BULLY IDENTIFICATION WITH MACHINE LEARNING ALGORITHMS

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Abstract

The purpose of this paper is to identify the bullies via informed surveys, using data from students of colleges and schools and take the results to concerned authority or guardian and list out ways to eradicate it. This paper adopts data mining techniques of the concerned survey results and convert into knowledge. Following a five step process of Data Selection, Pre- Processing/Cleaning, Transformation, Data Mining and Inter- pretation/Evaluation. Along with this the paper utilizes three unique approaches, Internal Labelling, Synthetic Labelling and Data Programming. To identify these data patterns effectively, incorporation of data validation and classification using suitable Machine Learning algorithms is utilized.

Key words: Learning Algorithms, Bully Identification, Teacher's Role.

INTRODUCTION

Evil is not born, but created is analogous to a modern life evil which transpires from school to college and even at a workplace known as bullying. Bullying in simple terms is a forceful action done to physically or mentally hurt someone over a repeated period of time. It has been the cause of several forms of crime, abuse for the bullies and depression, anxiety for the victim. To vanquish a problem we need to cut down the roots, similarly, the final goal is to eradicate bullying, but to accomplish that, one needs to identify the root, the bullies. Bullying at school has been in news for its negative impact on students. It has been negatively affecting students on the play area, in the classroom, and online while using Internet. Students guardian at school are teachers, so it is their responsibility to protect them in a school setting, bullying has a direct relation with the teacher's role.

Bullying at school is a widespread issue. According to the The National Institute of Child Health and Human Development conducted survey of a sample size of over 15,000 students from grades 6 to 10 in private and public schools[1]. The survey revealed that - one student out of five- 1.7 million out of 6 million - admitted that they bullied their classmates. Over 10 percent admitted to bullying classmates "several times" and 9 percent "once a week"[1]. The trend showcased bullying being the most frequent in grade 6, 7 and 8. It was similar with rural, suburban and urban schools.

According to the study reports, bullies are accustomed to aggression. They believe that fighting makes them popular, it is an effective way to tackle a situation and victims deserve their doing. The general belief of bullies considering themselves as low self-concept, has not been supported by the studies.

On the other hand, bullies with a negative approach towards others are most likely to indulge in disciplinary violations than others. These findings support the need for a school counselor to identify bullies to protect them from victimization and to assist aggressive students in an appropriate interaction with their classmates.

Bullying is tough to identify as it is often clandestine, which serves as a challenge for counselors and teachers to assist the victims and prevent it from taking place. It occurs on school buses, playrooms, in the washroom, and so on. Ultimately at all those places, which lacks supervision from the staff. The victims hesitate to report bullying to authority as they fear they will be unheard or no effective action will be implied.

In recent times, bullying has taken another dimension, in the form of "cyberbullying", owing to the Internet revolution. The term cyber-bullying gain its momentum nowadays. The age of globalization, defined as the age of electronics, brings a huge advancement of the use of social media, can be used in a positive way, but recently some negative impact also appears. Some of the academia discuss the high potential of using social media as a means of bullying. They found also that the advancement of technology can be used to make a threat against other children or peers. Cyber-bullying becomes a serious problem inflicting psychological, social harm to many victims.

In simple terms, the usage of technology to bully someone is Cyber-Bullying. It is gaining momentum since the past few years as social networking sites are being more prominent and serving as a platform for the teenagers to be bullies in order to harm someone.

Since the arrival of technology being human's first approach for communication and the ubiquitous spreading of it through social networking sites, young adults have embraced several devices and online platforms. The research reports on yearly online experience of children across Europe turned out to be 94 percent for ages 6 to 17 from years 2007 to 2010 for using internet and six percent aged 8 to 11 use social media[2].

Social networking is one of the best way to be in touch with your friends and family. On the contrary, with social networking spreading its wings along with it newer illegal and unethical ways are finding its way in these platforms. We witness that people, especially teenagers and adults in their low 20's, are finding new ways to bully each other online. Symantec conducted a study and revealed that approximately 25 percent of parents reported that his/her child had been linked to a cyber incident[3].

Cyberbullying is accustomed to traditional bullying in several ways. Apart from the physical violence and aggression, all the fundamentals match up. Such as, misuse of power, intent to harm and repetition of action. Behaviors also include: threats via texts, email or posts; exclusion from close group/community; impersonation; spreading private information (photos or texts); posting of embarrassing videos/photos; stalking; and harassment in social platforms. Studies have shown that whatever one does in the adolescent age gets hard- wired in the brain and stays with him/her in future. If stopped at the early stage, it can be prevented from getting hardwired. Implementation of counseling and specific

"bully intervention programs" should be a part of the school's curriculum. Gender also is of utmost importance as male students are more likely to indulge in violent behavior resulting into direct bullying, where else females employ indirect forms.

