International Journal of Cyber Behavior, Psychology and Learning
Volume 13 • Issue 1

Psychological Study of Cyber-Bullying Against Adolescent Girls in India Using Twitter

Kavya Sharma, Symbiosis Centre for Information Technology, Symbiosis International University (Deemed), India*

https://orcid.org/0000-0002-5860-5649

Krishna Kumar Singh, Symbiosis Centre for Information Technology, Symbiosis International University (Deemed), India

https://orcid.org/0000-0003-3849-5945

ABSTRACT

Due to the rise in digital activity of students as well as increased social media presence, the lack of regulation of platforms has given rise to another form of bullying, popularly known as cyberbullying. Cyberbullying is one of the most adverse issues prevalent in schools nationwide. Cyberbullying refers to bullying that happens over any web-interfaced or electronic platform. It is an activity that significantly affects the mental and physical health of its victims. With increased secrecy, the frequency and propagation of cyberbullying remain high due to the information technology infrastructure available today. Understanding cyberbullying trends and preventing them, using suitable machine learning algorithms, could help numerous school students lead better lives, as well as make better decisions, which help them grow and flourish into capable future leaders. Hence, the authors' aim for this research paper is to focus on adolescent girls using various tools and techniques like text analytics and image analytics. For this paper, the authors study a sample of netizens. The location where the analysis is conducted is New Delhi, and the real-world data is extracted from Twitter in English. The real-world data is extracted using appropriate data mining algorithms to find hidden patterns and then conduct the analyses required to understand the psychology of girls and boys and the tonality and voice of the tweets/posts. This is done from the open-source information available on the platform (Twitter) from tweets by the users. There is little to no bias as the entire process can be automated; hence, tweets will be filtered or flagged based on data. Such a method allows one to get access to unbiased data. Bias, in this case, can be defined as prejudice in action and response received from a participant. The results are then analysed using polarity and subjectivity. Understanding psychology and personality traits helps in drawing insights from the expressions collected. The authors will be studying the sample bios, likes, and comments of the sample using a lexical and syntactical approach. Six thousand top tweets are extracted, and the 15 tweets which score the highest on polarity and subjectivity values are taken for further analysis. The tweets are filtered based on 16 responses from a focus group filtering the 20 most popular profane words. Since the data is extracted using Twitter (i.e., a secondary data source), the authors address the gap in current psychological analyses. In such studies, one usually circulates questionnaires to understand the participant, but, for this research though, the authors will be studying the data without bringing the concerned individual into play, thereby eliminating the human bias, which is a significant limitation of gathering responses through a questionnaire. There is increased scope for further streamlining the model. The inferences include understanding the regulation of a social media platform, the degree of aggression on the platform, and an effort to distinguish those who cause such aggression.

DOI: 10.4018/IJCBPL.327867

*Corresponding Author

KEYWORDS:

Cyberbullying, Sentiment Analysis, Twitter Extraction, Psychology, Polarity, Subjectivity, Tweepy, Python Programming, Twitter Data Scraping, Social Networking, Mental Health, Cyber World, Cybercrime, Internet, Web Safety, Cyber Awareness, TextBlob

INTRODUCTION

Using technology to annoy, intimidate, shame, or target another individual is called cyberbullying. Threats made online and meant offensive or disrespectful emails, comments, blogs, or notifications are all considered under this. Posting personal information, photos, or videos intending to harm or shame another person is also prohibited. Cyberbullying often involves images, tweets, or web pages that are not taken down until the user has called for them to be removed. When discussing adolescence, one must realize that it is an increasingly sensitive period of one's life, where one is vulnerable to external duress. Discrimination is described as intimidation or derogatory remarks directed at a person's gender, sexuality, sexual identity, ethnicity, or physical distinctions and is illegal in several states. As a result, the police could get involved, and bullies may suffer drastic consequences (Ben-Joseph, 2018). Although several scholars have studied the impact of cyberbullying on teens and attempted to develop automated tools for detecting cyberbullying, those techniques have failed to take into account the vastly different social media world that teenagers currently live in, which is unlike the one that existed even five or ten years ago. Teenagers are well-known for their prolific use of image and video-sharing applications and limited-time tweets. Visual content, in particular, accounts for more than 70% of all online traffic. Around the same time, image and video imagery use for cyberbullying has increased significantly, with some claiming that "cyberbullying grows bigger and meaner with images and videos." In reality, the growing prevalence of image and multimodal content for cyberbullying was one of the major themes found in recent cyberbullying reports. Although it is widely recognized that decoding multimodal content is critical for cyberbullying detection, the cyberbullying detection literature is still primarily based on (sophisticated) text processing, and their accuracy is minimal. There are currently few projects that use visual features to spot cyberbullying. Understanding cyberbullying trends and preventing them using suitable Machine Learning algorithms could help numerous school students lead better lives and make better decisions, which help them grow and flourish into capable future leaders. Hence, this research paper aims to focus on adolescent girls using various tools and techniques like Text Analytics and Image Analytics (Reynolds et al, 2011). Hate speech tends to be an offensive form of interaction in which a hate agenda is expressed through misconceptions. Hate speech targets protected characteristics such as gender, sexuality, race, and disability. As a result of hate speech, unwelcome crimes can result from someone or a group of people being disheartened. The real-world data can be extracted using appropriate data mining algorithms to find hidden patterns and then conduct the analyses required to understand the psychology of girls and boys and the tonality and voice of the tweets/posts. Understanding psychology, color, and personality traits will help draw insights from the expressions collected. The authors will be studying the sample's user bios, likes, and comments using a lexical and syntactical approach. Since the data is extracted using Twitter, i.e., a secondary data source, the authors will address the gap in current psychological analyses. They understood the extracted database and ensured that the authors looked at textual data and heavily focused on geospatial locations and images. It is a known fact that 70% of web-based social media websites' content comprises images. Hence, it is essential to focus not just on the posts or captions but also on the images to get a clear picture of the online scenario. Girls are much more vulnerable to perceiving negative comments and taking them negatively and seriously, which is more likely to harm their mental health. This severely impacts the quality of their mental health and hinders them from achieving their potential to the fullest. It is also noted that cyberbullying is a phenomenon that has been around for a while, yet very few literature pieces focus on the research gap taken up by the authors. Through this article, the authors will comprehensively understand and scrape through the respondents' profiles. They will ensure that they can obtain all the information about the users through their profiles, assess textual, social, and visual clues to form their analysis, and finally declare a tweet flagged due to its explicit content. They will be using Machine Learning algorithms for the analysis and create a system that constantly keeps learning – one system that can change the life of not just one adolescent but many more. Such a comprehensive methodology will try to eliminate the need for self-administered questionnaires that are subject to responder bias and are used widely worldwide to understand practices like cyberbullying, cyber victimization, etc. A self-administered test will enable the respondents to choose the option that applies to them most manually. This leads to an unknown bias between the respondent's thoughts and how he is. Such a system can constantly keep learning and eliminate this bias, thereby providing a clear picture of the internet Twitter scenario. The authors will use a corpus from data scraping via Twitter and refine their results. Once the authors have the right sample size and population, the next step is to ensure the data is pre-processed and ready for analysis. In this paper, they will use other techniques on numerical datasets, like transformation, to get a balanced dataset that provides accurate results. Once this is complete, the next phase would be to move on to a number of machine learning models and choose the one that provides the most accurate results. Extensive experimental evaluations of real-world multimodal social network datasets demonstrate and validate the fact that the authors' approach outperforms current cyberbullying identification models. They will concentrate on the data collection and feature engineering process, emphasizing feature selection algorithms before employing a variety of machine learning algorithms to predict cyberbullying behaviors. Finally, the problems and obstacles have been identified, presenting new investigative avenues for researchers to investigate. The authors will focus on deepening the role of ML in cyberbullying detection and prevention. Specifically, the following issues (Angelis & Perasso, 2020) are addressed:

- ML models predicting cyberbullying;
- Identifying the most used ML algorithms and their evaluation methods;
- Understanding the implication of ML for prevention;
- Highlighting the main theoretical and methodological issues of ML algorithms in predicting cyberbullying.

