IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-6, Issue-9, Sept. 2018 E-ISSN: 2347-2693

An Efficient Tweeter Sentiment Analysis Sfcetr: Selective Feature Based Case Content Extraction Using Maximum Entropy Classifier To Rank The Tweets

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Available online at: www.ijcseonline.org

Accepted: 23/Sept/2018, Published: 30/Sept/2018

Abstract- Real world analysis the data based on the realistic approach to deal any objectives in online environment. Specifically social remedies have various approach of projective comments to share the information about products, innovative technologies etc. in this thing tweeter is a main platform to provide communication mammon the sharable users. In this provision most used by the people have the onions to make sentimental key terms to notify the originality. The sentiments about specific data be pointed by the comments in content format with sort text opinions. The opinions are extracted from the comments statement to analyst the tweeter data. By the fact of analyzing tweets have the hidden sentimental approach the problem arise due to right choice of sentimental extraction to classification is difficult. To overcome the problematic issue to propose a selective feature based case content extraction using maximum entropy classifier (SFCETR) to rank the tweets. This initially preprocess the tweets data the content reason from the comments statement. to aim the case reasons of relational features observed from the tweet contents are key term as contents .the comment case sentimental relation keyword terms are extracted synonmically to classify the data base on the reference key variable . Finally the rank case resultant categorize the sentimental case reasoning onion s about the predicative approach are classifies as class. This improves the tweets case opinions extraction are carried with the high performance sentimental research.

Keywords: Opinion mining, rank analysis, tweeter analysis, sentiment classification, features election

I. INTRODUCTION

Since quite a long while, there is an expanding of twitter interest for new administrations in view of the investigation of data originating from online informal communities. Such administrations can, for instance, give the reputation of an item or an organization, identify new patterns in a business, social or political setting, and so on. The enormous amount of data is an open door in term of representativeness but on the other hand is hard to oversee. Inside Twitter, for instance, it sentimental opinions gives the idea that the colossal stream of data is, more often than not, inconsistent with an adaptable examination except if to have high PC assets. The main down to extract the sentiment arrangement is regularly to see statically a restricted bit of a marvel in a constrained availability. This paper is given to the investigation of essential conditions to give a balance between the PC design multifaceted nature and the examination adaptability.

A few existing frameworks store old tweets and perform sentiment examination on them which gives results on old data and uses up a considerable measure of room. In any case, in this framework, the tweets are not put away which is financially savvy as no storage room is required. Additionally all the investigation is done on tweets ongoing. So the client is guaranteed that, getting new and important outcomes.

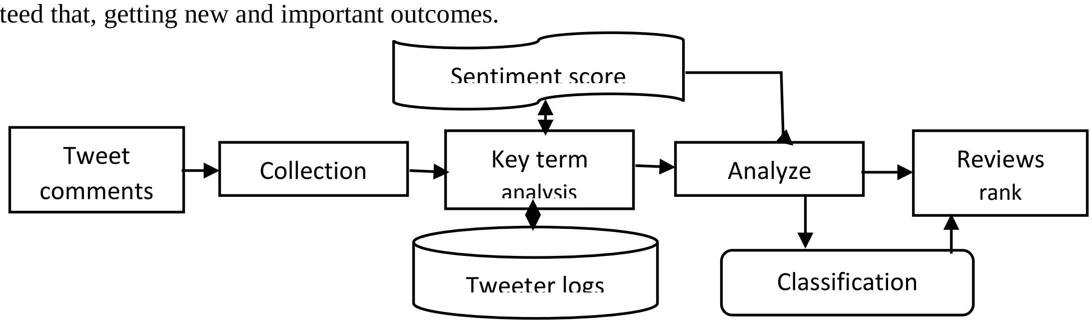

Figure 1 Process of sentimental tweet comments analysis

Enormous unstructured data is accessible in numerous structures like tweets, surveys or news articles and so forth which can be delegated positive, nonpartisan or negative extremity as indicated by the sentiment that is communicated by them. The primary focal point of the paper is to fabricate a framework which can construct a classifier from an extensive data set toward the startup and afterward can perform characterization of tweets in view of the classifier manufactured. Performing sentimental examination on the tweets in view of credulous Bayes' classifier prepared from a vast data set and give time variation investigation in light of the outcomes got. Preparing ought to be performed on an expansive data set which is the real criteria to get effective classifier.

