iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 10 **Issue:** VI **Month of publication:** June 2022

DOI: https://doi.org/10.22214/ijraset.2022.44293

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 10 Issue VI June 2022- Available at www.ijraset.com

Emotion Detection on text using Machine Learning and Deep Learning Techniques

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Abstract: Emotion detection on text is an important field of research in Artificial Intelligence and human-computer interaction. Emotions play key role in human interaction. Emotion detection is closely associated with sentiment detection, in which we detect the polarity of the text.
But in emotion detection, we detect emotions such as joy, love, surprise, sadness, fear, and anger. Emotion detection helps the machines to understand human behavior and ultimately it provides users with emotional awareness feedback.
In this paper, we are going to compare Machine Learning and Deep Learning techniques with their accuracy and f1 scores. The experimental results show the results provided by deep learning techniques (Bi LSTM and Bi GRU) with word embeddings are more accurate than the other techniques.
Keywords: Emotion detection; GRU; LSTM; Deep Learning; Machine Learning;

I. INTRODUCTION

Emotion is subjective, complicated, and sensitive to the context. Emotional acceptance is used in several fields like medicine, law, advertising, etc. There are numerous techniques to detect human emotions, a few of them are by perceiving facial expressions, body movements, pressure level, heartbeat rate, etc.

But detecting emotion from the text is the difficult one, since all the previously mentioned processes have an environment and context. There is a lot of textual data on the internet that is to be classified to improve human-computer interaction. Emotion detection can be used in applications like-, Public sentimental analysis, social-media communication, and human-computer interaction.[3]

This paper considers six basic emotions joy, sadness, love, fear, anger, and surprise.

In this paper, we are going to use two machine learning (Random Forest classification and Logistic Regression) and two deep learning algorithms (Bi-LSTM and Bi-GRU). In deep learning, we are going to use pre-trained word embeddings .

Model performance is evaluated by prediction and accuracy. In the end, we compare the performances of models to predict the best model.

II. LITERATURE SURVEY

As emotion detection in text has lots of applications, the research in it is still developing and ongoing. There are various methods developed by researchers.

There are traditional methods that use the keywords in the sentence, which are called as lexicon-based methods and there are methods that use traditional machine learning algorithms, and find the emotion of the sentence [6] and there are some methods where deep learning methods like LSTM[2] and CNN are applied to the classification.

Word embedding is a technique that is used to replace the text with feature vectors that can be used to embed the text .

Though many researchers have proposed many different methods, there is always room for development. Therefore we aim to develop a method based on Bi LSTM and Bi GRU.

III. PROPOSED SYSTEM

This section describes various steps of our proposed system. Fig 1 shows the machine learning approach architecture and Fig 2 shows the deep learning approach architecture.

A. *Machine Learning Approach*

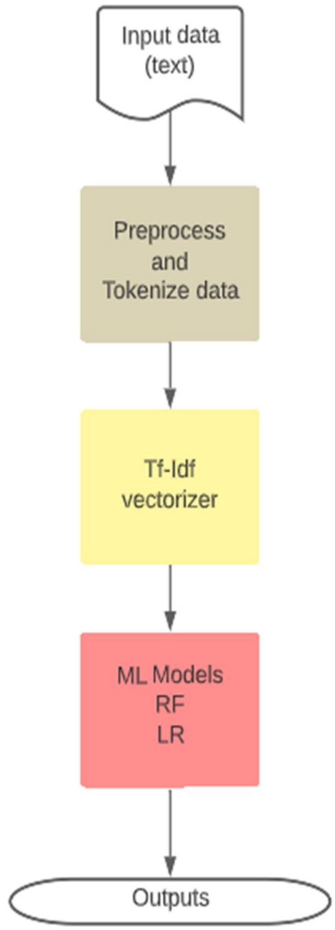

Fig. 1 . Machine Learning Approach Architecture

There are three steps involved in the machine learning approach.

1) *Preprocess and tokenize text:*

a) *Preprocess:* In this step, we are removing all the punctuations, Html markups, hashtags, URLs, @names, and extra whitespaces and we are removing stop words, lemmatizing, and, stemming text.

b) *Tokenize:* Here we are converting all the sentences into tokens of words.

