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Improved Performance of Machine Learning Algorithms via Ensemble Learning Methods of Sentiment Analysis

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ABSTRACT: Sentiment analysis is very useful for extracting subjective information from online user generated textual document. Mostly machine learning classification algorithms work together in sentiment classification. When the classification algorithm applies individually on the review dataset then that can classify sentiments erroneous with limited performance. To deal with this problem, we used ensemble methods with machine learning algorithms. Ensemble methods are combination of several classifiers prediction to get classification model with predictions of multiple classifiers to obtain a classification model with higher prophetic performance. In this research, we used four classification algorithms like Naïve Bayes, K-Nearest Neighbor, Maximum Entropy, and Support Vector Machine combined with three ensemble methods like Bagging, Boosting, and Random subspace applied on different review datasets. We know that, the ensemble learning methods predicted accurately sentiments on different review dataset. Experiential results revealed the performance of base learners (machine learning algorithms) improved by ensemble methods for sentiment classification. At last, the highest accuracy generated by Support Vector Machine with boosting and random subspace ensemble methods. The Maximum Entropy classifier also generated good accuracy individually as well as combined with bagging ensemble method.

Keywords: Sentiment classification, Machine learning classification algorithm, Ensemble learning methods.

I. INTRODUCTION

Machine learning results can be improved with the help of combining several models in ensemble learning models. In ensemble method one model performance compared to another model and select higher prognosticative performance model. Ensemble methods also known as meta algorithm that is combination of several machine learning into one prognosticative model. By the ensemble model to decrease variance of bagging, bias of boosting, and improve predictions of stacking. Sentiment analysis is common, easy and helpful tasks in language process. It aims is to predicting the polarity of text, usually a sentence or a review. As an example, movies or products are usually rated with a particular variety of stars that indicate the grade to which the reviewer was glad.

The amount of text data available online has increased day by day by social media, industries, business firms and public services. Government organizations generated text to keep opinions in public mind for policy formation [1]. Today is a trend of IT to generate contents by user online everywhere [2]. To find out polarity of text of documents, that is positive or negative within the field of sentiment analysis? Social media play important role to analyzing and predict people moods, polarity of the sentiment, and understanding social happenings and customary society leanings [3].

The analysis of sentiments rises to figure out folk's opinions, attitudes associate degree emotions to a posted review [4]. There are many sources are available to generate texts, reviews, posts, forum debates. These textual data size increased day by day known as big data. So, the texts have some sentiments such as feeling, emotions, etc. This sentiment analysis becomes a hot issue for researchers. There are many challenges in this area. Therefore, researchers created reliable and efficient machines to understand human emotions and feelings. It is very important inside the present state of affairs as a result. The lots of user have narrow-minded texts and put them out on the internet presently. Machines are capable to work on natural language processing understand human emotions and feelings and produce accurate polarity or sentiments.

The sentiment analysis is known as sentiment classification task. There are some comparative studies done by [5-7]. This performed on sentiment classification through bagging, boosting and random subspace ensemble methods. The data have in many varieties of transmission like texts and videos. This will offer valuable data generated by social firms, government's organizations, and specific choice. Sentiment analysis used as application in marketing field, when customer review help to marketing research to make product and service best [8].

II. LITERATURE REVIEW

In this study [9], authors shown a comparative valuation of ensemble methods and machine learning classifier methods. They used bagging, boosting, and random subspace ensemble methods combined with support vector machine, decision tree, naïve bayes, k-nearest neighbor, and maximum entropy applied on diverse review data sets. The practical work concludes that ensemble methods can better perform than machine learning classifier methods for sentiment classification task.

In this study, authors worked on forward search, multi objective differential evolution algorithm, and majority voting error, based on static classifier selection with the help of ensemble method. In this research used combination of machine learning methods and ensemble learning method such as logistic regression, support vector machine, Bayesian logistic regression, linear discriminant analysis, and naïve Bayes along with bagging, adaboost, majority voting, and random subspace. The terms precision and recall are used to determine weight adjustment values performance. Lastly, find out the proposed classification scheme can predict better than conventional ensemble learning methods for credit risk modeling, spam filtering, software defect prediction, classification tasks, sentiment analysis, and semantic mapping [10].

