# Chapter 4 Proposed Framework

This chapter illustrates the detailed research methodology that was adopted to achieve the objectives. This chapter also discusses the various ML and DL algorithms experimented on the proposed work dataset.

Before discussing the detailed research work first of all theoretical background about various algorithms used in the proposed research is discussed.

## 4.1 Various machine and deep learning model used for proposed work

This section describes the various ML techniques used for the experimental analysis of the proposed research. We applied following ML based techniques:

4.1.1 Random Forest

4.1.2 AdaBoost

4.1.3 Boosting

4.1.4 Hard voting classifier

### 4.1.1 Random forest

Random forest (RF) provides an effective approach of classification (Breiman, 2001). This technique create multiple decision tree that are trained on various subset of the training data. Figure 4.1 depicts the structure of random forest algorithm. The average value is concluded to calculate the final accuracy. Random forest includes the prediction of every tree and based upon majority votes of predictions it calculate the final output. Random forest takes less training time and produce output with higher accuracy. Even it produces good accuracy whenever there are large numbers of missing values (Dietterich, 2000).

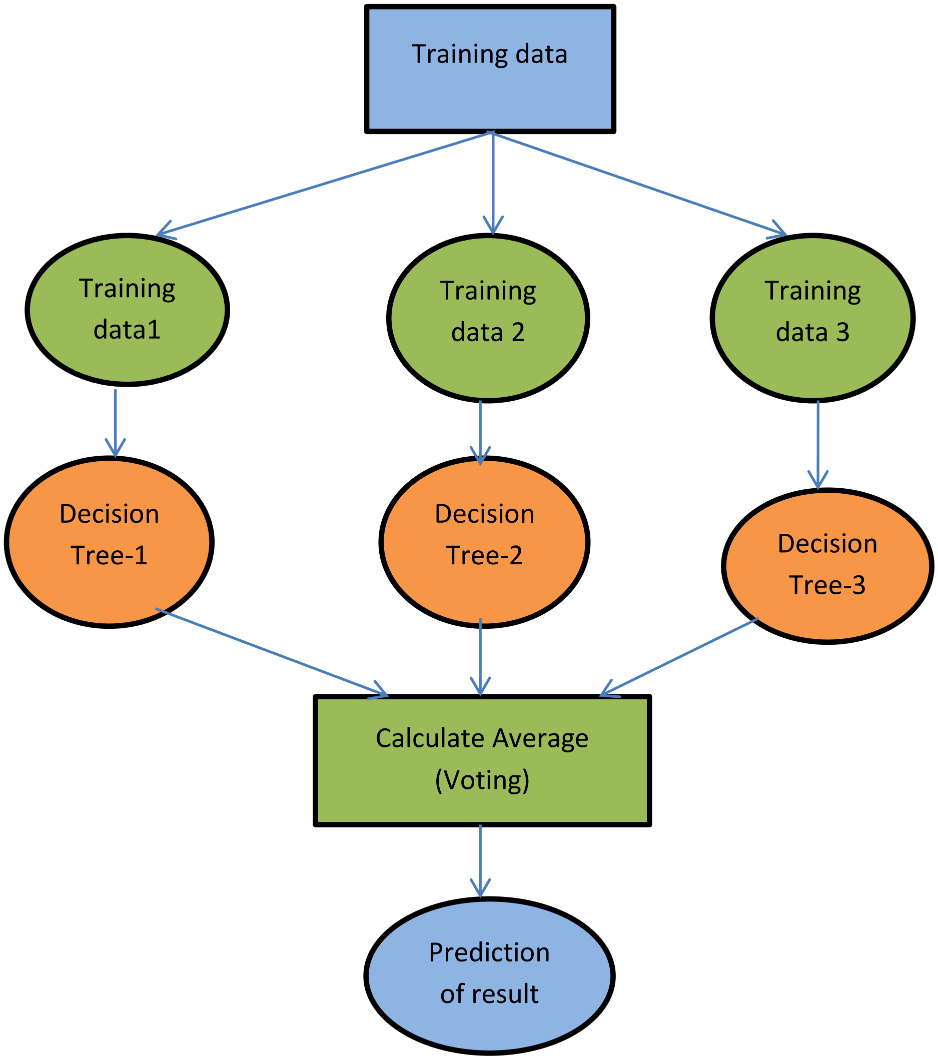



Fig. 4.1 Structure of Random Forest algorithm (Dietterich, 2000).

### 4.1.2 AdaBoost

Boosting technique produces a strong classifier from a weak classifiers. During the boosting process a model is created from the training data and then a second model is created that rectifies the errors of the first model. Numbers of models are added until the model created from training data not predicts the result accurately. AdaBoost was the first boosting algorithm created for binary classification. AdaBoost work efficiently with weak learner. The most suitable and hence most common technique used with AdaBoost are decision trees up to one level (Freund and Freund, 1977).

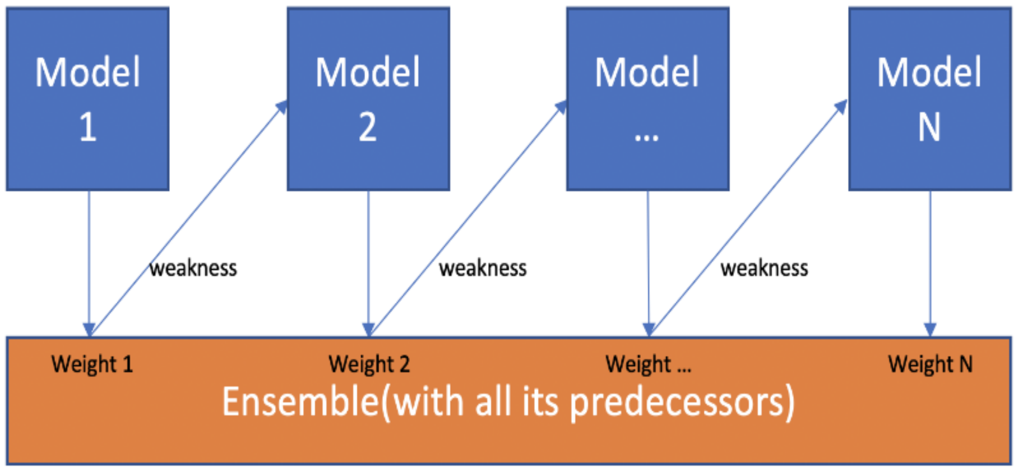



Fig. 4.2 Structure of AdaBoost algorithm (Freund and Freund, 1977).

### 4.1.3 Gradient Boosting

Friedman (Friedman, 2001) created a gradient boosting algorithm. GB contains loss function, weak learner and an additive model to add weak learner. The loss function of the weak learner is calculated after its training. New learner is fixed over the previously created loss function and same loss function is calculated for the new over fitted model. Thus consecutively a collaborative tree is formed where every specific learner is created at-a-time. The sum of the entire model is calculated to predict final results.

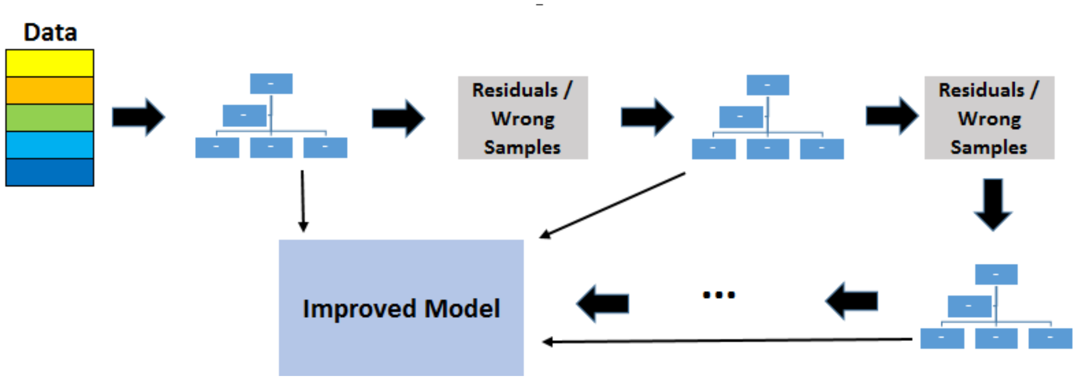



Fig. 4.3 Structure of Gradient Boosting algorithm (Friedman, 2001)

### 4.1.4 Hard Voting Classifier

Voting classifiers are one of the best models to combine the prediction of multiple machine learning algorithms. These models calculated the prediction of sub models and then results are analyzed by combining output of every tree. Two kinds of voting classifier are hard and soft voting. Hard voting also known as majority voting classifier. In this classification process every classifier votes and the final output class having highest votes. In soft voting a prediction value from every class is chosen and the class having largest prediction is the output class (Mishra et al., 2021).