2) *TF-IDF Vectorizer*

TF-IDF Vectorizer is used to transform the text to feature vectors which can be used as inputs to the models. Here we transform input data into features.

3) *ML Models*

Here we are using two machine learning models

a) *Random Forest Classifier:* Random forest classification is an ensemble learning technique, which uses a technique called Bagging and it is easy to implement and provides better results than other traditional machine learning algorithms.

b) *Logistic Regression:* Logistic Regression is a statistical model that is used to predict probabilities of different possible results (outputs). This paper uses Multinomial logistic regression. This machine learning approach is used to compare the traditional methods with the RNN methods. The actually proposed method follows from here.

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B. Deep Learning Approach

After preprocessing and tokenizing the data, we have converted those tokens into sequences and created an embedded matrix using pre-trained word vectors. By using the embedded matrix as weights we have created an embedded layer. Then we added the Bidirectional LSTM / Bidirectional GRU layers.

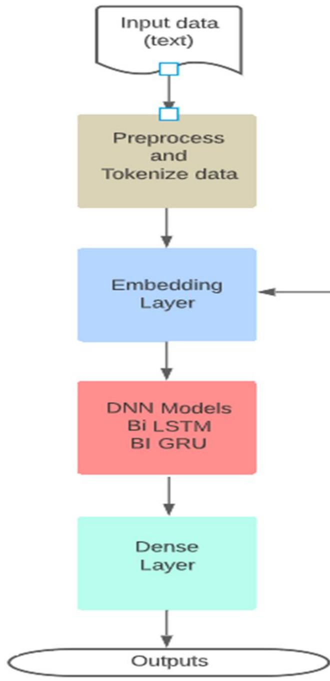

Fig. 2 . Deep Learning Approach Architecture

1) DNN Models

a) Bidirectional LSTM

Bidirectional LSTM is a type of RNN, that consists of two LSTMs, that take inputs in both directions.

LSTM unit has cell, an input gate, an output gate, and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information in and out of the cell.

Forget gate is used to choose whether to remember the previous information or not.

Input gate is employed to quantify the importance of the new information carried by the input.

The output gate is used to determine the information in the state to be routed to the output.

