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Emotion Classification On Unison Model Using POMS Categories With SMO Classifier

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Abstract - The examination of interpersonal organizations is a difficult research zone while a key angle concerns the discovery of client networks. The existing work of emotion recognition on Twitter specifically depends on the use of lexicons and simple classifiers on bag-of words models. The vital question of our observation is whether or not we will enhance their overall performance using machine learning algorithms. The novel algorithm a Profile of Mood States (POMS) represents twelve-dimensional mood state representation using 65 adjectives with combination of Ekman's and Plutchik's emotions categories like, anger, depression, fatigue, vigour, tension, confusion, joy, disgust, fear, trust, surprise and anticipation. These emotions classify with the help of text based bag-of-words and LSI algorithms.

Keywords- Emotion Recognition, Text Mining, POMS, Recurrent Neural Networks, Convolutional Neural Networks, Unison Model, Sequential Minimal Optimization, Twitter

I. INTRODUCTION

Emotions can be defined as conscious affect attitudes, which constitute the display of a feeling. In recent years, countless investigations have concentrated on feeling recognition utilizing assessment mining via web-based networking media. Due to some intrinsic characteristics of the texts produced on social media sites, such as the limited length and casual expression, emotion recognition on them is a challenging task. Previous studies mainly focus on lexicon-based and machine learning based methods. The performance of lexicon-based methods relies heavily on the quality of emotion lexicon and the performance of machine learning methods relies heavily on the features. Therefore, we work with three classifications that are the most popular, and have also been used before by the researchers from computational linguistics and natural language processing (NLP). 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, POMS(Profile of Mood States)is a "psychological" tool that characterizes a six-dimensional temperament state portrayal utilizing content mining. The novel algorithm a Profile of Mood States (POMS) generating twelve-dimensional mood state representation using 65 adjectives with combination of Ekman's and Plutchik's emotions categories like, anger, depression, fatigue, vigour, tension, confusion, joy, disgust, fear, trust, surprise and anticipation. Past work commonly considered just a single Emotion arrangement. Working with various characterizations at the same time not just empowers execution correlations between distinctive Emotion classifications on a similar sort of information yet additionally enables us to build up a solitary demonstrate for anticipating numerous characterizations in the meantime.

Motivation

The framework created dependent on our proposed method-ology would have the capacity to consequently recognize what individuals feel about their lives from twitter messages. For instance, the framework can perceive:

- percentage of individuals communicating better degrees of life fulfillment in one gathering rather than another gathering,
- percentage of those individuals who feel happy and chipper,
- percentage of those individuals who encounter quiet and peace- ful, and
- percentage of those individuals who communicating large amount of frenzy or trouble.

II. LITERATURE SURVEY

In [2] paper, explore whether open mind set as estimated from expansive scale accumulation of tweets posted on twit- ter.com is corresponded or even predictive of DJIA values The result show that adjustment in the general population inclination state can to be sure be followed from the substance of extensive scale twitter channels by methods for or may be straight for word content preparing methods and that such changes react to an assortment of socio-social drivers in an exceedingly separated way. Advantages are: Build the execution open mind-set investigation from twitter channels offers a programmed,

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quick, free expansive scale expansion to this toolbox that might be stream lined to quantity an assort- ment of measurements of the general population disposition state. .Disadvantages are: It avoids geographical and cultural sampling mistakes.

The paper [3] Broke down budgetary web journals and online news articles to build up an open state of mind dynamic forecast display. For securities, exchanges, referencing the points of view of conduct back and the qualities of online money related networks. An open mind-set time arrangement forecast show is likewise exhibited, incorporating highlights from informal organizations and conduct fund, what's more, utilizes huge information examination to evaluate passionate substance critique on current stock or money related issues to estimate changes for Taiwan stock record. Advantages are: It is helpful for highlight word development and handling speed more widely used. Disadvantages are: Only uses for stock prices.

