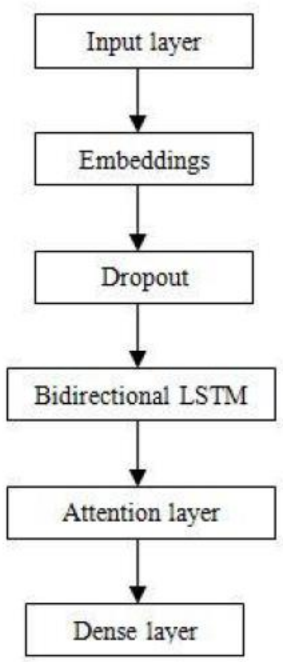

Fig.4 Proposed BiLSTM model

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

A proposed hybrid of ACNN and LSTM models for fake news detection is shown in Figure 5.

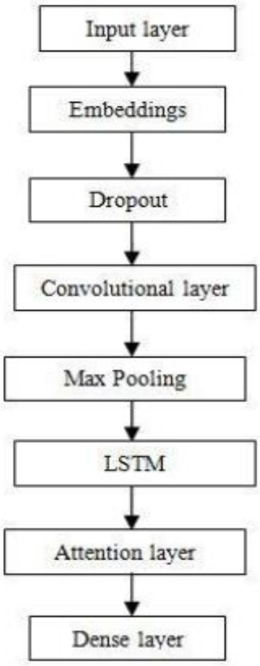

Fig. 5 Proposed CLSTM Model

IV. EXPERIEMENTAL SETUP

The attention-based deep learning-based false news detection model proposed in this study is implemented in Python version 3.5, utilizing other relevant packages. Development was carried out on the Lubuntu 16.04 LTS operating system.

3.3.1 Parameter Settings

TABLE I PARAMETERS AND METRICS

Network Models	ACNN,ALSTM,CLSTM & ABiLSTM
Optimisation Algorithm	Adam
Learning Rate	0.001
Loss Function	binary_crossentropy
Embedding_Dimension	100
Vocabulary_Size	40000
Other Parameter	Keras Defaults
Number of Epochs	10
Training Batch Size	128

The details regarding the various layers and their configurations within the proposed ACNN model for fake news detection are presented in Table II.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⋈ Peer-reviewed & Refereed journal ⋈ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

TABLE II VARIABLES OF THE SUGGESTED ACNN TECHNIQUE

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 300, 100)	924900
dropout_1 (Dropout)	(None, 300, 100)	0
conv1d_1 (Conv1D)	(None, 298, 128)	38528
max_pooling1d_1 (MaxPooling1)	(None, 74, 128)	0
flatten_1 (Flatten)	(None, 9472)	0
dense_1 (Dense)	(None, 1)	9473

Total params: 972,901
Trainable params: 48,001
Non-trainable params: 924,900

The configuration details for the various layers within the ALSTM model, designed for fake news detection, are presented in Table III.

TABLE III VARIABLES OF THE SUGGESTED ALSTM TECHNIQUE

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 300, 100)	924900
dropout_1 (Dropout)	(None, 300, 100)	0
lstm_1 (LSTM)	(None, 128)	117248
dense_1 (Dense)	(None, 1)	129

Total params: 1,042,277
Trainable params: 117,377
Non-trainable params: 924,900

The configuration details for the layers within the ABiLSTM and CLTSM models, used for fake news detection, are provided in Table IV and V, respectively.

TABLE IV VARIABLES OF THE SUGGESTED ABILSTM TECHNIQUE

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 300, 100)	924900
dropout_1 (Dropout)	(None, 300, 100)	0
bidirectional_1 (Bidirectional)	(None, 256)	234496
dense_1 (Dense)	(None, 1)	257

Total params: 1,159,653
Trainable params: 234,753
Non-trainable params: 924,900

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

TABLE V VARIABLES OF THE SUGGESTED CLSTM TECHNIQUE

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, None, 100)	924900
dropout_1 (Dropout)	(None, None, 100)	0
conv1d_1 (Conv1D)	(None, None, 128)	38528
max_pooling1d_1 (MaxPooling1)	(None, None, 128)	0
lstm_1 (LSTM)	(None, 128)	131584
dense_1 (Dense)	(None, 1)	129

Total params: 1,095,141
Trainable params: 170,241
Non-trainable params: 924,900

Trainable params: 117,377
Non-trainable params: 924,900

V. RESULTS AND DISCUSSIONS

The four different deep learning models implemented: ACNN, ALSTM, CLSTM, and ABiLSTM, are trained using training dataset and the performance of the models is validated using a validation dataset at each epoch of training. Metric calculations are carried out batch-wise and differ significantly from those done using the entire dataset for the same metric. Only the metrics computed batch-wise are displayed in the training and validation graphs. Every batch of data is trained during the training process, and the metrics for that batch are computed along with the average of the batches that have already been computed. However, in practice, those values differ slightly from those that are computed batch-wise during training if the same metric is measured for all the applicable data at once during testing.

