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Emotion Recognition by Textual Tweets Classification Using Voting Classifier (LR-SGD)

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Abstract: The proliferation of user-generated content on social media has made opinion mining an arduous job. As a microblogging platform, Twitter is being used to collect views about products, trends, and politics. Sentiment analysis is a technique used to analyze the attitude, emotions and opinions of different people towards anything, and it can be carried out on tweets to analyze public opinion on news, policies, social movements, and personalities. By employing Machine Learning models, opinion mining can be performed without reading tweets manually. Their results could assist governments and businesses in rolling out policies, products, and events. Seven Machine Learning models are implemented for emotion recognition by classifying tweets as happy or unhappy. With an in-depth comparative performance analysis, it was observed that proposed voting classifier (LR-SGD) with TF-IDF produces the most optimal result with 79% accuracy and 81% F1 score. To further validate stability of the proposed approach on two more datasets, one binary and other multi-class dataset and achieved robust results.

Keywords: MS Sentiment analysis, text classification, machine learning, opinion mining, emotion recoginition, artificial intelligence.

1.INTRODUCTION

Automatic emotion recognition, pattern recognition and computer vision have become significantly important in Artificial Intelligence lately with applications is a wide range of areas. Recently, social media platforms such as Twitter have generated enormous amounts of structured, unstructured and semi-structured data. One of the most recent. Example is COVID-19 pandemic that shows misinformation in social media can be far more important and devastating than a disaster such as a pandemic.

There is a need to analyze to accurately assign sentiment classes on a large scale. To perform such tasks, accurate NLP techniques and machine learning (ML) models for text classification are required. Twitter provides an opportunity to its users to analyze its data on a large and broader point of view.

Efficient methods are important to automatically label text data due to its noisy nature. In the past many studies have been performed on Twitter sentiment classification [1]. As Twitter is very fast and an efficient micro-blogging examination that facilitates the end users to transmit small posts are said to be tweets. Twitter is a highly demanding app in the world and is a successful platform in social media. Free account can be created by using Twitter that can provide an enormous audience potential. With the purpose of business and marketing, Twitter can be proved as the best platform, through which one can get in touch with very rich and famous personalities like stars and celebrities, so their purchasing can be very charming for them as well as for advertisers. Using Twitter, every celebrity is linked with fans as well as to grant a communication to followers. Such a platform is one of the superlative approaches for lovers as well. But,it has a short note range; only 140 letters for each post and it can type a post or link on the website since it has no cost and also open as the advertisements as well. There is no problem with clusters of personal ads which are similar to other social networking sites. It is quick because as a tweet is posted on Twitter, the public who is subsequent to respective business will get it without delay.

Companies and advertisers can compose utilization of this source to check the diverse operational point of views which are very considerable. With help of this, they will obtain an immediate response from their followers. Remarkably, a lot of businesses with the intention of purchase, Twitter followers increase their deals. Twitter facilitates the followers by making them identify regarding fresh business, products, services, websites, blogs, eBooks etc.

Consequently, Twitter clients might tick lying on link and also optimistically endow in a manufactured goods or examine the products presented and to get share in profit. It is extremely effortless to utilize as people can follow to get the news and updates, as organizations can tweet or re-tweet, they can mark favorite or selected people to send the tweets, also know how to propel the posts plus to be able to endow their money and instance through it. Academy, Industry, super bowls and Grammy Awards of such major Sports and Entertainment events generate a lot of buzz in the global world by using it. Competition is rising among different products on Twitter. People love to express their feelings about a particular

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product on social networks like twitter. Product owners are ready to spend more money on social media platforms to better advertise their products and to generate more revenue. When a person shares experience about a product, it helps the owner to change their market strategy, selling schemes, and improving the quality. Customer reviews serve as a feed back to the owners or manufacturers too. The data generated in such a way is of large amount and requires an analysis expert team to classify the customer sentiment from the reviews. Experts can make a human error in sentiment analysis; therefore it requires machine learning and ensemble learning classifiers to accurately classify the sentiment of the customers. This study compares various machine learning models for emotion recognition by tweet classification using Tf and TF-IDF.