In [4] paper the product of profound repetitive neural system to the test of sentence-level assessment articulation extraction. DSEs (direct subjective expressions) comprise of explicit notices of individual states or discourse occasions commu- nicating non-open states; and ESEs (expressive subjective ex- pressions) include articulations that demonstrate assumption, emotion,and so forth etc; without expressly passing on them. Advantages are: Profound RNNs outflanked past(semi)CRF baselines; accomplishing new cutting edge results for fine- grained on sentiment articulation extraction.. Disadvantages are: RNNs do not have access to any highlights other than word vectors.

III. System Design

The third step is the preprocessing which includes stemming, spell correction using Porter algorithm. The NLP using Part-of-Speech tagging represents the tags of every word which is very helpful for identifying adjectives. The N-gram generation method is to design the similarity score of tweets using text clustering algorithm. The fourth step is the topic modeling using Latent Dirichlet Allocation (LDA) algorithm for extraction of topics using clustered tweets. Finally identifying the emotion of the tweets with the help of adjectives includes in emotion categories.

The sixth step is the data preprocessing which shows at machine learning algorithm preprocessing step including data transformation and normalization methods. The seventh step is to select the features which required for detection of emotion. The Sequential Minimal Optimization (SMO) classifier is an algorithm for solving the quadratic programming (QP) problem that arises during the training of support vector machines. This is used for emotion classification system for multi-class classifier at eighth step. Finally, the ninth step is used to predict the emojis with the help of emoji dataset and analyze the performance of emotion recognition system.

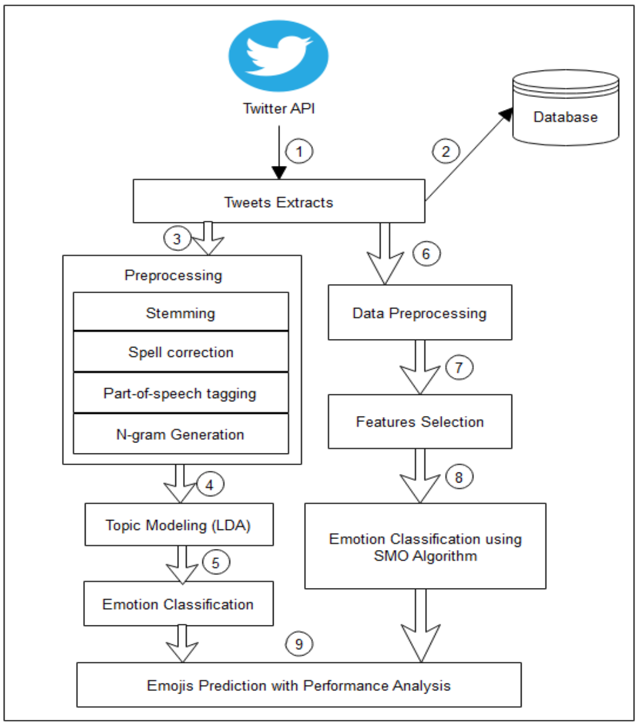

Fig.3.1 System Architecture

The Fig.3.1 shows the proposed system architecture of emotion recognition system. This system is working on Twitter API tweets dataset collecting at first step. There are two parts of the emotion recognition system. First, using NLP language algorithms and second one is working on machine learning classifier algorithms.