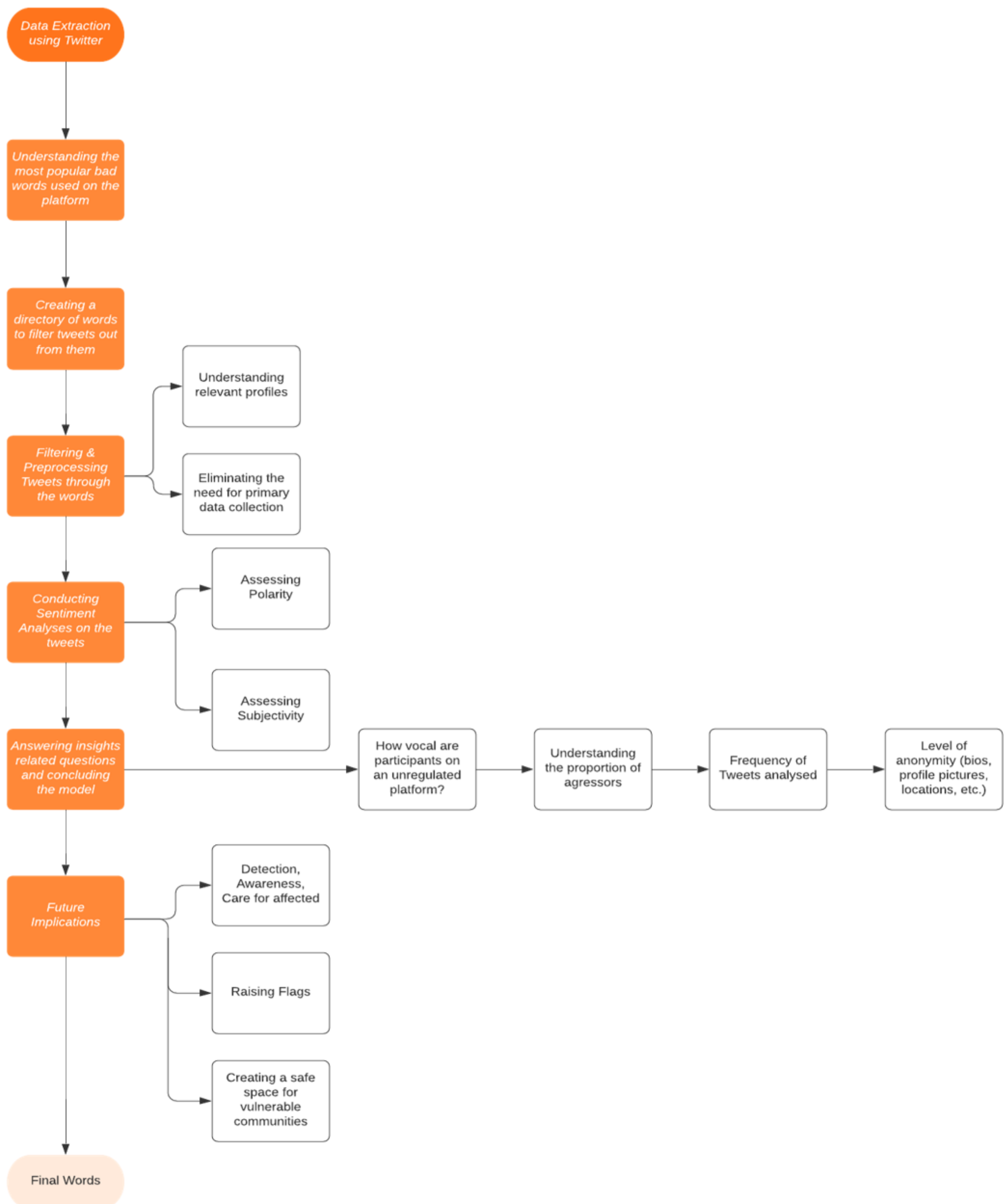
BACKGROUND/REVIEW OF LITERATURE

Huang et al. (2014) discuss detecting cyberbullying using textual and social features. The authors use a Twitter corpus and ask three students to label the tweets as bullying or not bullying. They then analyze the social networks features, like the number of friends and network embeddedness, and focus on improving the accuracy of detection. They use the ego network to understand and draw insights from the corpus and use algorithms like J48, SMO, Dagging, Naïve Bayes, ZeroR, etc., to classify the tweets by balancing them using SMOTE. Singh et al. (2017) discusses cyberbullying and how to detect it on Instagram. The corpus contains 2000 posts that are used for detecting offensive content. The authors study three different dimensions focusing on textual, visual, and combined factors. They use a bagging algorithm for classification and conclude by considering the Receiver Operating Characteristic (ROC) Curve. The visual factors include aspects like age, sex, median age, image type, image category, etc., features that may be extracted from Twitter using APIs, and textual features like tone, words used, third-party pronouns, etc., making it a multimodal detection. Chatzakouy et al. (2017) propose a principled and scalable method for detecting bullying and offensive activity on Twitter in their article. They suggest a rigorous approach for extracting content, user, and network-based attributes, with the aim of determining what distinguishes bullies and aggressors from casual users. Bullies make fewer posts, engage in fewer online forums, and are less well-known than regular users. Aggressor posts tend to be more negative. Machine learning recognition algorithms like J48, LADTree, LMT, NBTree, Random Forest (RF), and Functional Tree are used to identify users displaying bullying and violent activity using a corpus of 1.6M tweets shared over three months, using a corpus of 1.6M tweets with 90% AUC accuracy. Cheng, Li et al. (2019) investigate the novel issue of detecting cyberbullying in a multimodal setting by collaborating on social media information extraction through text, spatial location, and visual cues. However, this challenge is difficult due to the complex combination of cross-modal similarities across various modalities, systemic dependencies between separate social network sessions, like Instagram and vine, and diverse attribute knowledge of different modalities. They suggest XBully, a novel cyberbullying identification system that reformulates multimodal social media data as a heterogeneous network and then attempts to learn embedding node representations from it. Extensive experimental evaluations of real-world multimodal social network datasets demonstrate that the XBully system outperforms current cyberbullying identification models. Al-Hashedi et al. (2019) conducted an observational analysis of the efficacy and efficiency of deep learning algorithms combined with word embeddings in identifying cyberbullying texts performed in this article. GRU, LSTM, and BLSTM were three deep-learning algorithms that were tested. Four separate word embedding models were investigated for function representations, including word2vec, GloVe, Reddit, and ELMO. Elmo took control of word sense by extracting detail from the word's environment, removing any flaws of pre-trained word embedding models. The 10-fold cross-validation methodology was used to ensure correct performance. The findings of the experiments revealed that BLSTM outperforms ELMO in identifying cyberbullying messages. Formspring. me provided the results, which included 12,772 posts. Chen et al. (2012) elaborates that current literature on message-level offensive language identification cannot reliably identify offensive content because the textual contents of online social media are highly unstructured and informal. A more practical solution is to track user offensiveness. The authors propose the Lexical Syntactic Feature design to detect offensive content and classify possible offensive users of social media. In terms of detecting aggressive material, the LSF system outperformed current methods substantially. In sentence offensive detection, it has a precision of 98.24 percent and a recall of 94.34 percent. In user offensive detection, it has a precision of 77.9 percent and a recall of 77.8 percent by taking 10 msec per sentence. Li and Tagami (2014) concentrate on identifying relation-based cyberbullying, which is a human-to-human assault. Relationship-based cyberbullying has recently gained recognition as a new form of cyberbullying and finding it remains a challenge. When it attacks a human relationship, the detection should keep track of how the relationship changes. They suggest generating a communication network as the first step in relation-based cyberbullying identification. The system is divided into two steps to reduce false negatives, which occur when students are friends in school but are not detected as friends in the Social Networking Service (SNS), a major issue in identifying cyberbullying. Capua et al. (2016) think that using methods derived from NLP (Natural Language Processing) and machine learning, the authors suggest a potential solution for the automated identification of bully traces through a social network. They create a model based on Growing Hierarchical SOMs that can effectively cluster documents containing bully traces based on semantic and syntactic features of textual sentences. The GHSOM Network model was perfectly all right to be used for Twitter, but it was also checked against other social media platforms like YouTube and Formspring. Finally, the findings suggest that the proposed unsupervised solution can be used successfully in certain situations with decent results by adopting K-Fold validation. In their paper, Foong and Oussalah (2017) outline an online framework for detecting and tracking cyberbullying incidents in online networks and groups. Insults, swear, and second-person pronouns are the three basic natural language elements that the machine detects. A classification scheme and ontology-like logic were used to identify the presence of certain entities in the forum documents, which would send a warning to security, prompting them to take necessary action. The machine has been reviewed on two different forums and has shown to be capable of detecting objects. The authors have wisely used the support vector machine (SVM) classifier because of its demonstrated utility in binary classification and theoretical soundness. Misuse of emerging networks, such as social media (SM) sites, has spawned a modern breed of online aggression and abuse. Garadi et al. (2019) highlight a new way of demonstrating violent behavior on social media platforms. The reasons for developing prediction models to combat offensive behavior in SM were also discussed. The authors examine cyberbullying prediction models in depth and discuss the major problems that arise when building cyberbullying prediction models in SM. This paper gives an outline of the general mechanism for detecting cyberbullying and, most specifically, the approach. Despite the fact that the data collection and function engineering processes have been detailed, the focus is always on the data. Despite the fact that the data collection and feature engineering processes have been detailed, the focus is mostly on feature selection algorithms and then the application of various machine learning algorithms to forecast cyberbullying behaviors. Ratadiya and Mishra (2019) believe that Classic convolution and recurrence-based sequential models have been used in deep learning-based methods to simplify the method. This version, on the other hand, is computationally inefficient and requires more memory. The authors suggest a multiheaded attention-based method for detecting profane text in this paper. The model is combined with power-weighted average ensemble techniques to boost efficiency even more. In comparison to previous methods, the current solution needs no extra memory and is less complex. Their model's enhanced performance on publicly accessible real-world data further supports this claim through flexible and lightweight models to understand the evils of cyberspace. Andleeb et al. (2019) note that in contrast to a previous analysis on the same dataset that only considered textual features, this study extracts three categories of features from the dataset: textual, behavioral, and demographic features. Textual characteristics contain such bullying terms that, if present in the text, can result in a true cyberbullying outcome. Personality attribute characteristics are derived for users who have been bullied in the past and may bully again in the future. Age, gender, and position are among the demographic characteristics derived from the dataset. The method is tested using various consistency metrics with both classifiers used, and the SVM classifier outperforms the Bernoulli NB with an average accuracy of 87.14 percent. As per Abbass et al. (2020), using data derived from social media websites, a system is created to forecast significant categories of social media crimes. Data (tweet) pre-processing, classifying model generator, and prediction are the three modules that make up the proposed architecture. To construct a predictive model to classify given data into various types of crime, Multinomial Naive Bayes (MNB), K-nearest Neighbors (KNN), and Support Vector Machine (SVM) are used. Furthermore, the N-Gram language model is used in conjunction