A COMPARATIVE ANALYSIS OF EMOTION PREDICTION ON A TEXT BY CNN, LSTM AND BI-LSTM

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ABSTRACT

Sentiment Analysis is a field of Natural Language Processing (NLP) that develops the system that tries to automatically identify and extract the emotions depicted by the text. Nowadays people can generate their opinion, views, and attitude about a product, person or issue in social media whenever and wherever possible. This opinionative and user-generated content occupies the major source of information on the World Wide Web. Identifying the emotion depicted by this text is very useful in many applications such as marketing analysis, public relations, product reviews, net promoter scoring, product feedback, and customer service. Generally, it identifies sentiment like joy, sadness, fear, anger and the like. And also the attributes of the expression such as its Polarity, Subject and the Opinion holder who express the sentiment. Ciphering of emotion and emotion intensity portrait by a text is a very challenging task. The crucial step of emotion analysis is feature extraction from the text because it defines the accuracy of emotion prediction. In this paper, emotion prediction is computed by using Convolutional Neural Network (CNN), Long Short Term Memory (Conv - LSTM) and Bidirectional Long Short Term Memory (BI-LSTM). As a result, BI-LSTM outperforms all the models with high accuracy. (***Keywords** - Sentiment analysis, CNN, LSTM, BI-LSTM)*

I. INTRODUCTION

Millions of users share opinions on a different aspect of life every day in microblogging sites. Analyzing these data in microblogging sites gives more fruitful information. Sentiment computing is the most salient branch of Natural Language Processing. It deals with the text classification in order to determine the intention and emotion of the author of the text. Text in social media is short, fast-evolving and informal which presents challenges to sentiment analysis.

Emotions sculpt a very imperative and elementary aspect of people's existence. Whatever people do and say, somehow does reflect some of their emotions, though may not be direct. The emotional analysis organizes a radical part of the field called affective computing. Emotion stands for “Affect” and measure or calculate stands for “computing” implies the term “Affect Computing”. Affective computing is all that takes us to design the devices or systems that process, recognize, interpret and simulate the human affects, thus making it possible for us to analyze the human and machine interactions.

Accuracy of predicting emotion from the text based on affective text faces issues based on features have been selected for evaluation. After selecting the features from the text the final vector is prepared and given as an input to neural network models CNN [11], LSTM [12] and BI-LSTM. This paper analyzes four emotions such as joy, fear, anger and sad. As a result BI-LSTM comes up with a high average than all other models in calculating the emotion.

II. RELATED WORK

The core purpose of this paper is to create a positive environment by affording a platform for serving only good news [1].To make this vision into action at first they did a classification and then feature extraction. For classification they used Naïve Bayes, Support Vector Machine, and Maximum Entropy algorithm. Among these algorithms Support Vector Machine is considered to be a popularly used classification algorithm. After the classification step then they built a model using training data. Once it is developed which is then used to classify the new dataset based on built model.

For concept level sentiment analysis SenticNet 3 [2] is a publicly available semantic and affective resource. SenticNet 3 is scheduled to link the conceptual and affective gap between word-level natural language data and the concept- level opinions and fetch the sentiments conveyed by them.

The Noisy nature of data generated by Twitter is a major challenge of sentiment analysis methods. A famous Method to reduce the noisy nature is to remove stop words [3] by using pre-compiled lists of stop-words or by using dynamic stop-word identification by using more sophisticated methods. This paper investigates whether removing stop-words helps or hampers the effectiveness of sentiment classification.

This Paper describes the UWaterloo affect prediction system [4] developed for EMOINT 2017. They tend to find out affect intensity, affect presence, sentiment intensity and sentiment presence, lexical alongside pre-trained word embedding's, which are utilized to extract emotion intensity signals from tweets in an ensemble learning approach. This System utilizes gradient boosted regression as the primary learning technique to predict the final emotion intensities.

This paper [5] proposes and scrutinizes a new problem called social affective text mining, which courses to explore and model the association between online documents and user-originated social emotions. In terms to predict the sentiment from a text they intent to find the correlation between social emotions and affective terms.

This paper [6] proposed a hybrid system to depict the emotion from the medium. Due to the small requirements of textual data this paper focus only on text medium. This paper uses two methods, keyword based and machine learning based method to identify the emotion by the text.

