JOURNAL PUNJAB ACADEMY OF SCIENCES (Peer Reviewed Open Access Journal)
JPAS, 23: 85-94 (January-December, 2023)
Available online at www.jpas.in
ISSN 2229-7014 (P)

EMOTION RECOGNITION USING TWITTER DATA: AN ENSEMBLE MACHINE LEARNING TECHNIQUE

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ABSTRACT

Due to the expansion of world of the internet and the quick acceptance of platforms for social media, information is now able to exchange in ways never previously imagined in history of mankind. A social networking site like Twitter offers a forum where people may interact, discuss, as well as respond to specific issues via short entries, like tweets of 140 characters and fewer. Users may engage by utilizing the comment, like and share tabs on texts, videos, images and other content. Although platforms for social media are now so extensively utilized, individuals are creating as well as sharing so much information than shared before, which can be incorrect or unconnected to reality. It is difficult to identify erroneous or inaccurate statements in textual content autonomously and find emotions of people. In this paper, we suggest an Ensemble method for sentiment and emotion analysis. Different textual features of actual and Emotion and sentiment have been utilized. We used a publicly accessible dataset of twitter sentiment analysis that included total 48,247 authenticated tweets out of 23,947 of which were authentic positive texts labelled as binary 0s and 24,300 of which were negative texts labelled as binary 1s. In order to assess our approach, we used well-known (ML) machine learning models such as Logistic Regression (LR), Decision Tree (DT), AdaBoost, SGD, XG-Boost, and Naive Bayes. In order to get more accurate findings, we created a multi-model sentiment and emotion analysing system utilizing the ensemble approach and the classifiers stated above. Our recommended ensemble learner method outperforms individual learners, according to an experimental study.

Keywords: Emotion recognition, Sentiment analysis, Machine learning (ML), Social media, NLP, Ensemble.

INTRODUCTION

The essential phase in performing emotion analysis is categorizing retrieved data distinct emotion polarity like negative and positive classifications. A variety of emotions may be examined, becoming the subject of the growing disciplines of effective computer vision and text analytics. It has other ways that split feelings based on study subjects. For instance, in political discussions, sentiments or emotions might be classified into angry and satisfied and furious. Text analytics with ambiguous handling may be used to provide for extremely fine outcomes and Sentiment classification is undoubtedly the most frequently used text-ordering tool.

This really is analogous to beginning to uncover what's beneath and giving up the high-value information that is completely buried. So how would a novice approach the lesser fruit? As just a result, text processing algorithms are more adaptable (Imran, A. S. 2020, Pardeshi, S.M. 2021).

Wenyu C and colleagues define Recognition system is a subfield of sentiment classification that deals also with evaluation and extraction of emotions. With the emergence of web technologies, text categorization and analysis have risen to the top of organizational performance (Wenyu, C. A. 2020, Lexalytics. 2023).

Aykuth uven et al. state the smart technologies used during everyday life defined as a comprehensive on the customers via sensors linked to it. Data collected is primarily physical information, but applications capture much more, including system resource trends as well as personal preferences (David, 2019). Syal Varun et al. address the problem of recognizing, categorizing, and measuring moods within text almost in any format. It consider English language into consideration. Identifying and categorizing fundamentalist tweets really a contentious issue (Salminen, J. 2023).

Table 2 signifies authenticated metadata represents approach used like text based or other, corpus dataset links, social media platform used like twitter or other and states of emotion-sentiment by researchers. Emotion assessment in the text, as defined by Khaled Shaalan et al. is a relatively new topic in sentiment classification. Emotion evaluation is the method of analysing and classifying a message through group based on prior research using feelings qualitative models presented in psychology theory. To recognize emotional states inside writing, emotion evaluation and categorization are utilized (Salloum, Said A. 2017).

RELATED WORK

Figure 1 represents collected dataset of total 48,247 authenticated tweets segmented into positive and negative tweets. Binary 1 consider for positive tweets and binary 0 for negative tweets. After segmentation identified 23,947 are positive tweets and 24,300 are negative tweets (Nemes, L. 2021, Pardeshi, S. M. 2022).

