Cyber Bullying Recognition System for Facebook using ML Algorithms for Sentiment Analysis

Alok Sinha, Sushrut Ghimire, Bibek Singh, Rishav Raj, Ramanathan L

Abstract: *Cyberbullying has been around for some time currently, however individuals have quite recently started understanding that difficulty. Society has developed from numerous points of view but then remained the same in numerous others. Just the techniques have changed. In this paper, we took a gander at a portion of the causes behind cyber-bullying and have prepared a statistical analysis of various algorithms used in the cyber-bullying detection systems. Several techniques contribute in cyber-bullying detection, mainly Machine Learning (ML) and Natural Language Processing (NLP). Sentiment analysis has popularized due to the availability of abundant opinions that resides in social networks such as Facebook. In this paper we present sentiment analysis of Facebook comments using Naive Bayes Classifier, logistic regression, Random forest, Decision tree and Support Vector Machine (SVM). The essential and basic thought of the paper is that, realizing how individuals feel certain Facebook comments can be utilized for classification.*

Keywords: *Machine Learning, Naïve Bayes, Support Vector Machine, Decision Tree, Logistic Regression, Random Forest.*

Introduction:

Cyberbullying can cause huge mental pain and tension. Much the same as some other survivor of harassing, cyberbullied kids experience nervousness, dread, sadness, and low confidence. They likewise may encounter physical indications, and battle scholastically. In any case, focuses of cyberbullying likewise experience some exceptional outcomes and negative sentiments. Cyberbullying often attacks victims where they are most vulnerable. Targets of bullying may feel intense dissatisfaction with who they are. As a result, targets of cyberbullying often begin to doubt their worth and value. They may respond to these feelings by harming themselves in some way. Victims of cyberbullying often succumb to anxiety, depression and other stress-related conditions.

Due to the emergence of the internet and much engaging social media, the ability of people to connect across borders have become very easy. People share their opinions in the form of statuses, stories, comments and reactions. In social medias such as

Facebook, cyberbullying has impacted lives of many people. The number of people engaging in social medias are increasing day by day and various sentiments are being shared among the users. Some harsh words impact the lives of people every day, especially children. The number of social media users increases every day and it is estimated in 2019 there will be up to 2.77 billion social media users worldwide.

Facebook comments and statuses will be the main concern of this paper. Facebook in contrast to Instagram and twitter is focused on this paper due to its overall use by all kinds of users from across the world. The quantity of the users makes it easier to collect the corpus for our research. It has a greater number of words and the number of bullying cases in Facebook is way more than compared to other social medias. The need for the research aroused from the fact that variety of algorithms were used to detect cyberbullying across social medias. But the use of these algorithms used to differ across different situations. Thus, the main focus of this paper would be to provide a

statistical comparison of the efficiency and accuracy of ongoing algorithms that are currently used in Cyber-bullying detection systems.

Consequently, various algorithms are compared in order of their efficiency. The algorithms that are mostly used were selected which are Naive Bayes Classifier, Logistic Regression, Random Forest, Decision Tree and SVM (Support Vector Machine)

I. Naive Bayes Classifier

It is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature.

II. Logistic regression

Logistic regression is the appropriate regression analysis to conduct when the dependent variable is dichotomous (binary). Like all regression analyses, the logistic regression is a predictive analysis. Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables.

III. Random forest

Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes or mean prediction of the individual trees.

IV. Decision tree

A decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. •

V. Support Vector Machine (SVM)

In machine learning, support-vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis.

The pattern analyzer was classified into three categories based on the different forms of feedback that are-

1. Positive Response
2. Negative Response
3. Neutral Response

These three conditions are going to be examined to get the feedback for the abusive comments or status made by users. With the appropriate tools and technique, we are going to see the action of different techniques used by the machine learning algorithm.

Key Challenges of Proposed Algorithms:

Naive Bayes has the strong assumption about the features to be independent which is hardly true in real life applications. It has Data scarcity and also has chances of loss of accuracy. It requires Zero Frequency i.e. if the category of any categorical variable is not seen in training data set then model assigns a zero probability to that category and then a prediction cannot be made.

We can’t solve non-linear problems with logistic regression since its decision surface is linear. Logistic Regression is also not one of the most powerful algorithms out there and can be easily outperformed by more complex ones. Another disadvantage is its high reliance on a proper presentation of your data. This means that logistic regression is not a useful tool unless you have already identified all the important independent variables. Since its outcome is discrete, Logistic Regression can only predict a categorical outcome. It is also an Algorithm that is known for its vulnerability to over fitting.

One of the biggest problems in machine learning is overfitting, but most of the time this won't happen thanks to the random forest classifier. If there are enough trees in the forest, the classifier won't overfit the model. The main limitation of random forest is that a large number of trees can make the algorithm too slow and ineffective for real-time predictions. In general, these algorithms are fast to train, but quite slow to create predictions once they are trained. A more accurate prediction requires more trees, which results in a slower model. In most real- world applications, the random forest algorithm is fast enough but there can certainly be situations where run-time performance is important and other approaches would be preferred. Random forest is a predictive modelling tool and not a descriptive tool, meaning if you're looking for a description of the relationships in your data, other approaches would be better.