II. LITERATURE SURVEY

Twitter messages (tweets) is frequently used to impart insights and sentiments about the encompassing scene [1]. The accessibility of social substance produced on locales, for example, Twitter makes new chances to examine popular assessment about the element. This examination we took twitter data for sentiment grouping.

Numerous individuals keep up steady contacts with various companions and relations by means of IM all the while at whatever point they are on the web, in the case of taking a shot at different applications or not. Notwithstanding permitting moment trade of content data [2,3], a special element of texting (IM) is its utilization of graphical symbols that express feelings, known as passionate symbols or emoji's.

Endeavoring to arrange a subset of these records utilizing extremity measurements can be an overwhelming assignment. After an overview of past research on sentiment extremity [4], this approach in light of Support Vector Machines. Past strategies utilized just formal vocabulary to order the sentiments behind the sentences [5]. Be that as it may, these strategies are inadequate in ordering writings since web clients make sentences utilizing casual vocabulary. It usually alludes to encouraging endeavors spread using PCs in an offer to give information in a non-conventional classroom condition [6]. As an essential for a viable advancement tweet analyzing frameworks, it is imperative to have certain information about clients' assessments and construct an assessment with respect to them.

Tweets with positive or negative sentiment are viewed as polar. They are considered non-polar generally [7,8]. Sentiment investigation of tweets can conceivably profit diverse gatherings, for example, shoppers and advertising analysts, for getting feelings on various items and administrations.

The rundown of terms, without advising how the terms are identified with each other [9]. Both would be valuable data in the investigation of micro posts because of the very powerful and interrelated nature of the substance. To characterize data and sentiments from Twitter all the more exactly. The data from tweets are removed utilizing watchword based learning extraction [10,11]. Consequently microblogging sites are rich wellsprings of data for conclusion mining and sentiment investigation. Since microblogging has showed up moderately as of late [12], there are a couple of research works that were dedicated to this theme.

Categorization of issue is testing on the grounds that a micro-blog entry is generally short and informal [13, 14], and conventional supposition mining calculations don't function admirably in such kind of content [15]. As Twitter can be viewed as a huge wellspring of short messages (tweets) containing client suppositions, the majority of these works make sentiment examination by distinguishing client states of mind and assessments toward a specific subject.

The data they use for preparing and testing is gathered via seek questions and is consequently one-sided. Conversely, we present highlights that accomplish a noteworthy increase over a unigram standard [16, 17]. In sentiment examination space, the writings have a place with both of positive or negative classes. There may likewise be multi-esteemed or twofold classes like positive, negative in cross breed type of surveys and unbiased [18, 19]. The center many-sided quality of order of writings in sentiment investigation as for that of other theme based inventorying is expected to the non-convenience of watchwords. The approach tends to challenges related with the special qualities of the Twitter dialect [20], and the review of gentle sentiment articulations that are important to mark administration experts

2.1 Problem definition

- From the literature survey the sentimental analysis holds massive irrelevant data points from high dimensional data sets from various opinions of users. This leads to reduce the classification accuracy.
- The resultant reduce the performance of classification accuracy leads lower end optimization data takes more data tweets.

- Probably reduce the sentimental and classification accuracy because of mismatch values.
- The existing methods does not consider the sentimental relative depthless of data point closeness to perform classification.

The earlier methods only identify the sentimental closeness of data point toward specific class and assigns the data point to the class. They does not look on the closeness of other dimensions with other class data points

III. IMPLEMENTATION OF THE PROPOSED SYSTEM

Twitter analyze is great impact based on the knowledge learning theory. The tweets terms are opinions from the user directed to the specific the reviews in the form of positive negative comments. The sentimental terms of comments are hidden knowledge to observe the opinions of user. Using frequent mining apriority, classification techniques doesn't provide sequential representation identifying the opinion category. The problem arise doesn't find the right opinion about the reviews from the user opinion. The most challenging factor is finding sentiment pattern in tweets become non redundant terms. To overcome the difficulties to improve the features selection based cluster methodologies is used to analyze the tweet terms

By improving the selective feature measure for sentiment prediction, using an efficient content extraction using maximum entropy classifier (SFCETR) to rank the tweets algorithm in the intension to stipulate the tweet data analysis.

