ISSN 2347 - 3983
Volume 8. No. 7, July 2020
International Journal of Emerging Trends in Engineering Research
Available Online at http://www.warse.org/IJETER/static/pdf/file/ijeter02872020.pdf
https://doi.org/10.30534/ijeter/2020/02872020

Hybrid Model using Stack-Based Ensemble Classifier and Dictionary Classifier to Improve Classification Accuracy of Twitter Sentiment Analysis

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ABSTRACT

Ensemble classifiers are widely used for the enhancement of accuracy of twitter sentiment classification. In the present research, a hybrid model based on stack based ensemble classifiers and dictionary based classifier is used for tweet classification as positive and negative. To enhance accuracy of classification, sentiment score retrieved from dictionary based classifier is added to the feature vector to get enhanced feature set and the hybrid stack based ensemble model is implemented on this enhanced feature set. Three machine learning classifiers svmRadial, C5.0, NB are used to build stacked based ensemble classifier using GLM and RF as Meta learners. Three data sets viz. Kaggle - US Airline Twitter Sentiment Data Set, Sentiment 140 Twitter Data Set, and Real time manually labeled data set related to 'Clean India Mission' are used for the implementation of the proposed model. Caret library of R Studio is used for creating the stack based ensemble of classifiers. The results show that the proposed hybrid model that used sentiment score as one of the features in feature set performed better with an accuracy of 0.8742223 for Kaggle - US Airline Twitter Sentiment Data Set, 0.8881453 for data set related to 'Clean India Mission' and 0.9953593 for Sentiment 140 Twitter Data Set, as compared to machine learning classifiers and other ensemble classifiers.

Key words: C5.0, Dictionary Based Classifier, NB, svmRadial, Stack Based Ensemble, Sentiment Score, Twitter Sentiment Analysis.

1. INTRODUCTION

Social media is largely becoming popular worldwide, due to the availability of internet and smart devices to almost everyone, everywhere and anytime. People freely give their opinion on social media and this leads to a huge repository of valuable data that attract researchers for various analyses. Twitter is popular social networking media that is used by millions of people across world for sharing their opinion. The tweets shared by users have made twitter a data rich source that attracts number of data scientists for research and analysis. Twitter Sentiment analysis [1] – [3] also termed as opinion mining is an area of artificial intelligence and natural language processing that is used to find the sentiment of text as negative, positive or neutral. This analysis can be very helpful in decision support in various fields like Business Predictions [4], Health care [5], Sports [6], Election Monitoring [7], Tourist satisfaction analysis [8], Social campaign [9], Government Policy Analysis [10], Location Based Sentiment Analysis [11] and Disaster management [12]. Public feedback is very helpful in decision making in these fields mentioned above.

Various techniques used for twitter data sentiment analysis include Machine learning classifiers, Dictionary based classifier, CNN based classification and Ensemble classifiers. Dictionary based or lexicon classifiers [13],[14] are easiest of all the techniques that give fast results in terms of sentiment score, but efficiency of this classifier is not as good as other techniques. Most widely and effectively used machine learning algorithms [15],[16],[17] like SVM, KNN, Decision tree, NB are widely explored in many researches and are very effective in Twitter sentiment classification. Classification accuracy of machine learning classifiers is far better than dictionary based classifiers. Efforts are made to further improve the efficiency by using other techniques like CNN [18] and Ensemble techniques [19] – [21]. Stack based ensemble also produces good results if algorithms are smartly selected for building stack based ensemble. Here in the present research also we are building stack based ensemble classifiers by using different base classifiers and Meta learners.

Twitter Sentiment analysis is widely explored in recent times, but lots of Challenges are encountered while sentiment classification which have given new and attractive possibilities of innovations in research [22]. In the Maximum work done in this field, dual class classification is approached. Multiclass classification is comparatively difficult and results are not as accurate as in case of dual class classification [23]. In machine learning, class imbalance is a big issue that remarkably affects the result of classification [24]. Data retrieved from twitter is high dimensional data. Processing and analyzing high dimensionality data is an issue that needs to be rightly addressed by using proper feature selection and reduction techniques [25],[26]. Various feature selection techniques are used for dimensionality reduction. There are other issues also like heterogeneous data, multilingual data, misspellings, URL's etc. that make the classification trickier.

