IJCRT.ORG ISSN : 2320-2882
INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

EMOTION ANALYSIS OF ELECTRONIC WORD OF MOUTH (eWOM) USING MACHINE LEARNING

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Abstract: World Wide Web corpus such as social networks, forums, review sites and blogs generate large volume of data in the form of emotions, opinions and arguments about different social events, government policies, political events etc. The social network sites and micro blogging sites are considered a very good source of information nowadays because people share and discuss their opinions about a certain topic freely. With the increased use of technology and social media, people proactively express their opinion through social media sites like Twitter, Facebook, and Instagram. Emotion analysis of social media can help decision makers to understand how people react to policies and events. The unstructured data from the social media is needed to be well-structured for this purpose. This is a challenging task due to the complexity of natural language processing of social media language. Often these messages reflect the emotion, opinion and sentiment of the public through a mix of text, image, emoticons etc. We cannot use standard natural language processing tools to analyze the emotion. People use popular emoticons like smiling face (☺), angry face (☹) etc., to express emotion instead of words. These statements are often called electronic Word of Mouth (eWOM) and are much prevalent in business and service industry to enable customers to share their point of view. Labeling the emotion as angry, happy or sad is a classification problem. We propose to use a two-step approach to identify the emotion of social media content. Without getting into the complexity of understanding the eWOM, we use machine learning algorithm to solve this classification problem**.**

***Index Terms* - Emotion Analysis, Social Media Analytics, Electronic Word of Mouth.**

I. INTRODUCTION

Emotions form a very important and basic aspect of our daily life. People openly discuss their opinion using short messages in social media sites. These messages often reflect their emotions on public policies, politics etc. Analyzing the emotions from the textual data over the internet has its own significance. For example, we can measure the well-being of a community, degree of satisfaction of customers of a product etc. This can quickly alert someone when customer preferences and desires change. Emotion analysis uses natural language processing and text analysis to determine the emotions hidden in a particular text. This analysis can be done at document level, sentence level and word level. Work in emotion analysis focuses primarily on short text because they are easy to handle as opposed to long texts where emotions may be difficult to detect. The sentence level methods rely on lexical resources like bag of words, ontology etc. However, this approach fails with eWOMs due to the complexity of social media language. The messages are not written as per grammatical standards. The unique characteristics of eWOMs are; short and noisy content, diverse and fast changing topics, large data volume etc. The research on social media analysis is still evolving. It might be just impossible to write natural language parsers to understand the context of these messages. Emotions can be expressed in two modes; one being the vocabulary of words and other affective items. In eWOMs, the affective items are emoticons. Affective computing is the field that devices systems to process, recognize and interpret the human affects from text, voice, and facial expressions. But, the mixture of text, emoticons, and hashtags is a new style of writing and conventional approaches fail to recognize eWOMs. This makes the emotion analysis of eWOMs a complicated process. We propose an approach that focuses in identifying six major discrete classes Happy, Anger, Sad, Fear, Disgust and Surprise from social media. Our experiment is based on this limited set; however this approach can be extended to include vide variety of emotions (Sorrow, Anxiety, Hate). We try to model the problem as a classification problem and our objective is to attach one of the six classification labels to the message. Without getting into the complexity of natural language processing, we use supervised machine learning to classify the emotion. The k-nearest neighbors (KNN) algorithm is a simple, easy-to-implement supervised machine learning algorithm that can be used to solve this classification problem.

The remainder of this paper is organized as follows. In section 2, we discuss related work. We formally formulate the problem and propose our research methodology in Section 3. Section 4 describes how KNN is used to classify emotion and the results of our experimentS are described. Finally, the paper is concluded in Section 5.

