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# FAKE NEWS DETECTION USING HYBRID APPROACH

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**Abstract**

In According to the definition of fake news, it is "misleading information from news sources that pretend to be real but are fake." The dissemination of false information seeks to spread rumours, damage someone's reputation, or generate revenue through clickbait, among other things. Everyone has access to the internet and has a social media profile, so bogus news might spread quickly. Fake news is on the rise, which creates a serious issue that needs to be addressed. In our work, we evaluate and examine each of the mentioned Deep Learning and Machine Learning models: CNN, RNN, LSTM, Bi-LSTM, Random Forest Multinomial Naive Bayes, Decision Tree, and so on. Eighty-eight to ninety-nine percent accuracy is what these algorithms can achieve. Our hybrid FND (Fake News Detection) model, includes layers of Convolution Neural Networks, Bi-Long Short Term Memory, and Bi-Recurrent Neural Networks. The ISOT dataset is used to train the FND model. There are twelve thousand six hundred false and real news articles each in the dataset. Comparing the FND model to the other studied techniques, it has demonstrated superior accuracy. We discovered optimistic outcomes in terms of success rate using this method.

**Keywords:** Fake News Detection, Deep Learning, Hybrid model, FND model, CNN-Bi-RNN-Bi-LSTM, Machine Learning

## Introduction

Technology has gifted us with great comforts but it brings its dark side along with it. For example, in addition to various useful applications, Social Media is being used to spread misleading information. Fake news is one such aspect. It has many different forms, including clickbait (false headlines), misinformation, hoaxes, rumours, satire, deceptive news, etc. [1]. Fake news, sometimes, spreads at lightning speed on a large scale [2]. Due to this, a field of research study for fake news has evolved that deals with determining the accuracy of the news and spotting false information [3].

The spreading of false information is not new and has been present since print media times. However, advances in technology and social media platforms have led to an exponential increase in fake news. Remedies should be taken to prevent the spread of fake news. Therefore, we have analysed various machine learning algorithms such as Random Forest, Decision Tree and Multinomial Naïve Bayes and Deep Learning models such as CNN, RNN, LSTM and Bi-LSTM [4]. This analysis was done in the programming language Python. These models have shown remarkable accuracy ranging from eighty-eight to ninety-nine per cent [5]. We created a hybrid model combining CNN, Bi-RNN and Bi-LSTM known as the FND model. The FND model has reported accuracy of ninety-nine per cent.

## Related Work

A model of Bi-directional LSTM paired with sentence transformers has been used to combat the damaging problem of fake news identification. The architecture was created to address the issue of multi-class, cross-lingual, and fake news identification. [6].

Fake news is largely propagated through social media [7]. A system that uses social media content to identify fake news is represented by a shared study [8]. The design, which consists of a transformer where the encoder learns the representation of fake news and the decoder anticipates the classification of news, has been discussed.

The convolutional and recurrent neural networks are used in a novel hybrid deep learning model for fake news detection discussed in this study [9]. The study is based on datasets from ISOT [18] and FA-KES. The model incorporates the capacity of LSTM to learn long-term dependencies and CNN to extract features. Further, output from LSTM and CNN is RNN classifies outcomes using the local features that the CNN retrieved and has learned long-term dependencies of local features to classify results. The reported result is superior to other non-hybrid baseline techniques.

Machine learning has demonstrated impressive accuracy in detecting fake news [10]. Both the bag-of-words and TF-IDF approaches were used to test a number of ML algorithms, including Naive Bayes, SVM, and KNN. The accuracy of both Naive Bayes and the Passive-Aggressive classifier was observed to be increased by switching from the bag-of-words to the TF-IDF vectorizer [11]. A vector space model's 3D representation of the world creates a more realistic representation that generates relative word importance, which helps the algorithms produce more accurate predictions [12]. To determine which method produced the best results, comparative analyses of K- Nearest Neighbour (KNN), Linear Regression, XGBoost, Naive Bayes, Decision Tree, Random Forests, and Support Vector Machine (SVM) were conducted [13].