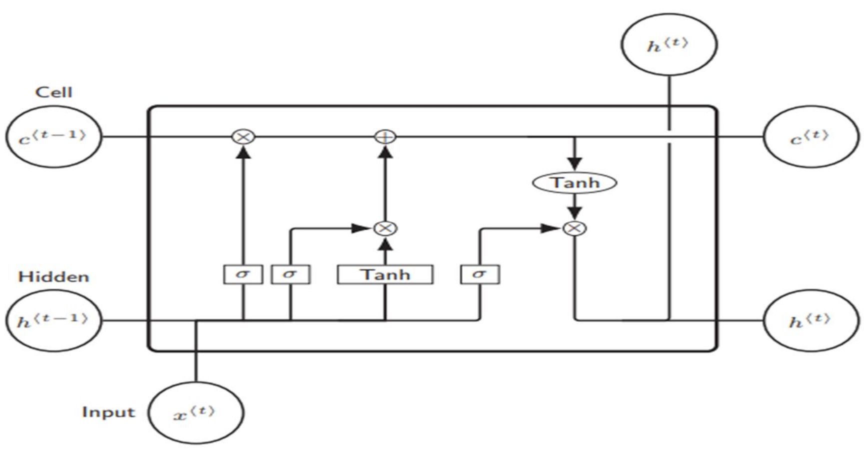

Fig. 3. LSTM Unit

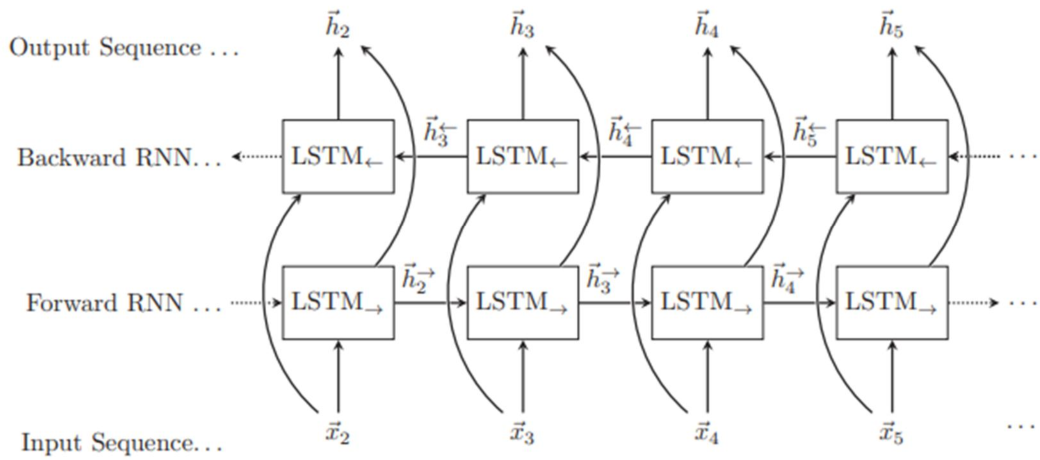

Fig. 4 . Bidirectional LSTM architecture

b) Bidirectional GRU

Bidirectional GRU is a type of RNN, that consists of two GRUs, that take inputs in both directions.
GRU unit has two gates, an update gate, and a reset gate.

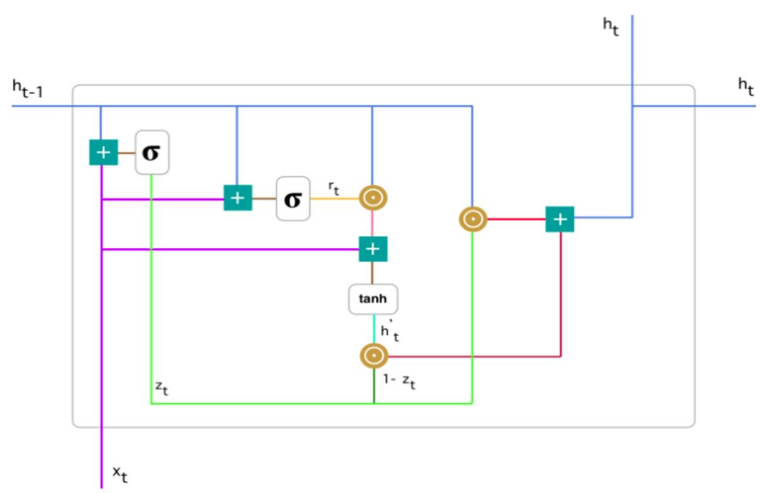

Fig. 5. GRU Unit

Update gate is used to see what proportion of the past information must be passed along to the future.
Reset gate is used to see what proportion of past information to forget.

2) Dense Layer

A dense layer is a deeply connected layer that is used to change the dimension of the output.

IV. EXPERIMENT AND RESULTS

A. Experimental Environment

In this paper, we have used Ubuntu 20.04 as the operating system, with 8GB RAM – 1TB Disk space as hardware, we used python 3.10 as the programming language and jupyter notebook as IDE.

B. Evaluation Metrics

We are using accuracy and f1 score as metrics to evaluate the model.

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C. Emotion Recognition Dataset

The dataset we used is from Kaggle ('Emotions Dataset for NLP'), it has two CSV files, one is for training and the other is for testing. It has two columns, content and sentiment. The training dataset has 16000 rows and the test dataset has 2000 columns. There are 6 labeled classes in the dataset – joy, sadness, anger, surprise, fear, and love.

Fig shows the training data class distribution.

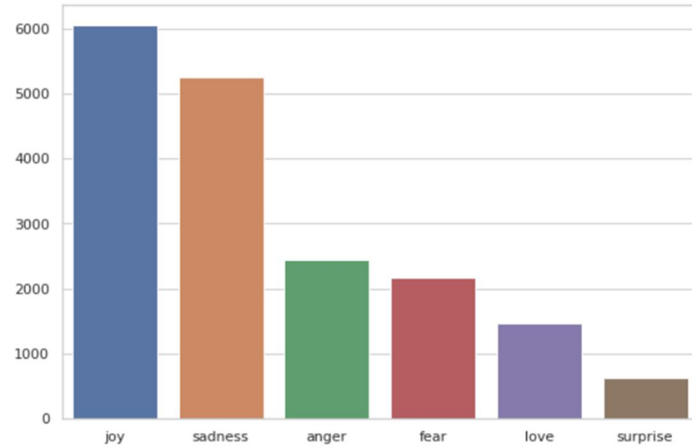

Fig. 6. Class distribution of training data

D. Data Preprocessing

In section IIIA data preprocessing is covered.

