DEEP LEARNING BASED FAKE NEWS DETECTION ON SOCIAL MEDIA NETWORKS

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Abstract
Fake news exist even before social media but it has multifold since it's advent. Fake news is a news designed to deliberately spread hoaxes propaganda and disinformation. Fake news stories usually spread through social media sites like Facebook, Twitter, and Instagram We detected fake news deep learning to examine the account's behavior by utilizing a number of features, including some news content features that are associated with the Facebook account. This research is conducted on CNN, LSTM, KNN, RNN, decision tree models with five experiments using fake news dataset. Proposed model achieved best accuracy 96% for fake news detection as compared to other models.

INTRODUCTION

Fake news means the false information about a specific event that happened on a particular date. Since the last decade, the internet is one of the integral parts of our daily routine [6]. Traditional ways of getting news such as newspapers or TV channels are getting boring and unpopular. With the help of the internet, news can transmit from one part of the world to another without any delay. Fake news can spread through social networking feeds, news blogs, and online newspapers. The news of news channels or newspapers is somehow verified by using authenticated mechanisms adopted by newspapers and news channels [7][8]. However, information sharing through social media is not based on any authentication mechanism. According to one report, 50% of Facebook posts referral links are fake and only 20% of referral. Links are from reputable web sites. So, most of the information or news which are getting viral on social media platforms is not verifiable and most of them are fake. Misleading information on the web is divided into three categories [9][10][11]:

a) Fake news includes, large scale fabrication in news and hoaxes, etc
b) Rumors include the information that is not verified by the source
c) Normally these are breaking news and other includes clickbait, which are also one of the wide contributors in the fake news.

Social media platforms without knowing the news is valid or not. According to the study it is observed that only more than 60% young generation have information through social media [14]-[18]. The term "fake news" first surfaced during the 2016 U.S. presidential election, when

President Donald Trump used it to denigrate news outlets who published stories critical of him. "A broad definition is that ''the fake news is the false news'', while narrowing down this concept the given definition is "fake news is the deceptive news" [19][20]. However, despite of the absence of a universal definition the most accepted is that fake news is the news which is intentionally and verifiably false [37]. Accepting this definition, two words stand out, the intention and the authenticity" [38][39].

The preceding definition of news which was a report of a new event from reliable authority has improved as a result of digitalization [31, 34]. Now, anyone can conduct a perfect interview and spread false information. Fake news uses words like propaganda, misinformation, incorrect news, and rumors among others. The type and goal of the information, whether it aims to inform or mislead and whether it is news or formation differentiate these concepts from the concept of fake news [24]

- **Satires and parody:**
- are the way that comedy shows present the truth especially in comical way. It tends to present funny stories like they are true but mostly they are false [21].

- **Rumors:**

are categorized as unconfirmed information which are in doubt. Rumors tend to feast fast with no intention to deceive the spectators. The content of the rumors is false and fake [25].

- **Spam**:
- about advertising users without it cannot be considered a news. Also intention is not very clear because spams do not deceive public directly but it is used for advertising purpose [22][23].

- **Scams and Hoaxes:**

contain information that is half true or completely inaccurate. The intention is to mock and deceive the audience. [26].

Click bait is a small part of the text users to view a specific website. The snippet characterized by sensational language users. Type of fake news is used for making purpose gaining profit based on the number of click article in the article for spreading fake news. [27].

. **Disinformation** is a part of news that mislead the people[28]-[32].

Moreover, deep learning techniques have revolutionized the field of artificial intelligence by enabling machines to learn and make predictions from vast amounts of data [48]. Among the various deep learning techniques, Recurrent Neural Networks (RNN), K-Nearest Neighbors (KNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Decision Trees have emerged as popular and powerful methods for solving complex problems. Each of these techniques have their unique capabilities [40]. **Recurrent Neural Networks** (RNN): RNNs are designed to handle sequential data by processing inputs in a sequential manner while maintaining a hidden state [49].This makes them well-suited for tasks like speech recognition, natural language processing, and time series analysis. **K-Nearest Neighbors (KNN)**: KNN is a simple yet effective algorithm used for both classification and regression tasks. It works based on the assumption that similar data points tend to belong to the same class [41]. KNN calculates the distance between a query point and its neighboring points to determine its classification. **Convolutional Neural Networks (CNN):** CNNs are primarily used for analyzing visual data such as images and videos [33]. They leverage convolutional layers to automatically extract relevant features from the input data. CNNs are known for their ability to capture spatial hierarchies by using filters to scan local regions and pooling layers to reduce dimensionality [42]. **Long Short-Term Memory (LSTM):** LSTMs are a type of RNN architecture specifically designed to address the vanishing gradient problem, which can hinder the learning process in traditional RNNs [53]. LSTMs introduce memory cells and gates that selectively retain or forget information over long sequences. **Decision Trees:** Decision trees are a popular method for both classification and regression tasks [34]. They organize data into a hierarchical structure of decisions and create rules for prediction based on these decisions. Decision trees are interpretable, easy to understand, and can handle both categorical and numerical data [52]. They can also handle missing values and outliers, making them robust in real-world scenarios [35][36].

Deep learning techniques such as RNN, KNN, CNN, LSTM, and Decision Trees have distinct capabilities and are applied in various domains [54]. Understanding their strengths and appropriate use cases can help data scientists and machine learning practitioners effectively solve complex problems and make accurate predictions. Therefore, we have devised a mechanism to detect the fake new using deep learning approaches to effectively detect and control the spread of fakenews on social media platforms.

2. LITERATURE REVIEW

It is quite challenging to discern the topic to which the information is connected on social media platforms because of the huge volume of data available. Additionally, news websites which are regarded as trustworthy sources can provide false information when it serves their interests and goes against what the public expects. It is to provide precise, accurate, and true news that is appropriate for news organizations. Unfortunately, media outlets can disseminate false information when it suits them, and in the modern day with the capabilities of internet, false information may spread at an astounding rate. [11].

This instance demonstrates the critical need of study as a first step in a challenging undertaking. This field is the subject of several investigations. The CNN, LSTM, RNN, KNN, and Decision tree models were used to find a simple approach to identify bogus news. At this point, Facebook data was utilized as opposed to online news stories. In addition to having a low accuracy rate, employing social media data just for analysis is insufficient. Due to this, we have used news data sets from more than 10 sources in this research. [12].

Rubin et al. contributed to this study which deals with the subset of parody news that is false. Satirical tales include hints that purposefully expose their falsehood. Satire news should be viewed as a gesture at the end, but fake news asks readers to trust a false truth. The writers' reporting style and the qualities of humor and satire news are thoroughly examined in this study. The newspaper examined news stories from twelve current news themes in the following four categories: business, social news, science, and citizenship. In this study, deep learning algorithms are used to identify news satire based on attributes. The models had a 98% accuracy rate and a 91% recall rate. [13].

Deep learning techniques are still under development, but they have the potential to be a powerful fake news detection [51]. As these techniques continue to improve, they will become more and more effective at identifying fake content [43]. Table 1 shows the comparison of various deep learning models.

Here are some of the benefits of using deep learning techniques for fake news detection [44] [45] [46].