Sentiment analysis is a method that can be used to identify fake news by categorising the polarity of emotions (positive or negative) in a given text. Sentiment analysis aids in the identification of fake news [14]. Fake news is categorised using linguistic and sentimental characteristics. Additionally, sentiment analysis is being utilised to assess public opinion on COVID-19, and it is being further analysed to look into how people react to fake news in the real world. [15,16].

Explaining the fundamentals of numerous machine learning algorithms and how they can be used in a variety of real-world application domains, including cybersecurity systems, smart cities, smart transportation, smart healthcare, e-commerce, agriculture, and many more, is the study's core contribution. [17].

**Dataset**

The dataset was obtained from the University of Victoria's ISOT Research lab website [18]. It includes false news databases as well as real news datasets. True news datasets have been compiled by the ISOT Research Lab from authentic sources. It was accomplished by crawling news articles from Reuters.com. Additionally, the ISOT Research lab collected fake news datasets from shady websites and fact-checked them on Politifact (a USA and Wikipedia fact-checking organisation).

There are two CSV files, one for real news and the other for fake news. The fake news dataset contains more than twelve thousand six hundred articles. Twelve thousand six hundred articles from Reuters.com are included in the collection. Each article includes details like the title, text, type, and publication date.

**1.1 Pre-processing**

The ISOT dataset was the one used in this investigation. We started by integrating the two datasets of real and fraudulent news articles. The combined dataset underwent data cleansing by having null and missing values removed. The rows with null values were removed. We added the column "label" to our data frame. The values 0 and 1 in the label column correspond to fake news and real news, respectively. With the aid of the NLTK library, we prepared our data. We removed stop words from our corpus. After that, we dismantled words like "can't," "won't," and so forth. HTML tags, URLs, symbols, and words with numeric characters were eliminated. All of the text was changed to lowercase once the corpus was cleared of all undesirable things. Using Word Cloud, we performed data visualisation. Words are shown visually in word clouds.

Depending on how frequently and pertinently the words occur in the corpus, they emphasise well-known words and phrases. It painted a precise picture of word frequencies for us. The frequency of a word indicates its significance within our corpus. Table 1 displays an example of a sentence taken from the ISOT dataset, and Table 2 shows feature extraction from that sentence.

| | |
|---|---|
| **Train Data** | **Yahoo under scrutiny after latest hack, Verizon seeks new deal terms** |
| **Test Data** | **Yahoo is not under scrutiny after latest hack, Verizon seeks old deal terms** |

**Table 1:** Example of a training and testing sentence

| Features extracted from train data | Features extracted from test data |
|---|---|
| Yahoo | Yahoo |
| under | scrutiny |
| scrutiny | after |
| after | latest |
| latest | Hack |
| Hack | Verizon |
| Verizon | seeks |
| seeks | old |
| new | deal |
| deal | terms |
| terms | |

**Table 2:** Feature extraction from sentences

### 1.2 Data Preparation

Data preparation was done to apply deep learning algorithms. First, padding was performed on the data. LSTM and CNNs take inputs of the same length and dimension, and the sentences present in our corpus are padded to the same length. Padding the sequence of words requires taking an average of all words in sentences. We have calculated a maximum size of a hundred words by taking the average of all sentences. Tokenization was performed on this pre-processed data. Then our data was passed through the word embedding layer which converted each word into a numerical vector.

### Deep Learning and Machine Learning Approaches for Fake News Detection

To categorise a piece of given news as accurate or false, we used a variety of machine learning and deep learning techniques. We evaluated our dataset using a variety of classifiers, including CNN, RNN, LSTM, Bi-LSTM, Decision Tree, Multinomial Naive Bayes, Logistic Regression, and Random Forest. For superior outcomes in contrast to previously examined approaches, a hybrid model incorporating CNN, Bi-RNN, and Bi-LSTM is suggested. Python programming is used to test all algorithms and the hybrid model. In Table 1, a sample of a real news sentence is shown as a training dataset, while a sample of false news is presented as a test dataset. Observations of various algorithms are discussed further.