Pre-processing of data in order to better handle the unbalanced data increased the performance of these algorithms (Dharmaraj. 2022, Wang, Y. 2018). Nordberg, P., et al. developed critical methodologies for automated emotion detection in order to provide the framework for an end-user support system designed to help consumers identify as well as prevent false news (Salminen, J. 2023, Al-Emran, M. N. H. 2019). For dataset, Ashraf, N. et al. developed many classifiers utilizing ML algorithms for the objectives of new allegation and subject categorization (Ahmad, S. 2022, Al-Emran, M. 2018). Perez Rosas, et al. focused on the classification of false material automatically through social media. To identify emotions, they offered two more datasets spanning seven unique news categories (Gaind, B. 2018, Irfan, R. 2019).

Text mining seems to be a machine intelligence technique that distinguishes between right and wrong lexical objects such as words or phrases and revises them into new concepts. Text analytics is a subfield of extracting information, machine learning methods, retrieval of information and semantics. The volume of published information has expanded considerably since the advent of social networking sites and it continues to grow on a routine basis. People interact digitally by interpersonal conversation, creating or transferring multimedia learning assets via digital streaming platforms, participating in providing ratings, comments and evaluations in blogging and recommender systems (Wang, Y., 2018, Acheampong, F. A. 2020).

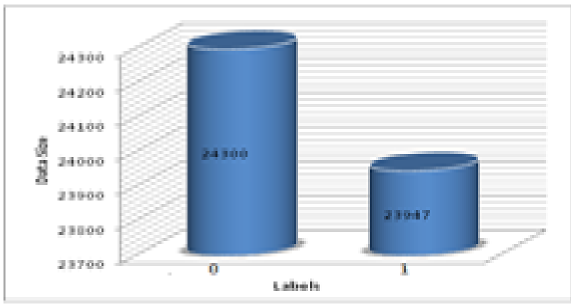


Fig. 1: Visualization of positive and negative texts available in dataset contains 23,947 are positive tweets and 24,300 are negative tweets.

MATERIALS AND METHODS

It is difficult to directly develop machine learning models using real-world data since it frequently contains noise, insufficient data, & may be in an unfavorable format. Preparing the data for a machine-learning (ML) model by cleaning it is important in order to increase the model's precision and efficiency (David. 2019, García, S. A. 2020).

A. 1) Feature Extraction

The extracted features include TF-IDF weights and CountVectorizer. The extracted features are subsequently sent with the edited text.

2) TF_IDF Features

The abbreviation Term Frequency is referred as TF and IDF Document Frequency Inverse. This method analyzes the number of words within a collection of information to quantify a word's significance to the document and corpus, a score is often assigned to it. This method is frequently used in purposes for retrieving data and analysis of texts. The information can then be vectorized, which allows us to carry out additional operations like ranking, clustering and locating the pertinent documents.

$$TF\text{-}IDF = TF(t, d) * IDF(t) \tag{1}$$

Whereas t is number of times term appears in doc d. Term frequency-inverse document frequency, or TF-IDF, is a statistical metric that evaluates a word's relevance to an article within a group of texts. To do this, along a document's word intensity as well as variational document group of documents are multiplied. We need to determine the length of the document and how many word each vocabulary phrase has in order to compute TF. The TF value for a particular document will be zero if the word is missing from it. If the manuscript solely contains similar words, the worst-case situation is that TF will be 1. The final value of the normalized TF value will lie in the range [0, 1] among 0 and 1 (Liu, X. 2016).

Every document and word has its own TF, thus we can define it as below:

$$tf(t,d) = \text{count of } t \text{ in } d \,/\, \text{number of words in } d$$

3) Count Vectorizer Features

Text must be analyzed to eliminate certain terms before it can be used for predictive modeling; this procedure is known as tokenization. These words must then be encoded as integers or floating-point values so that they can be used as input data in machine learning techniques. This method is referred to as feature extraction (Kilimci, Z. H., 2019, Al-Emran, 2018).

B. Emotions and Sentiment Analysis using Machine Learning Classifiers

Decision Tree (DT), XG-Boost (XGB), Extra Trees (ET), Random Forest (RF), AdaBoost (AB), Logistic Regression (LR), Stochastic Gradient Descent (SGD), Support Vector Machine (SVM) and Naive Bayes were the nine machine learning classifiers whose performance we evaluated for the detection of Emotion and sentiment (NB). We designed a multi-model classification model using these nine machine learning classifiers, with ensemble methods being the deciding factor. Each classifier was implemented in Python using the scikit-learn library (Al-Emran, 2018). Each classifier is discussed briefly below.