- Accuracy: Deep learning techniques have been shown to be very accurate at detecting fake news [50].
- Scalability: Deep learning techniques can be used to process large amounts of data, which is important for detecting fake news, as it is often spread widely online.
- Robustness: Deep learning techniques are robust to noise and other challenges, which can make it difficult to detect fake news using traditional methods.

Deep learning techniques are a promising approach for detecting fake news [55]. However, there are still some challenges that need to be addressed before these techniques can be widely used [47]-[56].These are some significant research gaps including limited labelled datasets [57], and detecting fake news across platforms and languages [58] [59]. Moreover, a mix of textual, graphic, and audiovisual information is frequently used to promote fake news. The rich background offered by other modalities is largely ignored in current research, which mostly concentrates on text-based analysis. It is crucial to comprehend how users assist in the spread and consumption false news. Hence, there is a need to fill up the research gaps to considerably aid in the creation of methods for detecting false news that are more precise, reliable, and all-encompassing. As a result, we have developed the solution to encounter fake news on social media.

Table 1: Deep learning classification models comparison

References	Methodology	Results	Pros	Limitation	Uses
[1]	CNN	Accuracy:91% Precision:96% Recall:87% F-1 Score:91%	Effective at capturing local patterns in text data	May struggle with long-range dependencies	Text classification tasks
[2]	RNN	Accuracy: 91% Precision: 82% Recall :95%, F1 Score: 90%	Captures sequential dependencies	Can suffer from vanishing/exploding gradient	Text classification with long-range dependencies
[3]	KNN	Accuracy:62% Precision:61% Recall:77% F-1 Score:68%	Simple and easy to implement	Computationally expensive during classification	Small to medium-sized datasets
[4]	LSTM	Accuracy:96% Precision:94% Recall:73% F-1 Score:82%	Captures sequential dependencies	Can suffer from vanishing/exploding gradient	Text classification with long-range dependencies
[5]	Decision Tree	Accuracy:75% Precision:83% Recall:65% F-1 Score:73%	Interpretable and easy to understand	Can over fit or be sensitive to small changes	Text classification tasks

3. METHODOLOGY

In this research we have used deep learning algorithms such as LSTM, CNN, KNN and DTs to detect false news. Dataset, data preparation, feature extraction, model training, and assessment are some of the processes in the technique. The following subsections describe each step and the specific models used in detail.

3.1 DATASET

The first step in our methodology is to collect a suitable dataset our fake news detection. We obtained a publicly available dataset from the true and false information data is selected for GitHub. The 1st dataset contain four labels “Title”, “Text”, “Subject”, “Date.” The first dataset has fake news the second dataset, real news, comprises 21417 rows and 4 columns, whereas the first has 23481 rows and 4 columns. Total dataset true and fake news 44888 rows and 4 column depicted in Figure 1.

Out[20]:

	subject	date	news	output
0	News	2017-12-31	Donald Trump Sends Out Embarrassing New Year'...	0
1	News	2017-12-31	Drunk Bragging Trump Staffer Started Russian ...	0
2	News	2017-12-30	Sheriff David Clarke Becomes An Internet Joke...	0
3	News	2017-12-29	Trump Is So Obsessed He Even Has Obama's Name...	0
4	News	2017-12-25	Pope Francis Just Called Out Donald Trump Dur...	0
...	...	...	...	...
21412	worldnews	2017-08-22	'Fully committed' NATO backs new U.S. approach...	1
21413	worldnews	2017-08-22	LexisNexis withdrew two products from Chinese ...	1
21414	worldnews	2017-08-22	Minsk cultural hub becomes haven from authorit...	1
21415	worldnews	2017-08-22	Vatican upbeat on possibility of Pope Francis ...	1
21416	worldnews	2017-08-22	Indonesia to buy $1.14 billion worth of Russia...	1

44888 rows × 4 columns

Figure 1: True and fake news dataset

3.2. Data Preprocessing

False news is a significant issue that has been on the rise in recent years. It can have a negative impact on society, as it can spread misinformation and erode trust in institutions. There are several techniques to identify false news, and one of the most important steps is the text's preprocessing. Text preprocessing is the process of preparing text data for future analysis by cleaning and modifying it. Preprocessing can aid in the removal of noise from the data and the identification of characteristics that can be used to differentiate between true and false news in the case of fake news detection. A number of different techniques that can be used for text preprocessing. Some of the most common techniques included.

3.2.1 Lowercasing

This involves converting all of the text to lowercase letters. This can help to normalize the data and make it easier to process.

3.2.2. Punctuation Removal

This involves removing punctuation marks from the text. This can help to remove noise from the data and focus on the words themselves.

3.2.3. Stop Word Removal

This involves removing common words from the text that do not add much meaning. Stop words are typically words that are used frequently, such as "the," "and," and "of."

3.2.4. Tokenization

To achieve this, separate the text into its component words or tokens. This can aid in locating the text's main ideas.

3.2.5. Stemming

This entails reverting to the basic form of words This can help identify words that are related to each other, even if they are spelled differently.

3.2.6. Lemmatization

This involves converting words to their lemmatized form. This is similar to stemming, but it takes into account the context of the word.

Feature Extraction

In true and false news detection using DL, the process of removing important structures from the copy data that can be used to Dl model. The aim of article removal to represent the text data way that captures its important characteristics and patterns, making the model to learn detection true and false.

Detection of Fake News Models

3.3.1. CNN Model

CNN model false data detect strength convolutional layers to extract useful information from the textual material. In this approach, the CNN model treats the news articles as One-

dimensional sequences of words or characters. By applying convolutional filters of varying sizes, the model can capture local patterns and relationships within the text. Max pooling layers are commonly employed to reduce the dimensionality and retain the most salient structures.
The removed structures are then served into linked layers for taxonomy. The CNN model learns to discriminate news by leveraging hierarchical structure the convolutional layers to identify important patterns and linguistic cues. This approach is effective in capturing both local and global dependencies within the text, enabling accurate fake news classification.

3.3.2. K Nearest Neighbors (KNN)
Fake news detection using the KNN involves comparing similarity feature vectors the news articles to determine their classification as fake or real. In this approach, each news article characterized as a feature path multi features based on relevant features extracted from the text. During the classification phase, the k-NN model compares the feature vector of an unknown news article with the feature vectors of labeled articles in the training set and assigns it popular discussion among its KNN. The choice the k determines the number of neighboring articles considered. The KNN model relies on the assumption that articles with similar feature vectors are likely to belong to the same class. By measuring the proximity between articles, the k-NN model can make predictions for new, unseen news articles.

Decision Tree
Fake news detection using a decision tree model involves constructing DL or attribute, every node represent classification (fake or real news). The DL model learns to data based on the most informative features, creating rules that separate the two classes. During classification, a news articles features are traversed through the decision tree, following the path based on the feature values until a leaf node is reached, which determines the news article's classification. The decision tree model provides interpretability by revealing the feature importance and rules used for classification, enabling users to understand the factors influencing the model's decisions.