This research presents a voting classifier (LR-SGD) and aims to estimate the performance of famous ML classifiers on twitter datasets. The key contributions are as follows:

- Machine learning-based classifiers including support vector machine (SVM), Decision Tree Classifier (DTC), Naive Bayes (NB), Random Forest (RF), Gradient Boosting Machine (GBM) and Logistic Regression (LR) trained on Twitter dataset are compared for emotion recognition.
- A voting classifier (VC) designed to classify tweets which combines LR and SGD and outperformed using TF-IDF.
- The proposed model stability is further validated by applying it on two different datasets, one binary dataset (containing hatred or non-hatred classes) and other multi-class dataset (containing product reviews having 1 to 5 ratings). The rest of the paper is organized as follows. Section II discusses literature related to the current research work. Section III presents the proposed methodology as well as detailed description of the tweet dataset used in the experiment.
- Results are presented in Section IV and the stability of proposed model is given in Section V. Section VI finally conclude the research work and also suggest future work.

2.LITERATURE SURVEY

Sentiment analysis inspires corporations to define clients' preferences about products, services, and brands. Further, it plays an important role in interpreting information about industries and corporations to reserve them in making entity review. Sarlan et al. [2] established a sentiment analysis through extracting number of tweets with the help of prototyping and the results organized customers' views via tweets into positive and negative. Their research divided into two phrases. The first part is based on literature study which involves the Sentiment analysis techniques and methods that nowadays are used. In the second part, the application necessities and operations are described preceding to its development.

In another research Alsaeedi and Zubair Khan [3] analyzed various kinds of sentiment analysis that is applied on to Twitter dataset and its conclusions. The distinct approaches and conclusions of algorithm performance were compared. Methods were used which were supervised ML based, lexicon-based, ensemble methods. Authors used four methods that were Twitter sentiment Analysis using Supervised ML Approaches; Twitter sentiment Analysis using Ensemble Approaches. Twitter sentiment Analysis is using mexicon based Approaches.

Lexicon based approaches have been explored by many researchers for emotion classification. Bandhakavi et al. [4] performed emotion-based feature extraction using domain specific lexicon generation. They captured association of words and emotions using a unigram mixture model. They used tweets that are weakly labelled to classify emotions. Their proposed architecture outperformed other state-of-the art approaches such as Latent Dirichlet Allocation and Point wise Mutual Information. Event related tweets are identified by researchers on geo related tweets [5]. They used specific tweets of local festivities in one year. They also identified different parameters that helped in event discovery. Alsinet et al. [6] analyzed tweets from political domains. They claimed accepted tweets are stronger as compared to the rejected tweets. Rumor detection in tweets is performed by using an encoder to analyze human behavior in comments [7]. Hakh et al. [8] used SMOTE method to remove excessive challenges of Twitter dataset. In addition, they applied different feature selections for rapidity of sentiment analysis method. Authors projected methodology that was estimated beside the dataset application decision, squashy favorable results on all operated evaluation metrics. Pre-processing steps were applied on their dataset after that they used TF-IDF features that were used to measure important weight of terms. Then classification methods were used (i.e. AdaBoost, Linear SVM, Kernel SVM, Random Forest, Decision Tree, Naïve Bayes and K-NN) and at last to relate classification's effectiveness: Accuracy and F1-score measures were used.

In [9], Xia et al. created the proportional training of the efficiency about collaborative method on behalf of Sentiment's arrangement. They set two types of feature in the context of sentiment analysis. Firstly, the feature set was totally depended on the part of speech and word relation was depending on the feature set. Secondly, the following familiar text classification algorithms that were maximum entropy, support vector machines and naive Bayes. Thirdly, the following ensemble strategies, that was the fixed combination, meta-classifier combination and weighted combination. They used 5 document-level datasets broadly utilized along with arena of Sentiment's arrangement. Experiments shown in this research the ensemble techniques are more effective than rest of the classifier which is also shown in our search

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that ensemble of two classifiers that are Logistics regression and stochastic gradient decent classifiers ensemble and give better result than other classifiers.

Deep learning has been utilized by many researchers for image classification [10] and tweet classification [11]. Rustam et al. [12] presented a Tweets Classification for US Airline Companies Sentiments. The researcher applied pre-processing on the dataset. The influence about feature extraction methods, together with TF, TF-IDF, along with word2vec, proceeding the classification accuracy has been examined. In addition, execution about the long short-term memory (LSTM) was studied in certain dataset. Paper of researcher proposes a Voting Classifier (VC) who helps to process similar administrations. Voting Classifier must dependent the Spatial Estimation (SE), Stochastic Gradient Descent classifier (SGDC) along with simple ensemble method for concluding results. Various types of ML classifiers tested with the use of precision, accuracy, recall and F1-score by way of working metrics. Results indicate that proposed VC is more efficient than one of the phase actors. The experiment also demonstrated the efficiency of machine learning students improved while TF-IDF utilizes a feature input.