with these machine learning algorithms to determine the best value of n and assess the system's accuracy at various stages, including Unigram, Bigram, Trigram, and 4-gram. The results show that all three algorithms achieve accuracy values greater than 90%, with the Support vector machine outperforming the others marginally. Alasadi et al. (2020) suggests a fairness-aware fusion mechanism that guarantees that fairness and consistency remain essential considerations when integrating data from different modalities. The contributions from various modalities are incorporated in this Bayesian context in a way that considers the different trust levels associated with each function and the interdependencies between features. This system, in particular, applies weights to various modalities depending on their precision and their justice. The results of using the system to solve a multimodal (visual + text) cyberbullying identification problem show how effective it is at achieving accuracy and justice. Roy et al. (2020) believe it is important to monitor user posts and filter hate speech-related content before it spreads. On the other hand, Twitter gets over 600 messages every second and about 500 million tweets daily. It is almost impossible to manually filter any detail from such a large amount of incoming traffic. In this regard, a Deep Convolutional Neural Network is used to create an integrated framework. The proposed DCNN model uses the tweet text and the GloVe embedding vector to extract the meanings of tweets through convolution, and it outperformed current models with precision, recall, and F1-score values of 0.97, 0.88, and 0.92 for the best case, respectively. According to Behzadi et al. (2021), many people use their social media platforms to spread hatred online, which is why many experts have focused on the issue of cyberbullying awareness over the last decade. The authors of this paper use transfer learning to address this problem. They use a variety of small BERT models that they fine-tune with hate-speech information. They often use the Focal Loss feature to deal with class mismatch data. On the hate-speech dataset, the writers were able to obtain state-of-the-art findings of 0.91 accuracies, 0.92 memory, and 0.91 F1-score using this method. The more lightweight BERT models are considerably faster in detection and ideal for real-time cyberbullying implementations using a transfer learning pipeline. In this paper, Gutiérrez-Esparza et al. (2019) discuss findings from studies on identifying instances of cyber-aggression on social media, focusing on Spanish-language users in Mexico. To promote the characterization of offensive remarks in three specific cases of cyber-aggression: bigotry, abuse based on sexual identity, and violence against women, they used Random Forest, Variable Importance Measures (VIMs), and OneR. Experiments with OneR show that it improves the comment classification process in the three cyber-aggression cases by more than 90%. The proper definition of cyber-aggression remarks will aid in developing strategies to combat the phenomenon. Potha and Maragoudakis (2014) take a sequential data modeling approach to the issue, formulating the predator's questions using a Singular Value Decomposition representation. This procedure aimed to see if classification techniques could accurately forecast the severity of a cyberbullying attack and look for similarities in each predator's linguistic style. Every signal is parsed by a neural network that predicts the degree of insult within a query given a window between two and three previous questions using feature weighting and dimensionality reduction techniques. They saw that the plot of the time series data was very similar to the plot of the class attribute after applying SVD to it and considering the second dimension. Hee et al. (2015) created and implemented a new cyberbullying annotation scheme that explains the presence and nature of cyberbullying, the status of the post author (harasser, perpetrator, or bystander), and various fine-grained cyberbullying categories such as insults and threats. They presented their findings on the automated detection of cyberbullying in web blogs and the possibility of detecting more fine-grained cyberbullying types. An F-score of 55.39 percent is obtained for the first mission. It was also found that detecting fine-grained categories is more difficult, owing to data scarcity and the fact that they are often articulated in a subtle and tacit manner. Meliana et al. (2019) believed that if words on social media were legally justified, one example is intimidation; intimidation is one of the ITE Law posts, and intimidation would be removed from Twitter's social media; everyone will find examples of how much intimidation there is on Twitter. There are many techniques for retrieving data from social network platforms, one of which is the clustering or data grouping process. The Naive Bayes and Decision Tree J48 classification methods were used in the analysis. The Naive Bayes method, which obtained an average value of 92 percent success rate and 8% not observed for the overall scenario, and the Decision Tree J48 method, which obtained an accuracy value of 100 percent, are the results to be obtained in this analysis. Psychology-based bullying or related cyberbullying is the most common form of cyberbullying.

RESEARCH DESIGN

Data Collection will be done through Twitter. Six thousand tweets are extracted from Twitter. Exploratory Data Analysis will follow this extraction. The authors will then try and understand the various user profiles on the available information. In the analysis, the authors will consider the tweets which have the most impact. These will be the tweets which have the highest polarity and subjectivity

Figure 1. The research design for the study (self-complied)



values in order to determine maximum impact. One may be able to sort the tweets to obtain the required information for deep-diving into the analysis. The steps must be performed cautiously to ensure the correct information is collected from the analysis. Beginning with Twitter extraction, the authors ask a sample population to filter the 20 most common bad words or profanities noticed on social media platforms. These words are then further used for the analysis. They are used to filter out tweets and then extract tweets which will be further analyzed. The pictorial flowchart representation of the research design is as follows:

Once the data is extracted and it is time to deep-dive into the tweets, the next step would be to focus on the following three major components and sub-components. They can be mentioned in the form of a summary table to ensure further clarity on why the software detected the tweets based on the high values scored in metrics (those are polarity and subjectivity). This helps keep the analysis accurate and ensures good results, which can be used to help those in need.

- Extract Data from Twitter using keywords.
  - Create bad words dictionary – noswearing.com
  - User profile
  - Retweets
  - Likes
  - Comments
- Understand User Profiles
  - Location
  - Age (if available)
  - Frequency of tweets
  - Profile Picture – Yes/No
- Examine information from profiles

OBSERVATIONS AND INFERENCES

The authors have conducted a sentiment analysis on a set of 6,000 tweets. The tweets were extracted through the Tweepy library available in Python. Through the TextBlob package available, they could perform sentiment analysis. Sentiment analysis is a tool that enables us to understand tweets relating to a particular subject or topic. In this case, the sentiment analysis helped us understand the overall sentiment about the degree of cyberbullying that takes place on this platform. For this technique, once the tweets were extracted from Twitter, they were arranged in a data frame. This will form the corpus. A corpus is a collection of text documents which contains data that lets us capture sentiments. The data frame was further streamlined, and the polarity and subjectivity of tweets were assessed. The tweets were filtered using some of the most common swear words on social media platforms. The list of these words was decided by floating a questionnaire to respondents from the age of 18-29 residing in urban areas. The respondents selected a list of the 20 most common swear words, and their various variations were accounted for. This helped further streamline the program and search for the most relevant tweets based on common filters. The polarity is a measure that gives each tweet a score. This ranges from -1 to +1. A score of -1 denotes a strong negative sentiment, whereas a score of +1 denotes a strong positive sentiment. Subjectivity denotes the degree of opinion present in the tweet. As the name suggests, it simply denotes how subjective a tweet is. The score for subjectivity also lies between -1 to +1.

In the analysis, the authors find that multiple tweets were retweeted and favorited by others on the platform. The top 10 tweets by retweets are listed as follows (Table 1).

Furthermore, it is noticed that the count of tweets which are positive in nature, was only 1,871, out of 6,000. This means that about 30% of the tweets contained a positive connotation and were not negatively impacting people's emotions (Table 2).

What is interesting about this diagnosis is that multiple tweets scored a 1 out of 1, indicating that they definitely denote positive sentiments. A check-in factor that the algorithm works properly is the fact that none of the polarity digits exceed 1.

