# Emotion Extraction and Classification from Twitter Text

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***Abstract*—Emotion is one of the basic instincts of a human being. Emotion detection plays a vital role in the field of textual analysis. At present, people's expressions and emotional states have turned into the leading topic for research works.In this project, Our primary goal is to detect human's emotion from text input through some Deep Learning Model.**

***Index Terms*—Emotion Detection, GloVe 6B 300d, CNN, Bi-LSTM.**

## I. Introduction

Emotion is one of the basic instincts of a human being. Emotions refer to various types of consciousness or states of mind that are shown as feelings. They can be expressed through facial expressions, gestures, texts, and speeches. Emotion detection plays a vital role in the field of textual analysis. At present, people's expressions and emotional states have turned into the leading topic for research works. Emotion Detection and Recognition from texts are recent fields of research that are closely related to Emotion Analysis. Emotion Analysis aims at detecting and recognizing feelings through the expressions from sentences such as Joy, Surprised, Sadness, Anger, Love and Fear. For detecting emotions, CNN and Bi-LSTM models will be used.

### *A. Motivation*

As humans are the only most important part of social media so their emotions also play a vital role in it. Analyzing human emotions is essential for the country, business, or individuals for their existence. On Twitter, people share their opinion on the national or international election, games, international relationships, stock market, and other trending issues. By analyzing their opinions we will be able to know how the people are reacting to any changes and what is their thinking and this will help the socialists and researchers to think about what kind of measures they should take to change the society or related issues that are beneficial for the human being. By emotion extraction, we will be able to detect positive or negative sentiment towards an issue of people.

### *B. Challenges*

Humans are full of emotions and they are very excited about expressing them. Social media provides such a platform where people express their emotions willingly. Twitter is also this kind of platform. In machine learning, human emotions are categorized only into two classes which are positive and negative. But human emotions are more than these. They have different kinds of mixed emotions. In a sentence, a human can express joy and surprise at the same time. In this project, we are dealing with human basic emotions. The main challenge will be to detect these emotions from mixed emotions and classify them more than positive or negative.

## II. Related Work

This section briefly surveys previous works on sentiment and emotion detection of text.

Maryam Hasan, Elke Rundensteiner, Emmanuel Agu from Computer Science Department has published a paper on "EMOTEX: Detecting Emotions in Twitter Messages". On their work, they have introduced a new approach which is automatically classify text messages of individuals to infer their emotional states [1]. They have used hash-tag as label, that's why their proposed work is able to trains supervised classifiers to detect multiple classes of emotion without any manual effort.

Marina Boia, Boi Faltings, Claudiu-Cristian Musat, Pearl Pu on their research found that emoticons used in live streaming strongly coincides with the sentiment of the entire tweet [2]. For emotion detection emoticons is a very useful feature. So emoticons needs to be considered in sentiment classification.

Alec Go, Richa Bhayani and Lei Huang on their study of "Twitter Sentiment Classification using Distant Supervision" has used twitter text as input and Western-style emoticons to label and classify them into positive and negative sentiment [3]. To classify them, they have used Naive Bayes, Maximum Entropy, and SVM and achieved 80% accuracy.

Vinay Kumar Jain, Steven Lawrence Fernandes, Shishir Kumar have proposed journal on their work on "Extraction of emotions from multilingual text using intelligent text processing and computational linguistics" [4]. They have used multilingual text data for emotion detection. These data was collected using emotion theories which deals with psychology and linguistics.

Another work for emotion recognition on text data has been done by Douji yasamina, Mousannif Hajar and Al Moatassime Hassan on "Using Youtube comments for text-based emotion recognition". They have detected user's emotions from their textual exchanges, dealing with the complexity of char writing style and the evolution of languages [5].

Some researchers applied lexical approach to identify emotions in text. They contrived a vast lexicon annotated for six basic emotions: anger, disgust, fear, joy, sadness and surprise [6]. In another work, Choudhury et al [7] identified a lexicon of more than 200 moods frequent on Twitter. They collected posts which have one of the moods in their mood lexicon in the form of a hash-tag at the end of a post.