In Decision Trees, a small change in the data can cause a large change in the structure of the decision tree causing instability. For a Decision tree sometimes, calculation can go far more complex compared to other algorithms. Decision tree often involves higher time to train the model. Decision tree training is relatively expensive as complexity and time taken is more. Decision Tree algorithm is inadequate for applying regression and predicting continuous values.

SVM algorithm is not suitable for large data sets. SVM does not perform very well, when the data set has more noise i.e. target classes are overlapping. In cases where number of features for each data point exceeds the number of training data sample, the SVM will underperform. As the support vector classifier works by putting data points, above and below the classifying hyper plane there is no probabilistic explanation for the classification

Literature Review:

(Viktor Golem, Laden Karan and Jan ˇSnajder,2018) assemble a framework that can mark messages from a given dataset as openly aggressive, covertly aggressive, or not aggressive. They can handle the task using traditional machine learning models, logistic regression and support vector machine (SVM), and deep learning models like convolutional neural networks (CNNs) and long short-term memory networks (LSTMs). To perform the best of both, we performed exercising with a combination of both shallow and the deep learning models.

(Ivan Habernal, Tomas ptacek and Josef Steinberger,2013) aim to form document-level sentiment analysis based on three different datasets using supervised machine learning. The one of the datasets is created using a Facebook corpus consisting of 10,000 posts. Social media is analyzed focusing on Twitter and Facebook. Studying twitter and Facebook with very informal language benefits from involving novel features, like emoji character n-grams, POS and POS ratio, or word shape etc.

(Batoul Haidar, Maroun Chamoun and Ahmed Serhrouchni,2018) designed for preventing cyberbullying attacks, by detecting and stopping them. It uses Natural Language Processing (NLP) to identify and process Arabic words. Then Machine Learning techniques are used to classify bullying content. They show them-selves how to order the information dependent on likenesses and contrasts between information. At the point both supervised and unsupervised learnings are consolidated together by utilizing marked and unlabeled information.

(Dublin, Ireland, 2014) propose a deep convolutional neural system that abuses from character-to condemn level data to perform notion examination of short messages. The proposed organize, named Character to Sentence Convolutional Neural Network (CharSCNN), utilizes two convolutional layers to separate significant highlights from words and sentences of any size. The proposed system can without much of a stretch investigate the wealth of word embeddings delivered by solo pre-preparing. They perform tests that show the viability of CharSCNN for supposition examination of writings from two areas: film audit sentences; and Twitter messages. CharSCNN accomplishes best in class results for the two areas.

(V Kharde, 2016) utilize different component extraction strategy. They utilized the structure where the pre-processor is applied to the raw sentences which make it more fitting to understand. Further, the different machine learning strategies prepare the dataset with include vectors and afterward the semantic examination offers an enormous arrangement of equivalents and comparability which gives the extremity of the substance. They give an overview and near investigation of existing procedures for conclusion mining including AI and dictionary-based methodologies, along with cross area and cross-lingual strategies and some assessment measurements.

(Amrita Mangaonkar ; Allenoush Hayrapetian ; Rajeev Raje,2015) utilized different strategy for the discovery of cyberbullying in a given printed content. These incorporate Bag of-Words (BoW), Lexical Syntactic Feature (LSF), and distinctive Machine Learning-based methodologies. Lexicon based techniques, for example, the BoW or LSF, predominantly depend on the nearness of vulgarities and obscenities in the web-based life content. Albeit, literary cyberbullying may contain vulgarities and obscenities, all the profane content on social media may not be cyberbullying – contemplates show that, pace of utilizing hostile words is near twofold on Twitter than in ordinary life The aftereffects of these tests are empowering and recommend that approach can be reasonable for ordering a tweet either to be cyberbully or non-cyberbully conduct – and is utilized in the proposed research.

(F Del Vigna12, 2017) presented the principal of hate speech classifier for Italian writings. Thinking about a binary grouping, the classifier accomplished outcomes similar with those got in generally researched supposition examination for Italian language. Empowered by such encouraging result, they leave for future work the refinement of the classifier results while thinking about differentiation among hate levels and among different types of hate speech. They are developing the explanation process, both to build the corpus size and to gather more comments for a single comment. They are trying new explanation techniques, assessing the between annotator understanding or approving the explanation on the various degrees of hate speech.

(Liew Choong Hon, Kasturi Dewi Varathan,2015) make a web-based application, for example the Cyberbullying Detection Framework on Twitter. The usage of the Cyberbullying Detection System on Twitter depends on PHP and HTML with the MySQL and Twitter API. This framework will identify cyberbullying related tweets that have matching keyword from the database. This framework tells overall the general procedure on how the cyberbullying-related tweets can be recognized and alarms the NGOs, and hence action taken by police headquarters through email reports, likewise alert the cyberbullying client's or on the other hand the system administration in checking their cyberbullying exercises. At first, the client needs to login into the framework and then all other steps are taken by the system.

(Akshansh Malik, Aman Mahal, Aman Kamboj, Abhishek Sharma, 2020) found the ways to extract information from social media gave us several usages in various types of fields and researches. In Product Analysis, extracting information from social sites/media is providing number of advantages such as knowledge about the latest technology, update of a real-time situation in market etc. one of the social media is Twitter which allows the user to post tweets of limited number of characters and share the message(tweet) to their followers. It also allows developer to access the information for their purpose.

