International Journal of Engineering Applied Sciences and Technology, 2024
Vol. 8, Issue 12, ISSN No. 2455-2143, Pages 166-173
Published Online April 2024 in IJEAST (http://www.ijeast.com)

PERFORMANCE EVALUATION OF FEATURE EXTRACTION METHODS FOR OPINION CLASSIFICATION USING DIFFERENT MACHINE LEARNING CLASSIFIERS

Payal Jain
Govt. Holkar Science College, Indore-INDIA

Yasmin Shaikh
Assistant Professor (Senior Scale)
International Institute of Professional Studies, DAVV, Indore- INDIA

Sanjay Tanwani
Professor & Head,
School of Computer Science and IT DAVV, Indore-INDIA

Abstract: **Opinion mining, also known as sentiment analysis, pinion mining, or sentiment analysis, examines people's views, sentiments, reviews, attitudes, and emotions regarding various entities, including goods, services, organizations, people, issues, events, subjects, and their attributes. Sentiment analysis of social media is a methodical approach to gaining insight into the opinions of intended audience on product, brand image, services, and offerings. The Twitter API makes it possible to instantly gather enormous volumes of tweets about a certain subject. Opinion mining and social sensing may be carried out by doing sentiment analysis on these tweets. Twitter sentiment analysis has emerged as one of the most fascinating areas of study in recent years. It blends data mining methods with natural language processing techniques to create these kinds of systems. This paper present comprehensive overview of sentiment analysis technique based on recent research and subsequently explores machine learning (SVM, Navies Bayes, Logistic Regression and Random Forest) and feature extraction techniques available in Affective Tweet package of Weka (SentiScore Feature Vector, Embedding Feature Vector, and Lexicon Feature Vector) in context of Sentiment analysis over social media data set [1]. Further twitter data-sets are scrutinized and pre-processed with proposed framework, which yield intersecting facts about the capabilities and deficiency of sentiment analysis methods. Lexicon Feature Vector is most suitable feature extraction technique and SVM outperforms in almost all combinations.**

I. INTRODUCTION

Social media is a web-based technology that facilitates social interaction via networks amongst huge numbers of individuals. Twitter is one of the most popular micro blogging platforms. Various social media platforms, such as Twitter, LinkedIn, and Google+, are growing in popularity as they let users to send messages globally, engage in discussions with various groups, and share and express their opinions about many subjects [2]. Numerous studies have been conducted in the area of sentiment analysis using data from Twitter. Sentiment analysis and Twitter data categorization are useful tools for electronic text analysis.

Over the past decade, sentiment analysis of Twitter data has been popular in study. When it comes to sentiment analysis of Twitter data, there are more obstacles than there are in text categorization. The tweets are often casual, unorganized, and lack conventional vocabulary and grammatical soundness. However, tweets are typically annotated by their writers using emoticons and hashtags to convey their topic and attitude. The topic of identifying relevant characteristics for sentiment analysis of tweets is still open as text indexing techniques struggle with sparseness, while POS tagging techniques fall short since tweets lack grammatical structure. Due to their linguistic independence, character-based features—that is, n-grams of characters—are increasingly gaining popularity. Their efficacy is still quite modest, though. In this work, we contend that the finest feature set available for sentiment analysis of tweets is most likely the tokens used by people.

Sentiment analysis classifies the message according to their polarity whether it is positive, negative, or neutral. Recently researchers focused on lexical and machine-learning based method for sentiment analysis of social media post. Social media is a micro blogger site in which end users can post their comment in slag language that contains symbols, idioms, misspelled words and sarcastic sentences. Social media data also have curse of dimension problem i.e. high dimension nature of data that required specific pre-processing and feature extraction, which leads to improve classification accuracy [3].

The capacity of a computer programme to comprehend spoken and written human language is known as natural language processing, or NLP for short. It's a part of AI, or artificial intelligence. Sentiment analysis models concentrate on sentiments and emotions (angry, joyful, sad, etc.), urgency (urgent, not urgent), and even intents (interested vs. not interested), in addition to polarity (positive, negative, neutral). Sentiment analysis allows to assess customer satisfaction with different aspects of company without having to read through a lot of customer reviews at once.