### 1.3 Decision Tree

Visual representations of decisions and decision-making are decision trees. It is a tree structure that resembles a flowchart and is based on the node-splitting or feature-based split methods. One feature of creating a decision tree is the option to select the conditions to be used for splitting. It employs various techniques for selecting attributes, including ID3 or the CART approach. Figure 1 depicts the Decision Tree in action using a text from the dataset. The categorization report of the Decision Tree is displayed in

Figure 2.

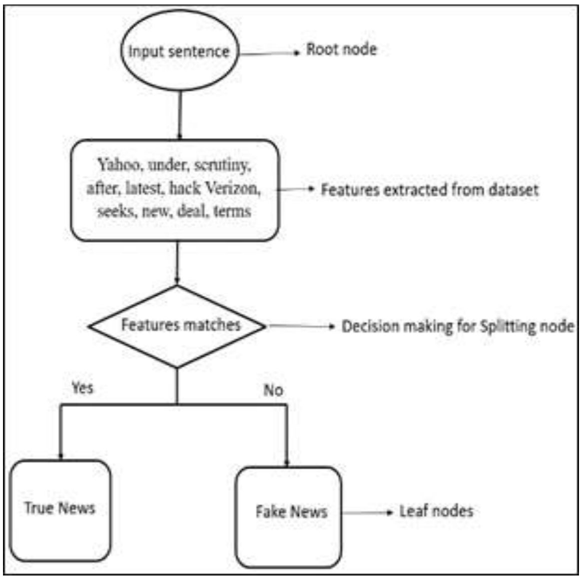


**Figure 1:** Working of Decision Tree

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.88 | 0.88 | 0.88 | 2587 |
| 1 | 0.88 | 0.88 | 0.88 | 2604 |
| accuracy | | | 0.88 | 5191 |
| macro avg | 0.88 | 0.88 | 0.88 | 5191 |
| weighted avg | 0.88 | 0.88 | 0.88 | 5191 |

**Figure 2:** Results of Decision Tree

### 1.4 Random Forest

The phrase "forest" is used since this collection of decision trees was trained using the bagging technique. The fundamental idea is to combine different learning models to achieve superior outcomes. To achieve better outcomes, random forest constructs many decision trees and combines them. Even without hyper-parameter adjustment, this produces better outcomes. Instead of focusing on the most important feature when splitting, it looks for the best feature within a random selection of features. Better models are created as a result of this. Figure 3 displays how Random Forest operates on a sentence taken from the dataset. Figure 4 shows the classification report of Random Forest.

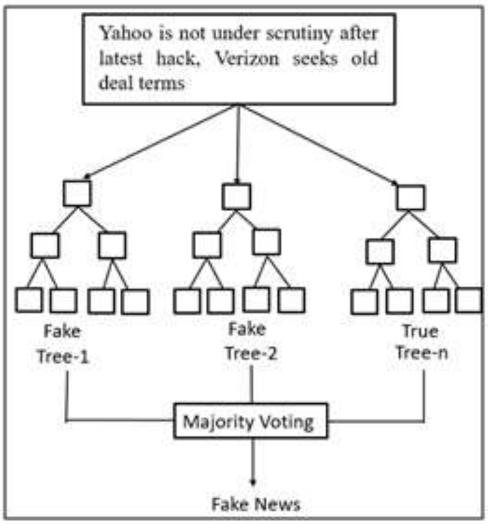


**Figure 3:** Random forest applied to the dataset

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| fake | 0.98 | 0.99 | 0.98 | 4730 |
| true | 0.98 | 0.98 | 0.98 | 4250 |
| accuracy | | | 0.98 | 8980 |
| macro avg | 0.98 | 0.98 | 0.98 | 8980 |
| weighted avg | 0.98 | 0.98 | 0.98 | 8980 |