Long Short Term Memory
False data detection using a LSTM model involves leveraging the sequential nature of text data to capture long-range dependencies and temporal dynamics. RNNs of the LSTM kind are intended to vanishing features difficult and retain information over longer sequences. In this approach, STM model processes the textual information word by word, capturing the contextual information and relationships between words. By learning from label data true and fake news article LSTM recognize underlying patterns and linguistic cues that distinguish between the two classes. During classification, the trained LSTM model analyzes the sequence of words in an unseen news article and makes a prediction regarding its authenticity. The LSTM model's ability to model sequential information makes it fake news detection tasks where considerate the temporal situation is crucial.

Recurrent Neural Network (RNN)
False news detect using Recurrent Neural Network models involves leveraging to sequential nature of text data to capture contextual information and dependencies between words. Unlike feed-forward RNN allowing information time. In this approach, the RNN model processes the news articles word by word, updating its hidden state at each step to retain information from previous words. This enables the model to fit the context and temporal dynamics features.
By training dataset on articles, the RNN model learns to recognize patterns and linguistic cues that distinguish between the two classes. During classification, the RNN model analyzes the sequence of words in an unseen news article and makes detect accumulated knowledge to preceding arguments. The RNN model ability to capture sequential dependencies make detect fake news tasks where understanding the temporal context is crucial.

Model Evaluation

Model assessment is a vital phase in the machine learning workflow since it enables you to gauge your model's effectiveness for the job at hand and measure its performance. A false news detection model's effectiveness may be evaluated using a variety of assessment measures, like:

Accuracy: Accuracy is used for evaluation parameters for binary classification tasks detection fake news.

Precision: It is the proportion of the model's overall positive predictions to the genuine positive forecasts.

Recall: That this is the ratio of all of the actual positive instances to correctly anticipated positive cases positive occurrences in the dataset.

F1 Score: Precision and recall have a harmonic mean. It offers a fair measure of accuracy and recall and is a widely used statistic for unbalanced datasets.

Hyper parameter Tuning

The Hyper parameter choosing the best settings DL model to maximize its performance on a certain task. "The learning rate layers, layer count, and number of neurons per layer are examples of hyper parameters" which are parameters that are established before the model trained. The display of the model may be significantly impacted by choosing the appropriate hyper parameters.

Output Fake News Detection Model

An article's categorization as "real" or "fake" is often indicated by a binary output from a fake news detection programmer. In this context, "real" news is used to describe news stories that are factually correct and founded on reliable information, whereas "fake" news is used to describe news pieces that include false or misleading information misleading the false information. Output of the false news detection model might take the form of a binary label (0 or 1) or a likelihood score (ranging from 0 to 1). The model predicts that an item if the probability score is closer to 0, and if the probability detect is greater than 1, is more likely to be real news. Present Figure 2.

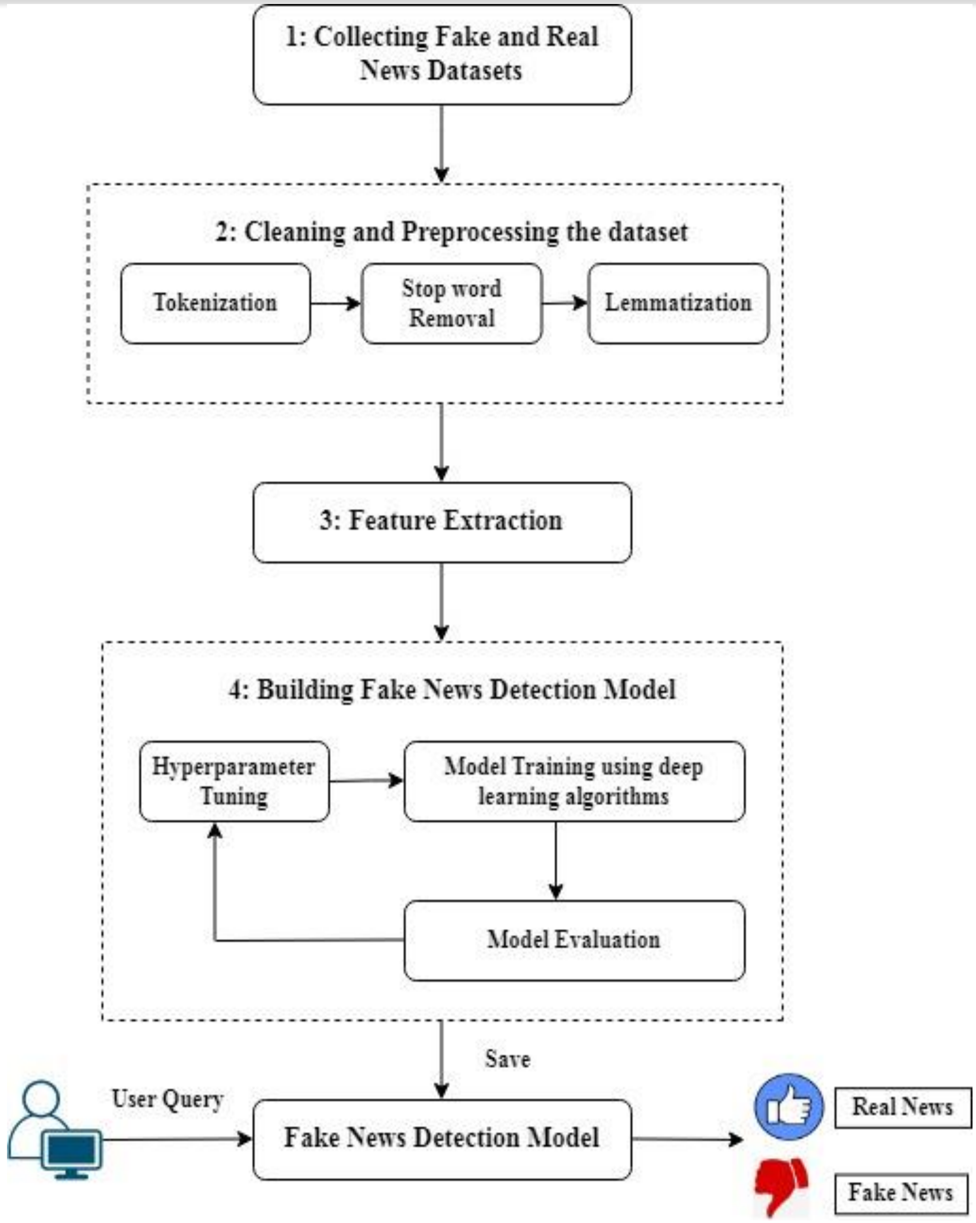

Figure 2: Fake news detection model

Fake News Detection Architecture

This research's primary contribution is the well-labeled schematic Figure 3 depicts a generic architecture for fake news detection. We looked at a lot of designs before settling on this one previous works in the field of false news. These are the key elements of this architecture.

Dataset:

The dataset is regarded as a major component of the fake news detection architecture since it provides data for both training and testing false news detection algorithms. Since we previously said that fake news detection models frequently apply machine learning or deep learning algorithms to determine the veracity of the connected news on social media, the proposed model needs to be trained and evaluated in order to produce an effective fake news detection system as a whole.