Most of the research work targets in improving the efficiency of classification with minimum overhead. Here in the present paper, we are using stack based ensemble techniques for twitter sentiment classification to enhance classification accuracy. Sentiment score extracted from lexicon based classifier is also added to the feature vector to further improve the accuracy of model. A hybrid of stack based ensemble and dictionary classifier is used for efficiency enhancement.

Section 1 gives the introduction of Twitter sentiment analysis and technology used for this. Literature survey of related work is given in section 2. Section 3 explains the methodology, data sets and classifiers used for tweet sentiment analysis. Section 4 discusses the result and analysis part. Results are concluded in Section 5.

2. RELATED WORK

Machine learning classifiers are extensively and effectively used for twitter data sentiment classification, but improving efficiency further is always a research concern. Research scholars are very much interested in ensemble classifiers to improve classification efficiency and lots of work is also done in this area.

C. Troussas et al. [27] implemented four different ensemble techniques bagging, Boosting, Voting and Stack based ensemble on three different data set. Stack based ensemble model is implemented by using NB, SVM, KNN and C4.5 as base classifiers and LR as Meta classifier. The result show that stack based model surpasses the efficiency of other classifiers.

Y. Emre Isik *et al.* [28] also used stack based ensemble classification techniques for sentiment classification of text. Ensemble is performed at two levels one at feature selection level and other at classifier level. As a less accurate feature selection can leads to poor classification, So two techniques are used at feature selection level to reduce error and for efficient feature selection. Two classification methods are used as ensemble to enhance classification accuracy. The technique shows good results as compared to other machine learning classifiers.

M. Naz *et al.* [29] used an ensemble of KNN and NB for sentiment classification. Results are further improved to an accuracy of 95% by using of KNN, NB and SVM based ensemble. J. Prusa *et al.* [30] implemented ensemble based classifiers Bagging and AdaBoost-r on seven base classifiers 5NN, C4.5D, C4.5N, LR, MLP, RBF and SVM.

Majority voting based ensemble are widely used to build classifier ensemble. Jordan J. Bird *et al.* [31] implemented various single classifiers viz. MLP, J48, NBM, NB, SMO SVM and various ensemble based classifiers based on the combination of above single classifiers. The research shows that majority voting based ensemble of NBM, RF, MLP performed best with 91.02 % accuracy. Y. Wan *et al.* [32] also implemented majority voting ensemble on multiple classification techniques including Naive Bayes, SVM, Bayesian Network, Random Forest and C4.5 Decision Tree by using ten fold cross validation on a data set having 12864 tweets related to airline service Twitter dataset. M. M. Fouad *et al.* [33] also used majority voting based ensemble of SVM, NB, LR by using information gain feature selection technique, for sentiment classification of twitter data.

R. Wijayanti *et al.* [34] used various feature representation techniques TF-IDF, sentiment lexicon score and term presence for implementing ensemble of machine learning algorithms. Voting based ensemble classifier based on SVM, Naïve Bayes, Logistic Regression (LR) and Decision Tree are implemented for all the feature selection methods.

Ensemble classification results are proved to be better than individual machine learning classifiers but ensemble accuracy highly depends on the selection of single classifiers used for creating ensemble classifier. After a survey we came up with the results that limited work is done in area on stack based ensemble classifiers. Also combination of stack based ensemble and Dictionary based classifier is also not well explored. The present paper implements a hybrid model as combination of Dictionary based classifier and Stack based ensemble technique to enhance accuracy of classification.

3. METHODOLOGY USED

Proposed Twitter Sentiment classification model is a hybrid model based ensemble of dictionary based classifier and stacked machine learning classifiers. svmRadial, C5.0 and NB are used as base classifiers in stack based ensemble model by using two Meta learners GLM (Generalized Linear Model) and RF (Random Forest).

