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Hate Speech Detection using ML algorithms

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***Abstract*— Social media is a growing platform where different users share their ideas and sentiments towards different topics because users spend a lot of time expressing their thoughts and views. There are various researches going on in detecting the sentiments of the user's comments but the main sentiment factor remain undiagnosed. In this paper, the aim is to detect hate speeches. The dataset was preprocessed and cleaned and cleaned text was explored to get a better understanding. Salient features were extracted from the data to train our model and to identify the hate sentiments of tweets. The vector model is created using genism to learn the relationship between words and based on that sentence are labeled. Stop words and port stemmer are used to filter unwanted data to build the vocabulary using CountVectorizer before it is used for model building. Using various machine algorithms, comparative study is done to check the performance of algorithms and promising results are attained.**

Keywords— ***sentiment analysis, a bag of words, NLP, model, and evaluation metric***

I INTRODUCTION

In the current world as the population is increasing the more users are joining the world of the internet. The Internet has changed the whole dimensions of the user's life and the way how people share their views and ideas through social media. The Internet has grabbed many user's attention and almost every five-person in the world in some way or the other is using the internet. Many people share their ideas mainly through social media [1] giants like Facebook, Twitter, Google, etc. These social media companies had given users the opportunities to share their valuable feedback and their views on a specific topic. Through social media, various people follow various media where influencers encourage and influence the other users. Moreover, social media allows companies to connect directly to their valuable customers and sell their products.

Social media is also a great medium to be up to date with various news and technologies. Talking about twitter another social media giant more than 20 million tweets are published in a day through Twitter social media where each tweet has its meaning. Every second almost 6000 tweets are uploaded on Twitter. The main problem that arises here is since there are so many tweets being published there may be the possibility of tweets that are not suitable for user's sentiments [2]. Various studies have proved that negative tweets may have a deeper impact on user's life. Users tend to face depression, trauma, and mental tension which in turn takes a drastic turn which results in suicide. So in this paper, the objective is to create a model that can classify whether tweets are hate/racist or neutral. Tweets can be racist, positive, and neutral. The main challenge to build the model, to find the relationship between words. Dataset from Twitter was taken to do pre-processing and training and tweets are visualized to get meaningful insights. At last comparative study is done to check the performance of each algorithm using various evaluation techniques.

II MACHINE LEARNING

Machine Learning [3] is part of AI application which provides training and learning of machines so that next time machine will automatically learn from his past experience that helps machines to be more adaptive in different situations and try to understand from different situations. ML helps in processing and developing software tools. The learning part is done using the help of past examples, their observations and based on that findings evidence are used to interpret knowledge patterns so that it makes reliable future decision The objective of ML is to make machines pro-active and have their own set of experience that does not require any manual interference.ML consist of two types namely supervised ML algorithm and non-supervised ML algorithms OF machine learning. Studies are going on where supervised learning[4] is helping us to predict the future chain of events using the data. For the evaluation of the learning data algorithm, a new learner algorithm is deployed so that it can predict the performance values. By applying supervised learning one can achieve goals after applying proper training, doing analysis of the algorithm can help us to detect the error moreover it also helps to improve the design and adapt to new output if there contain errors.

Semi-supervised machine learning[5] is also a part of ML. In semi-supervised learning of the algorithms, training is done first by combining the labelled and unlabelled data. Usually in this process, the ratio of labelled data is less and the ratio of unlabelled data is more. The programs that use this learning algorithm have more reading accuracy. The procedure involves firstly similar data are clustered using unsupervised learning and then try to predict the label of other unknown labelled data. Semi-supervised training is done so that it can learn and benefit from the information so that next time when same data comes it should be in a proper position to analyse that information, normally additional resources are needed for the collection of unlabelled data. Machine learning algorithm enhancements are a part of the learning process in which it interacts with outer data and finds relevant errors moreover it learns from their experience which contributes to their efficiency. Error detection and