There were 2,921 tweets that portrayed a polarity less than zero, indicating negative sentiments and hereby, were the main focus of the authors' study. This comprised of almost 50% of the dataset of tweets extracted and hence, these tweets were the tweets that could be perceived as offensive. The following were the tweets that could be indicative of cyber bullying on Twitter (Table 3).

Figure 2. Word cloud generated using extracted tweets (self-complied)

Table 1. Twitter extraction

Retweets	Favorites	User ID	text_clean
69	458	mmpadellan	historians look back years wonder much difficulty discrediting dumb deranged dipshit like donnie disgraceful
68	622	DragonflyJonez	can't believe raptors championship three years ago telling two champions since shit feels like whole ass era ago
49	375	fuckkkankan	take nigga goin live
21	75	l78lancer	sick hell hearing rich people bellyache inflation interest rates stock market ones driving inflation interest rates markets yet poor working people bearing costs brunt
9	45	lisa_liberal	dinesh dsouza losing shit melting fuck Twitter bill barr others debunked horse shit documentary 2000 mules
8	24	SNMilitary	wagner tonight shelling Donetsk civilians nothing ukraine army hell awaits donbass media
7	89	mikemajlak	stop even using word sell ride paralyzed flaming chariot pits hell together win team die team
7	44	piersmorgan	tonight worlds gone nuts speak worlds no1 spiritual wellness guru Deepak Chopra work hell tune 8pm
6	15	Noffa1111	referred kate moss rando like bitch everyone knows kate moss reason ppl know youre known textbook definition npd amberheardisnotavictim amberheardlsanabuser amberisaliar
6	8	Bridgeanne	home office admits refugees could persecuted sent Rwanda

Source: Self complied via Twitter extraction

It is again interesting to note that upon sorting the tweets in ascending order, the authors note that the smallest value obtained is -1, which also validates the authenticity of the algorithm used.

Table 2. Twitter extraction

Retweets	Favourites	User ID	text_clean	Polarity	Subjectivity
0	0	sugrbot	pussy best though bomb like aleppo	1	0.3
0	0	Buumbas_Rose	ass hair considered national problem best	1	0.3
0	0	Lily_GiRlll	yarrrr tww awesome ho yarrr superb sa bhi superb best buddy	1	0.825
0	0	pr0phet_chia	fuckkkankan u best take bacon boa u finna catch ass whoopin	1	0.3
0	0	jdzork	overrated ass combo like niggas impressed	1	1
0	0	waynewalls	hell yes thats awesome bro	1	1
0	3	ecto_demon	face like ass hole best lyrics ever	1	0.3
0	0	nescafeplusmilo	hell koreans always perfect playlist every occasion understood assignment way well	1	1
0	0	BigAkanni_	perfect response get ass	1	1
0	0	classichitradio	chr3 best songs rock pop dance latino np bitch meredith brooks	1	0.3
0	2	Zbedi_	contender best ongoing gimmick sitcom schmidt douchebag jar	1	0.3
0	2	SelacoGame	revenatn thank best also hell yeah revenant bus	1	0.3
0	0	mothflieto	clumsykth happy birth motherfucker youre awesome	0.9	1
0	0	dangerz23332517	dahliadirty yummy ass beautiful	0.85	1
0	0	BryanX_LA	icyslimm beautiful pussy	0.85	1

Source: Self complied via Twitter extraction

The third category is the neutral one. Here, the focus is to understand the number and proportion of tweets extracted which were neutral. These tweets could be facts or statements and do not have any impact on people's sentiments. These comprised of only 1,208 tweets which was about 20% of the entire dataset. Therefore, analyses of these statements are beyond the scope of this paper (Table 4).

The tweets which had a polarity ranging from 0 to -1 are arranged in ascending order. It is done to ensure that the tweets that have maximum impact are highlighted in the analysis. This will lead to a more accurate and effective implicative instance generation. This gives us the following results (Table 5):

It is seen that a negative 100% polarity value for the tweets is obtained when it is arranged in ascending order. Similarly, the lowest value the authors observe was a negative 1.11%, until the digits reach 0. A higher value indicates a higher probability of the tweet being perceived negatively. Conversely, the same logic follows all positive percentage amounts.

Looking at retweets, it is noticed that there are multiple tweets that rank high on polarity as well as subjectivity. These are the tweets that are flagged due to the severity of the negative sentiments associated with them. They can further understand the user behaviors by understanding the most popular users' follower counts, whether they have a profile picture, assessed pinned tweets, if any, to understand the online presence personality of the user. Later, this information may be used to understand the online persona of those who have violative content in their tweets.

Table 3. Twitter extraction

Retweets	Favourites	User ID	text_clean	Polarity	Subjectivity
0	0	EYIMOFE202	beatboxxmyheart pop crave worst sitcom nigga youre wildling stay yo lane	-1	1
0	0	__doyoudream	siiraii g0reguru damn bitch ask ive going maybe youll know im boring	-1	1
0	0	Typ3o_	d6ares still saved nasty ass pizza choice	-1	1
0	0	jayboiibihh	got ta boring ass life	-1	1
0	0	viscosupafresh	amount baddies seen crack ass prolly insane	-1	1
0	0	FrankandBeanDip	crap pride ass child abuse disgusting	-0.9	0.9
0	0	keona004	homeless man called hoeand shove sickening	-0.9	1
0	0	shutupmya	hate nigga w 2 phones	-0.8	0.9
0	0	tmitchyy	niggas annoying nigga dont give headache	-0.8	0.9
0	0	simplepics66	birminghamcivic bhamcitycouncil bloody hell f king world coming	-0.8	0.9
0	1	formulawah	Oh hell yeah used like dressing which could put head poke people pointy hat getting annoying	-0.8	0.9
0	0	callmebeenee	storm bitch annoying asf	-0.8	0.9
0	0	Michell30921381	todayshow savannahguthrie even giving crap click turd go hell believed years trial meme didnt change mind amberturdisanabuser	-0.8	0.8
0	0	Bigdogszues	guys fell stare carrying 50 pound box books landed shoulder ass im sitting chair feel like idiot	-0.8	0.8
0	1	TakeSnatch	aint seen hoe tweet getting fucked hoe real bad	-0.8	0.85

Source: Self complied via Twitter extraction

Table 4. Twitter extraction

Retweets	Favourites	User ID	text_clean	Polarity	Subjectivity
0	0	ajazjanet	chuckcjmmn yeah red lipstick around asshole	0	0
0	0	hoe_5911	44ployy	0	0
0	0	Bippitybipp	realdschmidt cultists talking jim jones level hopefully rational effect revolutionary change bring robots back human beings oh poc still bitch complain portray perpetual victims	0	0.05
0	0	scromblegronk	jane ignorant slut	0	0
0	0	mcnashprod	pussy gon na pussy	0	0
0	0	mariajazmin95	drake said ex think beefing bitch alright	0	0
0	0	welovnerds	hoe entrepreneur	0	0
0	0	ham4bot	hamilton tolling angelica build whore	0	0
0	0	PercyMacKinley	marcorubio ass wait vote	0	0
0	0	Magobholi_Z	nigga celebrates everytime misses celebrate well	0	0

Source: Self complied via Twitter extraction

Table 5. Twitter extraction

Retweets	Favourites	User ID	text_clean	Polarity	Subjectivity
0	0	EYIMOFE202	beatboxxmyheart pop crave worst sitcom nigga youre wildling stay yo lane	-1	1
0	0	__doyoudream	siiraii g0reguru damn bitch ask ive going maybe youll know im boring	-1	1
0	0	Typ3o_	d6ares still saved nasty ass pizza choice	-1	1
0	0	jayboiibihh	got ta boring ass life	-1	1
0	0	viscosupafresh	amount baddies seen crack ass prolly insane	-1	1
0	0	FrankandBeanDip	crap pride ass child abuse disgusting	-0.9	0.9
0	0	keona004	homeless man called hoeand shove sickening	-0.9	1
0	0	shutupmya	hate nigga w 2 phones	-0.8	0.9
0	0	tmitchyy	niggas annoying nigga dont give headache	-0.8	0.9
0	0	simplepics66	birminghamcivic bhamcitycouncil bloody hell f king world coming	-0.8	0.9
0	1	formulawah	Oh hell yeah used like dressing which could put head poke people pointy hat getting annoying	-0.8	0.9
0	0	callmebeenee	storm bitch annoying asf	-0.8	0.9
0	0	Michell30921381	todayshow savannahguthrie even giving crap click turd go hell believed years trial meme didnt change mind amberturdisanabuser	-0.8	0.8
0	0	Bigdogszues	guys fell stare carrying 50 pound box books landed shoulder ass im sitting chair feel like idiot	-0.8	0.8
0	1	TakeSnatch	aint seen hoe tweet getting fucked hoe real bad	-0.8	0.85
0	0	Iightningnymph	gautiercock hate bastard solidarity every mlm except	-0.8	0.9
0	0	Bryce_BadAzz	hate sht	-0.8	0.9
0	0	izadegiron	gag hate bitch	-0.8	0.9
0	2	reinieyy	one asshole go look like retarded	-0.8	0.8
0	0	themadyorkie	itsjefftiedrich blueresist22 must terrible foot cramps tiptoeing around crazy bastard	-0.8	0.95

Source: Self-complied via Twitter extraction

CONCLUSION

The authors notice that out of the 10 most popular accounts, 3 of these are actual verified accounts. This implies how influential account holders may also be the ones creating an unhealthy social world.