(Mohammed Nazrul Islam Arif, Sarwar Hussain Paplu, Prof. Dr. Karsten Berns, 2019) recognize the emotions present in the communication or the emotions of the involved users to make those interactions more humanly. This study summarizes different approaches that can be used to analyze the emotion from the text and recognize the emotion between Text-Based Communications. Approaches like finding subjective feeling through introspection, Word categorization, Kinetic Typography to convey emotion, Meta-analysis on mood induction, Emotion expression through text-based communication, Sentimental analysis are discussed.

(Pinkesh Badjatiya, Shashank Gupta, 2017) define the task as being able to classify a tweet as racist, sexist or neither. The complexity of the natural language constructs makes this task very challenging. They perform extensive experiments with multiple deep learning architectures to learn semantic word embeddings to handle this complexity. Their experiments on a benchmark dataset of 16K annotated tweets show that such deep learning methods outperform state-of-the-art char/word n-gram methods by ∼18 F1 points.

(Osama Mohammad Rababah, and Nour Alokaily, 2019) present novel system that offers personalized user experiences and solves the semantic-pragmatic gap. Having a system for forecasting sentiments might allow extracting opinions from the internet and predicting online user's favorites, which could determine valuable for commercial or marketing research. The data used belongs to the tagged corpus positive and negative processed movie reviews.

(Mikhail Bautin, Lohit Vijayarenu, Steven Skiena, 2008) explore an approach utilizing state-of-the-art machine translation technology and perform sentiment analysis on the English translation of a foreign language text. After applying certain normalization techniques, entity sentiment scores can be used to perform meaningful cross-cultural comparisons.

(Alexander Pak, Patrick Paroubek, 2010) focus on using Twitter, the most popular micro blogging platform, for the task of sentiment analysis. They show how to automatically collect a corpus for sentiment analysis and opinion mining purposes. They perform linguistic analysis of the collected corpus and explain discovered phenomena. Using the corpus, we build a sentiment classifier that is able to determine positive, negative and neutral sentiments for a document.

(Michelle Annett, Grzegorz Kondrak, 2008) propose a novel approach based on Support Vector Machines. They compare their method to previously propose lexical-based and machine learning (ML) approaches by applying it to a publicly available set of movie reviews.The algorithm will be integrated within a blog visualization tool.

(Wilas Chamlertwat, Pattarasinee Bhattarakosol, Tippakorn Rungkasiri, 2012) propose a system, the *Micro-blog Sentiment Analysis System* (MSAS), based on sentiment analysis to automatically analyze customer opinions from the Twitter micro-blog service. We used the product domain of smartphone as our case study. The experiments on 100,000 collected posts related to smartphones showed that the system could help indicating the customers' sentiments towards the product features, such as *Application*, *Screen*, and *Camera*.

(Mahtab, S. A., Islam, N., & Rahaman, M. M. ,2018) present an idea to target a special sector which is Bangladesh Cricket where people express their opinions in their native Bengali languages on social medias. With the help of prepared a dataset of three sentiment classes it categorized into real people sentiments. The generalized and processed dataset are functioned by removing unnecessary words from the Bengali texts. The result shows analysis for two of our datasets and for the machine learning models experiment is chosen. The precision, recall, support, f1-score result are given for each dataset. The observation shows criticism and sadness is similar in some cases with others sentiment.

(Agarwal, A., Xie, B., Vovsha, I., Rambow, O., & Passonneau, R. J. ,2011) proposed to introduce POS-specific prior polarity features and also exploring the use of a tree kernel to obviate the need for tedious feature engineering. The results show sentiment analysis on Twitter effectively. The investigation made to two kinds of models: tree kernel and feature based models and demonstrate that both these models outperform the unigram baseline. For our feature-based approach, the feature analysis which reveals that the most important features are those that combine the prior polarity of words and their parts-of- speech tags. The sentiment analysis of twitter data is not considered to be far from others genre.

(Hassan, A. U., Hussain, J., Hussain, M., Sadiq, M., & Lee, S., 2017) approach the way to find the depression level of a person by observing and extracting emotions from the text, using emotion theories, machine learning techniques, and natural language processing techniques on different social media platforms are generalized and implemented. The results show a comparison among SVM, NB and ME classifiers regarding sentence level sentiment analysis for depression measurement. This experiment indicates that SVM shows superior result as compare to Nave Bayes and Maximum Entropy classifiers.

(Oyebode, O., & Orji, R. ,2019) aim to identifying public sentiments towards two popular candidates with the aim of determining their chances of being elected based on social media into the highest position of authority in Nigeria. Using lexicon-based and supervised machine learning (ML) techniques with the aim of detecting their sentiment polarity, the operation was performed sentiment analysis on election related posts from Naira land. The methods are implemented based on lexicon-based classifiers and others ML-based classifier which leads to analysis of sentiment based on positive and negative response.