In this paper [11] researchers used collective ensemble methods to analyzed sentiments for twitter data sets. After experiment outcome, they find out to improved accuracy of twitter sentiment classification by using base machine classifiers with ensemble methods. In the discussion section authors detection some shockingly best approach to beneficial their research than traditional approach. In last section, they enhance this research work on some other areas such as online marketing and e-learning.

In this study [12] authors investigates several techniques to achieve maximum accuracy for classifying the sentiment of review data sets. They applied individually unigram and bigram vectorization models to assigned vector values to each terms. After that, extract features from data used tf-idf combined with unigram and bigram. In proposed methodology used ensemble machine learning algorithms Gradient Boost, Ada Boost, Bagging Classifier, Extra Tree, and Random Forest. In lastly, they finding which mishmash like vectorization models along with feature extraction method and ensemble classifier performed better for sentiment classification.

In this study [13] authors used machine learning classification algorithms as decision tree, support vector machine, logistic regression, and naïve bayes. They investigated the predictive performance of all classification algorithms. These classifiers also combined with ensemble learning methods as boosting, stacking, voting, and meta cost for pay-per-click campaign management.

In this study [14] used supervised classification methods combined with ensemble method and evaluate methods to discover best one out of them on Botnet detection. Authors also investigated strong classifier and weak classifier based on previous studies. In botnet detection ensemble method is very beneficial. This study done on public data set and find out how much time taken by data set with different scenarios by F-measure and MCC score.

In this study [16] evaluated performance of real and binary based ensemble methods. Authors also used different parameters to evaluated performance of classifiers such as SVM, NB, DT, MBL, ME, CRF, and HMM.

III. PROPOSED METHODOLOGY

In this section some important steps involved which are describing below;

A. Review dataset collection, we collected online data form different sources like electronics product review data sets and music review data sets for sentiment classification.

B. Pre-processing, it is also known as text filtering technique. This steps involved some important sub-steps such as eliminate noisy data, unreliable and partial data by considering tokenization, white space removal, stemming method etc.

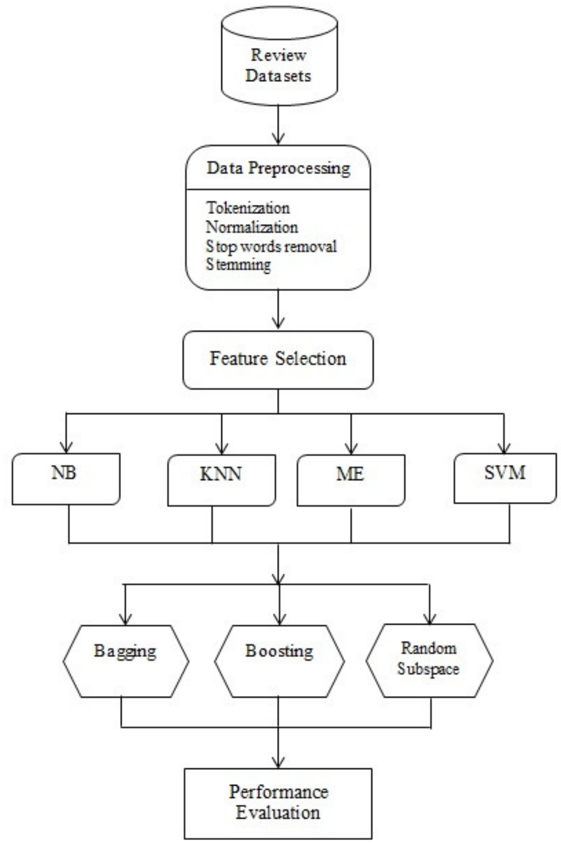

Fig. 1. The proposed model for sentiment classification.

C. Feature selection method; in sentiment analysis have acquired a significant role in increasing classification accuracy and identifying relevant attributes [17]. In machine learning methods are change text in vector form for sentiment classification. In feature selection or variable selection to include only appropriate information and also free from each other [33]. The bag-of-words (BOW) frame known as feature demonstration method leading the sentiment classification [34]. The every text contained some vector values. This research used N-gram vectorization to generate numeric values to consider binary presence or absence of a feature in a document. The feature score 1 presents in a document otherwise 0. Combined all feature subsets from top ranked features sub list.