When it comes to categorizing opinions, supervised learning has proven to be a very successful technique with encouraging outcomes. In sentiment analysis, supervised classification methods such as Support Vector Machine (SVM), Naïve Bayes (NB), Maximum Entropy (ME), Artificial Neural Network (NN), and Decision Tree (DT), Random Forest (RF), K-Nearest Neighbor (KNN), Bayesian Network (BN), and Logistic Regression (LR) classifiers are frequently employed. Feature extraction is a crucial stage before executing machine learning classification. Sentiment-based classification is much improved by an effective feature extraction technique.

In the present research, the labeled data is trained using three different unsupervised filter (SentiScore Feature Vector, Embedding Feature Vector, and Lexicon Feature Vector) and then the tweets are classified using four supervised classifier (BN, LR, SVM, RF). The input dataset is labeled (positive and negative) dataset taken from Internet. The rest of this research paper is organized as section 2 gives a brief description of related work. Section 3 presents the detailed methodology for sentiment analysis using base classifiers and filters. Section 4 contains the experimental analysis. Section 5 concludes the paper with future scope.

II. LITERATURE REVIEW

Sentiment analysis is a method of using a dataset that includes feelings, attitudes, or ratings that evaluate how people think. [4]. Support Vector Machines (SVM) algorithm, Naïve Bayes (NB) algorithm were utilized for sentiment analysis because of their good performance in text classification problems [5-6].

In [7], experiments utilized the Unigram, Bigram, and Trigram modes. According to the findings, the performance of Linear SVC, Perceptron, Passive Aggressive Classifier, and Logistic Regression is quite similar and can obtain more than 98% maximum accuracy score in classification (unigram, bigram, trigram).. The AdaBoost Classifier has the lowest average accuracy out of all the classifiers.

In [8], two datasets are used, the first one is a hand annotated dictionary for emoticons and second one is an acronym dictionary gathered from web. The approach uses different machine learning classifiers and feature extractors. Naive Bayes, Maximum Entropy (MaxEnt), and Support Vector Machines (SVM) are the machine learning classifiers combined with unigrams, bigrams, unigrams and bigrams, and unigrams with part of speech tags as the feature extractors. The results shows that the manually indicated tokens combined with a Decision Tree classifier outperform any other feature set-classification algorithm combination.

In [9] several features, including unigram, POS features, senti-features, and tree kernel model, were merged into their feature sets. SVM was utilised with several feature set combinations for the classification assignment. They used a set of 11,875 manually annotated tweets to test their proposed approach. Their findings showed that, at around 75.39%, the feature set comprising the unigram and senti-features had the best accuracy rate. The majority of machine learning-based sentiment analysis techniques that were demonstrated relied on a single classifier to complete the classification job. However, a new method called the classifier ensemble technique trains several classifiers and combines their results to answer a single classification task. By merging many classifiers, this strategy aimed to address some of the shortcomings of the individual classifiers and provide a generalised decision boundary for the classification input [10]. While there's no assurance that the classifier ensemble will perform better than the sum of its individual classifiers, in some situations it lowers the chance of choosing an ineffective classifier using unknown data [11].

Different base classifiers are utilised in each of the proposed classifier ensembles, and their judgements are combined in different ways. The majority voting ensemble, for instance, was employed in the studies of [12-13]. By using trained Naïve Bayes classifiers, employed the weighted voting ensemble [14]. A bootstrap model that integrated several datasets, features, and classifier parameters while utilising around six base classifiers was shown in [15].

In [15], three machine learning algorithms Naïve Bayse Maximum Entropy, and SVM were used with three feature extractor namely unigram, feature based model and tree kernel model. SVM in combination with feature based model outperformed all other combinations.

A collection of tools called AffectiveTweets is used to evaluate the mood and emotion of social media posts like tweets [1]. It offers techniques for determining cutting-edge affect analysis characteristics from tweets that can be fed into Weka's machine learning algorithms. It is developed as a package for the Weka machine learning workbench.

Sentiment, emotion, mood, and other associated mental processes are all included under the umbrella word "affect." Three categories of filters are offered by Affective Tweets: 1) Distant supervision filters; 2) Word-level filters; and 3) tweet-level filters.

