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RECOGNITION OF EMOTION IN TEXTUAL TWEETS USING SVM AND NAIVE BAYES ALGORITHMS

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ABSTRACT

we proposed a emotion recognition system where it recognize the emotions in tweets. As emotions play a vital role in our lives. As we can see that many people use social media where they use the platform for many purposes, some of them tweet in a good way and some of them in a bullying way. Emotion and opinions of different people can be carried out on tweets to analyze public opinion on a news and social events that are taking place in present society. In this project, by using machine learning algorithms we have implemented emotion recognition by classifying tweets as positive and negative. By recognizing these positive and negative tweets we can identify people emotions where we can reduce the forged statements. Initially we have divided our dataset into train and test dataset, where it is used to train the model and by comparing the train data with the test data, the model recognizes the emotions in tweets. By using svm and naïve bayes algorithms we classify the text based on twitter into different emotions and predicted emojis like love, fear, anger, sadness, joy. Based on the performance analysis we predicted optimal result with 79% accuracy and 81% F1 score.

Keywords: LR-SGD, Emotion, Machine Learning models, TF, TF-IDF

1.INTRODUCTION:

Artificial Intelligence has recently seen a substantial rise in the importance of automatic emotion identification, pattern recognition, and computer vision, having applications in a broad variety of industries. Social media sites like Twitter have lately created vast volumes of structured, unstructured and semi-structured data in the last few years Information like COVID-19 info emic, which showed how damaging

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and essential disinformation in social media can still be, is among the most recent examples. In order to correctly classify sentiments on a broad scale, analysis is required. These kinds of activities need precise NLP approaches and machine learning (ML) models for text categorization. Twitter gives its users the option to look at their data from a much larger perspective. Because text data tends to be noisy, it's critical to use effective approaches when automatically labelling it. Twitter sentiment categorization has been the subject of several research in the past. The term "tweet" refers to a short message that may be sent quickly and easily using Twitter, a micro-blogging service. Twitter is one of the most popular social media platforms and an app in great demand throughout the globe. Creating a free Twitter account opens the door to a massive audience. Twitter is the finest platform both business and marketing since it allows you to connect with wealthy and renowned people, such as stars and celebrities, whose purchases may be both attractive to them and to advertising. Every celebrity may connect with their fans and maintain open lines of contact with their following thanks to Twitter. Another of the best techniques for lovers is to use such a site. Although each post may only include 140 characters, it can be used to write a post or a link on the website since it is free and open like the advertising. Clusters of personal advertising, similar to those seen on some other social networking sites, are perfectly acceptable. It is rapid since the public who is following the appropriate company will get a tweet as soon because it is posted on Twitter.

Using this source, businesses and advertising may examine the many operational viewpoints that are highly important. They will get a quick reaction from their followers thanks to this method. Surprisingly, a large number of companies looking to buy Twitter followers have seen a rise in sales. Twitter makes it easier for users to find out about new businesses, goods, services, websites, blogs, eBooks, and other online content. As a result, Twitter users may click on a link that seems to be lying on the page, and they may also be hopeful about the items or services that are being offered and hope to gain a piece of the profit. You don't need a degree in computer science to use it since it's so simple for people to watch to receive the latest news and updates, for companies to tweet or re-tweet, and for individuals and organisations to designate their favourite or preferred people to send tweets. Major sporting and entertainment events like the Academy Awards, Super Bowls, and Grammys create a lot of attention by employing it. On Twitter, there is a lot of competition between various products. Twitter is a great place for people to voice their opinions on a product. In order to better promote their items and produce more income, product owners are willing to spend more money using social media platforms. Product owners may improve their products' quality and market strategy by listening to customers' feedback. Owners and manufacturers both benefit from customer reviews. The volume of information collected in this manner necessitates the use of a data analysis department to go through the evaluations and determine the general mood of the customers. Machine learning and ensemble learning classifiers are required to effectively categorise consumer sentiment since

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experts on sentiment analysis may make a human mistake.