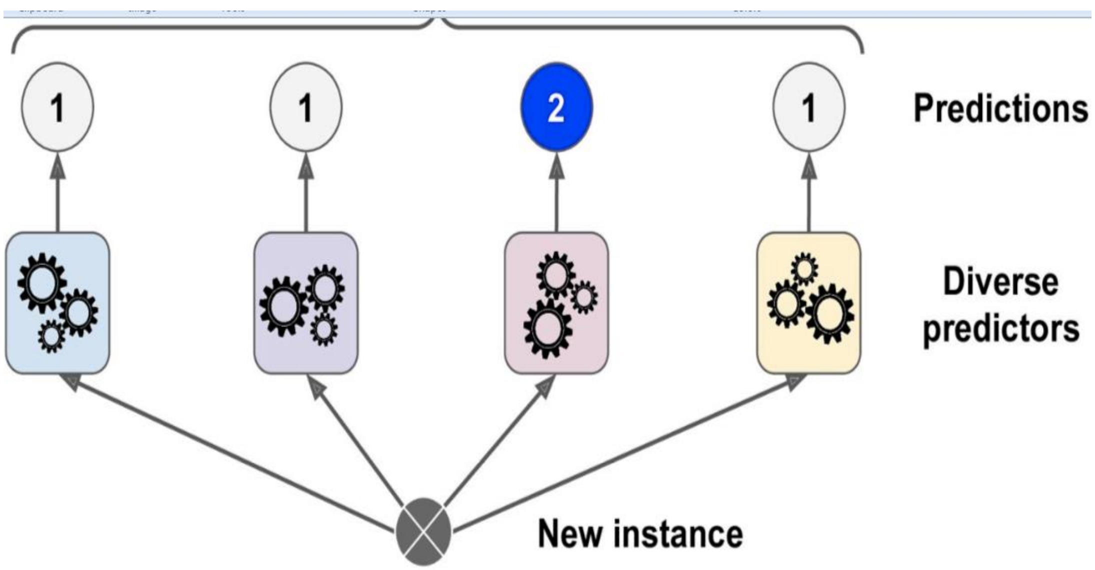



Fig. 4.4 Structure of Hard voting classifier (Mishra et al., 2021)

## 4.2 Deep learning algorithm

Deep learning represents the data through multiple layers. The layers used in deep learning models represents the depth of the network. Deep learning provide fast learning facility to the model and  it execute the features extracted from the data as its own. The deep learning techniques through which proposed model is created are listed below:

### 4.2.1 Convolutional Neural Network (CNN)

The CNN network used to analyze visual images. CNN is same to multilayer perceptron. Multilayer perceptrons typically fully linked networks in which every neuron of first layer connected to each neuron in subsequent layer. Very little preprocessing is required by CNN because the neurons learn from the automated procedure. The architecture of CNN contains input, hidden and output layer.

The CNN perform efficiently in various domains. Nowadays, researchers have endeavored to examine the impact of CNN in NLP area due to its speed as well as proficiency as compared to another deep learning methods( Rehman et al., 2019).

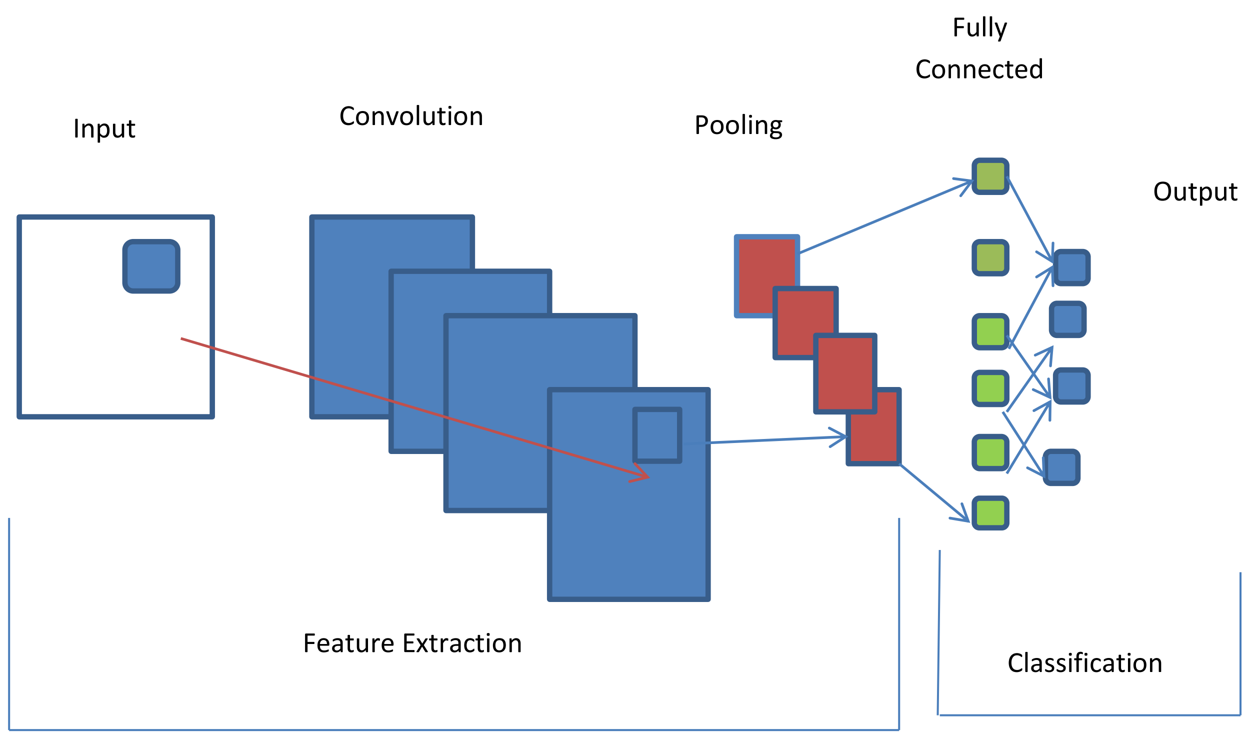



Fig. 4.5 Architecture of CNN ( Rehman et al., 2019).

Figure 4.2 Describe the basic architecture of convolution neural network. Basically there are two main parts of CNN architecture

- A convolution tool that extract various feature from the image.
- Fully connected layer that predict the output from the extracted features.

Following are various layers used in CNN architecture:

#### 4.2.1.1 Convolutional Layer

This layer is used to extracts the various input features. In this layer the mathematical calculations are performed among the input and particular filter. The output which is produced by this layer is the features map that provides the various information about the image like its edge and corner. Further the output produced by this layer feed as an input for other layers.

#### 4.2.1.2. Pooling layer

This is the second layer of CNN. The main task of this layer is to reduce the features produced by convolutional layer. The pooling layer work as a bridge between convolutional and fully connected layer.

#### 4.2.1.3 Fully connected layer

The fully connected layer contains various weights. This layer provides neurons to the various layers. This layer placed before the output layer.

#### 4.2.1.4 Dropout layer

When all the features are associated with FC layer then it produces overfitting among the training dataset. Overfitting caused when any model work perfectly on the training dataset and put the negative impact on the model performance when it is used for new type of dataset (Sakib et al., 2019).

## 4.3 Applications of CNN

### 4.3.1 Natural Language Processing (NLP)

Convolutional Neural Networks are conventionally useful in the area of computer vision. CNN models are useful for several natural language processing problems and accomplished glorious outcomes in text classification, semantic analyzing (Grefenstette, et al., 2014), query retrieval (Shen et al., 2014), classification (Kim, 2014) , NLP tasks (Collobert et al., 2011). In this work we are explaining applications of CNN in categorization of text and classification of sentence.