II. RELATED WORK

Emotion analysis has been of much interest in the recent days and we present an overview previous work done in this field. Researchers identified two major approaches to analyze the emotion from text messages, namely emotional categories and emotional dimensions. The emotional categories follow the approach of dividing the emotions into discrete emotion labels, one of its notable works presented by Cecilia et al [12]. Neviarouskaya et al. [18] have also used a rule-based method for determining Ekman's basic emotions in the sentences in blog posts. The emotional dimensions approach represents the emotion classes in a dimensional form: either 2D or 3D, with each emotion occupying a distinct position in space. Bradley [13] proposed a 2D approach which consists of two vectors pointing in two directions assuming the presence of an underlying arousal dimension with valence dimension vector determining the direction in which a particular emotion lies. Plutchik gave a 3D model arranging the emotions into concentric circles with inner being the basic and the outer more complex emotions [14]. We try to understand the emotion category approach in details since our goal is to identify six major varieties of emotions. Computational approaches involve collecting a data set and applying systematic algorithms to detect the hidden emotion. Emotion analysis algorithms can be classified into two major types as follows:

i) **Lexicon based**: An emotion lexicon is a knowledge repository containing textual units annotated with emotional labels. They rely on the lexical resources like lexicons, bags of words or ontology.

ii) **Machine Learning based**: The machine learning approach relies on machine learning algorithms that can learn from data by making use of document similarity between text messages.

Machine Learning based algorithms are broadly divided into supervised and unsupervised learning methods. The supervised methods make use of a large number of labeled documents. Unsupervised methods are used when it is difficult to find these labeled training documents. Supervised machine learning algorithms form a model based on the input data. Using this model they take decisions on how to map the future data to appropriate output. The SVM is a traditional approach in this regard. Mishne [19] used emoticons in LiveJournal posts to train a mood classifier at the document level. He used SVM as the classifier and identified the intensity of the community mood. Mao and Lebanon [20] trained a Conditional Random Field model on sequential sentiments with a movie review dataset. Dario [17] uses convolutional neural network architecture for emotion identification in Twitter messages. Their approach uses unsupervised learning, whereas we use supervised learning. Most of the approaches use plain text and text based emoticons to analyze the emotions. But, nowadays the social media sites emit huge number of messages every day with symbolic cues like emojis. So, we propose a two-step approach that uses supervised learning on the output of Feature Extractor. This novel approach gives better accuracy than the previous results.

III. RESEARCH METHODOLOGY

Social media messages are not well formed English sentences. These are unstructured content with mix of words, acronyms/abbreviations, emojis etc. Our model for analyzing emotion is tailored to handle the style and specifics of this informal writing style. The motivation behind our approach is to improve social interactivity and emotional expressiveness of real-time messaging. In order to estimate emotion in text, our model processes symbolic cues, such as emojis, transforms them to words, and then employs machine learning techniques to classify the emotion category. For example, the sentence 'Enjoying my lazy Sunday ☺' represents a happy message. Though it does not contain the word 'happy', the word 'enjoy' and the emoji '☺' express happiness. It would be easy for the ML Model to classify this into 'Happy' category if we perform the following two operations and convert to plain text as follows.

- Replace the emoji ☺ with the phrase 'Smiling face'.
- Mapping of 'Happy' with synonyms from dictionary.

After feature extraction, our ML model will be able to identify the emotion category easily. We propose to identify six major categories of emotion (Happy, Anger, Fear, Sad, Disgust, and Surprise) as shown in Table 3. We propose to use a supervised algorithm for classification. Machine learning is very influential nowadays than lexicon based methods. So, our first step is to develop a feature extractor that will produce a plain sentence from eWOM. Our Feature Extractor (FE) works as follows.

- Pick up only English text messages. Remove other language messages.
- Convert all words to lowercase.
- Remove stop words and punctuation like periods, commas, and brackets.
- Remove all words not purely comprised of letters (words having special characters and numbers).
- Replace emojis with CLDR meaning, if a mapping is available (Table 1). Remove otherwise.

The cleaned-up sentence is now used for emotion analysis. The algorithm produces better results than NLP based approaches.

3.1 CLDR Mapping

The following table shows examples of few emojis translated using Unicode Common Locale Data Repository (CLDR).

