Volume: 14 Issue: 06 Pages: 5734 - 5733 (2023) ISSN: 0975-0290

A 1-Gram Sentiment Analysis Algorithm for Detecting Cyberbullying in Online Social Networks

C.N. Udanor
Department of Computer Science, University of Nigeria Nsukka, Nigeria
Email: collins.udanor@unn.edu.ng
A.H. Eneh
Department of Information Technology, University University of Nigeria Nsukka, Nigeria
Email: agozie.eneh@unn.edu.ng
D. Goji
Department of Information Technology, University University of Nigeria Nsukka, Nigeria
Email: gojidon52@gmail.com

ABSTRACT

Online social networking (OSN) sites in addition to providing business and recreational opportunities are fast becoming a breeding ground for cyberbullying activities. Cyberbullying is an act of harassing or insulting a person by sending messages that are hurting or threatening in nature using electronic communication. Such messages include threats, harassment, and humiliating messages to victims. Other forms are sexual harassments, sexual predating, etc. Cyberbullying poses threat to the physical and mental health of the victims. In this study, sentiments analysis was used to computationally recognize and categorize the opinions, views, and ideas expressed in a piece of text in social media to determine and establish whether the writer's attitude towards a particular topic, person, or a product is positive or negative. The study adopted both quantitative and qualitative approaches. Posts from Facebook were collected and analyzed. The software developed during the research was able detect the presence of cyberbullying in user contents. Results showed promising ability of the software to detect and suspend cyberbullying contents.

Keywords - **Social Networks, Cyberbullying, Sentiment analysis, Hate speech**

Date of Submission: September 23, 2023 Date of Acceptance: Jan 13,2023

I. INTRODUCTION

Online Social Networks (OSN) have become a significant means of sharing information. Most people have come to trust the services available on the internet for information sources in carrying out their diverse business activities because of its availability and ubiquity [1]. Today the social media offer great communication opportunities. They also increase the exposure of people online, including exposure to cyberbullying. Cyberbullying is a form of bullying using electronic means such as cell phones, or other devices over the Internet to send or post text messages, videos, images, etc. deliberately to hurt a person. It is also known as online bullying [2]. Recent studies show that cyberbullying constitutes a growing crisis among young people. The detection of potentially negative messages/posts on social media requires systems to identify such impending risks automatically. The victims of cyberbullying attacks are more often innocent children and youths of secondary schools and institutions of higher learning. Their open-mindedness and carefree lifestyles predispose them to being victims or targets of malicious attackers in online social media, intentionally or unintentionally. It has become expedient to detect these cyberbullies to protect victims from imminent catastrophe and attacks [3]. Cyberbullying can be as easy as continuing to send emails or text messages defaming a victim's character, threats, harassment, etc; it may also include public events such as frequent abuse, sexual remarks, pejorative labels, false accusations, ganging up on a victim by making the person the subject of mockery in online fora, hacking into or vandalizing sites belonging to a person, posting fake statements as facts aimed at discrediting or embarrassing the targeted person. It also involves recurring behavior with intent to harm, perpetrated through sending or posting abusive messages and falsehoods to damage reputation, fraudsters creating fake accounts, etc [3].

The online social network provides users with a big and convenient platform to exchange views, ideologies, and opinions, share stuff with friends around the globe. Thus, along with this extreme openness and convenience, the online social network is a delicate environment that is used every day to increase unsocial and uncivilized events which may be considered as cyberbullying. Cyberbullying uses technology to upset, or target a person or group of persons, commonly occurring among young people [4].

The implications of cyberbullying turn out to be severe when a victim fails to get by with effecting strain from defamation, abusive, and other malicious posts. One of the challenges in dealing with cyberbullying is that younger victims are usually unwilling to share their problem with an adult, out of the fear of losing their Internet access privileges· Other challenges in combating cyberbullying include: detecting online bullying when it occurs; exposing it to law enforcement agencies, Internet service providers, and others, and identifying bullies and their sufferers [5],[6].

Sometimes cyberbullying can be easy to spot, for instance, if one’s child shows one a text, tweet, or reply to a status update on Facebook that is malicious. Other acts are less clear, like threats, abuse, defamation, etc. Some kids report that a fake account, webpage, or online individual has been created with the sole aim of threatening and bullying others. The unfriendly nature of text messages, IMs, and emails makes it very rigid to detect the sender's tone, one person's joke could be another's upsetting abuse [6]. Nevertheless, a persistent pattern of emails, texts, and online posts is rarely accidental. Because many kids are unwilling to report being bullied, even to their parents, it's impossible to know just how many are affected. But recent findings of cyberbullying rates have found that about 4 in 10 users of social media had been victims of cyberbullying, and about 5 in 12 admitted to having cyber-bullied someone [7]. In some findings, more than half of the young boys and girls questioned said that they have experienced abusive words through social media.