Santos and Bayser [13] examined a sentiment analysis of short texts. In the experiment, researchers suggest a first-hand profound convolution neural network that achieve from character to sentence level material to accomplish sentiment analysis of little texts. Mohamed [14] evaluated a sentiment analysis of mining halal food consumers. This examination fills this gap through the investigation of an irregular example of 100,000 tweets managing halal food. To lead the examination, a specialist predefined dictionary of seed descriptors was utilized. By investigating halal food feelings communicated via web-based networking media, this examination adds expansiveness and profundity to the discussion over such an underrepresented region. Distinct investigation recognized for the most part positive estimation toward halal food, while geo-found Twitter maps indicated that "strict diaspora" broadly utilizes computerized presents on impart about halal food.

Parveen and Pandey [15] studied sentiment analysis on Twitter dataset that uses NB algorithm. Analyst use Hadoop Framework for preparing film informational collection which is reachable on Twitter site as reviews, input and opinions. Sentiment analysis on Twitter data is explored in three classes that are positive, negative and neutral. Alomari et al. [16] analyzed SVM utilizing TF-IDF. The study presented the Arabic Jordanian Twitter corpus where Tweets are explained seeing that any positive or negative. It researched distinctive directed machine learning opinion examination classifiers when applied to Arabic client's online life of general subjects that are found in either Modern Standard Arabic (MSA) or Jordanian tongue. Analyses were conducted to assess the utilization of various weight plans, stemming and N-grams terms strategies and situations.

Gamal et al. [17] built Twitter benchmark dataset for Arabic Sentiment Analysis. A benchmark Arabic dataset suggested in experiment for estimation investigation demonstrating social event strategy about the latest tweets in various Arabic vernaculars. The experiment dataset incorporates in excess of 151,000 unique assessments which marked into two classes, negative and positive. ML algorithms are functioned in SC; ML algorithm attached through learning arrangements. Sentiment analysis ordinarily executed using one fundamental methodology from a ML(lexicon-based approach) based approach. The calculations functioned via SC on the dataset accomplished 99.90% precision utilizing TF-IDF.

Kumar and Garg [18] explored the sentiment analysis of multimodal Twitter data. The experiment utilized a multi-method feeling examination approach to decide slant extremity mark for approaching tweet that is printed picture information realistic. Picture estimation marking was accompanied by utilizing Senti-Bank along with SentiStrength marking for regions with convolution neural network (R-CNN). For a picture posted in Twitter, the picture module is executed which utilizes a current module of Senti-Bank along with R-CNN that decide the feeling estimation mark of the picture. After pre-processing, the content module utilizes an AI-based troupe strategy gradient boosting to characterize tweets into extremity classifications, to be specific, positive, negative or neutral High execution exactness of 91.32% is watched on behalf of arbitrary multi method tweet dataset utilize assess the planned model.

Sailunaz [19] investigated the feeling through the dataset that analyzed by a sentiment analysis from Twitter texts. The objective this work was to recognize and investigate assessment and feeling communicated by individuals from content in their Twitter posts and to use them for creating suggestions. The dataset is utilized to recognize slant and feeling from tweets and their answers and estimated the impact scores of clients dependent on different Tweet based and client-based parameters. The strategy we utilized in this paper include several fresh approaches: (I) remembering answers to tweets for the dataset and estimations, (II) presenting understanding score, slant score and feeling score of answers in impact score computation, (III) producing customized and general proposal consisting rundown of clients who conceded to a similar subject and communicated comparable feelings.

3.RESULTS

This section provides the details of the experiment conducted in this research and the discussion of obtained results. Classification algorithms are tested using TF and TF-IDF features. Voting Classifier as an ensemble of Stochastic Gradient Descent and Logistic Regression gives highest accuracy. Table 2 presents the Accuracy, Recall, Precision and F1-score of classification with TF features.

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Figure 4 presents the results of all the classifiers and comparison between them. By using the TF feature. It can be seen that the Voting Classifier is best with accuracy 78% among all classifiers. A Voting Classifier displays best outcome when it works with Stochastic Gradient Descent and Logistic Regression and provides maximum accuracy. Table 3 shows the accuracy, recall, precision and F1-score of classification with TF-IDF technique.