(Yuliyanti, S., Djatna, T., & Sukoco, H. ,2017) visualize present sentimental analysis from every activity's comments based on their tweet using social media-based activities. The effective way of implementation was being modeled based on activity classification by using support vector machine. The term score by calculating term frequency, which combined with term sentiment scores based on lexicon. The final result shows the models provided sentiment summarization that point out the success level of positive sentiment. Sentiment mining models which were built capable for extraction textual data into structure so that produce sentiment and classified to determine the public response to the activities in community development programs.

(Ali, K., Dong, H., Bouguettaya, A., Erradi, A., & Hadjidj, R. ,2017) focused on the spatial-temporal properties of social media users' sentiments to identify the locations of disease outbreaks. Also proposed a service composition mechanism that composes multiple services for sentiment analysis based on social information service classification. We utilized spatiotemporal properties and sentiment analysis to identify the locations of disease outbreaks. Basically, experiments on the real-world dataset are conducted and results show the applicability of our proposed approach.

(Abd El-Jawad, M. H., Hodhod, R., & Omar, Y. M., 2018) proposed a set of techniques of system gaining knowledge of with semantic evaluation for classifying the sentence and product opinions based totally on twitter facts. In this paper, a methodical survey of supposition examination and sentiment mining, the multifaceted nature of data Presentation and dimensionality, distinctive use necessities, the conclusion examination or sentiment mining developed as basic research objective thinking since that 10 years. The sentiment evaluation is having potential scope for destiny research and certainly one of that is exposing and scope of evolutionary computational or soft computing strategies and the hybridizing these techniques in the direction of Function extraction, selection to categories the sentiment.

(Poecze, F., Ebster, C., & Strauss, C., 2018) uses Social media metrics and sentiment analysis to evaluate the effectiveness of social media posts. The participants included YouTube gamers. The main focus on content of their communication on Facebook to identify significant differences in terms of their user-generated Facebook metrics and commentary sentiments. Methodologically, ANOVA and sentiment analysis were applied. ANOVA of the classified post categories revealed that re-posted YouTube videos gained significantly fewer likes, comments, and shares from the audience. The results mainly urged the necessity to utilize natural language processing techniques to optimize brand communication on social media and highlighted the importance of considering the opinion of the masses for better understanding of consumer feedback. The results of this study suggest the importance of not relying on and utilizing solely retrievable user-generated metrics. The sentiment of the text commentary accompanying social media posts should also be incorporated in the following analysis.

(Isah, H., Trundle, P., & Neagu, D. ,2014) reports the work that was held progress with contributions including: the development of a framework for gathering and analyzing the views and experiences of data's using machine learning, text mining and sentiment analysis. This application of the proposed framework on social for brand analysis, and the description of how to develop a product safety lexicon and training data for modeling a machine learning classifier was found. The result signifies the usefulness of text mining and sentiment analysis on social media data while the use of machine learning classifiers for predicting the sentiment orientation to monitor brand or product sentiment trends in order to act in the event of sudden or significant rise in negative sentiments.

(John Hani Mounir Misr,Eslam A. Amer Misr, Mohamed Nashaat Misr, Mostafaa Ahmed Misr, Janu, 2019) utilize few classifiers to prepare and perceive tormenting activities. The assessment of the proposed approach on cyberbullying dataset shows that Neural Network performs better and accomplishes exactness of 92.8% and SVM accomplishes 90.3. Additionally, NN beats different classifiers of comparative work on the equivalent dataset.

(Maral Dadvar, Franciska de Jong, 2015) recommend that consolidation of the clients data, their attributes, and post-irritating conduct, for example, posting another status in another interpersonal organization as a response to their harassing experience, will improve the exactness of cyberbullying recognition. Cross framework investigations of the clients conduct - observing their responses in various online conditions - can encourage this procedure and give data that could prompt more exact discovery of cyberbullying.

(Maral Dadvar and Kai Eckert,2016) research the discoveries of an ongoing writing and duplicated the discoveries of this writing and approved their discoveries utilizing the equivalent datasets, to be specific Wikipedia, Twitter, and Form spring. At that point they extended their work by applying the created techniques on another YouTube dataset (~54k posts by ~4k clients) and explored the exhibition of the models in new internet-based life stages. They likewise moved and assessed the presentation of the models prepared on one stage to another stage. Their discoveries show that the profound learning-based models beat the AI models recently applied to the equivalent YouTube dataset and accept that the profound learning-based models can likewise profit by coordinating different wellsprings of data and investigating the effect of profile data of the clients in informal organizations.

(Rekha Sugandhi, Anurag Pande, Siddhant Chawla, Abhishek Agrawal, Husen Bhagat , 2015) survey the various techniques and calculations utilized for discovery in digital tormenting and give a similar report among them in order to choose which strategy is the best methodology and gives the best exactness. They understand bolster vector machines have given the best result. In expansion to this, the usage of help vector machines to recognize harassing follows from non-harassing ones will give us a superior outcome. This information is than utilized to forestall harassing at its source.

(Qianjia Huang,Vivek K. Singh,Pradeep K. Atrey, 2015) explores the case of examining interpersonal organization highlights can improve the exactness of digital harassing identification. By dissecting the interpersonal organization structure among clients and inferring highlights, for example, number of companions, arrange embeddedness, and relationship centrality, they find that the location of digital harassing can be fundamentally improved by incorporating the literary highlights with informal community highlights. Their outcomes demonstrate that social highlights are valuable in distinguishing digital tormenting. In actuality, it recommends that understanding the social setting in which a message is traded is similarly as significant as the message itself.