The training phase exhibits increasing performance in terms of accuracy in each epoch. It reduces loss with increasing training in the case of ACNN and ABiLSTM. However, it transpires from the validation performance that for ACNN and ABiLSTM, the validation performance does not increase in any way while the training increases. Although ALSTM and CLSTM exhibit consistent and high training performance in terms of F1- Score and recall, they do not receive any training over the epochs and perform the lowest in terms of accuracy and precision. Table VI presents the performance metrics obtained using the LIAR training dataset.

TABLE VI Analysis of Algorithm on Training Database

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.803	0.792	0.924	0.847
ACNN	0.693	0.693	0.913	0.781
ALSTM	0.616	0.616	1	0.792
CLSTM	0.616	0.616	1	0.792
Bi-LSTM	0.737	0.77	0.803	0.781
ABiLSTM	0.649	0.649	0.979	0.781

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

TABLE VII Analysis of Algorithm on Validation Database

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.594	0.594	0.825	0.693
ACNN	0.583	0.583	0.935	0.726
ALSTM	0.572	0.572	1	0.748
CLSTM	0.572	0.572	1	0.748
BiLSTM	0.594	0.605	0.715	0.66
ABiLSTM	0.572	0.572	1.034	0.737

TABLE VIII Analysis of Algorithm on Testing Database

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.594	0.627	0.803	0.704
ACNN	0.616	0.638	0.913	0.748
ALSTM	0.616	0.616	1	0.792
CLSTM	0.616	0.616	1	0.792
BiLSTM	0.605	0.649	0.704	0.671
ABiLSTM	0.616	0.627	1.023	0.77

In this section, the training, testing, and validation dataset performance of the deep learning models ALSTM, ABiLSTM, ACNN, and CLSTM is presented. Even though the models were trained on a large dataset from LIAR, their performance on unseen data isn't perfect. After 10 training epochs, they can accurately identify around 75% of the examples they were trained on. This is evident when we analyze the accuracy, precision, and F1-scores for these three separate datasets. Figure 6 shows an accuracy comparison of the models using three distinct datasets and six different architectures.

In terms of training dataset, CNN outperforms all other models with a significant lead, achieving a highest accuracy score of 0.73.ACNN performs moderately well with a accuracy score of 0.63.ALSTM and CLSTM both models have the same performance score of 0.56, indicating similar effectiveness. ABiLSTM performs better than ALSTM and CLSTM but worse than CNN, ACNN, and BiLSTM, with a score of 0.59.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

Fig. 6 Comparison of the Models for Accuracy

In terms of validation dataset, BiLSTM and CNN both models achieve the highest performance score of 0.54. ACNN performs moderately well with a score of 0.53. ALSTM, CLSTM, and ABiLSTM models have the same performance score of 0.52, indicating similar effectiveness. ACNN performs slightly lower than BiLSTM and CNN but better than ALSTM, CLSTM, and ABiLSTM. In terms of test dataset, ACNN, ALSTM, CLSTM, and ABiLSTM all have the highest performance score of 0.56. This indicates that adding attention mechanisms (ACNN, ALSTM, ABiLSTM) provide a marginal performance. BiLSTM has a performance score of 0.55, slightly lower than other models. CNN has the lowest performance score of 0.54 among the models compared.

