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Research Article

Sentiment Analysis of Twitter Data Using Hybrid Classification Methods and Comparative Analysis

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Abstract

Recently, there are emergence and advent of data Inter-personal interaction web sites, micro blogs, wikis, in addition to Web applications and data, e.g. tweets and web-postings express views and opinions on different topics, issues and events in many applications, in addition to, different domains that includes business, economy, politics, sociology, and etc., which are resulted from offering immense opportunities for studying and analyzing human views and sentiment. The objective of sentiment analysis is to classify a speaker's or a writer's attitude towards various events or topics and arranging data into positive, negative or neutral categories. Sentiment analysis means determining the views of a user from the textual content regarding that topic i.e. how one feels about it. It might be used to classify the text content. Various researchers have used a widespread sort of methods to teach the classifiers for the Twitter dataset with various results. The research uses a hybrid method of using Swarm Intelligence optimization (PSO) algorithms with classifiers.

The Support Vector Machine (SVM), k-nearest neighbours algorithm (KNN), k-nearest neighbor (KNN), hybrid classification method, Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and planned optimised feature sets model is offered to progression the tweet features and to recognise the out of sight sentiments from these tweets. These essential concepts when used in combinations become a very significant tool for analysing millions of variety conversations with human echelon accurateness. The projected optimised feature sets model Sentiment Analysis exercises the assessment metrics of Precision, Recall, F-score, and Accuracy. Also, average measures weighted F1-scores are constructive for categorization of Positive, Negative and Neutral multi-class problems. Sentiment Analysis with planned optimised feature sets achieves 82 percent accuracy, compared to SVM's 78.6% and ACO 75%. Furthermore, we measured only tweets in English that were acknowledged by the Twitter streaming API while evaluating sentiments of tweets.

Keywords - *Sentiment Mining, Naïve Bayes (NB), Support Vector Machine (SVM). k-nearest neighbor (KNN), hybrid classification method, Ant Colony Optimization (ACO)****,F1-score*** *, Sentiment analysis, Twitter.*

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Introduction

Sentiment analysis is a subgroup of computational methods that naturally extract and epitomise those findings from opinions that contain a massive amount of data that the average reader cannot process. [9]. Through social media web sites such as Facebook, Google+, Twitter, Instagram, and others, people all over the world are a part of each other's lives in the advanced Internet age. With Feature Optimization, Twitter has almost 300 million active users and millions of tweets every day, making it a big social networking internet platform worldwide. Twitter has traditionally been used as "an analytical resource by numerous organisations to study public sentiment and gather critical input" due to its large user base and vast data.(#11).Users may write their opinions on any subject or general thoughts in a tweet that is no longer than 140 characters long. Because of the short duration of tweets, people write in a rather succinct way, sometimes using slang, making sentiment analysis difficult.

Similarly, sentiment analysis can be described as the process of categorising opinions expressed through tweets in order to better understand the user's perspective on a given subject.

"It is beneficial for marketers to review and analyse consumer perceptions of their brand and existing/newly launched goods, as this will help them measure and enhance their results" [12].

Swarm Intelligence Optimization Methods are used, which are based on the actions of groups of insects found in nature. Ants' normal activity is inhibited by ACO tactics, which the HCTS use to get to their colony in the shortest possible time. When returning to the colony, they keep track of each direction by depositing pheromones, which eventually evaporate. Since it is taken more often, a shorter path would have a higher pheromone density. The same behaviour has been incorporated into computer artificial ants in order to find the best solutions to a problem. Birds' social activity is inhibited by PSO because they choose to live in flocks. All of the birds are attempting to locate food in a given location.

They are, however, mindful of the distance between them and the food. This behaviour has been integrated to help identify the best optimised solution by iteratively improving the candidate solution locally and globally. To identify tweets as positive or negative, machine learning techniques will be used. The use of a supervised machine learning model will provide slightly better results. For this study, two learning methods were considered: NB, KNN, ACO, PSO, and SVM.

Furthermore, we will make useful recommendations for the application of various algorithms to various classes of social network data. The model was built in Java and then tested against tweets, with its output measured using four parameters: accuracy, precision, recall, and F-score.

Related Work

Sentiment Analysis is the thorough research of how opinions and perspectives can be related to one's emotion and attitude shown in natural language with respect to an event. Recent events show that the sentiment analysis has reached up to great achievement which can surpass the positive vs. negative and deal with the whole arena of behavior and emotions for different communities and topics. A sufficient number of studies have been completed in the field of sentiment analysis using various techniques for the prediction of social opinions.*Ankita Gupta et al*. [1] In this paper, SVM and KNN based hybrid models are presented to improve the classification accuracy. The proposed method classified the tweets into positive, negative and neutral sentiments, whereas much of the literature in this field is associated with 2-way classification.

The work of the proposed model has gone through the preprocessing stage, features generation stage and classifier learning stage. The analytical evaluation of model is done in terms of accuracy and f-measure. The comparative observations are taken against the SVM and KNN methods. The comparative results show that the model has improved the accuracy and f-measure of tweet class prediction. *Bharat Naiknaware* et al. [2] if the MAE is smaller than accuracy. The results show that the performance of the classifiers is the same. There is a marginal difference in the MAE. The performance of the classifiers was made for seven datasets (Budget2017, Demonetization, GST2017, Digital India, Kashmir, Make in India, Startup India). In the Budget2017 dataset, Naïve Bayes performs best. In the Demonetization dataset, Naïve Bayes performs best. In the GST2017 SVM is showing the best performance, whereas in the Digital India, Kashmir, Make in India and Startup shows, Max Entropy performs best. Here, we also find that the Mean Error for predicting the Mean Absolute Error easily. *Christianini and Taylor*. [3] Published and shared the knowledge about SVM, which is machine learning algorithm. The authors manage to give deep understanding of the algorithm and how to approach the SVM algorithm in order to implement it to solve the practical problems. The approach will be theoretical, as research was being conducted in all fields at the time the book was published.