UNICODE	EMOJI	CLDR MEANING
U+1F600	😀	Grinning face
U+1F642	☺	Smiling face
U+1F609	😉	Winking face
U+1F615	😕	Confused face
U+1F622	😢	Crying face
U+1F602	😂	Tears of joy
U+270C	✌	Victory hand

Table 1: CDLR mapping of emoticons.

3.2 Feature Extractor

The following table shows the examples of translation done using our feature extractor. The translated sentence captures the sentiment without losing the original emotion.

eW OM	English Sentence
Salute to our warriors 😂 who taught us to raise voice against evil!	Salute to our warriors with tears of joy who taught us to raise voice against evil.
Enjoying my lazy Sunday☺ !!	Enjoying my lazy Sunday with smiling face
Samsung Galaxy M12 is out ✌!	Samsung Galaxy M12 is out with victory hand.

Table 2: Sentence formation using Feature Extractor

Our model learns to associate a given input (sentence) to the corresponding output (emotion category) based on the test samples used for training. The following diagram shows the architecture of our proposed system.

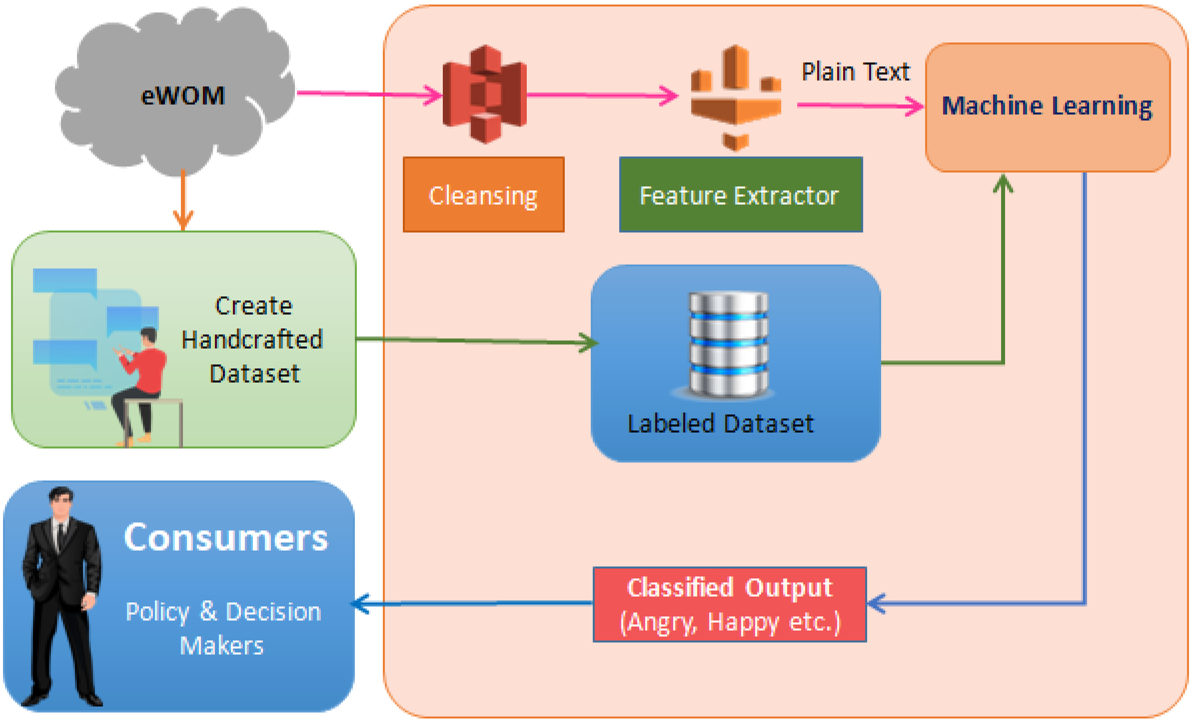

Figure 1: Architecture of emotion analysis system

Pairs of feature vectors and tags (e.g., happy, anger) are fed into the machine learning algorithm to generate a model. The well-trained model generates predicted tags (happy, anger, etc.) for a given input.