The goal is to identify bullies by employing survey as the method. A self-report questionnaire shall be developed using scales to assess physical, verbal, social and cyber-bullying. It shall ask the user for their age and their place of study. Based on their responses to the above questions, the users shall be asked to answer scenario-based questions, based on the situations that they come across in their daily lives.

The questionnaire shall have around 10 scenario-based questions, covering all aspects of possible bullying, such as physical bullying, verbal bullying, social bullying and cyber-bullying. The user shall submit their responses, and the algorithm shall grade their responses and provide a result as to whether the user is likely to be a bully in the future, or if they are a victim of past bullying.

EXISTING SYSTEM
A.   The School Climate Survey
This survey is a based self-report questionnaire which uses scales and items from previous tools in order to evaluate three forms of bullying, verbal, physical and social [4]. Items used were identical to the the verbal, physical and social manipulation scales of Multidimensional Peer-Victimization Scale [5]. Six items utilised to measure the type of bullying and its frequency are: Physical Bullying: 1. "I hit or kicked someone on purpose" 2. "I caught someone or shook on purpose" Verbal Bullying: 1. "I threatned to hurt someone or take their things" 2. "I teased or called someone by names" Social Bullying: 1. "I told someone not to be their friend" 2. "I did not let anyone join what I was doing" The corelation between the pair of items from this above sample was R = 0.61 for Physical, R= 0.36 for Verbal and R= 0.31 for Social Bullying. The results excluded were: 1. Demographic items left blank or marked with an inappropriate value (gender, age) 2. Validity item not checked as "Agree" or marked as "Disagree/ Strongly disagree" The survey was conducted after a month since the school started with the consent from students. Students were asked to give anonymous responses, but seal it in an envelope with their names printed on the outside. A code was assigned to each student in order to compare the self report with the peer enrollment database.

Students were given a standard definition of bullying taken from the Olivus Bully/Victim Questionnaire: If he/she kills, catches, shouts, or hurts, on purpose is known as bullying. Also if a threat is made or even if a student tries to stop one from being a friend or stop sharing what they are doing. However, it is not bullying if two individual have clash of thoughts when they are in the same power.

Based on this definition, students were asked about the number of times they had bullied in the past month, "I have bullied others". The response categories were: a. Never b. Once per week c. Several times per week Students who chose (b) or (c) were classified as self-informed bullies.

B.   Detection of Cyber-Bullying on Social Media using Data Mining/Machine Learning
This is a more computer oriented approach. It is a multi- stage process. First stage is collecting Log Data from Twitter, and then do pre-processing or data cleaning to make sure that the acquired data is structured. Next, the TF-IDF is done for weighting and validating the data[6]. Lastly the machine learning classification is done using Naïve Bayes Classifier.
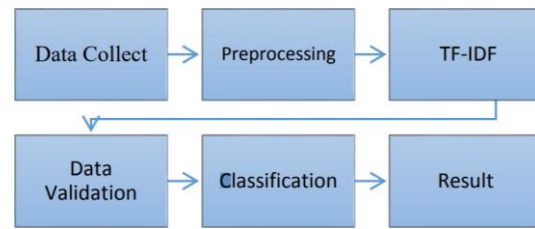

Fig. 1: Research Flow [6]

1.   Log Data Collection: Data collection is done from the twitter database. First, a developer twitter account is created, and registration is done to get the access tokens for the API, create a script and input access tokens that have been ob- tained beforehand, do the search data with Boolean searching technique that is use the operators "AND", "OR", "NOT" depending on the needs of the data. Lastly the data will be collected in a JSON file format[6].
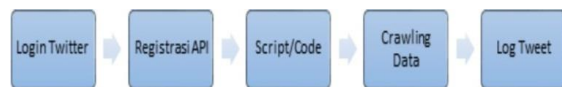

Fig. 2: Twitter Data Flow [6]