D. Classification algorithms, the sentiment classification algorithm used to classify texts into positive or negative sentiments. We used four base learning classification methods like Naïve Bayes, k-Nearest Neighbor, Maximum Entropy, and Support Vector Machine, with ensemble methods like Bagging, Boosting, and Random subspace for classification the dataset.
Researchers worked on textual data from long time to classify text in various form [18] but sentiment based

classification was introduced more lately [19]. The primary object of this research work is to explore the outcome of several machines learning classification through ensemble methods. The proposed model is represented in above Fig. 1.

IV. CLASSIFICATION ALGORITHMS

Machine Learning Classification Algorithms broadly used in the field of text mining and sentiment analysis. In this research, there are four classification algorithms are used followed as;

A. Naïve Bayes

Naïve Bayes (NB) is a kind of supervised machine learning algorithm. It is known as probabilistic method. NB categorized text based on Bayes theorem. It holds an assumption of independence among predictors. It classified features; one feature present in a class does not depend on another feature present or absence in the class. It is classifying text document with the help of probabilistic for out of classes. Probabilistic information of features is helpful to represent and learn a feature very clearly. It's functioning is very simple and statistical formulation described in details through [20].

B. K-Nearest neighbor

K-Nearest neighbor (KNN) finds out unfamiliar samples from the class. In the training data set algorithm checked the k-closest cases and creating a prediction based on majority which majority belongs of its closest neighbors. It is almost used in regression and classification. This algorithm functionality is very simple and effective to classify the textual document in good way. This algorithm initially used review data set to trained the system and after that take test data set for test the system. The whole process described by [21], how to sampling used in KNN algorithm.

C. Maximum Entropy

Maximum Entropy (ME) also known as a probabilistic classifier. It sometimes used in NLP applications. This algorithm classified text documents belongs to a particular class. It produced extreme entropy of classification document in a given framework. When the features are temporarily independent of each other them this technique does not create some hypothesis. This classification results are more accurate and reliable than Naïve Bayes algorithm. The ME trained the system using training data set can take some extra time than NB. To select good evaluation factors of the model to solved the optimization problem. The main goal of this algorithm is to classify textual data with accurately [22].

D. Support Vector Machine

Support Vector Machine (SVM) is a supervised learning method. It was announced by [23] for nonlinear and linear binary classification. The data sets are largely nonlinear indivisible. This classifier selects some best points which located near the surface. The selected points are exist near the surface as indicated positive samples and other negative samples. The term used in this method is called empirical risk means training set and test set error for minimization principal. This is also defined decision boundary with hyperplanes in a high-dimensional feature space. These vectors document divided into two classes with the help of hyperplane. The accurate results find out [24] with the help of support vector. The goal of SVM to decide the best decision boundary to divide data points in two different classes. The text mining [20] displayed with great dimensional feature space for some irrelevant features and linearly discrete cataloging.

V. ENSEMBLE LEARNING METHODS

Ensemble methods combined different predictions of several classifiers to create the best classification model that perform best. The process of combined the different classifier, the variance and bias of classification can be reduced and the dependency of results. The features of a single training set may be eliminated [25]. The ensemble methods have two types; first is dependent method and second is independent methods [26].

A. Bagging

It is also known as bootstrap aggregating. It was very first [27] method of ensemble learning. Bootstrapped models are used to obtained many bagging models. During training [28, 29] the data created subsets and randomly arbitrarily replaced from best training dataset. This training data is used to trained model of base learner. It combined results or output of base learner and chooses best one based on majority vote scheme. It reduced variance when joined base methods. Bagging work in parallel way, means different training dataset apply on different base learner model then combined all models results. The pseudo code of bagging algorithm describes follow as;

Input: Review Dataset R = {(a_1, b_1), (a_2, b_2)… (a_n, b_n)};
Machine learning algorithm M;
Number of learning iteration N.
Process:
For n = 1, 2,……,N;
Rn = Bootstrap (R): // *make a bootstrap sample from R*
k_n = L (D_n) // *train a machine method k_n from the bootstrap sample*
End.
Output: K(a) = $\text{argmax}_{b \in B} \sum_{n=1}^{N} 1(b = k_n(a))$

