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[Kavitha, 5(8): August 2018] ISSN 2348 – 8034
DOI- 10.5281/zenodo.1407450 Impact Factor- 5.070

GLOBAL JOURNAL OF ENGINEERING SCIENCE AND RESEARCHES

TWITTER SENTIMENT ANALYSIS BASED ON USER OPINION MINING USING MICROBLOG SUBSPACE ENSEMBLE CLASSIFICATION APPROACH IN SOCIAL WEB BLOG

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ABSTRACT

Sentiment analysis rapidly used to manages content relation and variety of tweets terms from tweet comments which the comments are sentimental or opinion of the user. Online networking is producing a large measure of sentiment obtain from information as tweets, notices, blog posts and so forth. Sentiment analysis of this client produced realistic information is precious to identify the tweets texts of the group. Sentiment analysis from tremendous tweets is troublesomely contrasted with wide-ranging user thoughts, because of the closeness of words and different considerations create problem. The criticism about differential reviews formalize the tweets of note reviews to the inward sentimental opinion. To solve this problem, we propose a microblog subspace ensemble classification given entropy variety in Knowledge process of tweet mining and rank prediction approach are the two procedures utilized for examining tweets content are realize sentiment from the tweet. To improve the sentiment analysis to break down the twitter posts about item reviews among thing sets using frequent mining approach. Maximal stable to determining the sentiment analysis is specific filed require a point of purpose to know feature. To recognize the originality of key terms to optimize the result. It addition touse feature selection fromkey terms are categorized into positive, negative and neutral classes obtained from the feedback opinion tweets data.

Keywords: *security, cloud storage, encryption and decryption, cloud service, auditing. Data authentication feature analysis, opinion mining, tweet mining, relational sentiment analysis, frequent mining.*

I. INTRODUCTION

Internet-based life has gotten more consideration these days. The directed approach bout any product is open to discuss as reviews as opinions to tweet the comments using various web-based communities. Content analyses in tweets is from the online networking that is picking up prevalence. Opinion from tweeter is a group associations a quick and compelling approach to examine clients' points of view toward the basic to achievement in the commercial center to know about the originality. Tweeter analysis is Symbolic systems or deep learning, and optimized classification are the two fundamental strategies utilized as a part of relational analysis. Information based content analysis are relationally contains the unstructured database of predefined emotions and an active learning portrayal for distinguishing sentiments. Classification approaches is used to extract the category of mining relational terms depending upon the sentimental terms. To build a semi supervised classification based on the microblog subspace classification approach to extract the sentimental key terms to analyze the opinions are categorized into tweets.

Opinion mining otherwise called sentiment analysis to obtain the user impact about the discussion forums in specific fields. This can be carried out the classification techniques be analyzed through sentiment keyword extraction model. The micro blogs carries the deep integrated approach related to specific contents. Depending upon the subjectivity about the products the opinions are varied contents as good or bad opinion. Numerous organizations do diverse kinds of studies like Product satisfaction study, aggressive details and market study, mark value review, client benefit overview, new item acknowledgment and request study, client trust and steadfastness study and numerous different studies for the organization and item upgrades. These sort of studies require a parcel of the spending plan, labor, and part of the time. The report created by this procedure probably won't be bona fide. This is tedious, and high spending plan included and manual process.

Classification of extremity to ordered the tweets utilizing emotions of sentimental keyword analyze to categorize the realized forms proceeding optimally to the content relation. The emotions are positive content with positive key terms as well same as negative and neutralized. Here, the creators utilize a half and half approach, joining administered learning with the information on sentiment-extraction words, which they remove from the sentiment lexicon. The tweets datasets are initially preprocess to reduce the dimensionality for incomplete comments which they are measured. To calculated the indexing term of opinion carried out by user about specific tweets and its relation the subspace clustering notify the syntactic rules to predict the index terms . Further he terms are analyzed as semantic meaning which are other form of meanings. This will considered as tweet of terms to analyze the opinion sentiment. The creators infer that the essential features are those relating to sentiment learning elated words. At long last classify sentiment communicated on beforehand given focuses in tweets. They include data with sentimental key terms are opinion about the product reviews. In this manner, they utilize subspace ensemble approach base on similarity measure and the Opinions are categorized into positive, negative, neutral and non-class based on the classified category tweets comes out.