Figure 7 shows the comparison of the models with respect to precision across three datasets and six network models. In terms of training dataset, CNN achieves with a precision score of 0.72, indicating its strong capability in capturing relevant textual features for fake news detection. BiLSTM model close behind with a precision of 0.70, showing that understanding text context bidirectionally is highly effective. ACNN performs well with a score of 0.63, indicating that attention mechanisms add value but not enough to surpass CNN. ABiLSTM shows a moderate performance with a score of 0.59, suggesting the combination of attention and bidirectional processing is beneficial but not optimal for this task. ALSTM and CLSTM both scoring 0.56, indicating that while useful, they do not provide a significant edge over the other models.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

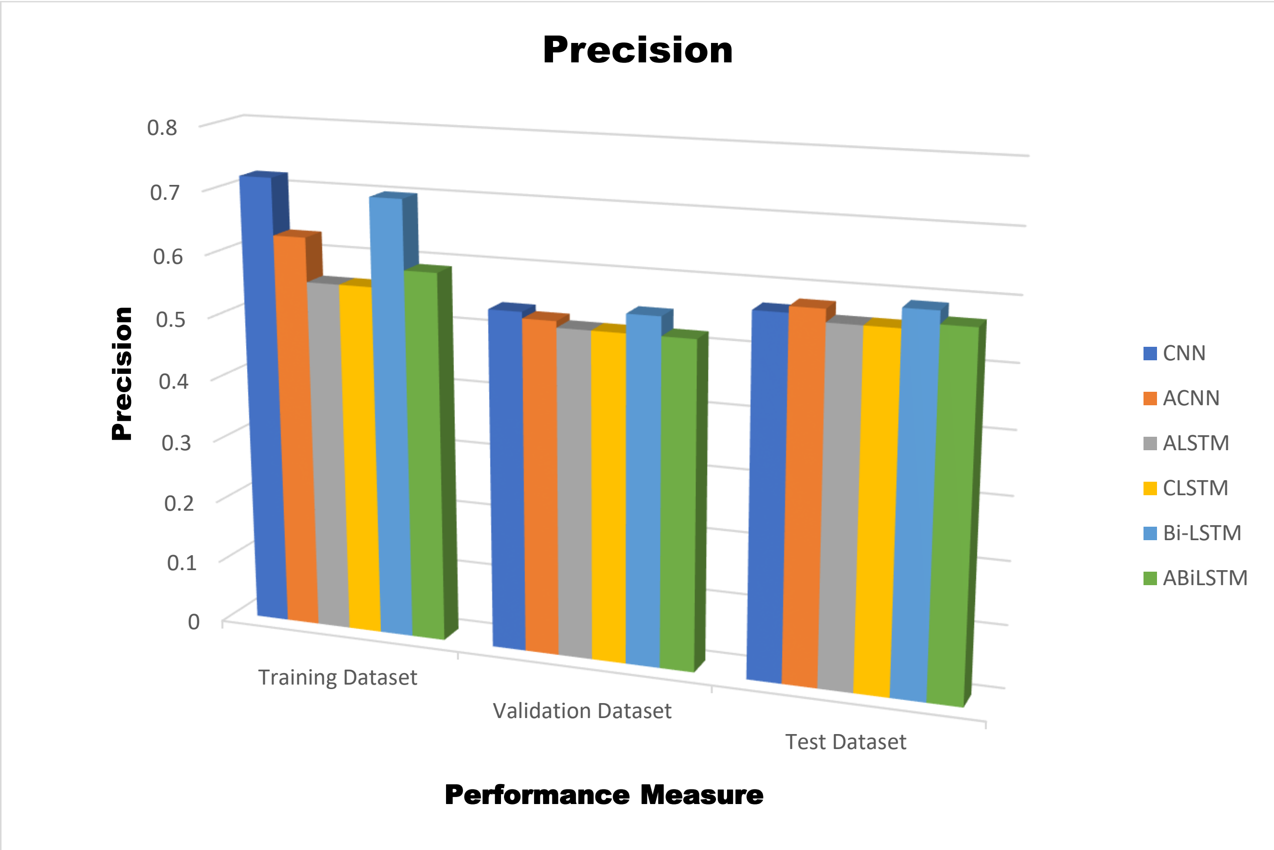

Fig. 7 Comparative Analysis of Techniques for Precision

In terms of validation dataset, BiLSTM with a precision score of 0.55, indicating its strong ability to minimize the false positives and accurately detect false news. CNN and ACNN achieve the precisions of 0.54 and 0.53, individually. The CNN slightly outperforms ACNN. ALSTM, CLSTM and ABiLSTM achieve the precision score of 0.52, all showing similar performance.