(Amanpreet Singh, Maninder Kaur, 2019) represents an orderly basic examination to collect, research, secure and investigate the examples and study holes in an efficient way. The examination depicts an extensive efficient writing audit of systems proposed in the field of substance based cybercrime. In this audit, exact examination strategy is used dependent on a complete chosen 27 exploration papers out of 51 examination papers distributed in superior workshops, discussions and gatherings and obvious diaries. The overview identifies with a few information preprocessing strategies, content-based element, AI system, online person to person communication datasets and assessment boundary utilized in setting of identifying content-based cybercrime. This Methodical examination of the exploration work goes about as a right hand for the scientists to find the critical qualities of substance-based Cybercrime identification strategies.

(B.Sri Nandhinia , J.I.Sheebab, 2015) identify cyberbullying exercises via web-based networking media. The identification technique can recognize the nearness of cyberbullying terms and arrange cyberbullying exercises in interpersonal organization, for example, Flaming, Harassment, Racism and Terrorism, utilizing Fuzzy rationale and Genetic calculation. The adequacy of the framework is expanded utilizing Fuzzy standard set to recover significant information for characterization from the info. In the proposed strategy Genetic calculation is likewise utilized, for streamlining the boundaries and to get exact yield. It centers around recognizing the nearness of cyberbullying action in interpersonal organizations utilizing fluffy rationale which causes government to make a move before numerous clients turning into a casualty of cyberbullying.

(Mingmei Li, Atsushi Tagami,2015) propose a system to create a contact arrange. The structure comprises of two stages for a decrease of bogus negative, for example understudies are companions in the school however recognized as non-companion in the Social Networking Service (SNS), which is a significant issue for the digital tormenting identification. At long last, this paper dissects the gathered SNS information with the genuine human connections, and assesses the proposed structure. They broke down human connections on SNS with nitty gritty qualities that were distinguished by the collaboration of the instructors and the school; and proposed a system to produce a contact arrange for the initial step of the connection based digital tormenting location. The examination demonstrated the prevalence is exponentially appropriated.

Comparative Analysis:

Reference No	Method involved	Advantage	Disadvantage	Future Scope
9	Proposed framework on Facebook comments and data from Twitter for brand analysis.	They provide a useful tool for users, product manufacturers, regulatory a	Fails to comparing different machine learning sentiment classification performances.	Considers comment spamming, comparing different machine learning sentiment classification performances, temporal analysis for detecting up or down trend of sentiment of a particular brand or product as well as clustering tweet and user sentiments by location.

6	Spatial-temporal properties a nd sentiment analysis.	A new quality model to assess the quality of social information services.	Requires effective mechanisms to integrate and compile large scale analysis results.	Aim to test and validate the performance of our proposed approach with the real-time large data.
8	ANOVA a nd sentiment analysis were applied.	Importance of not relying on and utilizing sole ly retrievable user-generated metrics.	Lack of user activity paired with a high ratio of negative user commentaries called into question such a communication strategy.	Should clarify the weights and r project utilizing a larger Sample and possibly stepping out the domain of YouTube gamer brand personalities.
1	TF-IDF Vectorizer for vectorization and the classifier SVM to classify our data.	Processed dataset by removing unnecessary words from the Bengali texts.	Limited amount of data where used only 10% of dataset as test set and found around 64% accuracy only.	Working on Bengali language where we have not done the stemming, spell-checking and Bengali parts of-speech tagging for our current research and will definitely go on to workout with the accurate natural language processing.
2	Tweet extracted directly from Twitter API, then cleaning and discovery of data performed.	Several algorithms to enhance the accuracy of classifying tweets as positive, negative and neutral.	Previously labeled data do not exist at first using lexicon-based algorithm.	An algorithm that can automatically classify tweets would be an interesting area of research.

26	Lexicon analysis to find or calculate the polarity and Machine Learning involves formation of models from labeled training dataset	widely used on big data to gather public critics in order to assess internaut's satisfaction of a subject (services, products, events, topics or different persons) in different domains	It cannot understand emoticons. Second, they used only Twitter data. Third, cannot be accessed large data for this algorithm	Propose a more efficient and global model that can work on larger volumes of Data.
27	Introspection, Word categorization, Kinetic Typography to convey emotion, Meta-analysis on mood induction, Emotion expression through text-based communication.	Generate relevant emotional expression and verbal replies as the robot's reaction based on its personality and they improve the user engagement in conversation with the robot in real-time.	Topic detection system contributed more to their engagement than the sentiment-analysis system, though the differences between their statistical means is too high.	This particular method of analysis seems to be more appropriate for finding the emotional expression in Text-Based communication.
28	Multiple deep learning architectures to learn semantic word embeddings to handle this complexity	Investigated the application of deep neural network architectures for the task of hate speech detection and found them to significantly outperform the existing methods	Require much more data than traditional machine learning algorithms, as in. At least Thousands if not millions of labeled samples.	They plan to explore the importance of the user network features for the task.
32	Support Vector Machines, lexical- based and machine learning (ML)	With this SVM approach, it is quite easy to obtain an acceptable level of accuracy when classifying movie	Classifying blog reviews according to star rating not explained.	Extend their application to take into account the user's attitudes and preferences toward specific