Tweet sentiment analysis is one territory of analysis of Twitter information that is utilized as a part of a scope of exercises: stock expectation, decision forecast through to eatery determination. There are anyway numerous difficulties in using tweets to perform sentiment analysis. Tweets ordinarily need contextual content and incorporate clamor, which can effect on the exactness of sentiment analysis.

II. LITERATURE SURVEY

The following are the various reviews that are Programmed sentiment analysis is a point inside data extraction that lone as of late got enthusiasm from the scholarly network [1]. In the earlier decade, a bunch of articles has been distributed regarding this matter. It's just over the most recent five years that we've seen a little blast of distributions.

To analyze the tweet viability of introducing classification procedures to determinate opinion mining [2, 3]. A testing part of this issue appears to recognize it from conventional point-topics are measured by indefinite regularity measure regularly identifiable semantic relation of key term classifications which is communicated additional inconspicuously to tweets terms ar prescribed. Their powerlessness to deal with all information [4], adapt to missing information focuses, the spread of information focuses and in particular absence of thinking abilities. The relational analysis carried the opinions acquired by joining different relational analysis using sentiment feature terms [5. 6]. To sorting the relations based on the tweet sentiments required the classification approach defending the realized words from data. Most cases to abscond distinguishing proof classification calculation because of Naive Bayes and MetaClass [7], which settled the issue that excellent and complex deformity is hard to classify. Respect Naive Bayes calculation to develop the double tree in multi-class MetaClass classification calculation.

These big tweet marks were given by a couple of sentiment location sites over twitter information. To all the more likely use these sources [8], to confirm the potential estimation of utilizing and joining them, giving an analysis of the gave names, examines an approach where a pitched microblogging webpage are grouped by stream of tweeted with their passionate classes are categorized into different opinion sets as positive or negative [9]. The investigations are carried out twwet comments by execution of different categorized calculations in light of their accuracy and review in such cases. Most prominent microblogging stage, for the errand of sentiment analysis [10]. This consequently gathers a set of tweets analyses comments to retain the sentimental terms to identify the tension of revives. A troupe of machine learning classifiers structure for taking care of the issue of subjectivity and sentiment analysis of client surveys [11]. Right off the bat, three celebrated text classification calculations, to be specific classifiers live word corpus, SVM ,KNN are some of the traditional to retain the opinion extraction directed from tweet datasets investigated as of late with shifting outcomes [12]. The discussed reviews implement the sentimental approach of including semantics as extra features into the preparation set for sentiment analysis.

Dimensionality to extract the tweet patterns from a delegate test of the whole Twitter. We at that point utilize text mining procedures to contrast these Twitter topics and topics from networks surveys [13], mulling over theme classes and sort opinions. Another test of microblogging is the unimaginable broadness of theme that is secured. It's anything but a misrepresentation to say that individuals tweet in regards to everything without exception [14]. Accordingly, to have the capacity to assemble frameworks to mine Twitter sentiment. The reason for sentiment analysis is to decide the general opinion or disposition, in term of positive or negative, communicated in text accessible over the Internet [15]. Sentiment analysis might be as straightforward as the essential sentiment based order of text archives to more mind-boggling and propelled strategies to separate opinion at various granularity levels.