Malhar and Ram [4] employed supervised machine learning techniques and artificial neural networks to classify twitter data along with case study of Presidential and Assembly elections which results SVM outperforming all other classifiers. The authors model a methodology to predict the outcome of election results by utilizing the user influence factor. To carry out the reduction in dimension, the authors combined the Principle Component Analysis with SVM. *Martineau and Finin*. [5] Model a technique called Delta TFIDF which measures word scores efficiently before classification. Delta TFIDF was easy to understand, implement and compute. For sentiment classification, the authors used support vector machines to achieve better accuracy with Delta TFIDF and using data sets of movie reviews. According to the authors, Delta TFIDF is superior to the TDFIF feature in that it counts term raw for all document sizes and weights for congressional detecting support for bill, sentiment polarity classification, and subjectivity detection.

The authors stated Delta TFIDF is the first measuring approach to boost and identify the relevance of selective words using the calculated unsupervised distribution of features before classification between the two classes. *Mohammad et al.* [6] developed two SVM classifiers. One is a term level task which determines the sentiment of a word in the message and one is a message level task which determines the sentiment of messages such as SMS and tweets. The authors competed in a competition with 44 teams, and their submissions placed first in work on tweets, with an F-score of 88.93 in the term-level task and a F-score of 69.02 in the message-level task.The authors executed sentiment, semantic and surface-form features. The authors also produced two big term-sentiment associations, first with emoticons from tweets and second with sentiment –term hashtags from tweets. *Neri et al.* [7]. performed sentiment analysis on newscast over more than 1000 Facebook posts and then compared the sentiment for dynamic company La7 and Rai – the Italian social broadcasting company which is an emerging company. The authors' observations were mapped with the study conducted by the Osservatorio di Pavia, an Italian research institute highly specialized in the empirical and theoretical study of media, which is occupied with the study of political communication in the mass media.The authors conducted an experiment using the Knowledge Mining System, which is used by security agencies and government institutions in Italy to control information contained in Web Mining and OSINT.

Pablo et al. provided versions of Naive Bayes classifiers for identifying the polarity of English tweets. Two distinct versions of (NB) classifiers have been constructed, particularly Baseline (educated to categorise tweets as positive and tweets as negative, neutral), and Binary (uses a polarity lexicon and classifies tweets as positive and tweets as negative. Those characteristics recognized by means of classifiers were taken from (noun and verb and adjectives also adverbs). Multi phrases from special resources and Valence Shifters. *Po-Wei Liang et.al* [9] Model a system in U.S. elections 2012 for presidential candidates using real-time evaluation of sentiment on online microblogging site twitter. In order to collect the poll data, the traditional analysis of elections takes time, but with the help of this system it takes data from more people with the help of twitter, a microblogging service. It helps social people like scholars, media and politicians to broadcast their future perspective of the public opinion and electoral process. The authors finally concluded that the system and approach are generic, and should be adopted easily and spread across various other domains.

Methodology

Figure 1 demonstrates the working of Sentiment Analysis in the extraction phase where social media acts as a data source. Data from social media like twitter is updated frequently. So, it gives the feeling of real time representation of sentiments. To obtain data on run-time an internet both known as web crawler is used. This browses through the World Wide Web in an organized manner to index web pages. In pre-processing, the extracted data is cleaned as it has large amounts of noise before sending the text for analysis. Extracted text has grammatical errors as text is of limited length. In analysis, sentiments in data, number of repetitions observed in tweets and their location is analyzed. In Knowledge Discovery phase, to find opinions of people regarding any particular occurrence, it is essential to store data related to the event. Once sentiments polarity is known it generates statistical graphs and charts.

There are four groups used in sentiment analysis:

Syntactic feature: It employs word or Part Of Speech (POS) ticket, Ngrams, punctuation, or phrase patterns one among all. The authors identify that “phrase patterns like “n+aj” (positive adjective) symbolize positive sentiment direction, at the same time as “n+dj” (negative adjective) articulate negative sentiment”.

Semantic feature: Semantic feature concentrate on relation between signifiers like phrases, words, and score-base method classify these stands on title figure of encompass positive or negative semantic feature.

