CYBER BULLYING DETECTION USING MACHINE LEARNING AND DEEP LEARNING

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Abstract*—The use of information and technology to bully a person online is referred to as cyberbullying. Individuals use Information and Communication Technology (ICT) to ridicule, embarrass, taunt, defame, intimidate, and criticise a person without making a direct eye contact. With the rise of social media, bullies have created a "virtual playground" in Facebook, Instagram, WhatsApp, Twitter and YouTube by targeting specific set of individuals or groups. It is necessary to deploy models and mechanisms in place for bullying contents, where the content is automatically detected and resolved, as the repercussions could have societal ramifications. This paper proposes a unique hybrid model for detecting cyberbullying in three different types of social media content such as textual, visual, and infographic data.

Keywords*—ICT, Cyberbullying, Machine Learning, Deep Learning.

I. INTRODUCTION

World wide web is developing and evolving in relation to the volume, speed, and range of information allowed to start across the many online social platforms, demonstrating that social networking sites are now extensively utilized and have a worldwide presence. The widespread reach of social multimedia had unintended repercussions, with people discovering unlawful and unethical ways to use socially connected virtual groups. There are numerous advantages to social media, yet many people misuse it. One of the most serious consequences is cyberbullying, in which people develop new ways to abuse one another through the Internet. Bill Belsey, an anti-bullying activist, coined the phrase "cyberbullying" in 2003. Tokunaga defined cyberbullying as "any activity by people or groups that repeatedly sends hostile or violent messages designed to inflict harm or discomfort on others through electronic or digital media". This definition emphasises various aspects such as the technological component, the adversarial behaviour of the act, and an important cause for producing suffering, all of which are deemed very vital to the definition and repetitiveness by many researchers [6]. Cyberbullying on social media has previously been identified as a significant concern or threat. Bullying can take place on any device, including devices associated with that ecosystem. E-mails, instant messenger, chat sessions, podcasts, photographs, videotapes, and texting are all examples of electronic communication and therefore they are also examples of cyberbullying. Cyberbullying has evolved into a social hazard that has a harmful impact on both the victim and the bully's psyche. It is a more persistent form of bullying a person in front of a whole online network, namely social networking sites, which can lead to the victim's emotional and psychological collapse, including sadness, stress, a loss of self-confidence, anger, and other negative emotions. sadness, loneliness, health degradation, and suicides. This study proposes a novel hybrid methodology for detecting cyberbullying in three different types of social data: textual, visual, and infographic (text embedded along with an image). The CNN-BoVW-SVM all-in-one architecture consists of a convolution neural network (CNN) for textual bullying content prediction and a support vector machine (SVM) classifier trained using bag-of-visual-four-words (BoVW) for visual bullying content prediction. The text in the infographic is separated from the image using Google Lens in the Google Photos app. The hybrid architecture is used to process textual and visual components. The main goal is to get a high level of accuracy for detecting cyberbullying after optimising several hyper-parameters.