3.3 Classification using k-Nearest Neighbor (KNN) algorithm

KNN is a very popular algorithm for text classification. This algorithm classifies objects into one of the predefined categories of a sample group that was created by supervised learning. Our training data set consists of six categories as mentioned in table 3. KNN algorithm classifies a document by only looking at the training documents that are most similar to it. The algorithm assumes that it is possible to classify documents in the Euclidean space as points. Euclidean distance is the distance between two points in Euclidean space. The distance between two points in the plane with coordinates p=(x, y) and q=(a, b) can be calculated using the formula

$$d(p,q) = d(q,p) = \sqrt{(x-a)^2 + (y-b)^2}$$

Hence, identifying a suitable method to calculate the Euclidean distance between two text messages is crucial and important for the success of our algorithm. We use Term Frequency-Inverse Document Frequency (TF-IDF) method to find the similarity between two documents. TF-IDF method determines the relative frequency of words in a specific document through an inverse proportion of the word over the entire document corpus. In TF-IDF, similar text must result in closer vector. TF-IDF is the product of the TF and IDF scores of the term.

TF = number of times the term appears in the doc/total number of words in the document.

$$f_{ij} = frequency\ of\ term\ i\ in\ document\ j$$

IDF = ln (number of docs/number docs the term appears in)

$$idf_i = log_2\left(\frac{N}{df_i}\right)$$

Hence,

$$\text{TF-IDF} = tf_{ij}idf_i = tf_{ij} \times log_2\left(\frac{N}{df_i}\right)$$

Higher the TF-IDF score, the rarer the term is and vice-versa. TF-IDF is successfully used by search engines like Google, as a ranking factor for content. Smaller Euclidean distance between the documents indicates their higher similarity. Distance 0 means that the documents are complete equal. KNN classification algorithm combined with TF-IDF for distance calculation during our experiments yielded prediction accuracy of more than 84%. We discuss the experiment and results in the following section.

IV. EXPERIMENTS AND RESULTS

Manually screening thousands of tweets, customer support conversations, or surveys is complex and time-consuming. AI-based emotion analysis helps businesses process large amount of data in an efficient and cost-effective way. Since social media language differs from news articles and movie reviews, we can't rely on other data sets for training. A hand-crafted training data prepared from eWOMs is needed to train the model. Our experiments were conducted on a large twitter data set spread over the period from Sep. 2021 to Nov. 2021.

4.1Training Data Set

We created a data set from social media for supervised learning. Our experts collected around 13,000 tweets, cleansed, and classified them manually into six categories. More than one word may be used to convey the same emotion. Words synonymous with the emotions like happy, anger, etc., were used by experts as shown in the below table during classification.

No	Emotion Category	Synonyms in Dictionary	Count
1	Happy	Joy, Smile, Laugh, Enjoy, Cheer, Glad	3524
2	Anger	Ballistic, Furious, Outraged, Infuriate	2543
3	Fear	Terror, Horror, Unease, Worry, Anxiety	1987
4	Sad	Sorry, Regret, Depress, Dejected. Depress	2405
5	Disgust	Dislike, Revolt, Objection, Hatred, Repel	1104
6	Surprise	Astonish, Amaze, Marvel, Wonder, Shock	1346
		Total	**12909**

Table 3: Dictionary for emotion lookup

Though impactful emotions are few (six in our experiment), not all people use the same word to express a particular emotion. Our approach of using synonyms increases the breadth of coverage and hence improves the efficiency of our ML algorithm. The hand crafting also helps us to be highly subjective and capture context sensitive information. For example, a message containing 'Don't worry' will be classified as 'Happy' and not 'Fear'.

4.2 Population and Sample

Emotion analysis using artificial intelligence makes the life of decision makers easier. A company that sells hundreds of products cannot afford to employ many reviewers to read all the customer reviews manually and classify them. Automated analysis can identify critical issues in real-time, for example:

- Is a public crisis on social media escalating?
- Is an angry customer about to churn?, etc.

Artificial intelligence based emotion analysis is an efficient and cost-effective analytics tool for commercial organizations and government agencies. We used Twitter data related to product reviews and social events for our experiments.