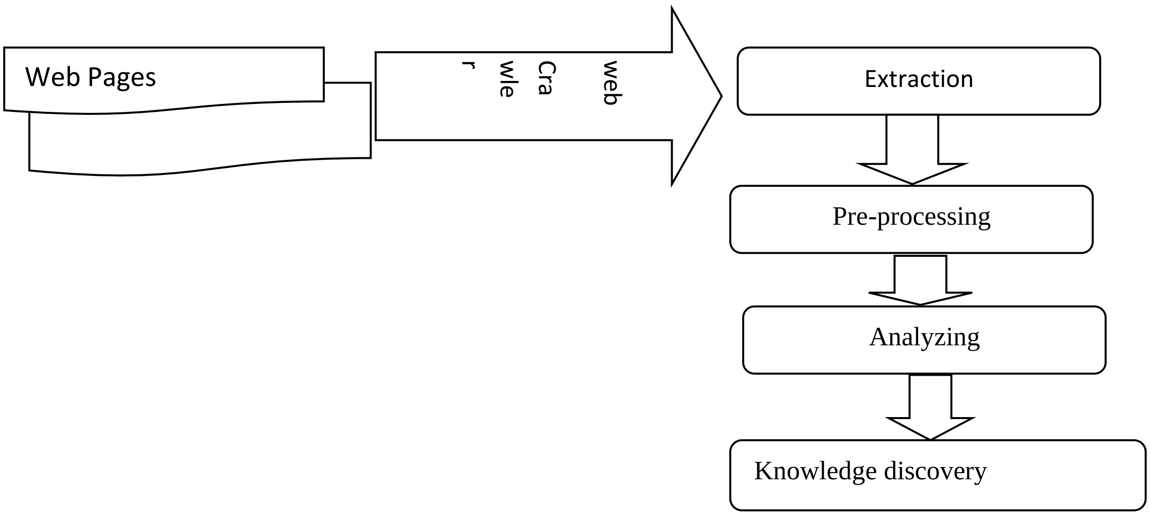


Figure 1Working of Sentiment Analysis

Link base feature: Using links present among relation and relations, link base samples are classified.

Stylistic feature: Artist’s use this to go by a message to us.

Use of symbolism: This is where a writer or an artist employs a symbol to illustrate, symbolize or differentiate a person, thing or place.

The planned system encloses various phases of growth. A dataset is fashioned using twitter posts of movie reviews. As we know that tweets hold jargon words and misspelling. So, we carry out a sentence level sentiment investigation on tweets. This is completed in three stages. In a first stage preprocessing is prepared. Then feature vector is formed by means of applicable features. Lastly, using dissimilar classifiers, tweets are classified into positive, negative and neutral classes.

Algorithm

Input: Training and Testing Datasets

Step 1: Browse Training dataset

Step 2: Delete stopwords from training dataset.

Step 3: Tokenization of training dataset.

Step 4: Stemming of training dataset.

Step 5: Browse Testing dataset

Step 6: Delete stopwords from testing dataset.

Step 7: Tokenization of testing dataset.

Step 8: Stemming of testing dataset.

Step 9: Extract special keywords.

Step 10: Extract positive and negative keywords.

Step 11: Extract positive and negative tags.

Step 12: Form 8-features based vector

Step 13: Perform Classification

Step 14: Form BoW vector.

Step 15: Form Hybrid Vector by fusion of vector 1 and 2.

Step 16: Measure Precision, Recall and Accuracy Performance for existing and proposed method. So as will perform sentiment analysis, would needed with gather data from the desired source (here Twitter).

This data undergoes various steps of pre-processing which makes it more machine sensible than its previous form. One of the best things that happen on machine learning is that the algorithms can memorize the data and when we need to use it for another data it has a poor performance, this behavior is called over fit. To avoid this problem, I work with test driven methodology. Each dataset is divided in three random parts and each part in three more divisions:

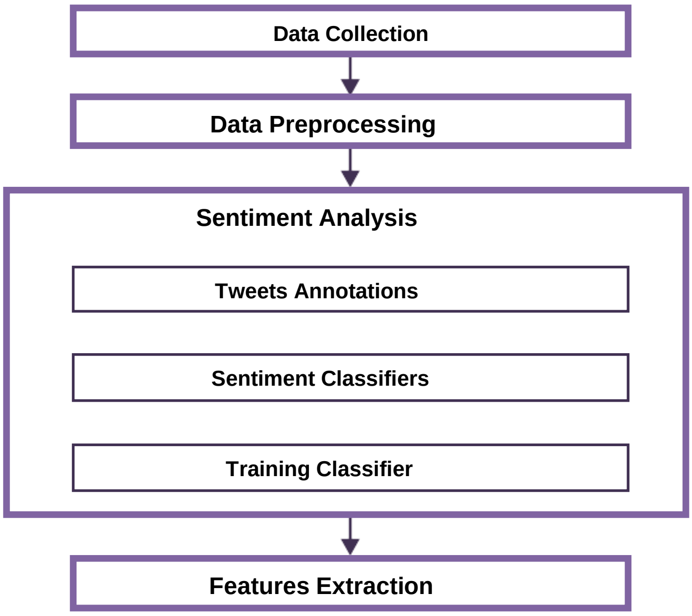


Fig. (1) : Methodology for sentiment analysis

Data Collection

Is concerned with the correct acquisition of data; regardless of the various methods depending on the field, the accentuation for guaranteeing accuracy stays those same. The number one aim of any data collection attempt is to obtain quality data that may be easily translated to analyze rich data evaluation which can result in dependable and conclusive answers to questions that need been posed.

So, it is Tweet collection involves gathering relevant tweets about the particular area of interest. The tweets are collected using the API. These API helps us to gather the data for the input. Basically, it is an interface between the user and the source website from where the input tweets data could make fetched. As it's far a prolonged process, for this research purpose the data has been collected of various websites rather than collecting tweets from the Twitter itself.

Pre-processing

Those pre-processing of the information may be a significant step Likewise; it chooses the effectiveness of the different steps down in line. It involves syntactical correction of the tweets as desired.