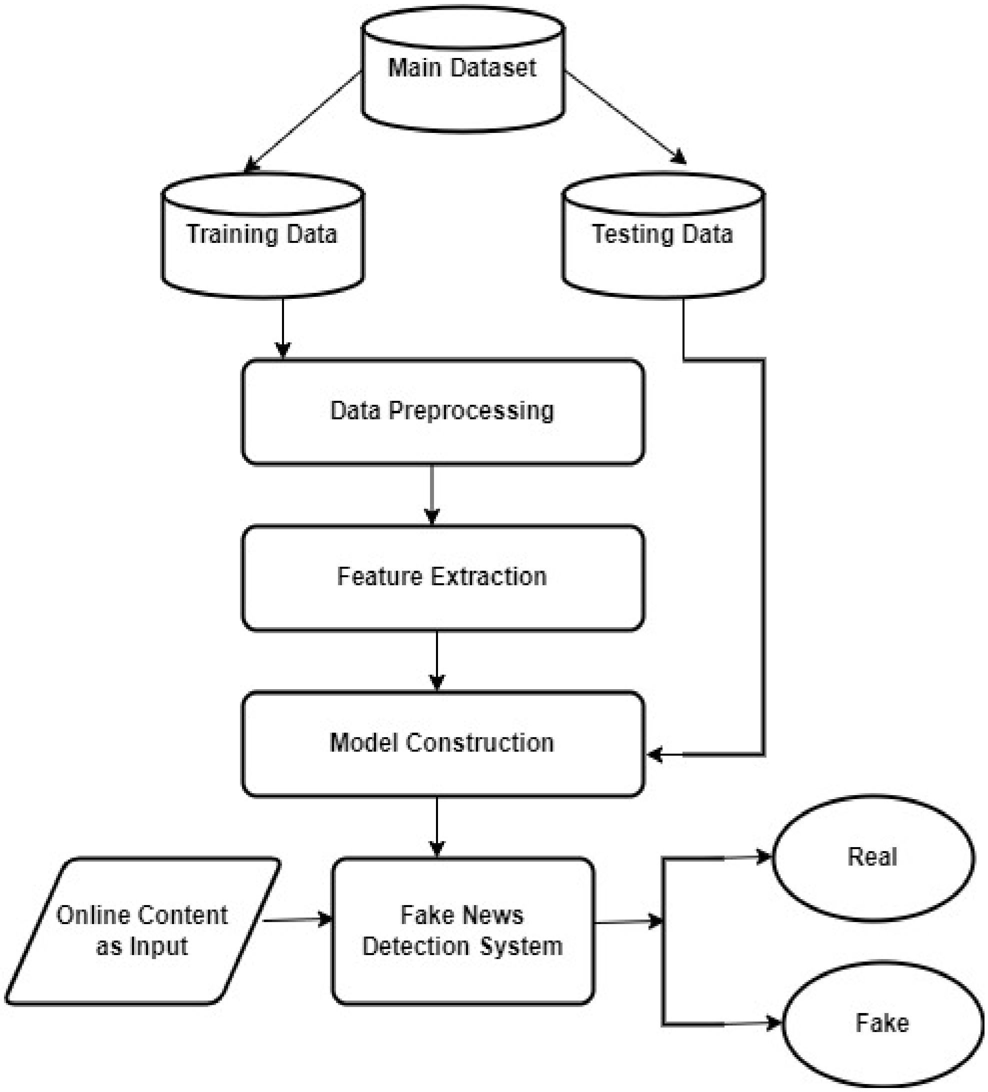

Figure 3. Basic Fake News Detection Architecture.

Preprocessing:
All preprocessing operations required to handle training data collected from the main dataset must be carried out by the data preprocessing component. It verifies missing or null performs preprocessing procedures like tokenization on the training data, stemming.

Feature Extraction:
In true and false news detection using DL. The process of removing important structures from the copy data that can be used to Dl model. The aim of article removal to represent the text data way that captures its important characteristics and patterns, making the model to learn detection true and fake news.

Deep learning Models:
By enabling machines to learn from and make predictions from large volumes of data, deep learning techniques have revolutionized the area of artificial intelligence. Recurrent neural

networks (RNN), K-nearest neighbors (KNN), convolutional neural networks (CNN), long short-term memory (LSTM), and decision trees are a few of the several deep learning methods that have emerged as popular and powerful methods for solving complex problems. In this article, we will explore each of these techniques and their unique capabilities

In this Figure 4, the detailed model is represented. The methodology may be broken down into four key steps: The dataset utilized in this study is called "Fake News Dataset". Dataset is organized in four columns, Tile, Subject, Text, Data preprocess the input text using the same steps as during training. Feed the preprocessed text into the trained LSTM model to obtain the predicted class (fake or real). The classification model should be trained and put to the test using a set of test data that represents a collection of unclassified fake news along with the classification rate and confusion matrix. Five metrics have been defined for performance assessment. Recall is just the division of the total number of linked documents that have been retrieved, whereas precision is the ratio of related instances to all recovered instances. The F1-score, which is the product of recall and accuracy, is what we monitor. On the other hand, a confusion matrix evaluates a variety of variables to determine how well classification works algorithms.

According to study's conclusions, K-nearest neighbor, and CNN, LSTM, RNN, and decision trees. Even if deep learning algorithms provide a reasonable level of accuracy, our analysis of the various metrics reveals that LSTM perform better than other learning techniques. This is because LSTM provided a very high level of accuracy of 96%. If F1-score is greater 75 the print true news or F1 score is less than 25 then print fake news.

EXPERIMENT AND RESULTS

The results of the proposed false news detection system using conventional ML and DL techniques are covered in this chapter. All the models are evaluated once the dataset has been properly processed and trained. The accuracy, confusion matrix, recall, precision, F1-score, ROC-AUC curve, and other metrics are checked for all the models in this study.

4.1. EVALUATION PARAMETER

We calculate accuracy, precision, recall, F1-score and the confusion matrix. True positive rate accurately identified true news. True negative (TN) represents the figure of accurately recognized true news. False negative represents value inaccurately detect fake news. FP represents the value of inaccurately detect false news.

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Precision:

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall:

$$Recall = \frac{TP}{TP + FN}$$

$$\text{F1} - \text{score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

F1 score:

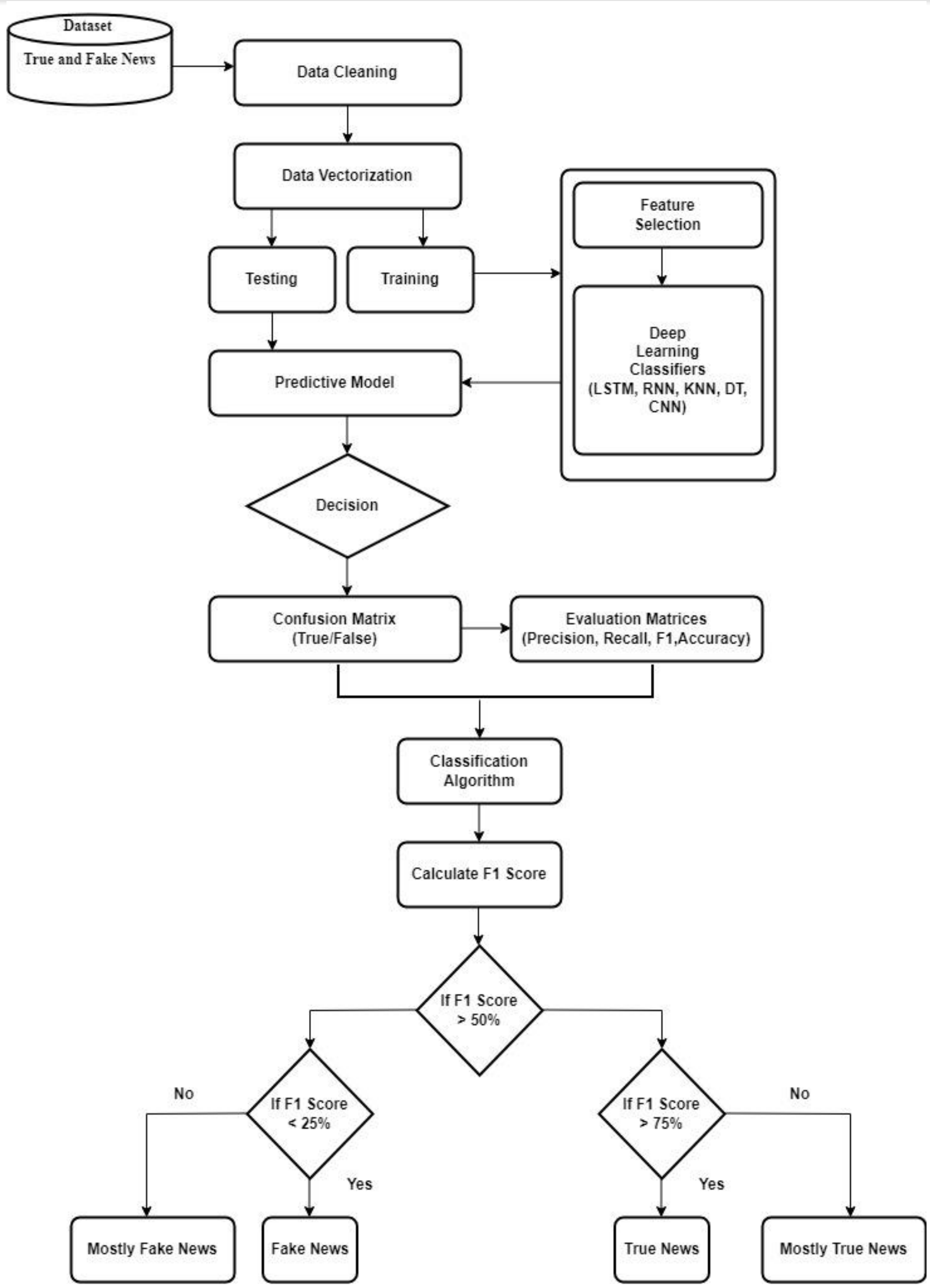

Figure 4. Proposed Methodology

3.2. Experiment 1: LSTM Model

The confusion matrix of LSTM as shown in Figure5, includes TP, FP, FN, and TN. The confusion matrix, however is an efficient procedure to quantity the show the confusion matrix. The CM contains 6390 detected the true news and 1387 are predicted false news. Display the ROC curve that is plotting FP rate against TP rate at various threshold values between 0.0 and 1.0. By checking at the model's performance under the curve is evaluated. LSTM model performance has been measured through evaluation parameters. Table 2 depicts an accuracy of 96%, precision 94%, recall 73%, F1- score 82% output.

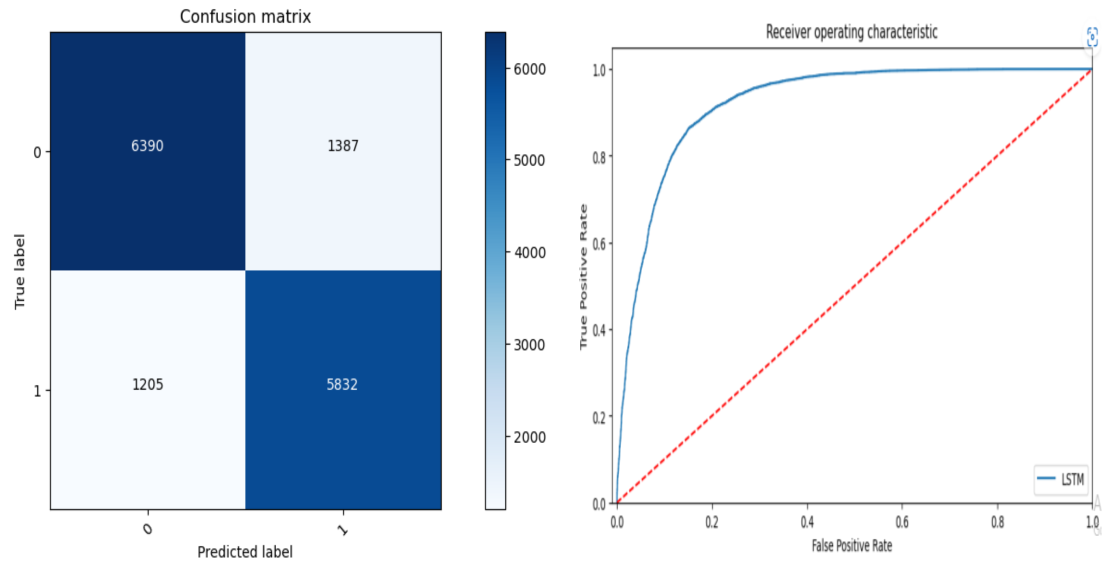

Figure 5. Confusion matrix and ROC for LSTM

Table 2. LSTM Model Performance Metrics

Accuracy %	Precision %	Recall %	F_1-score %
96%	94%	73%	82%

Figure 6 shows accuracy of LSTM classification. Here model's accuracy that reached approximately 96%.whereas, loss of model for LSTM classification. Here model's loss for training and validation reached approximately 0.1 and that are decreasing gradually.

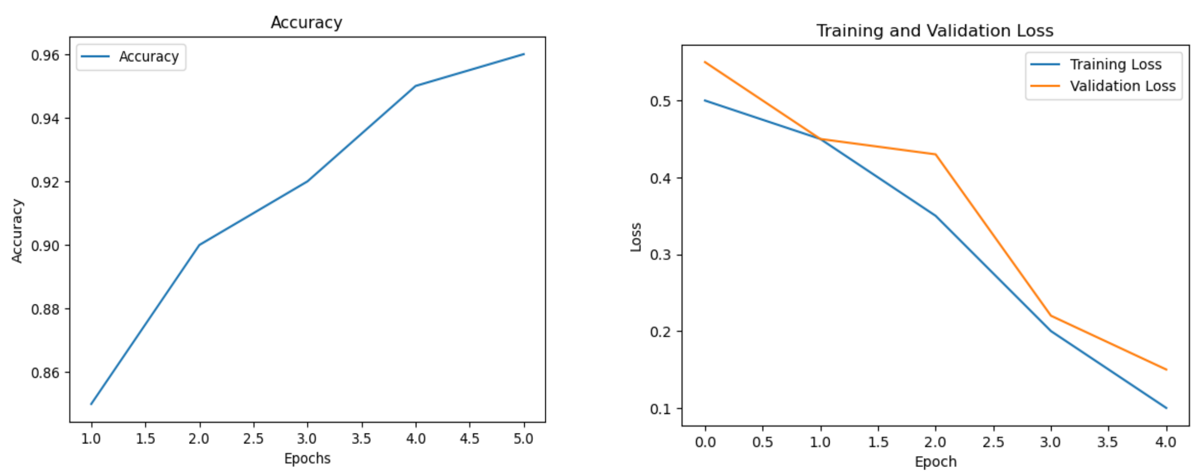

Figure 6. Accuracy and Loss of LSTM

4.3 Experiment 2: KNN Model

Figure 6 displays the confusion matrix of KNN, which includes TP, FP, FN and TN. The confusion matrix, however is an efficient procedure to quantity the show the confusion matrix. The CM contains 32.96% detected the real news and 19.54% are predicted false news. It also displays the ROC curve that is plotting FP rate against TP rate at various threshold values between 0.0 and 1.0. By checking at the model's performance under the curve is evaluated

