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*Research Article*

# Novel approach to recognition of Customers feedback using Facial and Textual review

**Vrushali Rajendra Shete [1] and Dr. Devendra P Gadekar[2]**

Department of Computer Engineering, JSPM's ICOER, Wagholi, Pune- 412207, Maharashtra, India

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**_Abstract_**

*Analysis of post by use of emotions is challenge as they contain less contextual information. Emotions used in microblog environments are used many times and their meaning is clear in respect to emotions shown. As they form basis to importance for microblog emotion analysis. Earlier studies have overlooked emotions, emotional potentiality and have used emotions only as noisy emotion labels or indicators to train classifier. This issue is resolved by constructing a separate space for emoticon as emotional space which is represented as feature matrix and projections of emotions and words is done here. this is based on semantic composition. In this system we have proposed Emotion recognition on Twitter using Python. This is based on new Emotion Sematic Enhanced convolutional neural network model (ECNN) which improves the performance of emotion analysis. Emoticon embedding in emotional space as projection operator. Performance of emotion analysis is improved as proposed method is capable to capture more emotion sematic then other models which is done by projecting emoticons and words into emoticon space. This helps identify subjectivity, polarity and emotion in microblog environment. This paper in course gives insights for design of ECNN. Facial expressions give important clues about emotions. Sentimental analysis is other natural language processes for more task. Thus, many approaches have been put forth to classify human affective states In Facial expression analysis, features used are local spatial position or missing points or regions of face. In audio analysis, global statistics of acoustics is used as feature.*

***Keywords:*** *Emotion Recognition, Twitter, Text Mining, Natural Language Processing (NLP), Hashtags, Sentiment Analysis, Convolution Neural Network*

## 1. Introduction

The development of social network platforms has given people a new way to generate and consume a great deal of information on the web. In the past, people used to get information from portal websites. A large number of websites provide a long list of topics varying from politics to entertainment. These traditional online information sources are useful but less efficient because they often contain redundant information. However, since the arrival of online social network platforms, people tend to get information from these platforms because of their fast and efficient features. These platforms are available for users to choose the information source they are interested in. Social Network platforms such Facebook, Instagram, Twitter provide worldwide information to users. In all the social network platforms, twitter has become most popular microblogging platform which connects all world. It has dominant position in area of microblogging and is fast growing. More than 340 million twitter messages are posted by 500 million registered users worldwide. These messages include their daily activities as well as their opinions about certain subject

Compared with regular microblogging platforms, Twitter messages are much shorter. You are only allowed to post 140 characters or less in one Twitter message. This feature makes Twitter easier for people to get the main point from the massive amount of information available online. Depending on need of user he can follow any other news if he prefers to do same. With All above mentioned points contributing to success of twitter, twitter is widely used from Spreading rumours to purchasing products. Information streams of twitter are experiencing large amount database from large number of users with different interests and preferences which calculate their emotional state of mind. Hence there is urgency to have method or system which can contribute to find state of mind of specific user. There is urgency for users to have personalized services.

Nowadays, more and more personalized services are provided to benefit the users. People need this personalized service to make their fast-paced lives more efficient. Every day, a large amount of information is published by users on the Twitter platform. These data relate to user's behavior and many research studies therefore focus on Twitter and this data collection. One of the research studies in the field of Twitter is user modeling. In order to provide a personalized service, researchers started to explore ranking and recommendations of web resources referenced from Twitter. A large amount of research focus on modeling users' interests based on users published tweets data.

## 2. Review of Literature

A method to detect mood or emotion in any specific tweet is proposed in paper [1]. The authors classify the message under emotional category such as happy sad, angry under emoticons which are appeared. This approach is two steps based for classification, one of which is rule based approach while other in Machine learning Approach. Machine learning approach performance is better than rule based approach, the performance has been improved as we have removed the error data while training the model.

The Authors logic is detection of emotion for non hash tagged data and the labeled data creation for machine learning approach without manual creation. This technology can measure public mood of people in a community, which may help social scientists to understand the quality of life of population.[1]

Rule Based Approach described in this 2017 paper first detects the emotion in message of tweet, from this mood can also be detected. The next thing done is to classify the message under emotional category. The paper has determined 85% of accuracy in system thus proposed system helps to understand more deeper levels. In sentiments the level is coarse grained while with emotion it becomes finer grained.

