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Multi-Input Deep Learning Algorithm for Cyberbullying Detection

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Abstract: Due to rapid increase in day by day use of social media; online threats to users are growing. Cyberbullying is offensive and intentional act committed by a group or individual is categorized as online threat. It is caused by sending, posting and sharing negative, harmful and fake content online. Today multiple types of data are used to communicate in the social media. Text, image and video are important mediums of cyberbullying. Many cyberbullying detection approaches have been introduced; however, they were largely based on single input model such as text or image. The literature on visual cyberbullying detection and multi input model detection is relatively sparse. This paper presents a deep neural model for cyberbullying detection in three different modalities of social media data, namely textual, image and video. Key frames are extracted from video and checked for bully content. The experiments are conducted to detect cyberbullying in text, images and video. The results of this experiment combine a deep learning model that can simultaneously detect text, image and video cyber threats using both CNN and LSTM.

Keywords — Cyberbullying detection, Hybrid Deep Learning Model, Image based Cyberbullying, Multi-modal cyberbullying, Text based cyberbullying, Video based Cyberbullying detection.

I. INTRODUCTION

Cyberbullying is one of the major societal issues which is rising at an alarming rate which is defined as an individual's intended, deliberate and repeated acts of cruelty to others through harmful posts, messages. It is carried out by a group or individual. 58.11% of world population are using the social media platforms like Telegram, Facebook, WhatsApp, etc. reported higher cyberbullying issues [22][23]. The effects caused by cyberbullying include isolation, mental effects of depression, academic issues, suicidal thoughts, self-harm, and skipping regular activities [25][26]. The occurrence of cyberbullying can vary from multi-mode input sources such as text, images and videos. There has been significant growth in using text, image and video content for cyberbullying. Initially Cyberbullying was unorganized and the usage of medium was text and most of research studies have mainly focused on analyzing of textual content, such as comments, text messages and images. Currently, multi-model data based bully events are increasing. Social networking websites exclusively emphasizes on sharing photo, video and messages. The trends make a shift from text, image to multi-input data to commit cyberbullying behaviors among victims. S. Salawu et al. presented a survey about the different automated detection methods to find cyberbullying and listed few research gaps in cyberbullying detection [28].

The research on multi-input based cyberbullying detection is very limited. The majority of research is to identify bullying in the single source input and looked at the problem from socio-psychological and educational views. Growing online bully events may distress a person both mentally and physically. Prediction and prevention of cyberbullying is most essential here. Most of the communications in the social media are multimodal such as images or videos often accompany text. There is the requirement of an automatic system which has the capability to detect and prevent cyberbullying from the multi-input data source.

Machine learning algorithms efficiently predict and detect undesirable words and images, such as cyberbullying data sources. Machine Learning (ML) techniques are used in the most of the existing studies to detect cyberbullying incidents. Now, deep neural based models have shown substantial development over traditional models in detecting cyberbullying. It uses deep neural network (DNN) to learn features from the multiple input data with multiple stacked layers. The deep learning algorithms able to process multiple data features which proves to be more effective.

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Here a multi-input deep learning technique is proposed which can detect cyberbullying from text, image and video at the same time.

The remainder of this paper is organized as follows. Section 2 presents a detailed review of literature related to cyberbullying detection. The proposed multi-input deep learning technique discussed in the section 3. The experimental results are discussed in Section 4, and the paper is concluded in Section 5.

II. Review of Literature

In the recent years several works were proposed related to cyberbullying detection machine learning and deep learning techniques for multiple input data source. Our research focuses on multiple input data source such as text, image and video based cyberbullying detection because single input either text or image cannot detect the motive of the victim in social media. The detail literature review is presented based on the dataset used, nature and method of detection.