E. Hyper Parameter Setting and Training

1) *Machine learning Techniques:* We have used random forest and logistic regression. Table I and Table II provide the details of the parameters used in our model.

TABLE I
HYPERPARAMETERS OF RANDOM FOREST

Parameter	Random Forest
n_estimators	50
max_features	"auto"

TABLE III
HYPERPARAMETERS OF LOGISTIC REGRESSION

Parameter	Logistic Regression
solver	"lbfgs"
Multi classes	"auto"
Max iterations	200

2) *Deep Learning Techniques:* We have used BiLSTM and BiGRU. Table 3 provides the details of the parameters used in our model.

TABLE III
HYPERPARAMETERS OF BI LSTM BI GRU

Parameter	Bi LSTM / Bi GRU
batch size	128
Learning rate	0.001
Drop out	0.2
epochs	15
optimizer	adam

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F. Results

We have used accuracy, f1score(weighted) metrics, and confusion matrix, to show our results.

1) *Machine Learning Techniques:* Among the machine learning approaches Random forest achieved the highest accuracy of (73.95%) and an f1score of (73.14) and Logistic Regression achieved an accuracy of (70.35%) and an f1score of (65.26).

Fig 7 and Fig 8 show the confusion matrices of Random Forest and Logistic Regression respectively.