In Paper [7] they presented the model for sentiment analysis of language learning using Naive Bayes Classifier. This paper utilizes Facebook status as data for the sample. The proposed system predicts whether the depicted emotion is positive, negative or neutral by using sentence level classification.

In paper [8] the author proposed a novel approach for emotion estimation from the text entered by the user on social networking sites. The author developed a visual image generation approach that generates images according to emotion in text.

This paper [9] proposed a system that automatically identifies the emotional state in the text which can be used to render facial expressions. In this, the author used a corpus of children’s stories. This study used a supervised machine learning technique to classify children stories into one of the predefined emotion classes.

Generally, Text [10] can be written in two writing styles that are formal and informal. This paper analysis sentiment classification in both formal and informal text pieces. For emotion classification, they use different machine learning based methods SVM (support vector machine), NB (Naïve Bayes), Decision Tree.

III. METHODOLOGY

3.1 DATA PRE-PROCESSING

Pre-processing which is a very indispensable key step for sentiment analysis on a text. Here Data cleansing, Stemming and then Tokenize the document by 1, 2 or n words are done.

3.2 FEATURE EXTRACTION

Two primary methods for feature extraction from the tweets namely annotated lexicons and pre-trained word embeddings [13] are used.

3.2.1 Annotated lexicons

- NRC affect intensity Lexicon
- NRC Emotion Lexicon
- NRC Hashtag Emotion Lexicon
- NRC Emoticon Lexicon and NRC Hashtag sentiment Lexicon, NRC Emoticon Affirmative Context Lexicon and NRC Emoticon Negated Context Lexicon & NRC Hashtag affirmative context sentiment Lexicon and NRC Hashtag Negated Context Sentiment Lexicon
- SentiWordNet
- Emoji Valence
- Depeche Mood

3.2.2. Word embeddings

Pre-trained Word embedding also takes part of vector representation of each tweet in addition to the features extracted from the annotated lexica.