1) Emotions and Sentiment Analysis Using Machine Learning Ensemble Methods

a) Ensemble Voting Classifiers

Due to its ability to combine two or more learning approaches that have been trained on the Complexity whole dataset, voting ensemble is typically used for classification tasks (Dong, X. 2022). Each model makes a prediction for a hypothetical sample of data, and this prediction is regarded as a "vote" in favor of a class chosen by the framework. Following the prediction of each model, the final predictions are based upon that majority of votes for a particular class (Al-Emran, M., 2019). Voting collective algorithms are easier to implement than boosting & bagging. As previously discussed, bagging algorithms generate a number of datasets at random sampling and replacing all of the dataset's data. A model is then trained using each dataset, and the outcome is an amalgamation of the results from every model. A generic model which can accurately classify the issue is created in the instance of boosting by developing a number of models successively, each one learning from the one before it by enhancing weights for points that were incorrectly categorized (Alfaro, C., 2021, Tsytsarau, M., 2022). Voting ensemble, in contrast, combines a number of distinct models to produce classification results that agree with the majority's overall prediction. In this case, it breaks down a conceptual framework in to the two or more sub-models. There are five in total. The ensemble technique is used to incorporate predictions from each sub-model. It is a meta-classifier that, through a majority vote, determines whether two machine learning classifiers are conceptually equivalent or dissimilar. We use ensemble technique to predict last class name, that corresponds to the categorical variable has categorization methods frequently forecast.. We predicted the class label y using formula and also the majority vote of the each classification model Cj (Wong. 2016, Wang, Y., 2018).

b) Decision Tree (DT)

One of the categorization techniques that is most frequently used is tree-based modeling. It is quite effective and also has classification accuracy that is equivalent to different learning strategies. The tree of decisions has structure that represents knowledge-based classification algorithm. It uses a classification of decision trees paradigm that is simple to understand. The approach assesses each practical data divides test as well as selects the one the particular that provides the most new knowledge (Berry Michael, W. 2004).

c) Boosting Ensemble Classifiers

Another well-liked ensemble method for converting ineffective models into effective learners is boosting. The final prediction is based on the outcomes of the majority vote of each tree in a forest of randomized trees that has been educated for that purpose. This strategy enables poor learners to incrementally and correctly identify data points that are typically misclassified. To categorize a specific issue, initial equally weighted coefficients are applied to all data points. The weighted coefficients change in the subsequent rounds, going up in order to properly categorized data points & down for ones that were misclassified (Kumari, S. 2021). Each successive tree created in a round gains knowledge by properly identifying data points that have been incorrectly classified in earlier rounds, hence reducing the errors from previous round and improving overall accuracy. Over fitting to the training data, which can result in inaccurate predictions for cases that have not yet been observed, is a significant issue with boosting ensemble (Robinson, R., 2018). There are numerous boosting techniques for solving categorization and issues with regression. For purpose of classification in our trials, we employed the AdaBoost and XGBoost (Dong. 2023) algorithms.

d) Logistic Regression (LR)

A logistic regression (LR) approach is utilized because it offers the straightforward algorithm to categorize challenges into basic or multiple groups because it allows for categorizing content using an extensive feature collection that produces an outcome as binary (true, incorrect or true article) (Alfaro, C., 2021). While several parameters were tested before obtaining the maximum levels of We performed parametric tuning in order to acquire optimal result for every piece of dataset so as to improve performance from the LR model.

e) Stochastic Gradient Descent

The stochastic gradient descent (SGD) technique is a simple but powerful way to adapt linear classifiers & regressors under convex loss functions, such as those used by (linear) Support Vector Machines and Logistic Regression. SGD has been around for a while in the field of machine learning, but it has only lately gained a lot of traction in relation to massive computing. Large-scale as well as unstructured algorithms issues, which frequently arise in text classification and text mining, have been effectively addressed using SGD (Al-Emran, 2018). In essence, the SGD algorithm uses a simple SGD method of learning that supports different classification loss functions and penalties. Scikit-learn provides the SGDClassifier module to perform SGD classification modul (Berry Michael, W. 2004).