Optimization

In this paper, ACO and PSO are utilized to for the optimization process. This phenomenon is referred to as 'combinatory optimization'. It may be multi-objective functions that need which means of searching on the preliminary values aiming to decrease the final results of our function. It is a process in which the relevant features are selected from the set of the feature. This process is done by using some algorithm which is done better in optimization Ant colony optimization and Particle swarm optimization both are based totally at the biological behavior of the ants and swarms. By this technique it found the most brief way or routes of ants. Those yield for the experiment demonstrate that the optimize algorithm not just reduce the number for paths in the ACO, but also discovering the briefest way at the place of largest path. These algorithms use the same principle that are utilized by the ants and provides us optimized features

Supervised Classifiers

In this stage, classify the features as stated by their properties. Classification in this work is done by way of the usage of the Support Vector Machine and Naïve Bayes Classifier.

Naïve Bayes*:*

The Naïve Bayes classifier in a standout amongst the simplest probabilistic model meets expectations positively on text classification and utilized looking into Bayes rule with self-supporting feature collection [13] meets expectations positively around quick text classification and works on Bayes rule. With Self-supporting feature collection [13], it is flexible in way of handling with whatever number of classes or attributes. For a given tweet d, C* is a class variable which defines the sentiment given by

$$C^* = \mathrm{argMax}_C P_{\mathrm{NB}}(\mathrm{C}|\mathrm{D})$$

Bayes Probability $\mathrm{P_{NB}(C|D)}$ described as

$$P_{NB}(\mathrm{C}|\mathrm{D}) = \frac{(P(C)\sum_{i=1}^{m} P(F\backslash C)^{n_i(d)})}{P(d)}$$

Here, f is feature and $n_i(d)$ is feature count found in d, m represents total number of features and P(c) and P(f|c) are found through maximum likelihood estimates [14]. During classification phase we found a word which was not found in training phase then we will give zero as probability for positive, negative and neutral classes. To end this problem, we tend to make probability equal using Laplacian smoothing constant *k*=1.

$$\frac{Term\_count + k}{Tota\_Terms + k|c|}$$

Support vector machines:

Support vector machines (SVM) is a blend of a linear modeling Furthermore occurrence-based learning in a high-dimensional space. SVM may be carried out for the ones problems whilst data can't make separated by way of line[17]. SVM use nonlinear mapping – It transforms the instance space into some another space which need higher size over the first. Kernel idea gave upward push to support vector machines. Kernel is a function which fulfil mapping of a nonlinear data to another space.

Kernel function *K* will be an inward item Φ *x* • Φ *y*) between of two points *x* and *y*:

$$K(x,\ y) \ = \ \Phi(x) \ \bullet \ \Phi(y) \qquad (4.4)$$

where Φ *x* and Φ *y*) are mapping operators. The feature, that kernel characteristic is formulated as an internal product, offers a possibility to update scalar product with a few preferences of kernel [15] [18]. The problem of finding parameters of SVM steady with a convex optimization trouble, which means that that nearby result may be is global optimum as well. In general, the categorization task usually dividing data under traineeship and experiment sets[19]. Those objective of SVM may be to prepare a model (primarily based at the traineeship data). SVM for classification may be utilized to discover a linear model of the following form:

$$y(x) = w^{T}x + b \qquad (4.5)$$

wherein x is enter vector, w and b are parameters which may be modified for a certain model and estimated in an experimental method. In simple linear classification type may be to cut down a regularized error function given by means of Equation 4.6.

$$C \sum_{n=1}^{N} \varepsilon_n + \frac{1}{2} \|\omega\|^2$$

whereas $\xi_n \geq 0$, $\forall\, n = 1, \ldots, N$, and

$$y(\omega^{T} x + b) \geq 1 - \varepsilon_n \qquad 4.6$$

Here the SVM constructs an isolating hyper plane and then tries to maximize the" margin" betwixt the two classes. With figure that margin, the SVM constructs two parallel hyper planes, one on each side of the initial one. These hyper planes are then "pushed" perpendicularly away from one another until they come in contact with the closest examples from either class. These examples are referred to as SVM and are illustrated in bold in Figure 3.5.

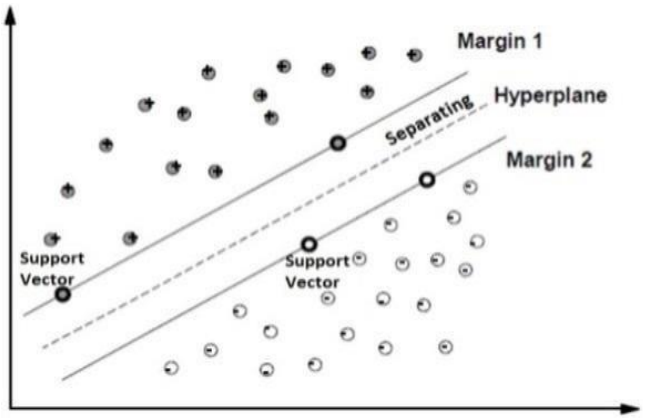


Fig. (1): Support Vector Machine: Classification

Kernel Functions:

Following are forms of SVM kernel functions used for the categorization. In research [16] the four following basic kernels are described:

- Linear kernel:
  $K(x, y) = x^{T} Y + C$
- Polynomial kernel :
  $K(x, y) = (x^{T} Y + C)^{d}$
- Radial basis kernel :
  $K(x, y) = \exp\left(\frac{-\|x - y\|^2}{2\sigma^2}\right)$
- Sigmoid kernel :
  $K(x_i, y) = \tanh(\gamma x^{T} y + C)$

Results

Performance Evaluation:

Should figure that accuracy to classifier, we required to measure which accuracy might a chance to be acquired. There are two measures on which accuracy may be dependent: **Accuracy, Precision, Recall, F Score.**

True Class

Prediction Class	**Positive**	**Positive**	
		True Positive (TP)	**False Positive (FP)**
	Negative	**False Negative (FN)**	**True Negative (TN)**

Table (1): Confusion Matrix

The result is produced from where of Precision, Recall, F score, and Accuracy.