- The method first performs preprocessing to identify the sentimental data as key terms and removes the noisy data points.
- Further, the method computes selective feature extraction with entropy classifiers with different positive, negative case.
- The similarity estimation is performed in entropy tweet rank classifier finally a categorization of class has been selected for tweet as weightage factor.
- The weightage factor compare with all classified and could identify the tweeter opinion analysis.

The proposed architectural flow of sentiment analysis given below shows that,

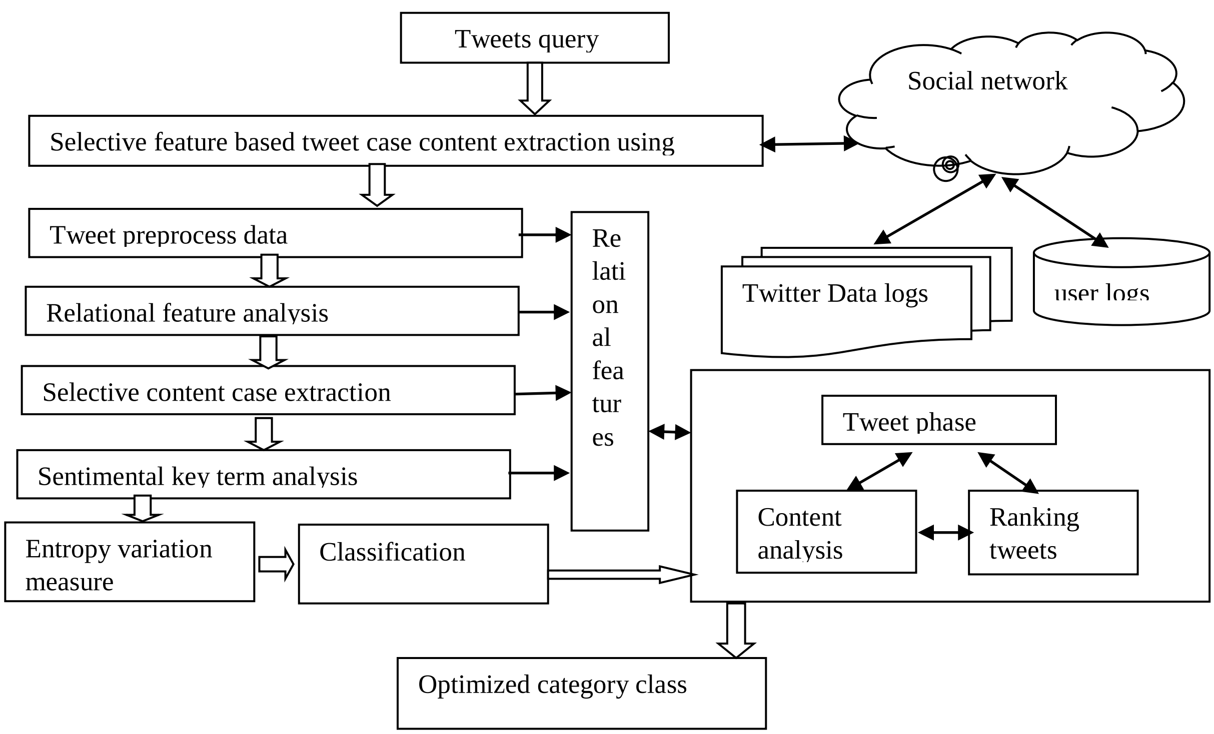

Figure 2 architecture of proposed system for analyzing sentimental tweets

The above figure 2 shows the proposed system extracts the data using selective feature based case content extraction using maximum entropy classifier to rank the tweets which is done using Streaming of tweets. The extracted tweets are loaded into feature case classification to categorize the sentiment opinions as positive negative case followed by classification which uses NLP and machine learning techniques.