Cyberbullying has become a serious problem to online social media today, the consequence of which can be far-reaching. Early detection of cyberbullying attempts is therefore of key significance to young people’s psychological well-being. Successful detection depends on effectual monitoring of online contents by detecting any malicious post made, but the amount of information on the Web makes it virtually not viable for moderators to check all user-generated contents manually as a result of the existing methods. In this research, sentiments analysis was used to detect cyberbullies’ activities in the online social network. Sentiment analysis is the process of analyzing pieces of writing to determine the emotional tone they carry or recognizing and categorizing views, expressed in a text, to establish whether the writer's attitude toward a particular issue, is positive or negative [8]. The focus of this research work was on detecting cyberbullying in social media using sentiment analysis.

II. REVIEW OF RELATED LITERATURE

There are several ways used to detect cyberbullying in online social media. Many research works had been carried out in this regard showing various methods of detecting cyberbullying in online social networks. In a recent study of cyberbullying [9] in social media, online threat, sexual harassment, pejorative labeling (i.e., hate speech), etc, detection in social networks, gender-specific qualities were used and users are categorized into male and female groups. It was constrained only to gender features. In other learning, NUM and NORM features were developed by handing over a severity level to the awful words list (nosewaring.com). NUM is a count and NORM is a normalization of the bad words, respectively. The dataset consisted of 3,915 posted messages crawled from the website. It showed only 58.5% correctness, which is very low in accuracy [9]. Since the research field of cyberbullying detection is still up-and-coming, there is only a limited amount of work obtainable. At present, three online cyberbullying detection techniques or approaches exist wordlist-based, machine learning, and rule-based approaches. The first approach is based on wordlists containing known blasphemous words. A document is interpreted as a bag-of-words model which is put together against the wordlist. The document is classified as Online bullying if a match is found. Since the bag-of-words model treats all words in an isolated way, these approaches are not able to model relations between persons and profane words. Thus, the classification performance varies significantly depending on the wordlist used by [11].

Majority of study on cyberbullying detection have alerted on improving the accuracies of cyberbullying detection classifiers. Several cyberbullying detection applications have been developed in recent years. Most of these applications (e.g., Mobicip) introduced parental control including group blocking, time limits, Internet activity reports, blocked phrases, and YouTube filtering, whereas others, e.g. iAnon and GoGoStat looked for specific curse words. Precise keyword-based research on event detection has also been performed. Thus, in [12] a study carried out by the Massachusetts Institute of Technology, introduced a technique to detect cyberbullying on social media through the writing context in YouTube video commentary. Developing a scheme classifies the assertion in a range of sensitive topics such as sexuality, threat, intelligence, and physical attributes and determining what topic it is. The scheme shows less precise categorization outcomes and enhanced false and positives views.

Thus,[13], introduced a structure for regular detection of cyberbullies' identity on social networks using classification method like Support Vector Machine methods, Naive Bayes, and evaluation trees to detect bullies’ profiles. Reddy et al. [13] also suggested two main statistical variance detection methods: parametric and nonparametric, for detecting cyberbullying in the social network. Either of them has been useful to fit a statistical model. Kansara et al [14], introduced merging text and picture analysis methods and suggested a

Volume: 14 Issue: 06 Pages: 5734 - 5741 (2023) ISSN: 0975-0290

basis for detecting likely cyberbullying threats in social media that look at texts and images using a bag of words and a bag of visual word models correspondingly. Djuric, and Benevenuto [5], developed a new system for detecting cyberbullying on social media, a footnote built on the bullying of the role of the post's author, and several fine-grained categories linked with all sorts of bullying activities.

Authors in [15] revealed that large wordlists result in the detection of a high percentage of the online cyberbullying posts while smaller wordlists result in less misclassification. The second approach is based on machine learning techniques. These methods can learn classification rules mechanically by detecting patterns in online cyberbullying posts. They require manually annotated training data to learn such rules. Meanwhile, due to the sparse amount of Online cyberbullying posts, it can be awkward to collect an ample amount of training data. The third approach is based on rule engines to analyze semantic relations within documents. Wordlist and machine learning methods rely on clearly formulated statements in a text.

Pitsilis, Heri, and Helge [16], used data collected from Yahoo, then presented cyberbullying detection framework employing n-gram, linguistic, syntactic, and distributional semantic structures and get an F-score of 81% for the aligning of all features. In this study, they presented a dataset encompassing question-answer pairs from ask.fm, which are branded as positive or negative. Their data was conversational data from young people. They also had a metadata containing data about the users that ultimately helped them to focus on users who are being bullied with regular malicious words and also scrutinizing the forms used by bullies. Authors in [15] also examined the effect on the performance by incorporating a knowledge database and a rule engine in the classification process. Online cyberbullying content which is built upon understood knowledge can be detected by such techniques. For instance, the sexually biased message sent to a male: “why did you stop wearing makeup?” [15]. Such methods require the thorough building of knowledge databases. For the problem of detecting sexuality-linked harassment alone [15] built around 200 assertions. These assertions allow the rule engine to figure out conclusions whether a given statement is sexual harassment or not. Gao et al. in [17] used an online spam filtering method that could be used as a module of online social networks platform to check text messages generated by cyberbullies in real-time. Their approach focused on detecting each post cyberbullies made on social media. A group of researchers was fascinated in determining the text messages that are of interest to online social network users based on their text data. In this study, they collected information from online groups, the internet, and social networks. Sirivianos, et al. recommended a tool for checking cyberbullying in the Online Social Network, named SybilRank [18]. It depends upon public graph properties to grade bullies on the social network, and their likelihood to be fake. The device SybilRank proposed by the authors is computationally able and is elastic to graphs with hundreds of millions of nodes.