#### 4.3.1.1 Text Categorization

Text categorization means assigning predefined classes to those documents written in NLP. Many kind of text categorization associated with different kind of documents such as topics related to education, sports, sentiment classification, spam detection (Sahami et al., 1998). A distinctive technique to text categorization is to exemplify documents through bag-of-words.

#### 4.3.1.2 Sentence Classification

In the field of sentence classification CNN achieved an extraordinary performance. Here first of all every sentence is converted into vector and then a matrix is created which is used as an input. Yoon Kim used one layer CNN that achieved better result among many dataset.

Therefore the extraordinarily vigorous results gotten with this moderately CNN design (Joachims, 1998). More complex deep learning models for classification of text can absolutely to be developed, these developed applications probably be less complicated. They affords speedy training and estimation times.

### 4.3.2 Image Recognition

CNNs are frequently used in image recognition methods. During 2012, 0.23 % error rate on the MNIST database was calculated. CNNs achieved less error rate in face recognition applications. CNNs also used to evaluating video quality after manual training. In the ILSVRC 2014, all extraordinarily teams used CNN for their framework. The precision value increase to 0.439329 deduct classification error rate 0.06656 by the Google Net winner team (Szegedy et al., 2015).

## 4.4 Bidirectional LSTM (BiLSTM)

BiLSTM is a distinctive version of RNN, It helps to assist previous as well as next content of an encoded tweet. BiLSTM overcome the drawback of unidirectional LSTM.

The unidirectional LSTM hidden state ($h_t$) considers the previous information. To learn information from previous and next state BiLSTM consider forward LSTM and backward LSTM layer (Salur and Aydin, 2020).

**Forward LSTM**

Forward LSTM process from left to right by considering current input “x1” and previous input also known as hidden state “ht-1”. LSTM process input sequence x1, x2……xz-1 and produce “$\overrightarrow{h}$” output sequence.

**Backward LSTM**

This layer process right to left via concatenate the present input ‘$s_1$” and next state “ht+1”. This layer process the sequence xz+1,….x2,x1 and an output sequence “$\overleftarrow{h}$” is generated. The output generated by forward and backward layer are merged together and a new sentence is created H = [h1, h2, h3,…..hz], H ∈ $R^{zxm}$.

The element wise sum is calculated to join both forward and backward output. The BiLSTM model has the ability to examine a large volume of contextual information for the context efficiently.

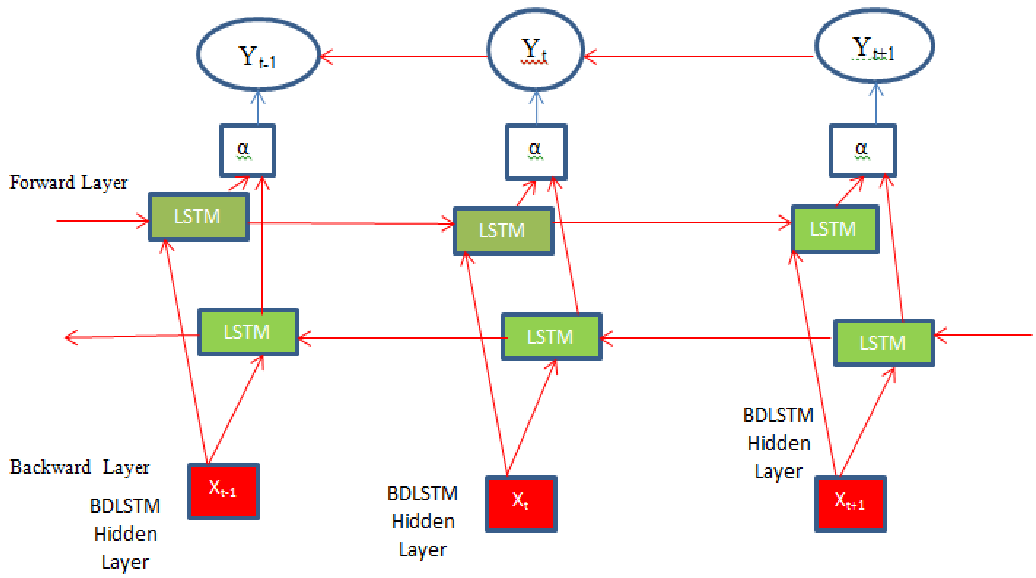



Fig .4.6 Architecture of BiLSTM (Salur and Aydin, 2020)

## 4.5 BiGRU

GRU was developed by (Cho et al., 2014), it is a type of RNN and proposed to solve the problem of long term memory and gradient during back propagation. RNN take sequential data as an input and neurons are linked in the form of chain. Cyclic factor are performed in the hidden layer hence neurons get the information from their own moments as well as other neurons. RNN having the sharing ability of parameters and memory. RNN is good to learn the features from linear data. The main problem of RNN is the gradient and it is not able to learn the long term memory historical data. To overcome the problem of RNN, LSTM is proposed by the researcher. In recent year to avoid the limitation of LSTM with extreme parameters and slow convergence GRU is proposed.

The architecture of GRU is simpler to LSTM. It provide better performance as compared to LSTM in many application. The architecture of LSTM having input, output and forget gate . GRU structure having reset, update date. GRU consume less memory and its calculation is faster as compared to LSTM (Chollet, 2018).

The BiGRU, is a sequential model which contains two GRUs. One for forward direction and another for backward direction.

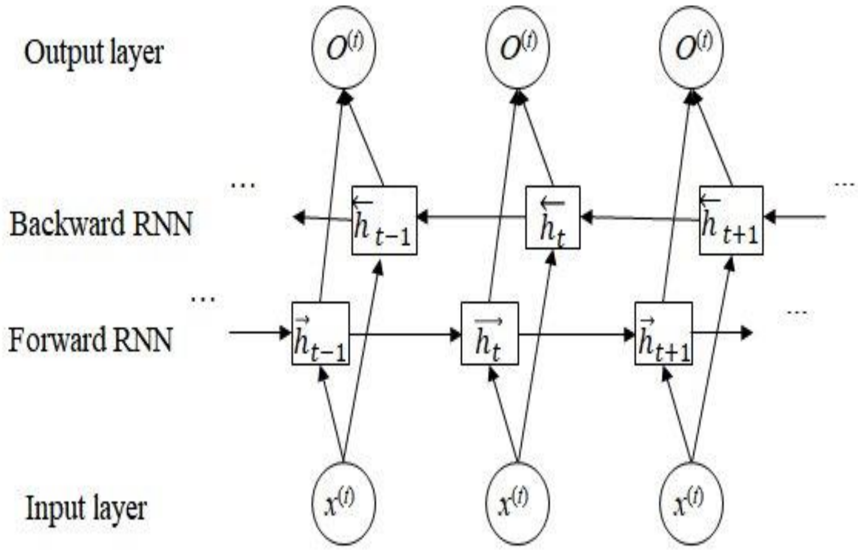



Fig.4.7 Architecture of BiGRU (Zhang et al., 2019)

## 4.6 Activation Functions

This is the most important parameter of neural network. The activation function decide which type of information processed further and which to discard. The activation function put in between or at the end of network. There are various types of activation functions used in CNN network.

### 4.6.1 Sigmoid Function

It is the non-linear activation function used in feedforward neural network. This function perform on the output layer and it predict output based on probability.

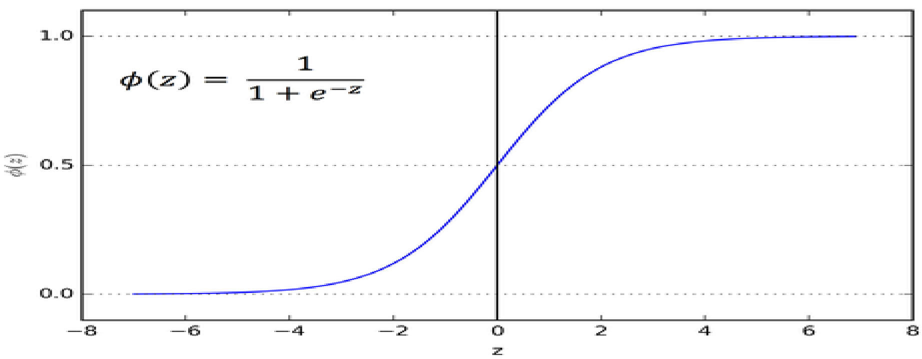



Fig. 4.8 Sigmoid activation function (Montavon et al., 2012)

This function shows the range value between 0 and 1 and from -1 to 1. The curve of sigmoid function look like S (Montavon et al., 2012).