**Figure 4:** Results of Random Forest

### 1.5 Multinomial Naive Bayes

A family of classifiers known as the Naive Bayes classifier is based on the Bayes theorem and the idea that features are independent of one another. Due to its quick learning rate and simple design, multinomial Naive Bayes are generally used with NLP issues. It offers a method for categorising data that cannot be expressed numerically. The likelihood of a text fragment is calculated to provide a class prediction (as fake or true). Equation 1 illustrates the Naive Bayes or Bayesian probability formula. It determines the likelihood that event A will occur after event B has already happened, which is known as the posterior probability of a class. P(A) is the likelihood of event A occurring, P(B) is the probability of event B, and P(B|A) is the prior probability. Figure 5 displays the Naïve Bayes classification report.

$$P(A|B) = P(B|A) * \frac{P(B)}{P(A)} \ldots\ldots\ldots\ldots (1)$$

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| fake | 0.94 | 0.94 | 0.94 | 4730 |
| true | 0.93 | 0.93 | 0.93 | 4250 |
| accuracy | | | 0.93 | 8980 |
| macro avg | 0.93 | 0.93 | 0.93 | 8980 |
| weighted avg | 0.93 | 0.93 | 0.93 | 8980 |

**Figure 5:** Classification Report of Naïve Bayes

### 1.6 LSTM

Long Short-Term Memory helps recurrent neural networks overcome their long-term reliance issues. It can pick up on order and aids in solving problems involving sequence prediction. It exits the network via a set of gates that regulate the data in the sequence of stored data. Figure 6 depicts how the LSTM performed on the dataset. Figure 8 displays the outcomes of using LSTM on the test dataset.

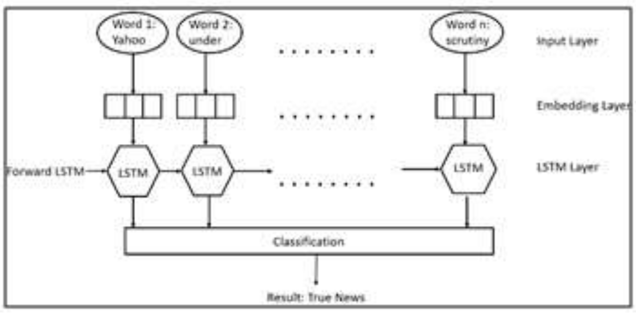


**Figure 6:** Working of LSTM

### 1.7 BI-LSTM

The bidirectional LSTM combines two separate LSTMs. This network enables forward and backward information about the sequence at each time step. The inputs will be processed twice: once from the past to the future and once from the future to the past. In contrast to bidirectional information, which is preserved from two hidden states, LSTM that runs backwards will preserve information utilising the future. Figure 7 depicts how the Bi-LSTM performed on the dataset. The outcomes of the Bi-LSTM on the training and test datasets are displayed in Figure 8.

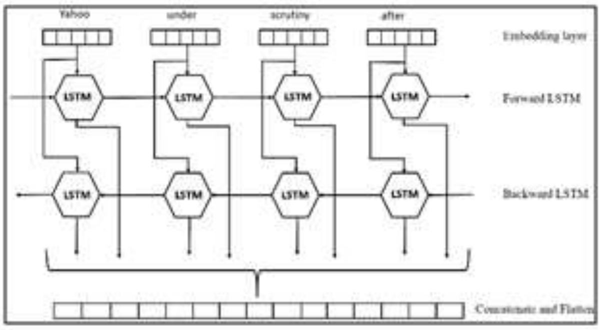


**Figure 7:** Working of Bi-LSTM

dftest

Figure 11: Working of RNN

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | LSTM | 0.997186 | 0.998979 | 0.996767 | 0.997843 | 0.997305 |
| 1 | BI-LSTM | 0.998312 | 0.999959 | 0.998705 | 0.998058 | 0.998381 |

