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Sentence Level Sentiment Analysis of Cyber Trolling Tweets Using Machine Learning Technique

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Abstract: People are utilizing the networking site Twitter not only for social interaction but also to express their opinions, thoughts, news, and personal information in the form of text, videos, and pictures. Many of these tweets are cyber-trolling-related, psychologically devastating, and should be on the notice of the police. However, analyzing these tweets manually is quite difficult. Therefore, an intelligent mechanism is required to examine and polarize those cyber trolling-related tweets. Thus, in this paper, Valence Aware Dictionary Sentence (VADsentence) Miner has been proposed to perform Sentence Level Sentiment Analysis (SLSA) using machine learning (ML) techniques. For this purpose, tweets are pre-processed and sentences are extracted on the base of adjectives, adverbs and noun phrases. For SLSA, a combination of lexicon and rule-based approach named Valence Aware Dictionary and Sentiment Reasoner (VADER) is used to compute the sentiment polarity of tweets based on sentences. The proposed VADsentence Mines experimented with the feature selection technique TF-IDF and machine learning algorithms. Results of VADsentence Miner are compared with TextBlob in that VADsentence Miner outperformed 90% in accuracy, 82% in precision, 74% in recall, and 78% in F1-score on the Random Forest machine learning classifier and Term Frequency Inverse Document Frequency (TF-IDF). Textblob however, could archive 67% of accuracy on Random Forest and Term Frequency Inverse document frequency (TF-IDF).

Keywords: Sentement Anaysis; Machine Learning; cyberbullying; Textblob; Trolling.

1. Introduction

Twitter is the largest Micro-blogging site where millions of people share their news, ideas, and thoughts daily and you can follow celebrities and see tweets without the need for their follow back[1] According to studies on Twitter data, people have started using Twitter to express their viewpoints and report numerous types of crimes[3]. Some people agree with each other viewpoint, while some do not resulting they received frequently hostile and abusive tweets; this causes a risk of Cyberbullying [4]. Cyberbullying is a constant demonstration that pesters, embarrasses, compromises or bothers individuals. Cyberbullying through the social networking sites is thought of as furthermore riskier than any type of harassing done previously. Therefore, this problem requires a comprehensive solution. This has been resolved by employing machine learning (ML) algorithms to identifying and avoiding Cyber Bullying tweets by evaluating, polarizing, and classifying text into sentimental classes [5], [6].

To detect aggressive sentiment in brief texts, like comments and tweets, text-mining techniques are among the most promising approaches used. Sentiment analysis is a popular topic of computer science study that is used to extract and classify opinions. Typically, it refers to the process of automatically identifying whether a text has a positive, negative, or neutral polarity [7] . Most sentiment analysis (SA) studies have been carried out at three granularity levels: Document level Sentiment Analysis which involves analysing the entire document and categorizing it as neutral, positive or negative. The aspect level Sentiment Analysis considered opinions according to the target. The sentence level Sentiment Analysis where each sentence is rated as either neutral, positive or negative to classify crime tweets. VADER [8] method is used to detect the proposed aspect level sentiment analysis [9]. VADER, a combination of lexicon and rule-based technique, is employed in sentence sentiment analysis. Recently, researchers proposed machine learning approaches integrated with Deep Learning to classify the tweets relating to cyberbullying [10]. However, sentence level sentiment analysis on cyber trolling tweets dataset is still needed to research [11][21][22]. Thus, to classify these tweets into abusive and non-abusive categories there is need of an automated tool.

The proposed model implemented to mine sentence features and perform sentence-level sentiment analysis using ML algorithms on cyber trolling tweets. In the context, abusive tweets are considered as the tweet that need police action whereas non-abusive tweets are the other general tweets. In the proposed model, TF-IDF is utilized to extract features and after extraction, features are transformed into vectors. For sentiment classification, transformed vectors were passed to ML algorithms. Moreover, in developed model every adjective, adverb and noun phrases are considered for computing users' opinion polarity instead of frequent words.