Most of the papers are using mostly available public datasets such as Formspring.Me, ask.fm, twitter, YouTube, Kaggle etc... Author Ç. ACI et al. used multiple datasets with different classifiers like multilayer perceptron (MLP), stochastic gradient descent (SGD), logistic regression and radial basis function have been developed for cyberbullying detection [13]. L. Cheng et al. used Instagram dataset using Bi-directinal GRU-RNN and Random Forest, Linear SVM, Logistic Regression by multi modal cyberbully detection [6][8][11]. Similarly, M. Yao et al. used Instagram datasets and detect cyberbully by develoing CONcISE framework [10]. V. Banerjee et al. identified the cyberbullying text in Twitter dataset using deep neural network techniques [5]. M. A. Al-Ajlan et al. used deep learning algorithm - CNN and twitter dataset for cyberbully detection [15].

N. Tahmasbi et al. used Twitter dataset for detecting cyberbullying in text by considering textual and socio-contextual features in the prediction model [16][4]. A. Bakshi et al. used methods like Random Forest, k-Nearest Neighbor, Sequential Machine Optimization, and Naive Bayes and used YouTube dataset in their research [12]. C. Emmery et al. used Ask.fm and crowdsourced dataset for cyberbullying detection[7]. H. Rosa et al., conducted an in-depth analysis on automatic cyberbullying detection using formspring data [9]. NPDI Pornography-800 and NPDI Pornography-2k dataset to detect abuse content by CNN is used by A. Gangwar et al. [20]. M. Dadvar et al. presented deep learning algorithms to detect cyberbullying [31].

Multi modal and lingual based on cyberbullying detection place a major role in prediction. N. Lu et al. used Chinese weibo dataset, English tweet dataset [2] and proposed a Character-level Convolutional Neural Network with Shortcuts model to classify whether the text in social media contains cyberbullying. M. F. López-Vizcaíno et al. suggested an early detection method of cyberbully detection in social media networks [27]. C. Van Hee et al. [14] presented automatic cyberbullying detection in social media by modelling posts written by bullies, victims, and bystanders of online bullying in English and Dutch dataset. K. Wang et al. presented a multi-modal approach in research work for detecting cyberbullying event[30]. Gaming platforms are also another major source of cyberbullying. M. Garaigordobil et al and S. Murnion used various gaming platform data to detect cyberbullying by Machine Learning and Semantic Analysis [17][18].

Machine learning and deep learning models are proposed in cyberbully detection. Talpur BA[1]. V. Balakrishnan et al.[3]. A. Bakshi et al., [12], S. Murnion et al. [17] applied machine learning techniques to detect the cyberbullying. A. J. Sánchez-Medina et al. used machine learning methods to explore cyberbullying incidents [29]. H. Rosa et al., implemented a simple CNN, a hybrid CNN-LSTM and a mixed CNN-LSTM-DNN [9][19] and trained via the word2vec model with Google-News, Twitter and Formspring data set. Similarly, the use of CNN and NSFW data set is used by Q. H. Nguyen et al. for detection of pornographic content [21]. Vijayakumar V and Hari Prasad D discussed a deep learning based LSTM algorithm to detect and prevent the cyberbullying incident with chatbot [24].

The existing system uses machine learning and deep learning techniques for the detection of cyberbullying on different publicly available data source. But these approaches limit the correctness of the detection on multiple data source and work effectively on single classified features of cyberbullying. To overcome this problem, the proposed paper uses hybrid neural networks and deep learning for processing multiple input data sources which gives better results. The hybrid model supports to work with a large amount of multi-model data easier. The system uses CNN and LSTM neural network models for efficient and perfect results.

III. Proposed Multi-Input Hybrid Deep Model of Cyberbullying Detection

The proposed model describes the cyberbullying detection framework which consists of two major parts. The first part is called multi-input data collection and the second part is named as Hybrid deep learning based detection.