II. LITERATURE REVIEW

Today, because of the enormous development of web2.0, the online presence of individuals is normal and permanent. Additionally, the risk of cyberbullying and the pessimism brought about by cyberbullying is expanding [3]. Hence a lot of research is currently being done around there, particularly for Cyberbullying Detection. The accuracy of the multi-modal model is around 89%, which is higher than the accuracy of the text and picture modules when validated separately. A portion of the work that offers sight to this issue is done by scientists. Theoretical aspects of cyberbullying and how it is prevailing among youths and youngsters have been examined. introduces the characteristics of wrongdoers and victims, as well as potential prevention techniques. Until now, the majority of the work has been devoted to text analysis [4,5]. The work is essentially a Cyber-Aggression study that used a text analysis approach on the comments. The work done uses text-based analysis for identification of cyberbullying utilizing the dataset from formspring.me and Myspace. Deep learning-based algorithms have recently been used to detect cyberbullying [1,2]. The findings showed a significant enhancement when linguistic elements were contrasted to traits or criteria namely the group of contacts, networking situatedness, and association value. Some classification based on rules. The use of the FormSpring data set for the detection of bullies was also done. Using the Youtube database, it was created a new utterance screening algorithm that uses morphological relationships between collocation to rationally exclude aggressive statements in comments. Cyberbullying is prevailing and research is still carried out in this area in a broad way, however, it is still rare to detect cyberbullying using a mixed approach of image and text. Different aspects of cyberbullying detection are emphasized by surveys of the literature. Some research studies say that "characteristics information and post-harassing behavior. Users' behaviour is analysed by Cross-system i.e., detection of cyberbullying can be done more accurately if the reactions of users in various social media platforms are monitored. This recommended technique for detecting cyberbullying is based on text analysis of a few terms that appear frequently in comments or posts on social media. One of the analysing factors in this study is whether the comment was made by a man or a woman. This study used only a few words to test the identification of bullying content using text analysis and proposed methodologies. Thomas Vanhove et al. presented a pluggable architecture with reusable components that are generally capable of swiftly detecting dangerous content. To detect improper information, the platform employs text, image, audio, and video-based analysis modules. M. Rybnicek et al. suggested a study application in 2013 that provided a platform for detecting cyberbullying. The research platform presented in this study includes text, audio, video, pictures, and social media analysis, however for implementation, the domain services aggregate this data and flag user profiles if necessary. The legitimacy of the highlighted accounts is checked by censors on nine social networks. The advanced topic studied in this study is that it provides efficient knowledge about important platform demands, crucial architecture and design elements, and hurdles to dealing with cyberbullying using sound, clip, message, and photographs. However, only a poll of methods proposed can ensure an effective outcome because adaptation strategies have not proven the result analysis. The relevant literature describes computerized standard single algorithms for detecting cyberbullying on social networking sites. The goal of this study is to create two additional methodology models which can predict cyberbullying in textual, visual, and mixed-modal graphical media. The framework lacked any implementation and result details. This research offers a comprehensive model using a hybrid of deep learning for text analytics and BoVW with supervised machine learning for image analytics. However, as far as we know, apparently, there isn't any other work that is based on image features combined with text analysis in cyberbullying identification. Work has been done in which images are often used to detect cyberbullying using deep learning algorithms such as CNN and RNN, or where image representation attributes have been used to detect mistreatment [7-10].

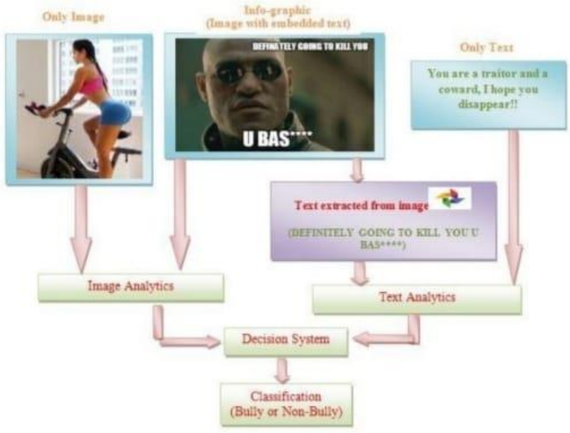

Fig 1: Generic high-level classification for bullying and non-bullying.

However, no such work has been done yet where all the potential outcomes of cyberbullying have been considered in one framework, so far either just image has been investigated or just content yet here with those two sorts of inputs, image with text embedded on it is additionally considered and after that choice is made where both image as well as text are contributing to the cyberbullying detection (shown in Fig. 1 and Fig. 2).

III. METHODOLOGY

The four modules that make up the proposed CNN-BoVW-SVM model. The general structure of the work has been outlined below. The steps can be summarised as follows:

1. Analyzing the sort of information.
2. Passing it to the separate module for processing.
3. Decision module is utilized to analyze the outcome.

Analyzing the sort of information includes checking whether the input is just text or it is a picture or it is a picture with text embedded on it. This is vital in light of the fact that once we have investigated this then we can perform further handling in the respective modules.