To generalize the tweet analysis using opinion mining and sentimental case reasoning analysis are the two investigation of individuals' user decision, demeanors, and relational tweet substance process to obtain categorized result[16, 17]. The material can speak to people, occasions or topics. These topics are well on the way to be secured by audits. The two articulations SA or OM are tradable. The naïve bass classifier denies the category based on the feature vector specification to point the data elation on tweens segmentation [18], semantic orientation are tested with SVM features with supportive word corpus data to be trained with tweet opinions. Feature extraction calculation is one of the NLP methods. It can be utilized to extricate subject-particular features, remove the sentiment of every sentiment-bearing vocabularies [19, 20], and relate the separated emotion with a particular subject. It accomplished preferable outcome over machine learning calculation, the LDA modes enhance the relational extraction which is pattern substitutions to increase the background possibility s of additional data's, this mush increase the dimensionality problems[21]. These frontal area topics can give potential elucidations of the sentiment varieties. The classifiers intents additionally improve the intelligibility to extracting the patterns contain relational analysis. Hybrids are likewise intended to gain from certain portions as pseudo-criticism [22] iteratively. Investigations on two tweet datasets demonstrate categorize the tweet measure is altogether enhanced by pattern extraction model and nearby relational sentimental terms contrasted and utilizing ordinary meaning alone.

All in all the viable stage for the articulation of their musings and thoughts. These musings can be an outfit for extraction of sentiments of individuals identified with different issues [23, 24]. Be that as it may, since the articulation of the verbal musings contrasts separately, recognizing the correct sentiment from the central part of information turns into the positive test.

III. IMPLEMENTATION OF THE PROPOSED SYSTEM

The various retaining approach are carried out the similarity by opinion entered as tweets of data by publically as different twitters. The proposed implementation carries the dataset to the ensemble sentimental analysis using information similarity measure between the tweet terms to find the relational analysis.Tweets comments are point out in different dimension in point of sentiment, keyword analysis to survey the products of approach which they are attained from the feedback.Analysis the system which prefers product reviews by varying class of posts in comments to analyze the defects and its future enhancements. The analyzing the facts of tweets contains differential comments in data mining role to impact the key term analysis. To reduce the task of analysis using online social analysis. The objective aims the relational analysis from tweets by measure the semantic measure to process the sentimental analysis. This aims to categorize the sentimental terms about the reviews comes under which the category. Also splits by class by preference using the knowledge mining to rank the results for order the sentiment comments.