In this section, we describe the evaluation tasks, the data sets used, and the experimental results of the proposed approach.

Evaluation Tasks:

i) We evaluate our approach on Twitter data set.
ii) We evaluate our approach on popular benchmarks.

Our goal is to provide real-life solution using our approach. We aim to evaluate the quality of emotion classification. The empirical result is compared with real-time data to harness the accuracy. The results show promising output..

4.2.1 Twitter Data Set

Twitter is a micro blogging site used by people nowadays to openly express opinion and emotion. Every day more than 500 million tweets are generated by people around the world, and this text-rich social media serves as a desirable platform to analyze information from many perspectives like politics, elections, consumer products, and many more. Twitter API provides facility to search for messages using filters like place, language, etc. Our data for evaluation was a large set of tweets from Sep. 2021 to Nov. 2021 in the English language.

DESCRIPTION	SEP 2021	OCT 2021	NOV 2021
Total number of tweets	5,234,667	5,201,745	5,134,443
Tweets with emotion	1,465,706 (28%)	1,352,454 (26%)	1,386,299 (27%)
Tweets with emotion and hashtag	628,160 (12%)	572,191 (11%)	616,133 (12%)

Table 4: Twitter Data Set for Experiment

From the above table, we observe that an appreciable number of tweets with emotion are available for analysis. Our experiments were conducted with values for k = 3, 5, 7, 9, 11 and k = 9 produced high accuracy. The below figure shows the classification of tweets using KNN (k=9) during our experiment.

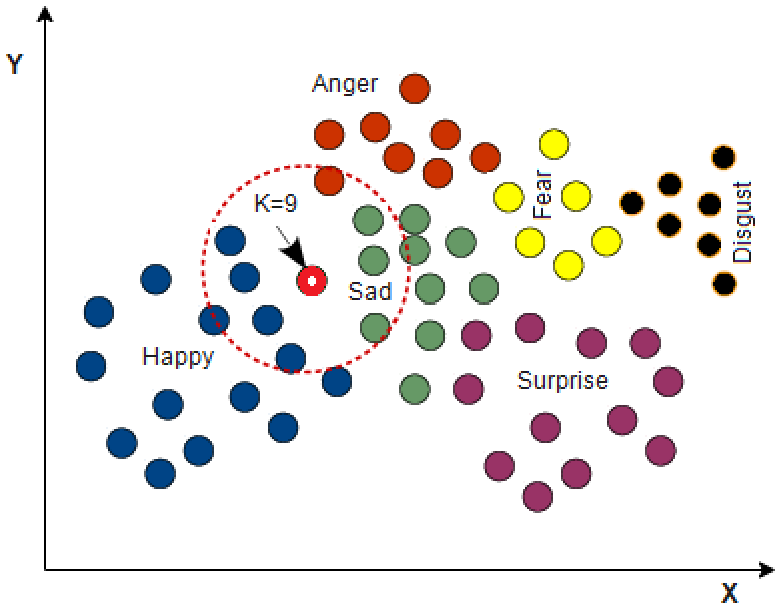

Figure 2: KNN classification with k=9

4.3 Popular Metrics

In this section, we first describe a set of metrics commonly used for evaluating the performance of our model and then present a quantitative analysis of the performance using popular benchmarks.

Precision, Recall, and F1 Score: These are primary metrics and are more often used for imbalanced test sets. Precision and recall for binary classification are defined in Eq. 1. The F1 score is the harmonic mean of the precision and recall, as in Eq. 1. F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0.

$$\textbf{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \textbf{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad \textbf{F1-score} = \frac{2 * \text{Prec} * \text{Rec}}{\text{Prec} + \text{Rec}} \tag{1}$$

For multi-class classification problems, we can always compute precision and recall for each class label and analyze the individual performance on class labels or average the values to get the overall precision and recall.