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evaluation play an important role in training and optimizing the data. This type of approach helps devices to examine the error using minimum actions that eventually lead to improved efficiency in a particular context. The contradicting data should be eliminated as it leads to confusion and machines don't work at their normal efficiency. In Machine learning, processing and storage of large data are involved. Although computers are capable of delivering faster outputs to detect various opportunities and harmful threats more time is required to properly train them. The combination of machine learning with AI with the support of technologies makes it more capable, reliable, and accurate to produce a large amount of data. Soon there will be a time where the machine will be capable of doing things on its own. Users will be able to track, record, and fetch data using machine and deep learning. One of the main features of machine learning is that it can predict the data once trained.

III Literature Review

Guntuku et al[6] collected data in form of features, variables are taken from social media like user's word, time, language, these features were divided and examined as independent variables in an algorithm. Linear Regression was used with inbuilt variable selection, support vector machines for the outcome. Predictive methods are trained using various algorithms. For collecting data different approaches were used like survey responses, forums, taking posts depicting depression. The data sets were compared based on performance in prediction. The study showed that mental issue is detected but it needs more samples and gold standard based clinical criteria that are still to be done yet.

Reece et al[7] analysed the data from text and concluded that there is the presence of depression and post-traumatic stress disorder with a .87 score for depression and .89 for PTSD. Data were collected for weeks, which somewhat outperformed aggregation to days, and modelled as longitudinal trajectories of activity patterns that differentiated healthy from mentally ill users.

Tsugawa et al[8] used CES-D for assessment and find depression from Twitter data. Tweets were taken for the past 6 weeks and preceding the administration of the CES-D (center of epidemiological studies depression scale) was enough to conclude that accepting depression and predictions that were based on data used for a longer period were less accurate.

Schwartz et al[9] concentrated on personality survey questions to determine user's depression reading. Facebook user's data were taken and analysed. The result analysis concluded that depression was higher in winter. Their research also provided related words like phrases, topics depicting depression.

De Choudhury et al[10] used Reddit users' posts to do their research. he took the post that has the presence of mental health involvement and then researched upon suicidal inclination in the future. He concluded the result was because of poor linguistic style, decrease in social engagements and expression related to anxiety, depression, loneliness.

Xinyu Wang1, Chunhong Zhang1[11] this paper applies data mining algorithms in the physiology sector. Their proposed sentimental analysis method by using vocabulary and their own rules and then it calculated the depression inclination of the blog. The Depression detection model was created based on their proposed method, and deployed 3 classifiers for evaluation which gave 80% accuracy.

R.Vanlalawmpuia et al[12], For analysing depression depressing linguistic and physiology were studied and interpreted, however negative comments and sudden change in polarity related to comments which are eventually a part of syntactic word semantic languages. With more no of studies in this field, more people are doing research but one thing is understood more the depressing word will be the success in detecting the depression. People with depression will show some signs like irregular posts, putting posts in odd timings, commenting words related to depression.

Thorstad et al.[13] has taken anxiety, bipolar, and depression into consideration, based on user's depression posts and created their dataset, and applied the machine learning model onto it. The classifier gave the best performance with ADHD(anxious, depression and bipolar) with F=.39 and PR=.37 and worst for depression and anxiety.

Akshi Kumar et al [14] Mental surroundings and social networks are interrelated to each other and the main domain of study. In this research 3 models were proposed (a novel model, AD prediction model, for anxious depression prediction with real-time tweets). This disease (anxiety) or disorder is somewhat related to different thinking-,curiosity, restless and tension. Based on the linguistic style and posting frequency, 5 vector tuple vectors are given. A lexicon is built on anxiety so that presence of anxiety can be detected. Time of the user and their frequency of tweet were taken into consideration for suspicious behaviour in addition user opinion polarity analysis is done to find any changes in posting patterns. For their experiment, 3 classifiers were used namely (multinomial naïve Bayes, gradient boosting, and random forest) and for the final prediction ensemble, the voting classifier is used. The result was analysed based on 100 users' tweets and their proposed model was able to achieve a classification accuracy of 85.09%.