2.RELATED WORK

Companies may use sentiment analysis to learn more about their customers' preferences for certain goods, services, and brands. The ability to understand data on industries and businesses and reserve for use in entity reviews is also a key function of this tool. By extracting tweets via prototype, Sarlan et al. [2] created a sentiment analysis that classified consumers' opinions expressed through tweets into two categories: positive and negative. It was a two-step process for them. The first portion of the research is developed based on the literature of the current methodologies and techniques for sentiment analysis. In the second section, the requirements and operations of the application are discussed before it is developed.

This study looked at the results of several types of sentiment analysis performed just on Twitter dataset by Alseedi and Zubair Khan [3]. We examined and contrasted the various methods and results of our algorithm performance analysis. ML-based, lexicon-based, and ensemble approaches were used. Combining Twitter sentiment analysis with supervised ML approaches and ensemble approaches were two of the four strategies used by the authors. When it comes to Twitter sentiment analysis, lexicon-based methods are used.

Many scholars have experimented with the use of emoticons to classify emotions. Bandhakavi et al. [4] used domain-specific lexicon creation to extract emotion-based features. Unigram mixture models were used to study the relationship between words and emotions. Classifying emotions was done using tweets that were only vaguely labelled. Other current techniques, such as Latent Dirichlet Allocation and Pointwise Mutual Information, were beaten by their design. Researchers use geo-related tweets to identify event-related tweets [5]. One year, they utilised tweets from a particular event in the area. They also came up with a list of criteria that might be used to find out more about an event. A study by Alsinet et al. [6] looked at political tweets. They asserted that tweets that were allowed were superior than those that were rejected. Twitter rumours are detected using an encoder that analyses user comments [7].

In [9], Xia et al. developed a proportionate training approach for Sentiment's organisation of the effectiveness of collaborative method. For sentiment analysis, they use two different kinds of features. An important feature set was completely dependent on the part of speech, and word relations were also dependent on the feature set. ” Secondly, the well-known text classification methods, such as maximum entropy, support vector machines, and naive Bayes, were used. Thirdly, the fixed combination, meta-classifier combination, and weighted combination ensemble techniques. In addition to Sentiment's layout,

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they employed five document-level datasets. It has also been proven in this research's tests that ensemble approaches such as logistic regression and stochastic gradient decent classifiers are much more successful than just the rest of both the classifiers and provide superior results than other classifiers.

Many academics have used deep learning to classify images [10] and tweets [11]. There was a Tweets Classification for All us Airlines Sentiments by Rustam et al. [12]. The dataset was subjected to pre-processing by the investigator. Analysis of the impact of feature extraction approaches, including TF, IDF/TF-IDF, and word2vec on classifier has been carried out. An additional dataset was used to study the execution of long-term memory (LSTM) execution. Voting Classifier (VC) is proposed in a paper by a researcher who wants to handle comparable administrations. Spatial Estimation (SE), Stochastic Gradient Descent (SGDC) and a basic ensemble approach must be used to determine the voting classification results. Precision, accuracy, recall, and F1-score were used as working metrics for a variety of machine learning classifiers. The suggested VC is more efficient than either of the phase actors, according to the results. Machine learning students' performance increased when TF-IDF used feature inputs, according to the experiment.

Short texts were studied by Santos and Bayser [13]. An experiment suggests a first-hand deep convolution neural network that reaches from character to sentence level material to do sentiment analysis on small texts. ' A survey of halal food customers was conducted by Mohamed [14]. This study fills up that vacuum by looking at a seemingly random sample of 100,000 tweets on halal meals. A preset vocabulary of seed descriptors created by an expert was used to guide the investigation. This study broadens and deepens the conversation on halal cuisine by looking at how people express their views about it on social networking sites. Research into the "strict diaspora" discovered that they use electronic presentations to share information about halal cuisine in large numbers, which is consistent with the generally good perceptions of halal food reported in general.