Rahman et. al. [12], developed FRAppE, a classifier for detecting cyberbullying as to post made on social network media applications. However, [19], analyzed the real-time message of microblogging events on social media. In their belief, the client may be considered as a sensor for checking cyberbullies' posts, most especially newly posted text messages, and to identify their various events. A method of detecting cyberbullying in an online social network by using a system mining technique was developed by [20]. In the method, the record first gets trimmed by scoping. Scoping means just focusing on data stored in a precise variety of times. The time-scoping concept looks at exact data at a definite range of periods. The scope set is a subset of all record traces $t/ \subseteq T$, in which T is a set containing all recorded file traces. Djuric et al. in [21] used paragraph2vec loom which was adopted a method from Le and Mikolov to detect cyberbullies' messages. The models were built by some authors to find out a low-dimensional vector representation for each post made by cyberbullies.

Bolla [8] proposed several models such as Bag of Words based, Latent Semantic Analysis, and LDA based models to detect cyberbullying. The main input of the paper was to show that, with suitable natural language processing techniques, social media can be a very rich source to detect posts as to whether they are positive, negative in text messages posted on social media. Djuric et al. [21] implored automatic cyberbullying detection in social networks, hence cyberbullies applied several clouding tricks, such as substituting a single character in malicious words. They applied a binary classifier onto a paragraph2vec symbol of words. Thus, [22] projected a set of measures that could be used to detect cyberbullying in social networks like Facebook to be displayed to classified users' posts. Sirivianos, et al. [18] developed an unverified learning system in which Principal Component Analysis (PCA) that detects cyberbullies' actions correctly and finds the most important deviations from their various post was used. Sakaki et al. in [19], designed a regular monitoring method particularly interesting, given the inherent impossibility of manually monitoring the millions of units of generated content on daily basis, messages/posts made on the social network to detect cyberbullying.

Sakaki et al. [19] introduced the instant detection method for cyberbullies on social network platforms using automatic text categorization tools as proven applications such as spam filtering topic detection, email routing, etc. A detection model for cyberbullying in social network media was formed in [22]. It is a rule-based, built by hand machine learning technique trained on sets of labeled reduced dataset. Jensen et al. [23] designed a comprehensive dataset to detect cyberbullies' actions on social media. They used syntactic and real datasets. The data in the syntactic set are stimulated intellectually by Color Petri Nets (CPN) tool. A simple and very effective method for identifying and detecting cyberbullying in social media that conform with malicious words was proposed in [24], while [25] focused on four CNN models skilled on nature n-grams, word vectors based on semantic information built by way of word2vec, arbitrarily generated word vectors, and word vectors joint with character n-grams to develop a cyberbullying text classification system for detecting bullies activities on the social network media. Authors in [26] carried out an experiment with multi-channel CNN, BiLSTM, and CNN+BiLSTM models for identifying exact posts from a big dataset of Twitter posts for detection of cyberbullies on the social network media.

The goal of this research is to create an effective a new hybrid prediction model that can recognize racist, xenophobic, and sexist comments published in English on Twitter, a popular social media platform, and provide efficient and accurate findings. 7.48 percent of the data were classified as racist, genderist, and xenophobic in the used dataset. A new hybrid LSTM Neural Network and Recurrent Neural Network based model was developed in this study and compared with the most popular supervised intelligent classification models such as Logistic Regression, Support Vector Machines, Naive Bayes, Random Forest, and K-Nearest Neighbors

Al-Ajlan & Ykhlef [35] proposed a system that designs a model that uses sentiment analysis to automatically identify and categorize opinions expressed in a piece of text in the social media, in order to determine the emotional tone, they carry, whether the writer's attitude in that piece of text is positive or negative, and to provide a functionality that will append the misbehaving user or nullify their activities.

III. METHODOLOGY

The researcher used a sentiment analysis algorithm in detecting cyberbullying in online social networks. The Object-Oriented Analysis and Design (OOAD) method was exploited for the analysis and design of the system while Unified Modeling Language (UML) notation was selected for indicating different models of the system for an example use case, class, sequence, and activity diagrams. The system is modeled after Facebook's online social media. It allows users to interact with each other and exchange their views online. The system comprises of two modules: the administrator's module which is used to manage the system, view detected malicious messages and suspend users with malicious act. And the user module, that is used by users to communicate with friends. The new users of the system are required to sign up to the system before usage. Thereafter, they can log in to the system to edit their profile, search for friends, send friends requests, accept/ignore friends' requests, chat with friends, upload photos, share their views with friends, view notifications, post comments for friends' view and log out when done. Also, a filter is incorporated, which is designed to extract a user's posts before sending them to their friends. Thereafter, the sentiment analysis technique is applied to the posts to identify if they are malicious or not. If any of the posts is malicious to the receiver, the system will automatically detect and block it from being forwarded. In addition, the system will log the malicious post to the database and as well alerts the administrator. On receiving the alert, the admin will suspend the sender after discovering that the post is malicious. This will help curtail crime rate in the country and the world at large.