2. Literature Review

In literature, various ML Techniques have been used to extract features to detect cyberbullying on Twitter from the given dataset. ML techniques can be further categorized into three major sets: Unsupervised Learning, Supervised Learning and Reinforcement Learning. Yuvaraj et al. suggested a supervised learning model for the detection of cyberbullying [12]. The proposed approach combines both the classification engine and the feature extraction engine. To increase the classification performance, they utilized Deep Reinforcement Learning (DRL) for simulation to test the ANN-DRL model's efficacy using several metrics such as accuracy, f-measure, precision, and recall. Simulation results suggest that the ANN-DRL outperforms with traditional machine learning classifiers in classification.

Another machine learning model was suggested by [13] to identify the similarities of words in the tweets by bullies. To cognize and stop bullying on Twitter machine learning methods are used to develop a model that can automatically identify online bullying behaviour. Tweet data were gathered from different sources like GitHub, Kaggle etc. The authors [13] used Support Vector Machine and Naïve Bayes classifiers for testing and training the bullying material on social media. True positives were detected with 71.25% accuracy by Naive Bayes and 52.70% accuracy by SVM (Support Vector Machine). However, SVM performs better than Naive Bayes in comparable studies on the same dataset. Additionally, tweets were retrieved via the Twitter API, and the model was then used to identify whether the tweets were bullying. [14] presented a novel method to identify cyberbullying on Twitter to lessen and reduce potential risks from cyberbullies and overcome the usual social media patrolling procedures[14]. By using combination of k-nearest neighbor, Naïve Bayes and support vector machine, classifier model. Theng, et al., have used keywords ('gemuk', 'bodoh, 'babi', 'anjing' and 'sial') for testing and analyzing the results and the Support Vector Machine has the maximum accuracy for each keyword, averaging 68.20%, followed by k-Nearest Neighbor and Naive Bayes, which has the minimum accuracy. The model also can group tweets into cyberbullying subcategories such as blackmail, harassment or swear words well.

Dvoynikova et al., presented a hybrid technique to conduct a more precise analysis using aspect-based sentiment analysis for Twitter. A unique classification method of sentiments was proposed by integrating the feature selection technique for Twitter [16]. There is classification accuracy comparison by the feature selection methods which are Random projection (RP), latent semantic analysis (LSA), and principal component analysis (PCA) [17]. The experiments show that their hybrid approach to sentiment classification improves the aspects based on sentiment analysis performance by 76.55, 71.62, and 74.24% compared to the current existing baseline classification techniques.

3. Proposed Solution

The proposed framework concentrates on the flow of the research process for the development and application of the model. Fig.1 shows the proposed model framework for the VADsentence Miner, which mines the sentence features on the base of nouns, verbs, and adjectives, and performs SLSA using machine learning techniques. The proposed model used the dataset of Cyber-Trolls, downloaded from Kaggle (http: //www.kaggle.com). Pre-processing is necessary step to build the model for classification of crime and non-crime tweets. After pre-processing the tweets, the spaCy library is used to check the dependency of tagged words. The goal of dependency checking is to detect sentence features. With the use of the VADER [8] library, adjectives were examined for emotion polarity computation from tagged words. VADsentence Miner extracts feature using TF-IDF and convert them to vectors. For categorization and decision making, the transformed feature vector was passed to Supervised Machine Learning algorithms (SML). Furthermore, the established models are used to analyze experimental data and are compared with different approaches and models.

	content	annotation/notes	annotation/label/0	extras
0	Get fucking real dude.	NaN	1	NaN
1	She is as dirty as they come and that crook ...	NaN	1	NaN
2	why did you fuck it up. I could do it all day...	NaN	1	NaN
3	Dude they dont finish enclosing the fucking s...	NaN	1	NaN
4	WTF are you talking about Men? No men thats n...	NaN	1	NaN

