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Competitive Analytics Framework on Bilingual Dataset of Amazon Food Product

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Abstract **:** Social networks have an increasingly attractiveness on the internet, in today's challenging business environment, it is essential to gather, monitor and examine the user data on their own and on their opponent's company, social influence analysis in social media is often use for diverse tasks such as information retrieval, recommendations, business intelligence, etc. big organizations recognize this thing, so they use a social media as a marketing tool It can be done by using social media sites like Facebook, Twitter, and blogs. Existing social media analytics frameworks do not deliver benchmarks that permit businesses to relate customer sentiment on social media to easily know where businesses are doing good and where they need to develop, Also current social media analytics framework does not consider all the reviews for analysis, if the reviews and tweets are in another language then existing system does not consider them for analysis purpose, so whatever result comes, in the end, is not accurate. This paper present a social media competitive analytics framework that can be used to gather industry-specific marketing intelligence and by using Microsoft language translator the paper can convert other languages reviews and tweet into English language so whatever the result came, in the end, is definitely more accurate than the current system because this paper considers all the reviews for the analysis. Based on the idea of the proposed framework, new social media competitive analytics with sentiment benchmarks can be industrialized to improve marketing intelligence and to recognize specific areas in which businesses are leading and lagging, By using proposed framework, The paper present an innovative business-driven social media competitive analytics tool to analyze tweets associated with food companies and to make meaningful business reports.

Keywords : Sentiment Analysis, Opinion Mining, Social Media, Classifiers, Topic Modelling.

1. INTRODUCTION

During the last decade, humans have enjoy exponential development inside the use of on-line assets, specifically, social media and microblogging websites inclusive of Twitter, Facebook, and YouTube. Many companies and agencies have diagnosed those sources as a rich deliver of advertising and marketing knowledge. commonly companies used interviews, questionnaires and surveys to get feedback and insight into how customers feel about their items. these ordinary techniques were frequently notably time-consuming and expensive and did now not continually display the outcomes that the corporations had been seeking out due to environmental elements and badly planned surveys. Microblogging has come to be a very popular communication device among internet users. millions of offers are seem each day in popular websites that give services for microblogging which includes Twitter, Facebook. users of those services write approximately their dwelling, share opinion on a mixture of subjects and speak about present issues. due to a free design of messages and an smooth comfort of microblogging structures, internet customers be possibly to shift from standard conversation equipment to microblogging offerings. As an increasing number of users publish approximately goods and offerings they use and say their political and spiritual view, microblogging websites become valuable supply of human beings opinions and sentiments. Such information

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may be professionally used for advertising and social take a look at. Sentiment analysis is a entire research subject which has been within the look at for decades. Its initial use become made to investigate sentiment based totally on long texts together with letters, emails and so forth. it's also deploy in the discipline of pre-and post-crime analysis of crook movements. versions of approaches had been observe for the identical. applying this field with the microblogging group is a tough job. This mission have become our notion. unnecessary to mention, we aren't the first ones to paintings in this location. there was substantial research in machine learning to sentimental look at for social networks. The paper tries to improve the present methods by means of growing options to the research.

Sentiments of tweets can be categorize into many category like high-positive, terrible, neutral, extremely high quality, extremely negative, and so on. the 2 styles of sentiments measured in this classification experimentation are positive and negative sentiments. The facts, being categorized by humans, has quite a few noise, and it's tough to get suitable accuracy. now, the pleasant results are received through Naïve Bayes classifier

2. RELATED WORK

Sentiment analysis caught interest as one of the maximum energetic research areas with the explosion of social networks. The large consumer-generated content material as a result of those social media contained valuable data in the shape of reviews, opinions, and so on. about merchandise, activities, and people. most sentiment evaluation studies use machine learning strategies, which require a big amount of consumer generated content material for training. The research on sentiment analysis to this point has particularly targeted on things: identifying whether a given textual entity is subjective or objective, and identifying the polarity of subjective texts. it has been a generally used region through the years and nevertheless it leaves plenty to be explored.

2.1. Sentiment analysis

Sentiment analysis has been finished on a number of topics. as an instance, there are sentiment analysis studies for movie opinions [4], product critiques [5], and information and blogs ([3], [6]).