		blog posts.		genres, actors or actresses
20	Used DNN based models.	DNN models were adaptable and transferable to the new dataset. DNN based models coupled with transfer learning outperformed all the previous results for the detection of cyberbullying	There were some details and settings that were not clearly stated. These might have been the reason for some the inconsistencies in our results	Look into the impact of profile information of the social media users and to investigate the improvement of the models by considering the above-mentioned sources of information.
21	Compared algorithms, and realize support vector machines have given the best result.	take social features into consideration to increase accuracy	limited amount of data where used only 10% of dataset.	Introduce Hidden Markov models to fust classify the data into a few predefined categories.
22	Considers the social relationships in which these bullying messages are ex-changed.	Our results indicate that social features are useful in detecting cyber bullying.	It suggests that under- standing the social context in which a message is exchanged is just as important as the message itself	In future, similar approaches can be applied over more fine-grained data about human behavior to detect cyber and physical social bullying in different settings, thus paving the way for a safer environment for bullied individuals in different social settings.

Software RequirementOperating System: Windows

Operating System: Window

Python Environment

Jupiter notepad

Packages

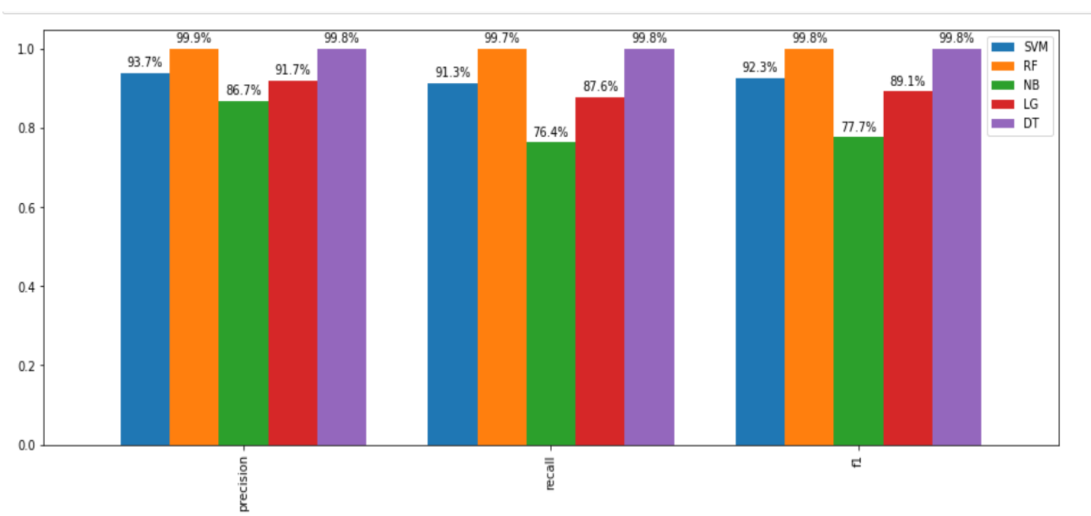
Numpy

pandas

matplotlib

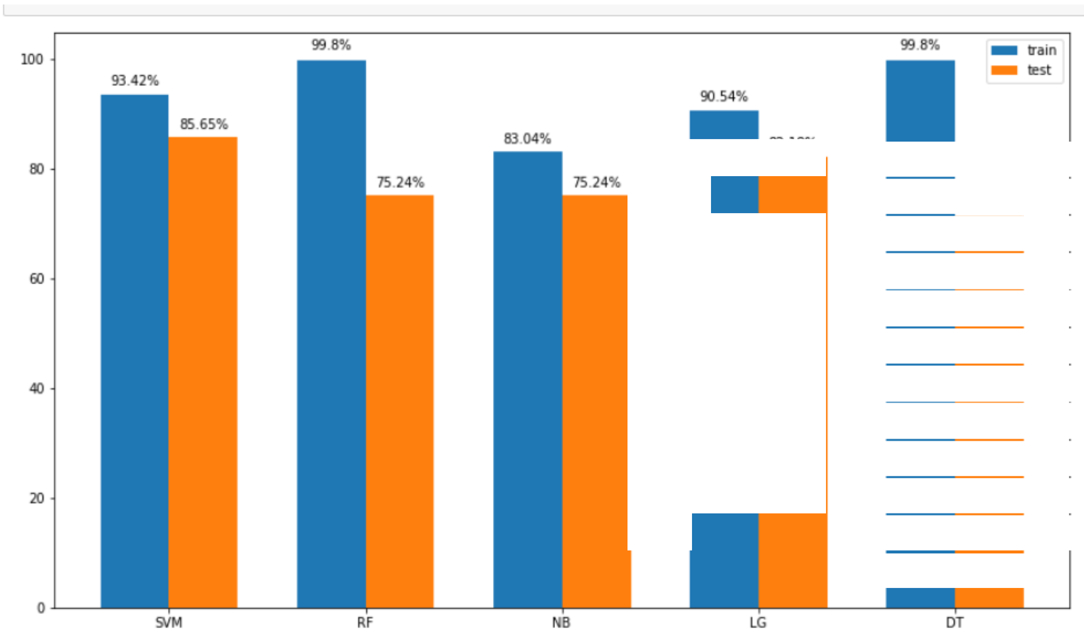
Visualizing Chart

The visualization chart is Machine Learning Algorithm which is demonstrated in Bar Graph presents the value based on the f1 score, precision, recall of all the al Another graph shows the comparing value of the of test and train data based on their respective score.