1. How the System Works

The main idea of the project is to calculate the Post Score for a post. To perform the analysis, posts exchanged by users were extracted within the application. The posts were picked up one after another and then were splinted by a blank space to get a list of all the words used in the post. The words, taken one at a time are checked if they are present in the stop words. If a word is present in the list of stop words, the word is ignored and the code moves on to the next word. If a word is not present in the stop words' list, it is checked for in the AFINN library which has been converted into a hash map with <word, score> as key value pair. The score of the word is fetched and added to the Post Score, which is the overall score for a post. The Post Score is the addition of scores of all the individual words present in the AFINN library. If a word is not present in the AFINN library, it is skipped. If the Post Score is negative then, the post/comment/message is deemed to be malicious. The working of the sentiment analysis is illustrated in fig. 1.

The algorithm of the system is graphically illustrated in figs 2 and 3, using use case and activity diagrams, respectively.

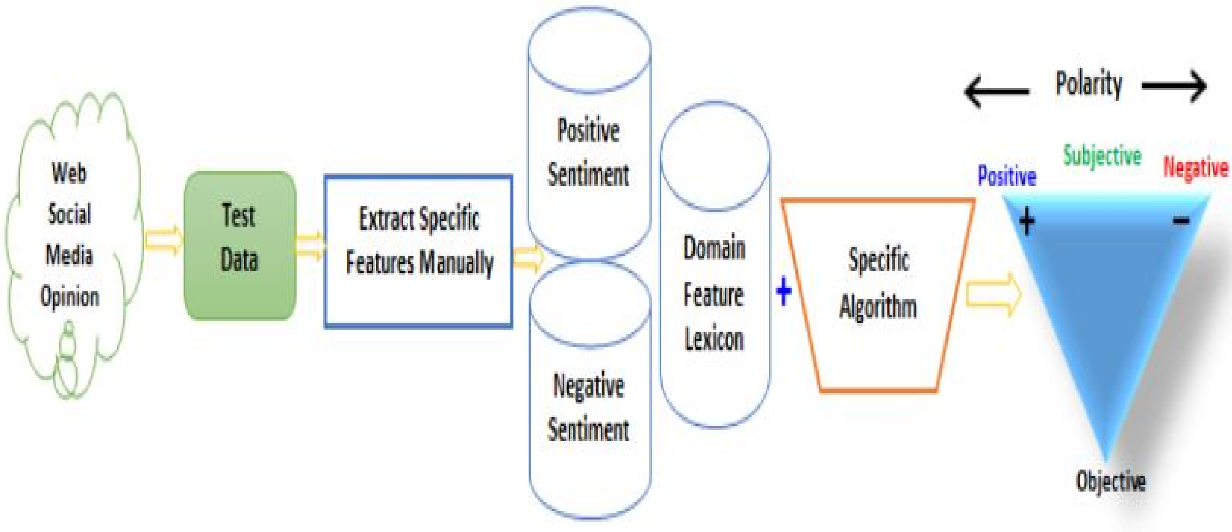


Fig. 1: Opinion analysis scheme

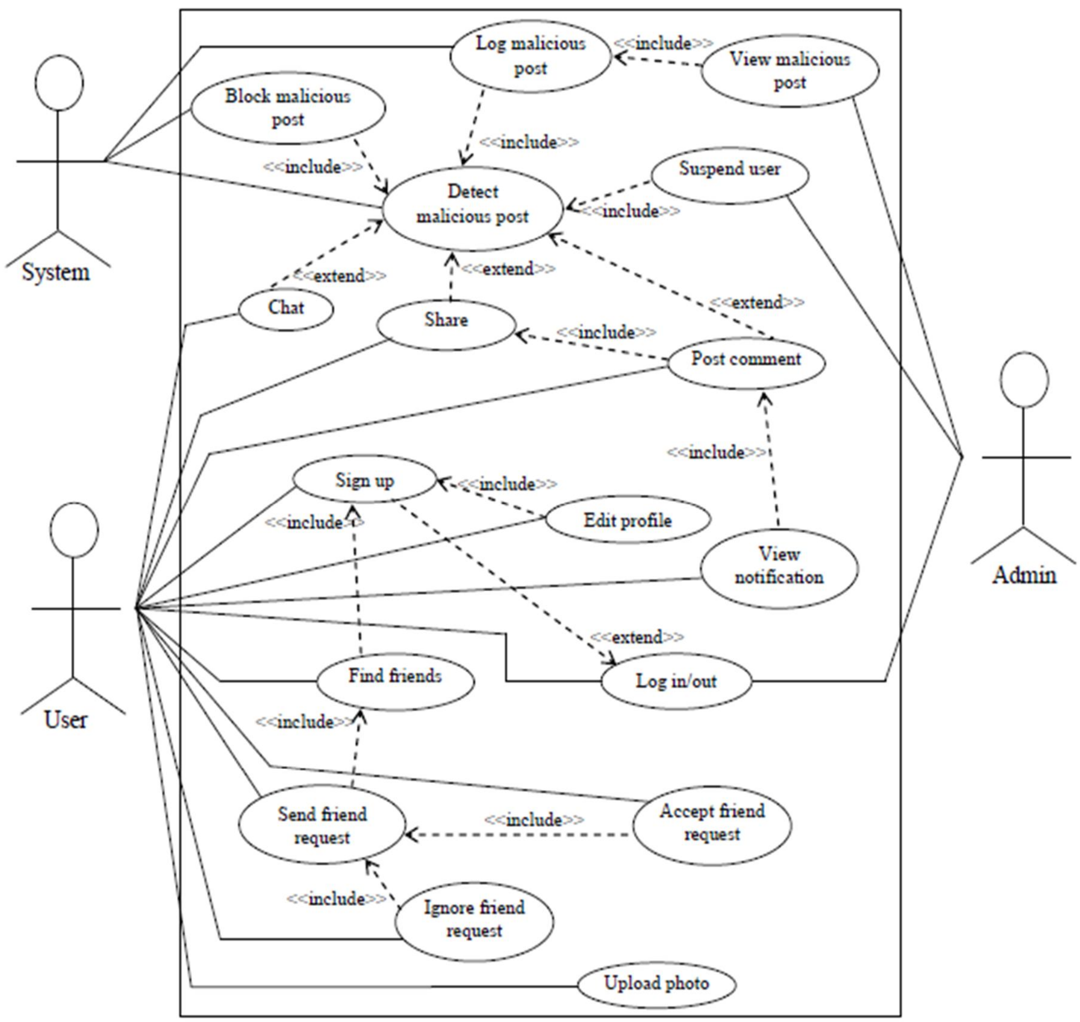


Fig. 2: Use case diagram of the system

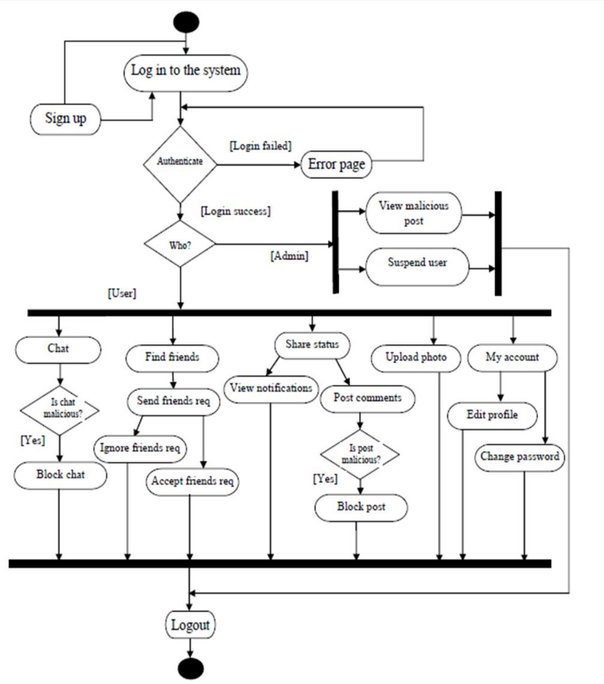


Fig. 3: Activity diagram of the system

3.1.1How Negative posts are Detected

Let Q be = 0 (Threshold between the positive post and the negative post)

It is a bag of word algorithm that contains a dictionary with negative words given a negative value of -1, -2, -3, -4, etc. with positive words given positive values of 1, 2, 3, 4, etc. The algorithm searches for a word contained in a post, and adds the values to them, if the total added values are less than Q, then it is a negative post, but if it is above Q it is a positive post. For instance, 'John likes to kill', The word 'likes' is a positive word with a positive value of +2, while the word 'kill' is a negative word with a negative value of –4. Therefore; +2 – 4 = - 2. Hence, the total added value is -2 which is less than zero, therefore the above post is a negative post. The detection mechanism is shown in the sequence diagram in fig. 4.

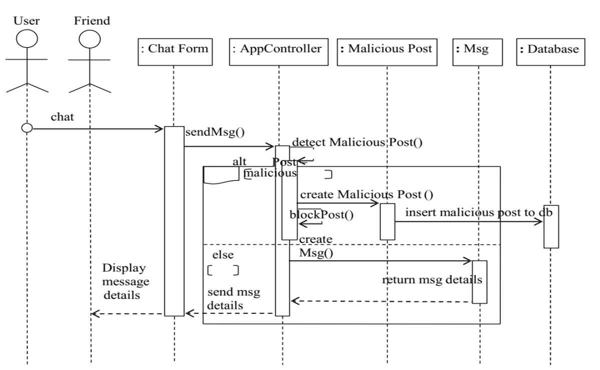


Fig. 4: The chat system and malicious contents detection sequence.