Figure 1. Cyber troll tweets dataset

3.1 Dataset

This section provides the complete knowledge of the dataset used in this research such as; sources, data collection, and data sampling approaches. The Cyber-Trolls dataset used has 20000 tweets in which 10000 (non-abusive) and 10000 (abusive). Information regarding Cyber Trolling tweets can be found in the dataset defined in Fig. 1. Dataset is stored in .csv file (Comma Separated Values) of size 1443KB. It is essential to pre-process data before providing it to the model to improve the classifier's accuracy. Pre-processing has been done to make the data useful and reliable. The dataset's vertical size decreases after pre-processing. There are still 20002 rows and 9 columns to go. The entire dataset was unsuitable for training. Because samples are always supposed to the representatives of the whole population. Here 60% of the data are selected randomly for training the model to give the best results and 40% of the data is separated for the testing of the model. In the Pre-processing phase unnecessary symbols, noises, inaccurate or deceptive data have been identified and removed from the raw Tweeter dataset collected. Fig. 2 shows the workflow of pre-processing. In English language, there are plenty of stop words such as pronouns, conjunctions, and prepositions that have no unique meaning and they are useless while we perform sentiment analysis. Pre-processing stage includes: case folding, text cleaning, case transformation, eliminates every undesirable character, stops word and punctuation removal to ignore frequently used words such as "the," "a," and "an," as well as stemming which reduces conjugated or infrequently derived words to their tokenization and word stems those separate sequences of strings into words. Stemming enables us to think of nouns, verbs, and adverbs with the same primary word in the same way. To reduce the number of words and have precisely matching stems, this strategy seeks to remove a lot of suffixes.

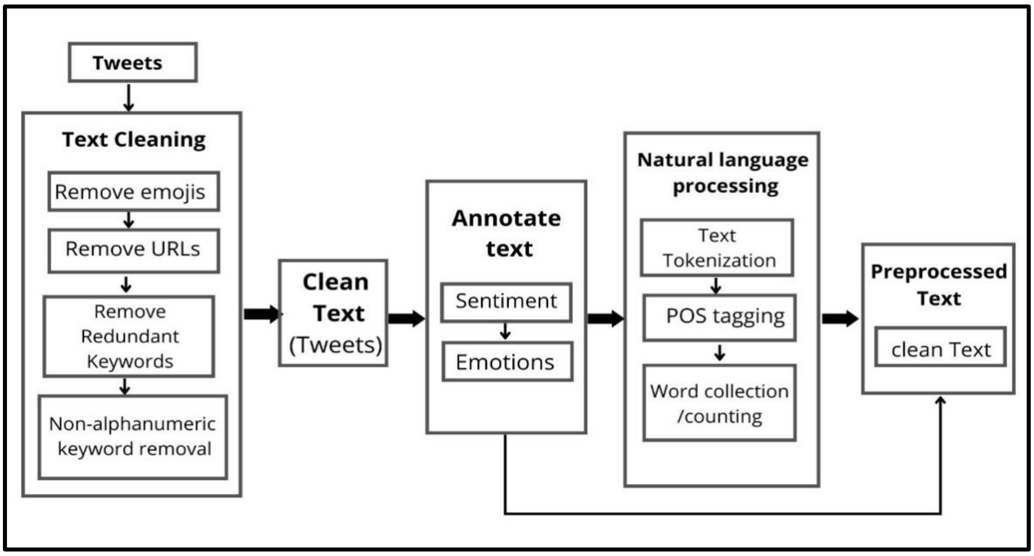

Figure 2. Pre-processing Workflow

The most important step in sentiment analysis or opining mining is parts of speech (POS) tagging. The most common POS categories are adjectives, nouns, pronouns, adverbs, conjunctions, interjections, and prepositions. It's a type of philological group that differs in terms of morphological behaviour. Each word is assigned a tag based on its characteristics during this process. For example,

“Ali is fatty fat”

POS Tagged Sentence 1: “Ali/NN is/ HV fatty/Adv fat/JJ”

Where NN referred as nouns, HV as helping verb and JJ as adjectives.