a) User tweet stage

Sentiment analysis alludes to the general technique to remove extremity and subjectivity from semantic introduction which alludes to the quality of words and extremity content or expressions. There has two primary methodologies for separating sentiment consequently which are the vocabulary based approach and machine-learning-based approach.

b) Application stage

At first when the client sign in, there will be no channels so the dashboard will be vacant. The client has been given choices to include/erase channels. At the point when the client begins including opinion then every one of the data can be examined in the UI Module. Consequently, results for each opinions from tweet can be seen by the client. In the UI module gives the interface to dissect the arranged data to classify. Here the client can set their own particular tweets for which they can envision the data through a sentimental chart for the delineation of time-based Analytics imported from the API. The clients can show the data over hourly, every day or week after week spans.

C) Sentimental advancement stage

Sentimental opinion strategies make utilization of predefined rundown of words where each word is related with a particular sentiment. The opinion mining techniques differ as per the setting in which they were made and include computing introduction for an archive from the semantic introduction of writings or expressions in the reports. In addition, additionally expresses that a dictionary sentiment is to recognize word-conveying opinion in the corpus and afterward to anticipate opinion communicated in the content. Has demonstrated the dictionary strategies which have an essential worldview which are:

I. Preprocess each tweet, post by evacuate accentuation

ii. Introduce an aggregate extremity score (s) break even with 0 - > s=0

iii. Check if token is available in a word reference, at that point If token is certain, s will be sure (+) If token is negative, s will be negative (-)

iv. Take a gander at the aggregate extremity score of tweet post If s > edge, tweet post as positive If s < limit, tweet post as negative

However, Highlighted one preferred standpoint of inclining based technique, is that it can adjust and make prepared models for particular purposes and settings. Conversely, an accessibility of marked data and consequently the low materialness of the strategy for new data which is cause naming data may be exorbitant or even restrictive for a few assignments.

3.1 Preprocess the tweet dataset

The preprocessing steps carries the tweeter dataset with number of sentimental factors that are considered to have opinions. Second, for each data point, the presence of all the dimensions are verified and their values also verified key terms and fill or remove invalid values. If any of the data point is identified as incomplete then it has been concluded that noisy and removed from the data set. For instance, to find a frequent data are removed with identical numerical values. Unfilled datasets values are filled constant values to process for tweet data prediction.

Algorithm

Input: tweet data Set Crds

Output: Preprocessed Set Ps

Step 1 Compute the tweet data Set
Start
Initialize to read crd1, crd2….crdn
Step 2 Read the attribute set
For each tweet data Set ket term value Ad_i from Crds

Attribute value V = Extract tweet data Set from Adi.
Check null ==empty:
Remove→crd;
Originate order of tweet data Set id ←crds
Step 3: compute the sentence in the tweet term.
Split the term sequence by line of string
Sentence set Ss = ($\sum_{n=1}^{size(Ds)}$ Text€Di) × Splitby(.)
Read sentence Rs← string line (SL)

For each tweet key term Di from Do
For each tweet term Tk from Ti
If Di€ then
Find the non-relational measure of tweet data
Non Relation Set Rs = ∑(sentiment of non-terms €Di)+Ci.
Remove the non-term tweet data Set Ni.
End
End
End

The relational term method first performs preprocessing to identify relative tweetkey term data and removes the noisy data points. Further, the method computes feature extraction with relational feature with different key term.

3.2 Relational feature analysis

The relative feature analysis identifies the sentimental terms from tweet dataset. The tweets are represented as opinion tweet aspects. To determine the polarity of summarized aspects tweets are taken as features. The sentimental words depends the opinion datasets wit positive negative term of tweets. Based n the relational category of positive negative features represent distance measures between the terms of analysis. The concrete features retains closeness of sentiment term by identify the entities of patterns.