IV. Results and Discussion

The application showed significant ability in detecting bullying-oriented contents using sentiment polarity classification. The result showed the ability of the application to detect, flag, and suspend cyberbullying posts made on social media like Facebook using sentiment analysis. Fig. 5 depicts a typical scenario where the word contents in posts are scrutinized, computationally weighted to discover the positive-negative balance in a post using our system.

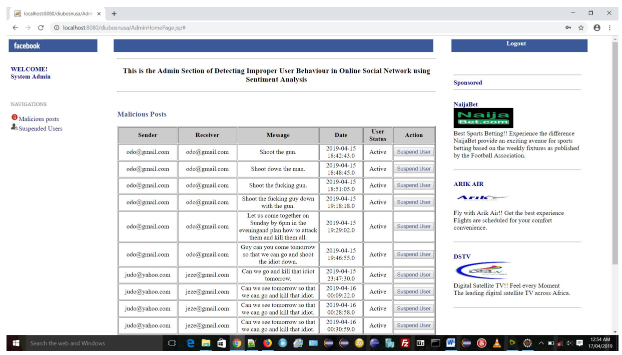


Fig. 5: Malicious Posts Page

The finding shows that bullying activities on social media are on the increase on daily basis judging by the frequency at which they were spotted. This is of grave concern to the global community as evidenced in many investigations. For instance, [27] observed that most cyberbullying among students is a result of relationship break-ups, envy, intolerance, and ganging up. Such attacks have powerful negative effects in the social well-being and can lead to reactive behaviours in the victims. Random samples of 1,000 youths of ages 16 to 20 in 25 European countries to determine the effects of cyberbullying [28] showed positive association between online and offline behaviours with the effect of low self-control on cyberbullying perpetration and victimization. More grave consequences are cyberbullying-related deaths reported in some studies. One of such reports in [29] suggest that victims of cyberbullying are at a greater risk of self-harm and suicidal behaviours than non-victims. Another study of 24 EU countries found that countries with higher rates of cyberbullying were found to be more likely to experience more frequency of unnatural child death [2]. The study found that a 1% increase in the prevalence of cyberbullying translates into a 28% likely risk of unnatural child death.

The implications of bullying in the social network turn out to be severe when a victim fails to get by with the affecting strain from abuse and other malicious posts. Detection of cyberbullying in the social network will curtail the bullying activities on the social network.

In summary, cyberbullying can result to the following:

1. Emotional Distress: Cyberbullying can cause emotional distress in victims, leading to anxiety, depression, and even suicide. According to a study by Hinduja and Patchin [31], "adolescents who experienced cyberbullying had a significantly greater likelihood of attempting suicide than those who did

Volume: 14 Issue: 06 Pages: 5734 - 5741 (2023) ISSN: 0975-0290

not." This highlights the severity of the emotional impact of cyberbullying.

2. Social Isolation: Cyberbullying can also lead to social isolation in victims. Victims may feel embarrassed or ashamed of the bullying and may withdraw from social activities. According to a study by Li [32], "cyberbullying victims were more likely to feel lonely and disconnected from their peers."
3. Physical Harm: Cyberbullying can even lead to physical harm. In extreme cases, cyberbullying can lead to physical violence or self-harm. According to a study by Beran and Li [33], "cyberbullying has been associated with an increased risk of physical harm, including self-harm and suicide attempts."
4. Long-Term Effects: Cyberbullying can have long-term effects on victims, including decreased academic performance and decreased self-esteem. According to a study by Sourander et al. [34], "cyberbullying victims were more likely to have poor academic performance and lower self-esteem than non-victims."

V. CONCLUSION AND FURTHER WORK

During the course of this research different approaches to the detection of cyberbullying in online social networks were studied. It was observed that sentiment analysis has not been extensively explored. Sentiment analysis can be said to be at the heart of cyberbullying detection since it is the perceived sentiments that triggers the reaction of the reader to the message. Cyber-bullied victims are mostly affected by the sentiments contained in the chats they read. This work therefore implemented a sentiment analysis based a system which matched the contents of the chats with an inbuilt 1-Gram dictionary and scored the words as positive or negative depending on the result of the computation. Expectedly, results revealed negative contents wherever they existed, which the system effectively classified as cyberbullying contents from the user chats sampled.

Cyberbullying is real as many news media report several incidences of teenage suicides which are usually traced to cyberbullying. One report [30] has it that a 14-year-old girl committed suicide due to the obscene post by another minor about her in Facebook. By virtue of improvements offered by sentiment analysis and in conjunction with existing works, it is hereby recommended that policy makers and schools should prioritize the inclusion of cyberbullying awareness in their programmes to prevent the damage it does to children and adolescents. This study and the result of our system will aid the government in policy development in terms of detecting cyberbullies in social media platforms. Security agencies will also find it of great assistance in tracking online threats, sexual harassment messages, etc. and apprehending cyberbullies in social networks.