In the first phase, datasets containing bullying texts, images, and videos are collected and prepared for the deep learning algorithms. The processed datasets are then used to train the learning algorithms for detecting any bullying message. The Hybrid deep learning algorithm is developed for multimodal

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based cyberbullying detection and is shown the Fig.1. Here data is selected from benchmark datasets and preprocessed. Keras Functional API is used to build the multi input deep neural network model. The model is tested with a real time input data and predictions are diagnosed.

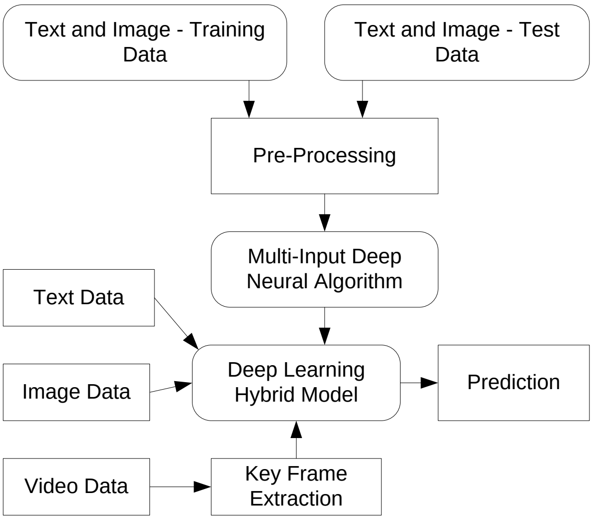

Figure 1: Proposed Hybrid Deep learning based Multi-Input Model Prediction

The detection method is discussed in the following steps:

A. Data Collection and preparation

The image dataset collected from the GitHub repository named NSFW scrapped "nsfw_data_scraper" which contains URLs of the image scrapped from different source of internet. Text is extracted from Kaggle Toxic Comment Classification Challenge dataset. This dataset is created from comments of Wikipedia talk pages by Conversation AI team, a research initiative founded by Jigsaw and Google.

B. Preprocessing

The data is preprocessed to avoid possibility of wrongly labeled data. The text messages are converted as tokens. Then, it constructs a sequence. The image data is converted into 90 X 90 size. Every image has same length and width. An image is represented by 0 – 255 values in the array. It makes smaller images by dividing it by 255 which results floating values. The entire video is separated into frame by frame. The key frames are extracted from the video using color histogram algorithms. The mean absolute difference and standard deviation of absolute difference are calculated. The threshold is calculated using the following formula.

$$TH = (2 * SD) + M$$

where, TH is threshold, SD is standard Deviation and M is mean absolute difference. The frame differences are compared with threshold. If the difference is greater than threshold, that frame is selected as key frame. This operation is continued till last frame. These Key frames are given input as images to the model.

C. Build & Train the hybrid deep learning model

The proposed hybrid deep learning model processes multi-modal (text, image and video) data inputs to detect cyberbullying in the data. A hybrid algorithm is developed with Convolutional Neural Network (CNN) for images and video key frames and Long short - term Memory (LSTM) for text. These models are combined together using Keras Functional API. Convolutional Neural Network (CNN) is used to image based analysis which contains multiple layers of perceptrons. Each neuron in one layer is connected with all neurons in the next layer. This network always does the mathematical operation convolution. The architecture consists an input layer, an output layer and in between there will be multiple hidden layers. After convolution operation, an RELU activation function is applied.

LSTM networks are similar to RNNs with one major difference that hidden layer updates are replaced by memory cells. It consists of cells, information flow, and gates. LSTM prediction model achieved through four gates such as forget gate, learn gate, remember gate and use gate. The forget gate recalls the necessary parts from the previous states based on the current event and forgets unnecessary portions. The learn gate learns from the current input and the recent events. The remember gate takes the input from the forget gate to get and learn the gate and remembers everything required for future reference of the model. The use gate maps the output from the forget gate and learns gate, considers all the factors, and provides the prediction of the current input. LSTM is used to avoid over fitting, dropping probability. The last layer is fully connected.