Md.Rafikul et al[15] focused on 4 approaches namely emotional process, temporal process, linguistic process, and combination of all processing(emotional, linguistic style for detection), Their methodology uses Ncapture for data collection and analysis through LIWC (linguistic inquiry and word count). Supervised learning was used as classifiers. For building their dataset ground label information was used. The Facebook data was divided into 2 sets one with a positive(YES) class (positive comments) and the second negative(No) class(negative comments) The LIWC package is used to find different affective, intellectual words related to depression. To characterize depressive behaviour attributes were used namely emotional process, temporal process, and linguistic style and their data consist of five variables namely (positive, negative, sad, anger, anxiety),(three temporal categories namely present focus, past focus, and future focus) and linguistic parameters like articles, pronouns, verbs, negations, and their values were calculated using LIWC 2015 scales. The analysis was done using MATLAB2016b. After executing decision was the best performing model but KNN gave the highest precision but the decision tree gave the highest recall and F measure.

Tadesse et al[16] built data sets and then applied NLP and text classifying techniques. Starting first remove all the unnecessary data using LIWC dictionary, LDA topics, and N-gram features and then apply classifiers for implementation. SVM gave 80% accuracy with a 0.80 F1 score but success was achieved when used with LIWC+LDA+Bigram and Multilayer Perceptron classifier together the accuracy reached 91% with 0.93 F1 scores.

Manas Gaur et al[17] to eliminate the limitation of existing health application PHKG(personalized health care graph) was created. It is depicting of accurate medical knowledge and personalized data for users/patients. PHKG can be used only in heterogeneous data, IoT devices with sensors are used to collect data, Alchemy API (used for semantic text analysis) was used to get medical datasets. An ontology catalog is used and a set of rules needs to follow in form of the algorithm. For continuous monitoring and generating reports of patients KHealth project was used. Khealth integrates data from different directions like medical records, environment data collected from sensors, and personal signals indicate mental health. Asthma datasets have been used that consist of discussed parameters like air quality, temperature. Oher datasets named Parkinson dataset (from Kaggle) were also used which has sensors like accelerometer, compass, and other parameters that also help to find body movement and related data. For reasoning purposes Khealth reasoner(it gives meaningful information from data that may be beneficial for physicians).

Zhisheng Huang et al[18] constructed the PHKG (personalized health knowledge graph) for depression. The four methods were used to integrate data in their graph ie direct entity identification, direct concept identification, and NLP tool combined with semantic annotation. The implementation was done using the depression KG system. By using the graphical user interface, depressionKG management plays an important role in their system, it launches a web server that is the interface of DepressionKG. Due to this, their system supports browsing and querying.

Maryam Mohammed Aldarwish et al[19], created a depression model for depression using RapidMiner and experimented on an SVM and naïve Bayes classifier, and analyzed the social activities of users One may see the user's depression levels based on their thoughts. The evaluation of performance was done based on three results the sentiment results, SVM results, and naïve Bayes results in which precision was 100% and accuracy is 69%.

Joe Rad et al[20] has surveyed various ontology approaches, namely gold standard, corpus-based, task-based and criteria based The survey was based on accuracy, efficiency, precision, adaptability. The survey ended by concluding that the gold standard was efficient in evaluating the accuracy of ontology but a Task-based approach is more useful if you want to check the adaptability of an ontology. Moreover, it can also be used to find the compatibility between the used tool and ontology.

Jung et al[21] developed an adolescent depression ontology. For developing the domain, scope questions were used. EAV (entity attribute value)triplet model was used to design the internal structure of the ontology, from clinical data and for social media, they collected the data, and for evaluation, applied mapping concepts, and developed an ontology for bipolar disorder (BDI) to support BDI diagnosis. For validation, the author studied the sentimental phrases using ontology and the EAV model and conducted an analysis on social media data based on concepts of classes.