In their study, Parveen and Pandey [15] used the NB algorithm to analyse sentiment on such a Twitter dataset. Information about movies may be found on Twitter, where users can provide reviews, comments, and other types of feedback using Hadoop's framework. The three types of good, negative, and neutral sentiments are examined in Twitter data. Alomari et al. [16] used TF-IDF to investigate SVM. The Arabic Jordanian Twitter corpus was given in the research, and Tweets were analysed for any positive or negative sentiment. Machine learning opinion assessment classifiers for Arabic clients' online lives of broad topics in either Modern Standard Arabic (MSA) or Jordanian dialects were studied. Various weight plans, stemming, and N-grams terminology tactics and scenarios were analysed.

A sentiment analysis from multimodal Twitter data was examined by Kumar and Garg [18-41]. In this experiment, researchers used a multi-method strategy to determine the slant extremity mark from tweets that

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are printed with accurate image information. SentiBank and SentiStrength marking for regions using convolution neural networks were used in conjunction with picture estimation marking (R-CNN). When an image is submitted to Twitter, the picture module uses SentiBank's most recent module and R-CNN to estimate the user's emotional state. In order to categorise tweets into good, bad, or neutral extremes, the content module use an AI-based classification approach gradient boosting. The intended model is expected to have a 91.32 percent success rate when it is tested on a random multi-method tweet dataset. Sentiment analysis using Twitter messages was used by Sailunaz [19] to explore the feelings of people. the idea was to find out what people are thinking and feeling via the content of their Twitter postings and then utilise that information in order to come up with new proposals.

3.METHODOLOGY

To achieve its goals, this study used a variety of methods in machine learning (ML). Experiments were conducted utilising a variety of approaches and procedures. The Voting classifier, an ensemble combining Logistic Regression and Stochastic Gradient Descent, beats all other ML models in terms of effectiveness, recall, precision, and F1-scores.

We scraped the Kaggle repository for our Twitter data. The dataset is first pre-processed by eliminating any unnecessary information from it. To begin with, the data was divided into two sets: one for training purposes, and one for testing. Each training set were given a 70% weighting, whereas the test set was given a 30% weighting.

Finally, feature engineering approaches are used to the training set. Upon that training set, several machine learning classifier is trained and evaluated. The evaluation parameters used in this experiment are: (a) Accuracy (b) Recall (c) Precision (d) F1-score.

(i) DATASET

There are a lot of conflicting tweets in the dataset. Under its sentimental polarity, each record is assigned a number between 1 and 0 to designate "happy" or "unhappy" status. English-language tweets are included in the final dataset since they are more likely to be recalled. There are a variety of characteristics in this collection.

(ii)DATA VISUALIZATION

To have a better understanding of the dataset, it is helpful to visualise the properties of the attributes. A comparison of how happy and dissatisfied two target groups are is shown in Figure 1. proportion classifications demonstrate that 67.4 % of tweets were associated with positive sentiment and 32.6 % with

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negative sentiment.

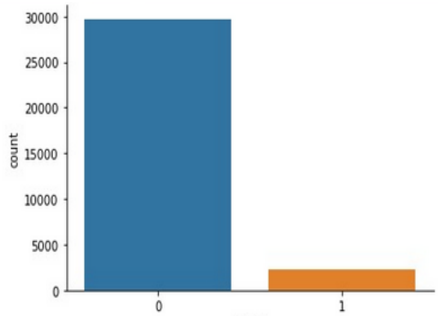

Fig 1: Count plot

(a) DATA PRE-PROCESSING

An unstructured or semi-structured dataset comprises of unused data. Machine learning (ML) models become more efficient and computationally efficient when pre-processing is performed prior to training.

(b) FEATURE EXTRACTION

Data pre-processing is the very first critical stage, followed by selecting characteristics from a refined dataset. Textual data into vector form is required for training supervised machine learning classifiers. TF and TF-IDF algorithms are used to transform textual characteristics into vectors. In this work, [21–23].

According to how many times the word is used in the text, what then is the term frequency (TF)? TF is used to quantify it. This is possible because the length from every document varies, thus a phrase will appear much farther in longer papers than in shorter ones.

During data recovery, the term frequency (TF) is being used to represent how often a phrasing (term, word) appears in a report.