2.2. Issues in Sentiment Analysis

Research reveals that sentiment analysis is more difficult than traditional topic-based text classification, despite the fact that the numbers of classes in sentiment analysis are less than the number of classes in topic-based classification [4]. In sentiment analysis, the classes to which a piece of text is assigned are usually negative or positive. They can also be other binary classes or multi-valued classes like classification into "positive", "negative" and "neutral", but still, they are less than the number of classes in topic-based classification. Sentiment analysis is tougher compared to topic-based classification as the latter relies on keywords for classification. Whereas in the case of sentiment analysis keywords a variety of features have to be taken into account. The main reason that sentiment analysis is more difficult than topic-based text classification is that topic-based classification can be done with the use of keywords while this does not work well in sentiment analysis [2]. Other reasons for difficulty are: sentiment can be expressed in subtle ways without any perceived use of negative words; it is difficult to determine whether a given text is objective or subjective (there is always a newline between objective and subjective texts); it is difficult to determine the opinion holder (example, is it the opinion of the author or the opinion of the commenter); there are other factors such as dependency on domain and on order of words [3].

2.3. Classification of approaches

Sentiment analysis is formulated as a computational linguistics trouble. The category can be approached from exclusive perspectives relying on the character of the undertaking to hand and attitude of the character carrying out sentiment analysis. The acquainted methods are discourse-driven, relationship-pushed, language-model-driven, or key-word-driven. The undertaking discusses these strategies within the next subsections.

2.3.1. Knowledge-based approach

In this approach, the sentiment is calculated as the function of some keywords. The main task is the construction of sentiment discriminatory-word lexicons that indicate a particular class such as positive class or negative class.

The polarity of the words in the lexicon is determined prior to the sentiment analysis work. There are variations to how the lexicon is created. as an instance, lexicons can be created by beginning with some seed phrases and then the usage of some linguistic heuristics to feature extra phrases to them, or starting with some seed words and including to these seed words other words based on frequency in a text [2]. For sure programs, there are publicly available discriminatory word lexicons for use in sentiment evaluation. Twitter affords opinion tracking service of public sentiments for Twitter sentiment evaluation.

2.3.2. Language models approach.

In this technique, the type is done by using building n-gram language fashions. A gram is a token or lexicon considered for training and type. N-gram represents a fixed of such chosen lexicons. generally, in this approach frequency of n-grams are used. In traditional records retrieval and subject matter-oriented class, the frequency of n-grams offers higher outcomes. The frequency is converted to TF-IDF3 to take time period's significance inside the record to be categorized. In a study, [3] display that inside the sentiment classification of film overview weblog, time period-presence offers higher effects than time period frequency. They indicate that uni-gram presence is more desirable for sentiment analysis. however later ([3], [5]) found that bi-grams and trigrams worked better than uni-grams in a study of sentiment category of product opinions.

2.3.3. Discourse structures and semantics approach

This approach is very dominant within the programs where the earlier type of instructions isn't viable. The text is assessed when it's miles encountered into the first-class class it fits (in the context of its goal). based at the similarity of the semantics of phrases within the textual content, they're grouped collectively and tagged into instructions. as an example in critiques, the overall sentiment is commonly expressed at the end of the text [2]. as a result of the technique, in this situation, might be discourse-pushed wherein the sentiment of the whole review is received as a characteristic of the sentiment of the unique discourse additives within the overview and the discourse members of the family that exist among them. for instance, the sentiment of a paragraph that is at the give up of the assessment might be given extra weight within the dedication of the sentiment of the whole evaluation. Semantics can be used in role identity of retailers wherein there is a want to accomplish that. for example "India beat Australia" is different from "Australia beat India".

most of the methods for sentiment analysis confirmed on polarity dataset are statistical processes. An exception is [Taboada, 2011] wherein creator presents a lexicon-based totally approach to eliminating sentiment from text primarily based on semantic route. The semantic direction is a measure of subjectivity and opinion that's gift inside the textual content. They deliver the semantic orientation fee of each form of phrase, with a noun, verb, and adjective. The very last value of the text is calculated by becoming a member of the cost of all tokens. finally, this approach achieves73.67% of accuracy. [15].

[Kennedy and Inkpen, 2006] suggests tactics for showing the sentiment stated with the aid of a film overview:

1. The have an impact on of valence shifters on classifying the evaluations- negations, intensifies and diminishes
2. ML set of rules, SVM with unigrams then add bigrams (bigrams includes a valence shifter and another phrase)