2.1 Tweet-level filters

Tweet-level filters in the package operate on string characteristics that hold the text of tweets and compute features appropriate for additional processing using Weka's learning algorithms. The most recent systems have made extensive use of these properties [16–17]. The following are the tweet level filters: the embedding feature vector filter, the lexicon feature vector, the sentiStrength feature vector, and the sparse feature vector.

2.2 Word-level Filters

Users may create their own emotional lexicons using the word-level filters, and then use the Lexicon Feature Vector filter to compute tweet-level features. Among the word-level filters are the Tweet Centroid filter and the PMI Lexicon Expander filter.

2.3 Distant Supervision Filters

Heuristic labelling functions called distant supervision models are employed to automatically generate training data from unlabeled corpora. Because the Twitter API makes it simple to access a huge number of unlabeled tweets, these models have been frequently used for training affective models for tweets. A set of unlabeled tweets and an ARFF-formatted polarity dictionary comprising positive and negative terms are the inputs for the filters that are explained below. The Glossary Remote monitoring filter The filter ASA The filter PTCM

III. METHODOLOGY

Figure 1 presents a complete framework for sentiment analysis. The framework is primarily composed of five modules. The first module is data preprocessing module that collects and preprocesses tweet data. Features are extracted using three feature extraction filters from preprocessed date. The preprocessed Tweet datasets are then split into training and test datasets. In the next step we applied four classification techniques and evaluated four parameters. Below is a detailed discussion of the various modules.

3.1 Data Pre-processing

Two datasets are selected from Twitter. The first one is about mobile review and contains 2975 records after data cleaning and labeling. Out of 2975 records 1505 are labeled positive and 1470 are labeled negative. The second one is about restaurant review and contains 966 records after data cleaning and labeling. Out of 966 records 486 are labeled positive and 480 are labeled negative

Tweet Cleaning

Tweet data cleaning involves removing unicode strings and noise, replacing URLs, removing user mentions and hashtags, removing numbers, removing repetitions of punctuation, replacing negations with antonyms, lowercasing, replacing elongated words, and spelling correction.