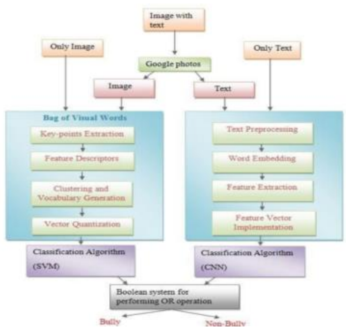

Fig 2: A detailed-level classification for bullying and non-bullying.

The whole architecture can be understood in four sub-modules:

1. Text Analytics Module
2. Image Analytics Module
3. Discretization Module
4. Decision Module

A. TEXT ANALYTICS MODULE

Deep learning architectures have shown that they can deduce advanced functionality from a small range of attributes in a testing phase and requiring human involvement or tagging everyone. Opposition to traditional approaches for deep learning, these have shown outstanding results for a variety of natural language processing tasks. The model employs a convolution neural network to assess textual bullying content (CNN). A CNN is a deep neural network that uses numerous copies of the same neuron in different locations to perform its functions. It has the ability to self-tune and learn abilities by extrapolating from training data. In an online post, a CNN model improves feature extraction (shown in Fig. 3).

Preprocessing: The data of the text can be of any size and can include misspelt words, picture, symbols, and other things. All of these are meaningless words that exemplify noise. In text classification, pre-processing is crucial. Emojis are removed or replaced, Cascodes, end letters are eliminated, clearly established, off being, and separating would be included, as are 25 hyperlinks and tags.

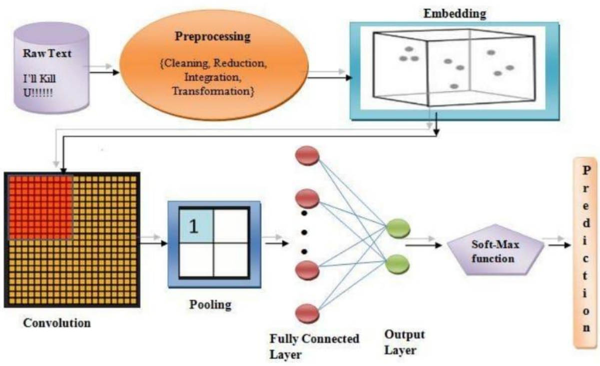

Fig 3: Prediction Process

Word Embedding: The embedding layer receives the pre-processed postings. The CNN learns feature representation and extraction in a hierarchical manner utilising word embedding, making it unique and superior to lexical or syntactic feature extraction. The embedding layer builds word embeddings using GloVe. Every paper's topological work as well as part (feature vector) are learned by the system. To run our algorithm on top of the GloVe language model, we employ 100-dimension vector representations of words. We train the program to understand the vectors for every word (which would otherwise be displayed as a single attractive vector); therefore, each phrase is transformed into a high - dimensional vector of numbers, and we have a commenting matrix.

Complete United Stratum: Here we use a feed forward network that is an n-dimensional feature vector which is created by concatenating every feature vector acquired after applying a number of filters. Hereafter we use the backward-propagation algo to train the network. Gradients are transmitted backwards, and we arrive at convergence.

B. IMAGE ANALYTICS MODULE

Local Binary Pattern which is a kind of visual descriptor is used for detecting any image. Visual vocabulary is formed using a clustering method such as k-means, in which comparable features form the core of the cluster and become one visual word. The features are extracted using LBP, and then mapped to an existing visual word in the vocabulary or codebook. A vector of visual word frequencies is eventually created. The appearance of a few visual words indicates the presence of offensive material in the image. Finally, the SVM classifier is used to classify bullying.

Pre-processing: Pre-processing is similar to text pre-processing, prior to performing any analysis on the image, pre-processing is done. Pre-processing is the process of transforming an image into a workable format. The noise 22 from the photographs is eliminated, the images are shrunk, and the images are converted to greyscale.