First, the positive and negative terms are taken then, the overview is taken into consideration fine if it covers more high quality than bad phrases, and negative if there are extra terrible terms. The valence shifters regulate the semantic orientation of every other word, which trade its sentiment. as an example, a negation headed a effective word will change the word to bad experience. sooner or later, the bigrams containing a valence shifter and opportunity sentimental time period are added to unigram to shape SVM version. The result is 86.2% of 10 fold CV [7]. [Wang and Manning, 2012] suggests using bigram functions for sentiment classification. This paper describes a method of SVM version the usage of NB log-depend members of the family as functions. They defined the accuracy of 10 fold CV is 89.forty five%. another declare is that NB resolves the sentiment analysis challenge better than SVM [17]. [Whitelaw, 2005] become supplied Appraisal businesses as a new approach. Appraisal concept is in the technique of system networks represented with the aid of classification of expressions. A full appraisal look is a piece of textual content expressing appraisal of some sort. Appraisal expressions are the primary debris for evaluation of ways terms are expressed in a text, and so getting rid of them is the primary task for appraisal analysis. It became said to achieve the accuracy of 90.2% with 10 fold CV [18]. [Martineau and Finin, 2009] presented a method in choosing and demonstrating the feature. Delta DFIDF become related with vintage TF-IDF to peer the advantages. In sentiment documents, sentimental phrases like “hate”, “love”, “angry”, “satisfied”, “unhappy”, and “worst”, incline for use in a large quantity of these documents, giving low IDF rankings. concurrently, the TF is low. for this reason, TFIDF isn’t always useful. They said the accuracy of 10 fold CV accuracy is 88.1% with early feature set is unigram [19].[Tu, 2012]

Convolution kernels guide the modeling of compound syntactic statistics in system learning tasks, but it’s far complex to the sort and size of syntactic structure used. Authors say that Pang and Lee 2004 considers a flat characteristic vector to represent the files, but it does no longer gather crucial facts observed from structural linguistic evaluation of the files. The paper studies diverse linguistic structures encoded as worry kernels with the characteristic is the classification of phrases, the sequence of POS tags and grouping of both. The final result of 10-fold move affirmation is 88.50% bag of words features the usage of vector kernel and POS replacement [20].[Pang and Lee, 2004] on this paper they’d a purpose to cast off objective sentences. The approach is to explain minimum cuts in graph principle. The technique is complicated the use of the subjectivity functions, however it’s far said to acquire 87.2% [21].

Table 2.1. Literature Survey

Author	***Technique***	***Source of data***	***limitation***
Tseng 2012 [22]	Naïve Bayes classifier	Twitter	Work on assumption of real world data
Mesuf kaya 2012 [23]	SVM, maximum entropy	Political news channel of turki	Not efficient in accuracy
Duan 2012 [24]	SERPERF model	Review of hotel	Analysis is not completely cover if sentence is more than one dimension
Claster 2011 [25]	Artificial neural network (ANN)	Movie review	This system requires visualization for better and accurate result
Xu 2010 [26]	Backpropagation network	BBS Hotness Topic	This system calculates the sentiment of entire document
Simm 2010 [27]	ReadMe, Tagger	VoiceYourView	For this system sentiword, dictionary is required
Chavlit 2005 [28]	N-gram classifier and semantic orientation	Movie review	Semantic orientation gives result for small amount of sample data
Pang 2002 [29]	SVM, maximum entropy	Movie review	Only work for document level analysis

3. ARCHITECTURE OF THE SYSTEM

The architecture of the proposed system is shown in Figure 3.1. Sentiment analysis process involves 8 main blocks, social media, data collection, pre-processing, translator, naïve Bayes algorithm, topic modeling, Result, and Visualization

Step 1 : In the first step, collect the information from different social media sites like Facebook and twitter, these social media sites contain a large amount of user-generated data in the form of text.

Step 2 : In second step, the data which is present on social media sites is collected by using API, there are two APIs use to collect the data from the social media sites, such as FACEBOOK4J and TWITTER4J.

Step 3 : Thethird step is pre-processing. In this step is done for cleaning the data. In pre-processing some basic steps are followed for cleaning the data such as,

1. **Removal of URL :** The URL which is present in the string is removed.
   For ex. www.pict.com/meit/pct.the day is beautiful.
   After removal of URL, the string is become like, the day is beautiful.
2. **Removal of email id:** The email address which is present in the text is removed.
   Ex. I am so happy pict@gamil.com.
   After removal of email id, the string is become like, I am happy.
3. Removal of Punctuation, special Character, and images.
   Ex. !@#$%^&*()_+<,>.?:;"{}' all of these are removed.
4. **Remove spaces :** If there is more the one space is present in the string between two words then that space is removed.
5. **Remove stop words :** All stop words like, is, the, am, are, etc. all are removed.

Step 4 : In this step the project use Microsoft Language Translator, the data gather after preprocessing is a mixture of Hindi and English language, convert all those words into English by using Microsoft Language Translator

Step 5 :

1 In this step, train the naïve Bayes classifier, for training purpose use amazon fine food review dataset. This dataset has a collection of reviews on food products, like, I love this chocolate or the cake is good or the lays chips are not that much tasty etc.