CNN and LSTM layers are concatenated by using Keras functional API. The Rectified Linear Unit (ReLU), and sigmoid activation functions are used in models. The function returns 0 if it receives any negative input, but for any positive value x, it returns that value back. So, it can be written as f(x)=max (0, x). Sigmoid activation function squishing values between 0 and 1. 0 means value will be disappearing and 1 remains same.

The Keras functional API is used to build the hybrid model. The system can pull any layer from anywhere. This property is used to build multi-input and multi-output models. The functionality is used to combine LSTM and CNN models.

D. Train a deep neural network model

The entire data of image and text is divided into 80:20 ratios for training and testing process. Manually verify for any repeated data in the contents.

E. Deployment and Test

The deep neural network is trained and deployed into flask server. The cyberbullying events are detected with real time sample data given.

The deployment is done using python flask which is used for web development. The deep learning model is loaded in the server. To test, the system takes inputs as text, image and video. The text taken through text processing area. Image data is extracted through image tag. The video is loaded in the text area and is showed by video tag. The

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video path is stored in the server.

Server loads the video by OpenCV. The key frames are extracted using color histogram method. If 50% or more key frames are detected on cyberbullying, then the video is considered positive for cyberbully otherwise negative. The data is sent to server from the client and cyberbullying is predicted. The results are sent back to client. The results are displayed to client as labels.

IV. EXPERIMENTAL RESULTS & DISCUSSION

The proposed hybrid model is implemented and tested in Intel i5 processor with 8 GB RAM at least speed of 1MbPS Internet. The system has in-build GPU Intel UHD Graphics installed Windows 10 Operating system installed and configured. OpenCV and Python libraries such as, Numpy and Tensorflow, Keras are used for the model development.

The model is trained with 4,590,756 parameters with separate input and output for image and text. For the text, the inputs are sent through LSTM layers and images are sent through CNN layers. Dense layers are added on both sides. The layers are concatenated. And the results are separated from the concatenated layer and two outputs are generated based on the image classes and text classes. The multi-input hybrid predictive model summary is shown in Fig. 2. For image, randomly choose 12,200 images from the dataset and trained.

```
Model: "model_1"
____________________________________________________________________________________________
Layer (type)                    Output Shape          Param #     Connected to
============================================================================================
text_inp (InputLayer)           [(None, 200)]         0
____________________________________________________________________________________________
embedding_1 (Embedding)         (None, 200, 128)      2560000     text_inp[0][0]
____________________________________________________________________________________________
img_inp (InputLayer)            [(None, 90, 90, 3)]   0
____________________________________________________________________________________________
lstm_layer (LSTM)               (None, 200, 60)       45360       embedding_1[0][0]
____________________________________________________________________________________________
conv2d_2 (Conv2D)               (None, 88, 88, 32)    896         img_inp[0][0]
____________________________________________________________________________________________
bidirectional_1 (Bidirectional) (None, 200, 120)      58080       lstm_layer[0][0]
____________________________________________________________________________________________
max_pooling2d_2 (MaxPooling2D)  (None, 44, 44, 32)    0           conv2d_2[0][0]
____________________________________________________________________________________________
global_max_pooling1d_1 (GlobalM (None, 120)           0           bidirectional_1[0][0]
____________________________________________________________________________________________
conv2d_3 (Conv2D)               (None, 42, 42, 16)    4624        max_pooling2d_2[0][0]
____________________________________________________________________________________________
dropout_4 (Dropout)             (None, 120)           0           global_max_pooling1d_1[0][0]
____________________________________________________________________________________________
max_pooling2d_3 (MaxPooling2D)  (None, 21, 21, 16)    0           conv2d_3[0][0]
____________________________________________________________________________________________
dense_7 (Dense)                 (None, 128)           15488       dropout_4[0][0]
____________________________________________________________________________________________
flatten_1 (Flatten)             (None, 7056)          0           max_pooling2d_3[0][0]
____________________________________________________________________________________________
dropout_5 (Dropout)             (None, 128)           0           dense_7[0][0]
____________________________________________________________________________________________
dense_5 (Dense)                 (None, 256)           1806592     flatten_1[0][0]
____________________________________________________________________________________________
dense_8 (Dense)                 (None, 256)           33024       dropout_5[0][0]
____________________________________________________________________________________________
dense_6 (Dense)                 (None, 84)            21588       dense_5[0][0]
____________________________________________________________________________________________
dropout_6 (Dropout)             (None, 256)           0           dense_8[0][0]
____________________________________________________________________________________________
concatenate_1 (Concatenate)     (None, 340)           0           dense_6[0][0]
                                                                  dropout_6[0][0]
____________________________________________________________________________________________
dense_9 (Dense)                 (None, 128)           43648       concatenate_1[0][0]
____________________________________________________________________________________________
dropout_7 (Dropout)             (None, 128)           0           dense_9[0][0]
____________________________________________________________________________________________
img_out (Dense)                 (None, 2)             682         concatenate_1[0][0]
____________________________________________________________________________________________
text_out (Dense)                (None, 6)             774         dropout_7[0][0]
============================================================================================
Total params: 4,590,756
Trainable params: 4,590,756
Non-trainable params: 0
```