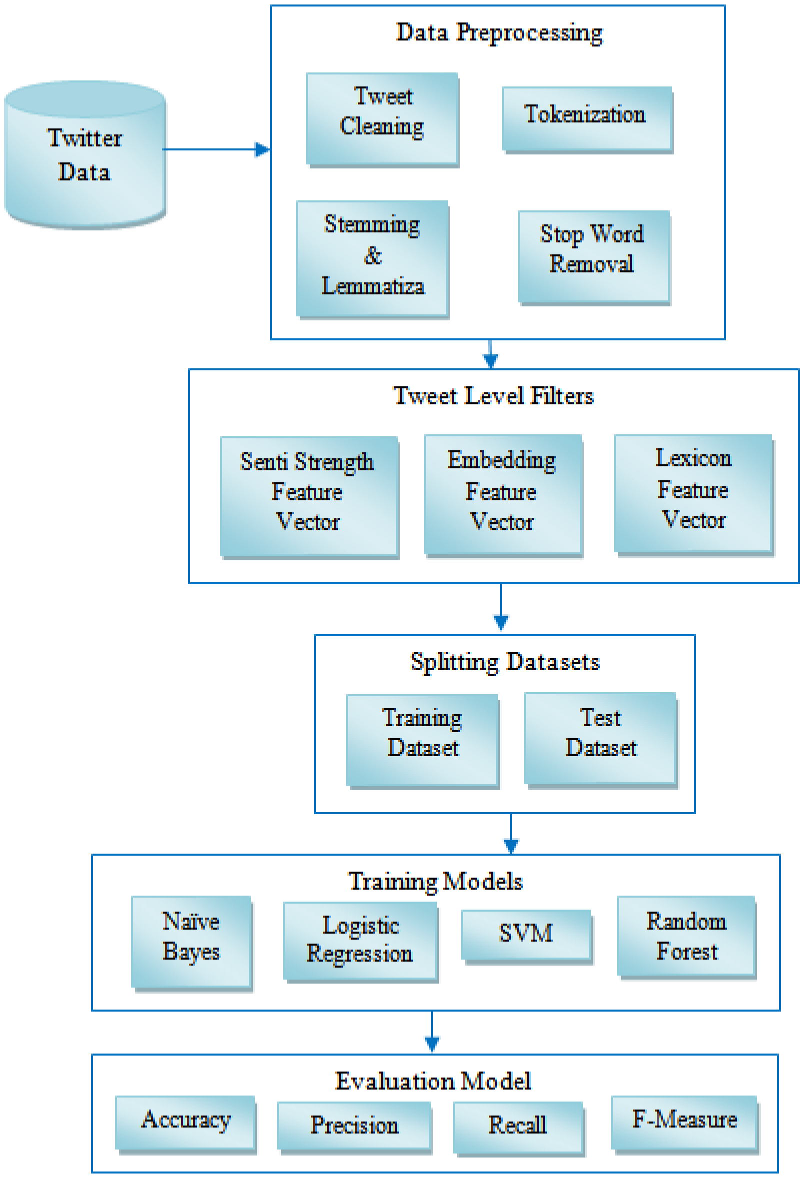
Tokenization

After data cleaning, the first step consisted of tokenizing the tweet text. Tokenizing the text is one of the first steps in most processes for natural language processing. In its most basic form, this involves dividing a text string into individual words,

Stop Word Removal

Stopwords are frequently used terms that could not contain much information and could be eliminated with little loss of information. Eliminating stopwords could enhance a natural language processing model's comprehension or precision.

International Journal of Engineering Applied Sciences and Technology, 2024
Vol. 8, Issue 12, ISSN No. 2455-2143, Pages 166-173
Published Online April 2024 in IJEAST (http://www.ijeast.com)



Stemming
By eliminating prefixes, suffixes, and infixes, stemming is the act of condensing inflected words into a single form (stem or root). The word roots are omitted during the stemming process. This makes it possible to identify terms with the same root that appear to be separate words. For instance, the comput roots of "computer," "computing," "computation," and "computes" are the same.

Lemmatization
The primary disadvantage of stemming is that it results in an ambiguous word representation. Meaningful words may or may not be returned by Stemmer. Lemmatization is used as a solution to this issue. The stemming algorithm eliminates any prefixes or suffixes from the word. Lemmatization, on the other hand, takes into account morphological analysis of the words and returns meaningful words in the correct form.

3.2 Data Splitting
Splitting a dataset into two or more subgroups is known as data splitting. The dataset is typically split into two sections: one is used to train the model and the other to assess or test the data. Weka does ten separate folds of data runs of the learning algorithm (training on nine folds and testing on the tenth) in a 10-fold cross-validation [18]. The learning method is then averaged to produce a performance evaluation, such as the number of properly categorised

cases. This is to make sure that testing on any of the training data will not taint the evaluation. For the evaluation of percentage split, Weka uses a similar process. Weka uses a similar process for evaluating percentage splits. By using a 66% split, it creates a model from two thirds of the dataset and tests it on the remaining third. Finally, it creates a final model from the entire dataset for further classification.

3.3 Tweet Level Filters

Lexicon Feature Vector Filter

Users can apply their own emotional lexicons in ARFF format to calculate features from a tweet using the Lexicon Feature Vector filter. The impact associations of the words that fit the provided lexicons are added or counted to determine the characteristics. Every nominal and numerical property from every lexicon is taken into account. Nominal labels are counted and numerical scores are applied [18].

SentiStrength Feature Vector

SentiStrength attribute Vector filter uses the SentiStrength lexicon-based approach to determine the positive and negative sentiment intensities for a tweet [19].

Embedding Feature Vector

Using pre-trained word embeddings, or word vectors, the Embedding Feature Vector filter computes a tweet-level feature representation by applying one of three aggregation schemes: concatenation of the first k word embeddings in the tweet, addition of word embeddings, or average of word embeddings. When using the WekaDeeplearning4j package to train deep neural networks, the concatenation approach is appropriate [20].