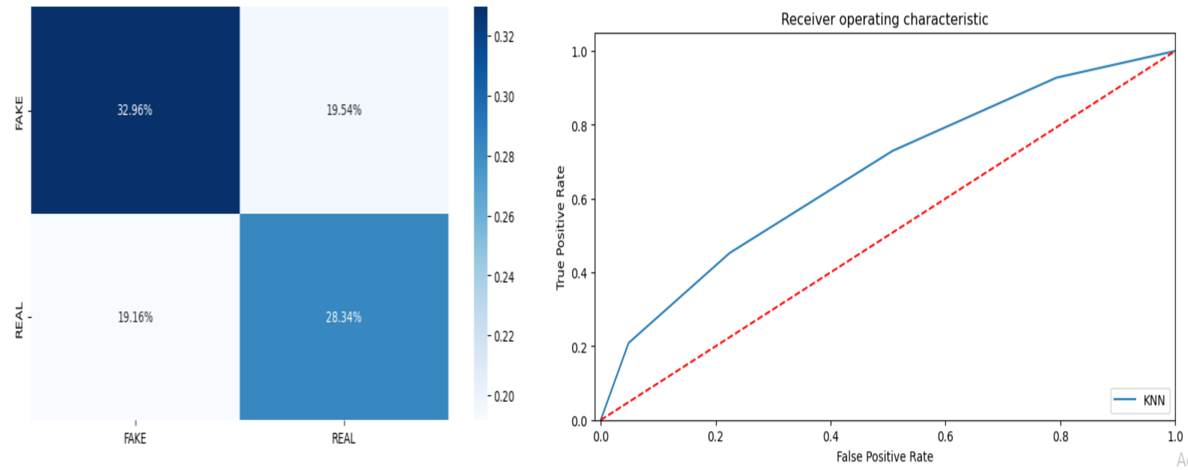

Figure 7. Confusion Matrix and ROC curve for KNN

KNN model performance has been measured through evaluation parameters. As above mentioned that evaluation parameter are accuracy, precision, recall, f score in table 4.2 mentioned, that model show obtained an accuracy 62%, precision 61%, recall 77%, F1- score 68% output. KNN shows model's accuracy for KNN classification (Figure 8). Here model's accuracy that reached approximately 62 % as shown in Table 3.

Table 3:. KNN model performance metrics

Accuracy %	**Precision %**	**Recall %**	**F_1-score %**
62%	61%	77%	68%

Display the training or validation loss of model for KNN classification. Here model's loss for training and validation reached approximately 0.2 and that are decreasing gradually as shown in Figure 8.

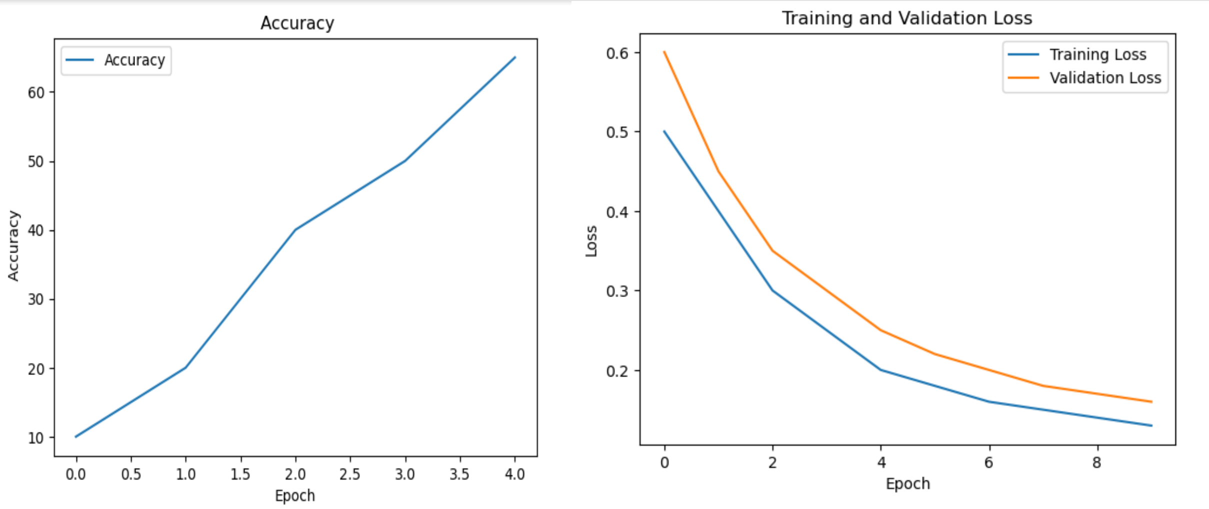

Figure 8. Accuracy and Loss of KNN

4.4. Experiment 3: Decision Tree model

Figure 9 displays the confusion matrix of decision tree, which represents includes TP, TN, FP, and FN. The confusion matrix, however is an efficient procedure to quantity the show the confusion matrix. The CM contains 34.27% detected the real news and 18.23% are predicted false news. It also displays the ROC curve that is plotting FP rate against TP rate at various threshold values between 0.0 and 1.0. By checking at the model's performance under the curve is evaluated.

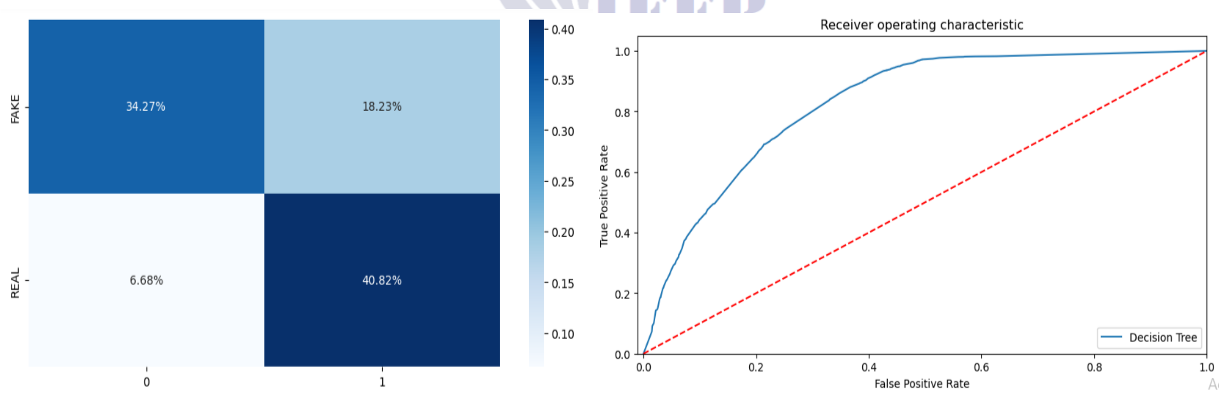

Figure 9. Confusion Matrix for Decision Tree

Decision tree model performance has been measured through evaluation parameters. As above mentioned that evaluation parameter are accuracy, precision, recall, f score in table 4.3 mentioned, that model show obtained an accuracy 75%, precision 83%, recall 65%, F1-score 73% output.as shown in Table 4.