Figure 2: Multi Input Deep Learning Model

The performances of the proposed project are measured in terms of the quality measures, namely precision, F1 score and Recall. Precision is the ratio between the true positive (correct predictions) and the total predictions. Recall is the ratio of the correct predictions and the total number of correct items in the set. F1 score is the weighted harmonic mean of precision and recall. Accuracy calculates the proportion of correctly identified cyberbully words.

```
Accuracy: 0.85

Classification Report - Text

              precision    recall  f1-score   support

         tox       0.95      0.91      0.93      1968
     non_tox       0.75      0.61      0.67       472

   micro avg       0.91      0.85      0.88      2440
   macro avg       0.85      0.76      0.80      2440
weighted avg       0.91      0.85      0.88      2440
 samples avg       0.85      0.85      0.85      2440
```

Figure 3: Accuracy and Classification Report – Text

Model attains 85% accuracy on the text data. The hybrid model attains higher precision on toxic data because the model has more confident on text consist of toxic comments. Lower recall because of the model's threshold is set so high, there will be fewer comments classified as toxic in testing. The quality measures such as precision, recall and accuracy of text and image are shown in Fig. 3. and Fig. 4.

```
Accuracy: 0.86

Classification Report - Image

              precision    recall  f1-score   support

   good_new1       0.84      0.88      0.86      1245
    bad_new1       0.87      0.83      0.85      1195

    accuracy                           0.86      2440
   macro avg       0.86      0.85      0.86      2440
weighted avg       0.86      0.86      0.86      2440
```

Figure 4: Accuracy and Classification Report – Image

Model attains 86% accuracy on the image data. In the prediction of SFW images, the Hybrid predictive Model predicts maximum number of SFW (good_new1) images having the non-toxic image content results higher recall. And also, Lower precision because maximum number of SFW images predicted having non-toxic content some of them won't actually have non-toxic content. In the prediction of NSFW images, the model attains higher precision because of the model has more confident that the image has toxic content. Lower recall because model threshold is set so high, there will be fewer images classified as having toxic.

	Text	Image	Video
Input Combinations	Non-Toxic	Non-Toxic	Non-Toxic
	Non-Toxic	Non-Toxic	Toxic
	Non-Toxic	Toxic	Non-Toxic
	Non-Toxic	Toxic	Toxic
	Toxic	Non-Toxic	Non-Toxic
	Toxic	Non-Toxic	Toxic
	Toxic	Toxic	Non-Toxic
	Toxic	Toxic	Toxic

Table 1: Possible Cyberbully events as input in multi modal

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The model detects cyberbullying events from the data in the form of text, image and video with hybrid deep learning model. Cyberbullying event is detected for inputted data from text, image and video. We have three types of inputs, so $2^3 = 8$ combination inputs of text, image and video can be detected which are listed in Table 1. and predictive results are presented in Appendix.