Voting classifier achieved the highest accuracy value with 79% and LR achieved 78%. LR achieved the highest precision value with 79% and the proposed model achieved 78%. Proposed model achieved the highest recall and f1 score with 84% and 81% values respectively. LR individually show reasonable results with 80% recall and 80% F1-score. Figure 5 shows the results of all the classifiers and comparison between them Using TF-IDF feature. It can be seen clearly that the proposed voting classifier is performing best in terms of accuracy, recall and f1 score among all classifiers.

4.OUTPUT

Fig : Login Page

Fig : Registration Page

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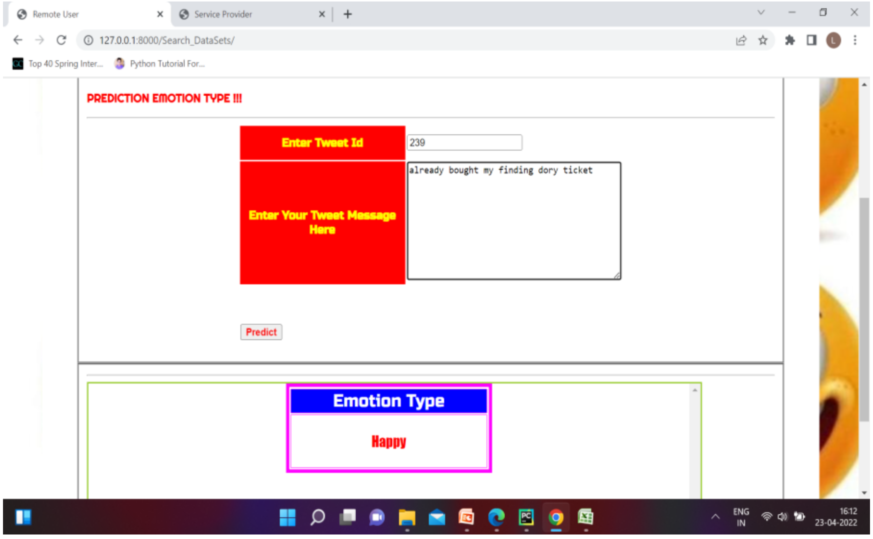

Fig : Home Page After Prediction

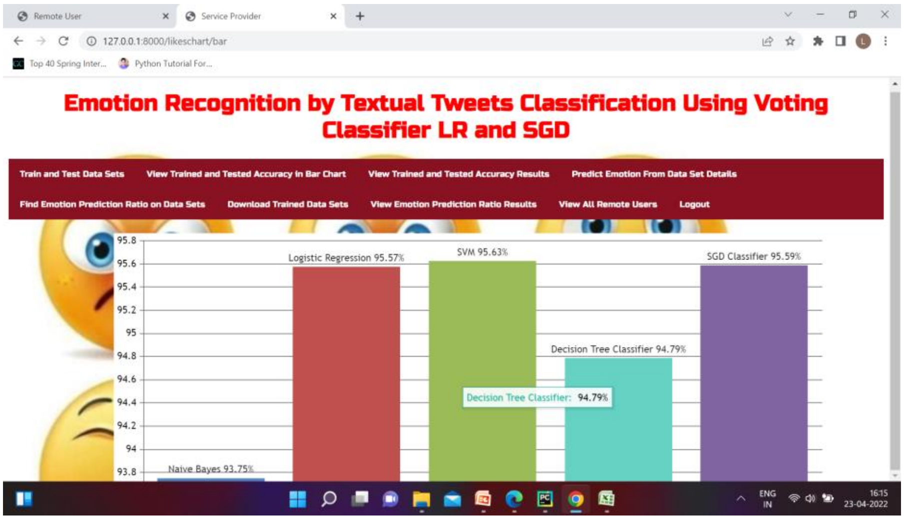

Fig : The Training Accuracy and validation Accuracy comes from those Prediction Bar Chat