Chryssa. H et al[22] aim was to provide an efficient patient monitoring system by integrating clinical support systems and electronic health records. Their model contains a Health level seven reference information model (HL7-RIM)and used CDSS based ontology that has semantic web capability. The proposed AI care monitoring system used knowledge-based systems for developing an ontology and is considered for ontology alignment. online monitoring tools were also used to monitor the performance of the system.

Sumit Dalal et al[23] proposed their architecture which is cost and time-effective and one step ahead in the self-diagnosis of patients with depressive disorder and examined various tools like NLP, ML, cloud computing that is critical in the smart healthcare sector.

IV. METHODOLOGY

Natural language processing is the growing research where one of the most common applications of NLP is sentimental analysis. From opinion data polls to marketing strategies NLP has completely changed the way humans think and how to find relevant patterns. For our research also sentimental analysis approaches were applied. Data were first preprocessed and tried to find some similarity then extraction of some features happened from it and finally use these features for our model building. The detailed system architecture of our proposed model is shown in figure 1.

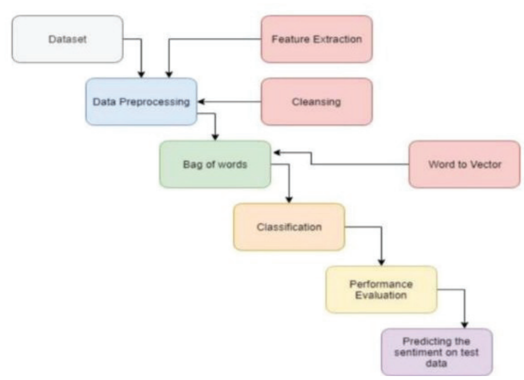

Fig 1. Model architecture

A. DATASET PREPARATION

For our model two datasets from Kaggle were taken, one dataset will be used to train our model and the second dataset will be used to validate our model accuracy. The dimensions of training data were 31962,3 and testing data were 17197,2. The dataset consists of negative and positive tweets.

Data is visualized first to get better insights. The length and frequency of train and test tweets are shown in figure 2.

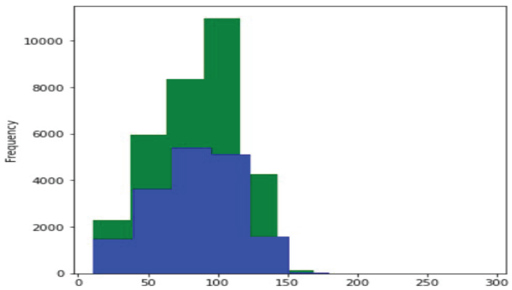

Fig 2. Frequency and length of train and test tweets.

B. DATASET OVERVIEW

The tweets contain lots of opinions and views of the person/user. The dataset for training is already labelled ie. hate/racist or positive polarity and hence performing sentimental analysis is slightly easier. The initial unprocessed data having polarity is highly prone to inconsistency. Pre-processing of the tweets includes collecting and extracting hashtags, removing punctuations, removing stop words, removing non-English tweets.

Pre-processing is done after the Word2Vec model. The most frequent negative and positive hashtags from the dataset are visualized as seen in fig 3 and fig 4.