f) Voting Ensemble Classifiers

Due to its ability to combine two or more learning approaches that have been trained on the Complexity 5 full dataset, voting ensemble is typically employed for classification tasks (Pérez-Rosas, V. 2017). Each model forecasts a result for a sample of data points, and this outcome is regarded as a "vote" in favour of the class that the system has forecast. The resultant prognostication is made a majority vote in favour of a class after early technique has predicted the outcome (Qian, L. 2022). Comparing voting ensemble to bagging & boosting algorithms, the former is easier to implement. As was mentioned, bagging algorithms produce several datasets at random selecting and updating all of the dataset's data. A model is then trained using each dataset, and the outcome is an amalgamation of the results between each model. In the instances of boosting, various models receive training sequentially whereas each model is trained from the prior by raising weights for the incorrectly categorized data, establishing a general model that is capable to categorize the issue appropriately (García, S. A. 2020).

C. Performance Metrics

To analyze the effectiveness of the algorithms, we used a variety of measures. The majority of them are built upon the confusion-matrix. A classification model's effectiveness on a testing sample with four variables true positive, false positive, false negative and true negative is displayed a table called the confusion matrix.

1) System evaluation and experimental results

A total of 48,247 verified tweets were gathered and split into good and negative tweets. Consider using binary 1 for positive tweets as well as binary 0 for negative tweets. After segmentation, 23,947 positive tweets and 24,300 negative tweets were discovered. The classifiers split the dataset into training and testing halves in an 80:20 ratio (Tsytsarau, M. 2022).

a) Metrics of Evaluation

Since that we are developing a system for classification in this case, a prediction of true for an item that was actually false (a false positive) can have adverse impacts. In the majority of instances, an excellent accuracy rating suggests that the model is effective. In a similar vein a prediction of false for an article that contains factual information can undermine trust.) As a result, we have utilized three additional metrics precision, recall, and F1-score that account for the wrongly classified observation (Salminen, J. 2023). At below equations TP is True Positive, TN is True Negative, FP is False Positive and FN is False Negative.

Accuracy = (TP+TN)/(TP+FP+FN+TN)

Precision = TP/(TP+FP)

Recall = TP/(TP+FN)

F1 Score = 2*(Recall * Precision)/ (Recall +precision)

2) Classifier Performance Evaluation Using the Emotion Dataset

The accuracy, precision, recall, and F1-score of the classifier on the Kaggle Emotion and sentiment dataset are shown in Table 1 and Fig. 2.

The Tree of Decision (DT) classifier achieved 66.18 % accuracy, 71 % precision, 66 % recall, and 74% on the F1 scale. The accuracy, precision, recall, and F1-score of the Linear Regression (LR) classifier were 85.4 %, 85 %, 85%, and 85 % respectively [22].

