EMOTION DETECTION THROUGH EMOJIS USING UNISON MODEL VERSUS LSSVM CLASSIFIER ON TWITTER

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Abstract: **The overall performance analysis of social networks is a completely massive observation area while a fundamental issues about concerns the finding of user communities. The previous work of detecting emotions on Twitter depends specifically on the use of simple vocabularies and classifiers in word-bag models. The vital question of our observation is whether or not improving its general 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. The contribution work is to apply machine learning algorithm for emotion classification, it gives less time consumption without interfere human labeling. The Least Square Support Vector Machine (LSSVM) classifier algorithm works on testing dataset with help of huge amount of training dataset. Measure the performance of POMS and LSSVM classifier algorithms on Twitter API. The result shows with the help of Emojis for emotion detection using tweet contents.**

Index Terms: **Emotion Recognition, Machine Learning, NLP, Recurrent Neural Networks, Convolutional Neural Networks,
Unison Model, LSSVM**

I. INTRODUCTION

Emotions can be defined as conscious affect attitudes, which constitute the display of a feeling. In today's

Life, a large number of investigations has been focused on emotion detection using opinion mining on social media. Due to some intrinsic characteristics of the texts produced on social media sites, such as the limited length and casual expression, emotion detection on them is a challenging task. Previous studies mainly focus on lexicon-based and machine learning based methods. The overall performance of lexicon-based methods has confident closely on the quality of the emotion lexicon and the performance of machine learning algorithms relies massively on the features. Therefore, work with three classifications that are the most popular and previously used by researchers in computational linguistics and natural language processing (NLP).

Paul Ekman specified six basic emotions when examining facial expressions. Robert Plutchik extended the categorization of Ekman with two other emotions and presented his categorization in a wheel of emotions. Finally, Profile of Mood States (POMS) is a psychological tool that defines a representation of six-dimensional mood by means of text 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.

The previous work generally studied only a classification of emotions. Working with multiple classifications simultaneously not only allows comparison of performance between different categorizations of emotions in the same type of data, but also allows us to develop a unique model to predict multiple classifications simultaneously.

1.1Motivation:

The system developed based on our proposed approach would be able to automatically detect what people feel about their lives from twitter messages. For example, the system can recognize:

- Percentage of people expressing better degrees of life satisfaction in one group as opposed to another group,
- Percentage of those people, who feel glad and cheerful,
- Percentage of those people who experience calm and nonviolent, and
- Percentage of those people who expressing higher levels of panic or distress.

II. REVIEW OF LITERATURE

J. Bollen, H. Mao, and X. J. Zeng investigates whether public mood as supervised from huge-scale collection of tweets posted on Twitter API is correlated or even revealing of DJIA values. The consequences show that changes in the public mood state can certainly be tracked from the content of large-scale Twitter feeds by alternatively simple textual content processing strategies and that such adjustments reply to a variety of socio-cultural drivers in a notably differentiated manner. Advantages are: Increases the performance. Public mood evaluation from Twitter feeds gives an automated, rapid, free and massive-scale extension to this toolkit that may be upgraded to measure a variety of dimensions of the public mood state. Disadvantages are: It avoids geographical and enlightening sampling errors [1].

J. Bollen, H. Mao, and A. Pepe analyzed financial blogs and online news attachments to build a public mood dynamic prediction version for stock markets, referencing the views of behavioral finance and the characteristics of online economic groups. A public mood time series prediction version is also provided, integrating capabilities from social networks and behavioral finance, and makes use of massive data analysis to assess emotional content of observation on current stock or financial issues to forecast modifications for Taiwan stock index. Advantages are: It is convenient for feature word expansion and processing speed. More widely used. Disadvantages are: Only uses for stock prices [2].

F. Godin, V. Slavkovikj, W. De Neve, B. Schrauwen, and R. Van De Walle, proposes a novel technique for unsupervised and content based hash tag recommendation for tweets. This technique is based on Latent Dirichlet Allocation (LDA) to model the underlying topic undertaking of language labeled tweets. Advantages are: The use of a topic dissemination to suggest preferred hash tags. Easily portable. Effective categorization and search of tweets. Disadvantages are: Need to show disambiguate tweets by using more semantic knowledge [3].

O. Irsoy and C. Cardie explored an application of deep recurrent neural networks to the mission of sentence-level opinion expression extraction. DSEs (direct subjective expressions) encompass explicit mentions of personal states or speech activities expressing personal states; and ESEs (expressive subjective expressions) encompass expressions that suggest sentiment, emotion, and so forth. Without explicitly conveying them. Advantages are: Deep RNNs outperformed previous (semi)CRF baselines; achieving new state-of-the-art results for fine-grained on opinion expression extraction. Disadvantages are: RNNs do not have access to any features other than word vectors [4].