Lemmatization is the procedure of reducing words to the base words. It uses a dictionary to change the words. The normalized format is root words. Root words are known as lemmas. One sentence may contain several aspects, each of which may consist of one or more words and every word in the dataset has a dependency on other words. We lemmatized the basic information from our text, enabling us to concentrate more on the important facts and noise-free data. After applying all the techniques of pre-processing word counter used to count each value from the croups which indicates how many times a word is used in the whole dataset as we can see in Fig.3.

```
[('hate', 2844),
 ('fuck', 2455),
 ('damn', 2367),
 ('get', 1776),
 ('im', 1650),
 ('as', 1636),
 ('suck', 1584),
 ('like', 1500),
 ('lol', 1319),
 ('dont', 1145),
 ('u', 1057),
 ('go', 992),
 ('know', 992),
 ('think', 938),
 ('would', 933),
```

Figure 3. Word count from dataset after prepressing.

3.2 Aspect Identification and Extraction

This is an important stage in the process of extracting information and identifying each aspect term used in the tweets sentence. In this work, Spacy library is used for checking the dependency of tagged words, this helps for the identification of aspects. For aspect feature extraction, Nouns, Adjectives, and adverbs phrases are extracted from the dependency of words (Fig.4) and add them to our dataset for further processing. After that, regarding any particular set of aspect terms, the polarity is identified as either neutral, bipolar, positive, or negative (i.e., both negative and positive). The description column is used to calculate the polarity and subjectivity of sentences which is built using nouns, verbs, and adjectives as a result of dependency verification.

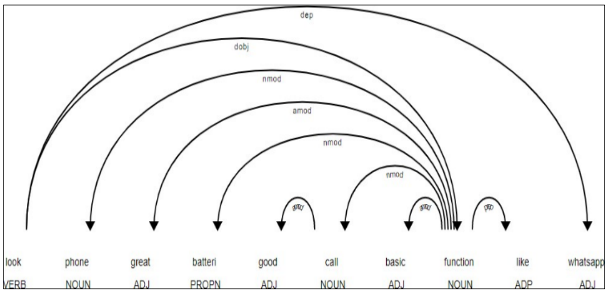

Figure 4. Dependencies of words for aspect extraction

The VADER library is used to compute polarity as it calculates the intensity as well as the sentiment score or polarity. It specifies a range of words scoring greater than 0 being positive and words scoring less than 0 being negative and words equal to 0 will be considered neutral. VADER estimates each word's sentiment score and then adds all of the scores to assign a single sentiment to a sentence or corpus. Results are presented in Fig.5 after computing the polarity from the dataset.

	content	annotation/notes	annotation/label/0	extras	aspects	description	polarity	subjectivity	sentiments
0	get fuck real dude	NaN	1	NaN		real	0.200000	0.300000	Positive
1	dirti come crook rengel dem fuck corrupt joke ...	NaN	1	NaN	joke	republican	0.000000	0.000000	Neutral
2	fuck could day let hour ping later sched write...	NaN	1	NaN	ping	write	0.000000	0.000000	Neutral
3	dude dont finish enclos fuck shower hate half ...	NaN	1	NaN	dude	enclos	0.000000	0.000000	Neutral
4	wtf talk men men that menag that gay	NaN	1	NaN		gay	0.416667	0.583333	Positive
...	...	...	...	...	...	...	...	...	...
95	ok im tell go hard fight inner grammar nerd il...	NaN	1	NaN		inner	0.000000	0.166667	Neutral
96	mythbust great nerdi show embrac inner nerdno ...	NaN	1	NaN		inner	0.000000	0.166667	Neutral
97	lol bitch damn	NaN	1	NaN		lol	0.800000	0.700000	Positive
98	damn that crazi earli wont hit citi til 930 bl...	NaN	1	NaN			0.000000	0.000000	Neutral
99	slurpe awesom damn realli realli want one oo	NaN	1	NaN			0.000000	0.000000	Neutral

Figure 5. Results after computing sentiment polarity

3.2.1 Feature Extraction

Feature extraction is an important step as it quantifies the text information represented by the feature words that were taken from the text, transforming them from the unstructured language into a kind of organized data that a machine can comprehend and interpret. Hence, after eliminating any unnecessary or redundant text features, the significant attributes (words, sentences, characters) are mixed with their weights to represent the text's contents. The TF-IDF algorithm is used in this study to weight and extract the dataset's keywords. A keyword may appear the kinds of variants that cause the variability. In terms of the various classes that contain this keyword, this variability measures how different the keywords are on a scale. Each word in the TF-IDF has its score for TF*IDF and those scores indicated the importance of that term in a document. The Euclidean norm is used to normalize the TF-IDF scores for each piece of the set of documents. The computations of TF*IDF are displayed in Eq. (1). The stages of proposed model framework shown in Fig.6.