In conclusion, cyberbullying is a serious issue that can have many negative consequences for its victims. It is important to educate young people on the dangers of cyberbullying and to take steps to prevent it from happening. Parents, educators, and policymakers should work together to create safe online environments for children and adolescents.

Further work will be aimed at extending from word specific i.e. 1-Gram to N-Gram to make the algorithm content-driven and more robust. This is because 1-Gram is limited to 1 word, and sentiment based 1-Gram analysis can only be used for posts in the English language as the dictionary limits its scope to other languages. The overall sentiment of the post depends upon the sentiment of words used in the post which can lead to a few false positives.

REFERENCES

[1.] ScikitLearn, "Sklearn.svm.SVC scikit-learn 0.17.1 documentation,"2018. [Onlin]. Available: http://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html.

[2.] Fu KW, Chan CH, Ip P. Exploring the relationship between cyberbullying and unnatural child death: an ecological study of twenty-four European countries. BMC pediatrics. 2014 Dec;14(1):1-6.

[3.] W. D. Daelemans *and* Y. Xia., "Automatic Detection and Prevention of Cyberbullying," The First International Conference on Human and Social Analytics, 2018.

[4.] K. Lee, and D. Z. Sui, 'Content-Driven Detection of Campaigns in Social Media'. 2015. Available at: lee11cikm.pdf (tamu.edu)

[5.] Geo, Djuric, and F. Benevenuto, 'Characterizing cyberbullying in Online Social Networks Categories and Subject Descriptors', pp. 49–6, 2017.

[6.] P. K. Smith, Mahdavi M. and N. Tippett, "Cyberbullying: Its nature and impact in Secondary School pupils," Journal of Child Psychology & Psychiatry, vol. 49, pp. 376-385, 20118.

[7.] R. M. Kowalski, G. W. Giumetti and M. R. Lattanner, "Bullying in the digital age: A Critical review and meta-analysis of cyberbullying research among youth," Psychological Bulletin, vol. 140, no. 4, pp. 1073–1137, 2018.

[8.] Bolla, Raja Ashok "Crime pattern detection using online social media" 2016. Masters Theses. Paper 732.

[9.] D. Yin, Z. Xue L, .Kontostathis A. and L. Edwards, "Detection of Harassment on Web 2.0," in Proc. Content Analysis of Web 2.0 Workshop, Madrid, Spain, 2018.

[10.] A. Kontostathis, L. Edwards, and A. Leatherman, "Chat Coder: Toward the Tracking cyberbullying and Categorization of Internet Predators," In Proceedings of Text Mining Workshop 2018 held in conjunction with the Ninth SIAM International Conference on Data.

[11.] Sood A, and Bolla, Raja, "Cyberbullying detection using online social media" 2016. Masters Theses. Paper 732.

[12.] Rahman M, Dadvar, F. and R. B. Trieschnigg, "Improved Cyberbullying detection using gender information," 12th Dutch-Belgian information retrieval workshop (DIR 2012), pp. 23– 25, 2018.

[13.] Reddy. S., Jamil J. M. Dadvar, D. and F. De Jong, "Improving Cyberbullying detection with user context," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol7814 LNCS, pp. 693–696, 2017.

[14.] Kansara M. K., Dinakar, R. Reichart, and H. Lieberman, "Modeling the Detection of Textual Cyberbullying," in Proc. IEEE International Fifth International AAAI Conference on Weblogs and Social Media, Barcelona, Spain, 2017.

[15.] Dinnakar V. Nobate N. and M. Shekokar, "A Framework for Cyberbullying Detection in Social Network," International Journal of Current Engineering and Technology, vol. 5, no. 1, pp. 494–498, 2016.

Volume: 14 Issue: 06 Pages: 5734 - 5741 (2023) ISSN: 0975-0290

[16.] Pitsilis, Georgios K., Heri Ramampiaro, and HelgeLangseth. "Detecting offensive language in tweets using deep learning." *arXiv preprint arXiv:1801.04433* (2018).

[17.] Gao A. K. Reynolds, A. Kontostathis, and L. Edwards, "Using Machine Learning to Detect Cyberbullying," In Proceedings of the 2011 10th Conference on Machine Learnin and Applications Workshops, vol. 2, pp. 241-244, December 2018.

[18.] Sirivanos R. Ahmed .Bashir, H. Hosseinmardi and S. Mishra, “Detection of Cyberbullying Incidents on the Instagram Social Network,” 2016.

[19.] Sakaki H. Lobe Dadvar, Van Kansars, and J. I. Sheeba, 'Online Social Network Bullying Detection Using Intelligence Techniques’, vol. 45, pp. 485–492, 2015.

[20.] Bezzera M. Kontosta D. and R. Peters,' Detecting Online Harassment in Social Networks’, no. Li 2017, pp. 1–14.

[21.] Djuric N, Warner H, Nobata P. Ramampiaro W., and H. Langseth, 'Detecting Offensive Language in Tweets Using Deep Learning', 2015, pp. 1–17.