Nathan Aston, Jacob Liddle and Wei Hu* represents the implementation feature reduction we were able to make our Perceptron and Voted Perceptron algorithms more viable in a stream environment. In this paper, develop methods by which twitter sentiment can be determined both quickly and accurately on such a large scale. Advantages are: Suitable for unbalanced classes. Simple computation. Suitable for incremental learning. Disadvantages are: Independence assumption for computing Pc often invalid. Conservative estimate [5].

S. M. Mohammad, X. Zhu, S. Kiritchenko, and J. Martin analyzes electoral tweets for extra subtly expressed information along with sentiment like, positive or negative, the emotion like, joy, anger, sadness, etc. The cause or purpose in the back of the tweet (to point out a mistake, to support, to ridicule, and so on.), and the design of the tweet (simple statement, sarcasm, hyperbole, and so forth.). There are two sections: on annotating text for sentiment, emotion, style, and categories such as purpose, and on automatic classifiers for detecting those categories. Advantages are: Using a multitude of personalized features such as emoticons, punctuation, elongated words and negation along with unigram, bigram and emotional lexicons, the SVM classifier has achieved greater accuracy. Automatically classify tweets into eleven categories of emotions. Disadvantages are: Does not summarize tweets. It does not automatically identifying other semantic roles of emotions such as degree, reason, and empathy target [6].

S. M. Mohammad and S. Kiritchenko suggest that emotion word hash tags are accurate guide labels of emotions in tweets. Proposes a technique to generate a large lexicon of word emotion institutions from this emotion-categorized tweet corpus. This is the 1st lexicon with real-valued word emotion association scores. Advantages are: Using hash tagged tweets can acquire big quantities of labeled statistics for any emotion that is used as a hash tag via tweeters. The hash tag emotion lexicon is performed significantly better than those that used the manually created WorldNet affect lexicon. Automatically detecting personality from text. Disadvantages are: This paper works only on given text not synonym of that text [7].

B. Nejat, G. Carenini, and R. Ng focuses on studying two fundamental NLP tasks, Discourse Parsing and Sentiment Analysis. The development of 3 independent recursive neural networks: two for the key sub-tasks of discourse parsing, specifically structure prediction and relation prediction; the 3rd network for sentiment prediction. Advantages are: The latent Discourse features can support to boost the performance of a neural sentiment analyzer. Pre-training and the individual models are an order of magnitude faster than the Multi-tasking model. Disadvantages are: Difficult predictions to multi-sentential text [10].

The ability of the human face to communicate emotional states via facial expressions is well known, and past research has established the importance and universality of emotional facial expressions. However, current proof has revealed that facial expressions of emotion are maximum as it should be diagnosed whilst the perceiver and expresser are from the identical cultural in organization. Paul Ekman explains facial expressions to define a set of six universally recognizable basic emotions: anger, fear, disgust, sadness, joy and surprise.

Robert Plutchik has defined a diagram similar to a wheel with a set of eight fundamental emotions that contrast between couples; joy - sadness, trust - disgust, fear - anger and surprise - anticipation. Consider each of these emotions as a separate category and ignore the different levels of intensity that Plutchik defines in his wheel of emotions.

Disadvantages:

A. Ekman's Facial expressions limitations:

1. Image quality

Image excellent influences how well facial-reputation algorithms work. The image satisfactory of scanning video is quite low in comparison with that of a virtual camera.

2. Image size

When a face-detection set of rules reveals a face in a photo or in a still from a video grabs the relative length of that face as compared with the enrolled photograph size influences how properly the face may be diagnosed.

3. Face angle

The reciprocal angle of the targets faces consequences the detection score profoundly. When a face is enrolled within the detection software, generally multiple angles are used (profile, frontal and 45-degree are common).

4. Processing and storage

Even though excessive-definition video is quite low in resolution when compared with digital camera images, it nonetheless occupies significant amounts of disk space. Processing each body of video is a massive task, so usually simplest a fraction (10 percent to 25 percent) is absolutely execute through a detection system.

B. Plutchik's algorithm limitations:

1. The FPGA Kit uses hardware that is expensive. Thus, making this approach a cost ineffective technological solution.
2. Also, there is an additional dimension which involves a lot of tedious calculations.

