Hybrid Classification Algorithm for Sentiment Analysis

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Abstract - Sentiments are the attitude, opinions, thoughts, beliefs or feelings of the writer towards something, such as people, artifacts, company or location. Sentiment analysis intends to conclude the judgment of a presenter or an author apropos to some subject matter or on the whole relative polarity of the manuscript. The classification techniques of SVM KNN etc are compared with the proposed algorithms. The proposed algorithm is the hybrid classifier for the sentiment analysis. The proposed algorithm give high value in terms of accuracy precision and recall

***Keywords** - SVM, KNN, Proposed, Sentiment Analysis*

I. INTROUDCTION

Sentiments are the attitude, opinions, thoughts, beliefs or feelings of the writer towards something, such as people, artifacts, company or location. Sentiment analysis intends to conclude the judgment of a presenter or an author apropos to some subject matter or on the whole relative polarity of the manuscript. The outlook could be the perception or assessment, emotional condition, or the projected poignant message of the person behind. Opinions are decisive influencer of our behavior. Our views and insights of veracity are conditioned on how others perceive the world. The rudimentary job in opinion mining deals with deducing the inclusive polarity of the document on some specific subject matter. Sentiment analysis is a 'suitcase' field of research that contains numerous diverse disciplines, not just associated to computer science but also to social disciplines, such as psychology, philosophy, and ethics [6].Mining of opinions is an artistry of trailing the frame of mind of the community regarding a certain creation or matter from a massive set of judgments or reviews openly obtainable in web. Opinion mining is useful as when we require making decision, we habitually hunt out for other opinions. For example: we could buy a camera or a mobile phone only after checking reviews or comments or by taking opinions of others. Sentiment analysis may occur at different levels. These levels are identified as document level, sentence level and aspect level. A brief description of all these levels is provided below:

1.1 Document Level

In document level analysis, the extraction of sentiment is carried out from the complete review and the classification of a complete opinion is done on the basis of general sentiment of the reviewer. Classifying an opinion document that expresses either a negative or positive sentiment is the major objective of this level. The Methods used for this approach are 70 to 80% accurate for different documents [16]. It is mainly used for product reviews and movies reviews. Document level sentiment analysis works on single entity. Document evaluation and comparison of numerous objects is not suitable for this approach.

Sentence level classification involves two tasks. The purpose of primary task is to verify the nature of statement i.e. subjective or objective. Subjective means individual's own interpretation and objective opinion means that you are looking as an outsider or another person. The main aim of second task is to verify if the subjective sentence is positive, negative, or neutral. There are mainly two steps included in this process:

- Subjective classification of a sentence into one of two categories i.e. objective and subjective
- Sentiment classification of subjective sentences into two categories i.e. positive and negative

Generally, truthful information is presented by an objective sentence whereas a subjective sentence articulates individual feelings, views, sentiments, or values. There are several techniques using which subjective sentence can be identified e.g. Naïve Bayesian classifier. Nevertheless, it is merely not sufficient to know whether the sentence contain a positive or negative opinion. This is an intermediary step that provides support in filtering out sentences having no opinions. A subjective sentence may include numerous opinions and subjective and truthful parts.

1.2 Aspect Level

Aspect level classification is also known as entity, feature or phase level. Fine grained scrutiny is carried out in this level. Aspect level emphasizes on the opinions instead of studying the language construct (i.e. document, paragraphs, sentence, clauses & phrases). It depends on the scheme that there are both positive and negative emotions in an opinion. Discovering object sentiments and its features is the main aim of this approach. Identifying and extracting the features of object expressed by the reviewer is the main aim of this approach. In this level, the grouping of synonyms of a feature is carried out. After that, a feature-based summary of many feedbacks is generated. There are mainly two tasks carried out in this level. These tasks are aspect extraction and aspect sentiment classification [20].

- The initial task is associated to recognize aspects of the object, and more commonly can be identified as a knowledge extraction task.
- The second task determines if the opinions are positive, negative or neutral on different levels.

II. LITERATURE REVIEW

Hu and Liu (2004) [7] performed opinion mining of online product reviews in 3 steps: (1) features of goods which have been remarked on by users are taken out first; (2) opinion sentences are discovered in each review and then decision is taken whether each opinion is positive or negative (3) demonstrating the result. They collected reviews of numbers of products sold online like MP3 Players, DVD's, digital camera and mobile phones from Amazon.com and CNN.net. Opinion word extraction and aggregation is the main technique used by them and features are preferred on the basis of opinion words itself. Their contribution resulted in efficient performance as compared to opinion sentences extraction for DVD-73%, and MP3-93%. The overall accuracy of five products is achieved from 64% to 84%.