SVM=Support Vector Machine
RF= Random Forest
NB=Naïve Bayes
LG=Logistic Regression
DT=Decision Tree

The bar graph shows scores of different values made on the five algorithms. The sentiment analysis is predicted on these algorithms and the scores we obtained are generalized and visualized with this chart. The value may differ from system to system. Another chart is made based on the test and train score which is shown below:



Conclusion: In the paper, we have generalized five different Machine Learning Algorithms for sentiment analysis of the Facebook data. The generalization of different approach and methods, we have studied all the different approach to make Sentiment Analysis in a better way. Different parameters are taken in consideration for different analysis that are positive, negative, and neutral. The presentation of these algorithm will make a good understanding for making the performance better. Any individual can predict which algorithm will work far better for making sentiment analysis. The post and status are posted in large number where the best technique will prove to be the best out of it and we are in approach to make a comparative analysis of different algorithms. We tentatively conclude which part of algorithm have effective on sentiment analysis because the algorithm should be good enough for the parsing, semantic analysis and able to handle errors with the help of tools.

Author Profile

Alok Sinha, Department of Computer Science and Engineering, Vellore Institute of Technology, aloksinha422@gmail.com

Sushrut Ghimire, Department of Computer Science and Engineering, Vellore Institute of Technology, sushrutghimire1@gmail.com

Bibek Singh, Department of Computer Science and Engineering, Vellore Institute of Technology, bibeksingh019@gmail.com

Rishav Raj Jain, Department of Computer Science and Engineering, Vellore Institute of Technology, rishavrajjain@gmail.com

Ramanathan L, Department of Computer Science and Engineering, Vellore Institute of Technology, lramanathan@vit.ac.in

References:

[1]. Mahtab, Shamsul & Islam, Nazmul & Rahaman, Md. (2018). Sentiment Analysis on Bangladesh Cricket with Support Vector Machine. 1-4. 10.1109/ICBSLP.2018.8554585.

[2]. Agarwal, A., Xie, B., Vovsha, I., Rambow, O., & Passonneau, R. J. (2011, June). Sentiment analysis of twitter data. In *Proceedings of the workshop on language in social media (LSM 2011*

[3]. Hassan, Anees Ul & Hussain, Jamil & Hussain, Musarrat & Sadiq, Muhammad & Lee, Sungyoung. (2017). Sentiment Analysis of Social Networking Sites (SNS) Data

using Machine Learning Approach for the Measurement of Depression. 10.1109/ICTC.2017.8190959.

[4]. Oyebode, Oladapo & Orji, Rita. (2019). Social Media and Sentiment Analysis: The Nigeria Presidential Election 2019. 10.1109/IEMCON.2019.8936139.

[5]. Yuliyanti, Siti & Djatna, Taufik & Sukoco, Heru. (2017). Sentiment Mining of Community Development Program Evaluastion based on Social Media. Telkomnika (Telecommunication Computing Electronics and Control). 15. 1858-1864. 10.12928/TELKOMNIKA.v15i4.4633.

[6]. Ali, Kashif & Dong, Hai & Bouguettaya, Athman & Erradi, Abdelkarim & Hadjidj, Rachid. (2017). Sentiment Analysis as a Service: A Social Media Based Sentiment Analysis Framework. 10.1109/ICWS.2017.79.Abd El-Jawad, M. H., Hodhod, R., & Omar, Y. M. (2018, December). Sentiment analysis of social media networks using machine learning. In *2018 14th international computer engineering conference (ICENCO)* (pp. 174-176). IEEE.

[7]. Wiles Chamlertwat, Pattarasinee Bhattarakosol, Tippakorn Rungkasiri (2012). Discovering Consumer Insight from Twitter via Sentiment Analysis. *Journal of Universal Computer Science, vol. 18, no. 8 (2012), 973-992*

[8]. Poecze, Flora & Ebster, Claus & Strauss, Christine. (2018). Social media metrics and sentiment analysis to evaluate the effectiveness of social media posts. Procedia Computer Science. 130. 660-666. 10.1016/j.procs.2018.04.117.

[9]. Isah, Haruna & Neagu, Daniel & Trundle, Paul. (2015). Social Media Analysis for Product Safety using Text Mining and Sentiment Analysis. 2014 14th UK Workshop on Computational Intelligence, UKCI 2014 - Proceedings. 10.1109/UKCI.2014.6930158.

[10]. Golem, Viktor, Mladen Karan and Jan Snajder. "Combining Shallow and Deep Learning for Aggressive Text Detection." *TRAC@COLING 2018* (2018).

[11]. Habernal, Ivan, Tomás Ptácek and Josef Steinberger. "Supervised sentiment analysis in Czech social media." *Inf. Process. Manag.* 50 (2014): 693-707.