## 4.6.2 Tanh

The Tanh is other form of AF used for deep learning and its several alternatives used among DL. The value of Tanh lies between -1 to 1. This provides better performance on multi-layer neuron network. However tanh not solve the vanishing gradient problem occurred during sigmoid processing. Tanh also produced some dead neurons. The problem of tanh motivates researchers to introduce another activation function. Hence ReLu function introduced to resolve the issue (Han and Monga,1995).

## 4.6.3 ReLU

This is the mostly used and it is one of the fast activation function (LeCun et al., 2015). It provides the better performance as compared to sigmoid and tanh function (Dahl, 2013).The ReLU signifies a linear function thus conserves the characteristics of linear models. The ReLU implements a threshold action to every input value. Wherever values small than 0 are assigned to zero hence the ReLU is expressed with the following expression.

$$f(x) = \max(0,1) \begin{cases} x1 & \text{if } x1>0 \\ 0= & \text{if } x1<0 \end{cases}$$

Relu function easily overfits as compared to other activation function. Limitation of this function fragile during the training period thus causing certain of the gradients to die. Some neurons also dead that not activated in future also. To resolve this problem leaky ReLU was proposed.

### 4.6.4 LReLU

This function introduced in 2013 to solve the problem of ReLu function. The alpha parameter created to solve the problem of dead neuron so that gradient value not becomes zero during training time (Mass et al., 2013).

The LReLU calculates by the following equation:

$$F(x)= ax+x = \begin{cases} x & \text{if } x>0 \\ ax & \text{if } x\leq 0 \end{cases}$$

Leaky ReLu produce the same result as compared to ReLU but it has non- zero value during the whole duration.

### 4.6.5 Maxout Function

This function proposed by Goodfellow and neuron in this function inherit the properties of ReLu and leaky ReLU. The main limitation of this function is the high computation cost because this function doubles the parameters (Goodfellow, 2013).

## 4.7 Proposed algorithm

The literature survey illustrates the effort of various researchers to mitigate the problem of rumour detection. Various machine and deep learning methods applied for rumour detection problem but the combination of these algorithms not applied by the researchers on this dataset. For the best of our knowledge we are applying this framework on this particular dataset for the first time.

To overwhelm the above said problem a new framework is developed. Various advance machine learning algorithms as mentioned in section 4.1 are implemented on the dataset and then deep learning algorithms mentioned in section 4.2 are implemented on the dataset. The proposed algorithm is the hybridization of various deep learning algorithms: CNN+BiLSTM+BiGRU.

Figure 4.9 represents the proposed framework that incorporates the various advance machine learning and deep learning algorithms.

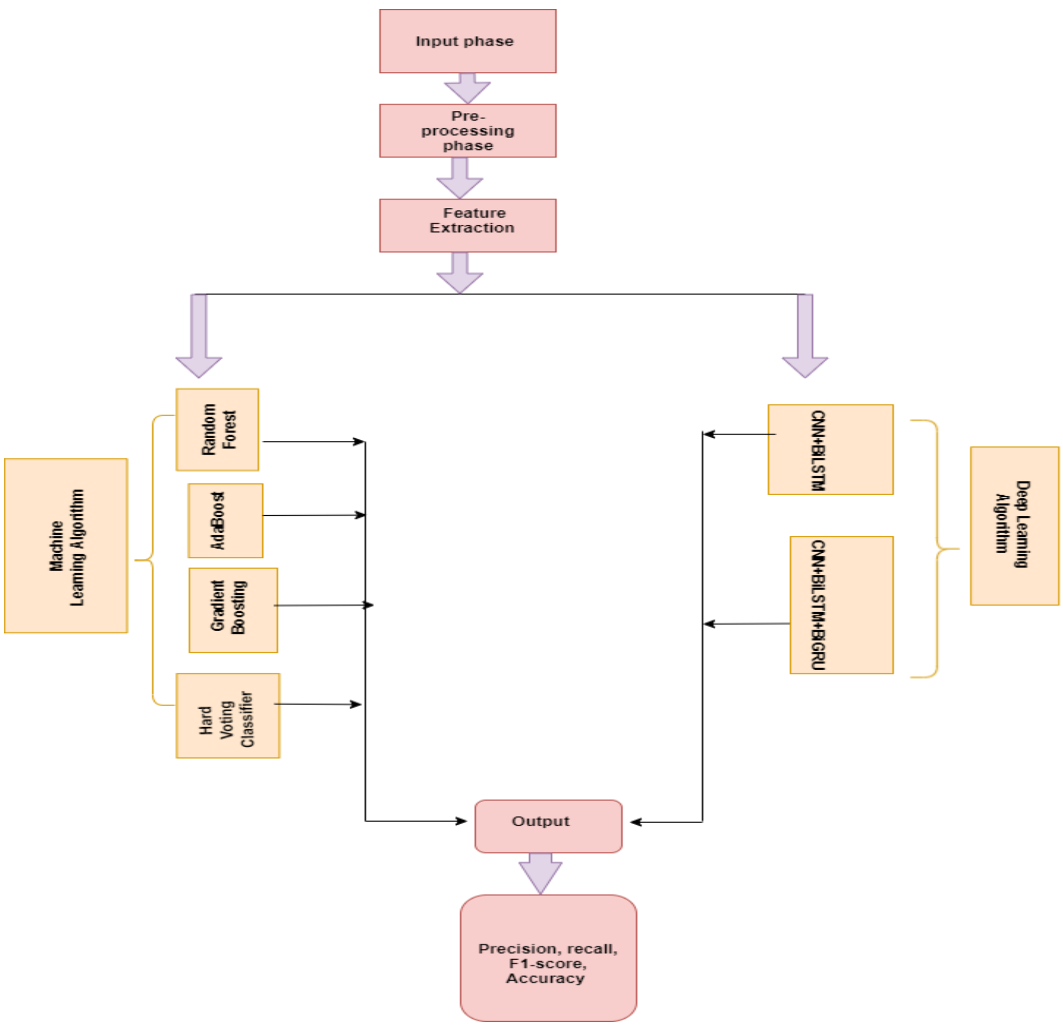



Fig.4.9 Proposed Framework

## 4.8 Methodology used

In the proposed work we emphasis for classification of tweets. To distinguish rumour tweet from non-rumour binary classification is performed.

The training data D={d1,d2….dn}€ $R^{zxm}$, where every row di ∈ Rn is the data and every column Ci ∈ Rz is the label of the class in the form of 0 and 1. If the value of the label is 1 then it is a rumour message otherwise it is non-rumour. Our aim to create hybrid model that label the tweets. During research various machines as well as deep learning models are experimented. The main contribution of the proposed study:

1. Tweets classification among rumour and non-rumour via hybridization of deep learning techniques.
2. Explore the classical feature over embedding layer using CNN, BiLSTM, BiGRU for classification of tweets.
3. Comparing the proficiency of the created framework with another baseline technique.
4. The proposed model provides better precision, recall, f1-score and accuracy as compared to another baseline models.

### 4.8.1 Platform Used

Colaboratory, or "Colab" for short is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser and is especially well suited to machine learning, data analysis and education. Colab is a hosted Jupyter notebook service that requires no setup to use and providing free access to computing resources including GPUs. The proposed work use google Colaboratory for implementing the various algorithms.

### 4.8.2 Dataset

The dataset used in the proposed work is open source and it is freely online available. This dataset is accessible from Kaggle and it contains 20,800 rows and 5 columns. The main advantage of this dataset as it is the combination of various sources from online platforms. The dataset not only restricted to politics domain but it also contains fake and real articles from another domain also. The dataset contains following columns.