Godbole et al. (2007) [13] proposed classification in a lexicon obtained from Word Net. They designed different lexicons for each topic. So, lexicon for politics is totally different from that for health. From an initial lexicon, they designed a graph model to expand polarities to other words. For instance, if the word "good" is marked as positive, all synonyms of "good" are marked as positive and all antonyms of "good" are marked as negative. Then, a new iteration is performed for next level (with the synonyms of the synonyms and the antonyms of the antonyms) and so on.

Esuli and Sebastiani (2007) [14] presented an extremely interesting scheme that applied page rank algorithm to determine term polarities. For this purpose, they used extended WordNet to build a graph where each synset has certain polarity depending on the polarity of its members. The main hypothesis is that there won't be huge variations and each synset will have a similar degree of negativity. This will produce a graph of relation between different synsets that will transfer its polarity properties to its neighbors..

K. Cai et al. (2008) [19] explained sentiment analysis which included a classification method along with an opinion based approach. The opinion classification element differentiated the comparative sentiment expressed by the terms in all fragments and then partitioned the fragments into positive, negative, and neutral groups. The sentiment subject recognition module identifies the important areas implied beyond every sentiment group by word support metrics.

M. Eirinakiet al. (2012) [21] proposed an opinion search engine scheme. The proposed approach integrated the pair of opinion mining algorithms. The outlooks are based on features and the position of these outlooks is also substantially built on the features as a substitute of an object as a whole. Inhabitants appear to dislike a precise object as of several features allied with the result. Their primary experimental assessment on numerous patron review data sets has exposed that their findings achieved extremely high level of accuracy.

Karamibekr and Ghorbani (2012) [22] firstly carried out an arithmetical exploration on the divergence among sentiment analysis of products and social issue. Then, on the basis of some conclusions, they proposed a scheme to consider the part of verb as the most imperative expression in conveying opinions concerning the societal matters. Statistical and experimental fallouts confirm that making an allowance for verbs not merely is essential and definite, other than that they also augment the concert of sentiments analysis.

K. Ghag and K. Shah (2013) [23] surveyed that Sentiment Analyzers are based on language. Various practices used a dictionary to collect opinion. Few techniques used training set while others used both training set and dictionary. No existing method is widespread sufficiently to be language independent. This clearly stated the necessity of hard work to demonstrate Sentiment Analyzer without utilizing training dataset.

K Xu et al. (2011) [24] introduced a new graphical model for extracting and visualizing the comparative relations between goods using the reviews given by users. In this work, the interdependencies among relations were considered to provide support to ventures in the detection of possible risks. Moreover, new products and marketing strategies were designed..

Pankaj Gupta et al. (2016) [25] studied that several sentiments analysis based fields have not yet been studied and it is important to use correct knowledge such that the previous techniques could be improved. Text summarization is an appropriate technique that can be applied for extracting only the useful information for users from the huge amount of collected textual data. The machine learning techniques could also be applied to design an intelligent model through which the data could be extracted, and sentiment analysis could be performed.

S. Zirpe and B. Joglekar et. al (2017) [26] reviewed various sentiment analysis techniques for polarity shift detection. The reviews showed that all kinds of polarity shifts could be detected and eliminated using the polarity shift detection, elimination and ensemble model. Thus, it is possible to detect and eliminate the various polarity shift detection issues through polarity shift. The machine learning classification algorithms performed better in this study.

M. Bouazizi and T. Ohtsuki, **et. al** (2019) [27] studied about the classification of online posts of Twitter users using multi-class classification. The merits and demerits of this approach were studied through this research. For representing the various sentiments and showing how this model helped in understanding the relations among sentiments, a new model was proposed in this research. The accuracy of multi-class classification was being improved and its challenges were eliminated using this model.

III. RESEARCH METHODOLOGY

In this work, sentiment analysis is performed on twitter data. The important steps followed in the novel methodology are mentioned below:

Extraction of Microblogs data and its pre-processing : Different clients post information in different forms in the form of tweets to express their sentiments on variety of topics. The pessimistic and affirmative are the two categorizations among which the Twitter data sample is applied. Tweeter data is generally collected using Twitter API. Twitter API stands for Application Programming Interface. Twitter API facilitates software developers to access and interrelate with openly available Twitter data. In order to interact with this API, Developers may write their own scripts or may use one of the public libraries accessible in various programming languages.