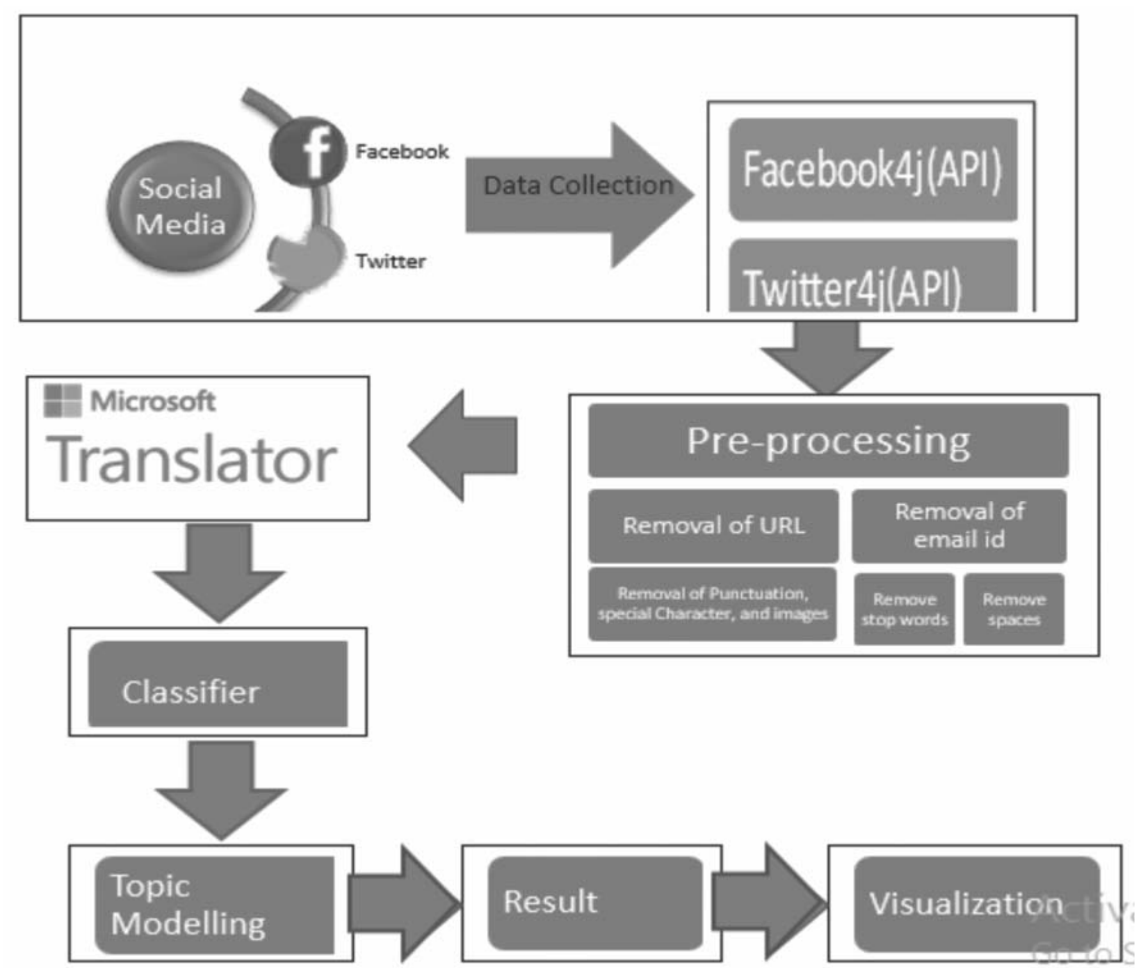

Fig. 3.1. System Architecture

2. This data set provides to our preprocessing model for preprocessing, after pressing provide this data to the Galileo API for labeling into positive and negative,
3. Now by using labeled preprocessed data train the naïve Bayes classifier
4. Once the classifier is trained save this classified naïve Bayes in CSV file.

   By using this CSV file the project can test no. of the different dataset as well as the live tweets or reviews collected from social media sites.

Step 6 : In this step use MALLET for topic finding which is present in the text document, mallet work on the frequency of words occurrence in the document. By using this technique The project can identify the hottest topic, that people are talking about, also can find that the reason of their opinion why they are positive or negative.

Step 7 : In the seventh step, show the results that what is the main topic present in document and whether it is positive or negative, also show the tweets and comments which are relevant to the topic, so the user of this system can understand the reason behind the topic that why it is positive or negative.

Step 8 : Finally result is also shown in the visualize manner which represents how many people are positive or negative, and their bar graphs.

3.1. BACKGROUND

3.1.1. Translator

The paper uses a Microsoft translator for converting the Hindi language words into English, to do so Microsoft translator API is used, which is open source and free to use. So the naïve base classifier can classify the provided data more accurately, and whatever result come in the end, that sentiment result is more accurate than the previously existing system Because no other system uses language translator for better result

4. EXPERIMENTAL WORK

Different experiments are performed to evaluate the performance of the proposed system for sentiment analysis. Evaluation of opinion mining (classification) approach is done by evaluation parameters such as accuracy, precision, recall, and F-measure.