Further analysis of the tweets of verified users shows that even though they are popular tweets, they are not all necessarily promoting a negative cyber environment. Only 1/3rd of the tweets have been flagged as portraying a negative emotion. 2 of the tweets extracted are either positive or neutral, as per the score obtained (Tables 6-9).

Further analysis of the top tweets portraying only a negative sentiment out of the most retweeted tweets in the corpus shows that there is a prevalent issue of cyberbullying on the social media website. These could be ranging from snide remarks to words intending to hurt someone or a community

Table 6. Twitter extraction

User ID	Name	Verified or Not Verified?
mmpadellan	BrooklynDad_Defiant!	Verified
DragonflyJonez	America Is Musty	Not Verified
fuckkkankan	Kankan	Not Verified
l78lancer	Larry Middleton - Democracy Forward in 2022!	Not Verified
lisa_liberal	Liberal Lisa in Oklahoma	Not Verified
SNMilitary	MI NEWS	Not Verified
piersmorgan	Piers Morgan	Verified
mikemajlak	Mike Majlak	Verified
Bridgeanne	Anne Booth	Not Verified
Noffa1111	MaJesstic	Not Verified

Source: Self complied via Twitter extraction

Table 7. Twitter extraction

User ID	Profile Picture	Cover	Following	Followers	Tweets	Retweets on Tweet Extracted	Favourites on Tweet Extracted
mmpadellan	Yes	Yes	42.5K	937.4K	124K	69	458
DragonflyJonez	Yes	Yes	2,428	215.6K	572.8K	68	622
fuckkkankan	Yes	Yes	16	69.1K	1,263	49	375
l78lancer	Yes	Yes	21.2K	22.8K	108.2K	21	75
lisa_liberal	Yes	Yes	7,412	7,559	19K	9	45
SNMilitary	Yes	No	304	35.3K	1,269	8	24
piersmorgan	Yes	Yes	2,048	7.9M	148.7K	7	44
mikemajlak	Yes	Yes	427	502.2K	8,695	7	89
Bridgeanne	Yes	Yes	8,358	8,127	214.2K	6	8
Noffa1111	Yes	Yes	81	17	754	6	15

Source: Self-complied via Twitter extraction

Table 8. Twitter extraction

User ID	Polarity	Subjectivity	Tweet
mmpadellan	-0.058333333	0.233333333	Historians will look back at these years and will wonder how we had so much difficulty discrediting such a a dumb, deranged dipshit like Donnie. Disgraceful.
mikemajlak	0.8	0.4	STOP EVEN USING THE WORD SELL. WE RIDE THIS PARALYZED FLAMING CHARIOT INTO THE PITS OF HELL TOGETHER. WIN AS A TEAM, DIE AS A TEAM.
piersmorgan	0	0.133333333	TONIGHT: As the world's gone nuts, I speak to the world's No1 spiritual wellness guru @DeepakChopra to work out what the hell we do about it…. Tune in at 8pm. https://t.co/YJ657BOa6v

Source: Self complied via Twitter extraction

Table 9. Twitter extraction

User ID	Tweet Text	Retweets	Favourites	Polarity	Subjectivity
mmpadellan	Historians will look back at these years and will wonder how we had so much difficulty discrediting such a a dumb, deranged dipshit like Donnie. Disgraceful.	69	458	-0.058333333	0.233333
l78lancer	I am sick as hell of hearing rich people bellyache about inflation, interest rates, and the stock market when they are the ones driving inflation up, interest rates up, and the markets down. Yet it's poor and working people bearing the costs and the brunt.	21	75	-0.246428571	0.735714
lisa_liberal	Dinesh D'Souza is losing his shit and, melting the fuck down on Twitter because Bill Barr and others debunked his horse shit documentary 2000 Mules.	9	45	-0.2	0.55
SSS_Shiv_007	It's been 2 years today 💔. jaha bhi ho khush rhna mere bhai @itsSSR #SushantSinghRajput 😢	6	10	-0.5	0.5
mylifemyview12	This @Abhii1012 you are getting a bad name for Karan's team, who the hell are you? Ppl think you are from Karan's team his team is getting unnecessarily blame for your stupidity, they keep distance from Twitter FD wars but because of you they are blamed #tejran https://t.co/iFlJz6rfCo	5	9	-0.566666667	0.855556
yinzian	Me n the bad bitch I pulled by smoking meth	4	46	-0.7	0.666667
FamNikki	@bollywood_life SLUT SHAME !! You have lost your authenticity & trust by publishing this bluff article over their erroneous breakup & saying Shamita set forth any sort of 'proud'. How a verified acc could publish such filth ? 1 Retweet = 1 Slap of @bollywood_life #RaqeshBapat #ShamitaShetty	3	8	-0.5	0.6
NatashaCL7	Miss me with that fake ass shit.	3	24	-0.35	0.9
rad_milk	gnomes are real they shit on my lawn all the time https://t.co/r622JIuV0U	3	21	-0.3	1
TheldlerWheel	He looks like a little slut in this picture… https://t.co/jA86oGeR4u	3	21	-0.1875	0.5
MKupperman	I saw Anger Management. Really, really terrible film. It gave the world the Jack Nicholson nodding gif. Adam Sandler is angry because Allen Covert's penis is too large. Rudy Giuliani saves the day. Keep the gif, throw the film away	2	75	-0.496428571	0.657143
TeenVogue	"If you don't feel like you can protest or act or organize by yourself or you're scared to speak up, you don't have to do this alone. There are a lot of people behind you." @Jack_Petocz talks to Teen Vogue ⤵ https://t.co/Tz5IiAAhrR	2	33	-0.2	0.35
wanlov	they burnt their food to hode the fact that they were feeding you shit https://t.co/hVmxgC5rMm	2	2	-0.2	0.8
bymyselfnoheIp	keep that shit bro 🤘🔥 https://t.co/jrWvQ18t0M	2	3	-0.2	0.8
TesolinJulian	Holy shit guys they put Zack Snyder and Matt Reeves in #ThorLoveAndThunder https://t.co/iRnTvVmgJ7	2	3	-0.2	0.8

Source: Self-complied via Twitter extraction

through words. These users are the to-be 'aggressors' or have the potential to be deemed as 'flagged' users as per the results of the Twitter extraction study.

The users who have been flagged by the analysis seem to have a large number of posted tweets. This indicates that they are active users who have been tweeting regularly and almost all of the users have a moderately high number of followers ranging in thousands (in one case, even millions). Furthermore, it is also noted that the users have maintained a certain frequency of tweets, which may be deemed high. With the lowest number of tweets being flagged amounting up to 754 and the highest being equivalent to 148,700. This shows that meanwhile the user's tweets do not conform to a pattern, there are certain conversations which have been flagged by the program. Although all profiles did have profile pictures, not all of these images were distinctly clear (barring the exception of few), which helped them maintain their anonymity and thereby, draft tweets which may not be suitable for all audiences. Hurting political or emotional sentiments is extremely easy and there is always a digital footprint or copy that is left. Hence, the audiences and masses must exercise caution in this day and age where information can be malleable and taken in a meaning not previously or futuristically intended.

FUTURE WORK AND LIMITATIONS

Although there are certain areas where the program needs further attention, there are also advantages to it, as discussed in prior sections. Understanding a tweet's true meaning as a human would perceive it requires much work. There may be many instances where tweets flagged are not profane – they have a certain amount of commonly used profane language in the bodies of their texts. This further illustrates that there will always be some error percentage, which will hamper the analysis. Since the participants are not taking questionnaires or surveys, the entire process is undertaken with the help of technology. Hence, a limitation of the analysis is that the participants are not voluntarily involved. This will make it difficult to reach out to such netizens to provide them with actual support in severe cases. Hence, it can be noted that although analyzing without a questionnaire will eliminate the bias component; it will make it difficult to ensure proper care to either the aggressor or the aggresse. What is offensive to one may not be so to another. Future work in this domain can include setting alarms to raise specific objections known as flags. This can further help in the regulation of the social media platform to bring down the severity of offensiveness on the particular platform. When an alarm goes off, it can be used to determine the following aspects:

- **To what extent was the tweet offensive:** This can be indicated with the help of certain metrics, including a percentage of offensiveness.
- **Why was it tweeted:** Was the tweet a religious, political, emotional, or psychological one? Was it based on current events? Or was it tweeted just to 'get back' at someone via a platform that protected the aggressor?
- **Did it make people feel inferior:** To what extent did the tweet not conform to social norms? Was it responsible for making people inferior? If yes, what segment of people felt directly attacked by such a tweet? Was it consistent across all geographies?