With a precision of 0.59 on the test dataset, the BiLSTM model shows the maximum efficacy in reducing false positives by accurately identifying fake news. ACNN and ABiLSTM achieves the precision score of 0.58, 0.57 respectively. ACNN shows a slight improvement over CNN, indicating that attention mechanisms enhance precision. CNN, ALSTM and CLSTM achieve the precision score of 0.57, 0.56 and 0.56 respectively. While CNN performs well, ALSTM and CLSTM show similar, slightly lower precision, suggesting that while they capture sequential dependencies and local patterns, they do not outperform the other models in precision.

Figure 8 below illustrates the comparison of the models for recall across three datasets and six network models. Concerning the training dataset, ALSTM and CLSTM with perfect recall scores of 1.00, indicating they are extremely effective at identifying all fake news instances in the training dataset. ABiLSTM, CNN and ACNN achieve recall score of 0.89, 0.84 and 0.83 respectively. These models are also very effective, but they miss a few instances of fake news compared to ALSTM and CLSTM. BiLSTM with a recall score of 0.73, indicating it is less effective at identifying all fake news instances, leading to more false negatives compared to other models.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ∺ Peer-reviewed & Refereed journal ∺ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

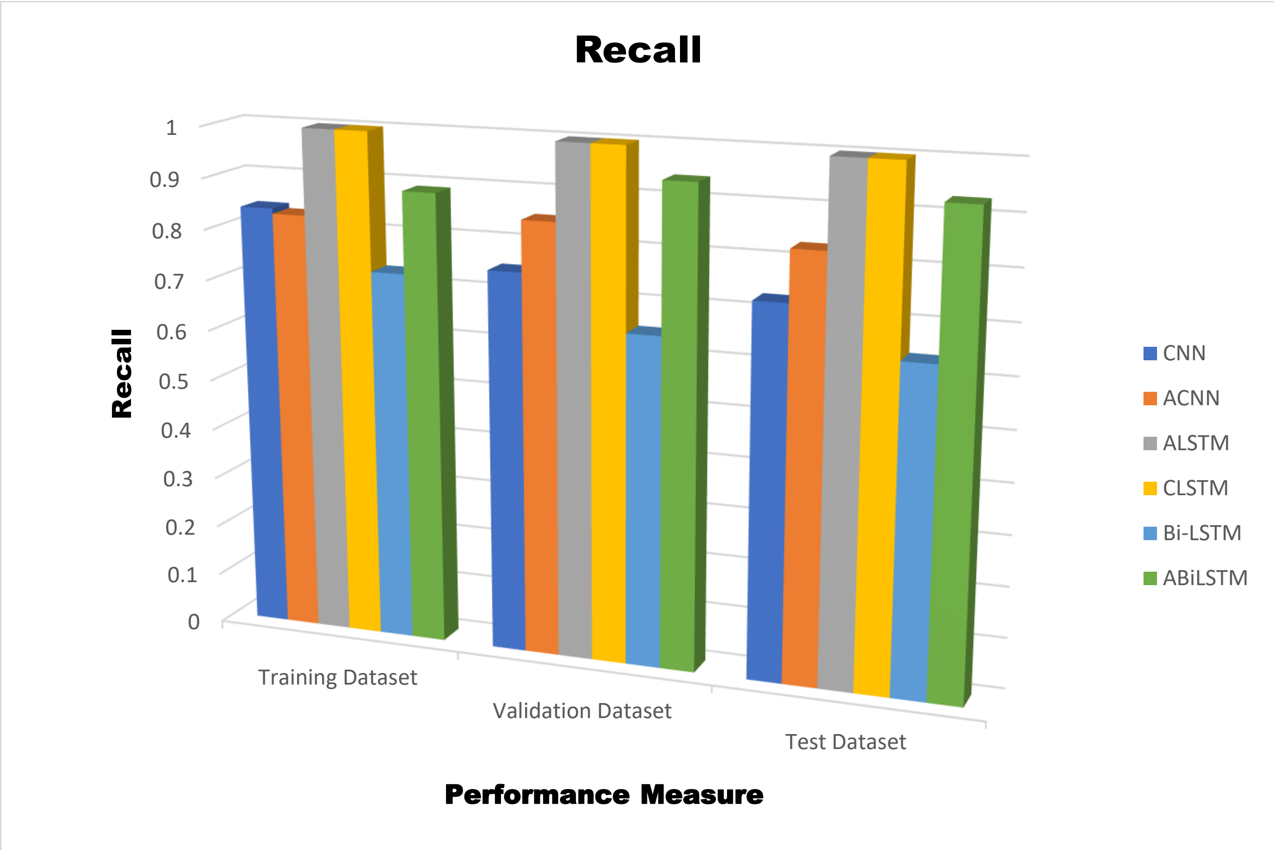

Fig. 8 Comparative Analysis of Techniques for Recall