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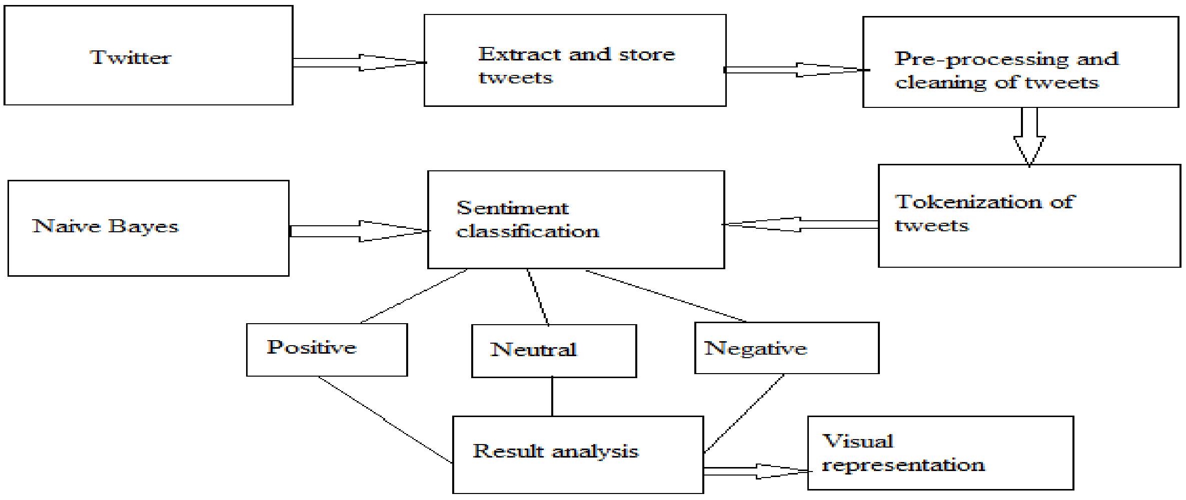

FIGURE 2**:** Methodology architecture diagram

4.MODELLING

We'll talk about the modelling methods that are used to sort tweets in this section. Five methods for supervised machine learning were used in this study: Support Vector Machine(SVM), Decision Tree (DT), XG BOOST model (XGB), Naive bayes (NB), Logistic Regression (LR) and Voting Classifier (Logistic Regression + Stochastic Gradient Descent classifier)

(1) SUPPORT VECTOR MACHINE

According to SVM's understanding, sentiment analysis works well [24]. Preferences, constraints, and processes for evaluation are used in SVM to review data obtained inside the index region. Dimensional information may be encapsulated in vector arrangements of all magnitudes. To do this, the data (represented as a vector) has indeed been organised by type. Next, strategy divides the boundary into two training sets. In the training samples, this is a considerable distance away from any of the areas.

(2) **DECISION TREE**

For tasks like regression and classification, DT algorithms are often utilised. Attribute selection is the most difficult part of constructing a tree at every level. There are two main strategies for attribute selection: Gini index and information gain.

(3) **LOGISTIC REGRESSION**

Just on basis on output, class probabilities are estimated in LR. For example, they forecast whether the input belongs to class X with probability x and to class Y using probability y. Predicted output class X if x > y; else Y. An insight, a logistic strategy for displaying the likelihood of a certain group or otherwise, occurrence was possible, for example, top-to-bottom, white-black, up-down, positive-negative, or happy-unhappy. There are many uses for this, such as making a judgement on whether a picture comprises

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snakes, hounds, deer, etc., and assigning a probability anywhere in the range between 0 and 1 with both the addition of one [31].

(4) XG Boosting

One of the most commonly used machine learning techniques is XG boosting. As an ensemble many weak prediction models, which are often decision trees, it provides a prediction model. [1][2] For weak learners, a technique called "XG-Boosting trees" may be used, which generally beats a random forest in comparison. While other boosting approaches use a stage-by-stage approach, XG boost trees allow for the optimization of such an arbitrary differentiable loss function.