[12]. Haidar, Batoul & Maroun, Chamoun & Serhrouchni, Ahmed. (2017). A Multilingual System for Cyberbullying Detection: Arabic Content Detection using Machine Learning. Advances in Science, Technology and Engineering Systems Journal. 2. 275-284. 10.25046/aj020634.

[13]. Nguyen, D., Trieschnigg, D., Dogruöz, A.S., Gravel, R., Theune, M., Meder, T., & Jong,F.D. (2014). COLING 2014, 25th International Conference on Computational

Linguistics, Proceedings of the Conference: Technical Papers, August 23-29, 2014, Dublin, Ireland. *COLING*.

[14]. Kharde, Vishal & Sonawane, Sheetal. (2016). Sentiment Analysis of Twitter Data: A Survey of Techniques. International Journal of Computer Applications. 139. 5-15. 10.5120/ijca2016908625.

[15]. Mangaonkar, Amrita & Hayrapetian, Allenoush & Raje, Rajeev. (2015). Collaborative detection of cyberbullying behavior in Twitter data. 611-616. 10.1109/EIT.2015.7293405.

[16]. Vigna, F. D., A. Cimino, Felice Dell'Orletta, M. Petrocchi and M. Tesconi. “Hate Me, Hate Me Not: Hate Speech Detection on Facebook.” *ITASEC* (2017).

[17]. Hon, Liew & Varathan, Kasturi. (2015). Cyberbullying detection on twitter. International Journal of Information Systems and Engineering. 3. 36-47. 10.24924/ijise/2015.04/v3.iss1/36.47.

[18] John Hani Mounir Misr,Eslam A. Amer Misr, Mohamed Nashaat Misr, Mostafaa Ahmed Misr; Social Media Cyberbullying Detection using Machine Learning, Article in International Journal of Advanced Computer Science and Applications · January 2019 DOI: 10.14569/IJACSA.2019.0100587

[19].Maral Dadvar, Franciska de Jong. Cyberbullying Detection; A Step Toward a Safer Internet Yard. Conference Paper · April 2012 DOI: 10.1145/2187980.2187995

[20]. Maral Dadvar and Kai Eckert. Cyberbullying Detection in Social Networks Using Deep Learning Based Models; A Reproducibility Study . Maral Dadvar and Kai Eckert. Web-based Information Systems and Services, Stuttgart Media University Nebenstrasse 8, 70569 Stuttgart, Germany

[21] Rekha Sugandhi, Anurag Pande, Siddhant Chawla, Abhishek Agrawal, Husen Bhagat. Methods for Detection of Cyberbullying; Department of Computer Engineering. MIT College of Engineering, Pune, India

[22]. Qianjia Huang,Vivek K. Singh,Pradeep K. Atrey.Cyber Bullying Detection Using Social and Textual Analysis

[23]. Amanpreet Singh, Maninder Kaur. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8 Issue-8

June, 2019. Content- based Cybercrime Detection: A Concise Review Amanpreet Singh, Maninder Kaur

[24]. B.Sri Nandhinia , J.I.Sheebab. International Conference on Advanced Computing Technologies and Applications (ICACTA- 2015). Online Social Network Bullying Detection Using Intelligence Techniques B.Sri Nandhini , J.I.Sheeba

[25].Mingmei Li, Atsushi Tagami. 2014 28th International Conference on Advanced Information Networking and Applications Workshops. A Study of Contact Network Generation for Cyber-bullying Detection Mingmei Li Atsushi Tagami. KDDI R&D Labs, Inc. Saitama, Japan.

[26]. Akshansh Malik, Aman Mahal, Aman Kamboj, Abhishek Sharma(June, 2020). International Research Journal of Computer Science (IRJCS). Big data & Sentiment analysis using Python. IRJCS/RS/Vol.07/Issue06/JNCS10089

[27]. Mohammed Nazrul Islam Arif, Sarwar Hussain Paplu, Prof. Dr. Karsten Berns (2019). Robotics and artificial intelligence 2019/20, rrlab, technische universitat kaiserslautern. Understanding Emotional Expressions in Text-Based Communication.

[28]. Pinkesh Badjatiya, Shashank Gupta (2017).International World Wide Web Conference Committee (IW3C2), published under Creative Commons CC BY 4.0 License. Deep Learning for Hate Speech Detection in Tweets.

[29]. Osama Mohammad Rababah, and Nour Alokaily (2019). The University of Jordan, Amman– Jordan. A novel machine learning system for sentiment analysis and extraction.

[30]. Mikhail Bautin, Lohit Vijayarenu, Steven Skiena (2008). Association for the Advancement of Artificial Intelligence (www.aaai.org). International Sentiment Analysis for News and Blogs.

[31]. Alexander Pak, Patrick Paroubek (2010).Twitter as a Corpus for Sentiment Analysis and Opinion Mining. Universit´e de Paris-Sud, Laboratoire LIMSI-CNRS, Bˆatiment 508, F- 91405 Orsay Cedex, France.

[32]. Michelle Annett, Grzegorz Kondrak (2008) A Comparison of Sentiment Analysis Techniques: Polarizing Movie Blogs. S. Bergler (Ed.): Canadian AI 2008, LNAI 5032, pp. 25–35, 2008