Recognition of Emotions on Twitter: Comparative Study and Training a Unison Model

Ashwini H R[1], Dr. Mohammed Rafi[2]

[1]*Department of Studies in Computer Science & Engineering University BDT College of Engineering (A Constituent College of VTU, Belagavi), Davanagere, Karnataka*

[2]*Department of Studies Computer Science & Engineering, University BDT College of Engineering (A Constituent College of VTU, Belagavi), Davanagere, Karnataka*

Abstract- **The recognition of basic emotions in everyday communication involves interpretation of different visual and auditory clues. The ability to recognize emotions is not clearly determined as their presentation is usually very short (micro expressions), whereas recognition itself does not have to be a conscious process. The amount of user-generated content on the web grows ever more rapidly, mainly due to the emergence of social networks, blogs, micro-blogging sites and a myriad of other platforms that enable users to share their personal content. Unlike objective and factual professional publishing, user-generated content is richer in opinions, feelings and emotions.**

Index terms- POM'S categories, posting, emotion recognition, find friends, tweets, emotion mining.

I. INTRODUCTION

Emotions are described as intense feelings that are directed at something or someone in response to internal or external events having a particular significance for the individual. And the internet, today, has become a key medium through which people express their emotions, feelings and opinions. Every event, news or activity around the world, is shared, discussed, posted and commented on social media, by millions of people. Business analysts can use this information to track feelings and opinions of people with respect to their products.

Paul Ekman defined six basic emotions by studying facial expressions. Robert Plutchik extended Ekman's categorization with two additional emotions and presented his categorization in a wheel of emotions. Finally, Profile of Mood States (POMS) is a psychological instrument that defines a six-dimensional mood state representation. Each dimension is defined by a set of emotional adjectives, like bitter, and the individual's mood is assessed by how strongly (she or he) experienced such a feeling in the last month.

The proposed system confirms that it is possible to train a single model for predicting all three emotion classifications whose performance is comparable to the three separate models. We show that recurrent neural networks, especially character-based ones, can improve over bag-of-words and latent semantic indexing models. Although the transfer capabilities of these models are poor, the newly proposed training heuristic produces a unison model with performance comparable to that of the three single models.

II. LITERATURE SURVEY:

The paper [1] states the One of these skills is the ability to understand the emotional state of the person. This thesis describes a neural network based approach for emotion classification. Here we learn a classifier that can recognize six basic emotions with an average accuracy of 77% over the Cohn-Kanade database. They developed a strategy that can automatically select comparatively better combination of these parameters. We also introduce another way to perform back propagation. Instead of using the partial differential of the error function, they use optimal algorithm; namely Powell's direction set to minimize the error function. Finally, they have performed several experiments and show that our neural network approach can be successfully used for emotion recognition.

The paper [2] addresses the problem of detection, classification and quantification of emotions of text in any form. Here, consider English text collected from social media like Twitter, which can provide information having utility in a variety of ways, especially opinion mining. Social media like Twitter and Facebook is full of emotions, feelings and opinions of people all over the world. This paper proposes a method to classify text into six different Emotion-Categories: Happiness, Sadness, Fear, Anger, Surprise and Disgust. In our model, we use two different approaches and combine them to effectively extract these emotions from text. The first approach is based on Natural Language Processing, and uses several textual features like emoticons, degree words and negations, Parts Of Speech and other grammatical analysis. The second approach is based on Machine Learning classification algorithms.

The paper [3] states the Speech and emotion recognition improve the quality of human computer interaction and allow more easy to use interfaces for every level of user in software applications. In this study, they have developed the emotion recognition neural network (ERNN) to classify the voice signals for emotion recognition. The ERNN has 128 input nodes, 20 hidden neurons, and three summing output nodes. A set of 97932 training sets is used to train the ERNN. A new set of 24483 testing sets is utilized to test the ERNN performance.

III. METHODOLOGY

It has 4 modules such as Bag-of-Words &Latent Semantic Indexing Models, Neural Network Models, Transfer Learning and Unison Learning.

Bag-of-Words & Latent Semantic Indexing Models:

Here it is first experimented with common approaches to emotion detection. one of the most frequently used approaches is to use simple classifiers on the bag-of-words (BoW) models. I studied two approaches for transforming raw text into BoW model. Vanilla BoW is a model without any normalization of tokens. The aim of these normalization techniques is to remove the features that are too specific. Hereafter, we will refer to the combination of unigrams and bigrams simply as bigrams.

Neural Network Models:

Among the most popular neural network (NN) architectures, we use recurrent (RNN) and convolutional (CNN) networks. The former were selected since they can naturally handle texts of variable lengths, and latter since they have already shown to be suitable for text classification. We experiment with two levels of granularity. In the first approach, we tokenize the tweet's content and then feed a sequence of tokens into the NN. Our second setting is an end-to-end learning approach: instead of preprocessing tweets into tokens, we treat the whole tweet as a sequence of characters and pass characters one by one into the NN.

Transfer Learning:

After selecting the best models and their parameters, we test their transfer capabilities and generality. The model is taken up to the final hidden layer and then re-train the final softmax or sigmoid layer on another data set. In this way, we re-use the embedding from one data set for making predictions on the other. The intuition behind these experiments is that if the final hidden state representation can be considered as a general lower dimensional representation suitable for predicting emotions, then the one trained on Ekman might also suffice for predicting POMS's categories.