$$TF_{t,c} = \frac{n_{t,c}}{\text{No of terms in Corpus}} \quad (1)$$

$$IDF_{t,c} = \log \frac{N_c}{N_{t,c}}$$

$$(TF\text{-}IDF)_{t,c} = TF_{t,c} * IDF_{t,c}$$

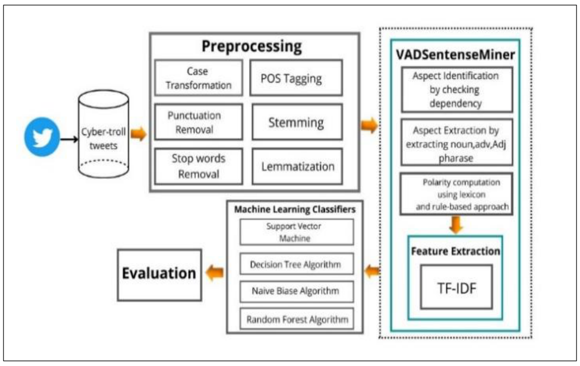

Figure 6. Proposed Model Framework of VADsentence Miner

3.3 Machine Learning Classifiers

This stage involves running Machine learning classifiers such as Naïve Bayes (NB)[18] , Support Vector Machine Classifier (SVM)[19], Random Forest (RF) [20] and Decision Tree (DT) on the normalized data for classification and providing the results. Any supervised machine-learning algorithm's performance can be analysed by using test data that has already been classified and comparing the output polarities to those polarities. As input data, we used datasets of pre-labelled tweets. F-measure, Recall and Precision are utilized to measure the efficiency of the results. The workflow of classifiers is explained in Fig.7.

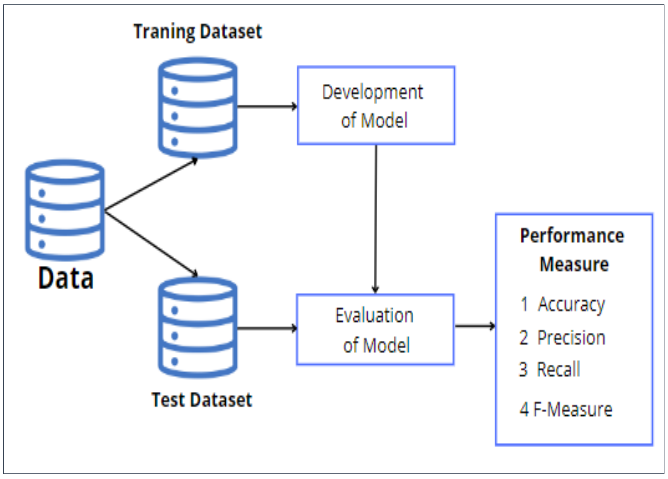

Figure 7. Workflow of Machine Learning Classifier

3.4 Performance Evaluation

It is possible to evaluate the model's effectiveness for a test set of Data based on the Confusion Matrix (i.e, CM), a mixed amount of accurate and correct forecasts. Two classification categories Actual Class and Predicted Class are created in the CM described in Table 1.

Table 1. Evaluation Matrix for model's performance

Evaluation Matrices	Description
Accuracy (A)	The number of tweets or instances that are accurately categorized

Precision (P)	The ratio of positive tweets that were successfully categorized by the system to all tweets considered positive.
Recall (R)	The proportion of positively classified tweets in the dataset that were correctly categorized.
F-measure (F)	Combined precision and recall make up this metric.

Based on the results of the confusion matrix, four efficient measures—True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) are used in this investigation as shown in Table 1. The TP displays the number of tweets that are successfully described to the appropriate type in the "matrix, while the FN displays the amount of incorrectly assigned tweets. Additionally, the FP displays the number of tweets that are erroneously categorized, and the TN displays the number of incorrectly" categorized tweets.