In general, two APIs are used by the Twitter API to retrieve tweets in significant manner. These are:

Twitter Streaming API: This API enables the interaction of streaming Twitter data and collects tweets in realistic way. It is possible to listen in all the Tweets corresponding to a certain keyword, mention or hashtag, along with collection of tweets of particular customers while they are posting tweets on the Twitter platform.Standard Search API: This API provides past tweets posted up to 7 days ago, corresponding to a predefined query (the keyword, mention, hashtag, etc. that you'd like to search). Different from real-time analysis, the information of past can be retrieved using this API.

Pre-processing: After capturing tweets required for sentiment analysis, the next step is to prepare the data. The data on social media exist in raw form. It implies that this data is noisy, rough and required cleaning. This is a vital step as the quality of the data will bring about more consistent outcomes. There are several tasks involved in preprocessing a Twitter dataset. For example, eliminating all sorts of inappropriate information such as emojis, special characters, and additional blank spaces. It may also perform more tasks such as improving format; deleting duplicate tweets, or tweets smaller than three characters.

Feature Extraction: There are several properties included in the preprocessed data sample. The features of developed data sample are extracted using the characteristic extraction method. Further, in a phrase, the optimistic and pessimistic polarity is calculated such that the individuals using replicas can be formatted. To perform dispensation, there are few machine learning methods that require representation of key features of contents. The characteristic vectors used for performing categorization are used for measuring input characteristics. This work makes use of N-grams for feature extraction. A brief description of this approach is provided below:

N-grams: N-grams of texts are widely employed to perform several tasks related to text mining and NLP (Natural Language Processing). These are mainly a set of co-existing words inside a specified window. In order to compute the n-grams, the movement of one word is done in forward direction

If variable X represents number of words in a given sentence K, the number of n-grams for sentence K would be:

$$Ngrams_K = X - (N - 1)$$

There are several tasks which can be performed using N-grams. For example, in order to develop a language model, n-grams are employed for not only developing unigram models but also develop bigram and trigram models. Google and Microsoft have developed web scale n-gram models. These models can be employed to carry out several tasks. These tasks include spelling correction, word breaking and text summarization. The one more aim of using n-grams is to develop features for supervised Machine Learning models such as SVM, MaxEnt models, Naive Bayes, and so on. The plan is to make use of tokens e.g. bigrams in the feature space rather only unigrams.

Training: For providing solutions to categorization issues, managed learning is known to be an important technique. To perform prospect forecasting of unidentified information, it is easier to perform training of classifier. To extract the dataset features, KNN classifier method is applied. To define the centroid points, k-mean approach is applied by KNN classifier. From these points, the Euclidian distance is calculated. In one class, the similar points are categorized. K-Nearest Neighbour is a very machine learning algorithm. This algorithm depends on supervised learning approach. This approach makes assumption about the similarity amid the novel case/data and accessible cases. This approach place the novel case into the category most analogous to the existing categories. This algorithm stores all the existing data and performs the classification of a new data point on the basis of similarity. It implies that new data can be effortlessly classified into an appropriate category with the help of this approach. This algorithm can be used for both Regression as well as Classification. However, it is mainly employed for the classification issues. It is a non-parametric algorithm. It means that this algorithm does not assume any underlying data. It is also known as a lazy learner algorithm. This algorithm does not learn from the training set instantaneously rather than it stores the dataset. During classification, this algorithm works on the dataset. At the training stage, this approach merely stores the dataset. After getting novel data, this algorithm performs the classification of this data into a category much analogous to the novel data.

IV. RESULT AND DISCUSSION

To predict the accuracy of machine-learning based algorithms there are several classifier available in previous work.

Precision is a part of applicable extracted examples. In case of class, the precision is the ratio of number of accurate results (i.e., true positives) and number of all returned results (i.e., the total of true positives and false positives) in classification.