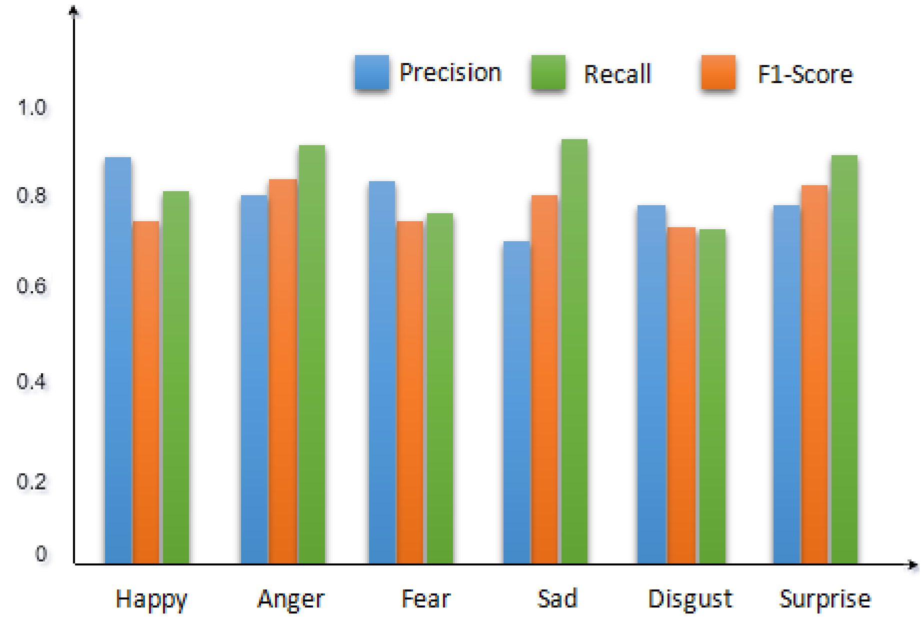

Figure 3: Quantitative metrics analysis

From the above results, it can be noticed that for Twitter eWOMs, better accuracy (as high as F1=0.84) is achieved during our message level classification.

4.4 Empirical Results

We aim to use our system to analyze social media and identify impactful events trending on Twitter. Following are examples of emotion-full events identified using our system.

No.	TWITTER eWOM	EMOTION	HASHTAG
1	Don't panic. India is banning private cryptos only. Not every crypto 😊!	Happy	#indiawantscrypto
2	Salute to our warriors who fought against evil 😂!	Happy	#2611Attack
3	We unite in grief as this painful tragedy only strengthens our bond and our resolute in fighting terrorism together 👏 We respect, value your sacrifices, we are forever indebted to your sacrifices 🙏	Disgust	#MumbaiTerrorAttack
4	26/11 tells us what hate can demolish and compassion can rebuild. Remembering the victims and saluting the martyrs 💪	Disgust	#MumbaiTerrorAttack
5	Market seems crashed! My money is already in loss... ☹	Sad	#cryptoban
6	Everyone crying for #cryptoban. Me who never invested in crypto currency 😊	Happy	#cryptoban
7	You all know we get a good news from Indian crypto market so, let's celebrate this news with Giveaway 👏	Happy	#indiawantscrypto

Table 5: Events identified from Twitter stream

From the above table, we observe that people talk about various events and express their emotions on social media. AI-based emotion analysis is an alternative to traditional polling and cost-effective solution for decision-makers to understand the situation and respond to any emerging crisis.

V. Conclusion

It's estimated that people agree around 60-65% of the time when expressing the opinion of an event in a public place. Tagging events by emotion is highly subjective, influenced by personal experiences, thoughts, and beliefs. By using a centralized emotion analysis system, organizations can apply the same criteria to all of their data, helping them improve accuracy and gain better insights. Emotion analysis in social media is challenging. While most studies focus on NLP based approaches, the differentiation between multiple emotion categories is more difficult. We investigate the problem as a classification task on the basis of six emotion categories. This can be extended further to include any number of emotions. We processed the content of messages after cleansing and feature extraction. The final prediction is suggested by classifiers deriving from the state of the art in machine learning. Results are convincing in the possibility to distinguish the emotions pairs in social media.

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