4. Discussion and Results

This section presents the experimental evaluation that were carried out by using the gathered datasets and performance indicators. All of the methods are implemented using Python 3.7 to ensure consistency in experimental outcomes. An Intel Xenon E5-1630 CPU, 8GB of main memory, and the Windows 10 operating system are used to imitate programmes on the computer. Python libraries are used for the initial analysis, which categorized the datasets into three categories (negative, neutral, and positive) based on their content. Sentence features extraction and sentence-level sentiment analysis is performed with proposed VADsentence Miner model. Additionally, for textual analytics, several visualization techniques are used to represent the data to improve visibility and understanding.

Besides, ML classifiers such as SVM, Decision Tree, Naive Bayes and Random Forest applied on VADsentence Miner for feature extraction technique with TF-IDF. Numerous tests using various classifier assessment metrics indicate that the RF and DT model has outperformed the other two models (Table 2). The effectiveness of a VADsentence Miner assessed using a confusion matrix (CM). The CM states that the accuracy is determined by the proportion of the sum of values on the main diagonal to the sum of all values on the matrix.

Furthermore, to determine the most effective strategy, the proposed model's accuracy is compared with the accuracy of other approaches such as TextBlob and VADaspectMinner with aforementioned supervised ML algorithms as shown in Table 2 and Fig 9. The proposed VADsentence miner achieved 89% accuracy for RF classifier with TF-IDF, while TextBlob's obtained 67% accuracy and VADaspect Miner obtained 86% accuracy. Textblob achieves 60% of accuracy and VADaspect Miner obtained 69% on SVM classifier, whereas proposed VADsentence Miner achieved 81% of accuracy. Similaly, VADsentence Miner outperformed Textblob and VADaspect Miner with 82% and 89 % of accuracy on NB and DT classifiers respectively.

Table 2. Comparative Accuracy of proposed VADsentence Miner with other existing approaches

Classifiers	VADsentence Miner with TF-IDF	TextBlob with TF-IDF	VADaspect Miner with TF-IDF
RF	0.89826	0.676712	0.86826
SVM	0.817522	0.602740	0.80101
NB	0.82089	0.561644	0.73353
DT	0.896762	0.605479	0.86939

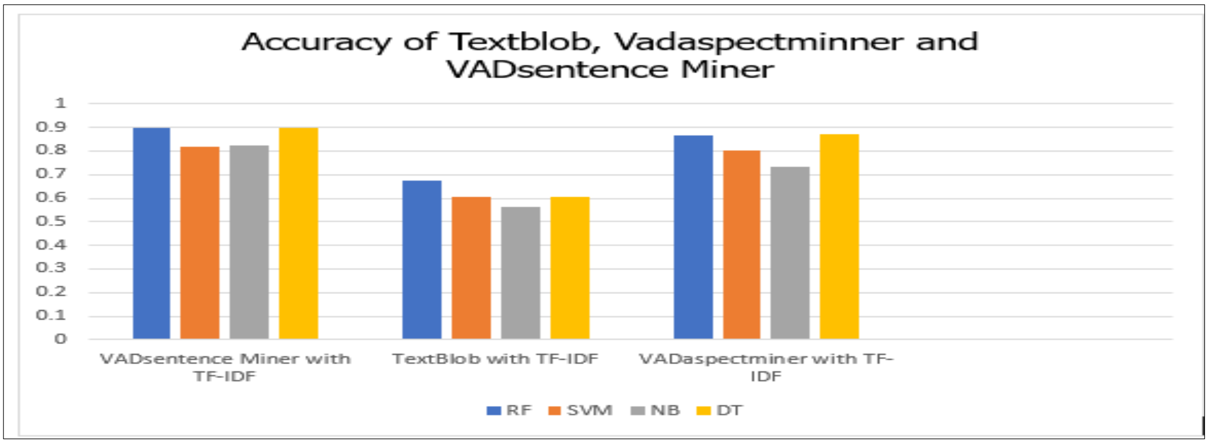

Figure 8. Graphical Representation of Comparative Accuracy of proposed VADsentence Miner with other existing approaches