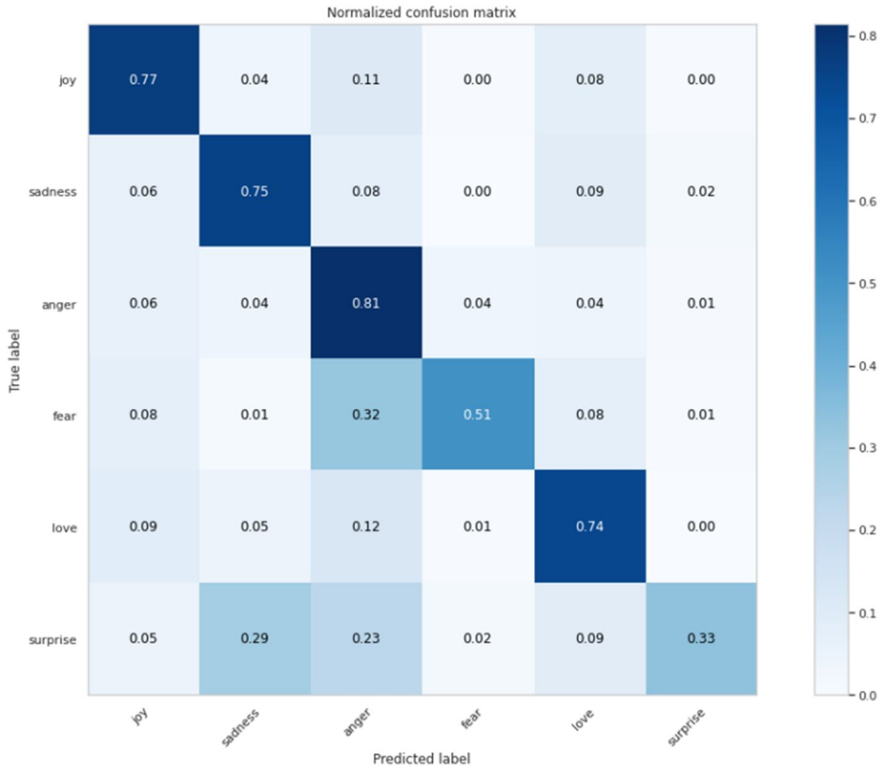

Fig. 7. Confusion matrix of Random Forest

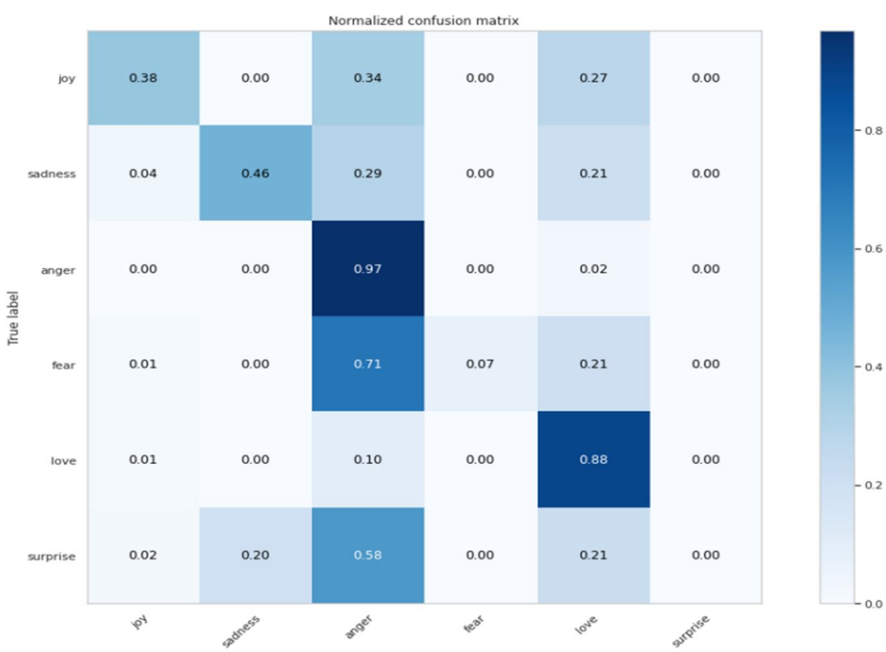

Fig. 8. Confusion matrix of Logistic Regression

2) *Deep Learning Techniques:* Both approaches (BiLSTM and BiGRU) gave almost the same accuracies. BiGRU achieved an accuracy of (78.70%) and an f1score of (78.06) and BiLSTM achieved an accuracy of (78.25%) and an f1score of (77.78).

Fig 9 and Fig 10 show the accuracy and loss of BiLSTM model.