III. PROPOSED METHODOLOGY

Profile of Mood States is a psychological tool to assess the mood of the individual. It defines 65 adjectives that are classified by the subject on the five-point scale. Each adjective contributes to one of the six categories. For example, feeling upset will positively contribute to the category of anger. The higher the score of the adjective, the more it contributes to the overall score of its category, with the exception of relaxed and efficient, whose contributions to the respective categories are negative. A POM combines these assessments into a six dimensional mood representation that consists of categories: anger, depression, fatigue, vigor, tension and confusion. With respect to the original structure, he discarded the blue adjective, since it only rarely corresponds to an emotion and not to a color, and the instruments of disambiguation of the meaning of the words have failed to distinguish between the two meanings. We also eliminate the relaxed and efficient adjectives, which have negative contributions, since the tweets that contain them would represent counter-examples for their corresponding category.

Contribution of this paper is to implement 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. The machine learning algorithm gives less time consumption without interfere human labeling. The Least Square Support Vector

Machine (LSSVM) classifier algorithm works on testing dataset with help of huge amount of training dataset. It gives same result as POMS tagging methods. The contribution work is prediction of Emojis for emotion detection using tweet contents.

Advantages of Proposed System:

1) Increases human-computer interactions
2) Low-cost
3) Fast emotion detection system
4) Scalable
5) Comparable quality to experts

A. Architecture

The Fig.1 shows the proposed system architecture.

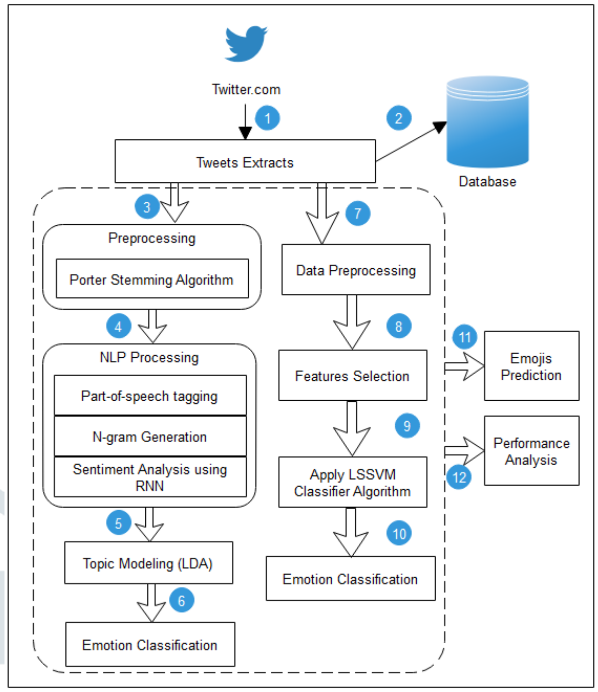

Fig.1. System Architecture

B. Algorithms

1. Latent Dirichlet Allocation (LDA) Algorithm:

First and most vital, LDA offers a generative model that elaborates how the documents in a dataset have been created. In this direction, a dataset is a collection of D documents and the document is a collection of words. So the generative model describes how each document collects its words. At the beginning, suppose that K topic dissemination for the dataset, meaning K multinomials incorporation V elements each, where V is the number of terms in the corpus. Let βi represent the multinomial for the i'th topic, where the size of βi is$V: |\beta i| = V$. Given these disseminations, the LDA generative model steps are as follows:

Steps:

1. For each document:

(a) Randomly select dissemination over topics (a multinomial of length K)

(b) For every word in the document:

(i) Probabilistically draw one of the K topics from the dissemination over topics gathered in (a), say topic βi

(ii) Probabilistically draw one of the V words from βi

2. LS-SVM Classifier Algorithm

Steps:

1) First, provided normalized and standardized training data $\{Xk, Yk = 1\}$ with inputs $\in Rn$, outputs $Yk = R$ R and N training data.
2) Select a working dataset with size M and introduce in this way a number of M support vectors (often M << N).
3) Randomly choose a support X^* from the working dataset of M support vectors.

4) Randomly choose a point X^{t*} from the N training data and replace X^* by X^{t*} in the working dataset. If the entropy increments by taking the point X^{t*} rather thanX^*. Then this point $X^{(t*)}$ is approved for the working dataset of M support vectors, otherwise the point $X^{(t*)}$ is dropped (and returned to the training data pool) and the support vector X^* stays in the working dataset.
5) Compute the entropy value for the present working dataset. Stop if the alter in entropy value is short or the number of repetitions is exceeded; otherwise go to (3).
6) Estimate w; b within the primal area after estimating the Eigen functions from the Nystrom approximation.