[22.] Sabastine B, Hovy K, Schwartz B., and J. I. Sheeba, 'Online Social Network Bullying Detection Using Intelligence Techniques’, vol. 45, pp. 485–492, 2015.

[23.] Jensen J. Berg Leanes, -H. Saale, and R. Peters, ‘Detecting Online Harassment in Social Networks’, no. Li 2016, pp. 1–14.

[24.] Wang W. Clark, Grieve M. Samghabadi N., and A. Sprague, 'Detecting Cyberbullying in Social Media', 2017.

[25.] Gamback W, I. McGhee, J. Kontostathis, L. and E. Jakubowski, "Learning to Identify Internet Sexual Predation, “International Journal on Electronic Commerce 2018, vol.15, PP, 103-122, 2011.

[26.] Mahata P., K. Dinakar, R. Picard, and H. Lieberman, “Common sense reasoning for detection, prevention, and mitigation of cyberbullying,” IJCAI International Joint Conference on Artificial Intelligence, vol. 2015-Janua, no. 3, pp. 4168–4172, 2018.

[27.] Hoff, Dianne L., and Sidney N. Mitchell. "Cyberbullying: Causes, effects, and remedies." *Journal of Educational Administration*, 2009.

[28.] Vazsonyi, A.T., Machackova, H., Sevcikova, A., Smahel, D. and Cerna, A., Cyberbullying in context: Direct and indirect effects by low self-control across 25 European countries. *European Journal of Developmental Psychology*, *9*(2), pp.210-227, 2012.

[29.] John, A., Glendenning, A.C., Marchant, A., Montgomery, P., Stewart, A., Wood, S., Lloyd, K. and Hawton, K., 2018. Self-harm, suicidal behaviours, and cyberbullying in children and young people: Systematic review. *Journal of medical internet research*, *20*(4), p.e129.

[30.] FP STAFF, 14-YEAR-OLD GIRL COMMITS SUICIDE, PARENTS BLAME OBSCENE FB POSTS AVAILABLE AT: FIRSTPOST.COM/INDIA/14-YEAR-OLD GIRL COMMITS SUICIDE, PARENTS BLAME OBSCENE FB POSTS-INDIA NEWS , FIRSTPOST

[31.] Beran, T., & Li, Q. (2007). Cyber-harassment: A study of a new method for an old behavior. Journal of Educational Computing Research, 36(3), 265-277.

[32.] Hinduja, S., & Patchin, J. W. (2018). Cyberbullying: An update and synthesis of the research. In R. L. Heath & M. Palenchar (Eds.), The SAGE Handbook of Risk Communication (pp. 337-350). Sage.

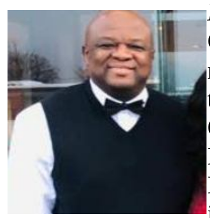
[33.] Li, Q. (2019). Cyberbullying in schools: An examination of preservice teachers’ perceptions. Journal of Educational Computing Research, 57(4), 847-866.

[34.] Sourander, A., Brunstein Klomek, A., Ikonen, M., Lindroos, J., Luntamo, T., Koskelainen, M., ... & Helenius, H. (2010). Psychosocial risk factors associated with cyberbullying among adolescents: A population-based study. Archives of General Psychiatry, 67(7), 720-728.

[35.] Kaya, Sule, and Bilal Alatas. "A New Hybrid LSTM-RNN Deep Learning Based Racism, Xenomy, and Genderism Detection Model in Online Social Network." *International Journal of Advanced Networking and Applications* 14.2 (2022): 5318-5328.

Biographies and Photographs

Dr. Collins Udanor is an Associate Professor in the Department of Computer Science, University of Nigeria Nsukka. He holds a Bachelor’s Degree in Computer Science & Engineering, a Masters Degree in Computer Science (Data Communications Specialist), and a Ph.D. in Electronic Engineering (Intelligent Agent Systems Specialist). He has advanced trainings in Cloud Computing & Network Virtualization, Internet of Things (IoT), Data Science. He has skills in Data analytics, and multi-agent learning systems pedagogy. Collins Udanor leads a University research group, the High Performance and Intelligence Computing group (HiPIC, hipiclab.org), a cross-disciplinary research group based in the Department of Computer Science. His research spans across NLP (sentiment analysis), implementation of IoT smart sensors in agriculture and healthcare for predictions of yield and disease outbreaks.



Dr. Agozie Eneh holds a Ph.D in Computer Science and his teaching and research interest includes but not limited to the following; Operations Research, Optimization (Shortest path problems, Network flow, Minimum cost flow, Linear and dynamic programming, and inventory management systems), telecommunications and networks, network and Internet security, ethical hacking, digital forensics, network risk assessment, business continuity planning and implementation, management and strategic information systems, online databases, algorithms, and operations research.

Donatus Goji had his Masters Degrees in Computer Science, specializing in Artificial Intelligence/Machine Learning. His research interest includes tracking cyberbullying in online social networks with sentiment analysis.