4.1. DATA SETS USED

Amazon fine food dataset is used for training and evaluation of algorithms for sentiment analysis. Weka tool is used for classification of reviews and tweets.

4.2. EXPERIMENTS PERFORMED

The performance of different machine learning classification algorithms for sentiment analysis of tweets and reviews is tested using Weka tool. The performance of proposed naïve Bayes with language translator and topic modeling based approach is compared with different machine learning algorithms.

- Required Dataset Information

  Experiment 1 is performed to evaluate the accuracy, precision, recall, F-measure and confusion matrix values of different classification algorithms and proposed naïve Bayes method with language translator and topic modeling approach. In this experiment, the paper trained and test different machine learning algorithms for Dataset of Amazon fine food which has12000 tweets and review [43].

- Classifier Accuracy for no. of Tweets And Reviews

  Experiment 2 performed to test the accuracy value of different classification algorithm and proposed naïve Bayes based method for sentiment classification against a number of tweets and reviews. In this experiment, the project test different machine learning algorithms and proposed naïve Bayes based method fora set of 1400, 5000 and 8000 reviews and tweets. The paper read and selected 50% are positive and 50% negative reviews in each test dataset.

Table 4.1. 8000 Amazon fine food reviews.

Procedure	*No. of Reviews*
Dataset	8000
Training Dataset	6400
Testing Dataset	1600
Positive Category(Training and Testing)	(Training 3200 and Testing 800)
Negative Category(Training and Testing)	(Training 3200 and Testing 800)

4. ANALYSIS PROCEDURE

4.1. ANALYSIS PROCEDURE OF SENTIMENT ANALYSIS

For analysis of a classifier Precision, Recall and F-measure are considered. Precision is the fraction of retrieved documents that are relevant to the find. The recall is the fraction of the documents that are relevant to the query that is successfully retrieved. F-measure is a combined measure of precision and recall.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4.1}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4.2}$$

$$\text{F-measure} = 2* \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4.3}$$

Where,

1. True positive(TP) – number of reviews correctly labeled as belonging to particular class(positive/negative)
2. False positive(FP) – number of reviews incorrectly labeled as belonging to particular class
3. False negative (FN) – number of reviews were not labeled as belonging to the particular class but should have been labeled

4.1.1. Comparison of Algorithms for Sentiment Classification

Analysis of sentiment analysis method is performed by comparing different algorithms with proposed naïve Bayes. For classification of a dataset of 280, 1000 and 1600 test reviews. The performance of different classification algorithms and proposed method is compared in Experiment 1, Experiment 2 and Experiment 3.Table 4.2, contains accuracy results. Table 4.1contains results of confusion matrix for different classification algorithms

EXPERIMENT 1: The objective of this experiment is to show that NB performs better than other algorithms which we have considered for comparison for a small set of reviews**.** The confusion matrix in Table 4.1 Shows the proposed naïve base method identifies positive and negative polarity review more accurately than other classifiers.

Table 4.1. Confusion Matrix Result for the Set of 1600 Test Review

SVM		***Random Forest***		***Decision Tree***		***KStar***		***NB***		***Classified as***
Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative	
704	73	718	59	660	117	703	74	690	110	Positive
105	718	133	690	159	664	223	600	22	778	Negative

Confusion matrix shows that accuracy of NB classifier is (91.75%) which is better than SVM (88.87%), Random Forest (88%), Decision tree (82.75%) and KStar (81%).It shows that NB classifier is more efficient than other algorithms.

Table 4.2. Classification Results for Set of 8000 Reviews

Total number of reviews in training	*6400 Reviews*				
Total number of reviews in testing	*1600 Review*				
Classifiers	*SVM*	*Decision Tree*	*Random Forest*	*KStar*	*NB*
No. of reviews correctly classified	1422	1324	1408	1303	1468
Accuracy	88.87 %	82.757%	88%	81%	91.75%
Precision	0.87	0.806	0.844	0.759	0.876
Recall	0.906	0.849	0.924	0.905	0.972
F-measure	0.888	0.827	0.882	0.826	0.921
Time is taken to build model	50.97 sec	71.13 sec	91.22 sec	0 sec	84.55 sec

Experimental results show that proposed Naïve Bayes algorithm is better than other algorithm in case of large size set of reviews. It provides high accuracy, precision and high recall for classification of text as positive or negative

4.2. COMPARISON OF ALGORITHMS FOR NUMBER OF REVIEWS

Table 4.7. Accuracy of Different Classifiers.