Feature extraction: Local elements of interest can be found around the borders and corners of images. The local points are described using local descriptors. Local descriptors define the identified points. Feature extraction is carried out with the help of a local binary pattern, which is based on texture analysis. Use a classifier to filter the screen with the central intensity values. Since it retains contrast level and patterning, it is extremely racist and discriminatory. Also, it's straightforward to figure out. The feature vector is created by partitioning the image into a set of 16 by 16 pixels or 32 x 32 pixels for every column. So each data point in a compartment is likened to all 8 of its neighbours and friends (pixels in the top-left, top-right, bottom-left, bottom-right, bottom-right, bottom-left, top-right, bottom-left, top-right, top-left, top-right, top-left, top-right, top-left, top-right, top-left, top-right, top-left, top-right, top-left, top-right, top-left, top-right, In its 8 x 8 neighbor, the amount is allocated as per the principle that even when the content of the grid cell is greater than the critical value of the neighbour image, the value 1 is written, otherwise 0 is authored. This approach generates an octal binary code, which is then converted to decimals for ease of understanding. The central pixel is then assigned that number. Then, for each block, a histogram is produced and concatenated to provide the image's feature vector. Before conducting the concatenation, the histogram can be normalised. This is mainly because the Bag-of-Visual-Words technique is a constrained characterization of an unravelling gathering of components. Metadata about the spatial configuration of components is ignored, hence this methodology only offers a small definition. As a consequence, the extraction of features is very precise.

Visual vocabulary -The amount of tangible form in a vocabulary could be characterised as vocabulary size. There are various visual words that occur in the vocabulary and those visual words can be very similar to each other thus we need to find a visual word so that it can act as a representative for the several same kinds of image patches. The k-means classification method is used, and each group symbolizes a graphical term. The picture's spectrum is then created using the input images and associated ratios.Finally a classifier, that is SVM here, is used to classify an image as bully or not. So the overall BoVW model can be summarized in these three steps

- Detects feature descriptors from training images and clusters them with k-means.

- Test the training and testing images feature descriptors in the k means classifier and make a histogram of classification results.
- Use these histograms as feature vectors for SVM classification.

Classification: To determine if an image is bully or non-bully, the image analytics module employs a supervised learning Support vector machine (SVM) trained on the BoVW features. SVM classifies a collection of items into categories by determining an optimal hyper-plane. SVM employs labelled training data to create a hyperplane that separates that may be used to classify new examples. A choice plane is a diagram that divides a group of elements into several classes. A single 24" connect as the high energy or judgment border for a 2d plane. In this image processing course, SVM analyzes the information and recognises fractal geometry. A collection of training instances is given to an automated system.

Discretization Module
If the source is an info-graphic i.e. pre, which is also a picture with word integrated on it, the CNN-BoVW-SVM model uses a Getty Picture Viewer to retrieve information from a photo. This graphical analysis tool separates the words from the photo, which is then examined as a separate entity and sent to the word and photo analysis units.

Decision Module
The bully element of conventional single is estimated using the appropriate classification techniques (text and image separately). An alternative validation has been introduced to support the multi-modal infographics content. This is a Logical assessment process that determines the outcome as bullying or non-bullying using an OR function.

TABLE 1: Boolean Decision Making

Modality	Text Classifier	Image Classifier	Classification
Text Only	+	Null	Bullying
	-	Null	Non-bullying
Image Only	Null	+	Bullying
	Null	-	Non-bullying
Info-graphic	+	+	Bullying
	+	-	Bullying
	-	-	Non-bullying
	-	+	Bullying

+: Positive of bullying content; **-:** Negative of bullying content

When either word or picture is classed as harassment, any change in class (bullying to non-bullying or vice versa) between the written and visual modalities kinds must not affect the categorization. This operation requires at least one input, and if text or a picture is provided, the platform's secondary input is set to 0. Table 1 depicts the rational OR.

IV. IMPLEMENTATION AND RESULTS

The data used here is in generally three forms with percentages shown below. The dataset prepared for experiments contains 10000 data out of which 55% data is in the form of text, 21% is in image form and there are 24% of data that contains images embedded with text is generated after giving the image to the image module defined. The features of the photos were extracted using the local binary pattern SIFT, and clustering was done using the k-means technique. The features employed by the algorithm to analyse text, picture, and text.

PERFORMANCE MEASURES Precision, recall, and accuracy were the three-evaluation metrics we employed.