Unison Learning:

The final set of experiments tests whether it is possible to develop a common model. We define the unison model as a model able of predicting all three emotion classifications while sharing all the parameters that project the input tweet into a final hidden state representation. Finally, when applying such model, we get predictions for all classifications in approximately the same computation time a single model would require for one classification. To build the unison model we propose the following architecture.

IV. IMPLEMENTATION

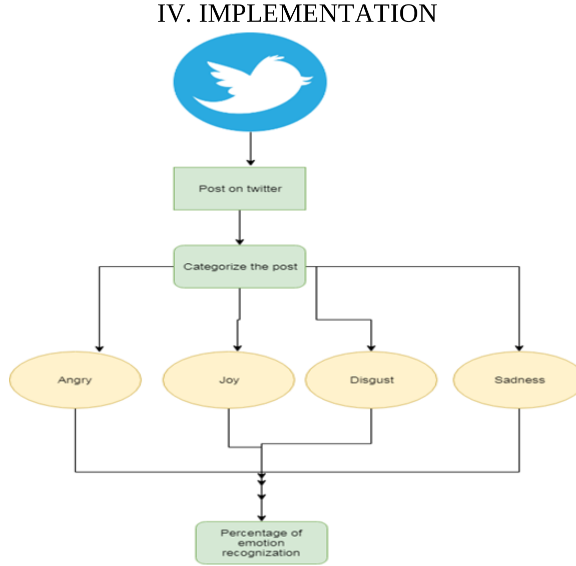


Fig. 1: Architecture of proposed system

In the proposed scheme, it has 4 modules

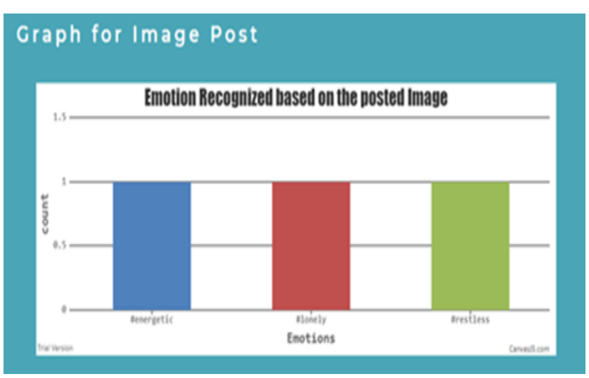
Posting: In first module of posting, the user first need to register their account and by using that details user can enter into the system. At the homepage itself, the twitter user like us can view the shared posts, recent post. And also the user can post the images, videos with some description including hash tags. Based on the posted hash tags the emotion for the user is mined in this paper. After our post the image or video will be visible to all twitter users in the recent posts.

Find Friends: In this module the login user can make their friendship with the Twitter users. Here the user can send the friend request to the people who are all known to us. While the requested user will accept our request, both are friends in the twitter. You can search the friends by using their display name what they given in their account.

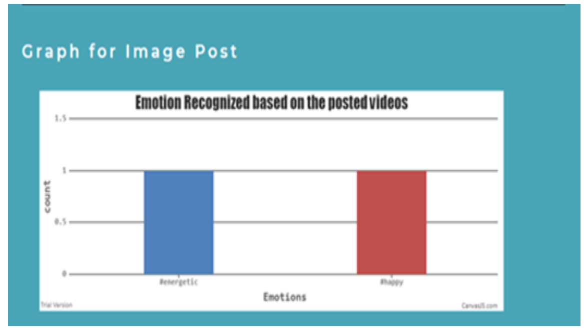
Emotion Mining: In this module of Emotion mining the user's emotion will be mined out by the Administrator. The emotion mined here by using the description in the post with hash tags. The hash-tags shows the individuals emotion in their post. Hash tags perform as a label of emotion. So, the Hash tag label is match with the dataset values. Hence, it will match and bring the category of the word in hash tag post.

Tweets: The twitter users can tweet the posts which are posted. The tweets also mined to know the positive or negative. For that the tweet should be match with the dataset includes some of the positive and negative text values. If any of the word match with the dataset and bring the result as positive means it will be shown as positive tweet. If the tweet will be negative means the admin can delete the tweet based on the comparison of post.

V. RESULT AND ANALYSIS



It is the graph for the emotion recognized based on the image posted in the twitter by the users who wants their emotions to be expressed. The graph values can vary for each emotion as each individual's emotions are different to each other.



Here, the users who are using the twitter can make tweets to the posts which are posted by their friends and they can make friends themselves by searching in the twitter. Once all the posts are viewed the admin can recognize the emotion category and the graph will be appeared such that the percentage of that emotion category will be recognized.

VI. CONCLUSION

The proposed method in the paper created three large collections of tweets labeled with Ekman's, Plutchik's and POMS's classifications of emotions. Recurrent neural networks indeed outperform the baseline set by the common bag-of-words models. Here, following method confirmed that it is possible to train a single model for predicting all three emotion classifications whose performance is comparable to the three separate models. As a first study working on predicting POMS's categories, we believe they are as predictable as Ekman's and Plutchik's. It also showed that searching for tweets containing POMS adjectives and later grouping them according to POMS factor structure yields a coherent data set whose labels can be predicted with the same accuracy as other classifications.

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