C. Mathematical Model

Topic Modeling:

The language models calculate the probability of occurrence of a number of words in a particular order. The probability of an order of T words $\{w1, \ldots \ldots wT\}$ is symbolically denoted as $P\{w1, \ldots \ldots wT\}$.Since the number of words coming before a word,wi, varies depending on its location in the input document, $P\{w1, \ldots \ldots wT\}$ is usually conditioned on a window of n previous words rather than all previous words:

$$P\{w1, \ldots \ldots wT\} = \prod_{i=1}^{i=T} P\ (wi|w1, \ldots, wi-1)$$

$$\approx \prod_{i=1}^{i=T} P\ (wi|wi-(n-1), \ldots, wi-1) \ldots \ldots \ldots (1)$$

Equations 2 and 3 show this relationship for bigram and trigram models.

$$P(w2|w1) = \frac{count(w1,w2)}{count(w1)} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (2)$$

$$P(w3|w1,w2) = \frac{count(w1,w2,w3)}{count(w1,w2)} \ldots \ldots \ldots \ldots \ldots \ldots (3)$$

IV. RESULT AND DISCUSSIONS

Experiments are done by a personal computer with a configuration: Intel (R) Core (TM) i3-2120 CPU @ 3.30GHz, 4GB memory, Windows 7, MySQL 5.1 backend database and Jdk 1.8. The application is dynamic web application used tool for design code in Eclipse and execute on Tomcat server. Some functions used in the algorithm are provided by list of jars like Twitter-core and Twitter-stream jars etc.

Tweets are extracted in a streaming way, and Twitter provides the Streaming API for developers and researchers to access public tweets in real time using Twitter4j jars. The aim of this paper is to bridge the gap by carrying out a performance evaluation, which was from two different aspects of NLP with recurrent neural network technique used for sentiment analysis and machine leaning algorithms. The Unison model is the combination of Ekman's, Plutchik's and POMS emotion categories and the Least Square Support Vector Machine (LS-SVM) classifier algorithm uses for emotion detection performance.

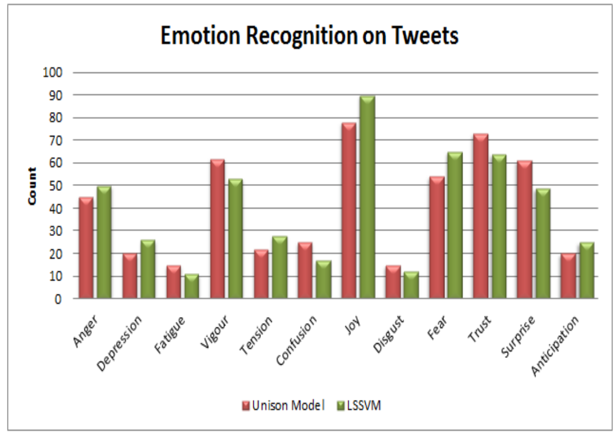

Fig.2. Emotion detection on tweets using Unison Model and LSSVM classifier algorithm

TABLE I Performance Analysis between Unison Model and LSSVM Classifier

	Unison Model	LSSVM
Precision	71.45	78.7
Recall	78.94	66.64
F-Measure	72.51	76.38
Accuracy	81.39	88.45
Execution Time(Sec.)	435	267

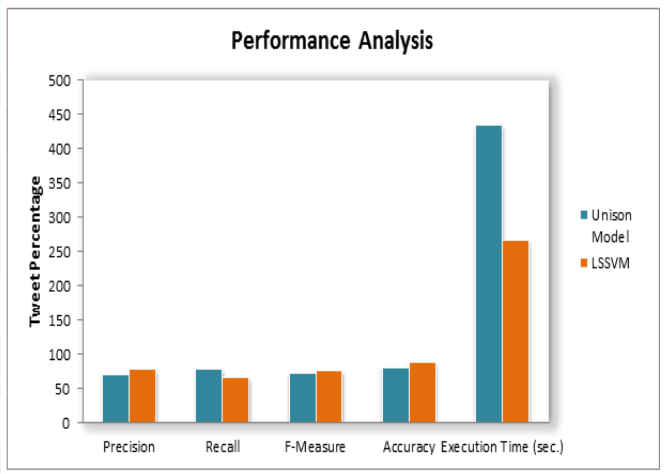

Fig.3. Performance Analysis between existing and proposed system

Fig. 3 shows the performance analysis between Unison Model and LSSVM classifier algorithm. The graph shows the Unison Model increases accuracy as compare to previous algorithms. But, the LSSVM classifier algorithm gives better results than Unison Model. Also LSSVM execution time is less than Unison model.

V. 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 LSSVM classifier is used to classify emotions, which gives results as accurate and less time consumption compares to POMS. 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.

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