Algorithm used for the implementation of model is explained in procedure 1. Tweets are cleaned and pre-processed by removing URL's, numbers, punctuations, Re-tweets, special characters and Hashtags. After cleaning, pre-processing and feature extraction, sentiment score retrieved as an output of dictionary based classifier is added as one of the features in feature vector to get enhanced feature set. Information Gain (IG) is used for ranking and selection of relevant features. NCR sentiment directory of R Studio is used for calculating sentiment score in dictionary based classifier. Although the efficiency of dictionary classifier is not as good as machine learning and ensemble models, but if the sentiment score retrieved from dictionary classifier is used as a feature in feature vector, can remarkably improve efficiency of machine learning and ensemble classifiers with little overhead.

Three data sets as mentioned in Table 1 are used for the implementation of all the models. Caret library of R studio is used for implementing stack based ensemble model. Accuracy and Kappa are used to represent efficiency of the models. The model is diagrammatically represented in Figure 1.

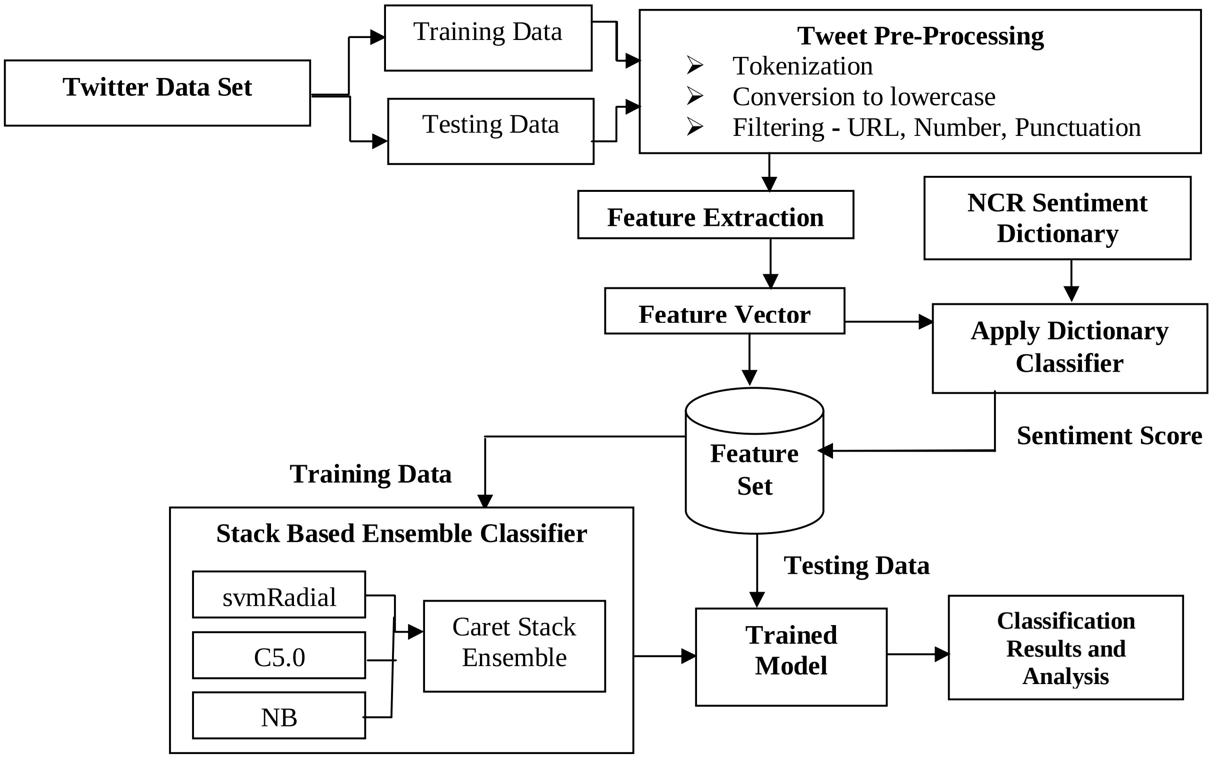

Figure 1: Proposed Hybrid classification Model for Twitter Sentiment Analysis.