B. Boosting

It is a collection of some methods [30]. During the training dataset, the boosting sequentially reweighting to instances of different base learners. Base learner instances have less weight of previous round than have larger weight for next round for the training. This process may take some iteration to find out best fits a base learner to the weighted training data. Each iteration reweights of training dataset. Boosting work in sequential way, means take a training data set apply on a base learner and make a model then apply second training data previous model and improved previous model. Boosting construct strong classifier by weighted voting of the weak classifer. There are several versions of boosting but mostly used AdaBoost proposed by Freund and Schapire [31, 30], The pseudo-code of boosting algorithm describes follow as;

Input: Review Dataset R = {(a_1, b_1), (a_2, b_2)… (a_n, b_n)};
Machine learning algorithm M;
Number of learning iteration N.
Process:
R_1(j) = 1/m. // *weight distribution initialization*
For n = 1, 2,……,N;
k_n = M (R, R_n); //*train a machine method k_n from R using distribution R_n*
$\varepsilon_n = Pr_{j\sim Rj}[k_n(a_j \neq b_j)]$; //*measure the error of k_n*
$\alpha_n = \frac{1}{2} 1s \frac{1-\epsilon_n}{\epsilon_n}$; //*determine the weight of k_n*

R_{i+1} (j) = $\frac{R_n(j)}{W_n} \times \begin{cases} \exp(-\alpha_n) & if\ k_n(a_j) = b_j \\ \exp(\alpha_n) & f\ k_n(a_j) \neq b_j \end{cases}$ *//update the distribution, where W_n is a*

= $\frac{R_n(j)\exp(-\alpha_n b_j k_n(a_j))}{W_n}$ *// normalization factor which enables R_{j+1} to be a distribution*

End.

Output: K(a) = sign $(g(a))$ = sign$\sum_{n=1}^{N} \alpha_n k_n(a)$

C. Random Subspace

Ho [32] proposed Random Subspace (RS) method. It is modified training dataset in Bagging. The feature space has modification not in the instance space. The RS is more beneficial to base classifier for constructing as well as for aggregating. The dataset always have redundancies and irrelevant features problem. The RS can select best base classifier than in the original feature space [32]. The different training dataset apply on different models and combined those models created best on the original training dataset in the complete feature sets. The pseudo-code of Random Subspace algorithm describes follow as;

Input: Review Dataset R = {(a_1, b_1), (a_2, b_2)… (a_n, b_n)};
Machine learning algorithm M;
Number of random subspace rate n';
Number of learning iteration N.

Process:
For n = 1, 2,……,N;
R_n = RS(R, g); // subspace sample generate randomly from R
k_n = M (R_n); // from the subspace sample train base learner k_n
End.

Output: K(x) = argmax$_{b\in B}\sum_{n=1}^{N} 1(b = k_n(a))$; *// the value of 1(α) is 1 if α is true*

// and 0 otherwise

VI. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experimental Setting

We performed entire experiments on the Laptop with Intel® Core™ i3-3110M CPU 2.40 GHz, 64-bit Operating System, x64-based processor and 4 GB RAM, using Windows 8 Pro Operating System. Entire experiments conduct on open-source Anaconda Python 3-5.2.0-Windows-x86_64 version. The CSV file load in python. First step preprocessing of raw text is done using NLTK. Some important libraries used like numpy, pandas, sklearnscipy etc. and NLTK tool.

B. Datasets

In our experiments used different review data sets from different online websites [35]. Today's in technology trend each domain have own online websites to provides best facilities to customers such as products purchasing, online educations, doctor appointments etc. and also give feedback for about their services. Everything's easily available online even some online jobs done by people at home. So, we take review data sets of camera, laptop, radio, TV, and music form their websites for sentiment analysis.