In terms of validation dataset, ALSTM and CLSTM have the highest recall scores of 1.00, indicating that they are performing exceptionally well in terms of correctly identifying relevant instances. ACNN follows closely with a recall score of 0.85, indicating strong performance but slightly lower than the LSTM models.

ABiLSTM also performs well with a recall score of 0.94, showing high capability in capturing relevant instances. While the CNN achieves a recall score of 0.75, which is lower, compared to the other models, it still indicates a respectable ability to identify relevant instances. BiLSTM has the lowest recall score of 0.65, indicating comparatively weaker performance in correctly identifying relevant instances. The models with the greatest recall scores of 1.00 on the test dataset are ALSTM and CLSTM, which demonstrate their consistently good performance in accurately detecting relevant events. Recall score of 0.83 for ACNN is little lower than that of LSTM models, however it still shows good performance in comparison. Comparable to the validation dataset, ABiLSTM likewise exhibits strong performance, demonstrating a high capacity for capturing important features with a recall score of 0.93. CNN scores worse than the other models, with a recall of 0.73. BiLSTM, which is comparable to the validation dataset, has the lowest recall score of 0.64. The performance of the models in regard to F1-score for three distinct datasets and six models is displayed in Figure 9.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁝ Peer-reviewed & Refereed journal ⁝ Vol. 14, Issue 6, June 2025