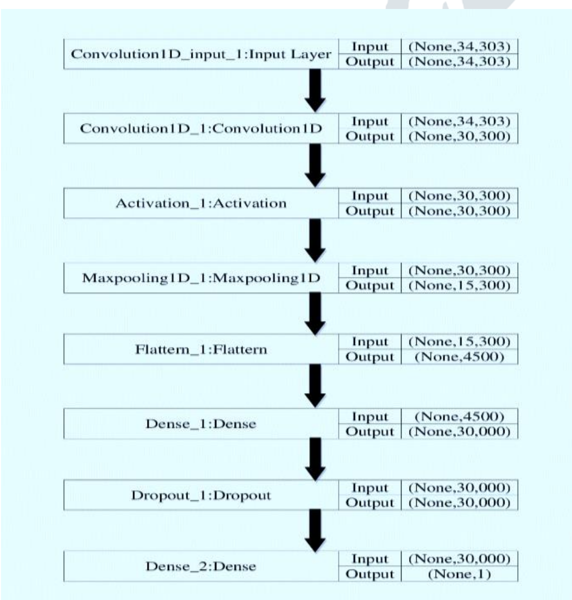
Here it uses two word embedding schemes

- Google News
- Glove Model

3.3 MODEL TRAINING

3.3.1 CNN

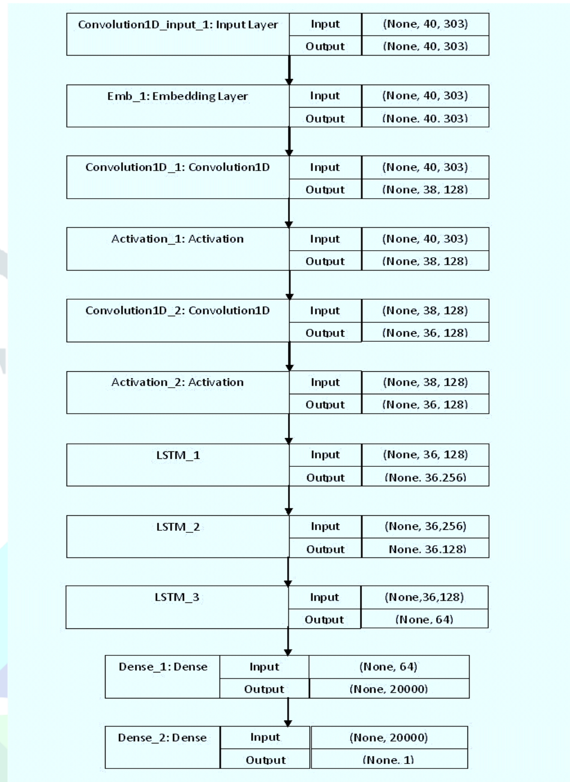
The input to the convolutional layer is of size (no of tweets*no of maximum occurred feature).First input layer of CNN is modeled with 300 filter each of length 5. ReLu is the activation technique used here. Followed by the input layer the next layer is of maximum pooling layer of size 2. Then the input is given to flatten and dense layer of size 30000. To avoid the over fitting issues of neurons we applied a dropout layer with rate of 0.5 to predict the emotion in more accurate way. Then the input is given to the dense layer of size 1 and the sigmoid activation technique is used. Finally the model is compiled with stochastic gradient descent (SGD) optimizer and mean square error loss function.



[Fig-1: CNN Layer specification]

3.3.2 LSTM

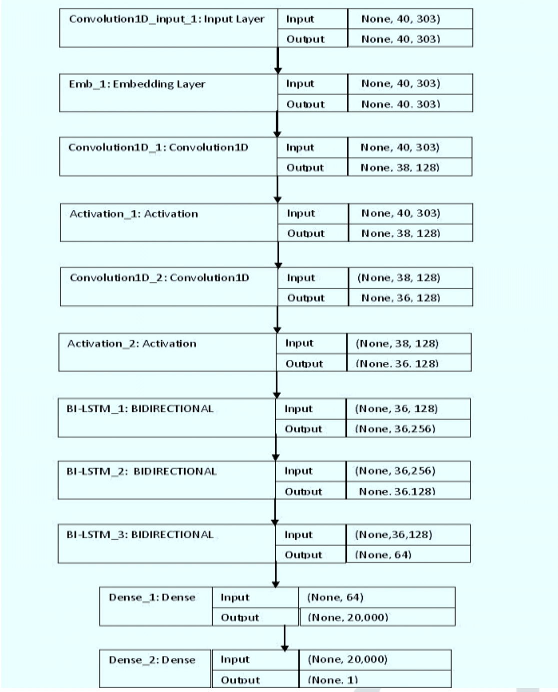
Initially one embedding layer is used then the input to the convolutional layer is of size (no of tweets*no of maximum occurred feature).Here 2 convolutional layer is modeled with 128 filters, each of length 3 and ReLu is the activation technique used. Followed by 3 LSTM layer of filter sizes 256, 128, 64 with 0.2 dropout and 0.2 recurrent. Next the input is given to the dense layer of units 20,000 with ReLu activation. Which is next followed by another one dense layer of units 1 with sigmoid activation. At last the model is compiled with stochastic gradient descent (SGD) optimizer and mean square error loss function. Finally keras regressor is used to predict the results.



[Fig-2: LSTM Layer specification]

3.3.3 BI-LSTM

At premier one embedding layer is used then the input to the convolutional layer is of size (no of tweets*no of maximum occurred feature).Here 2 convolutional layer is modeled with 128 filters, each of length 3 and ReLu is the activation technique used. Followed by 3 BI-LSTM layer of filter sizes 128, 256, and 128 with 0.2 dropout and 0.2 recurrent. Next the input is given to the dense layer of units 20,000 with ReLu activation. Which is next followed by another one dense layer of units 1 with sigmoid activation. At last the model is compiled with stochastic gradient descent (SGD) optimizer and mean square error loss function. Finally keras regressor is used to predict the results.



[Fig-3: BI-LSTM Layer specification]

4. DATASET

The evaluation dataset (Mohammad and Bravo-Marquez, 2017) [14] comprises of four emotions i.e. anger, fear, sadness and joy. The training set contains 857, 1147, 786 & 823 tweets for anger, fear, sadness and joy, respectively. The test set contains 760, 995, 673 & 714 tweets, respectively for each domain.