Precision: It is the proportion of documents of rightly classified under positive prediction class to all documents under positive prediction class.

$$\text{Precision} = \frac{TP}{TP - FP}$$

Recall: It is the proportion of documents of rightly classified under positive prediction class to the documents that are positive in the negative prediction class.

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

Accuracy: Accuracy and precision are two vital variables important factors to consider when bringing data estimations, we have to discover the accuracy of classifiers. Accuracy for any prediction model can be given as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

F-Score: (**also F-score or F-measure**) is the weighted common of Precision and Recall. Therefore, F-Score takes both false positives and false negatives into consideration. "F-score isn't always as easy to apprehend as accuracy, however it's far lot extra beneficial than accuracy, especially Assuming that you have got a uneven class distribution. Accuracy works best in cases like if the false positives and the false negatives have comparable cost.

$$\text{Accuracy} = 2 * \frac{(\text{Recall} + \text{Precision})}{(\text{Recall} + \text{Precision})}$$

Results and Discussions

This Paper displays and analysis the test outcomes and the assessment for our approach. First, we compare results of different methods applied for the sentiment analysis of data obtained from Twitter. Second, the discussions on the effects of various features are presented. Also, we discussed the best obtained results (which were given by SVM, KNN, ACO,PSO and NB methods). Comparison of NB, NB-SVM results in the form of bar chart having x-axis containing precision, recall, accuracy and y-axis contains percentage:

Comparison of NB,NB-SVM

□□□□□□□

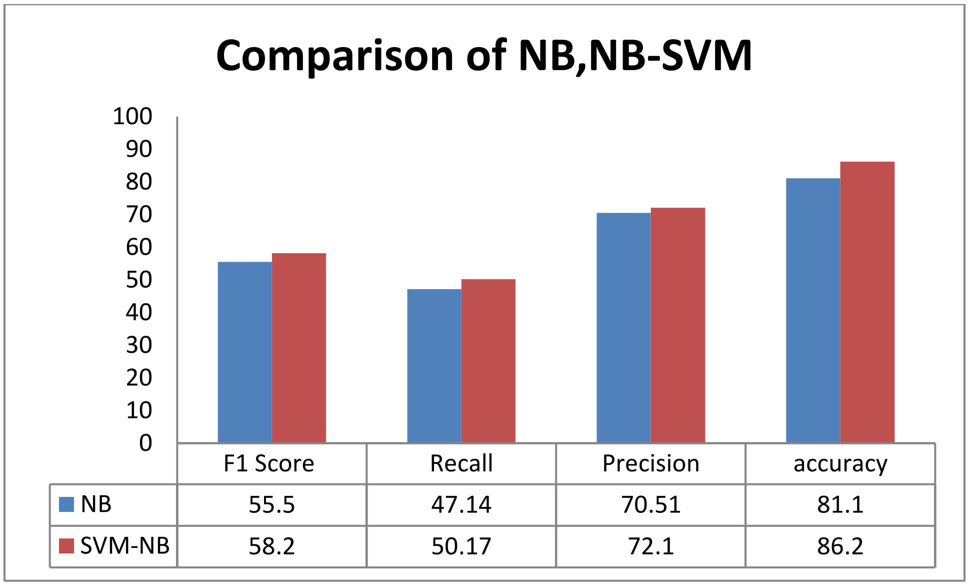


Fig. (2): Graph of results NB,NB-SVM

Comparison of SVM, SVM-ACO, SVM- PSO results in the form of bar chart having x-axis containing precision, recall, accuracy and y-axis contains percentage:

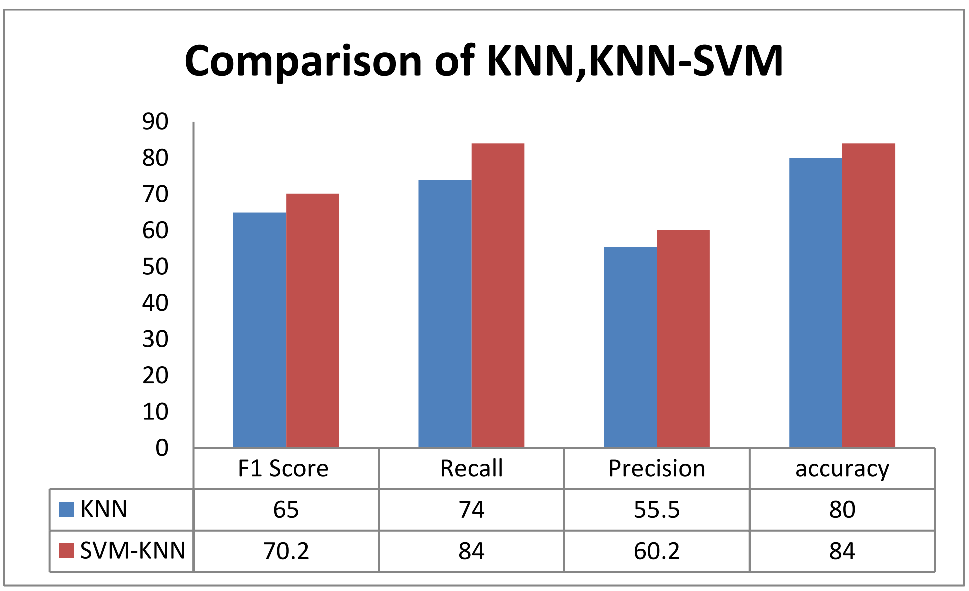


Fig. (3): Graph of results KNN,KNN-SVM

Comparison of SVM, SVM-ACO, results in the form of bar chart having x-axis containing precision, recall, accuracy and y-axis contains percentage:

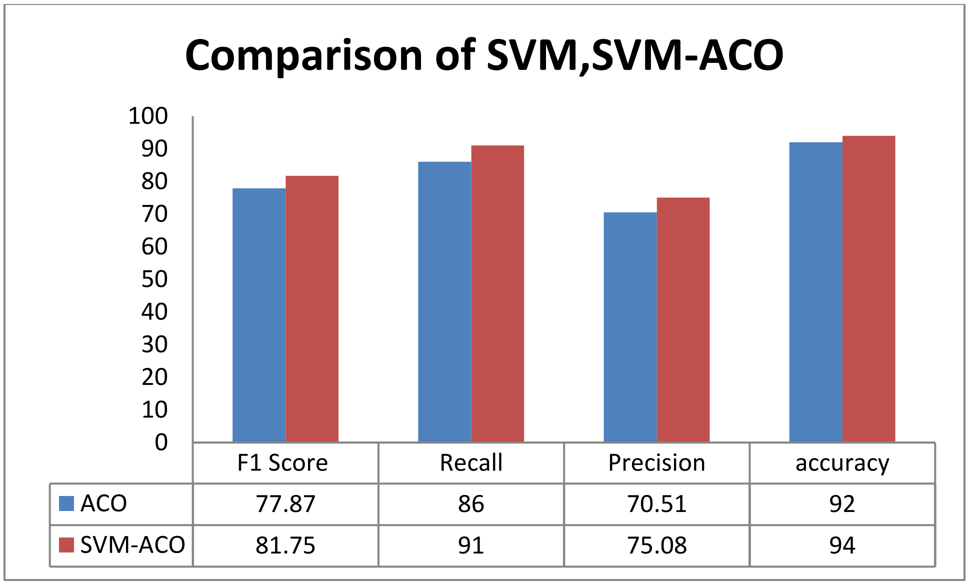


Fig. (4): Graph of results SVM, SVM-ACO

Comparison of SVM, SVM-ACO, results in the form of bar chart having x-axis containing precision, recall, accuracy and y-axis contains percentage:

Comparison of SVM,ACO-PSO

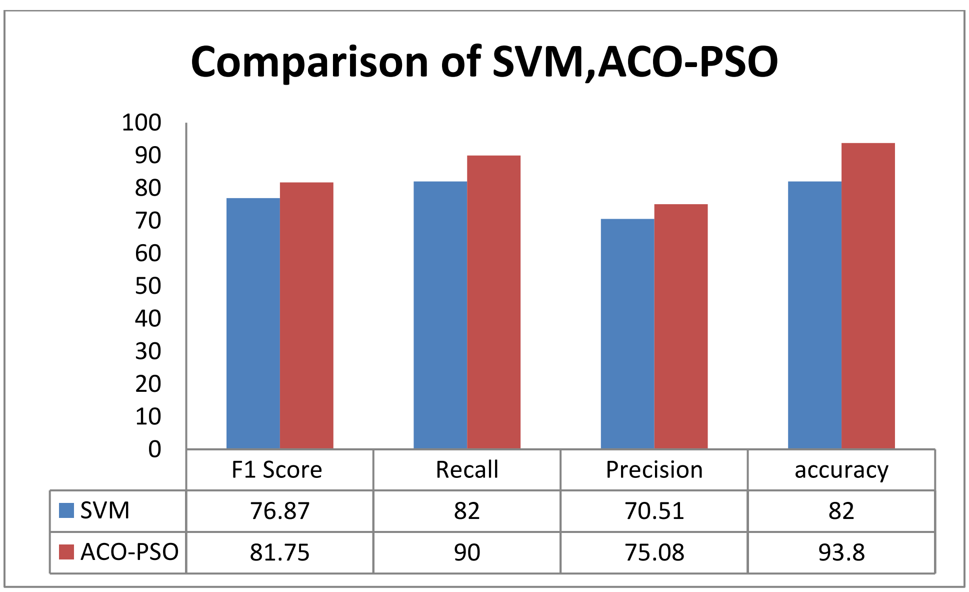


Fig. (5): Graph of results SVM, ACO-PSO

Comparison of SVM, SVM-PSO-ACO, results in the form of bar chart having x-axis containing precision, recall, accuracy and y-axis contains percentage:

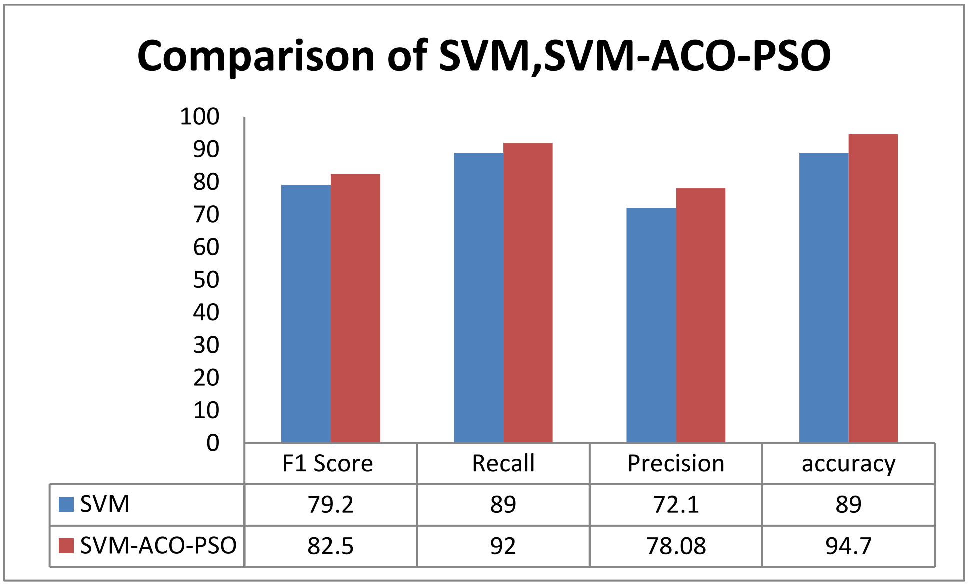
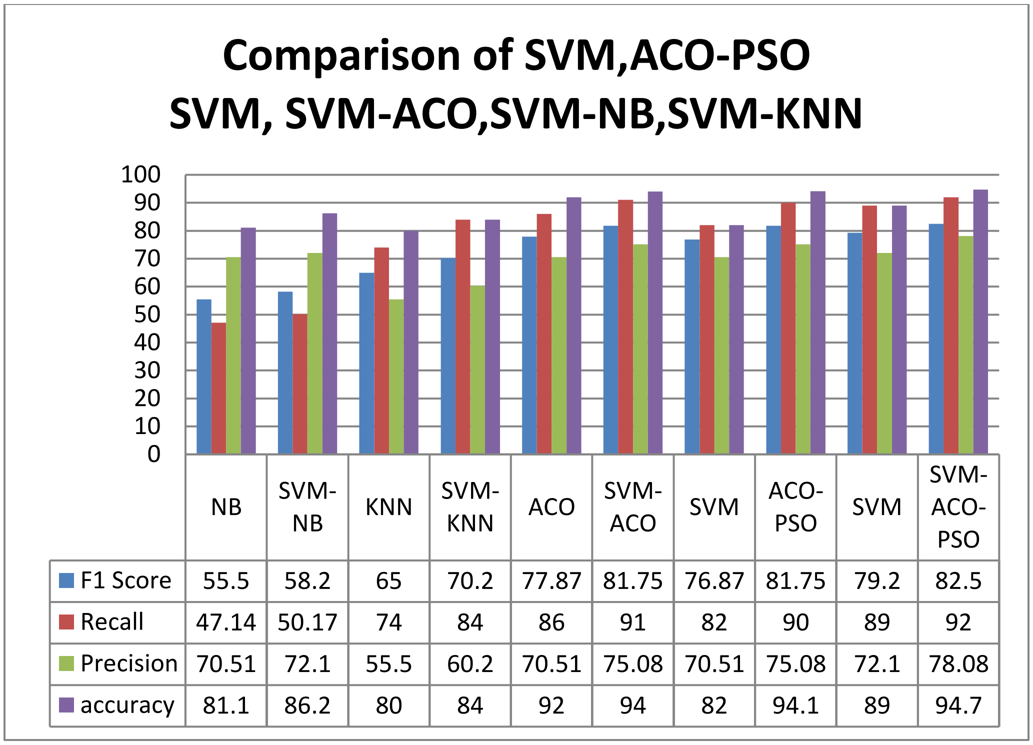


Fig. (6): Graph of results SVM, SVM-ACO-PSO

Comparison of SVM, ACO-PSO,SVM, SVM-ACO,SVM-NB,SVM-KNN,SVM-ACO-PSO results in the form of bar chart having x-axis containing precision, recall, accuracy and y-axis contains percentage:



	NB	SVM-NB	KNN	SVM-KNN	ACO	SVM-ACO	SVM	ACO-PSO	SVM	SVM-ACO-PSO
F1 Score	55.5	58.2	65	70.2	77.87	81.75	76.87	81.75	79.2	82.5
Recall	47.14	50.17	74	84	86	91	82	90	89	92
Precision	70.51	72.1	55.5	60.2	70.51	75.08	70.51	75.08	72.1	78.08
accuracy	81.1	86.2	80	84	92	94	82	94.1	89	94.7

Fig. (7): Graph of results SVM,ACO-PSO SVM, ACO-PSO,SVM-ACO,SVM-NB,SVM-KNN

Finally, In terms of accuracy, precision, recall, and F-measure, the SVM-ACO-PSO result outperforms other results based on comparative analysis with hybrid classification methods for sentiment analysis in this paper. Different type of hybrid Model further work as there is at present a considerable measure of room for improvement.