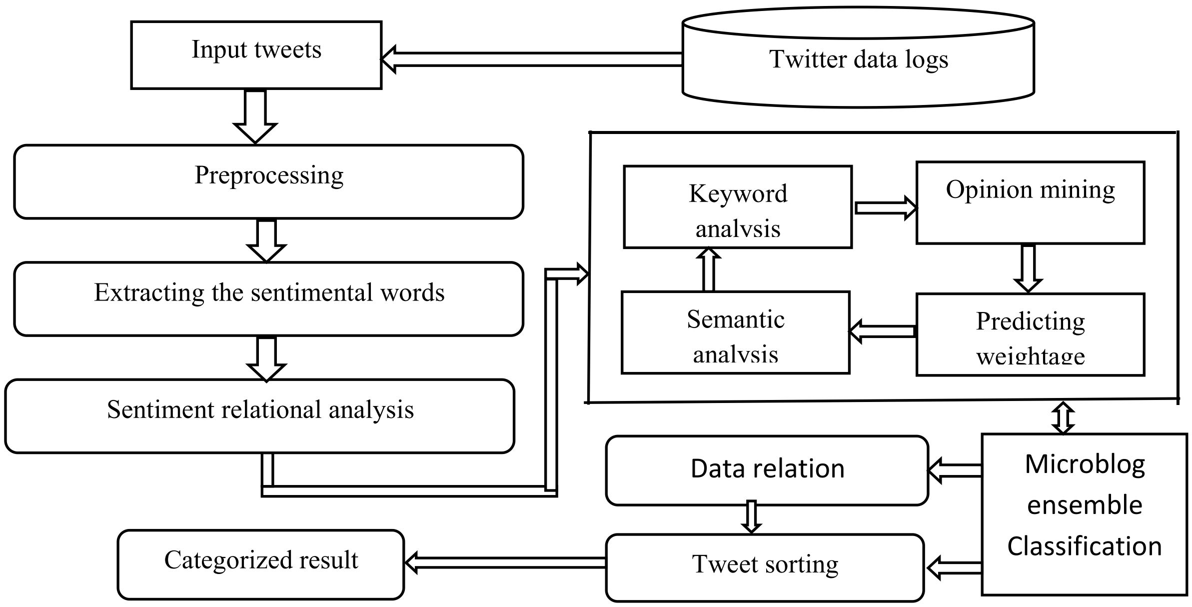

Figure 2 architecture diagram of the proposed system

Tweets segments are analyzed by data relation analysis by predicating the sentimental comments from dataset which they are contain most tweets about specific species. Initially the preprocessing analyses sentimental keyword from microblog analysis classification as shown in figure 2. The relation analysis are carried out by extracting the sentimental words. Each sentimental word are analyzed using keyword analysis. The opinions are intent word from tweets comments relationally gathered to train the dataset with trained sets.

The following are the various stages that our implementing consist to getting the sentiment from public terms, sentimental keywords, opinion rates to be analyzed the relation from tweet dataset.

1. **Tweets analysis from the user opinion:** The tweets comments are represented as sentimental words from the tweeters to complete the term of representation. The key terms are gathered from tweetsopinions entered specifically our realized forms.
2. **Open Data relation terms from tweets.** The information gathered from twitter advancements process are gathered through the relational qualification to getting originality of the data relation. Getting the fact by providing opinions are relationally dependent from open comments. all over the sentiment contains the relation are open available fact from social network
3. **Relational Sentiment Analysis:** Context analyze part is the relational analyze part to know the tweets to utilized as insight of meanings represented as the serious part which helms the data relation . This is measured by averagerelational score of content weightage measurement.
4. **Tweet report analysis:** the tweet report should be created for the top of the line clients about the analysis. The reports are outlined thorough graph for easy identification deferential tweet classes in unthinkable portrayals. Framework Architecture are carried from obtained report which most case positive comments are taken to the relational analyses from other revise. In this segment, to examine different outline problem of reviews and its usageis analyzed for future tweet opinion for improvingthe reviews.This comprises the enrollment with Twitter to come sentimental reviews. The information from tweet accompanying the advances are utilized as a part of the plan stage hold the opinion of mindset key terms to acquire the outcome and its interpretation.
5. **Tweet sorting reports:** The reporting sorts are carried by differential classes in the form of positive negative and neutral cases. All the carried dataset opinions are sorted by classes base on the weightage ranking process.

6. **Twitter enrollments application:** most of the web application issue test analyses to get the reviews from the user. This should sorted to gather the originality of deferential opinions from the user certifications. In twitter create subtitle process of order tweets, Twitter creates a new token key, and symbolic mystery get to keys, which should be installed in your application for validation reason.

Sentimental tweets is to assist the administration with understanding the excesses and general society reaction to attract using sentimental terms of product feature with offers attained. The review reports are carried by internal relational analyses of tweet terms given reviews, the contrasted reports are intent the tweets to improve the quality to know the originality of the resource. Most of the organizations determines the traditional part to utilize the sentimental reviews from commented tweet dataset. This much easy support to client to make the semantic relation between the client and administrations. The consequences of the analysis can be utilized as a part of cutting-edge advertising for the enterprise and to fulfill more clients. Later on, this will use grouping calculations to discover unique bunches of topics and clients naturally.

3.1 Preprocessing tweet term comments

In this stage, the method reads the text document and extract the textual terms from the record. Then for each term extracted, the method performs the stop word removal and stemming process. The method maintains the list of stop words which has no meaning and from the stop word removed content, and the technique eliminates the end tokens. Finally, the method identifies the list of simple nouns by applying the tagging process. To perform tagging the technique uses the Stanford part of speech tagger.