**Figure 8:** Classification Report of LSTM and Bi-LSTM

### 1.8 CNN

A subset of deep learning networks is convolutional neural networks. It incorporates matrix multiplication, which produces results for additional training procedures. Convolution is the term for this. To train a CNN for text format, words within sentences are represented as numerical vectors. A kernel size and several filters are specified to perform the training. We often employ a one-dimensional CNN called Conv1D for text. In a series of iterations, a filter with a set window size multiplies the input by the filter weights to create an output that is saved in an output array. Figure 9 depicts how CNN processed the dataset. The output of CNN on the training dataset is shown in Figure 10.

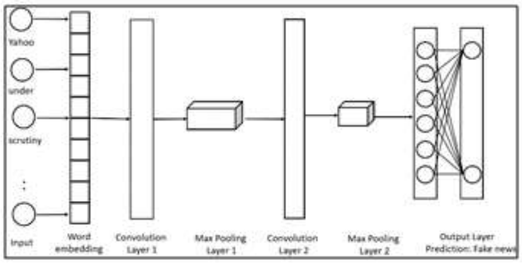


**Figure 9:** Working of CNN

dftest

| | classifier | Accuracy (%) | AUC (%) | Precision | Recall | f1 |
|---|---|---|---|---|---|---|
| 0 | CNN1 | 0.998312 | 0.999986 | 0.998920 | 0.997843 | 0.998381 |

**Figure 10:** Classification Report of CNN

### 1.9 RNN

This approach uses sequential data processing to assist in learning. The capacity of sequential processing to keep track of sequences that came before the one being processed justifies it. It is called recurrent because each time step's output can be utilised by recalling the output from the previous time step. Natural Language Processing is a supplement to RNN that recalls the features of multiple news articles at once rather than reading them one at a time. Figure 11 shows the working of RNN and Figure 12 shows the results of RNN on the test dataset.

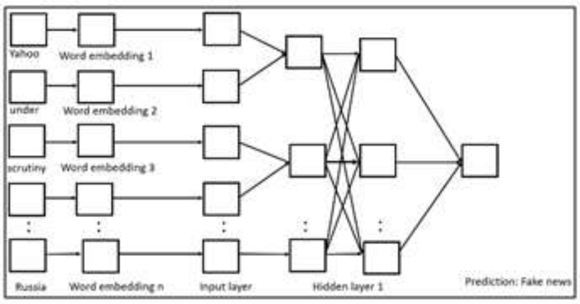


**Figure 11:** Working of RNN

dftest

| | classifier | Accuracy (%) | AUC (%) | Precision | Recall | |
|---|---|---|---|---|---|---|
| 0 | RNN | 0.988070 | 0.996557 | 0.989622 | 0.987487 | 0.988 |

**Figure 12:** Classification Report of RNN

## FND MODEL

The baseline models CNN, Bi-RNN, and Bi-LSTM were combined for our analysis, and we then performed a comparison using machine learning and deep learning models. The "FND model" is a suggested hybrid model that combines CNN layers with the Bi-RNN and the Bi-LSTM.

The FND model is a hybrid model that combines the capabilities of long short-term memory, recurrent neural networks, and convolutional neural networks. We employed the first layer in our hybrid CNN and RNN model as CNN, and the output from that layer was then supplied as input for the RNN layer. The feature extraction from the input data in this case is done using the CNN layer. We utilised Conv1D for that as our data was in text format. The output from CNN is then used by the RNN layer to find long-term dependencies in the text sequence. Conv1D was used in our model to extract the features, and the output was then supplied as input to the Bi-RNN input layer. The pooling layer has been replaced in this case with Bi-RNN. It would improve the efficiency with which long-term dependencies are captured and lessen the loss of local information's finer nuances.