Raising such flags would really help understand the geographic locations of netizens and further take actions to mitigate such instances, raise awareness, or just ensure that proper psychological care is imparted. This can be done with the help of various bots and 'talk to us' commands. Furthermore, on the basis of the user's profile, a system of verification can be implemented. Some starting points of this system include:

- **Colour the perpetrators 'Red'** -Those who're indulging in bad behaviour. This could be indicated publicly on the user's profile with the help of an exclamation mark emoji which could ensure that all users are on their best behaviour on the platform.

- This format can be helpful especially for girls or women who are harassed on a daily basis. They can ensure that all that needs to be done is reporting with the help of authentic proof which can be used to flag the accounts.

Sending a Friend Request (FR) to anyone should not mean that the party initiating contact is interested in the other**;** it can simply portray that they want to be academically attached. People Misinterpret it. For those who want to connect with industry experts or just make friends on the platform by sending requests to accounts – this could help them make better decisions and foster a safer online environment. This can be especially helpful to women who may seem too direct or leading someone on, which might not be the case.

ACKNOWLEDGMENT

The completion of this academic paper would not have been possible without the support of Dr. Krishna Kumar Singh, Associate Professor at Symbiosis Centre for Information Technology, Pune, India. The authors would like to extend their gratitude to the Director of Symbiosis Centre for Information Technology as well as the dignitaries at Symbiosis International University for providing them a means to conduct the research.

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

FUNDING AGENCY

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

Abbass, Z., Ali, Z., Ali, M., Akbar, B., & Saleem, A. (2020). A Framework to Predict Social Crime through Twitter Tweets By Using Machine Learning. In *14th International Conference on Semantic Computing (ICSC)* (pp. 363-368). IEEE. doi:10.1109/ICSC.2020.00073

Al-Hashedi, M., Soon, L.-K., & Goh, H.-N. (2019). Cyberbullying Detection Using Deep Learning and Word Embeddings: An Empirical Study. In CIIS'19 (pp. 17-21). Bangkok: CIIS'19.

Alasadi, J., Arunachalam, R., Atrey, P. K., & Singh, V. K. (2020). A Fairness-Aware Fusion Framework for Multimodal Cyberbullying Detection. In *Sixth International Conference on Multimedia Big Data (BigMM)* (pp. 166-173). IEEE. doi:10.1109/BigMM50055.2020.00032

Andleeb, S., Ahmed, D. R., Ahmed, Z., & Kanwal, M. (2019). Identification and Classification of Cybercrimes using Text Mining Technique. In *International Conference on Frontiers of Information Technology (FIT)* (pp. 227-232). Islamabad: IEEE Xplore. doi:10.1109/FIT47737.2019.00050

Angelis, J. D., & Perasso, G. (2020). Cyberbullying Detection Through Machine Learning: Can Technology Help to Prevent Internet Bullying? *International Journal of Management and Humanities*, *4*(11), 57–69. doi:10.35940/ijmh.K1056.0741120

Behzadi, M., Harris, I. G., & Derakhshan, A. (2021). Rapid Cyber-bullying detection method using Compact BERT Models. In *15th International Conference on Semantic Computing (ICSC)* (pp. 199-202). IEEE. doi:10.1109/ICSC50631.2021.00042

Ben-Joseph, E. P. (2018, April). *Cyberbyllying*. Retrieved from Kids Health: https://kidshealth.org/en/teens/cyberbullying.html

Capua, M. D., Nardo, E. D., & Petrosino, A. (2016). Unsupervised Cyber Bullying Detection in Social Networks. In *23rd International Conference on Pattern Recognition* (pp. 432-437). Cancun: IEEE. doi:10.1109/ICPR.2016.7899672

Chatzakouy, D., Kourtellisz, N., Blackburnz, J., Cristofaro, E. D., Stringhini, G., & Vakali, A. (2017). Mean Birds: Detecting Aggression and Bullying on Twitter. *Long Session I: Aggression, Controversy, Crime WebSci '17*, 13-22.

Chen, Y., Zhou, Y., Zhu, S., & Xu, H. (2012). Detecting Offensive Language in Social Media to Protect Adolescent Online Safety. In *IEEE International Conference on Social Computing and 2012* (pp. 71-79). Amsterdam: IEEE. doi:10.1109/SocialCom-PASSAT.2012.55

Cheng, L., Li, J., Silva, Y. N., Hall, D. L., & Liu, H. (2019). XBully: Cyberbullying Detection within a Multi-Modal Context. In WSDM '19, Session 6: Networks and Social Behavior, Australia (pp. 339-347). Melbourne: WSDM '19.

Foong, Y. J., & Oussalah, M. (2017). Cyberbullying System Detection and Analysis. In *European Intelligence and Security Informatics Conference* (pp. 40-46). Athens: IEEE.

Garadi, M. A., Hussain, M. R., Khan, N., Murtaza, G., Nweke, H. F., Ali, I., . . . Ghani, A. (2019). Predicting Cyberbullying on Social Media in the Big Data Era Using Machine Learning Algorithms. IEEE, 70701-70717.

Gutiérrez-Esparza, G. O., Vallejo-Allende, M., & Hernández-Torruco, J. (2019). Classification of Cyber-Aggression Cases Applying Machine Learning. *MDPI Applied Sciences*, 1-17.

Hee, C. V., Lefever, E., Verhoeven, B., Mennes, J., Desmet, B., Pauw, G. D., & Hoste, V. (2015). *Detection and Fine-Grained Classification of Cyberbullying Events. In Proceedings of Recent Advances in Natural Language Processing*. ACL.

Huang, Q., Singh, V. K., & Atrey, P. K. (2014). Cyber Bullying Detection Using Social and Textual Analysis. In *SAM '14: Proceedings of the 3rd International Workshop on Socially-Aware Multimedia* (pp. 3-6). doi:10.1145/2661126.2661133

Li, M., & Tagami, A. (2014). A Study of Contact Network Generation for Cyber-bullying Detection. In *28th International Conference on Advanced Information Networking and Applications Workshops* (pp. 432-436). Victoria: IEEE Explore. doi:10.1109/WAINA.2014.70

Meliana, N., Sunardi, , & Fadlil, A. (2019). Identification of Cyber Bullying by using Clustering Methods on Social Media Twitter. *Journal of Physics: Conference Series*, *1373*(1), 1–13. doi:10.1088/1742-6596/1373/1/012040

Potha, N., & Maragoudakis, M. (2014). Cyberbullying Detection using Time Series Modeling. In *IEEE International Conference on Data Mining Workshop* (pp. 373-382). IEEE.

Ratadiya, P., & Mishra, D. (2019). An attention ensemble based approach for multilabel profanity detection. *International Conference on Data Mining Workshops*, 544-550. doi:10.1109/ICDMW.2019.00083

Reynolds, K., Edwards, A., & Edwards, L. (2011, December). *Using Machine Learning to Detect Cyberbullying*. Retrieved from Research Gate: https://www.researchgate.net/publication/254051434_Using_Machine_Learning_to_Detect_Cyberbullying

Roy, P. K., Tripathy, A. K., Das, T. K., & Gao, X.-Z. (2020). *A Framework for Hate Speech Detection Using Deep Convolutional Neural Network*. IEEE Access.

Singh, V. K., Ghosh, S., & Jose, C. (2017). Toward Multimodal Cyberbullying. *Late-Breaking Work CHI*, 6-11.