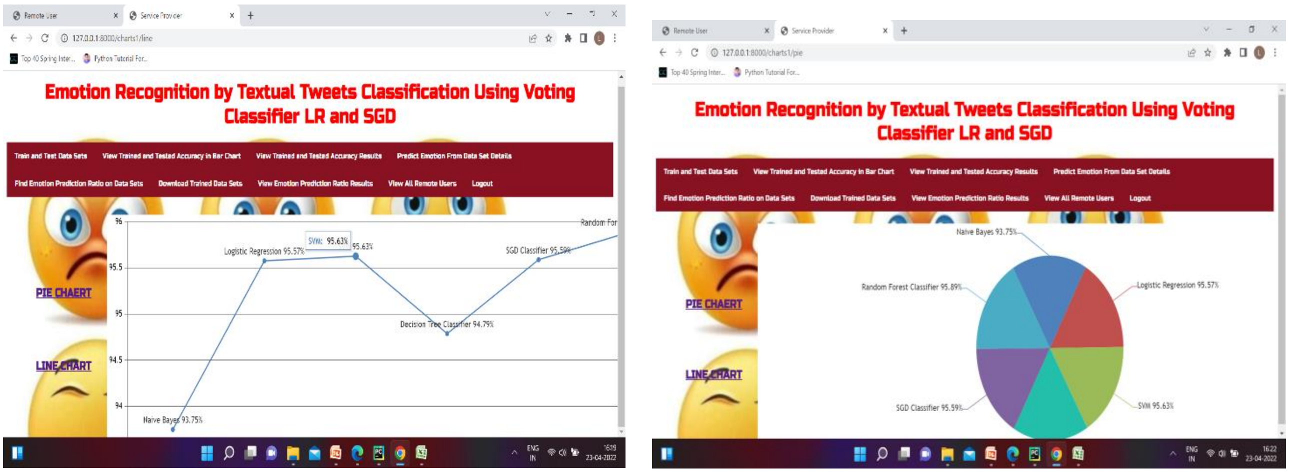

Fig : The Training Accuracy and validation Accuracy comes from those Line Chart & Pie Chart

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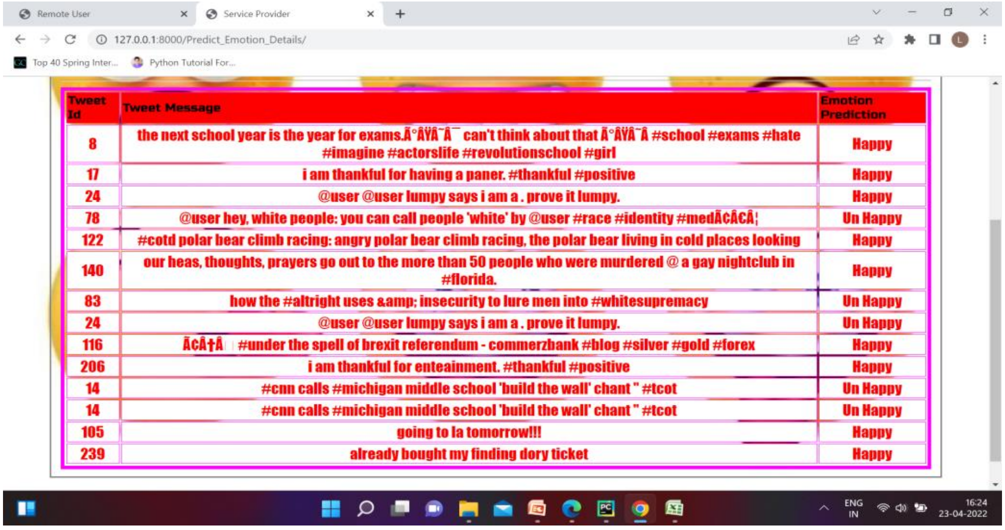