Earlier authors logic where only able to determine whether the specific sentiment is positive tweet or negative tweet with the proposal of new methods, the tweet is able to give deeper information about the tweet which can be used in various fields such criminology, psychology, Economics etc When a user is not specifically micro blogging about their personal emotive status, the message can reflect their mood.[2]

The Authors first describe the grounded theory approach used to develop a corpus of 5,553 tweets manually annotated with 28 emotion categories.

From our preliminary experiments, we have identified two machine learning algorithms that perform well in this emotion classification task and demonstrated that it is feasible to train classifiers to detect 28 emotion categories without a huge drop in performance compared to coarser-grained classification schemes. They examine if common machine learning techniques known to perform well in coarse grained emotion and sentiment classification can also be applied successfully on a set of fine-grained emotion categories. Due to the length limitation, language used to express emotions in tweets differs significantly from that found in longer documents (e.g., blogs, news, and stories). [3]

In this paper, authors propose a new approach for automatically classifying text messages of individuals to infer their emotional states. To model emotional states, we utilize the well-established Circumplex model that characterizes affective experience along two dimensions: valence and arousal. Twitter message provide large database which is diverse and free with embedded emoticons, so we select it as input data set.

In our methodology, Hashtags are used as labels which in course trains supervised classifiers, this detects multiple classes of emotions from tweeter databases. Several features for emotion analysis and detection does include detection of unigrams, punctuations, emoticons and negation remarks. Accordingly, tweeter feature includes casual tweeter language and noise, some may contain numerous punctuation and spelling corrections. These messages are limited to 140 characters. Potential large features include to categorize short messages according to emotions and are labelled as supervised learning. Text messages which are in raw form cannot be categorized thus cannot be labelled. However, in order to train a classifier, supervised learning methods require labelled data.[4]

## 3. Problem Statement

This system, proposes Emotion Recognition on Twitter using Python based new EmotionSemantic Enhanced Convolutional Neural Network (ECNN) Model.

## Proposed System

Twitter is most popular microblogging platform available with growing amount of data in form of messages shared by millions and billions of people.

As the data keeps on increasing it is difficult to extract relevant information from this growing data from different users. As the users are increasing each one will be in demand for personalised service from twitter for analysis of data available.

Extracting the semantic meaning of Twitter and modeling the interests of users allows people to enjoy a personalized service on Twitter. Meanwhile, research shows that people tend to express their emotions on Twitter. These emotional tweets usually clearly express the users preferences compared with other normal tweets. Therefore, the goal of this work is to design some emotion-based user modeling strategies which exploit these emotional data. This work introduces and analyze the approaches for detecting emotion on Twitter. First it evaluates and compares the performance of proposed approaches of emotion detection

Then use these approaches of emotion detection to analyze Twitter sample dataset for the purpose of user modeling.

### Face Detection

Given an image, detecting the presence of a human face is a complex task due to the possible variations of the face. The different sizes, angles and poses human face might have within the image cause this variation. The emotions which are deducible from the human face and different imaging conditions such as illumination and occlusions also affect facial appearances. The approaches of the past few decades in face detection can be classified into four: knowledge-based approach, feature invariant approach, template –based approach and appearance-based approach.

### Facial Feature Extraction

Contracting the facial muscles produces changes in both the direction and magnitude of skin surface displacement, and in the appearance of permanent and transient facial features. Examples of permanent features are eyes, brow, and any furrows that have become permanent with age. Transient features include facial lines and furrows that are not present at rest. In order to analyze a sequence of images, we assume that the first frame is a neutral expression. After initializing the templates of the permanent features in the first frame, both geometric facial features and Gabor wavelets coefficients are automatically extracted the whole image sequence. No face crop or alignment is necessary.