DOI: 10.17148/IJARCCE.2025.14681

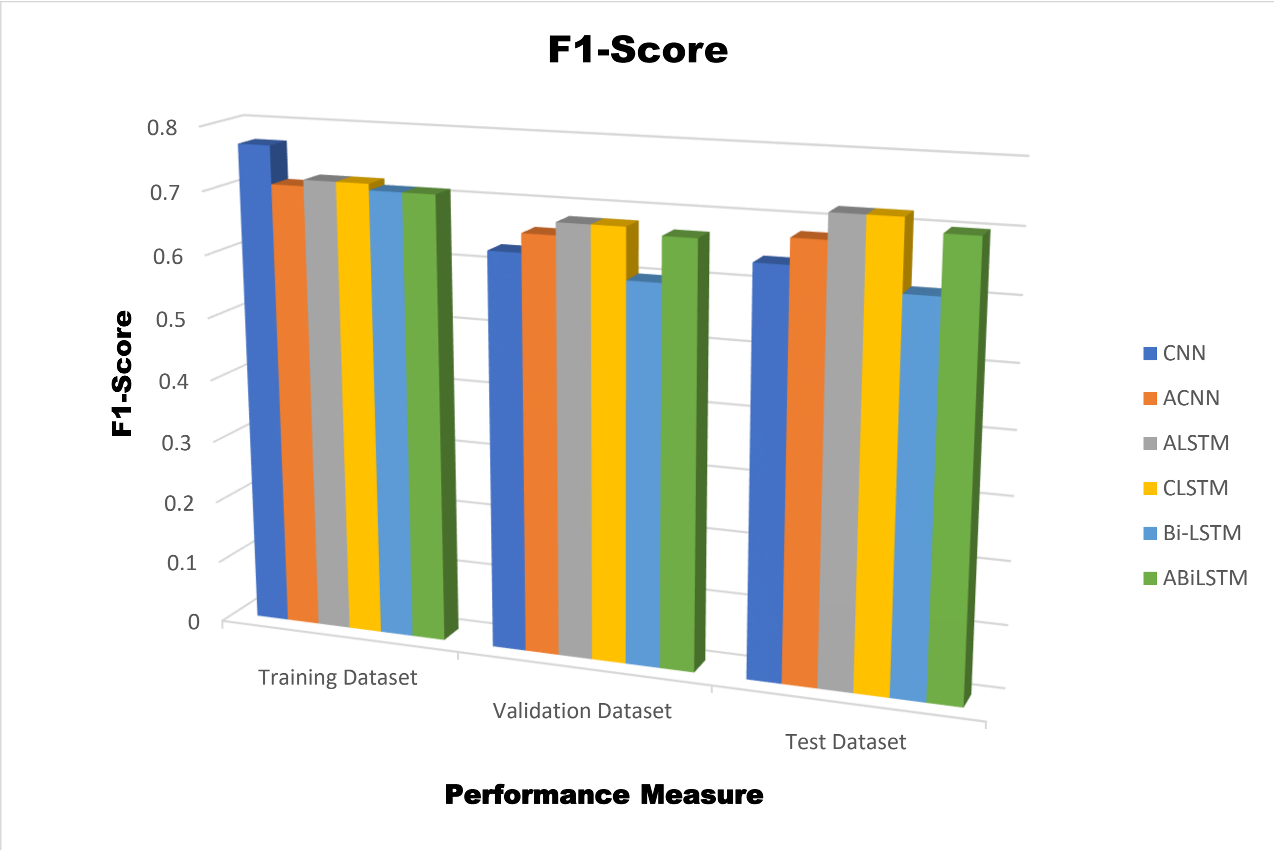

Fig. 9 Comparative Analysis of Techniques for F1-Score

The CNN model obtains a relatively high F1-score of 0.77 on the training dataset but exhibits a drop in performance on both the validation and testing datasets with the F1-score of 0.63 and 0.64 respectively. This suggests that the model might be overfitting to the training data. ACNN performs consistently across all datasets, with slightly lower F1-score of 0.71 compared to CNN on the training dataset but maintaining better generalization to the validation and testing datasets with F1-score of 0.66 and 0.68 respectively. Both ALSTM and CLSTM consistently achieve moderate to high F1-scores of 0.72, 0.68 and 0.72 across all datasets, indicating robust performance and generalization ability. BiLSTM shows a decrease in F1-score of 0.71 from the training dataset to the validation and testing datasets, indicating potential overfitting and less robust performance compared to other models. ABiLSTM demonstrates relatively consistent and good performance across all datasets, with a slight decrease in F1-score of 0.71 from training to validation, but a slight improvement on the testing dataset. This analysis highlights the effectiveness of CNNs and BiLSTMs for fake news detection, with CNNs slightly outperforming due to their strong feature extraction capabilities.

VI. CONCLUSION

In this paper, Attention-based models, such as CLSTM, ALSTM, ABiLSTM, and ACNN, provide viable methods for detecting fake news by utilising attention mechanisms to enhance model performance and capture significant textual elements. These models improve accuracy and resilience in false news detection tasks by efficiently handling contextual and sequential information in text data. The attention mechanism seems to slightly improve the test accuracy, as seen in ACNN and ABiLSTM models both achieving 0.56 test accuracy. Therefore, attention helps in focusing on important features, which improves model generalization. ACNN and ABiLSTM models with attention mechanisms generally maintain higher recall and better balance in precision and recall on test datasets, indicating effective feature selection and generalization. ACNN and ABiLSTM benefit from attention mechanisms, showing improved F1-scores of 0.66, 0.67 on the validation and 0.68, 0.70 on test datasets compared to their non-attention models (CNN and BiLSTM). Among them, ABiLSTM performs slightly better, indicating the effectiveness of combining bidirectional LSTMs with attention. These models find it challenging to recognize the subtle distinctions that separate authentic news from fabricated stories. Consequently, the enhancement in performance provided by attention mechanisms might be limited.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 6, June 2025
DOI: 10.17148/IJARCCE.2025.14681