Recently, Darmon and his colleagues [8] tried to predict the behavior of users on social media by modeling representations. They found that most users see only a few latent states of behavioral processing. Any model that is able to capture these states will do well at capturing the behavior of users.

In our selected paper for word embedding, they have used one-hot representation. In one-hot representation, it creates sparse. Sparse means when a vector contains lots of zeros than ones. Sparse is created when the size of the vocabulary is too large. In our proposed work, we used GloVe 6B 300d. Here, 6B means 6 Billion, and 300d means 300 dimensions or features. It doesn't produce sparse. Also gives meaningful weight to the vector which helps to maintain the sequence. On the other hand, one-hot representation tells whether the word does exist in the sentence or not.

## III. Project Objective

Our project objective of this project is to detect emotions from texts. To complete this project, we used deep learning to detect emotions after analyzing the texts. We have measured the accuracy of the models in detecting emotions. We used CNN and Bi-LSTM as our models. From the texts, we will detect six types of emotions such as Joy, Surprised, Sadness, Anger, Love and Fear.

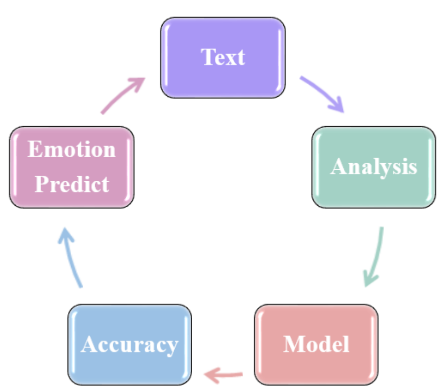


Fig. 1. Project Workflow

## IV. Methodologies

Two models are being used in this project. They are: CNN and Bi-LSTM.

### A. Convolutional Neural Network

In deep learning, a convolutional neural network (CNN) is a class of artificial neural network [9]. A convolutional neural network consists of an input layer, hidden layers and an output layer. In a convolutional neural network, the hidden layers include layers that perform convolutions. We used ReLU (Rectified Linear Unit) as activation layer in hidden layers. In the hidden layers, it includes other layers such as embedding layer, pooling layer, dropout layer, and fully connected layer.

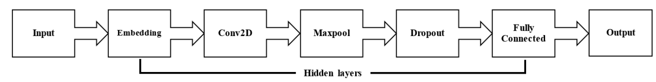


Fig. 2. Convolutional Neural Network

*1) Embedding Layer:* Embedding layer is the first layer of convolutional neural network. GloVe 6B 300d dataset is used as embedding layer.

*2) Convolution Layer:* We used one Conv2D layer that convolves the input and pass its result to the next layer.

*3) Pooling Layer:* We used one Max pool layer as the pooling layer that reduces the dimensions of data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer.

*4) Dropout Layer:* We used 0.1 dropout so that it can avoid the over-fitting problem.

*5) Fully Connected Layer:* Fully connected layer is the last layer of convolutional neural network. Fully connected layer connects every neuron in one layer to every neuron in another layer and gives us the output for six classes.

### B. Bi-directional Long Short Term Memory

Bi-directional long short term memory is a sequence processing model that consists of two LSTMs- one taking the input in a forward direction, and the other in a backwards direction [10]. Bi-LSTM model consists of an input layer, backward layer, forward layer and an output layer. We used ReLU (Rectified Linear Unit) as activation layer in hidden layers. In the hidden layers, it includes other layers such as embedding layer, pooling layer, dropout layer, and fully connected layer.