## 5. System Architecture

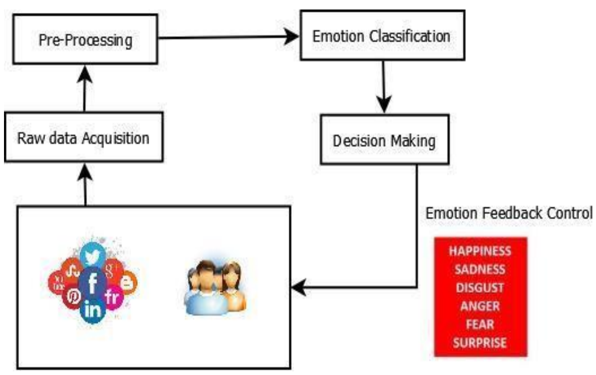


**Figure 1.** System architecture

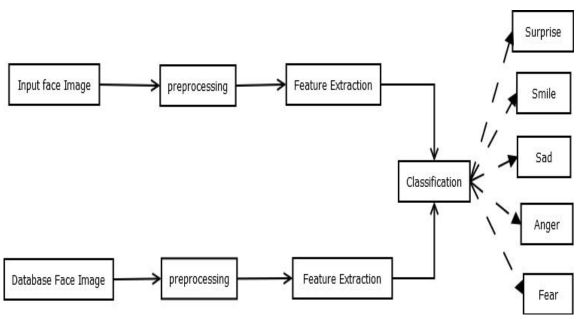


**Figure 2.** Method

## 6. Algorithm

### Algorithm 1: Alternate Batches strategy by Colbert and Weston

- Input:
  - DS = {d1, d2, ..., dn} /* data sets */
  - MODEL /* initialized NN model */
  - EPOCHS /* max number of epochs */
  - UPDATES /* number of updates in epoch */

➢

- Output: MODEL /* trained NN model */

1.: for epoch = 1→EPOCHSdo
2.: for update = 1→UPDATES /|DS|do
3.: foresides
4.: b←next train batch(ds)
5.: train on batch (b, MODEL)
6.: fords∈DSdo
7.: /* evaluate model on train and validation set */
8.: if early stopping criteria met then
9.: break

### Algorithm 2: Proposed Weighted Sampling Batches strategy

- Input: DS = {d1, d2, ..., dn} /* data sets */ MODEL /* initialized NN model */ EPOCHS /* max number of epochs */ UPDATES /* number of updates in epoch */

- Output: MODEL /* trained NN model */ 1: weights← [1/n, 1/n, ..., 1/n]

2: for epoch = 1→EPOCHSdo
3: for update = 1→UPDATESdo
4: ds random choice (DS, weights)
5: b←next train batch(ds)
6: train on batch (b, MODEL)
7: fords∈DSdo
8: /* evaluate model on train and validation set */
9: progress train acc(ds) - Val acc(ds)
10: weights[ds]←1/progress
11: weights←weights/sum(weights)
12: if early stopping criteria met then
13: break

### Algorithm 3: Support Vector Machine

In data analytics or decision sciences most of the time I come across the situations where I need to classify our data based on a certain dependent variable. To support the solution for this need there are multiple techniques which can be applied; Logistic Regression, Random Forest Algorithm, Bayesian Algorithm are a few to name. SVM is a machine learning technique to separate data which tries to maximize the gap between the categories.

Algorithm for classification of emotion.

Input: D Dataset, Semantic of Tokens, Tweets;
Output: Classification of Application
Step1: for each tweet tweet id in D do Step2: Get on-demand features and stored on vector x for tweet id
Step3: x.add (Get Features (tweet id));
Step4: end for
Step5: for each tweet in x vector do Step6: Fetch first feature and stored in b, and other features in w
Step7: h w, b (x) = g (z) here, z = (w T x + b)
Step8: if (z≤0)
Step9: assign g(z) = 1;
Step10: else g(z) = -1;
Step11: end if

**Algorithm 4: Convolutional Neural Network (CNN)**

A Convolutional Neural Network (CNN) is comprised of one or more convolutional layers (often with a subsampling step) and then followed by one or more fully connected layers as in a standard multilayer neural network. The architecture of a CNN is designed to take advantage of the 2D structure of an input image (or other 2D input such as a speech signal). This is achieved with local connections and tied weights followed by some form of pooling which results in translation in variant features. Another benefit of CNNs is that they are easier to train and have many fewer parameters than fully connected networks with the same number of hidden units.