Algorithm:
Input: Tweet Document TD
Output: Preprocessed Term setts
Step 1:Start
Read tweet Document TD as normalized tweet words.
Read tweet document text dTi = $\sum Text \in D$
Step 2 Identify term set from tweet data dTs = $\int Split(T, space)$
Read stop word list Sw
Step 3 omit the stop words to remove.
dTs = $\sum (Terms(Ts) \in sw) \cap Ts$
For each term dTi from dTs
Perform part of tweet tagging.
dTi = Tag(Ti).
If dTi==key term then keep
Originate tweet terms data
Else
Step 4 term redundant fact from tweet words
Remove a term from the set.
End
End
Stop.

The above-discussed algorithm identifies the list of simple nouns by performing stop word removal and stemming process.

3.2 Relational sentiment tweet analysis

If there is any relation present between the terms, then a link is generated between them and for each node is identified the semantic terms related with that and specify interior and exterior links identified the terms. The generated relational analysis will be used in sentiment terms of evaluation ofcategorized the ach opinion of task as class.

ISSN 2348 – 8034
Impact Factor- 5.070

Algorithm
Input: Tweet Document Set TDs, Sentiment Set Ss.
Output: Sentiment Semantictweet Set SGS.
Step 1: Start
Initialize Term Set Tssand tweets words
Initialize opinion Set Gs.
For each tweets tDi fromtDs
Sentimental Text T = Extract Text from tDi.
Step 2: Find the relational trained keyword terms of analysis
Sentence set Ss = (∑(n=1)^(relational size(Ds) term Text€Di)×Splitby(".")〗
For each term sentence TSi from sentiment SS
Step 3: Generate class of tweetpoint tGi.
Tweet Term Set Ti = ∑Terms@Si
For each term Tn from Ti
If Tn weightage sentimental term then
Order by relevant weightage Ti = Ti₵Tn
Else
Step 4 Perform tweets by segment
Apply Part of speech tagging by tweets term.
End
End
For each term Tk from Ti
Create Node Ni.; Add tweet term to Gi.
Gi = ∑(tweets €Gi)+Ni.
End.
Step 5 : Read sentiment tweet Do.
For each tweet term Di from Do
For each term Tk from Ti
If Di€ then
Step 6: Identify sentimental relation it has with other concepts.
Relation Set Rs = ∑(Concepts€Di)+Ci.; Add relations to the term Ni.
End End
End End
Stop

The above-discussed algorithm performs pre-processing of the text documents and generates a semantic graph for each of the sentence being identified from the record.

3.3 Sorting the tweet analysis

The sentimental analysis scores are evaluated as based on the frequency level by the key terms. the opinion are categorized as negative, positive, neutralized terms of classes from comments reviwed.in special case of mean estimation the ranking are sorted by computing sematic closeness measure of tweet terms. The official posts are categorized by order by relevanceusing the sorting most evaluated speciation of positive comments are ranked as top followed by other classes. This provide order by relevance of sorted tweet comments into specific order by opinion mining predictions.

Algorithm,
Input : Semantic tweet Set Tgs., sentimental objectsSo.
Output: Class Name positive, negative, neutral.
Start
Step 1: For each graph Gi from Sgs
For each grouptDi from So

Step 2: Computer Number of sentiment relations it has.
SNr = ∑Relations€Gi
Step 3: Computer Number of incoming links subspace point.
SNIL = ∑Links(Gi)<-∑Gk(Sgs)
Step 4: Compute the value of interior related links.
RILV = ∑Concept(Links(Gi)) € Di
Step 5: Compute the value of exterior links value.
ELV = = ∑Concept(sentimentLinks(Gi))) € ∑Concept(Dj)!=Di
Compute semantic linkage weight Slw.
Step 6:Sentimental evaluation score Slw = $\left(\frac{\text{RILV}}{SNr} \times \frac{\text{ELV}}{SNr}\right) + NIL$
Sort relation Add to weight set Ws = ∑Ws(Di)+Slw
End
End
For each tweets Di from So
Compute the mean value of semantic linkage weight.
Class average Mean Slw = $\frac{\sum \text{Slw(Ws(Di)}}{\text{size(Di)}}$
End
Choose the most valued tweet domain Di.
Class C = max(mean).
Step 7: Related terms are categorized with term positive high mean, negative, moderate category
Stop.