APPENDIX

Figure 3. Code snippet for all the tweets extracted

Out[17]:

	text	retweets	favorites	user	text_clean
0	@MythinformedMKE What the fuck is this?! 🤮	0	0	UhFreeAmerican	mythinformedmke fuck
1	@Ghost030371891 @Sn0wy76886886 @rossmac_d @rov...	0	0	rabbilo	ghost030371891 sn0wy76886886 rovinsmok sigmars...
2	@JewishTurtlee What. The. Fuck.	0	0	Sivoh__	jewishturtlee fuck
3	I think I'm catching feelings for her.\n\nI bl...	0	0	xHelmutLang	think im catching feelings blocked fine white ...
4	@DillonTepes @pulte Your a dumb ass that appar...	0	0	pate_megan	dillontepes pulte dumb ass apparently doesnt l...
...	...	...	...	...	...
5995	Oh and the fire? Is real. So fuck around and f...	0	0	capKisVenus	oh fire real fuck around find want jean grey c...
5996	@selectric401 @mikurubaeahina b list comic boo...	0	3	vehiclefan53	selectric401 mikurubaeahina b list comic book ...
5997	@_odunlade 30k mah solve shit mi!!. 😦 .#CoinW	0	0	RounmuD	30k mah solve shit mi coinw
5998	I kept taking my meds for my skin twice on acc...	0	0	Lexalupo	kept taking meds skin twice accident point wri...
5999	@uhSnoww he truly is the lil shit of the SDSO ...	0	0	ValkyrionRP	uhsnoww truly lil shit sdso

6000 rows × 5 columns

Figure 4. Code snippet for the most retweeted tweets

In [21]:

```
# most retweeted content
df_tweets.sort_values(by='retweets', ascending=False).head(30)
```

Out[21]:

	text	retweets	favorites	user	text_clean	polarity	subjectivity
2389	Historians will look back at these years and w...	69	458	mmpadellan	historians look back years wonder much difficu...	-0.058333	0.233333
4668	I cant believe the Raptors only won that champ...	68	622	DragonflyJonez	cant believe raptors championship three years ...	0.000000	0.600000
2987	take a nigga 🥓 then we goin live	49	375	fuckkkankan	take nigga goin live	0.136364	0.500000
4062	I am sick as hell of hearing rich people belly...	21	75	I78lancer	sick hell hearing rich people bellyache inflat...	-0.246429	0.735714
4778	Dinesh D'Souza is losing his shit and, melting...	9	45	lisa_liberal	dinesh dsouza losing shit melting fuck twitter...	-0.200000	0.550000
984	Wagner: After tonight's shelling of Donetsk (c...	8	24	SNMilitary	wagner tonight shelling donetsk civilians noth...	0.000000	0.000000
2683	TONIGHT: As the world's gone nuts, I speak to...	7	44	piersmorgan	tonight worlds gone nuts speak worlds no1 spir...	0.000000	0.133333
2141	STOP EVEN USING THE WORD SELL. WE RIDE THIS PA...	7	89	mikemajlak	stop even using word sell ride paralyzed flami...	0.800000	0.400000
3864	Home Office admits LGBTQI+ refugees could be p...	6	8	Bridgeanne	home office admits refugees could persecuted s...	0.000000	0.000000
3854	It's when she referred to #KateMoss as a "rand...	6	15	Noffa1111	referred katemoss rando like bitch everyone kn...	0.000000	0.000000
5030	It's been 2 years today 💔. jaha bhi ho khush r...	6	10	SSS_Shiv_007	2 years today jaha bhi ho khush rhna mere bhai...	-0.500000	0.500000
3188	This @Abhii1012 you are getting bad name for K...	5	9	mylifemyview12	abhii1012 getting bad name karans team hell pp...	-0.566667	0.855556
4568	PRICE DROP\nTake this for a great deal at $185...	4	4	RussCardz614	price drop take great deal 185 shipped buy shi...	0.400000	0.587500
509	I really just love who I am. My heart, my pers...	4	6	diorkenn	really love heart personality carry shit thoro...	0.150000	0.700000

Figure 5. Code snippet for the tweets with a positive sentiment

```
In [23]: df_tweets[df_tweets.polarity>0]
Out[23]:
```

	text	retweets	favorites	user	text_clean	polarity	subjectivity
3	I think I'm catching feelings for her.\n\nI bl...	0	0	xHelmutLang	think im catching feelings blocked fine white ...	0.183333	0.320000
4	@DillonTepes @pulte Your a dumb ass that appar...	0	0	pate_megan	dillontepes pulte dumb ass apparently doesnt l...	0.002273	0.330000
5	@SakuraNoSeirei This is precisely the level of...	0	0	kirstyboo79	sakuranoseirei precisely level contempt fan ne...	0.233333	0.866667
10	There will be converts. They will be accepted ...	0	0	DfrogMike	converts accepted conditionally conditions com...	0.150000	0.400000
12	I ain't Mention my tongue doin jumpin jacks on...	0	0	NimueKeri	aint mention tongue doin jumpin jacks yo pussy...	0.250000	0.500000
...	...	...	...	...	...	...	...
5987	You're a wrestling heel\nNothing 'bout you is ...	0	0	erbohbot	wrestling heel nothing real bitch even really ...	0.200000	0.250000
5990	Pretty bitch don't even want me for me so how ...	0	0	iheartjuggin	pretty bitch dont even want expect	0.250000	1.000000
5993	Don't let the face fool ya. Sir Richard is bec...	0	1	GretchenDenison	dont let face fool ya sir richard becoming roy...	0.450000	0.850000
5994	when i die my bitch better cremate me & st...	0	1	_ENVYQUE	die bitch better cremate stuff urn pussy wan fck	0.150000	0.325000
5996	@selectric401 @mikurubaeahina b list comic boo...	0	3	vehiclefan53	selectric401 mikurubaeahina b list comic book ...	0.375000	0.500000

1871 rows × 7 columns

```
In [24]: df_tweets[df_tweets.polarity>0].count()
Out[24]: text            1871
         retweets        1871
         favorites       1871
         user            1871
         text_clean      1871
         polarity        1871
         subjectivity    1871
         dtype: int64
```

Figure 6. Code snippet for the tweets sorted to portray the highest polarity (positive tweets)

```
In [26]: df_tweets.sort_values(by='polarity', ascending=False).head(30)
Out[26]:
```

	text	retweets	favorites	user	text_clean	polarity	subjectivity
1840	@fuckkkankan U best not take my bacon boa u fi...	0	0	pr0phet_chia	fuckkkankan u best take bacon boa u finna catc...	1.00	0.300
5590	@revenatn Thank you, we're doing our best ❤️ \n\...	0	2	SelacoGame	revenatn thank best also hell yeah revenant bus	1.00	0.300
2643	This overrated ass combo. Like niggas are impr...	0	0	jdzork	overrated ass combo like niggas impressed	1.00	1.000
561	@PTI_Bott Yarrrr you tww awesome ho yarrr.... ...	0	0	Lily_GiRlll	yarrrr tww awesome ho yarrr superb sa bhi supe...	1.00	0.825
4994	a contender for the best ongoing gimmick on a ...	0	2	Zbedi_	contender best ongoing gimmick sitcom schmidt ...	1.00	0.300
423	Ass hair should be considered a national probl...	0	0	Buumbas_Rose	ass hair considered national problem best	1.00	0.300
4514	#chr3 The Best songs rock pop dance latino np ...	0	0	classichitradio	chr3 best songs rock pop dance latino np bitch...	1.00	0.300
168	This pussy the best, though\nIt's bomb like Al...	0	0	sugrbot	pussy best though bomb like aleppo	1.00	0.300
2972	@sam_gzstrength Hell. Yes. That's awesome bro.	0	0	waynewalls	hell yes thats awesome bro	1.00	1.000
4016	Perfect response get your ass out of there htt...	0	0	BigAkanni_	perfect response get ass	1.00	1.000
3280	YOUR \n\nFACE\n\nLIKE\n\nMY \n\nASS\n\nHOLE \n...	0	3	ecto_demon	face like ass hole best lyrics ever	1.00	0.300
3426	how the hell koreans always have the perfect p...	0	0	nescafeplusmilo	hell koreans always perfect playlist every occ...	1.00	1.000
2430	@clumsykth HAPPY BIRTH YOU MOTHERFUCKER YOURE ...	0	0	mothflieto	clumsykth happy birth motherfucker youre awesome	0.90	1.000
2468	@dahliadirty Yummy 😋 ass so beautiful	0	0	dangerz23332517	dahliadirty yummy ass beautiful	0.85	1.000
3096	@ICYSLIMM Beautiful pussy😍	0	0	BryanX_LA	icyslimm beautiful pussy	0.85	1.000
3807	Might not have the nicest body or the fattest ...	0	0	niybndz_	might nicest body fattest ass face mf beautiful	0.85	1.000
3439	All 2010 you couldn't tell me I wasn't a part ...	0	0	215Pownz	2010 could tell part taylor gang niggas rockin...	0.80	0.900
1865	So happy my ass isn't going in office.	0	0	DiamanteSharae	happy ass isnt going office	0.80	1.000
3587	@javinator8 welcome to my world bitch	0	1	jemmabop	javinator8 welcome world bitch	0.80	0.900