- Input: User Twitter Tweets or post.
- Output: Extraction of topic.

## 7. Mathematical Model

Let S is the whole system consists:
- S={I,P,O}
- I= {I0, I1, I2, I3, I4, I5}

I0= Twitter dataset of user post
I1= Twitter bag-of-words I2= support of tweet
I3= confidence of tweet
I4= tweets of user
I5= MODEL
- P={P0,P1,P2,P3,P4,P5}

P0= read posts
P1= stop word removal
P2= tokenization
P3= train the model
P4= classification of tweets P5= update the MODEL
- O={O0,O1,O2,O3}

O0= token array
O1= bag of words array O2= trained model
O3= classification of MODEL

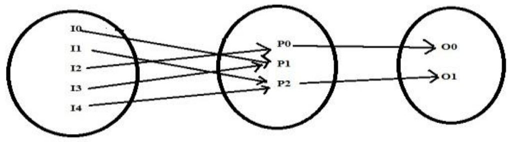


**Figure 3:** Venn Diagram

## 8. System Requirements

### A. Database Requirement

MySQL Database

MySQL is on open source database which is mainly a RDBMS i.e. relational database management system. As a database server, primary function of this software is to storing and retrieving data as requested by other from end software applications like Python which may or may not run either on the same computer or on different computer. This can be across the network either in internet or intranet.

### B. Software Requirement

1. Operating System: Microsoft Windows 7 and Above
2. Programming Language: Python
3. IDE: Jupyter Notebook

### C. Hardware Requirement

1. Processor: Intel Core I3 or Higher
2. RAM: 4 GB or Higher
3. Hard Disk: 100 GB (min)

## 9. Result and Analysis

Figure 4 shows the performance of the emotion recognition systems based on facial expressions, for each of the five facial blocks and the combined facial expression classifier. This table reveals that the cheek areas give valuable information for emotion classification. It also shows that the eyebrows, which have been widely used in facial expression recognition, give the poorest performance. Table 1 also reveals that the combined facial expression classifier has an accuracy of 85%, which is higher than most of the 5 facial blocks classifiers. Notice that this database was recorded from a single actress, so clearly more experiments should be conducted to evaluate these results with other subjects.

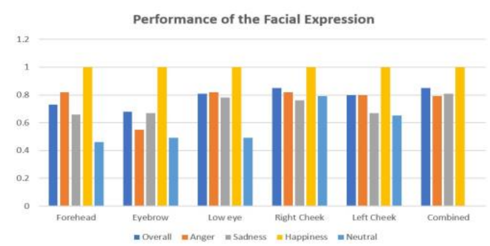


**Figure 4:** Performance of the facial expression classifiers

The combined facial expression classifier can be seen as a feature level integration approach in which the features of the 5 blocks are fused before classification. These classifiers can be also integrated at decision-level. Table 1 shows the performance of the system when the facial block classifiers are fused by the use of different criteria. In general, the results are very similar. All these decision-level rules give slightly worse performance than the combined facial expression classifier.

## 10. Advantages

- To detect emotion of users from Twitter
- To improve the accuracy of recognition of sentiments and emotions from Twitter.
- To identify Twitter user mood.
- To implement the algorithm and test it for real time Twits datasets.

## Conclusion

In this work, we investigate the effect of semantic classification on NLP tasks. We analyze the reason of why these emotion and sentiment analysis can improve the model accuracy. Although emotional words have good emotional semantic discrimination in word vector space, the sentiments have better discrimination than the emotional words in emotional semantic space. In this work, we propose a Emotion Recognition on Twitter using Python based new Emotion-Semantic Enhanced Convolutional Neural Network (ECNN) Model that construct the emotional space by using the vectors corresponding to the sentiments. The ECNN model is more capable of capturing emotional semantics than other models. Future scope of the system is to recognize the emotion based on uploaded multimedia (i.e. images) by user.

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