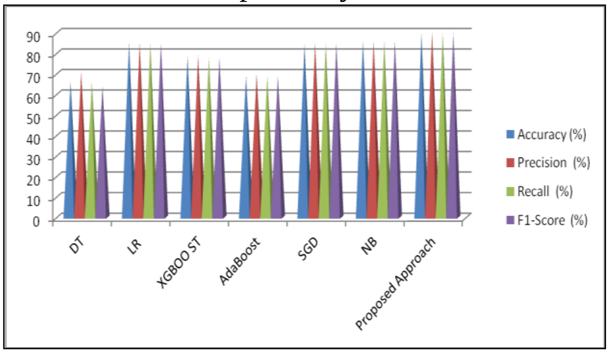


Fig. 2: Analysis of classifier performance on dataset

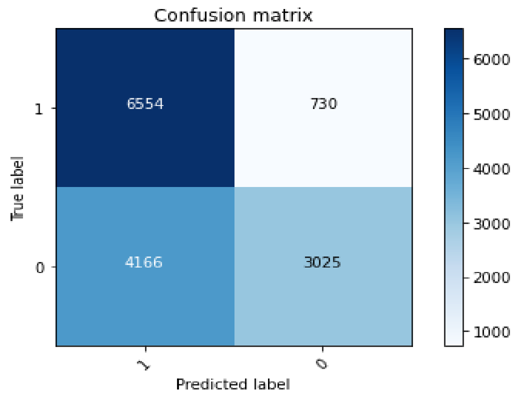
TABLE I. CLASSIFIER PERFORMANCE EVALUATION USING THE TWITTER SENTIMENT DATASET

	DT	LR	XG-BOOST	Ada-Boost	SGD	NB	Proposed Approach

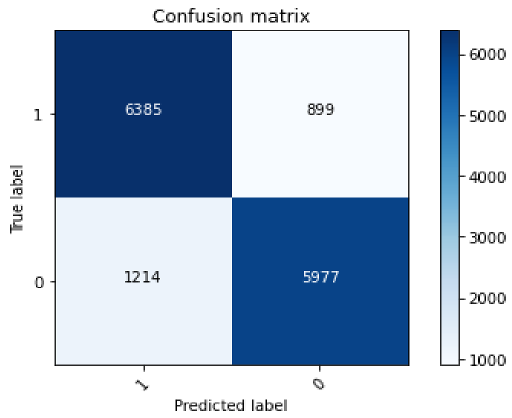
Accuracy (%)	66.18	85.4	78.43	69.05	84.64	86.11	**89.89**
Precision (%)	71	85	79	70	85	86	**90**
Recall (%)	66	85	78	69	85	86	**90**
F1-Score (%)	64	85	78	69	85	86	**90**

A 78.43 % accuracy, 79 % precision, 78 % recall, and 78 % F1-score were attained by the XGBoost classifier. The AdaBoost classifier achieved 69.05 % accuracy, 70% precision, 69% recall, and 69% F1-score.The Stochastic Gradient Decent (SGD) classifier achieved 84.64 % accuracy, 85 % precision, 85 % recall, and 85 % F1-score.The Naive Bayes (NB) classifier achieved an F1-score of 86.11 %, accuracy of 86 %, precision of 86 %, and recall of 86 % .

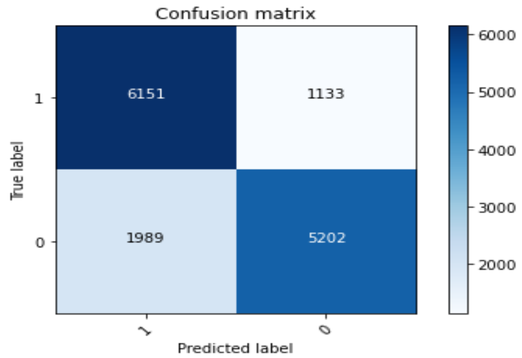
Our proposed multi-model classifier, which relies on ensemble technique, achieved 89.89% accuracy, 90% precision, 90% recall, and 90% F1-score. In comparison to the aforementioned classifiers, it was discovered that our proposed approach produced results that were more accurate and stable (Al-Emran, M. N. H. 2019). An method's efficacy in the area for learning by machine, especially the difficulty with respect to statistical categorization, can be visualized using a particular table structure known as a matrix of confusion, also known as an error matrix. The Confusion Matrix for the following methods is shown in figure 3: (i) the Decision Tree (DT), (ii) logarithmic regression (LR), (iii) X G Boost (XGB), (iv) the AdaBoost (AB), (v) the stochastic gradient descent (SGD), (vi) naive Bayesian (NB), and (vii) suggested technique via collective technique [26, 35].