3.4 Machine learning approach

Instead of relying on manually created rules, machine learning approaches use machine learning processes. Typically, a sentiment analysis job is treated as a classification problem, in which a text dataset is fed into the classifier, which outputs a class—such as positive, negative, or neutral [21]. The machine learning models that are most frequently employed for text classification are taken into consideration first for analysis because of their straightforward methodology and rather linear approach to data categorization. The classifiers such as Naïve Bayes, KNN, SVM and Decision Tree are considered.

Naive Bayes (NB)

The Naive Bayes algorithm is one of the intuitive methods among classification algorithms. It is a simple algorithm that makes use of the probability of every feature per category to get respective predictions. This algorithm runs great for the categorization of textual data. It is based on the Bayes Theorem which is used to describe the probability of an event based on its prior knowledge [22].

Support Vector Machine (SVM)

Supervised machine learning algorithms such as SVM examines data and identifies patterns utilized for categorization. SVM possesses the ability to identify separate hyperplanes which helps in maximizing the margin between the various classes [23]. The methodology for classifying using the SVM algorithm starts by transforming text data into weights. These weights are frequently fused to form TF-IDF values, by just multiplying them collectively.

Random Forest (RF)

A classifier called Random Forest is made up of several tree-based structures. It can handle hundreds of input variables and operates effectively on a huge dataset [24]. Estimates of the variables that matter in the categorization are also provided. The over fitting of data points may also be handled with this technique. The typical process for creating a Random Forest classifier for a dataset D that has N instances and A attributes is as follows.

A subset of the dataset D, d, is sampled with replacement serving as the training dataset for each iteration of the building process to create a candidate Decision Tree. An arbitrary subset of the attributes A, a, is chosen as the candidate attributes to divide a node in a decision tree for each node.

Logistic Regression (RF)

An approach for classification based on probability is called logistic regression [24]. The logistic function provides an output with a probability score between 0 and 1 when a specific amount of input passes through it. This method operates on more complicated cost functions, such as the logistic and sigmoid functions.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

Multiple metrics were employed to assess the effectiveness of this study, including accuracy, precision, recall, and F1-Score. Two Twitter data sets containing product reviews and restaurant reviews are used for this experiment. Thus, these metrics have been applied to assess the significance and insignificance of the features that were extracted. The accuracy criterion displays the percentage of successfully identified instances in the entire dataset. It facilitates the evaluation of the classifier's overall performance. For unbalanced datasets, the accuracy criterion is insufficient, nevertheless. Recall and precision criteria can be applied in this case. Precision is the ratio of the number of positively predicted true positive cases to the total number of instances that are expected to be positive, whereas recall is the ratio of the number of correctly classified positive examples to the entire number of positive instances. F-measure uses harmonic averages to integrate recall and precision requirements.

International Journal of Engineering Applied Sciences and Technology, 2024
Vol. 8, Issue 12, ISSN No. 2455-2143, Pages 166-173
Published Online April 2024 in IJEAST (http://www.ijeast.com)

4.1 Sentiment Analysis Results for Dataset -1

The objective of this experiment is to find out which tweet level filter achieves highest accuracy with higher values of precision, recall, and F-measure. The Table 1 shows the performance of combination of different tweet level filters with different machine learning classifiers for dataset-1. It is evident from the results that lexicon feature vector achieves highest accuracy with all the classifiers applied in the experiment. There is not much difference in the accuracy percentage of LR, SVM, and RF but NB gives comparatively less accuracy. Figure 2 gives graphical representation of performance analysis results for dataset-1.

Table 1: Performance Analysis for Dataset-1

	Senti Strength Feature Vector				**Embedding Feature Vector**				**Lexicon Feature Vector**			
Classifier	**Accuracy**	**Precision**	**Recall**	**F-Measure**	**Accuracy**	**Precision**	**Recall**	**F-Measure**	**Accuracy**	**Precision**	**Recall**	**F-Measure**
NB	77.27	0.777	0.773	0.772	70.05	0.71	0.71	0.698	**82.72**	**0.829**	**0.827**	**0.827**
LR	77.56	0.779	0.775	0.775	78.55	0.786	0.786	0.789	**85.04**	**0.851**	**0.85**	**0.85**
SVM	77.57	0.779	0.776	0.775	80.26	0.803	0.803	0.803	**85.37**	**0.854**	**0.854**	**0.854**
RF	74.75	0.748	0.748	0.748	76.2	0.763	0.762	0.762	**85.17**	**0.82**	**0.852**	**0.852**