	Classifier accuracy				
No.of reviews	*SVM*	*Decision Tree*	*Random Forest*	*KStar*	*NB*
1400	81.42%	73.57%	82.5%	75%	85.5%
5000	87.2%	82.2%	86.2%	80.8	97.5%
8000	88.87%	82.75%	88%	81%	91.75%

Different classification algorithms are compared for a number of reviews in testing. A set of 1400, 5000 and 8000 reviews is used to analyze classification algorithm for a number of reviews is Experiment 1, Experiment 2 and Experiment 3. Table 4.7 contains accuracy result for different classification algorithms. The result of sentiment classification accuracy against a number of reviews. The accuracy of NB varies 85-98% for sentiment classification of review text.

5. RESULT AND DISCUSSION

The performance of sentiment analysis classification methods is evaluated by different evaluation parameters such as precision, recall, f-measure and confusion matrix. Detail of this evaluation is explained below.

5.1. RESULT OF SENTIMENT CLASSIFICATION

Different aspects such as accuracy for a number of reviews, different sets of review and correctly classified sentiments are considered for evaluation of sentiment analysis classification results. Detailed discussion on results is given below.

5.1.1. Performance of Algorithms on Test Data

The papper evaluates and compared the proposed naïve Bayes based approach of sentiment analysis with existing machine learning algorithms in experiment 1. Graph of accuracy for a set of 5000 reviews for sentiment classification by different algorithms is presented in Figure 5.1. It shows that the accuracy of proposed method is 97.5%. It is greater than existing machine learning algorithms such as SVM (87.2%), Decision Tree (82.2%), Random Forest (86.2) and KStar (80.8). Thus higher results are obtained by proposed naïve Bayes method for sentiment analysis of the reviews as positive or negative opinion polarity review.

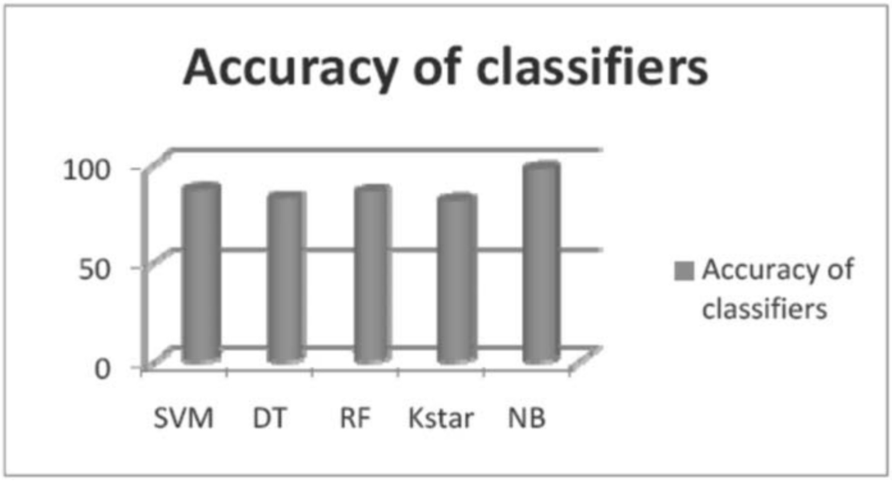

Fig. 5.1. Accuracy of Different Classification Algorithms.

Figure. 5.2 shows the graph of Precision, recall, and F-measure against different classification algorithms. It shows that the proposed Naïve Bayes method for sentiment classification obtained higher Precision, Recall, and F-measure values.

5.1.2. Performance on a number of reviews and tweets.

The classifiers behavior can vary for a number of reviews, so the performance of the algorithm is tested for a set of a number of reviews in experiment 2. The graph of results obtained for a set of a number of reviews by different algorithms is shown in Figure 5.3. The results of opinion classification accuracy against a number of reviews show that accuracy does not vary much for a number of reviews. The accuracy by naïve Bayes method varies (85.5-97.5%) for sentiment classification of review text. It performs better than SVM (81.42-87.2%), DT (73.57-82.2%), RF (82.05-86.2%) and KStar algorithm (75-80.8%)