Procedure 1:
Input: Tweets with class labels as positive and negative. **Output: Tweet classification Accuracy and Kappa.** Step 1: Retrieval of Tweets: Data Set 1: Standard Kaggle -US Airline Twitter Sentiment Data Set. Data Set 2: By using Twitter API – Real Time Tweets related to ‘Clean India Mission’. Data Set 3: Sentiment 140 Twitter data Set. Step 2: Tokenize and Pre-Process Tweets. Step 3: Feature extraction and selection of relevant features using Information Gain (IG). Represent features in form of Matrix **M** of uni-grams. Step 4: Apply Dictionary (Lexicon) based classifier using **NCR** Sentiment dictionary and retrieve sentiment score **Scr**. Step 5: Get the updated feature set **Mnew** by adding sentiment score **Scr** in **M**. Step 6: Create CaretList S1 to build stacked ensemble model: S1 → **CaretList (SVM, C5.0, NB)** Step 7: For both **M** and **Mnew** feature sets For **GLM and RF** Meta Learners Apply stack ensemble method **CaretStack** using S1 and classify tweets. Step 8: Classify tweets using individual Machine learning classifiers **SVM, NB, C5.0**. Step 9: Analyze and compare Accuracy and Kappa of stack based ensemble model S1 and machine learning classifiers. Step 10: END

3.1 Data Set

Three datasets viz. Kaggle - US Airline Twitter Sentiment Data Set, Real time manually labeled Twitter data set related to 'Clean India Mission' and Sentiment 140 Twitter data set are used for the implementation of proposed hybrid model. 'Clean India Mission' in data set-2 is an Indian government policy for making India clean and making masses aware about cleanliness. Details of all the data sets are given in Table 1. The actual number of tweets in Sentiment 140 Twitter data set is actually larger in number but only a subset is selected due to limited computation power of computing machine. Only dual classes, positive and negative are considered for twitter sentiment analysis.

Table 1: Data Set Details

Data Set	Data Set Description	Total Number of tweets	Positive Tweets	Negative Tweets
Data Set-1	Kaggle - US Airline Twitter Sentiment Data Set	11541	2363	9178
Data Set-2	Real Time Twitter Data Set related to "Clean India Mission"	1052	501	551
Data Set-3	Sentiment 140 Twitter Data Sub Set	3305	1422	1883

For Sentiment 140 Twitter Data Set only a subset of 3305 tweets are randomly selected out of 1048576 total tweets for implementation.

3.2 Classification Algorithms Used in Ensemble

A. SVM (Support Vector Machine)

Support Vector Machine (SVM) is a most commonly used, supervised machine learning algorithm to solve classification problems and also used frequently in twitter sentiment analysis. SVM solves the problem by finding maximum gap linear hyper plane, separating different classes by using already labeled instances of the training data set. New instances to be classified are mapped into different planes depending on the side of plane that instance falls. Higher the gap between classes, lower will be the error in classification. S. Naz *et al.* [35] used SVM for the classification of Twitter Data by using three weighted schemes to see the effect of different weighted schemes on accuracy of SVM.

R. N. Chory *et al.* [36] identified user satisfaction level of mobile data services by using SVM and a very high accuracy of 99.01 percent was monitored.

B. NB (Naïve Bayes)

Naïve Bayes are the probabilistic classification algorithms based on Bayes theorem of probability, as given in equation 1 and is frequently used to find the class of data instances in machine learning classification. Naïve Bayes is easy and fast to implement.

$$P(A|B) = P(B|A) * P(A) / P(B) \quad \text{.......(1)}$$

P (A|B) - Probability of *class* A given *predictor* B.
P (A) - Probability of *A*.
P (B|A) - Probability of *class* **B** given *predictor* A.
P (B) - Probability of *B*.