Precision is defined as the ratio of correctly classified data elements to the overall number of classified occurrences.

Recall: The proportion of correctly classified minority class occurrences to the overall number of minor class occurance.

F-Measure: For the calculation of Fmeasure, Precision and Recall are used. Precision & Recall's harmonic mean is used to calculate it.

$$\text{measure of F} = [2 / (1/P + 1/R)]$$

In our overall model the text used is the text without removal of emoticons during preprocessing. Table 4.4 shows an ambiguity matrix for various types of modalities, 4.5 and 4.6. For the textual module, five classifiers, namely, Naïve Bayesian (NB), Random Forest (RF), Support vector machine (SVM), K-nearest neighbor (KNN) and Sequential Minimal Optimization (SMO) were compared with CNN. CNN achieved the highest accuracy of 78.2%. By using BoVW characteristics for the visual analysis unit, classification techniques, KNN and NB, were contrasted against SVM, and it was discovered that SVM beat both of the other classification models. Tables 4.7 and 4.8 provide a comparison of the categorization techniques utilised for discontinuous text and images modes. A brief overview of the classifiers is as follows: - Bayesian Inference (Naive Bayes): - In the realm of machine learning, this classification relates to the stochastic group of learners. The Naive Bayes is the foundation of this classification, which assumes that the characteristics are autonomous of one another. Whenever it concerns categorisation, it is really prominent. It's a simplified method in which the predictive model assigns category tags to the trial (unknown) examples

EXPERIMENTAL RESULTS

In the overall model the text used is the text without removal of emoticons during pre-processing.Confusion matrices for all types of modalities are shown in table 2, 3 and 4.

TABLE 2: Confusion matrix for textual modality

Actual classification TEXT	Predicted classification			
	Bully	Non-bully	Precision	Recall
Bullying	5100	900	79.94%	85%
Non-bullying	1280	2720	75.14%	68.75%

TABLE 3: Confusion matrix for visual(image) modality

Actual classification IMAGE	Predicted classification			
	Bully	Non-bully	Precision	Recall
Bullying	4750	1250	76.86%	79.17%
Non-bullying	1430	2570	67.28%	64.25%

TABLE 4: Confusion Matrix for Info-graphic (image+text) modalities

Actual classification INFO-GRAPHIC	Predicted classification			
	Bully	Non-bully	Precision	Recall
Bullying	5510	490	84.25%	91.83%
Non-bullying	1030	2970	85.84%	74.25%

K-NN: As a prediction or class label, the K-nearest neighbouring prototype can be used. The source for an undeclared example is the k secret occurrences in a constrained region, and the declassified instance is allocated to the class with the most instances in that province. When K=1, the unclassified instance is assigned to the class of its closest neighbour; and no need to count since k=1. :- SVM :- It divides a group of objects into classes by identifying a hyper-plane that divides them effectively. SVM uses labelled training data to generate an ideal hyper-plane, which may subsequently be used to categorise new data that is actual classification INFO-GRAPHIC Predicted classification Bully Non-bully Precision Recall Bullying 5510 490 84.25% 91.83% non-bullying 1030 2970 85.84% 74.25%.

SMO: Sequential minimal optimization helped the support vector machine (SVM) with the problem of quadratic programming. It was developed at Microsoft Research in 1988 by John Platt. SMO is used in the training phase of the SVM so as to get rid of the problem. It was quite an important development as in early days it was very expensive to get rid of the quadratic programming problem of SVM using 3-party software. Random Forest: It is also known as -Forests of random decisions, it is a regression and classification strategy based on ensemble learning. In the training phase, it generates a huge number of decision trees, and in the test phase, it determines if the output is for classification or regression. It is better than decision trees as it removes its limitation of getting too precise depending on the training dataset. Its first creation was done by Tin Ham Ho in 1995.

The accuracy of the multi-modal model is almost 85%, which is higher (see Fig 4, Table 5 and 6).