Identify all the relative features have values.

$$CD = \int_{i=1}^{size(Md)} \sum Md(i) \in (\forall Ts(k))$$

Identify all possible features have values.

$$PD = \int_{i=1}^{size(Md)} \sum Md(i) \in (\forall \uparrow\downarrow Ts(k))$$

Compute similarity on concrete features.

$$CDSim = \int_{i=1}^{size(CD)} \sum_{j=1}^{size(Ts)} Dist(Ts(j,i), Dp(i)) \downarrow DThreshold$$

Compute similarity on possible features.

$$PDSim = \int_{i=1}^{size(PD)} \sum_{j=1}^{size(Ts)} Dist(Ts(j,i), Dp(i)) \downarrow DThreshold$$

Compute Eccentric Measure Em.

$$EM = \frac{CDSim \times PDSim}{Size(Ts)}$$

The eccentric measure identifies the similarity of sentimental collection with the retained classes. The redundant features have all the tweet key term of information the possibilities of sentimental keywords to differential distance between the keywords. The information are carried the eccentric measure to classify the result.

3.3 Selective content case extraction

In this stage, the method estimates the similarity between the tweet data points of the classifier among key terms and input data point in different levels. The estimation of similarity measure has been performed by relational feature classifier weight has been computed for each classier. Based on computed cluster weight, a single class has been identified by feature extraction for indexing the data point. Finally the weighted order classifier be predicted by making the sequential decision classifier. By comprehensive evaluation it's easy to find out the difference of students in different type, which used to support tweets originality, and it is valuable for teachers and students to improve their work. And for the other one evaluation, the classifier can relieve the insufficient of traditional grades which lack of flexibility to change with the change of external influences

Extract tweet Patterns(S) definition: Given a set S of word objects, extract patterns.

For each word-pair tweet pattern (definition A, implies B) ∈ S

While

D ← Get definition objects ("A sentimental tweets, B sentimental tweets")

N ← null

For each definition d ∈ D

Do N ← N + pattern tweet pattern word (d, A, B)

P ats ← CountFreq page (N) return (P)

End While

Partial classification algorithms are the fastest ones but frequents make to construct the classification system make effceint methods in constructing the rules. To identify the significant variables that affects and influences the performance of undergraduate students

3.4 Maximum entropy classification of tweet rank

Tweet pattern Dataset is a simple and effectual way of classification. There are many parameter and Procedures that can be built-in in the data models based on resemblance. Such models Are optimized to calculate posterior probability that a vector x, y belong to class Optimization includes the type of distance function, or the type of kernel x and y similarity tweets

$$\sum_{i=1}^{d}(x-x^2)(y-y^2)$$

Tweet distance D(x; y) that must be intended depending on the problem, selection of orientation Examples, allowance of their sway, and other elements. Correlation distance is also often used:

Cosine distance, equal to the normalized dot product D(x; y) = x –x1

Selective binary features D(x; y) = y-y1.

$$D(x,y)=\frac{\sum_{i=1}^{d}(x-x^2)(y-y^2)}{\sqrt{\sum_{i=1}^{d}x\,(x_i-x)^2}\sum_{i=1}^{d}y-y^{2)}}$$

Varied tweet pattern metric functions suitable for nominal data may be defined using conditional

Algorithm

Input: tweet pattern (WDs), query term Q tweet,pattern list sl

Output: optimized class

Start

Step 1: compute the productive tweet pattern list and query term

For each term Qt from sl

Compute tweet relation key terms measure →scsm = Nc/Tn.

Nc = Number of tweet pattern contains Ti→term index

Tn- Total Number of objective terms present in tweet pattern

End

Step 2: Compute tweet pattern ranking measure Fcm = $\int \frac{Scsm}{Numberofuser\ entries}$

For each tweet pattern query term search

Service list sl = weightage computation.
[sscm, S, Ne] =Compute reational measure(Ts).
Step 3 For each related term frequency
Compute term frequency Tf = $\frac{\sum Terms(Ts)\in O(c)}{Numberoftermsofc}$
Compute tweet pattern query termQTw = Sscm×sl
End
Step 4: Choose the top closure Ranking = O(Max(Sscm))

Return optimized tweet pattern query term Q→t

For each attribute A of transactional set T

Construct a class label positive, negative, neutral class.

