Emotion Detection from Textual Analysis

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***Abstract*—Emotion is one of the basic instincts of human being. Emotion detection plays an important role in the field of textual analysis. Presently, 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 emotions 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 human being. Emotions refer to various types of consciousness or states of mind that are known as feelings. Facial expressions, gestures, texts, and speeches help to express those feelings. Emotion detection plays a vital role in the field of textual analysis. At present, people's expressions and emotional states are one of the leading topics 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. For detecting emotions like Joy, Surprised, Sadness, Anger, Love, and Fear, we have used CNN and Bi-LSTM models.

A. Motivation

As human beings are the most significant part of social media, their emotions also play an important role here. Analyzing human emotions is essential for the country, business, or humans for their existence. People share their opinion on the national or international election, games, international relationships, stock market, and other trending issues on Twitter. So we will be able to know the people's reactions to any changes and about their thoughts by analyzing their opinions. These 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. We will be able to detect various sentiments towards a problem of people by emotion extraction.

B. Challenges

Humans are full of emotions. They are very excited about expressing themselves. Social media provides such a platform where people express their emotions willingly. Twitter is also like 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 a mixture of different kinds of emotions. At the same time a human can express joy and surprise in a particular sentence. In this project, we are dealing with the basic human emotions. The main challenge will be to detect these emotions from those mixed emotions and classify them into more than positive or negative.

II. Related Work

Here, the previous works on sentiment and emotion detection of texts are discussed briefly.

Maryam Hasan, Elke Rundensteiner, Emmanuel Agu from Computer Science Department has published a paper on "EMOTEX: Detecting Emotions in Twitter Messages". In their work, they have introduced a new approach that automatically classifies text messages of individuals to determine their emotional states [1]. They have used hash-tag as the 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 found that emoticons used in live streaming strongly coincide with the sentiment of the entire tweet on their research [2]. For emotion detection, emoticons are a very efficient feature. So emoticons need to be considered in sentiment classification.

In the study of “Twitter Sentiment Classification using Distant Supervision”, Alec Go, Richa Bhayani, and Lei Huang have used Twitter text as input and Western-style emoticons to label and classify them into positive and negative sentiment [3]. They have used Naive Bayes, Maximum Entropy, and SVM models to classify the emotions and achieved 80% accuracy.

Vinay Kumar Jain, Steven Lawrence Fernandes, Shishir Kumar have proposed a journal in 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 were collected using emotion theories that deal with psychology and linguistics.

Another work for emotion recognition on “Using YouTube comments for text-based emotion recognition” was done by Douji Yasamina, Mousannif Hajar, and Al Moatassime Hassan. They have detected users’ emotions from their textual exchanges, dealing with the complexity of char writing style and the evolution of languages [5].

Some researchers applied a lexical approach to identify emotions in text. They devised a vast lexicon with annotations for six basic emotions e.g. anger, fear, disgust, sadness, joy, and surprise [6]. In another work, Choudhury Et Al [7] identified a lexicon that has more than 200 moods frequent on Twitter. They collected posts that have one of the moods included in their mood lexicon that’s presented as a hash-tag at the end of a post.

Recently, Darmon and his colleagues [8] tried the modeling representations to predict the attitude of users on social media. They found that most users see only a few hidden states of human behaviors. The models that can capture the behavioral patterns of individuals on social media will do well at capturing the attitude 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

The main 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. We will detect six types of emotions from the texts like Joy, Surprised, Sadness, Anger, Love, and Fear.

Here, the workflow of our project is shown.

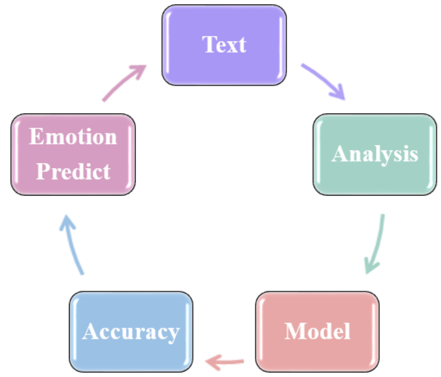

Fig. 1. Project Workflow

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) refers to 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 an activation layer in hidden layers. Other layers such as the embedding layer, pooling layer, dropout layer, and fully connected layer are among the hidden layers.