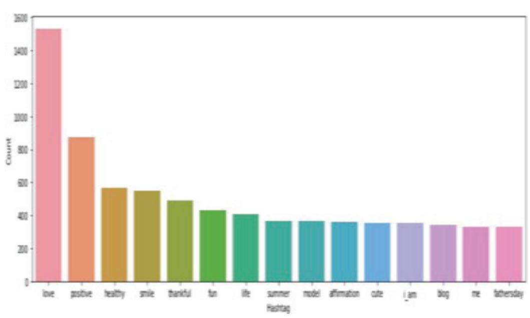

Fig 3.Top 15 non-racist hashtags

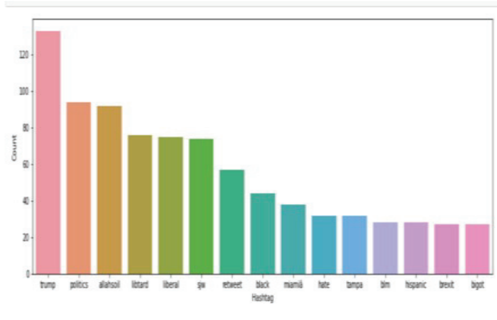

Fig 4. Top 15 racist hashtags

C. Word2Vec Model

Tweets are tokenized. Tokenizing is a process in which it divides the corpus into meaningful entities. It is the first step of NLP where each tweet is divided into unique meaningful entities. Word2vec model is created to learn associations from a big text corpus. Word2Vec algorithm once trained can find the related word and can suggest words closer to the given word.Word2Vec is simple and fast to train the model. It contains 2 important models namely Skip Gram and CBOW. In Skip Gram centre words window of context ie. neighbour as '5' were taken and our objective was to predict context words from each centre word. The size was taken as 200 and no of partitions was taken as 2.

CBOW (Continuous Bag Of Words model) can also be used. It is different from Skip gram in which prediction happens based on the centre word by encapsulating vector of surrounding words. The most similar words related to a given word are printed as output shown in fig 5.

```
model_w2v.wv.most_similar(positive = "smile")

[('grin.', 0.6781454086303711),
 ('#dogsarejoy', 0.6694209575653076),
 ('smile!', 0.6617622375488281),
 ('#dog.', 0.6598066091537476),
 ('face!!', 0.6467138528823853),
 ('#selenagomez', 0.6457967758178711),
 ('smiles', 0.6454964876174927),
 ('giggle', 0.6413540244102478),
 ('#invisalignjourney', 0.635764479637146),
 ('ð\x9f\x98\x8a.', 0.6351218819618225)]
```

Fig 5. Most relevant words

Using the genism model labelled sentences were imported to label the tokenized tweets.

D. Pre-processing

Stop words and port stemmer were used to further pre-process the tweets Stop words are used to filter out words that don't contain any meaning and are required for model building. Stemming is the method to reduce the word to its root words example going, going to, gone will be reduced to go. Stop Words and Port Stemmer algorithm is applied to the tweets in a corpus entity. For more understanding punctuations, abbreviations are removed.

E. Bag of Words

The bag of word method is used to extract features from the tweets. A BOW is a representation of text where the occurrences of each word are described. It involves 2 things:

- A dictionary/vocabulary of already recognized words
- The existence and occurrences of already known words.

A bag of words is created using CountVectorizer on both the datasets where max features were taken as 2500.

V. Result Analysis and Evaluation metrics

ML is part of an AI application which provides training and learning of machines so that next time machine will automatically learn from his past experience that helps machines to be more adaptive in different situations and try to understand from different situations. ML helps in processing and developing software tools. The learning part is done using the help of past examples, their observations and based on that findings evidence are used to interpret knowledge patterns so that it makes reliable future decision The objective of ML is to make machines pro-active and have their own set of experience that does not require any manual interference.ML consist of two types namely supervised ML algorithm and non-supervised ML algorithms OF machine learning. Five ML algorithms are used to check the accuracy using the F1 score and confusion matrix. The data is split into train and testing while taking test dataset as validation accuracy to test our model.

Random Forest Classifier is a supervised learning algorithm, it is an ensemble of different decision trees that can be trained with the bagging method. It is a very easy-to-use algorithm as its default hyperparameters often produce good results. It does not produce overfitting while classifying the model. The algorithm selects random datasets and constructs the decision tree for every sample and then gets prediction results from the decision tree next voting is performed on the predicted result and the most voted predicted result is selected as final output.