NB classifier assumes that predictors are independent, but in maximum cases predictors are dependent and efficiency is relatively low. Although NB performance is not as good as other machine learning classifiers, but NB is implemented in various ensemble techniques due to easy and fast implementation. M. Ahmad *et al.* [37] implemented NB and lexicon based classifier and show that NB performed better with accuracy 84 % as compared to lexicon classifier with accuracy 72%. N. Ardhianie *et al.* [38] also implemented NB on "Indonesian No Dating Campaign" and results in an accuracy of 74.77%.

C. Decision Tree

Decision tree is a supervised machine learning classification algorithm in which tree is constructed by features of training data set and leaf node tell the final class of instance after prediction. Internal nodes representing features, direct the search to particular leaf node that represents the final class. In the present research C5.0 of R Studio caret library is used which is a decision tree and rule based model. C5.0 performs very well when it is used as an ensemble with other classifiers. F. J. J. Joseph *et al.* [39] used decision tree model for classifying the tweets related to '2019 Indian Election Tweets'. R. Bibi *et al.* [40] also used decision tree for Urdu news classification and the results shows significant success in terms of accuracy.

D. Ensemble Classifier

Ensemble classifiers mean using multiple classifiers or models together to enhance the efficiency of classification as compared to single classifier [41]. Bagging, Boosting, Random Forest [42], Stack based ensemble are various ensemble based classification techniques. Bagging deals with building multiple models of same type on different subsamples of same training dataset and then combining their results. Boosting also deals with building multiple models of same type where each model learns to reduce the prediction error of the previous model in a chain. In the present research stack based ensemble classification is implemented by using different Meta classifiers. Stacking classifiers is an ensemble based classification technique in which multiple models of different types are combined by using different Meta learners. After training the base classifiers on complete training data, Meta learners are trained on the output of these base classifiers to best combine their results. Heterogeneous classifiers are used to build an ensemble at base level to combine the strength of all the base models. In maximum cases efficiency of stack based ensemble is better than the best classifier at the base layer.

4. RESULT AND ANALYSIS

The Stack based ensemble classification model represented in Figure 1 is implemented on three data sets, explained in Table 1. Hybrid model based on dictionary based classifier and stack based ensemble of svmRadial, C5.0, NB base classifiers are implemented by using RF and GLM Meta learners on all the three data sets. Classification accuracy and Kappa for all the ensemble models with and without dictionary classifier are mentioned in Table 2. Proposed Hybrid model with an ensemble of NB, svmRadial, C5.0 and dictionary based classifier performed better with an accuracy of 0.8742223 for US Airline Twitter Sentiment Data Set, 0.8881453 for Real Time Twitter Data Set Related to 'Clean India Mission' and 0.99559 for Sentiment 140 Twitter Data sub set. Ensemble classifiers also performed better as compared to individual machine learning algorithms but adding of sentiment score in feature set further enhance the accuracy of ensemble classifiers uniformly for all the three data sets. Figure 2 show the comparative analysis of accuracy of all models for all the three data sets. It is evident from the results that proposed hybrid of stack based classifier ensemble with dictionary based classification algorithm performed better as compared to single machine learning algorithms and other ensemble classifiers.