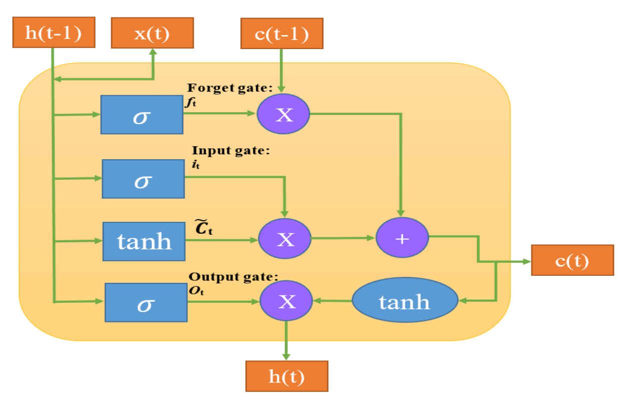


Fig. 3. LSTM model

*1) Embedding Layer:* Embedding layer is the first layer of Bi-LSTM model. GloVe 6B 300d dataset is used as embedding layer.

*2) Pooling Layer:* We used Average pool and Max pool layer as the pooling layer that reduces the dimensions of data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer.

*3) Dropout Layer:* We used 0.1 dropout so that it can avoid the over-fitting problem.

*4) Fully Connected Layer:* Fully connected layer is the last layer of Bi-LSTM model. Fully connected layer connects every neuron in one layer to every neuron in another layer and gives us the output for six classes.

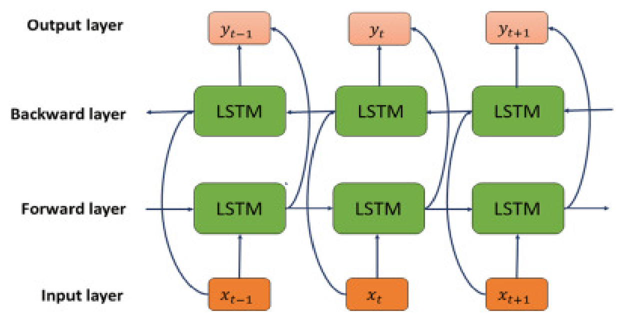


Fig. 4. Bi-directional Long Short Term Memory [11]

## V. EXPERIMENTS

### A. Dataset

In this project, Tweet Emotion dataset from kaggle is used. 80% dataset is used for training and 20% dataset is used for testing purpose.

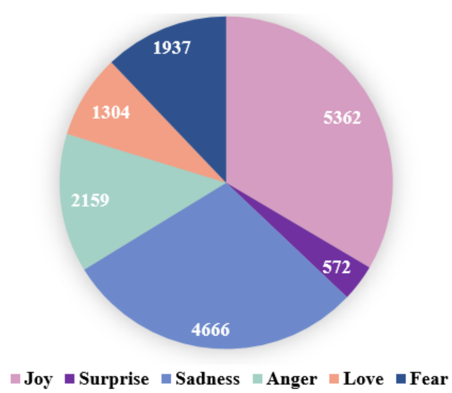


Fig. 5. Data Statistics of Emotions

TABLE I
SAMPLE OF THE DATASET

| Content | Sentiment |
|---|---|
| I have the feeling she was amused and delighted | Joy |
| I didn't feel humiliated | Sadness |
| I seriously feel so blessed for the support that I have at home it's amazing | Love |
| I think it's the easiest time of year to feel dissatisfied | Anger |
| I remember feeling amazed | Surprise |
| I am feeling pretty restless right now while typing this | Fear |

### B. Evaluation Metrics

To evaluate our models, we have chosen four different evaluation metrics. They are: accuracy, precision, recall, F1-score. Here is brief introduction of these metrics:

Here, TP = True Positive, FP = False Positive, FN = False Negative, TN = True Negative, P = Total Positive Predicted Class, N = Total Negative Predicted Class

*1) Accuracy:* It says how close a measured value is to the actual value.

$$Accuracy = \frac{TP + TN}{P + N}$$

*2) Precision:* It says how close a measured values are to each other.

$$Precision = \frac{TP}{TP + FP}$$

*3) Recall:* It is the ratio of all correctly predicted positive predictions. It measure how many the model missed.

$$Recall = \frac{TP}{P}$$

*4) F1-Score:* It is used when difficulties is faced to compare when model has low precision and high recall or vise-versa.

$$F1 - Score = \frac{2 * precision * recall}{precision + recall}$$

### C. Confusion Matrix

A confusion matrix is a summary of prediction results on a classification problem. It is also known as error matrix.