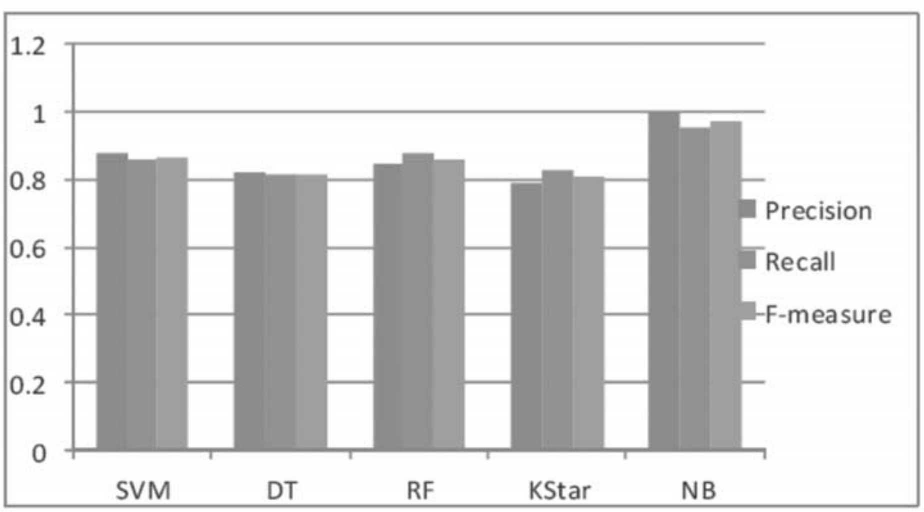

Fig. 5.2. Precision-Recall and F-Measure of Different Classification Algorithms

6. CONCLUSIONS AND FUTURE WORK

6.1. CONCLUSIONS

Recently every company are using social media sites to improve their business strategies, they provide verity of service to interact with customers, to understand the opinion of their product so they can build a strategy to improve them self, and as a result a huge amount of user generated data is created every day on social media site, from a business perspective it is necessary to analyze those data faster and more accurately, but previous systems are not accurate to do this job.

As the main contribution, this paper present a framework for social media sentiment analysis, that uses some methods for improving the sentiment classification of a customer's review, such as, use of language translator, Naïve Bayes algorithm, and MALLET topic modeling.

This paper uses a naïve Bayes algorithm which has good accuracy, but after using naïve Bayes with language translator and MALLET topic modeling, the accuracy of the total outcome is far more increase, because no other system uses language translator, they simply eliminate the tweets and comment which is in another language rather than English, so whatever result comes is not accurate, but this paper present a novel research on the combination of language translator, MALLET topic modeling, and naïve Bayes algorithm for better performance than previous systems.

6.2. FUTURE WORK

The proposed system performs sentiment classification of reviews. A generic framework can be developed which can perform opinion retrieval, opinion mining and summarization of user generated contents such as reviews, blogs, microblogs, comments, tweets etc. proposed system can translate only one language that is Hindi.

In future work, the project can improve the performance of the system by using different approaches to understanding many languages as we can. Also for finding a current topic the project can use other modeling tools like MALLET.

7. REFERENCES

1. He, Wu, Harris Wu, Gongjun Yan,Vasudeva Akula, and Jiancheng Shen, "A novel social media competitive analytics framework with sentiment benchmarks", Information & Management, Vol. 7,pp. 801-812, 2015.
2. P. Turney., "Thumbs up or thumbs down?" Semantic orientation applied to unsupervised classification of reviews", In Proceedings of the 40th annual meeting of the Association for Computational Linguistics, pp. 417-424, 2002.
3. B. Pang and L. Lee., "Opinion mining and sentiment analysis", Foundations and Trends in Information Retrieval, Vol. 2, Issue no.2, pp.1-13, 2008.
4. Pang, Bo, and Lillian Lee,"Using Very Simple Statistics for Review Search: An Exploration", In COLING (Posters), pp. 75-78, 2008.
5. Dave, Kushal, Steve Lawrence, and David M. Pennock, "Mining the Peanut Gallery: Opinion Extraction and Semantic Classification of Product Reviews", In Proceedings of the 12th international conference on World Wide Web, ACM, pp. 519-528, 2003.
6. Godbole, Namrata, Manja Srinivasaiah, and Steven Skiena, "Large-Scale Sentiment Analysis for News and Blogs", ICWSM 7, Issue no. 21, pp. 219-222, 2007.
7. A. Kennedy, D. Inkpen, "Sentiment Classification of Movie and Product Reviews Using Contextual Valence Shifters", Computational Intelligence, pp. 110-125, 2006.
8. J. Kamps, M. Marx, R. Mokken, "Using WordNet to Measure Semantic Orientation of Adjectives", LREC 2004, Vol. 4, pp. 1115-1118, 2004.
9. A.Andereevskaia, S. Berger, and M. Urseanu.,"All Blogs Are Not Made Equal: Explore Genre Difference in Sentiment Tagging of Blogs", In International Conference on Weblogs and Social Media(ICWSM-2007), Boulder, CO, 2007.
10. Turney, Peter D., and Michael L. Littman., "Measuring praise and criticism: Inference of semantic orientation from association", ACM Transactions on Information Systems (TOIS) 21, Vol. 4, pp. 315-346, 2003.
11. Hatzivassiloglou, Vasileios, and Janyce M. Wiebe, "Effects of adjective orientation and gradability on sentence subjectivity", In Proceedings of the 18th conference on Computational linguistics, Vol.1, pp. 299-305, 2000.