Table 4.1 Detail of dataset used (https://www.kaggle.com/c/fake-news/data)

| Field | Detail |
|---|---|
| Id | Distinctive id for a news article |
| Title | The title of an article |
| Author | Writer for the tweet |
| Text | Content written in the article |
| Label | Label that describe the reliable and unreliable status of the article |

Table 4.1 illustrate the properties of the dataset. The values of the label field lie between 0 and 1. The value 1 indicates it is reliable sample and 0 means unreliable. We divided the 80% data for training and 20 % for testing purpose.

### 4.8.3 Preprocessing

The text data available among the social media contains lot of noisy data, it contains lot of content. Hence such data is not appropriate for experiment purpose. So it is very important to clean the noisy data. The previous study defines preprocessing increase the proficiency of the classification task. In the propose research we used NLTK for machine learning and the Texthero a python based library for deep learning approach to clean the data and then further used it for processing task. Text hero is an open source library. Figure 4.10 depicts the data preprocessing task used to clean the dataset.

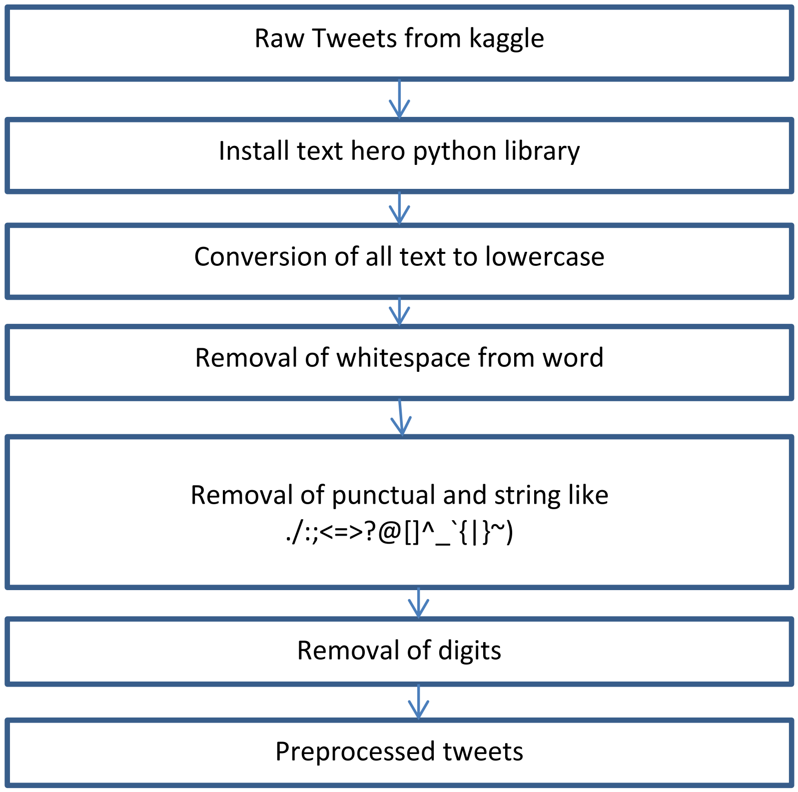



Fig. 4.10 Flow of data preprocessing

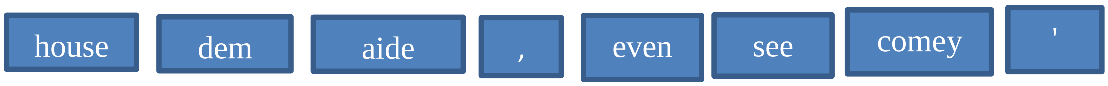
First of all data is loaded from the data dictionary. After loading the data, clean () method is used to pre-process the data. Several functions are used like fillna(), lowercase(),remove_digits(),remove_punctuation(),remove_diacritics(),remove_stopwords(),remove_whitespace() are used for preprocessing purpose.

During the preprocessing process all the text are converted to lowercase, replace the unassigned value with empty space, removal of stopwords , all white space among the words, all punctuation and string (!"#$%and'()*+,-./:;<=>?@[]^_`{|}~) are removed.

### 4.8.4 Tokenize the text

Tokenization is the fundamental step in both machine and deep learning based algorithm. The tokenization divide the piece of text into smaller segment (Bird, 2006). The token were converted to lowercase. For example in this tweet: House Dem Aide: Even SeeComey’s

The tokenization work as follow.




```
# pre-processing-2
text = hero.tokenize(df['text'])
text[:10]
```

```
Out[12]:

0    [house, dem, aide, ', even, see, comey, ', let...
1    [ever, get, feeling, life, circles, roundabout...
2    [truth, might, get, fired, october, tension, i...
3    [videos, civilians, killed, single, us, airstr...
4    [print, iranian, woman, sentenced, six, years,...
5    [trying, times, jackie, mason, voice, reason, ...
6    [ever, wonder, britain, ', iconic, pop, pianis...
7    [paris, --, france, chose, idealistic, traditi...
8    [donald, j, trump, scheduled, make, highly, an...
9    [week, michael, flynn, resigned, national, sec...
Name: text, dtype: object
```

Fig. 4.11 Data tokenization

### 4.8.5 Feature Extraction

During this process integer vector of the sentence are transformed into dense vector. Machine learning models unable to process the text directly so it is required to convert those texts into numerical form. To convert the text into number TF-IDF and CountVectorizer is used for machine learning and word embedding techniques are used for deep learning approach. There are numerous techniques to produce word embedding’s for the deep learning models, like as, one-hot encoding; TF-IDF, Word2Vec, custom embedding and GloVe embedding. We use the custom and Glove embedding which capture the semantic relationship among the text.

## 4.9 Activation Function

Activation function is used to calculate the weighted sum of input and based on the result it decide whether to fire the neuron or to discard it. Activation function control the output of the model among different domain (Md, 2017).

The proposed work use the sigmoid function also known as logistic or squashing in some studies (Turian et al., 2009). It is non-linear in nature and define by the Eq. (4.1).

$$f(x) = \left( \frac{1}{(1 + exp^{-x})} \right). \qquad (4.1)$$

The sigmoid activation function used in binary classification problem. In our case rumour detection is a binary classification between the range of 0 and 1.

It is nonlinear, so it can be used to activate hidden layers in a neural network. It provides clear predictions, i.e. very close to 1 or 0 which helps to improve model performance.

## 4.10 Library used

Numerous library and tools are used for model development. Kears is one of the most prominent used framework (Francois, 2015). TensorFlow used at the back end of the Keras and it provides support for both CPU and GPU (Abadi et al., 2016). In the proposed work both of these libraries run on the CPU.

## 4.11 Chapter Summary

This chapter depicts the work done on textual information for rumour detection. Various machine and deep learning based algorithm used in the proposed study are illustrated in 4.1. Further methodology used in the proposed research including dataset collection, data pre-processing, tokenization and feature extraction are defined this chapter.

# Chapter 5 Result Discussion

Accuracy is the key criteria used in this research for judging the outcome of the proposed framework. The measurements which are gotten through confusion matrix would be equated with other classification performance to demonstrate the proposed model. Precision, recall, f1-score, accuracy are gained through the confusion matrix (Salur et al., 2020).

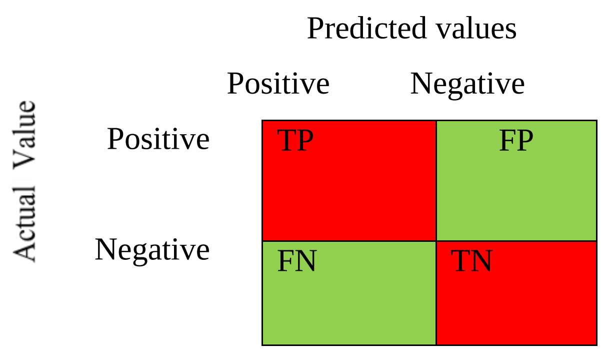



Fig.5.1 Binary classification confusion matrix

The abbreviation shown in the confusion matrix having following meanings.

True positive (TP): TP means predicted and actual both classes are positive.

True Negative: Predicted class value is positive and actual value are incorrect.

False positive (FP): Predicted class value is negative and actual value are incorrect.

False Negative (FN): Predicted class value is negative and actual value are correct.

Accuracy is calculated by the following equation.