Table 4. Decision Tree Model Performance Metrics

Accuracy %	Precision %	Recall %	F_1-score %
75%	83%	65%	73 %

Figure 10 shows accuracy of model for decision tree classification. Here is the model's accuracy that reached approximately 75%. It also model's loss approximately 0.20 that is decreasing gradually

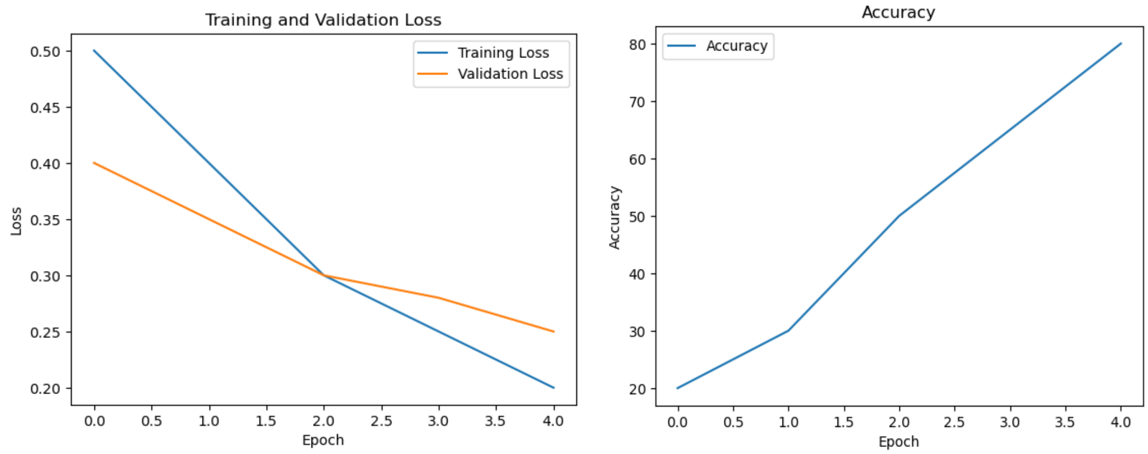

Figure 10. Accuracy and Loss of Decision Tree

4.5 Experiment 4: CNN Model

Figure 11 displays the confusion matrix of CNN. The CM contains 4694% detected the real news and 2% are predicted false news. It also display the ROC curve that is plotting FP rate against TP rate at various threshold values between 0.0 and 1.0. By checking at the model's performance under the curve is evaluated.

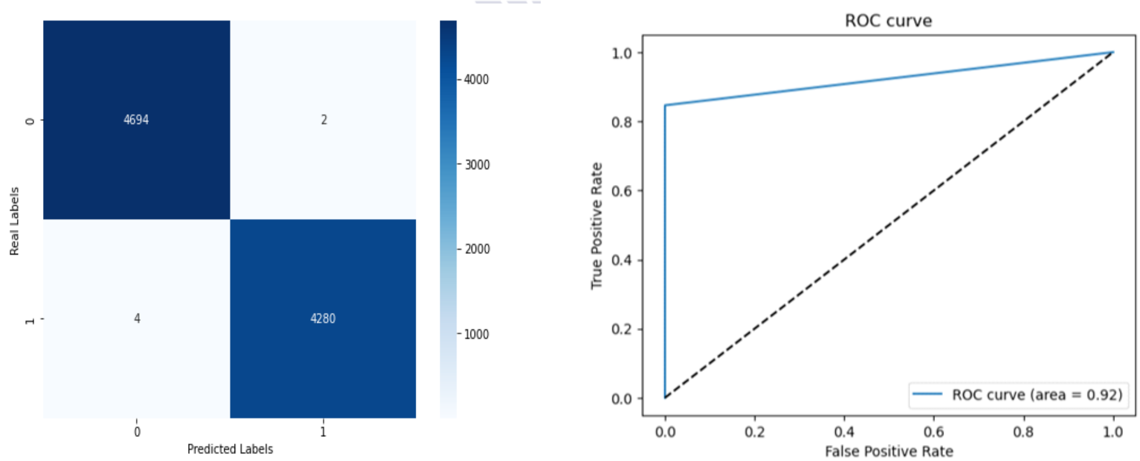

Figure 11. Confusion Matrix and ROC for CNN

CNN model performance has been measured through evaluation parameters. As above mentioned that evaluation parameter are accuracy, precision, recall, f score in table 4.3 mentioned, that model show obtained an recall 87%, accuracy 91%, precision 96%, and F1- score 91% output shown in Table 5.

Table 5. CNN Model Performance Metrics

Accuracy %	Precision%	Recall %	F_1-score %

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91%	96%	87%	91 %

Figure 12 represents the accuracy of model for CNN classification. Here is the model's accuracy that reached approximately 91%. It also shows the model's training and validation loss for CNN classification. Here the model's loss reached approximately 0.20 that is gradually decreasing.

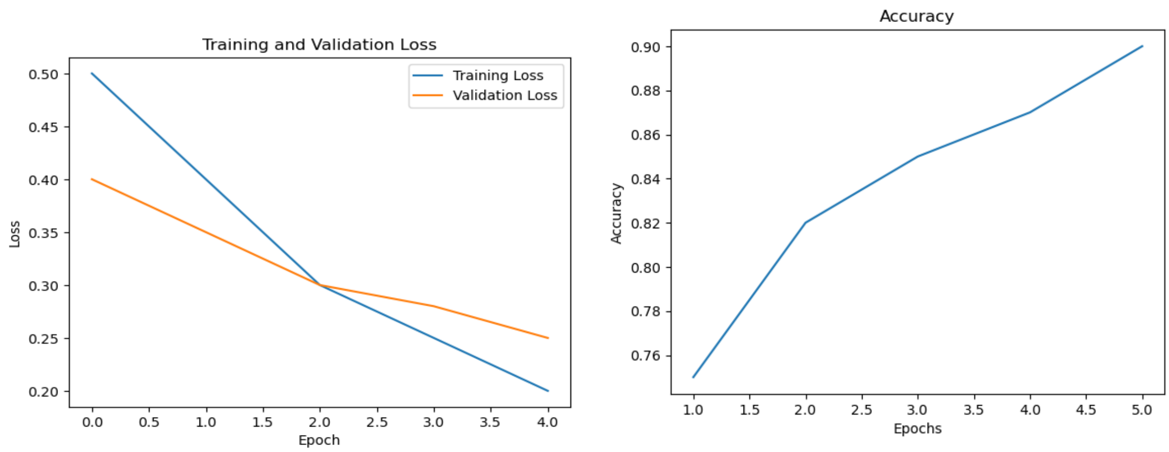

Figure 12. CNN Accuracy and Loss

4.6 Experiment No 5: RNN Model

Figure 13 displays the confusion matrix of RNN. The CM contains 5660% detected the real news and 2117% are predicted fake news. It also displays the ROC curve that is plotting FP rate against TP rate at various threshold values between 0.0 and 1.0.