Table 3 and Fig.10 depicts that proposed VADsentence miner with TF-IDF method achieved 90% precision for RF classifier, while TextBlob achieved 70% and VADaspect Miner obtained 82% precision. In case of SVM calssifier, VADsentence miner significantly achieved 83% of precision, whereas TextBlob and VADaspect Miner obtained 60% and 77% of precision respectively. Moreover, VADsentence miner achieved 82% of precision and VADaspect Miner obtained 78% on NB classifier while Textblob achieved 70%. Likewise, proposed VADsentence Miner achieves better performance on DT classifier with 90% of precision compared to Textblob with 72% and VADaspect Miner with 83% of precision.

Table 3. Precision for Comparison of Textblob, VAD aspect miner and VADsentence Miner

Classifiers	VADsentence Miner with TF-IDF	Textblob with TF-IDF	VAD aspect Miner with TF-IDF
RF	0.89826	0.676712	0.86826
SVM	0.817522	0.602740	0.80101
NB	0.82089	0.561644	0.73353
DT	0.896762	0.605479	0.86939

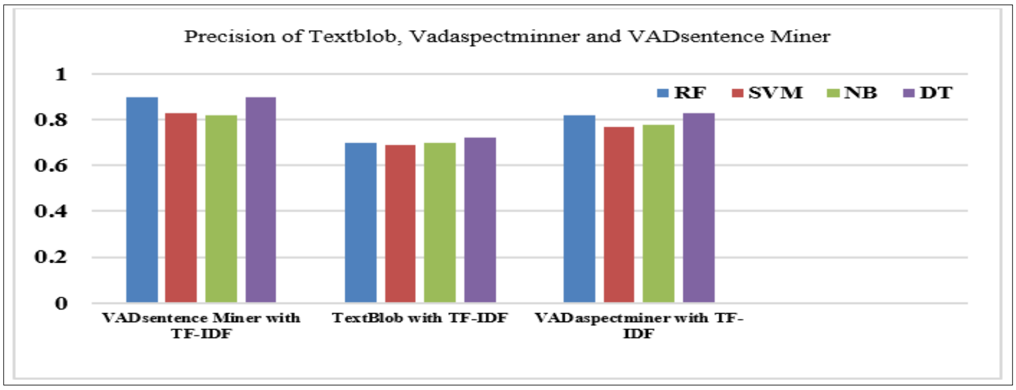

Figure 9. Graphical Representation of Precision for Comparison of Textblob, VAD aspect miner and VADsentence Miner

Furthermore, the significant results of recall and F-Score on all selected classifiers shown in Table 3 and Table 4 respectively confirms that proposed VADsentence miner technique is better than others other existing approaches.

Table 4. Comparative Recall of proposed VADsentence Miner with other existing approaches

Classifiers	VADsentence Miner with TF-IDF (Proposed)	Textblob with TF-IDF	VAD aspect Miner with TF-IDF
RF	0.90	0.71	0.83
SVM	0.81	0.68	0.73
NB	0.82	0.72	0.77
DT	0.90	0.73	0.79

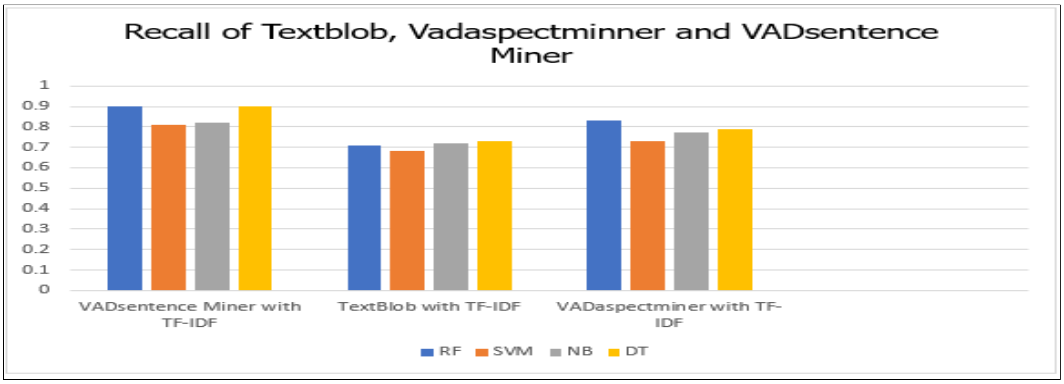

Figure 10. Graphical Representation of Comparative Recall of proposed VADsentence Miner with other existing approaches