Accuracy= TP+TN / TP+TN+FP+FN (1)

Precision : It is the ratio of relevant instance from the retrieved instance.

Precision =TP /TP + FP (2)

Recall : Recall is the ratio of the relevant instance that are effectively retrieved. It means it is the ratio of correct results divided through the total number of results that were retrieved.

Recall = TP/ TP + FN (3)

F1-Score

F1-score is another metrics to measure the accuracy. It combines the value of precision and recall.

2*((precision*recall)/(precision+recall)).                    (4)

## 5.1 Machine learning algorithms

Various machine learning algorithms mentioned in section 4.1 are experimented on the dataset and their precision, recall, f1-score and accuracy is checked. The Figure 5.2 defines the flowchart of machine learning algorithms used on the dataset.

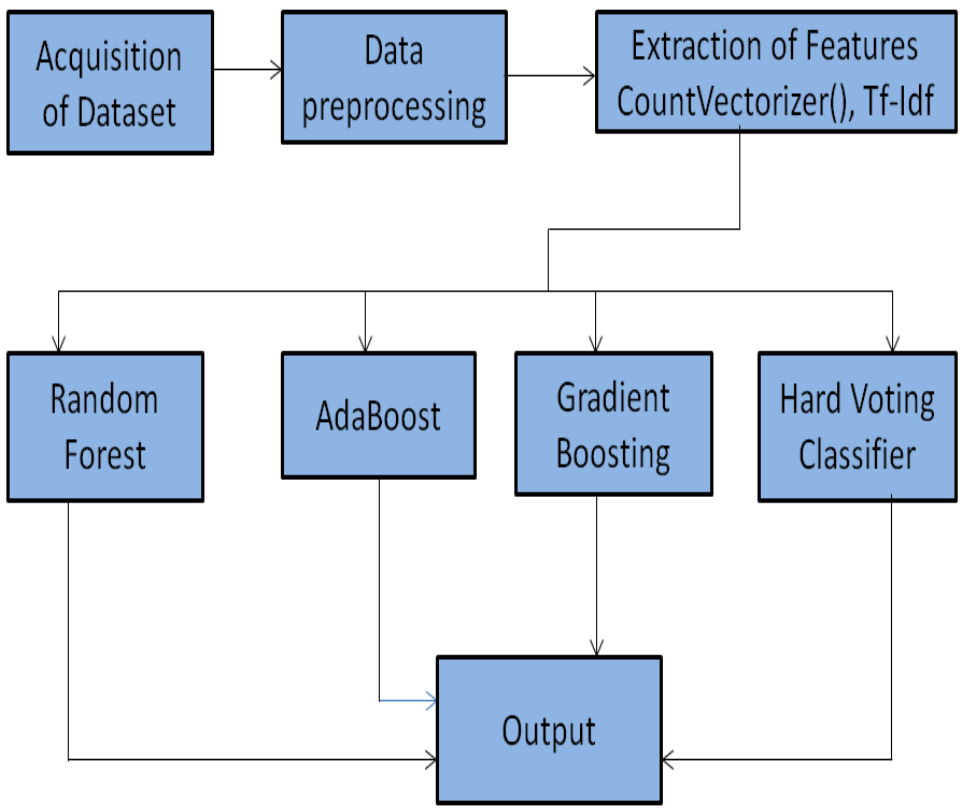



Fig. 5.2 Machine learning techniques

### 5.1.1 Random Forest

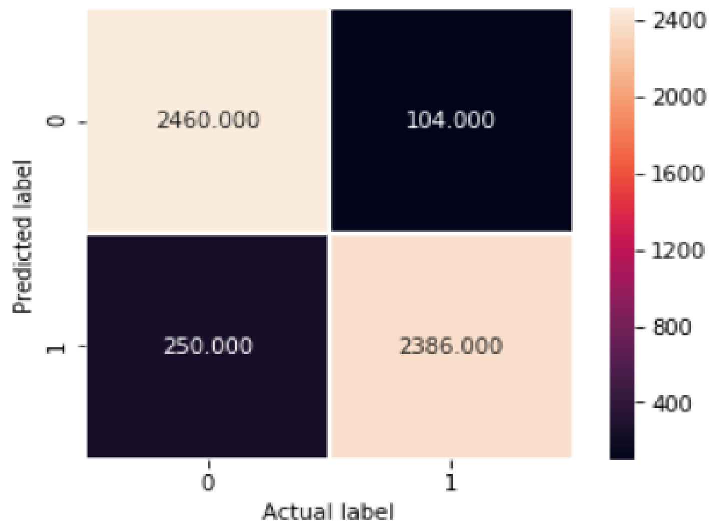



Fig 5.3. Confusion matrix of Random Forest

Figure 5.3 depicts the confusion matrix generated through random forest algorithm. Based upon confusion matrix this algorithm provides 93% accuracy, 90% precision, 96% recall and 92% F1-score.

### 5.1.2 Ada boost confusion matrix

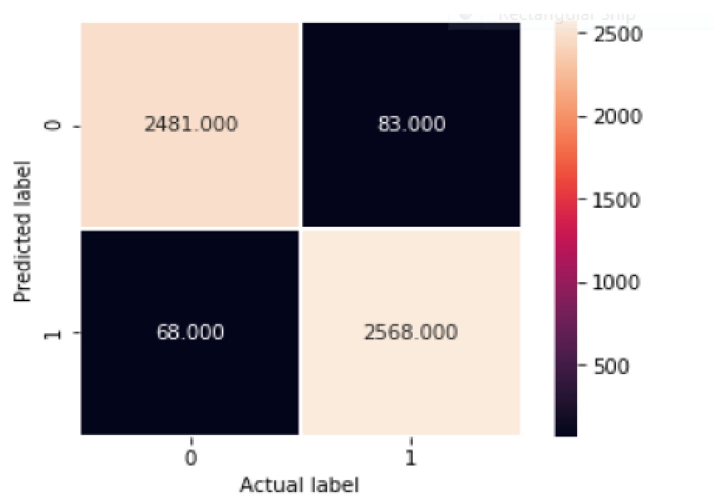



Fig 5.4. Confusion matrix of Ada Boost

Figure 5.4 depicts the confusion matrix generated through random forest algorithm. Based upon confusion matrix this algorithm provides 97% accuracy, 97% precision, 97% recall and 97% F1-score.

### 5.1.3 Gradient boosting confusion matrix

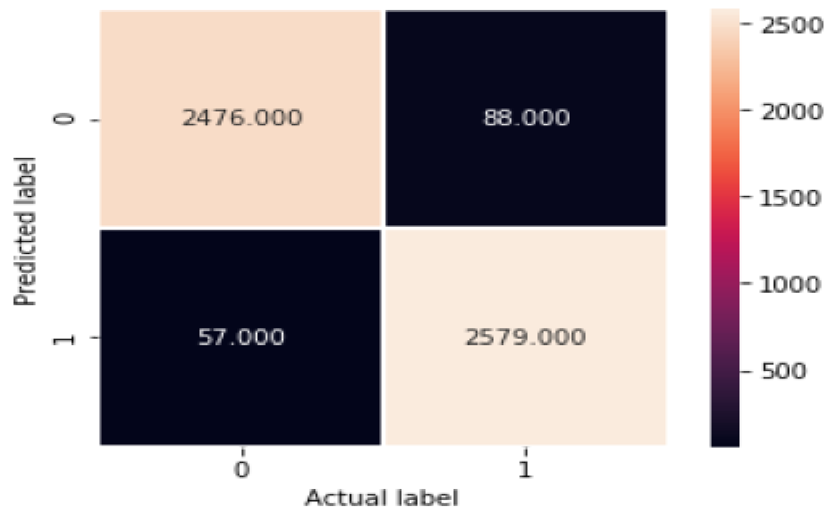



Fig 5.5. Confusion matrix of Gradient Boosting

Figure 5.5 depicts the confusion matrix generated through random forest algorithm. Based upon confusion matrix this algorithm provides 97% accuracy, 98% precision, 97% recall and 97% F1-score.