Logistic Regression is also a supervised learning algorithm, in the classification of the target variable, y can take discrete values for input variables, X.LR uses the sigmoid function. In classification, a threshold is set. The LR equation can be obtained from the Linear Regression equation. The mathematical steps to get the algorithms classification and regression prediction is given below :

Y=bo+b1x1+b2x2+b3x3+…….+bnxn eq.1

In Logistic regression, Y can be either 0 or 1 as we have trained our model it should give us the result as positive or negative tweets. We can divide the above equation by (1-y):

y/1-y;0 for y=0 and infinity for y=1 eq.2

The range can be -infinity to +infinity so after taking the logarithm final equation becomes :

Log[y/1-y]= bo+b1x1+b2x2+b3x3+…….+bnxn eq.3

The above is the final equation of LR that will be used for the classification of tweets.

Decision Trees are the most commonly used algorithms for classification and well as for prediction. The internal nodes denote the test of attributes, each branch is the result of the test and each end node contains the class label. If a target is a classification outcome taking on values 0,1,…,K-1, for node m, let

pmk=1/Nm∑y∈QmI(y=k) eq.4

be the proportion of class k observations in node m. If m is a terminal node, predict_proba for this region is set to pmk.

SVM is counted as the best-supervised learning algorithm which is mainly used in classification and regression. SVM algorithms create the best line or decision boundary to predict the classes. SVM chooses extreme points to create a hyperplane. The best fit line can be calculated using the below formulae:

g(x)=w^{T} x+b

Maximize k such that:

-w^{T} x+b >= k for d_{i}==1

-w^{T} x+b>=k for d_{i}==-1

Value of g(x) depends upon ||w||:

1) Keep ||w|| =1 and maximize g(x) or,

2) g(x) >=1 and minimize ||w||

XGB Classifier is also called gradient boosting. It is a boosting technique that consists of a collection of predictors with different models to provide better accuracy. The dataset is divided into training and testing where training accuracy and validation accuracy are calculated along with the F1 score and confusion matrix. XGB is a part of ensemble learning. The boosting ensemble technique has 3 parts: The F0 is defined to predict the target variable y. This model will be associated with a residual (y – F0)A new model h1 is fit to the residuals from the previous step. Now, F0 and h1 are combined to give F1, the boosted version of F0. The mean squared error from F1 will be lower than that from F0:

F_{1}(x)<-F_{o}(x)+h_{1}(x)

To improve the performance of F1, we could model after the residuals of F1 and create a new model F2:

F_{2}(x)<-F_{1}(x)+h_{2}(x)

This can be done for 'm' iterations until residuals have been minimized as much as possible:

F_{m}(x)<-F_{m-1}(x)+h_{m}(x)

Here, the additive learners do not disturb the functions created in the previous steps. Instead, they impart information of their own to bring down the errors.

TABLE1. ACCURACY COMPARISON

Algorithms-Existing Model	Accuracy of the existing model	Accuracy of proposed Model
SVM	76.6%	95.5%
Logistics Regression	84%	95.6%
Random Forest	75.99%	95.4%
Decision tree	88.5%	93.8%
XGBoost Classifier	85%	95.5%

Table 1 illustrates the comparison between the existing model and the proposed model based on various evaluation techniques. On comparing SVM, Logistic Regression, DT and XGBoost Classifier were giving slightly better accuracy than existing models hence it can be said that the proposed model performed better in certain algorithms and can be used for real-time scenarios.

VI. Conclusion

In this paper, our model architecture was provided as to how it can find the hate or positive tweets using sentimental analysis and ML algorithms. Word2Vec model was created to find the relationship between the words. A bag of words. was used to find the most frequent words in the dataset. Pre-processing was done to find the meaningful data before the final model generation using ML algorithms. On comparing the various algorithm's the result showed the highest validation accuracy on logistic regression followed by XGBoost classifier when the model was applied on test data but the F1 score was more on random forest followed by logistic regression. The logistic regression can be very effective in predicting the sentiments. It can be concluded that more data processing can lead to better accuracy. Using the Word2Vec model using skip-gram gives us better accuracy as compared to other models.

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