The predictive results of Non-Toxic Text, Non-Toxic Image and Non-Toxic Video is shown in the Figure 5. Figure 6 presents Non-Toxic Text, Non-Toxic Image and Toxic Video data based prediction. The results of Non-Toxic Text, Toxic Image and Non-Toxic Video prediction presented Figure 7. Figure 8 shows Non-Toxic Text, Toxic Image and Toxic Video based prediction.

Figure 9 shows Toxic Text, Non-Toxic Image and Non-Toxic Video based cyberbullying prediction. The predictive results of Toxic Text, Non-Toxic Image and Toxic Video are shown in Fig.10. Figure 11 presents the Toxic Text, Toxic Image and Non-Toxic Video based cyberbullying prediction. Figure 12 shows Toxic Text, Toxic Image and Toxic Video based cyberbullying prediction.

V. CONCLUSION AND FUTURE WORK

Due to increase of internet and social media application usage with text, image and video, cyberbullying events are growing. Cyberbullying needs to be early detected and prevented before it creates harm to users. The proposed system represents a effective method to detect cyberbullying in text, image and video mediums. A hybrid deep neural network model was developed which can detect cyberbullying in multimodal data. The benchmark data extracted from GitHub and Kaggle repository. This model process input text, image and video separately and predict consecutive outputs. The proposed hybrid deep learning model built with a combination of Convolutional Neural Network (CNN) for image based prediction and Long Short-term Memory (LSTM) for text based prediction. Kears functional API was used to concatenate the model. This model predicts results more accurately compared to machine learning models. The image attains 86% accuracy and text attains 85% accuracy after training the multi-input model. The developed enhanced multi-input hybrid model predictive system can detect and prevent cyberbully events in online social media platforms more effectively.

In future, memes and audio can be integrated cyberbullying detection. Emotion detection in videos, change of tone in sound can be considered in video based cyberbully detection. Live cyberbully detection in visual level and multi-language, cross language and mix language option in textual level can be integrated.