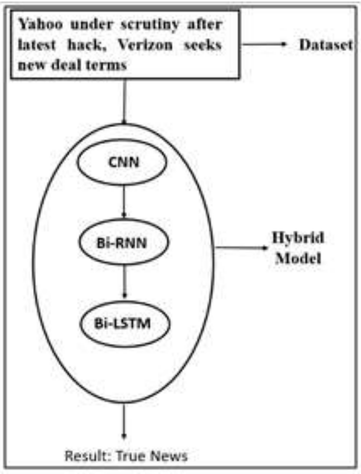


**Figure 13:** Working of FND model

The characteristics of earlier information are then kept in extended text sequences, and the Bi-RNN and Bi-LSTM use the preservation quality of earlier information to make predictions about whether the news is true or incorrect.

dftest

| | classifier | Accuracy (%) | AUC (%) | Precision | Recall | f1 |
|---|---|---|---|---|---|---|
| 0 | CNN+RNN+LSTM | 0.998424 | 0.999806 | 0.999281 | 0.997702 | 0.998491 |
| 1 | CNN+BI-RNN+BI-LSTM | 0.999175 | 0.999839 | 0.998852 | 0.999569 | 0.999211 |

**Figure 14:** Classification Report of Hybrid Model

The innovative method used by CNN to extract features from the input. Capturing long-term dependencies, however, requires stacking numerous layers because of the locality of the convolutional and pooling layers. As the input sequence gets longer, this gets worse. To solve this problem, we need a deep neural network with lots of convolutional layers. Therefore, utilising a hybrid strategy resolves this issue. Combining two conventional models allowed us to better utilise their combined powers. As the next layer after CNN, long-term dependencies of RNN and LSTM perform prediction using features supplied as output by the CNN layer. Additionally, this method effectively captures long-term dependencies while minimising the loss of localised specific information. This has been proven successful in classifying and regressing fake text classification models [19].

| MODEL NAME | ACCURACY |
|---|---|
| Decision Tree | 0.88036 |
| Multinomial Naïve Bayes | 0.93407 |
| Random Forest | 0.98262 |
| RNN | 0.98807 |
| LSTM | 0.99718 |
| BI-LSTM | 0.99831 |
| CNN | 0.99831 |
| CNN+Bi-RNN+Bi-LSTM | 0.99910 |

**Table 3:** Accuracy Comparison Table

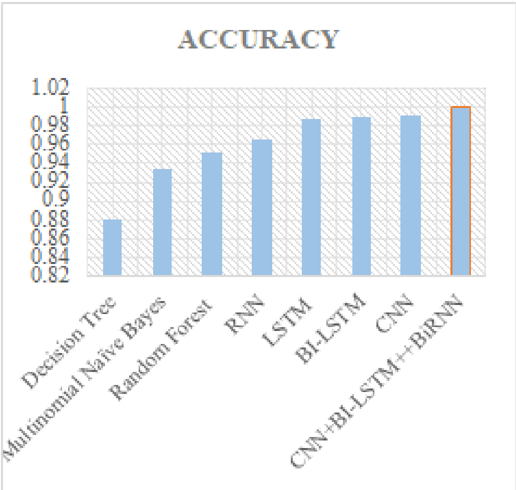


**Figure 15:** Graph for Accuracy Comparison

## 6. CONCLUSION

Fake news is an emerging challenge in society. Thus, the central idea of this paper is to create a model that successfully classifies news as fake or true. This paper discusses comparative analysis with ML models namely Multinomial Naïve Bayes, Random Forest, Decision Tree, and Deep Learning models (CNN, RNN, LSTM and Bi-LSTM). A performance of eighty-eight to ninety-nine per cent is reported for the ISOT dataset. We have further proposed a hybrid model named as "FND model" that combines the layers of CNN, Bi-RNN, and Bi-LSTM. The FND model has reported a success rate of ninety-nine per cent. Based on the accuracies obtained and the classification report, we have compared our model and found it to be performing better. It may also be noted that the traditional ones require more computation power, resources, and data usage.

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