Create properties as class by reference.

Assign values each category class rank

End.

End

: stop.

The classification performance tweets are assigns with ranked class based on the tweet ranks and opinions with ranked tweets are order by class by reference.by returning skewedness implementation proceeded carried the data based on the dependency retained lower errors data be obtained from the tweet patterns. Finally the based on the frequent term of access the classes are ranked.

IV. RESULT AND DISCUSSION

The sentimental tweet analysis from real entities are from tweet repository in twitter dataset be implemented with selective feature based case content extraction using maximum entropy classifier to rank the tweets was projected. The resultant was checked with carried extracted sentimental key terms observed from the opinion dataset. The tweet levels are varied with dependent key term dataset. The following are the parameters and values processed tabulated below

Table 4.1: evaluation of parameter and values in dataset

parameters	Values processed
Dataset used	Tweeter dataset
Opinion class	Positive negative, neutral
Number of tweets logs	3000
Content terms	Attribute text content

The above table 4.1 shows the parameter and values processed in tweeter analysis which utilize the features to extract the sentiments in the form of positive, negative and neutral class with identified number of logs. The sentimental approach of key terms are measured with precision and recall rate of relational closeness measure with count terms tweet words.

$$precision = \frac{\sum_{j=1\ sentiment\ match\ case\ keyterms}^{|D|} mat\ Gd\ (Dj)}{|D|} + \cdots$$

Ground representation of truth values are represented as G and predicted keyterm are D.

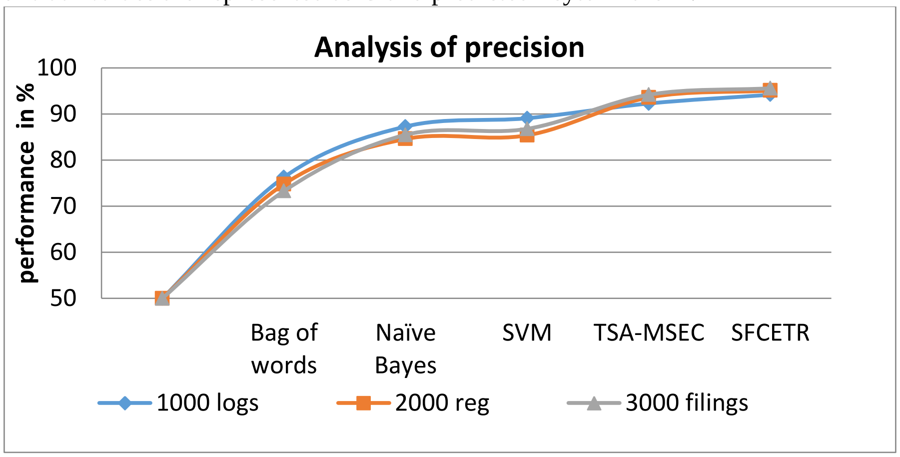

Figure 4.1: Comparison of a precision rate

The above figure 4.1 represents the comparison of precision sentimental approach to the other dissimilar methods. The resultant of precision rate is well improved by implementing the proposed system. The selective features is more observable to produce higher resultant.

Table 4.2: Evaluation of precision rate

	Evaluation of precision in %				
Methods/number of tweets	Bag of words	Naïve Bayes	SVM	TSA-MSEC	SFCETR
1000 logs	76.3	87.3	89.1	92.3	94.2
2000 registrations	74.8	84.6	85.4	93.6	95.1
3000 filings	73.2	85.5	86.8	94.2	95.6

The above table 4.2 represents the comparison of precision rate to analyses the sentimental terms from the tweet opinion data. The naïve Bayes produce 8.3 5% accuracy. SVM produce 89.1 % accuracy TSA-MSEC produce 92.3 5% accuracy. The proposed SPECTR produce 95.6% higher efficient than other methods