### 5.1. 4 Hard voting classifier

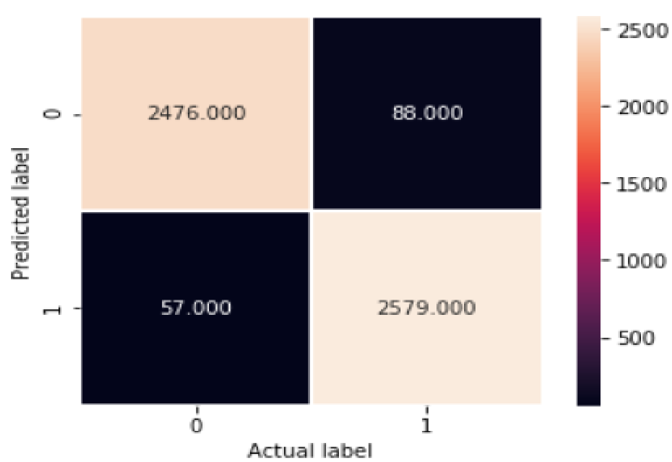



Fig 5.6. Confusion matrix of Hard voting classifier

Figure 5.6 depicts the confusion matrix generated through random forest algorithm. Based upon confusion matrix this algorithm provides 97% accuracy, 97% precision, 97% recall and 97% F1-score.

Table 5.1 Accuracy/Precision/Recall/F1-score of the machine learning algorithm

| Approach | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Random Forest | 93 | 90 | 96 | 92 |
| AdaBoost | 97 | 97 | 97 | 97 |
| Gradient Boosting | 97 | 98 | 97 | 97 |
| Hard voting classifier | 97 | 97 | 97 | 97 |

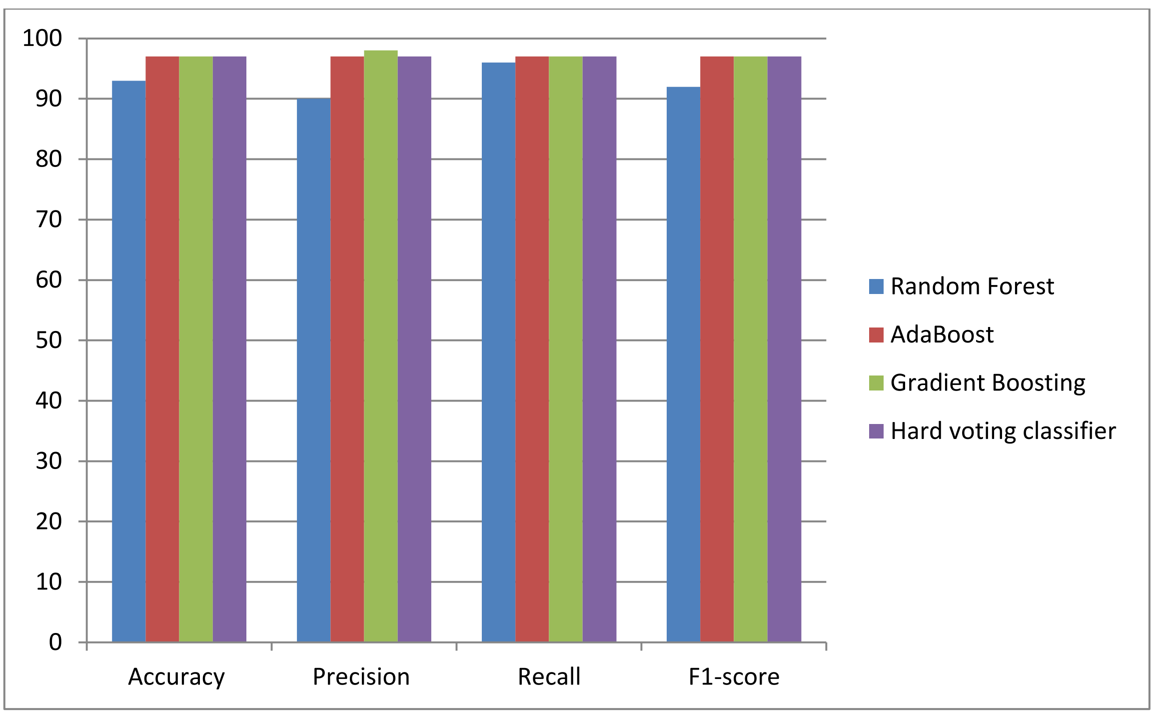



Fig. 5.7 precision, recall, f1-score , accuracy comparison of machine learning algorithms

## 5.2 Deep leaning based model

CNN-BiLSTM algorithm along with glove and custom embedding applied on the dataset and their accuracy is checked. Figure 5.8 defines the flowchart of deep learning algorithms.

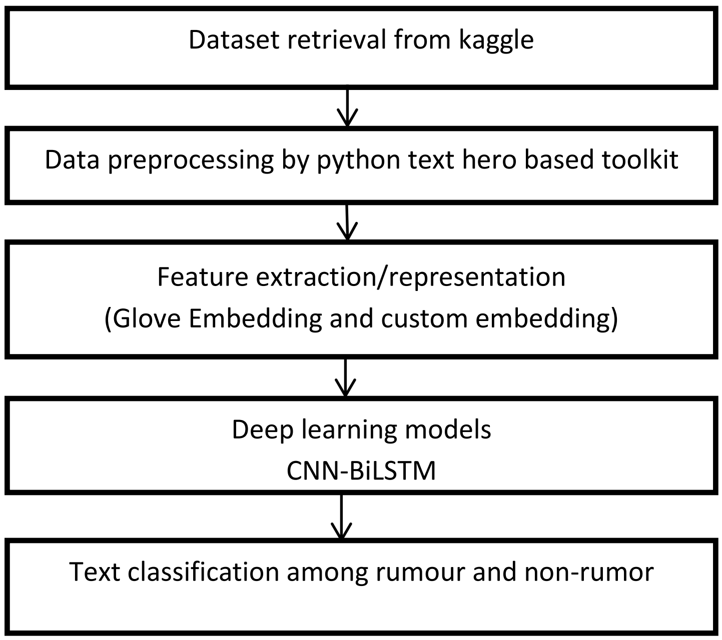



Fig. 5.8 CNN-BiLSTM Model

Table 5.2 Accuracy/Precision/Recall/F1-score provided by CNN-BiLSTM model

| Approach | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| CNN-BiLSTM (Glove Embedding) | 88 | 96 | 86 | 91 |
| CNN-BiLSTM (Custom Embedding) | 94 | 96 | 91 | 93 |