(5) NAIVE BAYES

Naive Bayes (NB) is a sorting method that relies on Bayes' Theorem for its independent assumptions about stabilities. In order for the NB classifier to correctly classify a given class element, it takes into account how many variables are in close proximity towards the class element in question. An apple is presumed to be a dark red natural organic product, if its shape is spherical and it has a diameter of around 3 inches. There are several "probabilistic classifiers" in machine learning that use Bayes' speculation and "gullible opportunity assumptions" between features to classify data. Naive Bayes classifiers fall into this category. They are regarded as the least difficult of the three options. a network of Bayesian nodes.

(6) VOTING CLASSIFIER

It is possible to get better results by using numerous individual classifiers and combining their predictions, rather than using a single classifier [34]. VC is indeed a cooperative learning method. The combination of numerous classifiers was shown to be more effective than using just one [35]. Cooperative learning is becoming more important to academics because it yields superior outcomes. Voting classifiers were created by combining two different classifiers in just this study, and the findings were optimised using this voting classifier.

5.RESULTS AND DISCUSSION

This section describes the experiment that was used in this study and discusses the outcomes that were discovered. Using Logistic Regression, the most accurate method in this study. Using TF-IDF features, overall classification accuracy, recall, and F1 scores are shown in Table 1.

Models	Accuracy	Recall	F1-score

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DT	75%	76%	75%
LR	77%	78%	78%
XG	74%	75%	74%
Voting	78%	80%	81%

TABLE 1. Classification result of various models

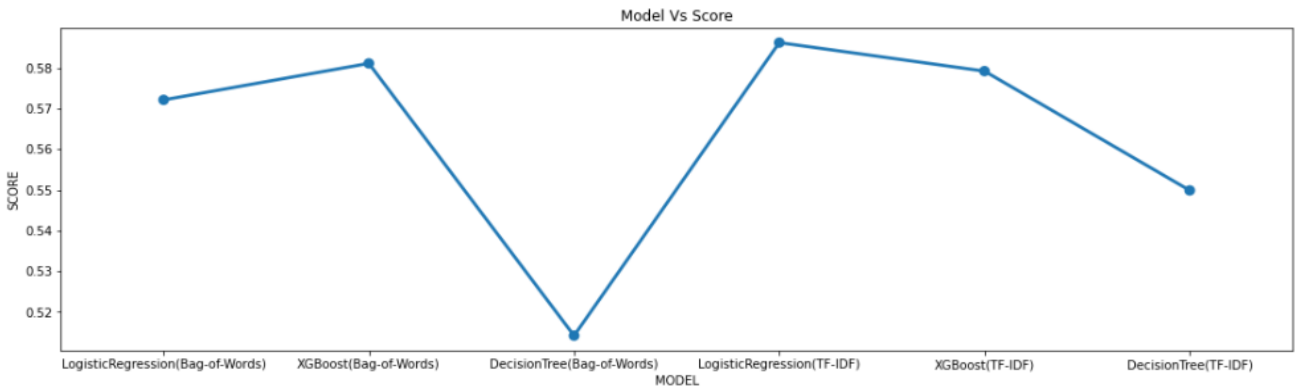

FIGURE 3. Classification result comparison of various machine learning models using TF-IDF features.

This work used a mixture of ML models for voting classifiers to address the shortcomings of the individual ML models. All datasets were outperformed by traditional ML-based models.

Obviously, the suggested voting classifier performs better in terms of accuracy, recall, overall f1 score compared to the other classifiers studied in this study.

6.CONCLUSION

As just a voting classifier with emotion identification, this research used LR and SGD to categories tweets as either joyful or sad. In our tests, we found that models may be improved by quickly identifying patterns and by effectively combining many models. GBM, LR, DT, and VC are some of the machine learning models that also are tested in experiments (LR-SGD). Two feature representation approaches, TF and TF-IDF, were also used in this work. Voting classifier VC(LR-SGD) beats the other models by employing both TF and TF-IDF, according to the findings of this study. This model has the greatest accuracy (78%), recall (80%) and F1-score (81%) of any TF-IDF model.

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