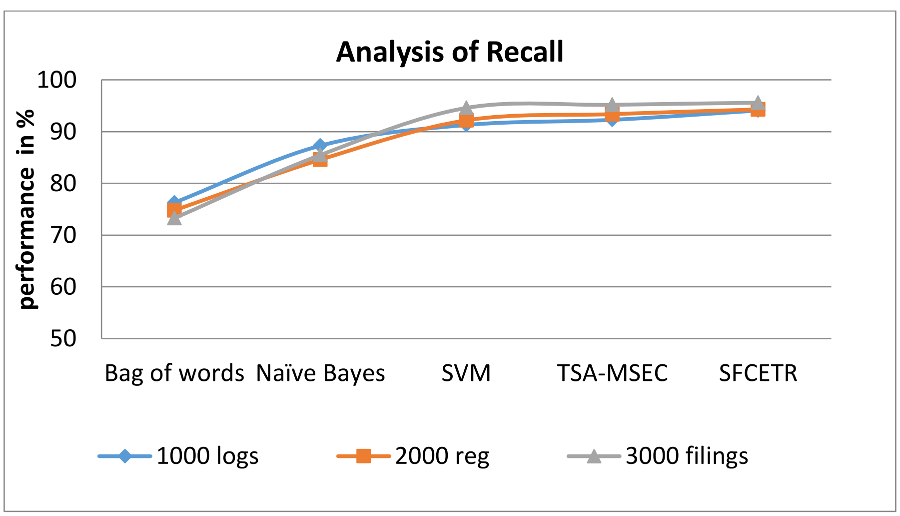

Figure 4.2: Evaluation of recall

The above figure 4.2 resemble to produce efficient recall rate of the proficient methods. The performance of this implementation had the higher resultant compared to the other dissimilar methods.

Table 4.3: Evaluation of recall

	Evaluation of recall in %				
Methods/number of tweets	Bag of words	Naïve Bayes	SVM	TSA-MSEC	SFCETR
1000 logs	76.3	87.3	91.3	92.3	94.1
2000 registrations	74.8	84.6	92.2	93.4	94.3
3000 filings	73.2	85.5	94.6	95.2	95.6

The above table 4.3 shows the evaluations of recall state repeatedly the iterated result to specify the relative methods. The intent methods projects with had the higher performance SPECTR 94.1 % higher than other methods.

False extraction Ratio (Fer) $=\sum_{k=0}^{k=n} \times \frac{total\ dataset\ failed\ \ tweets\ \ (Fer)}{Total\ no\ of\ extratedrate(Fr)} *\ 100$

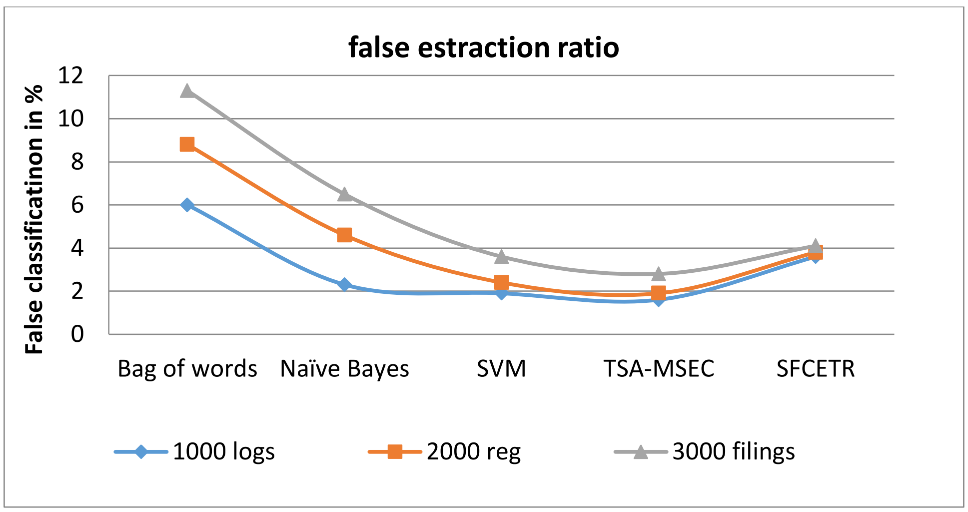

Figure 4.3: Evaluation of false extraction

The above Figure 4.3, reviews the false classification with compared to the other dissimilar methods. The intent methods produce the lower false classification compared to the other dissimilar methods.