Table 2: Efficiency of Different Classification Models

Data Set	Classification Model	Meta Classifier	Accuracy	Kappa
Data Set-1 US Airline Twitter Sentiment Data Set	svmRadial	-	0.8235	0.6232654
	NB	-	0.5633402	0.0008743169
	C 5.0	-	0.8079494	0.6012191
	Ensemble Classifier			
	NB, svmRadial, C5.0	GLM	0.8684404	0.7309959
	NB, svmRadial, C5.0	RF	0.8541161	0.7025414
	Proposed Ensemble Classifier			
	NB, svmRadial, C5.0 + Dictionary Based Classifier	GLM	**0.8742223**	0.743875
	NB, svmRadial, C5.0 + Dictionary Based Classifier	RF	**0.8673372**	0.7301921
Data Set-2 Real Time Twitter Data Set Related to 'Clean India Mission'	svmRadial	-	0.7976190	0.6002382
	NB	-	0.5237644	0.0000000
	C 5.0	-	0.8361870	0.6719481
	Ensemble Classifier			
	NB, svmRadial, C5.0	GLM	0.8633394	0.725961
	NB, svmRadial, C5.0	RF	0.8509712	0.7013507
	Proposed Ensemble Classifier			
	NB, svmRadial, C5.0 + Dictionary Based Classifier	GLM	**0.8881453**	0.7759951
	NB, svmRadial, C5.0 + Dictionary Based Classifier	RF	**0.8816031**	0.7627214
Data Set-3 Sentiment 140 Data Sub Set	svmRadial	-	0.7809061	0.4220494
	NB	-	0.3136758	0.0000
	C 5.0	-	0.7333650	0.4760125
	Ensemble Classifier			
	NB, svmRadial, C5.0	GLM	0.829175	0.560807
	NB, svmRadial, C5.0	RF	0.813357	0.52958658
	Proposed Ensemble Classifier			
	NB, svmRadial, C5.0 + Dictionary Based Classifier	GLM	**0.99559**	0.988928
	NB, svmRadial, C5.0 + Dictionary Based Classifier	RF	**0.9953593**	0.988839

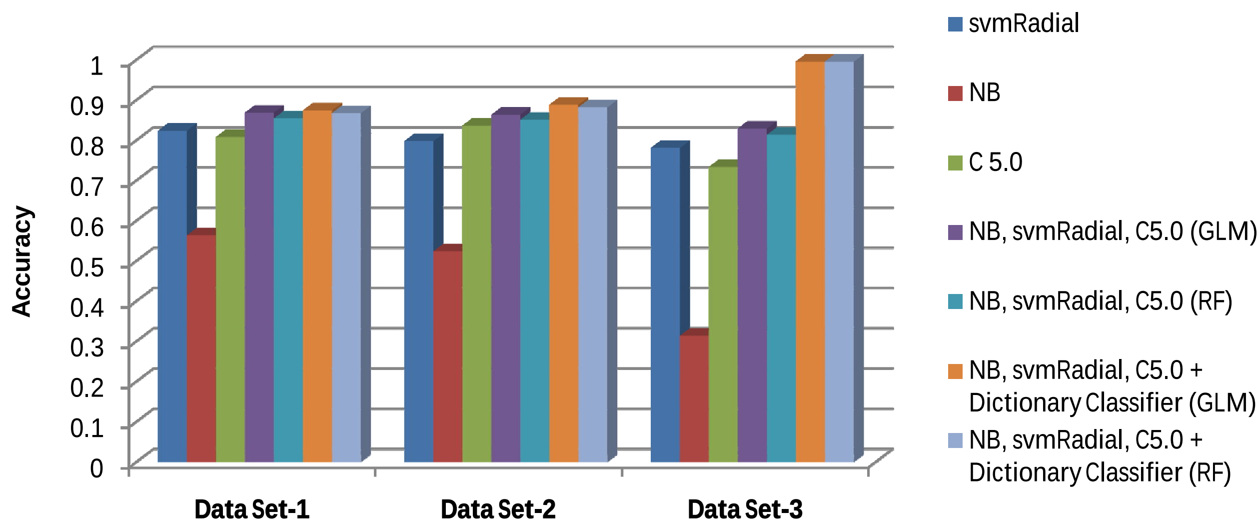

Figure 2: Comparative Analysis of classification Models for all three Data Sets.

5. CONCLUSION

Twitter Sentiment analysis is an important area of natural language processing and is frequently used for finding the common man sentiment about various topics. Stack based ensemble classifier is widely used for the enhancement accuracy of twitter sentiment classification. In the present research svmRadial, C5.0, NB classifiers are used to build a stack based ensemble classification model. A step is taken forward by adding results of dictionary classifier in feature set and then stack based ensemble model is implemented on that enhanced feature set. The resulting hybrid model performed better with improved classification accuracy uniformly for all the three data sets.

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