Table 1: Precision Analysis

Classifier	Precision
Naïve Bayes	0.82
Logistic Regression	0.81
SVM	0.35
Base paper (SVM, LR, NB, RF)	0.84
Proposed	0.87

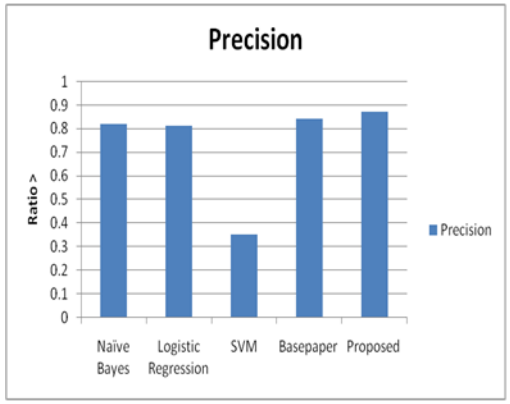

Figure 1 Precision Analysis

Classifier	Recall
Naïve Bayes	0.77
Logistic Regression	0.72
SVM	0.59
Base paper (SVM, LR, NB, RF)	0.79
Proposed	0.85

Table 2: Recall Analysis

As illustrated in figure 1, the precision value of the existing algorithms likes naïve bayes, logistic regression, SVM, random forest are compared with the proposed model. The precision value of the proposed model is high as compared to other classifiers

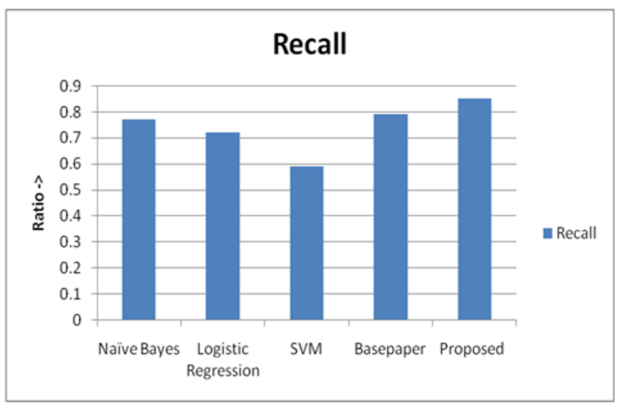

Figure 2 Recall Analysis

As shown in Figure 2, the recall value of the existing algorithms likes naïve bayes, logistic regression, SVM, random forest are compared with the proposed model. The recall value of the proposed model is high as compared to other classifiers

Table 3: Accuracy Analysis

Classifier	Accuracy
Naïve Bayes	77.48
Logistic Regression	72.2
SVM	59.01
Base paper (SVM, LR, NB, RF)	79.24
Proposed	84.87

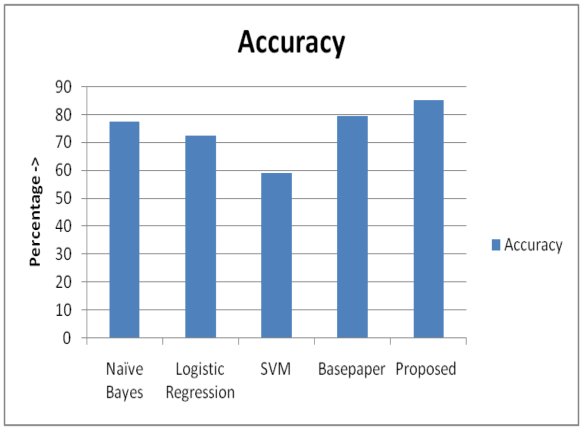

Figure 3 Accuracy Analysis

As shown in figure 3, the recall value of the existing algorithms likes naïve bayes, logistic regression, SVM, random forest are compared with the proposed model. The accuracy value of the proposed model is high as compared to other classifiers.

V. CONCLUSION

The sentiment analysis methods which are proposed so far have various steps. In the pre-processing stage, the missing and redundant values are removed from the dataset. The feature extraction method established relationship between attribute and target set. In the last step of classification, the classification method is enforced which can categorize data into certain classes like positive, negative and neutral. In the previous method, the hybrid classification method is applied to evaluate the sentiments of the twitter data, but still there's some room to improve accuracy and precision. In this study, a hybrid classification method is designed which is the mixture of KNN and random forest classifier for the sentiment analysis. The various classifiers like naïve bayes, logistic regression, SVM, random forest and proposed model are evaluated in terms of precision, recall and accuracy. It is examined that outcomes for the sentiment analysis of the proposed model is optimized up to 3 to 5 percent approximately.

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