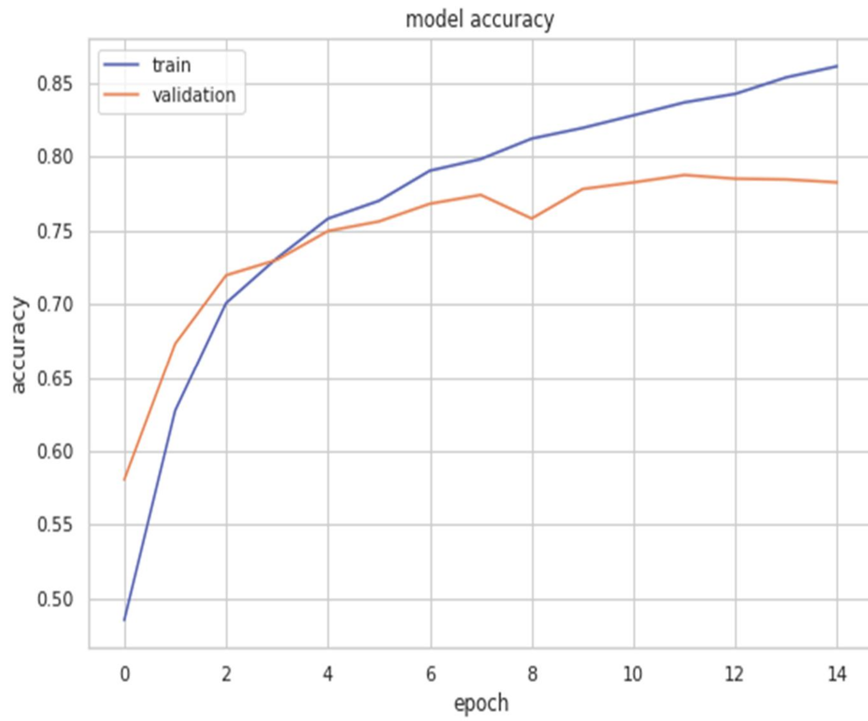

Fig. 9 Accuracy of Bidirectional LSTM Model

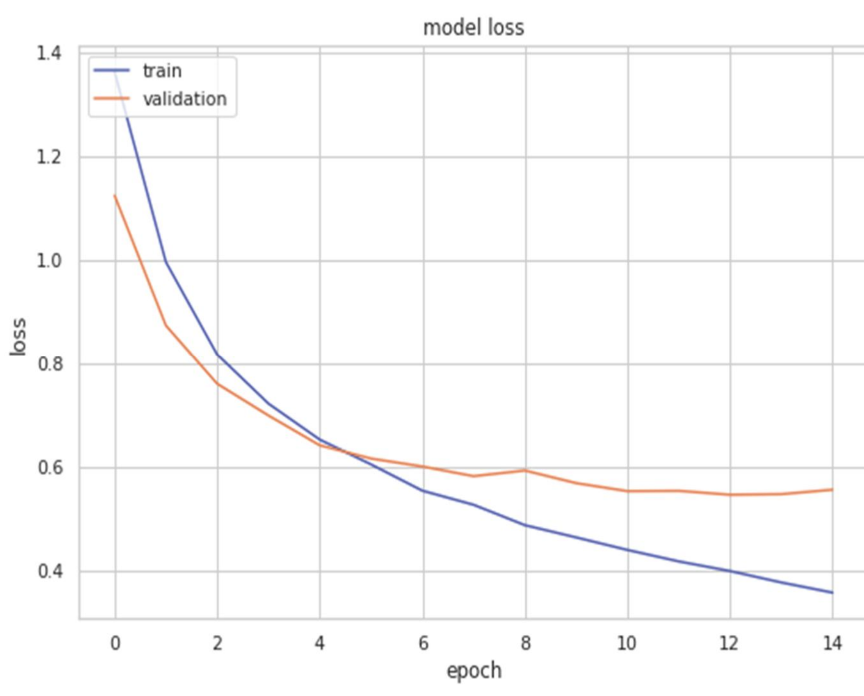

Fig. 10 loss of Bidirectional LSTM model

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Fig 11 and Fig 12 show the accuracy and loss of BiGRU model.