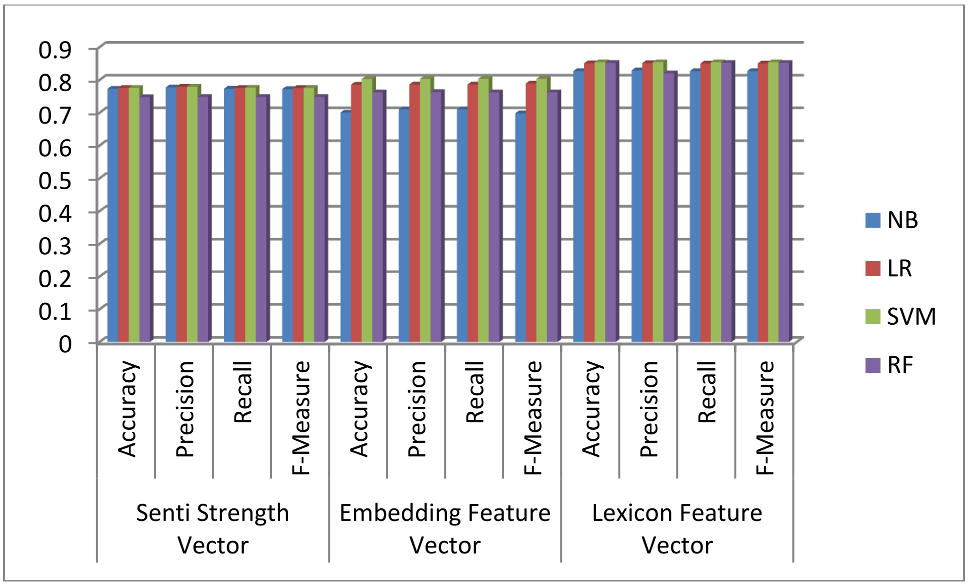


Figure 1: Performance of Different Tweet Level Filters with Different Classifiers for Dataset-1

1.1. Sentiment Analysis Results for Dataset-2

The Table 2 shows the performance of combination of different tweet level filters with different machine learning classifiers for dataset-2. Again, it is evident from the results that lexicon feature vector achieves highest accuracy with all the classifiers applied in the experiment. There is not much difference in the accuracy percentage of LR, SVM, and RF but NB gives comparatively less accuracy. Figure 3 gives graphical representation of performance analysis results for dataset-2.

International Journal of Engineering Applied Sciences and Technology, 2024
Vol. 8, Issue 12, ISSN No. 2455-2143, Pages 166-173
Published Online April 2024 in IJEAST (http://www.ijeast.com)

Table 2: Performance Analysis for Dataset-2

	Senti Strength Feature Vector				Embedding Feature Vector				Lexicon Feature Vector			
Classifier	**Accuracy**	**Precision**	**Recall**	**F-Measure**	**Accuracy**	**Precision**	**Recall**	**F-Measure**	**Accuracy**	**Precision**	**Recall**	**F-Measure**
NB	78.53	0.781	0.781	0.781	70.08	0.703	0.701	0.7	**81.15**	**0.82**	**0.812**	**0.81**
LR	78.26	0.783	0.783	0.783	77.12	0.772	0.771	0.771	**85.19**	**0.852**	**0.852**	**0.852**
SVM	78.26	0.783	0.783	0.783	80.64	0.807	0.806	0.806	**85.19**	**0.82**	**0.852**	**0.852**
RF	75.98	0.76	0.76	0.76	75.67	0.758	0.757	0.756	**85.5072**	**0.855**	**0.855**	**0.855**