The above algorithm sorts the tweet term by classification approach as well category by the point by tweets terms are order by relevance classes.

Table 1 sentimental tweet analysis by class

Tweets Comments count/class	positive	negative	neutral	Nonclass
500	247	153	100	2
1000	546	176	84	12
1500	735	634	126	16
2000	845	675	139	21

The sentimental classes are analyzed by comments taken the tweets to identify the positive comments, negative comments, neutral and non-relational terms of analysis which is active proportional to the differential classes. The classified sentimental results are tested by various stages to get different classes as shown in table 1. The communal approach tunes the sorting result to progressive trained result. The community fact make the tolerant relation to get better accuracy by order by class.

The most case relational comments are inverse point to gain the top most product reviews. The total comments process the sentimental comments. To compare the varieties of sentimental relations by likes on comments also considered. The positive comments and negative comments are matched by relevance case endorsement of communal links and other case on intermediate average point are neutral filtered by non-related comments.

IV. RESULT AND DISCUSSION

The tweet analysis is carried out by the common repository in twitter dataset be implemented with microblog ensemble classification was proposed. The sentimental tweet terms are depended to test tweet analysis framework was implemented in Microsoft visual studio frame work. The newly intended algorithm is implemented for tweet analysis framework. Sentimental keywords are obtained fromthe efficiency through logs, of user, filling comments, registration among tweets with previous stages test cases are validated by differential methods. The communal strategy based ensemble approach improve the evaluated results with testing precision, and recall rate for accuracy and constant values are observed with term accuracy with time complexity.

Results are classified the nativity open data relational analysis to present the comments about the specific products. Initially to profound 500 teats taken to the process of evaluation. Considered data analysis points the sentimental tags the prefers positive or negative comments. most of the comments are neutralized to classify the result in the form non sentimental approach.

The proposed algorithm produces higher efficiency and performance of precision rate is improved than other methods. The results carried the most sentimental key terms measured by using the below equation

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

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

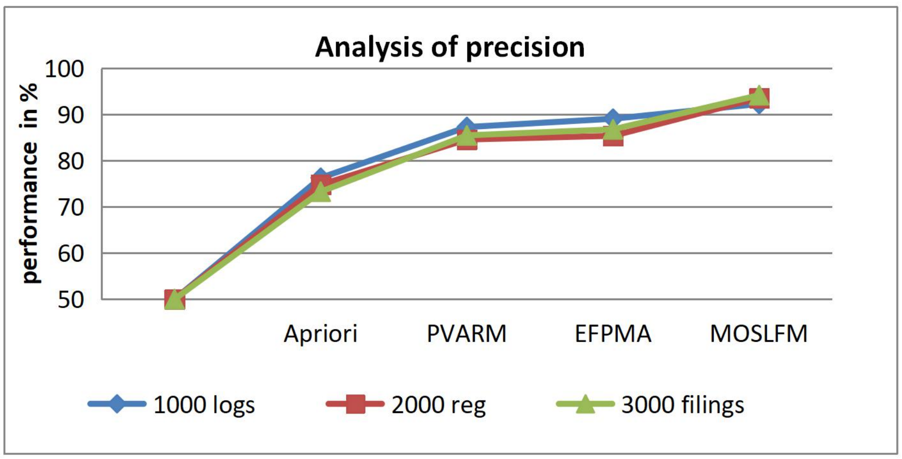

Figure 4.1: Comparison of a precision rate

Figure 4.1, represents the proposed method compared with other dissimilar ways. The performance of precision rate is higher resultant province than other methods has well impact.