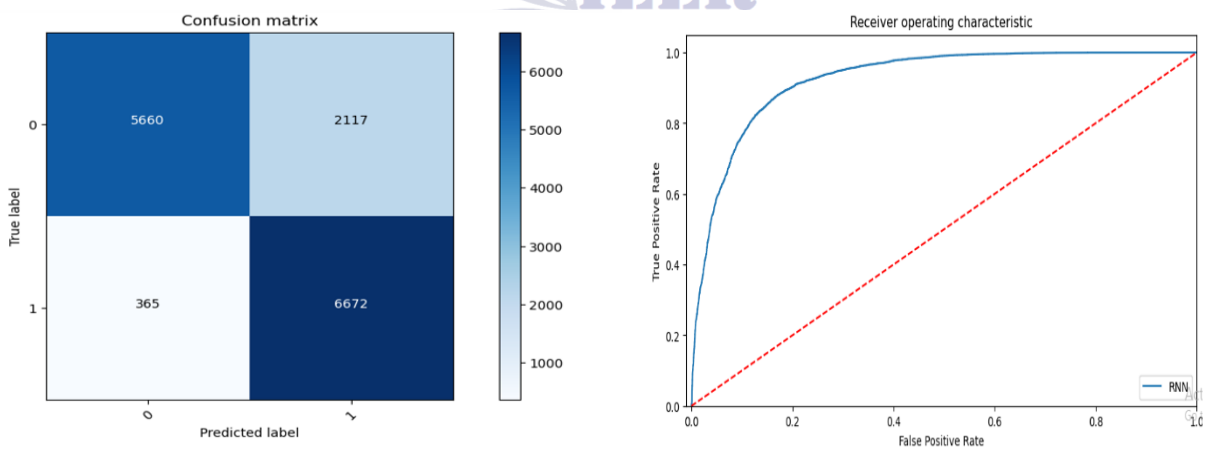

Figure 13. Confusion Matrix and ROC curve of RNN

RNN model performance has been measured through evaluation parameters mentioned in Table 6 that show obtained f1-score production of 91% accuracy, 87% precision, 96% recall, and 91% accuracy.

Table 6. RNN Model Performance Metrics

Accuracy %	Precision%	Recall %	F_1-score %

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91%	87%	96%	91%

Figure 14 shows accuracy of model for RNN classification. Here is the model's accuracy that reached approximately 91%. It also shows the model's train and validation loss that reached approximately 0.1 that is gradually decreasing.

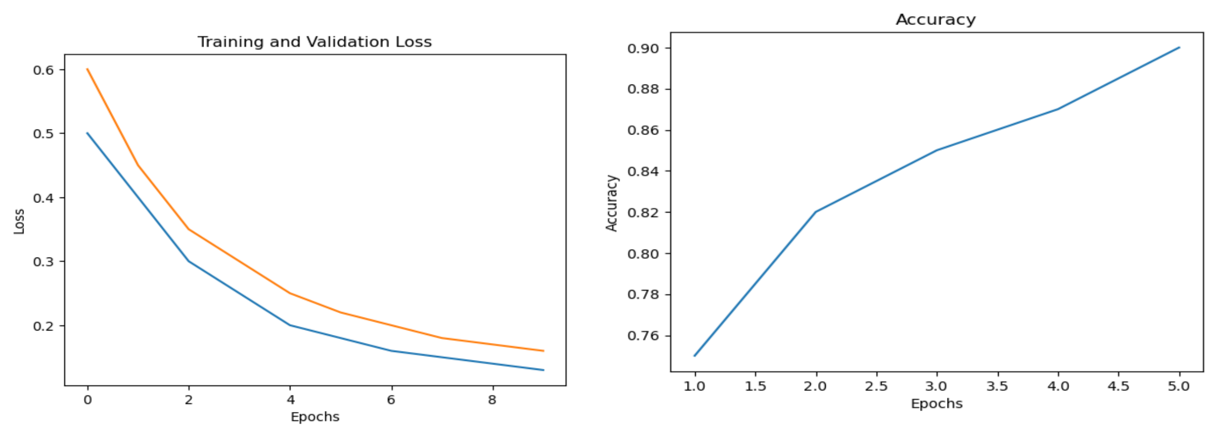
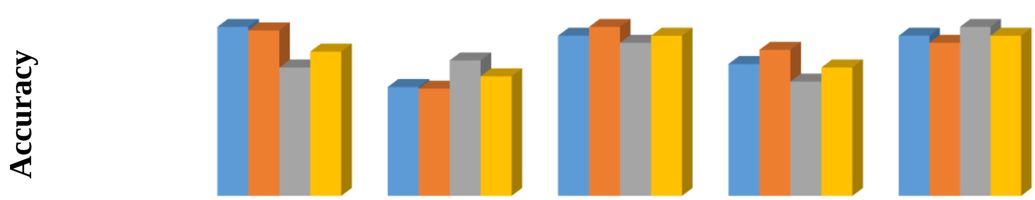


Figure 14. Accuracy and Loss of RNN

4.7 DISCUSSION OF RESULTS

We conducted experiments with different scenarios using proposed model and test it fake news dataset. Result of the experiments described the form of tables. Firstly, we compare all model of accuracy with other model. It can clearly be seen that model achieved best accuracy for LSTM experiments. LSTM achieved approximately 96% accuracy, Precision, Recall, F1- score output gives better results other models. Our model achieved best accuracy i.e. 96%, Precision 94%, Recall 73% and F1-score 82% as compared to other models classification shown in Figure 15.



	LSTM	KNN	CNN	Decision Tree	RNN
Accuracy	96%	62%	91%	75%	91%
Precision	94%	61%	96%	83%	87%
Recall	73%	77%	87%	65%	96%
F1-Score	82%	68%	91%	73%	91%

Models

Accuracy Precision Recall F1-Score

Figure 15. Performance Evaluation for Fake News Detection

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4. CONCLUSION

Nowadays, it's crucial to determine the veracity and authenticity of news and information available online. Recent research has revealed that numerous internet platforms have a considerable impact on propagating false information and spreading fake news, which may be used for multiple evil objectives and to the advantage of a large number of individuals. LSTM, DT, KNN, RNN, CNN bidirectional encoder representation from transformers. We obtained 96%, 91%, 75%, and 62%, 91% accuracy for the CNN, RNN, KNN, LSTM, and decision tree deep learning models, respectively. Finally, the neural network LSTM produced much superior performance.

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