Confusion matrix of CNN:

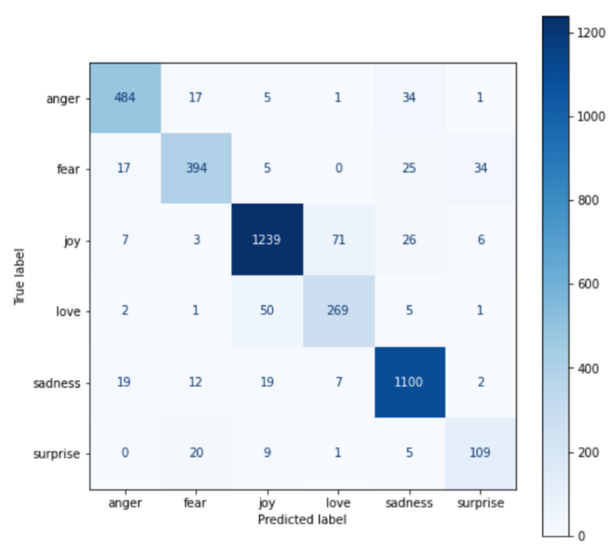


Fig. 6. Confusion Matrix of CNN

Confusion matrix of Bi-LSTM:

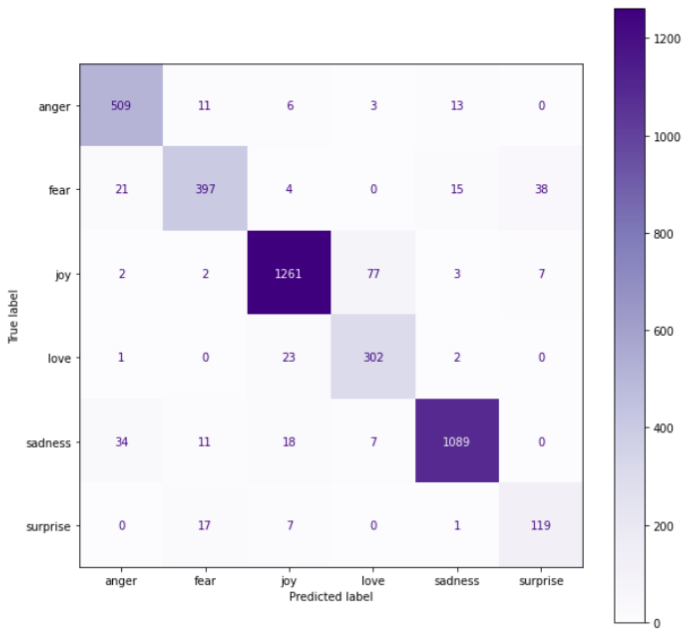


Fig. 7. Confusion Matrix of Bi-LSTM

## D. Results

*1) CNN Model Performance:* Accuracy curve and loss Curve of CNN are shown here.

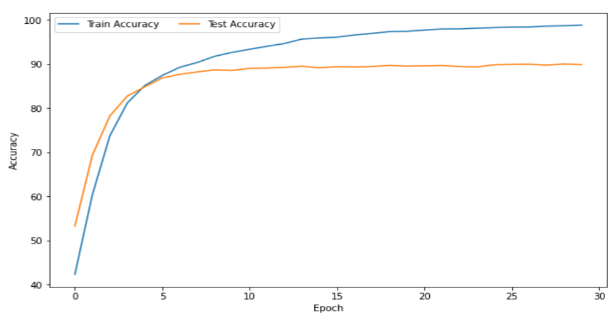


Fig. 8. Accuracy Curve of CNN

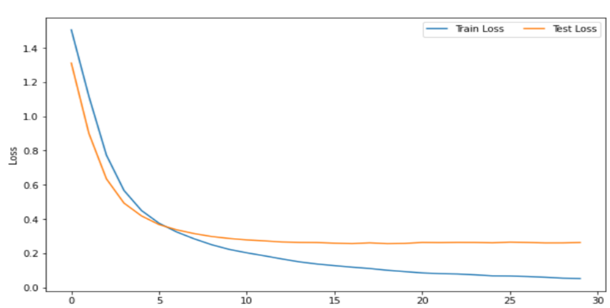


Fig. 9. Loss Curve of CNN

*2) Bi-LSTM Model Performance:* Accuracy curve and loss Curve of Bi-LSTM are shown here.