Table 5. Comparative F-Score of proposed VADsentence Miner with other existing approaches

Classifiers	VADsentence Miner with TF-IDF (Proposed)	Textblob with TF-IDF	VAD aspect Miner with TF-IDF
RF	0.90	0.70	0.73
SVM	0.78	0.68	0.69
NB	0.79	0.72	0.73
DT	0.90	0.71	0.75

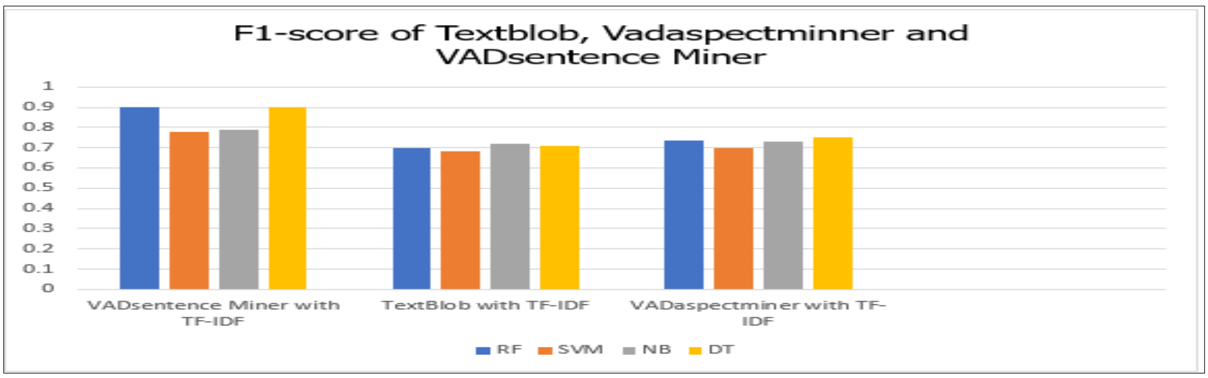

Figure 11. Comparative F-Score of proposed VADsentence Miner with other existing approaches.

5. Conclusions

Social networks have gained popularity for generating opinions and ideas. Hundreds of people share their emotions and thoughts on Twitter on daily basis. Some people express their anger and bully other people on Twitter this comes under cybercrime. Focusing on cyberbullying, which is increasing rapidly and affects everyone from local children to famous people, action must be taken in this area to stop the occurrence of more victims. A big dataset of tweets must be accurately classified according to their sentiment. Thus, in this study VADsentence Miner is proposed to address the issue of categorization and sentiment analysis at the sentence level. The suggested approach extracts aspect elements on the base of an adjective, adverb, and noun from the sentences of cyber trolling Tweets and bases sentiment analysis on those aspect features. The model preprocesses the trolling tweets by transforming the case, stemming, POS Tagging, lemmatizing, stopping words, and removing punctuation. Aspect features are extracted, by getting Adjective, adverb, and noun phrases from tagged words. TF-IDF is applied to extract feature and vector transformation to obtain the optimal feature vector. For further analysis of supervised machine learning methods, transformed feature vectors are used. Results of the suggested model with the results of another approach, in which aspect characteristics were retrieved and sentiment analysis was carried out using a text blob library. A comparison with selected four supervised ML algorithms reveals that VADsentence Miner outperformed them all. About the TF-IDF model, the Random Forest classifier surpassed 89% recall, 89% accuracy, 89% precision, and 89% f1-score. Currently, this study measures Twitter text data in the English language. The suggested paradigm addresses explicit negation, but implicit negation is also a critical subset of negation. In the future, handling implicit level negation would be the next target to perform a more precise analysis. Working towards incorporating other languages for the detection of abusive Tweets is also highly desirable.

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