TABLE 5: Comparative Analysis of different classifiers used for text modality

Classifier	P	R	A
NB	79.36%	66.66%	69.6%
RF	77.50%	68.33%	69.1%
SVM	76.62%	66.66%	67.8%
KNN	76.79%	71.66%	70%
SMO	74.75%	74%	69.4%
CNN	**79.94%**	**85%**	**78.2%**

TABLE 6: Classification results for Textual, Visual and Infographic modalities.

Modality	P	R	A
Text	79.94	85	78.2
Image	76.86	79.17	73.2
Info-graphic	84.25	91.83	84.8

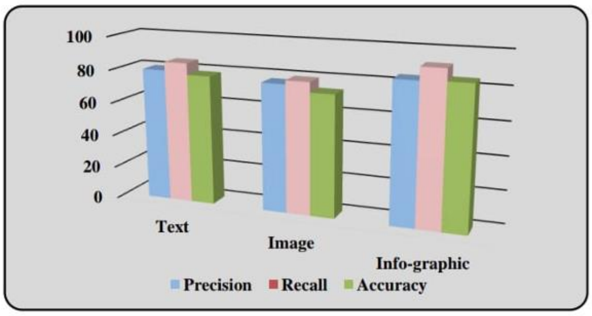

Fig 4. Depicts the results graphically.

V. CONCLUSION AND FUTURE WORKS

Our aim in this work is to detect a comment or post that is posted on social media whether it is a bully or not. The data set involved is crawled from the social media sites that are in trend for example Instagram, Facebook, Youtube. We have gathered the data from all these sites and built our own data set. We had the data instances labeled according to its comment contents as cyberbullied or non-cyberbullied. Then, with the help of descriptive captions of the instance and the user information, we try to build a model to accurately classify the multimodal posts.
We reviewed the non-technical and technical studies dedicated to cyberbullying. Cyberbullying is an epidemic phenomenon and is generating severe harm to people, especially teenagers. The work done in this field and also the background studies that are important for performing the analysis. In this thesis, our target media object consists of multimodal data that contains test, images and photos and their attached test information like caption and user information. Although there is barely any work trying to detect cyberbullying taking into consideration all these features, we have tried to implement such an all-in-one model here that will take care of all these aspects of bullying.
We have gathered the data from different social media sites and performed the process of data acquisition and Feature extraction. After the preprocessing of the data, we have them labeled as bully or non-bully. The proposed CNN-BoVW-SVM model consists of four modules, namely, text analytics module, image analytics module, discretization module and decision module. We further explained every module with the sub-modules involved within those. The explanation consists of techniques such as CNN, BoVW, SVM etc. The chapter also introduces the involved features like color histogram, local binary pattern, big of visual words and so on.

In this paper, we show the implementation of detritus, experimental setup and classification results. Here we have explained the setting of various partners that has been used for performing the experiments. We have defined the proper distribution of the data as in what proportion the modalities are used in our model. Further we have analyzed our model individually for each type of modality and analyzed the results. The results are also compared by using differ classification algorithms like naive bayes, SVM, KNN esc, and served CNN gave the heat resels for sot modality song all the methods and fir listage modality SVM pod to be the het classifier. The bed result stained after selling all the hyper-parts is BLAN for our model. Whereas the accuracy obtained for only test unsdality is 77.2% and the of only image modality is 72.

As stated, we have presented a model for cyberbullying detection that works for both, typo-graphic or info-graphic contents as well as simple text or image in order to capture this expressiveness. The proposed model for cyberbullying detection is unique in a way that it is able to handle various dimensions in the comments like: text, image and text in addition to image to analyze the bullying. Further, we have explored the use of deep learning technique and word embeddings for performing context-aware analysis of text. The performance results of the proposed model are motivating and improve the generic cyberbullying detection task. We have seen that if emoticons are taken into consideration, then it improves the accuracy of the entire model by 2.5 to 3 percent. The model works as a visual listening tool for brand management for enhanced social media monitoring and analytics. The main limitation from which the model suffers is that the text recognition for bullying is defined to only English language. As social media is a non-formal way of having communication, a prominent use of mash-up languages, like, a mix of English and Hindi is widely seen, but such content be it text or text within image could not be processed. Some new visualization techniques could be implemented to visualize the classifications in a better way [11-20].

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