Conclusion

Sentiment analysis is used to identify people’s opinion, attitude and emotional states. The views of the human beings may be positive or negative. Commonly, elements of speech are used as function to extract the sentiment of the textual content. An adjective performs a essential function in figuring out sentiment from components. Sometimes words having adjective and adverb are used together then it is difficult to identify sentiment and opinion. I established, examined and evaluated sundry machine learning methods for the Sentiment Analysis task. I learned a considerable measure for things about how to face a machine learning trouble and how to do data analysis to make the work easier to the machine to learn.

In this document, analysis is done by the effective weight by KNN, NB, PSO,SVM and ACO with discriminative classifier of SVM. Results shows SVM-NKK , ,SVM-PSO perform but not well comparison of SVM-ACO-PSO which is 94.7% accuracy because SVM-ACO-PSO iteratively changes the threshold if weight is different for different parameter.

For future work, we would like to make bigger the domain of our experiments and run the classifiers on multiple dataset considering number of different languages so as will have more representative inputs and thus better generalizable results.

References

Go, Alec, Richa Bhayani, and Lei Huang "Twitter sentiment classification using distant supervision." CS224N Project Report, Stanford 1 (2009): 12.

Pak, Alexander, and Patrick Paroubek. "Twitter as a Corpus for Sentiment Analysis and Opinion Mining." LREc. Vol. 10. 2010.

Spencer, James, and Gulden Uchyigit. "Sentimentor: Sentiment analysis of twitter data." Proceedings of European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases. 2012.

Kouloumpis, Efthymios, Theresa Wilson, and Johanna D. Moore. "Twitter sentiment analysis: The good the bad and the omg!" Icwsm 11 (2011): 538-541.

Narr,Sascha, Michael Hulfenhaus and Sahin Albayrak "Language-independent twitter sentiment analysis" Knowledge Discovery and Machine Learning (KDML), LWA (2012): 12-14.

Celikyilmaz, D. Hakkani-Tur and J. Feng “Probabilistic model-based sentiment analysis of twitter messages,” in Spoken Language Technology Workshop (SLT), 2010 IEEE, pp. 79–84, IEEE, 2010.

Y. Wu and F. Ren, “Learning sentimental influence in twitter,” in Future Computer Sciences and Application (ICFCSA), 2011 International Conference on, pp. 119–122, IEEE, 2011.

A.Pak and P. Paroubek “Twitter as a corpus for sentiment analysis and opinion mining,” in Proceedings of LREC, vol. 2010.

R. Xia, C. Zong, and S. Li “Ensemble of feature sets and classification algorithms for sentiment classification,” Information Sciences: an International Journal, vol. 181, no. 6, pp. 1138–1152, 2011.

Neethu M.S., Rajasree R "Sentiment Analysis in Twitter using Machine Learning Techniques", 4th ICCCNT 2013 July 4 - 6, 2013, Tiruchengode, India, IEEE.

Shenghua Liu, Xueqi Cheng, Fuxin Li, and Fangtao Li "TASC:Topic-Adaptive Sentiment Classification on Dynamic Tweets", IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING, MANUSCRIPT, 2014.

Rui Xia, Feng Xu, Chengqing Zong, Qianmu Li, Yong Qi and Tao Li" Dual Sentiment Analysis: Considering Two Sides of One Review", IEEE Transactions on Knowledge and Data Engineering, 2015. R. Suresh Ramanujam, R. Nancyamala, Nivedha, "SENTIMENT ANALYSIS USING BIG DATA", 2015 International Conference On Computation Of Power, Energy, Information And Communication

Saif, Hassan, Yulan He, and Harith Alani "Semantic sentiment analysis of twitter" International Semantic Web Conference. Springer Berlin Heidelberg, 2012.

Mukwazvure, Addlight, and K. P. Supreethi "A hybrid approach to sentiment analysis of news comments." Reliability, Infocom Technologies and Optimization (ICRITO) (Trends and Future Directions), 2015 4th International Conference on. IEEE, 2015

Khan, Jawad and Byeong Soo Jeong "Summarizing customer review based on product feature and opinion." Machine Learning and Cybernetics (ICMLC), 2016 International Conference on. IEEE, 2016.

Menaria H.K., Nagar P., Patel M. (2020) Tweet Sentiment Classification by Semantic and Frequency Base Features Using Hybrid Classifier. In: Luhach A., Kosa J., Poonia R., Gao XZ., Singh D. (eds) First International Conference on Sustainable Technologies for Computational Intelligence. Advances in Intelligent Systems and Computing, vol 1045. Springer, Singapore. https://doi.org/10.1007/978-981-15-0029-9_9.

Yadav, A., Vishwakarma, D.K. Sentiment analysis using deep learning architectures: a review. *Artif Intell Rev* **53,** 4335–4385 (2020). https://doi.org/10.1007/s10462-019-09794-5.

Ducange P, Fazzolari M, Petrocchi M, Vecchio M (2019) Engineering applications of artificial intelligence an effective decision support system for social media listening based on cross-source sentiment analysis models. Eng Appl Artif Intell 78:71–85. https://doi.org/10.1016/j.engappai.2018.10.014CrossRefGoogle Scholar.

Hassan F, Usman K, Saba Q (2018) Enhanced cross-domain sentiment classification utilizing a multi-source transfer learning approach. Soft Comput https://doi.org/10.1007/s00500-018-3187-9CrossRefGoogle Scholar