C. Evaluation Parameters

We used confusion matrix for performance evaluation of the proposed method. The basic sentiments are generates after classifying the data sets by the classifiers. These sentiments contains some terms or values. All these terms also called true positives, true negatives, false positives, and false negatives. So, these above terms are very helpful to calculate or evaluate average performance of our proposed classification algorithms and methods. The confusion matrix is very popular matrix for evaluation the performance of all algorithms and methods. The matrix is the proportion of the number of true positives and number true negatives achieved by classifiers of the total number of instances. The equation of confusion matrix is present in below.

$$\text{Avg. Acc.} = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

D. Result Discussion

The following experimental result from table 1 to table 4 are summarize of classification algorithms used as NB, KNN, ME, and SVM individually and also combination of ensemble methods as bagging, boosting, and random subspace in sentiment classification. The all experimental tables displayed the highest Avg. accuracy. The generated Avg. acc. used by individually classifier and with combined classifier methods in bold values in the table.

The table 1 presents average accuracy with base learning algorithms. The highest accuracy acquired by Maximum Entropy classifier 83.50% on Camera data set. The Maximum Entropy classifier achieved greatest accuracy 88.95% on Laptop data set. The highest accuracy acquired by Naïve Bayes classifier 82.89% on Music data set. The maximum accuracy obtained by Maximum Entropy classifier 84.76% on Radio data set. The Support Vector Machine classifier gained highest accuracy 84.73% on TV data set.

The table 2 presents average accuracy of base learning algorithm and Bagging ensemble method. The NB+Bagging classifier achieved maximum accuracy 82.48% on Camera data set. The greatest accuracy got by ME+Bagging classifier 83.45% on Laptop data set. The highest accuracy acquired by ME+Bagging classifier 81.81% on Music data set. The maximum accuracy obtained by ME+Bagging classifier 80.13% on Radio data set. The highest accuracy achieved by ME+Bagging classifier 76.89% on TV data set.

The table 3 presents average accuracy of base learning algorithms and Boosting ensemble method. The maximum accuracy obtained by SVM+ Boosting classifier 85.46% on Camera data set. The SVM+Boosting classifier achieved greatest accuracy 88.58% on Laptop data set. The uppermost accuracy acquired by SVM+Boosting classifier 84.62% on Music data set. The SVM+Boosting classifier got maximum accuracy 86.86% on Radio data set. The highest accuracy gained by SVM+Boosting classifier 85.32% on TV data set.

The table 4 presents average accuracy of base learning algorithms and Boosting ensemble method. The highest accuracy achieved by SVM+RS classifier 84.36% on Camera data set. The SVM+RS classifier obtained maximum accuracy 87.24% on Laptop data set. The SVM+RS classifier obtained highest accuracy 85.98% on Music data set. The highest accuracy obtained by SVM+RS classifier 86.23% on Radio data set. The greatest accuracy obtained by SVM+RS classifier 88.68% on TV data set.

Table 1: The base learner methods achieved Avg. acc.

	Datasets				
Methods	Camera	Laptop	Music	Radio	TV
NB	81.65	83.72	82.89	79.36	84.46
KNN	74.30	76.86	74.20	71.60	75.65
ME	83.50	**88.95**	65.43	84.76	68.87
SVM	82.49	85.60	80.14	81.38	84.73

Table 2: Average acc. achieved by combined base learner methods with bagging method.

	Datasets				
Methods	Camera	Laptop	Music	Radio	TV
NB+ Bagging	82.48	78.34	73.86	76.39	75.26
KNN+ Bagging	62.25	65.83	67.24	68.80	69.59
ME+ Bagging	81.68	**83.45**	81.18	80.13	76.89
SVM+ Bagging	81.89	75.55	74.36	76.23	75.35

Table 3: Avg. acc. achieved by combined base learner methods with boosting method.

	Datasets				
Methods	Camera	Laptop	Music	Radio	TV
NB+Boosting	83.12	84.86	82.76	83.28	82.80
KNN+Boosting	8034	85.83	81.36	82.68	81.36
ME+Boosting	84.82	87.75	83.48	83.98	83.14
SVM+Boosting	85.46	**88.58**	84.62	86.86	85.32

Table 4: Avg. acc. achieved by combined base learner methods with RS method.