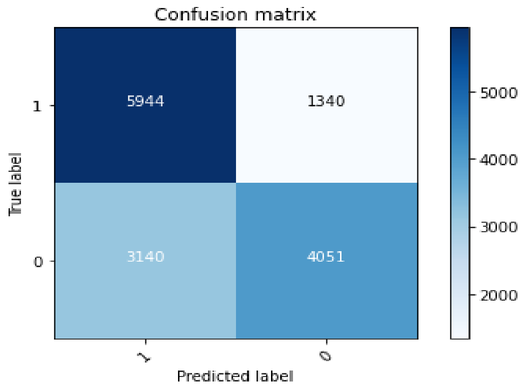
(i) Decision Tree



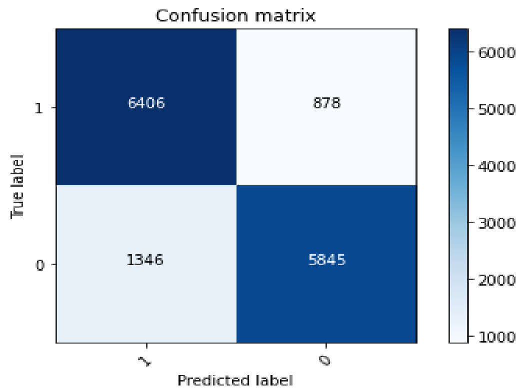
(ii) Logistic Regression



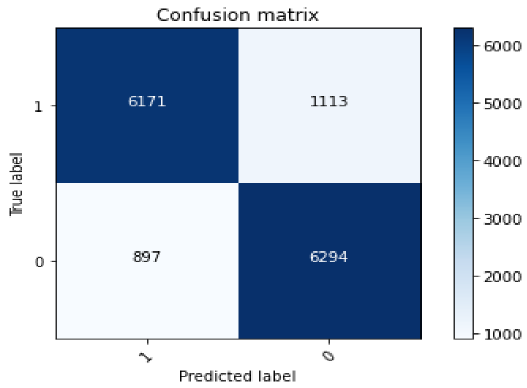
(iii) XGBOOST



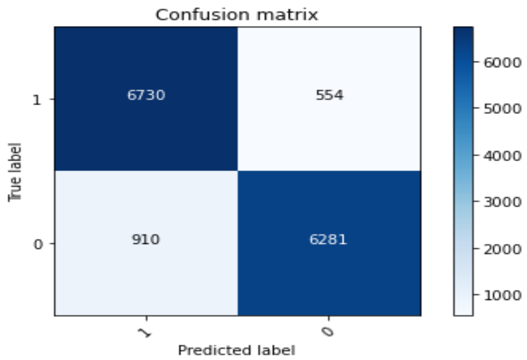
(iv) AdaBoost



(v) SGD Classifier



(vi) Naive Bayes Classifier



(vii) Recommended approach using ensemble method

Fig. 3: Confusion Matrix for (i) Decision Tree (DT), (ii) Logistic Regression (LR), (iii) XGBoost (XGB), (iv) AdaBoost (AB), (v) Stochastic Gradient Descent (SGD), (vi) Naive Bayes (NB) and (vii) recommended method using ensemble method.

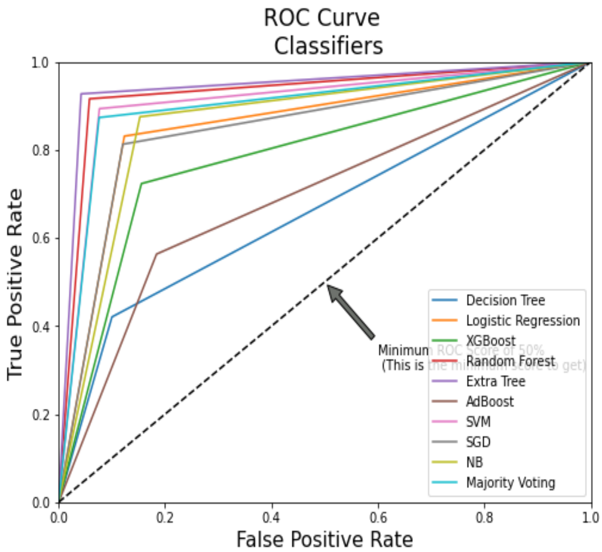


Fig. 4: ROC curve for depicts the effectiveness of a model for classification

A binary categorization system's diagnosing skills are illustrated visually by its ROC (Receiver operating characteristic curve) curved when its detection level is altered. A receiver's operating characteristic curve (ROC curve) is a graph that depicts the effectiveness of a model for classification over all classification levels. This graph depicts two parameters: The percentage of true positives. The percentage of false positives. Figure 4 visualize ROC curve for above used classifiers. It depicts in comparison to the aforementioned classifiers. it was discovered that our proposed approach produced results that were more accurate and stable (Punjabi, Vipul 2021).

CONCLUSION

With the rise of social media, fresh chances to broaden the variety of thoughts that individuals honestly share about themselves as well as their competition have emerged. Humans in the modern world are continuously sharing their emotions, feelings and sentiments via social media. His personal feelings, thoughts, sentiments, as well as other emotions, through social networks such as Twitter, are excellent places to begin exploring public sentiment. Data from social networking surveys are analyzed for emotion categorization & recognition. In this study, we compare several classifiers with different feature sets to reach the predicted results. To get more appropriate results, we constructed an emotion detection system with several models utilizing the Ensemble approach which mentioned classifiers and attributes. The experimental results show that our proposed strategy delivered more accurate and reliable outcomes.