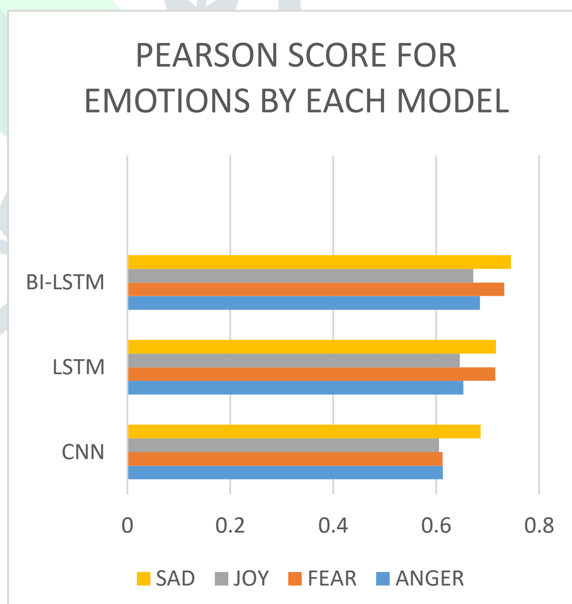
5. RESULT ANALYSIS

Here Pearson correlation as a analyze technique is used to check the accuracy of the result. It is a measure of the strength and direction of association that exists between two continuous variables. In Pearson correlation calculation for the emotion anger CNN scores 0.6127, LSTM scores 0.653 and BI-LSTM scores 0.685. For emotion fear CNN, LSTM, BI-LSTM scores 0.6124, 0.715 and 0.732 respectively. For emotion Joy CNN scores 0.6054, LSTM scores 0.646 and BI-LSTM scores 0.672. For emotion Sad CNN scores 0.6127, LSTM scores 0.653 and BI-LSTM scores 0.685. Here among all the models Bi-LSTM scores much better results for each emotion and get higher average score. As a result BI-LSTM comes with a high average score (0.7085) in predicting emotions.

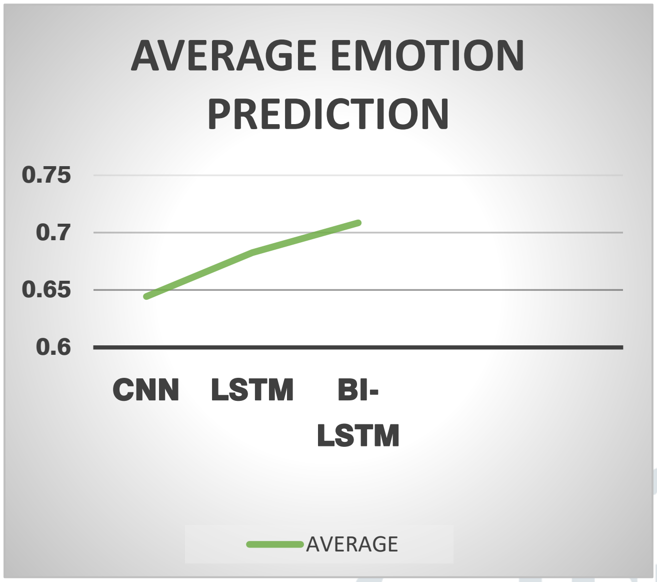
[TABLE-1: Pearson score for the models]

S.NO	MODELS	PEARSON SCORE				
		ANGER	FEAR	JOY	SAD	AVG
1.	CNN	0.6127	0.6724	0.6054	0.6865	0.64425
1.	LSTM	0.653	0.715	0.646	0.716	0.6825
2.	BI-LSTM	0.685	0.732	0.672	0.745	0.7085

[Graph 1: Representation of Pearson scores of all models computed by Pearson calculation]



[Graph 2: Representation of Average scores of all models computed by Pearson calculation]



6. CONCLUSION

This paper, analyzes the accuracy of three models CNN, LSTM and BI-LSTM in predicting emotion on a text. First it starts up with preprocessing then it extracts the features from the text and prepares the final vector representation. This finalized vector is only given as an input for the CNN, LSTM and Bi-LSTM model. As a result BI-LSTM model gets better accuracy in emotion prediction for all the four emotion datasets i.e. anger, fear, joy and sadness.

7. REFERENCES

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