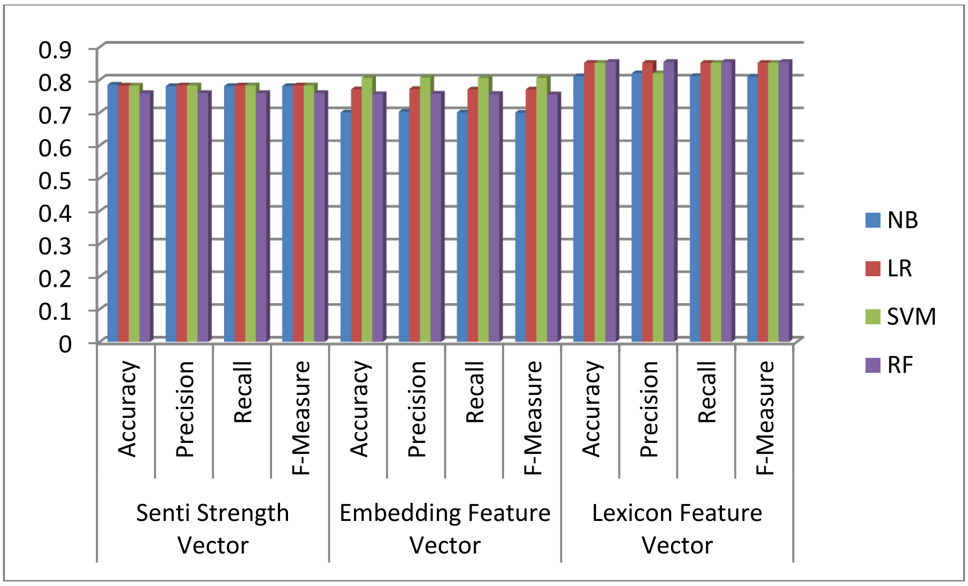


Figure 2: Performance of Different Tweet Level Filters with Different Classifiers for Dataset-2

V. CONCLUSIONS

This paper provides a thorough introduction to sentiment analysis, drawing on current research and examining machine learning and feature extraction methods found in Weka's Affective Tweet package for analyzing sentiment across social media data sets. For this work, two Twitter data sets with reviews of restaurants and products are employed. Four measures are used to assess the results: accuracy, precision, recall, and F1-Score. The best feature extraction method is Lexicon Feature Vector, whereas SVM performs better in practically all scenarios. The combination of Random Forest and Lexicon Feature Vector outperforms all the combination with more than 85% accuracy, precision, recall, and F1-Score. The work can be extended by applying other supervised and unsupervised filters for text data and evaluating their performance on base classifiers as well as deep learning models.

Conflict of Interest: There is no conflict of interest.

REFERENCES

[1] F. Bravo-Marquez, E. Frank, B. Pfahringer, and S. M. Mohammad AffectiveTweets: a WEKA Package for Analyzing Affect in Tweets, In Journal of Machine Learning Research Volume 20(92), pages 1−6, 2019.

[2] Vishal A. Kharde, S.S. Sonawane, Sentiment Analysis of Twitter Data, International Journal of Computer Applications (0975 – 8887) Volume 139 – No.11, April 2016.

[3] Singh, N.K., Tomar, D.S. & Sangaiah, A.K. Sentiment analysis: a review and comparative analysis over social media. J Ambient Intell Human Comput **11**, 97–117 (2020). https://doi.org/10.1007/s12652-018-0862-8.

[4] R. Feldman, " Techniques and Applications for

Sentiment Analysis," Communications of the ACM, Vol. 56 No. 4, pp. 82-89, 2013.

[5] Mohammad, S., Kiritchenko, S., Zhu, X.: NRC-Canada: building the state-of-the-art in sentiment analysis of tweets. In: Proceedings of the Seventh International Workshop on Semantic Evaluation Exercises (SemEval-2013), Atlanta, GA, USA (2013).

[6] Saif, H., He, Y., Alani, H.: Semantic sentiment analysis of twitter. In: Proceedings of the 11th International Conference on the Semantic Web (ISWC 2012), Berlin, Heidelberg 2012.

[7] Kuncheva, L.: Combining Pattern Classifiers: Methods and Algorithms, 2nd edn. Wiley, New York 2014.

[8] Apoorv Agarwal, Boyi Xie, Ilia Vovsha, Owen Rambow, Rebecca Passonneau, "Sentiment Analysis of Twitter Data" Department of Computer Science, Columbia University, New York, 2009.