Sentiment point of analysis are in most case to find that highly observable key terms of internal points from the small fractional sentimental approach given to negative thoughts. Because this is non sentimental internal approach among positive comments. The comparison gieven below reviews the precision rate.

Table 4.1: Evaluation of precision rate

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

The Table 4.1, shows the measure of precision rate which is sentimental focus of real key terms matched by trained set. The bag of words obtain 76.3 5%, naïve based 87.3%, SVM 89.1% and proposed produce 92.35% compared to the high performance than other methods.

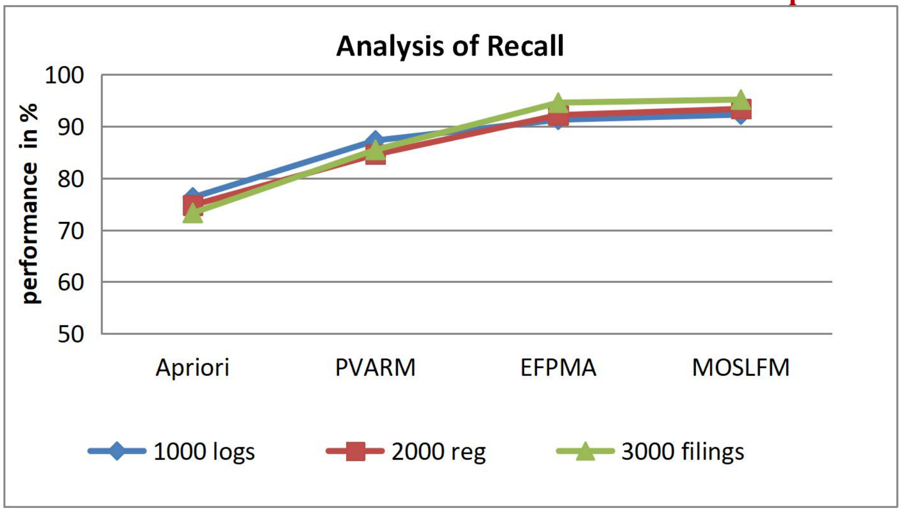

Figure 4.2: Evaluation of recall

The above figure 4.2, represents the proposed method compared with other dissimilar ways. The performance of recall rate is higher resultant province than different ways has well impact.

Table 4.2: Evaluation of recall

Methods/number of tweets	Evaluation 9of recall in %			
	Bag of words	Naïve Bayes	SVM	TSA-MSEC
1000 logs	76.3	87.3	91.3	92.3
2000 registrations	74.8	84.6	92.2	93.4
3000 filings	73.2	85.5	94.6	95.2

The above table 4.2reviews the similar methods evaluation result compared to the proposed system which produce relative high measure than other dissimilar methods like SVM 92.3% the proposed system Tsa-MSEC has better performance of 92.3 % relatively high. This analyses eth various relational of sentimental levels probably defense by key terms.

The similar datasets are ignored as unclassified region be considered as false extraction, the false extraction is calculated by