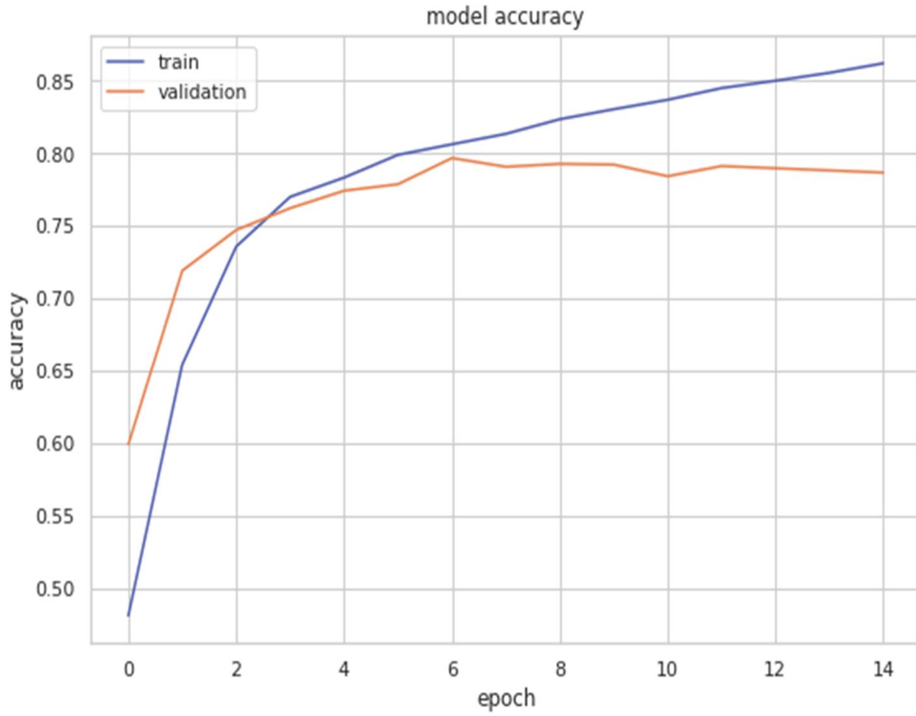

Fig. 11 accuracy of Bidirectional GRU model

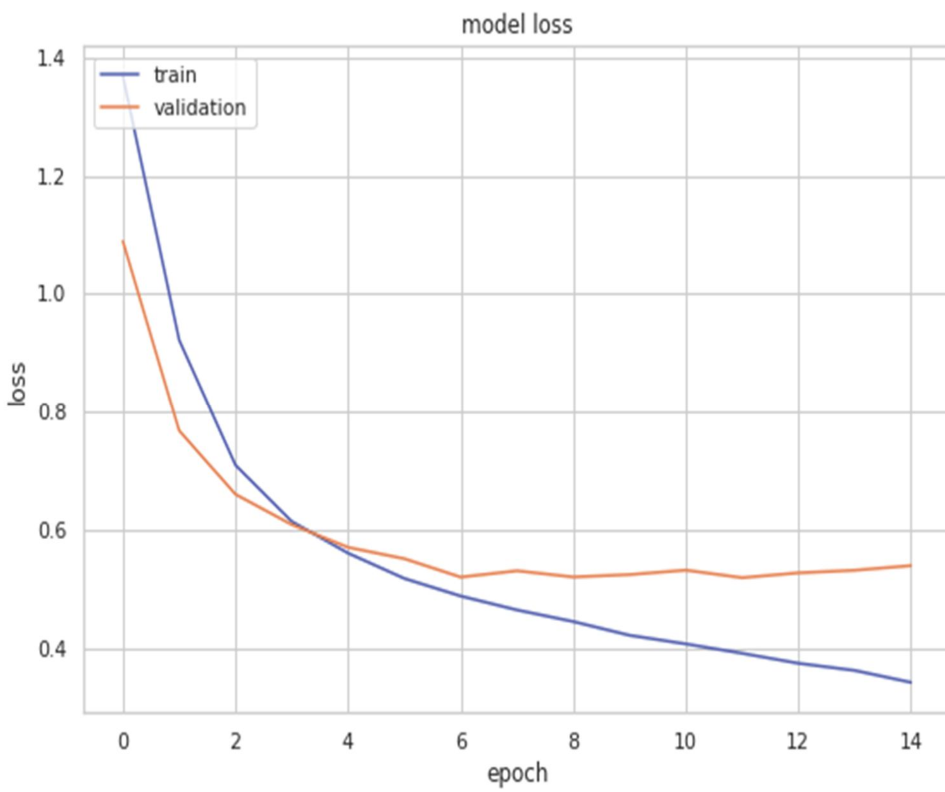

Fig. 12 loss of Bidirectional GRU model

Fig 13 and Fig 14 show the confusion matrices of Bi LSTM and Bi GRU respectively.