12. Liu, Bing, Xiaoli Li, Wee Sun Lee, and Philip S. Yu., ”Text classification by labeling words”, In AAAI, Vol. 4, pp. 425-430, 2004.

13. Melville, Prem, Wojciech Gryc, and Richard D. Lawrence, “Sentiment analysis of blogs by combining lexical knowledge with text classification”, In Proceedings of The 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining(ACM), pp. 1275-1284, 2009.

14. Pang, Bo, Lillian Lee, and Shivakumar Vaithyanathan., ”Thumbs up?: sentiment classification using machine learning techniques”, In Proceedings of The ACL-02 Conference On Empirical Methods in Natural Language Processing, Vol 10, pp. 79-86, 2002.

15. Taboada, Maite, Julian Brooke, Milan Tofiloski, Kimberly Voll, and Manfred Stede., “Lexicon-based methods for sentiment analysis”, Computational linguistics 37, Vol 2, pp. 267-307, 2011.

16. Kennedy, Alistair, and Diana Inkpen., “Sentiment classification of movie reviews using contextual valence shifters”, Computational intelligence 22, Vol 2, pp.110-125, 2006.

17. Wang, Sida, and Christopher D. Manning.,”Baselines and bigrams: Simple, good sentiment and topic classification”, In Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Short Papers, Vol 2, pp. 90-94, 2012.

18. Whitelaw, Casey, Navendu Garg, and Shlomo Argamon., “Using appraisal groups for sentiment analysis”, In Proceedings of the 14th ACM international conference on Information and knowledge management, ACM, pp. 625-631, 2005.

19.]Martineau, Justin, and Tim Finin., “Delta TFIDF: An Improved Feature Space for Sentiment Analysis”, ICWSM, Vol 9, pp.106-112, 2009.

20. Tu, Zhaopeng, Wenbin Jiang, Qun Liu, and Shouxun Lin.,”Dependency forest for sentiment analysis”, In Natural Language Processing and Chinese Computing, Springer Berlin Heidelberg, pp. 69-77, 2012.

21. Pang, Bo, and Lillian Lee., “A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts”, In Proceedings of the 42nd annual meeting of Association for Computational Linguistics, pp. 271-279, 2004.

22. Tseng, Chris, Nishant Patel, Hrishikesh Paranjape, T. Y. Lin, and SooTee Teoh., “Classifying twitter data with Naive Bayes classifier”, In Granular Computing (GrC), 2012 IEEE International Conference on, pp. 294-299,2012.

23. Mesut KAYA, GuvenFYDAN, Ismail H. Toroslu., ”Sentiment Analysis of Turkish Political News”, IEEE/WIC/ CM International Conferences on Web Intelligence and Intelligent Agent Technology, pp. 174-180, 2012.

24. Wenjing Duan, Qing Cao, Yang Yu and Stuart Levy., “MiningOnline User Generated Content: Using Sentiment Analysis Technique to Study Hotel Service Quality”, 46th Hawaii International Conference on System Sciences, pp. 3119-3128, 2013.

25. William B. Claster, DINH Quoc Hung, and SubanaShanmuganathan, “Unsupervised Artificial Neural Nets for Modeling Movie Sentiment”, Second International Conference on Computational Intelligence, Communication Systems and Networks, pp. 349-354, 2010.

26. Tao Xu, Ming Xu and Hong Ding., “BBS Topic’s Hotness Forecast Based on Back Propagation Neural Network”, International Conference on Web Information Systems and Mining, pp. 57-61, 2010.

27. William Simm, Maria Angela Ferrario, Scott Piao, Jon W hittleand Paul Rayson., “Classification of Short Text Co moments by Sentiment and Actionability for Voice Your View”, IEEE International Conference on Social Computing/ IEEE International Conference on Privacy, Security, Risk and Trust, pp. 552-557, 2010.

28. Pimwadee Chaovalit and Lina Zhou., ”Movie Review Mining: A Comparison between Supervised and Unsupervised Classification Approaches”, Proceedings of the 38th Hawaii International Conference on System Sciences, pp. 1 -9, 2005.

29. Bo Pang, Lillian Lee, Shivakumar Vaithyanathan., ”Thumbs up? Sentiment classification using machine learning techniques”, Proceedings of the Conference on Empirical Methods in NLP, pp.79-86, 2002.

30. “Amazon Fine Food Reviews | Kaggle”, Kaggle.com, 2016. [Online]. Available: https://www.kaggle.com/snap/amazon-fine-food-reviews.

31. “Microsoft Translator for Word”, Microsoft.com, 2016. [Online]. Available: https://www.microsoft.com/en-us/translator/word.aspx.

32. Blei, David M., “Probabilistic topic models.” Communications of the ACM 55, Vol. 4, pp. 77-84, 2012.