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

ISSN 2348 – 8034
Impact Factor- 5.070

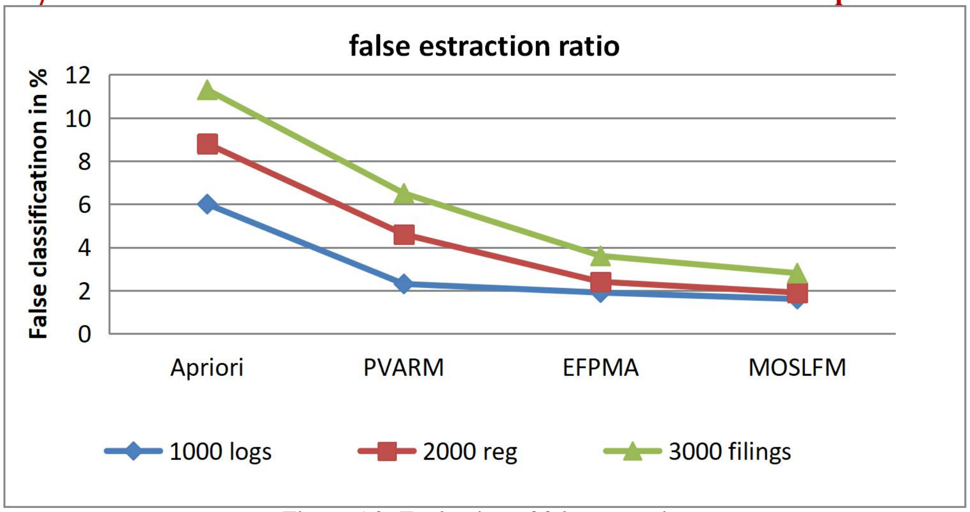

Figure 4.3: Evaluation of false extraction

The Figure 4.3, represents the proposed method compared with other dissimilar ways. The performance of false mining is lower resultant province than other methods has well impact.

. ***Table 4.3: Evaluation of false extraction***

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

The Table 4.3, shows the comparison of false extraction ratio produced indicates that the proposed approach produces less false extraction ratio.

The dissimilar methods shows the false classification prefers like naïve Bayes 5.3 %, SVM 5.2 % with proposed system TSA-MSEC 4.4 %higher performance compared to the other methods.

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

 ISSN 2348 – 8034
Impact Factor- 5.070

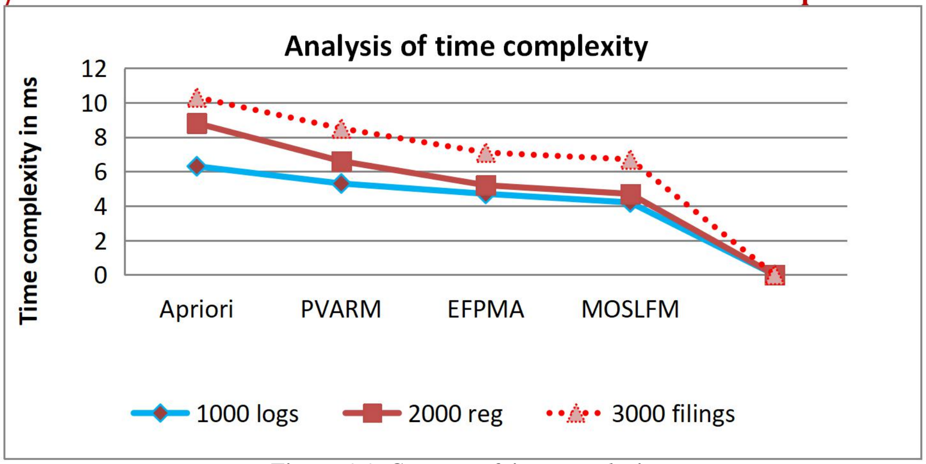

Figure 4.4: Contrast of time complexity

Figure 4.4, represents the proposed method is compared with other dissimilar ways. The performance of time complexity is lower resultant province than different ways has well impact.

Table 4.4: The contrast of time complexity

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

The Table 4.4, shows the time complexity evaluation by various methods like SVM 4.7 mille seconds, TSA-MSEC 4.2 milliseconds .as well previous methods are revealed the logs by variance concentrates the execution approach, this redundant fact reviews the improved time complexity.

V. CONCLUSION

To conclude the sentimental approach based on the sentimental analysis using ensemble communal feature in microblog classification approach. The sentimental approach are depended which is point the most relevant tweet term by class by reference. The relational sentiment classes are categorized positive, negative, neutral classes by opinion relation data weight age. Mainly the relational analyses based on the sematic meaning relates the deep learning key terms. the maximal features are ranked at finally prefers positive terms are considered as developing business fields supportive to management. As well proposed system produce higher performance of 95.2 %. With lower complexity maintain as 6.7 seconds. Every one of these classifiers has the relatively hiher precision, recall state. The proposed tweeter sentimental analysis produce high performance compared on he other related methods.

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