IV. Implementation

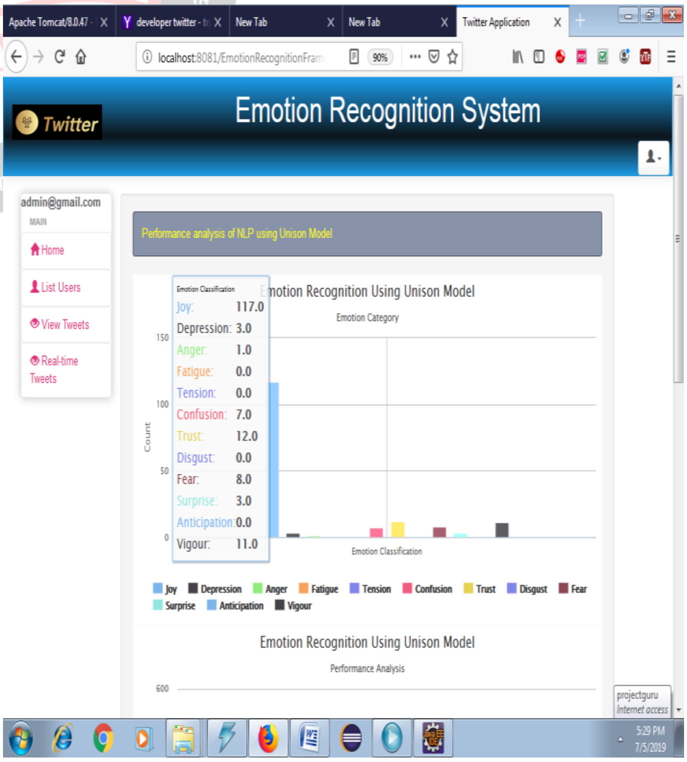

Fig 4.1. Shows the performance analysis between Unison Model and SMO classifier algorithm. The graph shows the Unison Model increases accuracy as compare to previous algorithms.

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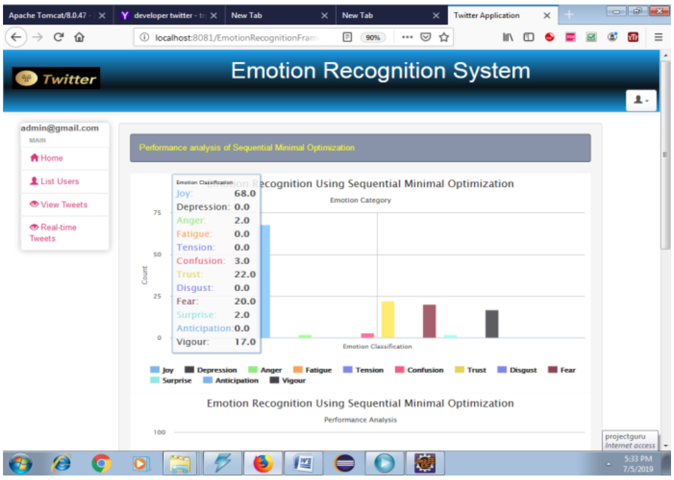

Fig 4.2. But, the SMO classifier algorithm gives better results than Unison Model. And SMO executes faster than Unison model.

V. EXPERIMENTAL RESULTS

Examinations are finished by a PC with a configuration:Intel (R) Core (TM) i3-2120 CPU @ 3.30GHz, 4GBmemory, Windows 7, MySQL 5.1 backend database and Jdk1.8. The application is web application used tool for designcode in Eclipse and execute on Tomcat server. Some functionsused in the algorithm are provided by list of jars like Twitter-coreand Twitter-stream jars etc.

Tweets are removed steamingly, and Twitter gives the steaming API for designer and scientists to get to open tweets continuously utilizing Twitter4j containers. The point of this paper is to conquer and hindrance via completing a execution assessment, which was from two distinct angles NLP and machine leaning algorithms. The Unison model is the combination of Ekman's, Plutchik's and POMS emotion categories and the Sequential Minimal Optimization (SMO) classifier algorithm uses for emotion recognition performance. Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. Recall is the ratio of correctly predicted positive observations to the all observations in actual class. F-measure is the weighted average of Precision and Recall. Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations.

The Table I shows performance analysis between unison model versus SMO classifier.

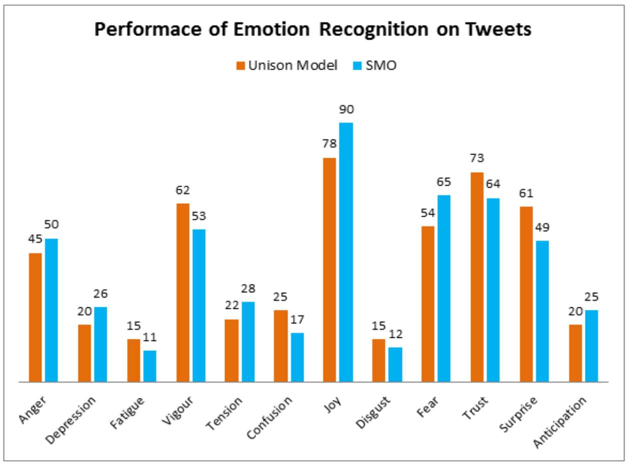

Fig. 5.1 Comparison of tweets with emotion recognition using Unison Model versus SMO Classifier Algorithm