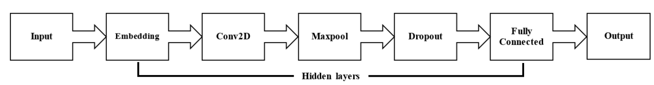

Fig. 2. Convolutional Neural Network

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

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

3) Pooling Layer: We used the Max pool layer as the pooling layer that reduced 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 dropouts that can avoid the over-fitting problem.

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

B. Bidirectional Long Short-Term Memory

Bidirectional 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 backward 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 an activation layer in hidden layers. The hidden layers include other layers such as the embedding layer, pooling layer, dropout layer, and fully connected layer.

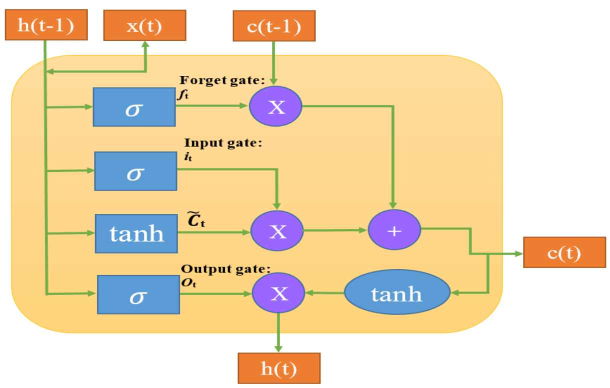

Fig. 3. LSTM model

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

2) Pooling Layer: We used the Average pool and the Max pool layer as the pooling layer that reduced 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 dropouts that can avoid the over-fitting problem.

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

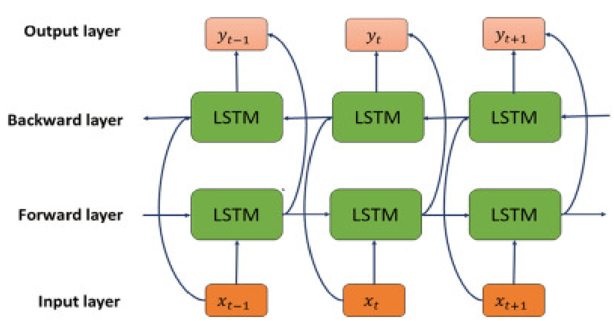

Fig. 4. Bi-directional Long Short Term Memory [11]

V. Experiments

A. Dataset

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

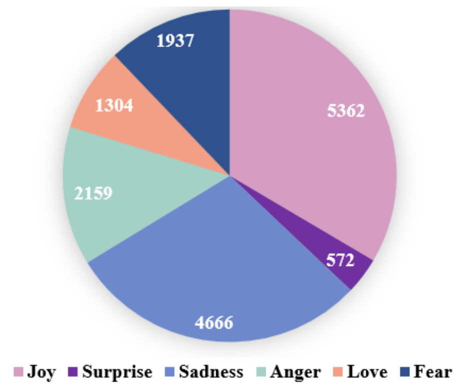

Fig. 5. Data Statistics of Emotions

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 a 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 an actual value.

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

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

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

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

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

4) F1-Score: It is used when difficulties are 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 the CNN model:

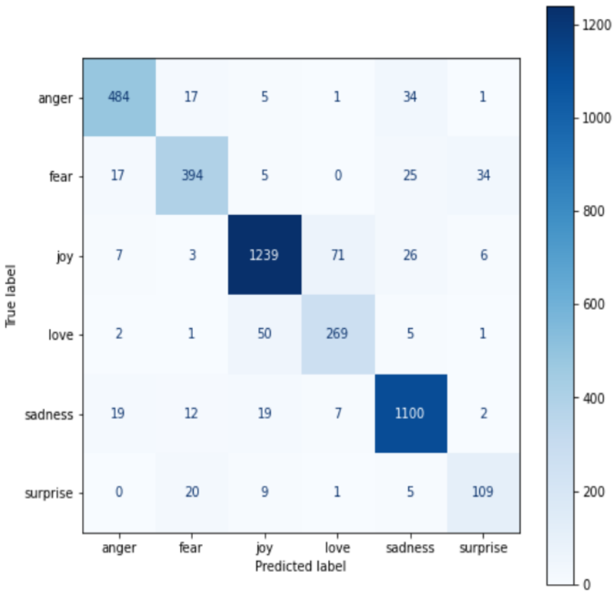

Fig. 6. Confusion Matrix of the CNN model

Confusion matrix of the Bi-LSTM model:

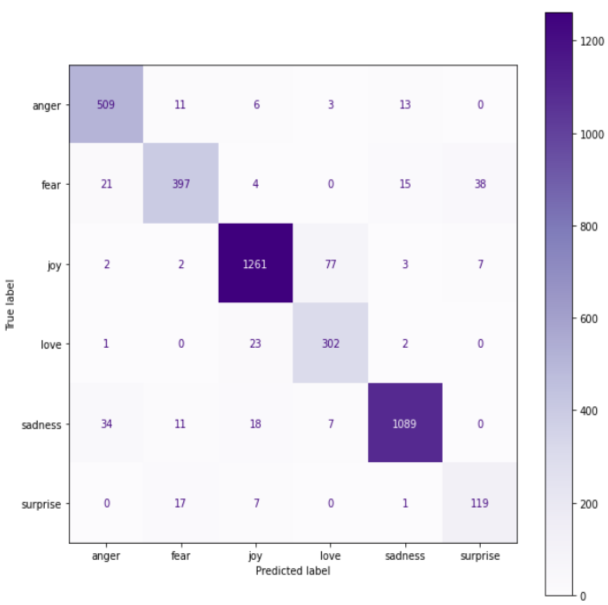

Fig. 7. Confusion Matrix of the Bi-LSTM model

D. Results

1) CNN Model Performance: Here, the accuracy curve and the loss curve of the CNN model are shown here.

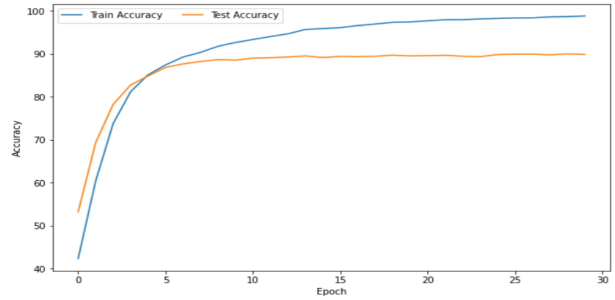

Fig. 8. Accuracy Curve of the CNN model

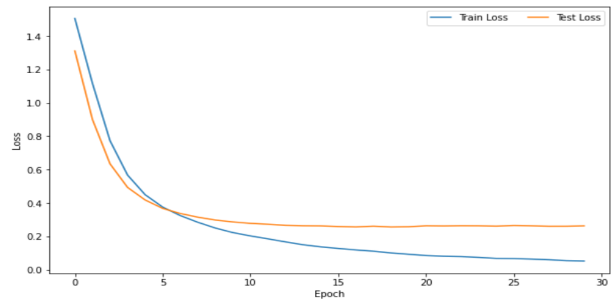

Fig. 9. Loss Curve of the CNN model

2) Bi-LSTM Model Performance: Here, the accuracy curve and the loss curve of the Bi-LSTM model are shown here.

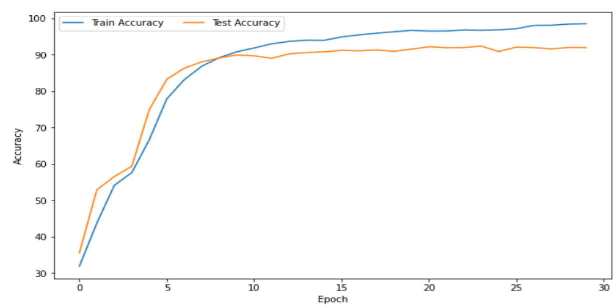

Fig. 10. Accuracy Curve of the Bi-LSTM model

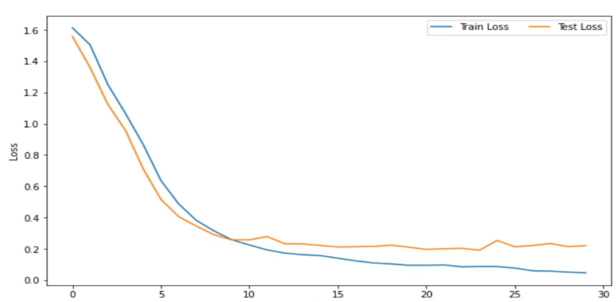

Fig. 11. Loss Curve of the Bi-LSTM model

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 our dataset. As this is a noisy dataset, we had to do the preprocessing. It includes punctuation removal, converted emoticon into texts, tokenization, contraction. Then we have implemented two models and compared them. After comparing them, we observed that the Bi-LSTM model gave the highest accuracy that is **92.33%**. After completion of our project, we observed that our project can detect emotions from texts.

VII. FUTURE WORK

In the 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 e.g. 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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