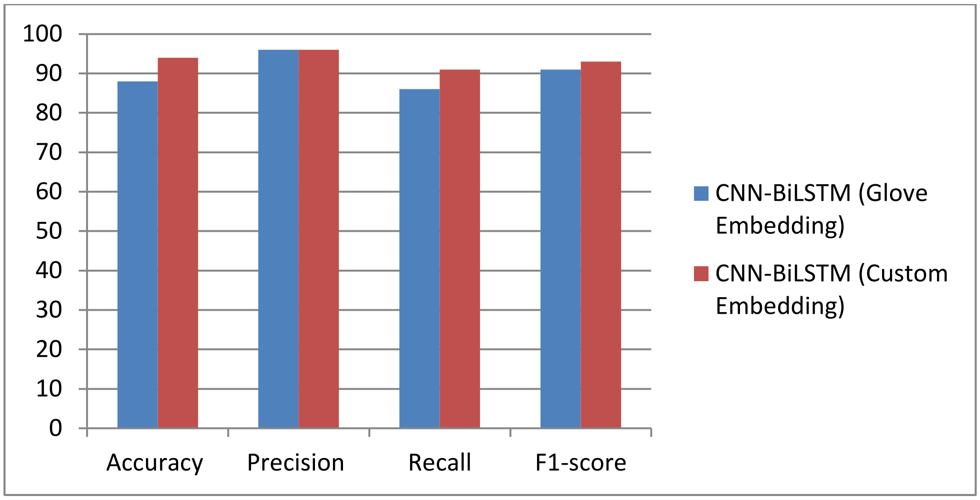



Fig. 5.9 precision, recall, f1-score , accuracy comparison of CNN-BiLSTM Model

## 5.3 Proposed hybrid model(CNN-BiLSTM-BiGRU)

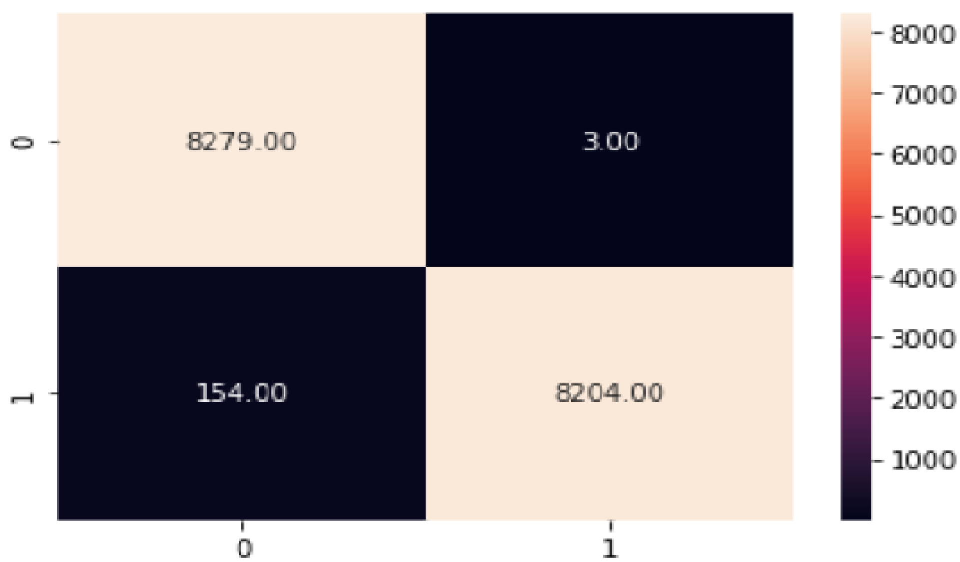



Fig. 5.10 Confusion matrix of the proposed model

Figure 5.11 depicts the confusion matrix generated through proposed hybrid model. The proposed hybrid model runs upon dataset. We also compare our created model to the previous research using the similar dataset (Ahmad, 2020).

Table 5. 3 Comparison with baseline study

| Approach | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Logistic regression (LR) | 91 | 92 | 90 | 91 |
| Voting classifier (RF, LR, KNN) | 88 | 88 | 89 | 88 |
| Bagging classifier (decision trees) | 94 | 94 | 95 | 94 |
| Boosting classifier (AdaBoost) | 92 | 92 | 93 | 92 |
| Perez-LSVM | 79 | 79 | 81 | 80 |
| Wang-CNN | 66 | 65 | 71 | 67 |
| Wang-Bi-LSTM | 52 | 43 | 59 | 44 |
| Proposed CNN+BiLSTM+BiGRU | 99 | 98 | 98 | 99 |

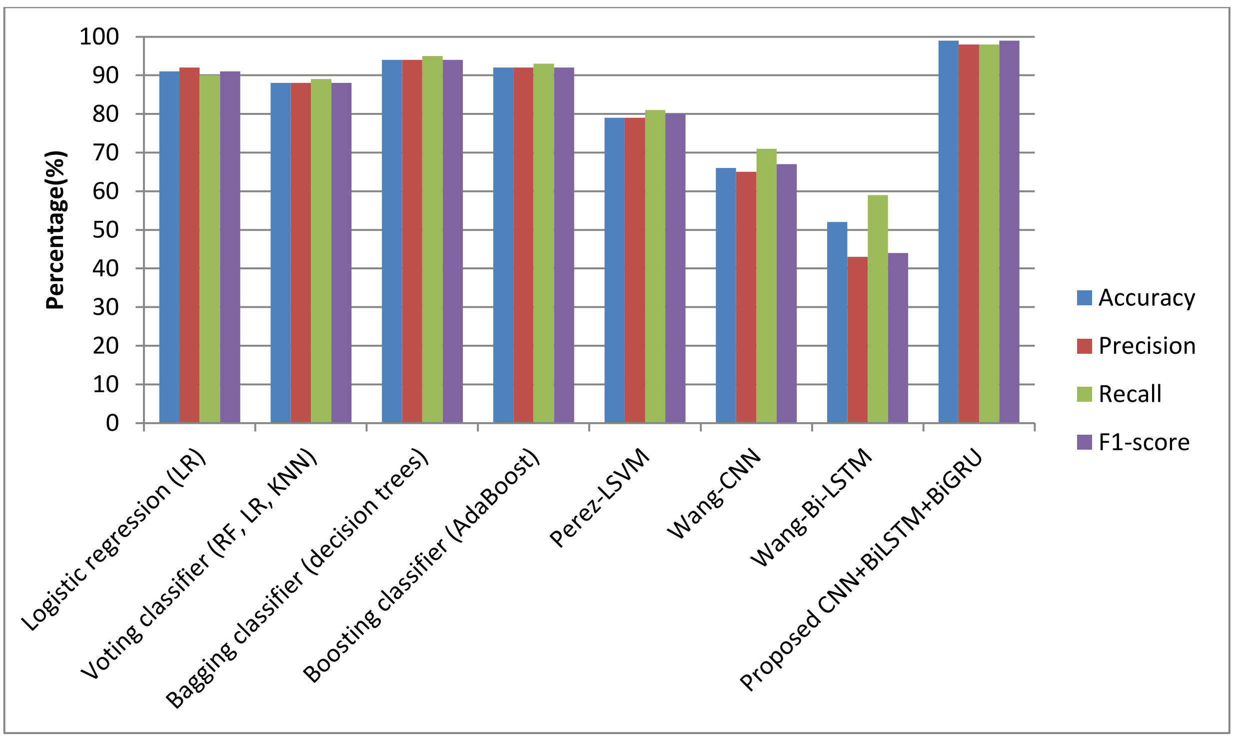



Fig.5.11 Comparison of Accuracy, Precision/ Recall/ F1-score with previous work

## 5.4 Chapter Summary

The chapter 5 deliberates the results of various machine, deep learning algorithms along with the proposed hybrid model.

# Chapter 6. Conclusion and Future Scope

This chapter presents the conclusion of the research in section 6.1. Limitation of the proposed research is discussed in section 6.2 and finally future scope is defined in section 6.3.

## 6.1 Conclusion

The advancement in social networking tools and applications make them prominent among different domain. User opinion on these tools has touched huge dimension. Nowadays, NLP and deep learning based techniques playing a vigorous role. During this research a novel hybrid deep learning techniques based model is created to create an association among the textual data.

During this research 2935 records fetched from the Web of Science database of 1989 -2021were subjected to bibliometric study, which included year-wise production and citation, most productive country and organisations, source journals, top contributing authors, keywords occurrence.

In this research we work on rumour detection task by developing a deep hybrid approach. The proposed approach contains (i) dataset collection (ii) data preprocessing (iii) feature extraction (iv) text classification.

Our proposed model work with custom embedding under CNN, BiLSTM and BiGRU algorithms. Extracted features are transmitted to sigmoid activation function for classification. Fake news dataset is used for experimental purpose and then the comparison of proposed method is done with work done so far. We achieved 99% classification accomplishment with our proposed hybrid model.

We investigated with many machine and deep learning techniques and described results on fake news dataset.

The aforementioned results define the word embedding methods enhance the classification outcomes of the method (CNN+BiLSTM+BiGRU) for classify tweets among rumour and non-rumour.

## 6.2 Shortcomings

The proposed method has the subsequent shortcomings:

1. The research only used textual features for classification. However the enclosure of other features might yield more vigorous outcomes.

2. Only English text used for experiment purpose.

## 6.3 Future scope

1. In accumulation to textual features, another kinds of feature such as images as well as contextual can be considered for getting proficient outputs.

2. Further experiments performed on text data including linguistic perspective.

3. Explore deep learning methods for detection of rumour.

Moreover for bibliometric analysis the data is selected only from the Web of Science. It might be possible many studies on the rumor detection are published in other journals and not accessible via Web of Science. Future bibliometric analysis in this area may observe numerous journals and other accessible databases such as Scopus, Google Scholar, EBSCOhost, and many more. Further research may achieve improved results by comparing various terms like rumor and techniques, rumour and framework and further analysis is done on each term separately. Future research may consider co-citation analysis of another terms not covered through this research.

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