APPENDIX - SAMPLE OUTPUT SCREENS

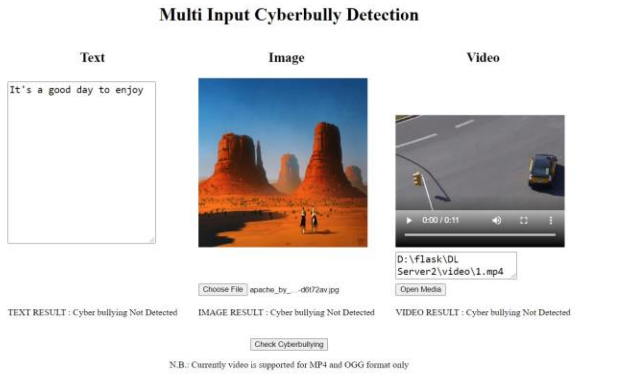

Figure 5: Non-Toxic Text, Non-Toxic Image and Non-Toxic Video

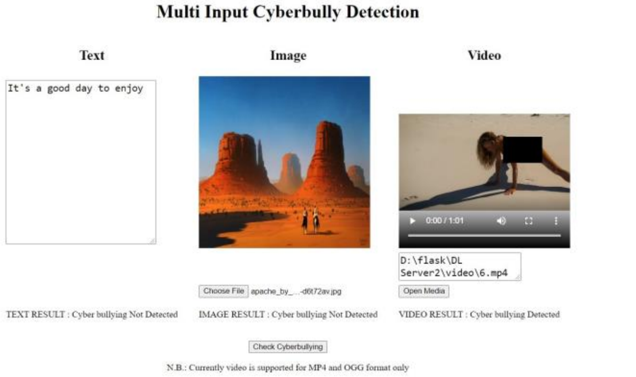

Figure 6: Non-Toxic Text, Non-Toxic Image and Toxic Video

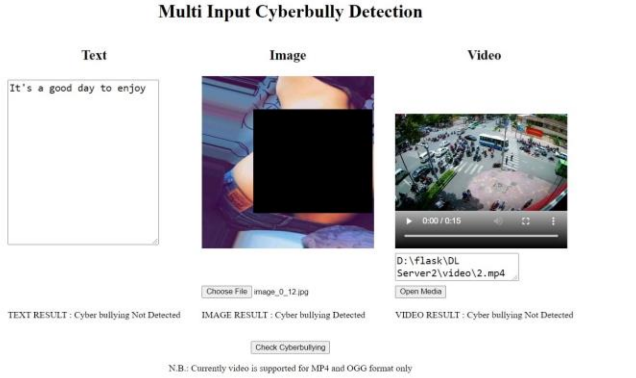

Figure 7: Non-Toxic Text, Toxic Image and Non-Toxic Video

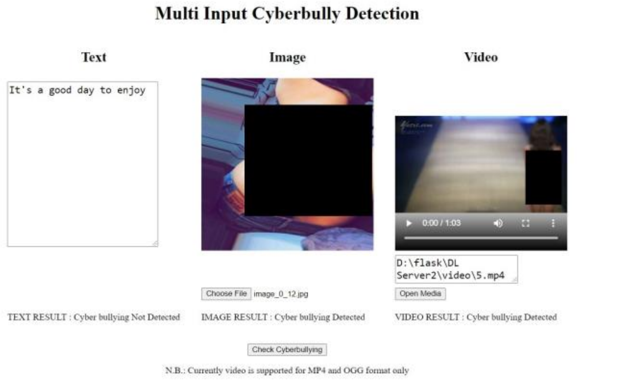

Figure 8: Non-Toxic Text, Toxic Image and Toxic Video

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Figure 9: Toxic Text, Non-Toxic Image and Non-Toxic Video

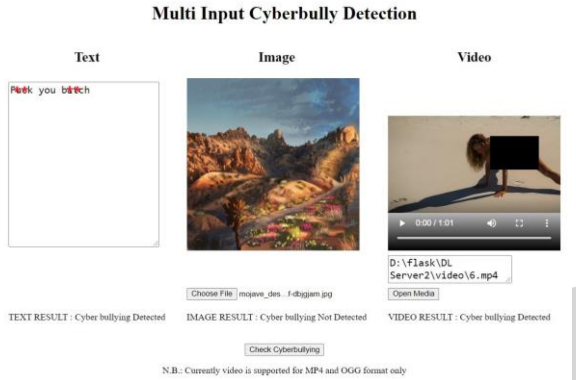

Figure 10: Toxic Text, Non-Toxic Image and Toxic Video

Figure 11: Toxic Text, Toxic Image and Non-Toxic Video

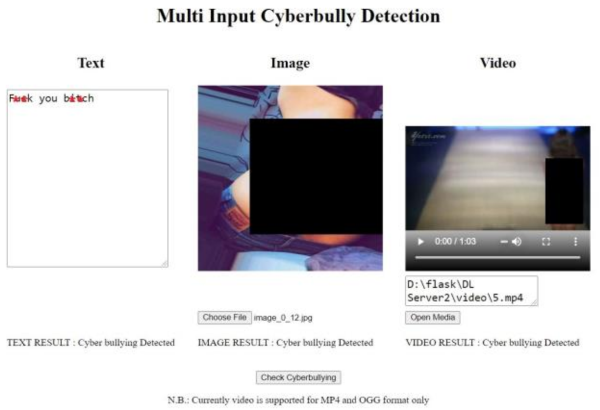

Figure 12: Toxic Text, Toxic Image and Toxic Video

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