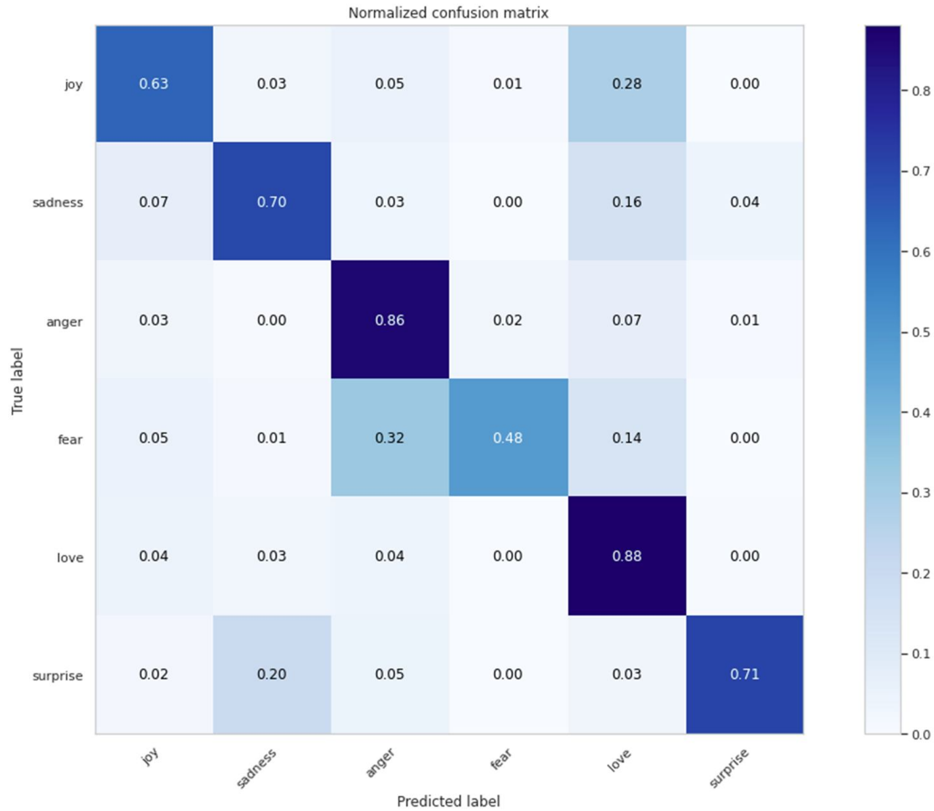

Fig. 13 Bidirectional LSTM - Confusion matrix

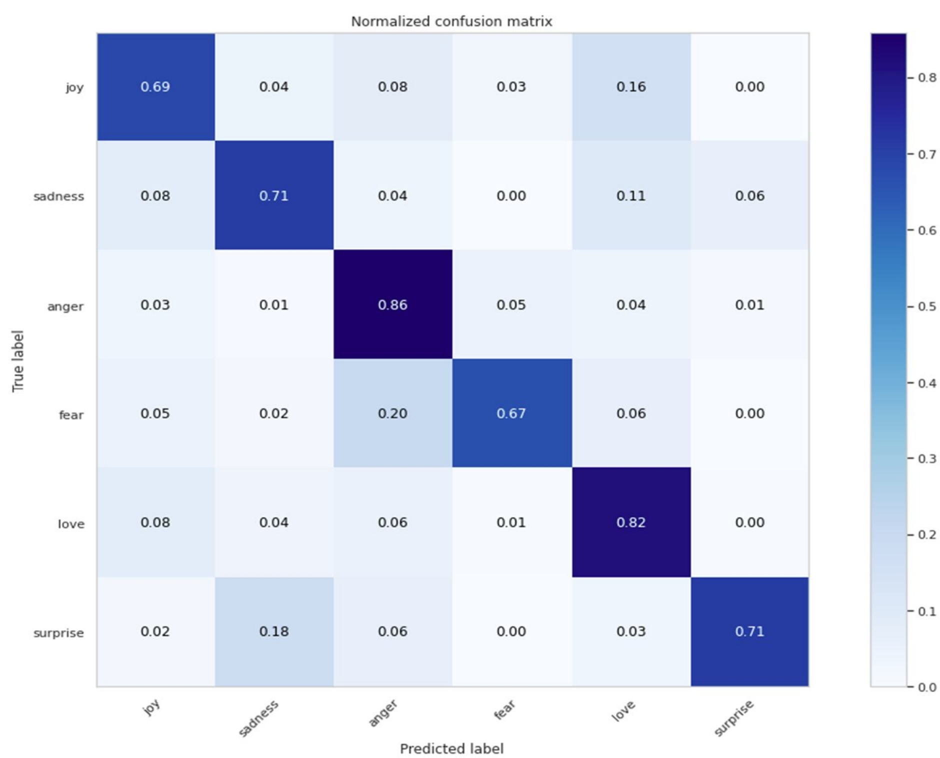

Fig. 14 Bidirectional GRU- Confusion matrix

Comparison of all models with their respective accuracy and f1 scores.

TABLE IIIV
ACCURACY AND F1 SCORES OF VARIOUS MODELS

Model	Accuracy	F1score (Weighted)
Random forest	73.95	73.14
Logistic Regression	70.35	65.26
Bi LSTM	78.25	77.78
Bi GRU	78.70	78.06

All the models worked well on the given problem. All the models classified anger and love pretty well.
But the RNN (Bi LSTM and Bi GRU) provided us with good accuracy with the other emotions.

V. CONCLUSION AND FUTURE SCOPE

This paper investigated many Machine Learning models and RNNs. By seeing the above results we can conclude that the RNNs are performing better than the traditional machine learning algorithms in text emotion detection. Since, LSTM and GRU are the sequential models that are mainly used for NLP, they give better results. And we can conclude that statement experimentally by proving Bi LSTM (78.25% accuracy) and Bi GRU (78.70% accuracy) are giving better results.
In the future, we can improve this area of research by implementing sophisticated deep neural networks or combining Neural network layers, and training the model with a lot of data.

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