	Evaluation of false extraction in %				
Methods/number of tweets	Bag of words	Naïve Bayes	SVM	TSA-MSEC	SFCETR
1000 logs	6.6	5.3	5.2	4.4	3.6
2000 registrations	8.8	4.6	4.4	4.3	3.8
3000 filings	11.3	6.5	5.6	4.5	4.1

Table 4.4: Evaluation of false extraction

The above table 4 .4 shows the dissimilar methods produce the various classification naïve Bayes 5.3 % with preferred various level of performance with other dissimilar methods. The proposed SPECTR produce well up to 4.1 false classification.

The variants of classification categories the results

Time complexity (Tc) $=\sum_{k=0}^{k=n} \times \frac{\text{total tweets handeletd to process in dataset}}{\text{Time taken(Ts)}}$

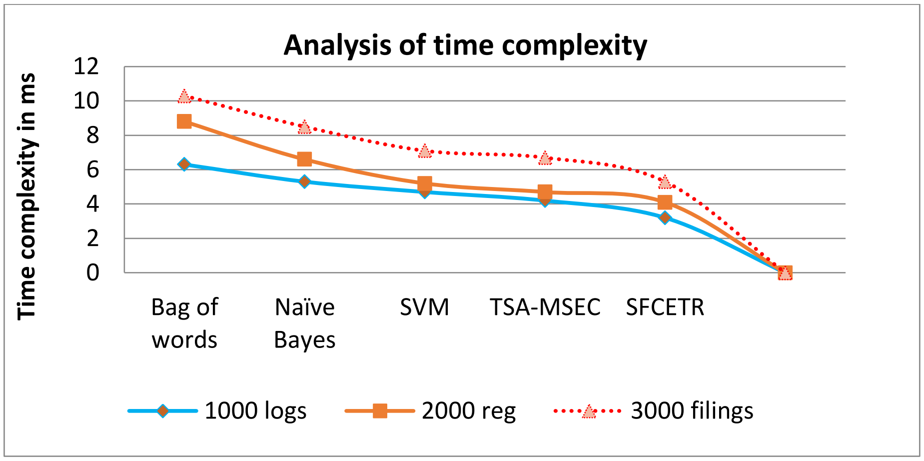

Figure 4.4: Analysis of time complexity

The above figure 4.4 resemble the various dissimilar comparison of time complexity compared to the proposed system. The proposed implementation produce the maintained mean time performance as good than dissimilar methods.

Table 4.5: The evaluation of time complexity

	Evaluation time complexity in seconds (ms)				
Methods/number of tweets	Bag of words	Naïve Bayes	SVM	TSA-MSEC	SFCETR
1000 logs	6.3	5.3	4.7	4.2	3.2
2000 registrations	8.8	6.6	5.2	4.7	4.1
3000 filings	10.3	8.5	7.1	6.7	5.3

The above table 4.5 shows time complexity exceeds based on holding non terms of processing in tweet dataset. By this features holds only redundant terms to ensemble the classifier. So the implementation maintains the least time of execution up to 3.2 milliseconds as well than other dissimilar methods. The proposed produce higher performance within the tie of execution.

V. CONCLUSION

The proposed system selective feature based case content extraction using maximum entropy classifier to rank the tweets (SFCETR) conclude the relational features are best to classify the tweets opinions observed from real entities. The relational based feature selection enrich the redundant features .to select the redundant features. The ensemble classifier finds the differential approach based on the opinion relation between the tweet terms. The implementation produce as well higher performance of precision, recall with lower complexity rate 3.2 milliseconds. The intent methods has produce the classification accuracy up to 95.7% as well on real world tweets comments. Finally a categorized has been computed for each cluster, the weightage are iterated classify the data. The soft commuting estimates final cluster data points which is required for phycology motivation that are given to students. This classifier relatively much improve the clustering accuracy to produce high quality results.

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