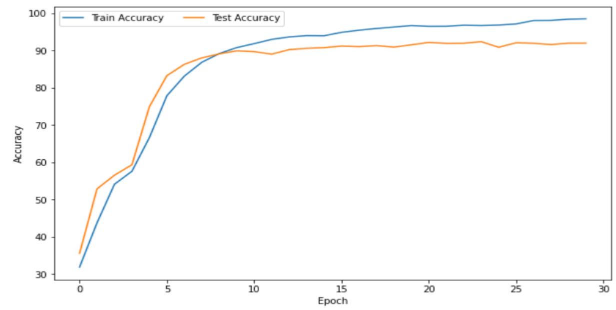


Fig. 10. Accuracy Curve of Bi-LSTM

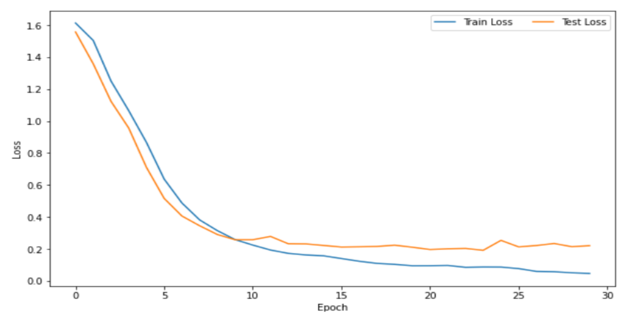


Fig. 11. Loss Curve of Bi-LSTM

*3) Precision for all Emotions:* According to CNN and Bi-LSTM models

TABLE II
PRECISION OF ALL MODELS

| | CNN | Bi-LSTM |
|---|---|---|
| anger | 91.49% | 89.77% |
| fear | 88.14% | 90.64% |
| joy | 93.37% | 95.60% |
| love | 77.08% | 77.64% |
| sadness | 92.05% | 96.97% |
| surprise | 71.24% | 72.56% |

*4) Recall for all Emotions:* According to CNN and Bi-LSTM models

TABLE III
RECALL OF ALL MODELS

| | CNN | Bi-LSTM |
|---|---|---|
| anger | 89.29% | 93.91% |
| fear | 82.95% | 83.58% |
| joy | 91.64% | 93.27% |
| love | 82.01% | 92.07% |
| sadness | 94.91% | 93.96% |
| surprise | 75.69% | 82.64% |

*5) Model Comparison:* Accuracy, Precision, Recall, F1-Score are evaluated after comparing between two models - CNN and Bi-LSTM.

TABLE IV
CNN VS BI-LSTM

| | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| CNN | 90.00% | 90.05% | 90.00% | 90.01% |
| Bi-LSTM | 92.33% | 92.34% | 92.32% | 92.27% |

## VI. CONCLUSION

In this project, we have used "tweet emotions from SemEval-2018 Affect in Tweets Distant Supervision Corpus (AIT-2018 Dataset)". As it's a noisy dataset, first we had to do the preprocessing such as punctuation remove and converted emojis into texts, tokenization, contraction. Then we have implemented two models and compared them. After comparing them, we observed that Bi-directional long short term memory model gave the highest accuracy which is **92.33%**. After completion of our project, we observed that our project can detect emotions from texts.

## VII. FUTURE WORK

In future we want to research and make improvements of this project. At first we want to make a chatbot that can be used in various platforms such as gaming platforms, retailer apps and websites to get customer feedback, social media platforms where people can chat and know the emotions of the other person. Secondly, We will use a balanced dataset or we will make our current dataset balanced so that our model can learn better. Lastly, if our model can learn better than now, we can also improve our accuracy and this project will give better performance.

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