REFERENCES

[1] Wang, W. Y. (2017). " Liar, liar pants on fire": A new benchmark dataset for fake news detection. *arXiv preprint arXiv:1705.00648*.
[2] Aljabri, M., Alomari, D. M., & Aboulnour, M. (2022), "Fake news detection using machine learning models", 14th International Conference on Computational Intelligence and Communication Networks (CICN), Al-Khobar, Saudi Arabia. doi:10.1109/cicn56167.2022.10008340.
[3] Khan, J. Y., Khondaker, M. T. I., Afroz, S., Uddin, G., & Iqbal, A. (2021), "A benchmark study of machine learning models for online fake news detection", Machine Learning with Applications, 4(100032), 100032. doi:10.1016/j.mlwa.2021.100032.
[4] Bhanu Prakash Reddy, P., Reddy, M. P. K., Venkata Manaswini, G., & Reddy, K. M. (2019), "Fake Data Analysis and Detection Using Ensembled Hybrid Algorithm", In 3rd International Conference on Computing Methodologies and Communication (ICCMC). doi:10.1109/iccmc.2019.8819741.
[5] Sreegar Prasad R, Dinesh R, Ahalya R, Dr. K. Padmavathi (2023), "Fake news detection using stacked ensemble of classifiers", International Research Journal of Modernization in Engineering Technology and Science, doi:10.56726/irjmets37167.
[6] Hakak, S., Alazab, M., Khan, S., Gadekallu, T. R., Maddikunta, P. K. R., & Khan, W. Z. (2021). An ensemble machine learning approach through effective feature extraction to classify fake news. *Future Generation Computer Systems*, *117*, 47-58.
[7] Alghamdi, J., Lin, Y., & Luo, S. (2022), "A comparative study of machine learning and deep learning techniques for fake news detection", Information (Basel), 13(12), 576. doi:10.3390/info13120576.
[8] Girgis, S., Amer, E., & Gadallah, M. (2018), "Deep learning algorithms for detecting fake news in online text", 13th International Conference on Computer Engineering and Systems (ICCES), Cairo, Egypt. doi:10.1109/icces.2018.8639198
[9] Lee, D. H., Kim, Y. R., Kim, H. J., Park, S. M., & Yang, Y. J. (2019). Fake news detection using deep learning. *Journal of Information Processing Systems*, *15*(5), 1119-1130.
[10] Dong, X., Victor, U., & Qian, L. (2020), "Two-path deep semi supervised learning for timely fake news detection", IEEE Transactions on Computational Social Systems, 7(6), 1386–1398. doi:10.1109/tcss.2020.3027639.
[11] Rohit Kumar Kaliyar, Anurag Goswami, Pratik Narang and Soumendu Sinha, (2020), "FNDNet – A deep convolutional neural network for fake news detection", Cognitive Systems Research, Elsevier.
[12] Yang, Y., Zheng, L., Zhang, J., Cui, Q., Li, Z., & Yu, P. S. (2018). TI-CNN: Convolutional neural networks for fake news detection. *arXiv preprint arXiv:1806.00749*.
[13] Yong Fang, Jian Gao,Cheng Huang,Runpu Wu. (2019), "Self Mult-Head Attention based Convolutional Neural Networks for fake news detection",https:// doi.org/10.1371/journal.pone.02222713.
[14] Vaishnavi. R, Anitha Kumari. S (2020), "Fake News Detection using Deep Learning", International Journal of Innovative Technology and Exploring Engineering (IJITEE). ISSN:2278-3075, Vol.9, Issue.9.
[15] Drif, A., Zineb, F., & Hamida, S. (2019), "Fake News detection Method Based on Text-Features", In Ninth International Conference on Advances in Information Mining and Management. Nice, France.
[16] Jaybhaye, S. M., Badade, V., Dodke, A., Holkar, A., & Lokhande, P. (2023), "Fake News Detection using LSTM based deep learning approach", ITM Web of Conferences, 56, 03005. doi:10.1051/itmconf/20235603005.
[17] Mehta, F., Dwivedi, A., Patra, A., & Kumar, M. A. (2021), "A Transformer based architecture for fake news classification", Social Network Analysis and Mining, 11, 1-12.
[18] Mina Schutz, Alexander Schindler, Melanie Siegel and Kawa Nazemi (2021), "Automatic Fake News Detection with Pre-Trained Transformer Models", Pattern Recognition, ICPR International Workshops and Challenges (pp.627-641), doi: 10.1007/978-3-030-68787-8_45.
[19] Qazi, M., Khan, M. U. S., & Ali, M. (2020), "Detection of fake news using transformer model", 3rd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), Sukkur, Pakistan. doi:10.1109/icomet48670.2020.9074071.
[20] Farokhian, M., Rafe, V., & Veisi, H. (2023), "Fake news detection using dual BERT deep neural networks", Multimedia Tools and Applications, 83(15), 43831–43848. doi:10.1007/s11042-023-17115-w.
[21] Selva Birunda, S. and Kanniga Devi, R. (2021), "A Review on Word Embedding Techniques for Text Classification", Innovative Data Communication Technologies and Application, Springer, Singapore, 267-281. https://doi.org/10.1007/978-981-15-9651-3_23.