[9] Agrawal, A., Xie, B., Vovsha, I., Rambow, O., Passonneau, P.: Sentiment analysis of twitter data. In: Proceedings of the Workshop on Languages in Social Media (LSM 2011), Stroudsburg, PA, USA 2011.

[10] Gulati, K., Kumar, S. S., Boddu, R. S. K., Sarvakar, K., Sharma, D. K., & Nomani, M. Z. M. (2022). Comparative analysis of machine learning-based classification models using sentiment classification of tweets related to COVID-19 pandemic. Materials Today: Proceedings, 51, 38-41.

[11] Fumera, G., Roli, F.: A theoretical and experimental analysis of linear combiners for multiple classifier systems. IEEE Trans. Pattern Anal. Mach. Intell. **27**(6), 942–956 (2005)

[12] Lin, J., Kolsz, A.: Large-scale machine learning at twitter. In: Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data (SIGMOD 2012), New York,NY, USA (2012).

[13] Rodríguez-Penagos, C., Atserias, J., Codina-Filba, J., Garcıa-Narbona, D., Grivolla, J., Lambert, P., Saur, R.: FBM: combining lexicon-based ML and heuristics for social media polarities. In: Proceedings of the Seventh International Workshop on Semantic Evaluation, Atlanta, GA, USA (2013)

[14] Clark, S., Wicentwoski, R.: SwatCS: combining simple classifiers with estimated accuracy. In: Proceedings of the Seventh International Workshop on Semantic Evaluation, Atlanta, GA,USA (2013

[15] Hassan, A., Abbasi, A., Zeng, D.: Twitter sentiment analysis: a bootstrap ensemble framework. In: The International Conference on Social Computing (SocialCom), Alexandria, VA (2013).

[16] Svetlana Kiritchenko, Xiaodan Zhu, and Saif M Mohammad. Sentiment analysis of short informal texts. Journal of Artificial Intelligence Research, 50:723–762, 2014.

[17] Saif M. Mohammad, Felipe Bravo-Marquez, Mohammad Salameh, and Svetlana Kiritchenko. Semeval-2018 Task 1: Affect in tweets. In Proceedings of International Workshop on Semantic Evaluation (SemEval-2018), 2018

[18] Eibe Frank, Mark A. Hall, and Ian H. Witten (2016). The WEKA Workbench. Online Appendix for "Data Mining: Practical Machine Learning Tools and Techniques", Morgan Kaufmann, Fourth Edition, 2016

[19] Mike Thelwall, Kevan Buckley, and Georgios Paltoglou. Sentiment strength detection for the social web. Journal of the American Society for Information Science and Technology, 63(1):163–173, 2012.

[20] Steven Lang, Felipe Bravo-Marquez, Christopher Beckham, Mark Hall, and Eibe Frank. Wekadeeplearning4j: A deep learning package for weka based on deeplearning4j. Knowledge-Based Systems, 2019.

[21] Aless.ia D'Andrea, Fernan.do Ferri, Pat.rizia Grifoni, Tiz.iana Guzzo Approaches, Tools and Applications for Sentiment Analysis Implementation, International Journal of Computer Applications, 125 (2015), pp. 26-33

[22] B. Pang, L. Lee, S. Vaithyanathan Thumbs up?: sentiment classification using machine learning techniques Proceedings of the ACL-02 conference on Empirical methods in natural language processing, EMNLP '02, ACL (2002), pp. 79-86

[23] Rawal G., Rawal R., Shah H., Patel K. (2020) A Comparative Study Between Artificial Neural Networks and Conventional Classifiers for Predicting Diagnosis of Breast Cancer. In: Kumar A., Paprzycki M., Gunjan V. (eds) ICDSMLA 2019. Lecture Notes in Electrical Engineering, vol 601. Springer, Singapore.

[24] Sarker, A., Zaman, M. S. U., & Srizon, M. A. Y. (2019). Twitter data classification by applying and comparing multiple machine learning techniques. International Journal of Innovative Research in Computer Science & Technology (IJIRCST) ISSN, 2347-5552.