ACKNOWLEDGMENT

I want to express the deepest appreciation to Prof. Dr. Dinesh Chandra Jain, my research mentor, for their continuous support, guidance along with insightful criticisms of this study.
I would also like to thank Dr. R. B. Wagh, Prof. V. D. Punjabi, Dr. D. R. Patil from R. C. Patel Institute of Technology, Shirpur and Prof. T. M.

Pattewar for their help in maintaining my development on course.

Finally, I would like to thank my parents, wife and complete family for their encouragement and support throughout my studies.

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Table II. Metadata represents approach used, corpus, social media platform and states of motion-sentiment by researches

Sr. No.	Authors	Approach	Corpus	Social Media Platform	Emotions/Sentiments
1	Francisca Adoma Acheampong,ChenWen yu, Henry Nunoo-Mensah [8]	Text based	1. https://www.kaggle.com/shrivastava/isears-dataset 2.alt.qcri.org/semeval2017/task4/index.php?id=download-the-full-training-data-for-semeval-2017-task-4 3.https://github.com/JULIELab/EmoBank 4.http://saifmohammad.com/WebPages/EmotionIntensity-SharedTask.html 5.http://people.rc.rit.edu/~coagla/affectdata/index.html 6. https://www.aclweb.org/anthology/I17-1099/ 7. https://www.crowdflower.com/wp-content/uploads/2016/07/text_emotion.csv 8.http://web.eecs.umich.edu/~mihalcea/downloads.html$delimiter%20%22005C317%20$#GroundedEmotions 9.http://www.site.uottawa.ca/~diana/resources/emotion_stimulus_data 10.http://wwbp.org/downloads/public_data/dataset-fb-valence-arousal-anon.csv	Twitter, News Headlines, YouTube comment, Facebook	Love, optimism, submission, awe, disapproval, remorse, contempt, aggressiveness. happiness, sadness, fear, anger, surprise, and so on
2	Ali Shariq Imran , (Member, Ieee), Sher Muhammad Daudpota , Zenun Kastrati , And Rakhi Batra [1]	Text based	Trending Hashtag # Data, Kaggle Dataset, SENTIMENT140 DATASET, EMOTIONAL TWEETS DATASET,	Twitter	Joy, surprise, sad, fear, anger and disgust
3	Zhenpeng Chen, Yanbin Cao, And Huihan Yao, Xuan Lu,Xin Peng,Hong Mei And Xuanzhe Liu [26]	Emoji based	Https://Github.Com/Sentimoji/Sentimoji JIRA Dataset, Stack Overflow Dataset, Code Review And Java Library	Twitter	Positive-love, joy, Negetive-sad, fear,anger, Discard-surprise
4	Joni Salminen* , Maximilian Hopf, Shammur A. Chowdhury, Soon-Gyo Jung1, Hind Almerekhi4 And Bernard J. Jansen [6]	Text based	1 Structured repository of regionalized, multilingual hate speech: https ://hateb ase.org/. 2 https ://githu b.com/t-david son/hate-speec h-and-offen sive-langu age. 3 https: //githu b.com/zeera kw/hates peech . 4 https: //githu b.com/t-david son/hate-speec h-and-offen sive-langu age. 5 https: //githu b.com/ben-aaron 188/ucl_aca_20182 019. 6 https: //githu b.com/punya joy/Hatem iners -EVALI TA. 7 https: //githu b.com/jing-qian/A-Bench mark-Datas et-for-Learn ing-to-Inter vene-in-Onlin e-Hate-Speech. 8https ://githu b.com/UCSM-DUE/IWG_hates peech public. 9 https: //githu b.com/aitor -garci a-p/hate-speec hdatas et. 10 https: //githu b.com/pinke shbad jatiy a/twitter-hates peech. 11 https: //bitbu cket.org/ceshwar/bag-of-communitie s/src/maste r/.Currently known as Figure-Eight. 12 https: //www.perspectiv eapi.com.	Twitter, YouTube, Reddit and Wikipedia	Positive and negative sentiment
5	NEMES, Rodrigo Masaru Ohashi[7]	Text and Emoji based	http://sentiment140.com/ fetched from the official API, Using the library tweepy	Twitter	Sadness, fear, anger, joy also used Plutchik's Wheel of emotions
6	Sh[illegible] M[illegible] Asghar, Fahad M. Alotaibi and Irfanullah Awan [9]	[illegible] based	Twitter streaming API to scrap tweets	Twitter	Word embedding