Fig : View Emotion Prediction from Datasets

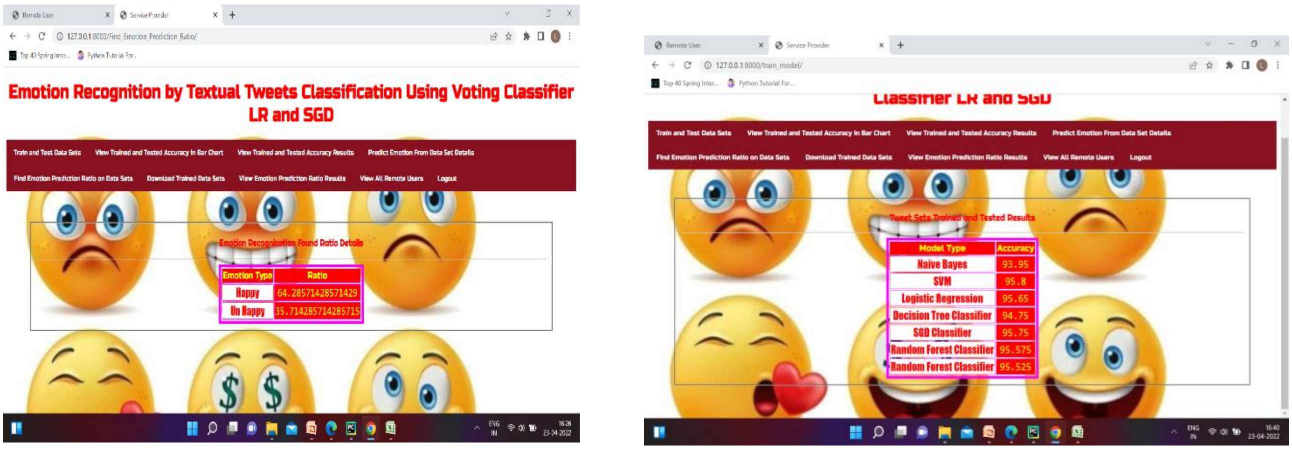

Fig : Emotion Prediction Ratio & Algorithms Used Accuracy

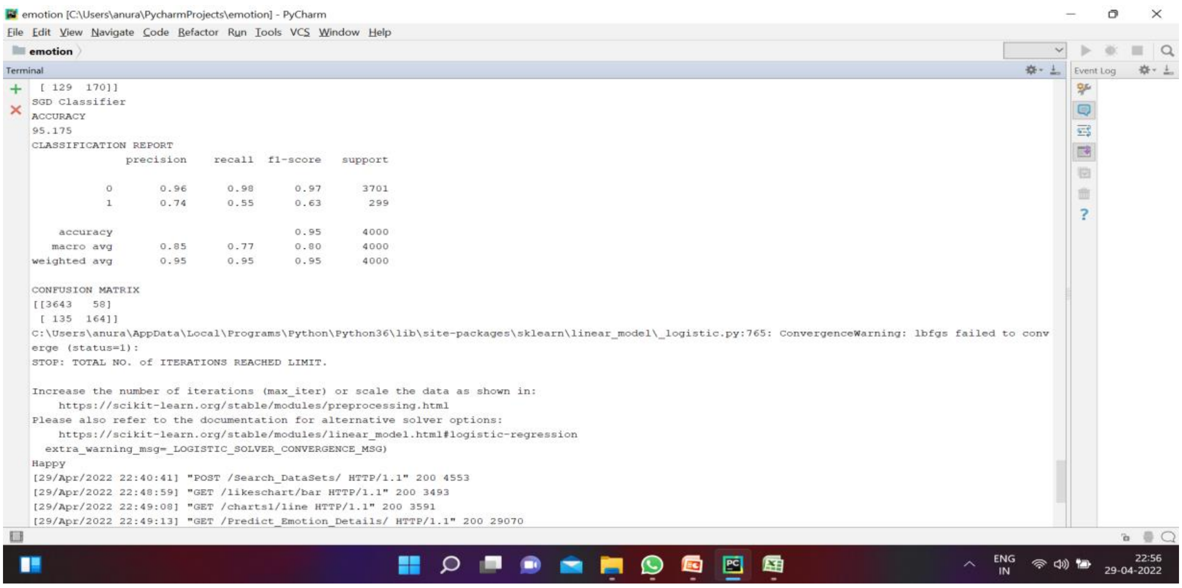

Fig : Accuracy increased in Stochastic Gradient Descent

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5.CONCLUSION

This paper proposed a novel combination of LR and SGD as a voting classifier for emotion recognition by classifying tweets as happy or unhappy. Our experiments showed that one can improve the performance of models by recognizing patterns efficiently and through effective averaging combination of models. Experiments are conducted to test seven machine learning models that are; (1) SVM, (2) RF, (3) GBM, (4) LR, (5) DT, (6) NB and (7) VC(LR-SGD). This study also employed two feature representation techniques Tf and TF-IDF. The results showed that all models performed well on tweet dataset but our proposed voting classifier VC(LR-SGD) outperforms by using both TF and TF-IDF among all. Proposed model achieves the highest results using TF-IDF with 79% Accuracy, 84% Recall and 81% F1-score. The proposed model is further validated on two more dataset and achieved robust results. The future work will compare more feature engineering techniques and explore more combinations of ensemble models to improve the performance. In addition, new techniques will be investigated to deal with sarcastic comments.

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