	Datasets				
Methods	Camera	Laptop	Music	Radio	TV
NB+RS	82.80	84.29	81.96	83.80	83.98
KNN+RS	81.12	85.46	83.76	79.28	82.42
ME+RS	83.43	86.70	85.23	80.78	83.89
SVM+RS	84.36	87.24	85.98	86.23	**88.68**

The classifier performance is shown in figure 2 to 5. The figures have shown average accuracy, datasets and classification methods with ensemble methods. The figure 2 shows is NB represented by blue color, KNN represented by maroon color, ME represented by green color, and SVM represented by purple color. Figure 1 shows highest is 88.95% accuracy by ME algorithm with laptop dataset. Figure 2 shown is highest accuracy is 83.45% obtained by combined ME+Bagging classifies with laptop dataset. Figure 3 shown is highest accuracy is 88.58% obtained by combined SVM+Boosting classifies with laptop dataset. And the Figure 4 shown the highest accuracy is 88.68% obtained by combined SVM+RS classifies with TV dataset.

Finally, the best performance generated by Support Vector Machine and Maximum Entropy classifier ensemble method.

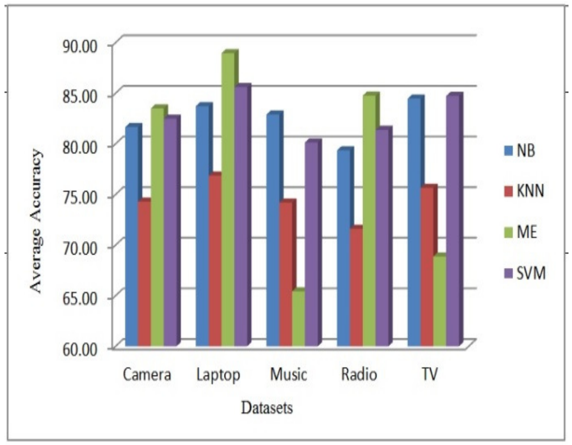

Fig. 2. Avg. acc. of individual machine learning algorithms.

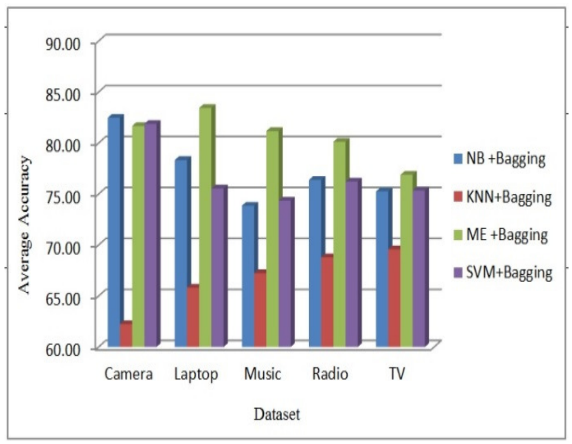

Fig. 3. Avg. acc. of machine learning method combined with bagging methods.

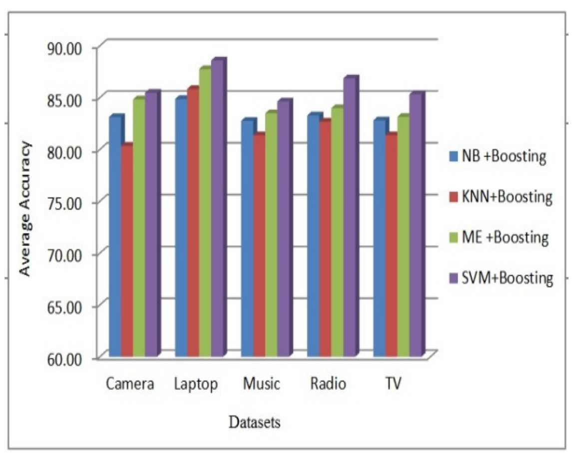

Fig. 4. Avg. acc. of machine learning method combined with boosting methods.