	Unison Model	SMO
Precision	68.45	78.70
Recall	79.44	65.64
F-Measure	72.11	74.31
Accuracy	80.29	87.26

TABLE I Performance Analysis Between Unison Model Versus SMO Classifier

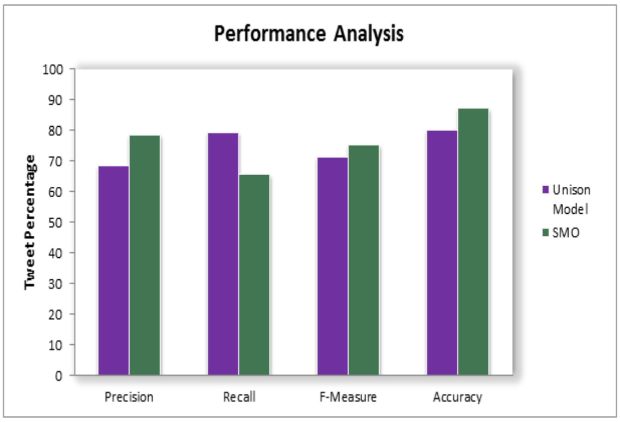

Fig. 5.2 Performance Analysis between existing and proposed system

Fig. 4.3 shows the performance analysis between Unison Model and SMO classifier algorithm. The graph shows the Unison Model increases accuracy as compare to previous algorithms. But, the SMO classifier algorithm gives better results than Unison Model. And SMO executes faster than Unison model.

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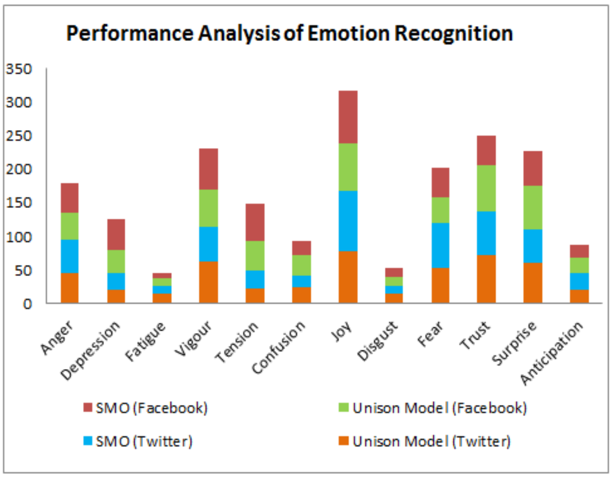

Fig. 5.3 Performance analysis using Twitter API and Face book API

VI. CONCLUSION

This project implements a novel algorithm Profile of Mood States (POMS) represents twelve-dimensional mood state representation using 65 adjectives with combination of Ekman's and Plutchik's emotions categories like, anger, depression, fatigue, vigour, tension, confusion, joy, disgust, fear, trust, surprise and anticipation. These POMS classifies the emotions with the help of bag-of-words and LSI algorithm. The machine learning Sequential Minimal Optimization (SMO) classifier is used to classify emotions, which gives results as accurate and less time consumption compares to Unison Model. Further work, after getting the emotion of the user, then recommending the tweet posts or motivational speech to the users when they are recognizing any negative emotion category like depression level.

VII. FUTURE SCOPE

- Use of this system is in online social networking for spam detection.
- Feature of spam tweets seems to be time varying.
- The ability to detect and track a user's state of mind has the potential to allow a computing system to offer relevant information when a user needs help –not just when the user requests help.
- Help people in emotion-related research to improve the processing of emotion data.

It can not only eliminate un useful information in the training data but also make it faster to train the model as the number of training samples decrease

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