Figure 7. Code snippet for the tweets with a negative sentiment

```
In [25]: df_tweets[df_tweets.polarity<0]
Out[25]:
```

	text	retweets	favorites	user	text_clean	polarity	subjectivity
0	@MythinformedMKE What the fuck is this?! 🤬	0	0	UhFreeAmerican	mythinformedmke fuck	-0.400000	0.600000
1	@Ghost030371891 @Sn0wy76886886 @rossmac_d @rov...	0	0	rabbilo	ghost030371891 sn0wy76886886 rovinsmok sigmars...	-0.200000	0.900000
2	@JewishTurtlee What. The. Fuck.	0	0	Sivoh__	jewishturtlee fuck	-0.400000	0.600000
6	@SassyandGeeky Dead ass! He coming back!	0	0	Reeta06572915	sassyandgeeky dead ass coming back	-0.100000	0.200000
8	G ; when I tell you I'm scarred for dis lul ni...	0	0	tikittytak	g tell im scarred dis lul nigga actually know wtf	-0.250000	0.550000
...	...	...	...	...	...	...	...
5992	@TheDINKLife Only if you've won the lottery an...	0	1	midsummerqueer	thedinklife youve lottery didnt tell shit expe...	-0.350000	0.750000
5995	Oh and the fire? Is real. So fuck around and f...	0	0	capKisVenus	oh fire real fuck around find want jean grey c...	-0.266667	0.466667
5997	@_odunlade 30k mah solve shit mi!! 😡 #CoinW	0	0	RounmuD	30k mah solve shit mi coinw	-0.200000	0.800000
5998	I kept taking my meds for my skin twice on acc...	0	0	Lexalupo	kept taking meds skin twice accident point wri...	-0.150000	0.400000
5999	@uhSnoww he truly is the lil shit of the SDSO ...	0	0	ValkyrionRP	uhsnoww truly lil shit sdso	-0.200000	0.800000

2921 rows × 7 columns

```
In [28]: df_tweets[df_tweets.polarity<0].count()
Out[28]: text            2921
         retweets        2921
         favorites       2921
         user            2921
         text_clean      2921
         polarity        2921
         subjectivity    2921
         dtype: int64
```

Figure 8. Code snippet for the tweets sorted to portray the least polarity (negative tweets)

```
In [40]: df_tweets.sort_values(by='polarity', ascending=True).head(30)
Out[40]:
```

	text	retweets	favorites	user	text_clean	polarity	subjectivity
58	@beatboxxmyheart @PopCrave Worst sitcom? Nigga...	0	0	EYIMOFE202	beatboxxmyheart popcrave worst sitcom nigga yo...	-1.000000	1.000000
2576	I gotta boring ass life 😕	0	0	jayboiibihh	got ta boring ass life	-1.000000	1.000000
909	@Liz93_xo @siiraii @g0reguru Damn bitch ask me...	0	0	__doyoudream	siiraii g0reguru damn bitch ask ive going mayb...	-1.000000	1.000000
4469	the amount of baddies that have seen the crack...	0	0	viscosupafresh	amount baddies seen crack ass prolly insane	-1.000000	1.000000
1563	@D6_izzy @D6Ares Still not saved with that nas...	0	0	Typ3o_	d6ares still saved nasty ass pizza choice	-1.000000	1.000000
1051	What is this crap? Pride my ass.... this is ch...	0	0	FrankandBeanDip	crap pride ass child abuse disgusting	-0.900000	0.900000
3536	Homeless man just called me a hoe 🤣 🤣 🤣 🤣 and "shov...	0	0	keona004	homeless man called hoeand shove sickening	-0.900000	1.000000
1267	@gautiercock i hate that bastard. i have solid...	0	0	lightningnymph	gautiercock hate bastard solidarity every mlm ...	-0.800000	0.900000
3255	I hate that shit https://t.co/iFQpGHW8Cw	0	0	Bryce_BadAzz	hate sht	-0.800000	0.900000
1121	I ain't seen no hoe tweet "you be getting fuck...	0	1	TakeSnatch	aint seen hoe tweet getting fucked hoe real bad	-0.800000	0.850000
713	@TODAYshow @SavannahGuthrie Not even giving th...	0	0	Michell30921381	todayshow savannahguthrie even giving crap cli...	-0.800000	0.800000
1046	Guys I just fell down the stare carrying a 50 ...	0	0	Bigdogszues	guys fell stare carrying 50 pound box books la...	-0.800000	0.800000
304	@_SaveOurStatues @BirminghamCivic @BhamCityCou...	0	0	simplepics66	birminghamcivic bhamcitycouncil bloody hell f ...	-0.800000	0.900000
226	niggas are annoying .. my other nigga dont giv...	0	0	tmitchyy	niggas annoying nigga dont give headache	-0.800000	0.900000
4591	@NoPauseTv_ I'd be that one asshole that don't...	0	2	reinieyy	one asshole go look like retarded	-0.800000	0.800000
4602	@itsJeffTiedrich @blueresist22 They must have ...	0	0	themadyorkie	itsjefftiedrich blueresist22 must terrible foo...	-0.800000	0.950000
9	i hate a nigga w 2 phones	0	0	shutupmya	hate nigga w 2 phones	-0.800000	0.900000
470	this storm bitch is annoying asf	0	0	callmebeenee	storm bitch annoying asf	-0.800000	0.900000
4938	@nmffriends Just hate those bitch	0	1	niiight_mare	nmffriends hate bitch	-0.800000	0.900000

Figure 9. Code snippet for the tweets with a neutral sentiment

```
In [29]: df_tweets[df_tweets.polarity==0]
Out[29]:
```

	text	retweets	favorites	user	text_clean	polarity	subjectivity
7	@ChuckCjmmn Yeah it has red lipstick around it...	0	0	ajazjanet	chuckcjmmn yeah red lipstick around asshole	0.0	0.00
11	🆔 44ployy\n\n#รับงานชลบุรี \n#รับงานอมตะนคร \n...	0	0	hoe_5911	44ployy	0.0	0.00
15	@RealDSchmidt The're cultists. We're talking J...	0	0	Bippitybipp	realdschmidt cultists talking jim jones level ...	0.0	0.05
16	Jane, you ignorant slut.	0	0	scromblegronk	jane ignorant slut	0.0	0.00
26	A pussy gonna be a pussy	0	0	mcnashprod	pussy gon na pussy	0.0	0.00
...	...	...	...	...	...	...	...
5966	My mom stay cooking the same shit , i told her...	0	0	zer08ghtt	mom stay cooking shit told buy chinese pot com...	0.0	0.25
5970	@irfhabib @yadavakhilesh @Mahmudabad What are ...	0	0	RazdanVijay	irfhabib yadavakhilesh mahmudabad planning als...	0.0	0.00
5980	@HERR0NSCLOUDS @jackaverymusic @JonahMarais @w...	0	0	BILLIESOLIVIA	herr0nsclouds jackaverymusic jonahmarais whydo...	0.0	0.00
5982	@RichardHeartWin @Mashinsky Blocking people on...	0	0	lth_wagmi	richardheartwin mashinsky blocking people twit...	0.0	0.00
5985	Please help support lesbian pride, add a #Twib...	0	0	FanGirl79462113	please help support lesbian pride add twibbon	0.0	0.00

1208 rows × 7 columns

```
In [30]: df_tweets[df_tweets.polarity==0].count()
Out[30]: text            1208
         retweets        1208
         favorites       1208
         user            1208
         text_clean      1208
         polarity        1208
         subjectivity    1208
         dtype: int64
```

Figure 10. Code snippet for the most popularly retweeted tweets

```
In [31]: # users producing most retweeted content
         df_tweets.sort_values(by='retweets', ascending=False).head(10)[['user','retweets','favorites']]
Out[31]:
```

	user	retweets	favorites
2389	mmpadellan	69	458
4668	DragonflyJonez	68	622
2987	fuckkkankan	49	375
4062	l78lancer	21	75
4778	lisa_liberal	9	45
984	SNMilitary	8	24
2683	piersmorgan	7	44
2141	mikemajlak	7	89
3864	Bridgeanne	6	8
3854	Noffa1111	6	15

Kavya Sharma is a practitioner of data science and analytics. After her master's degree in data science from Symbiosis International University Pune, she is working in Gartner Inc, India.

Krishna Kumar Singh is an educator and trainer with more than 20 years of experience. He is certified professional and trainer of smart IT infrastructure, big data analytics and decision science. He has been working as associate professor and Board of studies (BoS) member of Symbiosis International University, Pune, India. He is Board of studies (BoS) member of Dev Sanskriti Vishwavidyalaya Haridwar and Symbiosis University of Applied Sciences (SUAS), Indore. He has been providing training to personnel of different Industrial/corporate houses like Wipro Ltd Pune, Steel Authority of India Ltd, Oriental Bank, Axis Bank (Axis Bank Young Banker's program), Indian army, Navy, air force, and many more in the various sub-domain of IT / data science. Previously he was associated as a faculty member at Amity University Noida. He is an alumnus of Banaras Hindu University Varanasi and G. B. Pant engineering college, Pauri, Uttarakhand. Dr. Krishna received a Scholarship from World Bank (under TEQIP) for PhD program. He is an editorial board member of different SCOPUS-indexed research journals and IEEE conferences.