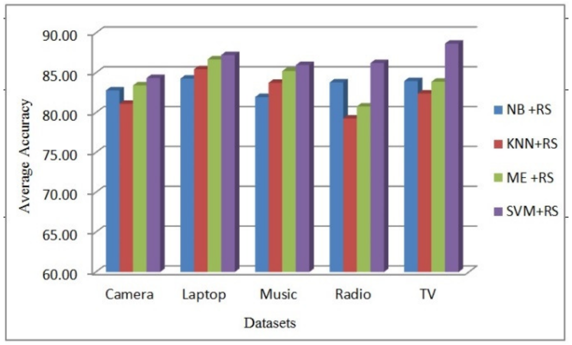

Fig. 5. Avg. acc. of machine learning method combined with RS methods.

E. Result discussion

The experiments include five machine learning classification algorithms NV, KNN, ME, and SVM performed individually and combined ensemble methods on review data sets. This study evaluated that well trained machine learning algorithm with ensemble methods to perform correctly classification on reviews sentiment analysis. The SVM+RS generated highest accuracy 88.68 on TV dataset. The SVM+Boosting generated highest accuracy 88.58 on laptop dataset. The ME+Bagging are generated highest accuracy 83.45 on laptop dataset. The ME individually generated highest accuracy 88.95 on laptop dataset.

Wang *et al.* [9] used machine learning as NB, ME, DT, KNN and SVM combined with ensemble methods as bagging, boosting, and random subspace. The authors compared performance of machine learning as well as ensemble methods used by different review data sets. The highest accuracies are achieved respectively as 80.86 by ME on camera data set, 85.48 by RS-SVM on camp data set, 85.97 by RS-SVM on doctor data set, 70.26 got by RS-SVM on drug data set, 92.62 by RS-ME on laptop data set, 84.09 by SVM on lawyer data set, 82.54 by RS-SVM on movie data set, 72.13 by RS SVM on music data set, 82.76 by ME on radio data set, 77.94 by SVM on tv data set.

Onan *et al.* [10] used adboost, bagging, dagging, random subspace, stacking, and StackingC along with NB, SVM, LR, BLR and LDA. The authors evaluated performance to applied above mentioned methods on review data sets. After experiments they obtained highest ACC respectively as 82.68% via Bagging+NB on camera data set, 85.31% via AdaBoost+NB on camp data set, 81.99% via Bagging+LDA on doctor data set, 81.26% via Bagging+NB on drug data set, 95% via AdaBoost+NB on laptop data set, 91.31% via Bagging+NB on lawyer data set, 79.98% via Bagging+LR on music datasets, 79.41% via RS+LDA on radio data set, and 85.14% via RS+NB on tv data set.

Ryu *et al*. [14] proposed this research for comparing performance of machine learning as well as ensemble methods. Authors used Naive Bayes, Decision tree, and Neural network combined with voting, adaboosting, and bagging. The experiments work performed on review data sets. After experiments the measures their performance accuracy trough F-measure and MCC score.

The author [15] planned this research for twitter data sets. They used ensemble classifier and lexicons to classified sentiments to twitter data. Authors also researched on feature representation techniques bag-of-words model and feature hashing technique and try to find out best technique among them. The experimental results presented SVM, MNB, RF, and LR performed with good accuracy on large amount of data sets. At last, they achieved uppermost accuracy is 79.11 via ensemble methods.

VII. CONCLUSION

The main objective of this research work is to discover performance of machine learning combined with ensemble learning. This research involved NB, KNN, ME, SVM as the base classifiers along with bagging, boosting, and random subspace as the ensemble methods. In experiments used online review data sets and found that the individually machine performed slow and with low accuracy than ensemble methods performed fast with high accuracy. The highest accuracy is 88.95% obtained individually by Maximum Entropy algorithm with the laptop dataset. The average accuracy is achieved of base learning algorithms with bagging ensemble method. The highest accuracy is 83.45% obtained by ME+Bagging with the laptop dataset. The average accuracy is achieved of base learning algorithms with boosting ensemble method. The highest accuracy is 88.58% obtained by SVM+Boosting with the laptop dataset. The average accuracy of base learning algorithms with Random subspace ensemble method. The highest accuracy is 88.68% obtained by SVM+Bagging with the TV dataset. We planned to extend this work to use more machine learning methods such as Neural Network, Logistic Regression, Decision Tree, Deep support Vector machine, Convolution Neural Networks, Linear Regression etc. on various sentiment analysis datasets.

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