2.   Pre-processing: On the data that has been collected, change the JSOSN file format to CSV file and next do pre- processing or data cleaning. Pre-processing is done in two stages, first is manually, and secondly, using machine learning WEKA[6]. Manual processing involves steps such as remove duplicate ID, remove special characters or URL, RT, hash- tag, picture, tokenization. Make a dictionary of slang words, stemming, and change the CSV file into the ARFF[6]. 3. Classification: The classification stage done by using Maching Learning (WEKA) can be seen below:
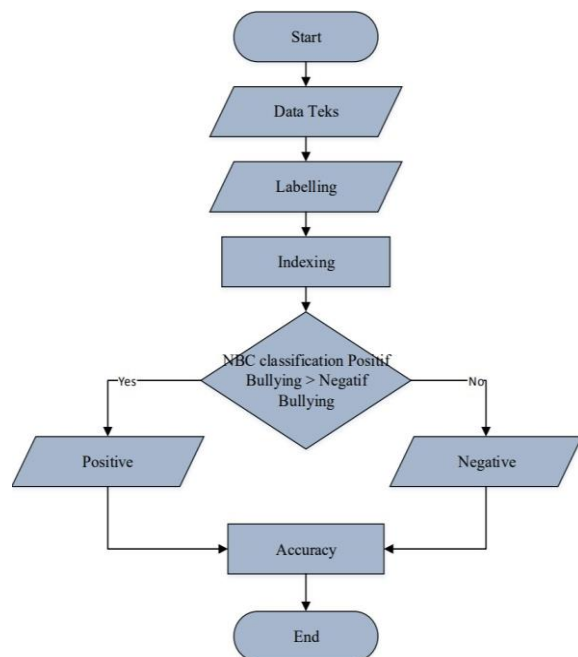

Fig. 3: Classification Flow Diagram [6]

Data text used is the clean data that has gone through pre-processing, labelled training data do manually, change file CSV into ARFF, then do TF-IDF weighting and validation data using 10 fold cross validation and then do classification using Naïve Bayes on WEKA, to the positive content of bulling on Group on class result bulling, and the negative content to group on class result negative[6]. So for this type content of cyber- bullying, such as cyberbullying which related to psychology will be in going on a group class related psychology and so on.

METHODS

A. Survey

The main method for data collection is a survey. A survey is basically a research method used for collecting data from a set of group of users to gain insights on a particular topic of interest. With the data being collected from survey, it can utilise various methods of instrumentation [8]. Survey gives an option to delve in to either quantitative research strategies (numerically enabled questions) or qualitative research strategies (open-ended questions).

Survey gives us the flexibility to choose a platform suitable according to how the end user can be reached. It can be conducted in 4 ways[9]:

1. Face-to-Face surveys 2. Telephone surveys 3. Self-administered Offline (pen and paper surveys) 4. Self-administered Online (computer surveys) Surveys provides sev- eral benefits such as:

2. Cost: Online surveys performed on computers or cell phones are relatively cheaper to conduct, compared to the offline surveys. As the number of responses online, can be in thousands. 2. Extensive: Survey have the ability to use a sample data and characterise it with a larger population. It helps to draw conclusion and derive vital decisions. 3. Flexible: It can incorporate mixed methods, online for some people and conduct offline for another set of people, according to their accessibility. 4. Dependable: A survey can be attributed as completely anonymous, with a confidentiality agreement. Having this tool, people tend to more honest and straight forward.

Data Collection Methods fall broadly into two main categories Questionnaires and Interviews.

Questionnaires: It can be in paper form or can be delivered via online tools. The user can get an option to choose from either. The questionnaires can provide visual aid along with sound, which can make the user experience even rich. With various options of font size, ordering items logically and clearly, without any form of bias, the response rate can be increased.

Interviews: They can be conducted face-to-face, on phone or on computer. It provides the interviewer the ability to comprehend the actual state of mind of the interviewee, deriving relatively accurate conclusions. If the interviewee is stuck or is unable to comprehend the question, there is an option for clarity. On the other hand, there can be touch of bias in response due to subsequent questioning and can be costly and time elapsing method.

We have employed questionnaires as our prime method of surveying as it is cost and time effective. Using online survey method for the questionnaires has helped us aim at a wide range of users and secure large amount of data.

We are trying to keep our focus on various aspects of bullying as mentioned earlier in the paper. The main focus will be on physical as well as cyber bullying. We have framed questions which focus on both of these and help us identify the bully.

Breaking the survey structure to its nuances we have focused on these set of questions:

1) Page 1: General Identification 2)Page 2: Rating Scale Questions 3)Page 3: Multiple Choice Questions 4)Page 4: Open Ended Questions

The reason behind each Page selection is in order to mitigate the disadvantages of Surveying. As survey can be tricked to be bias according to the questions asked. But, using a form of Rating Scale questions/Multiple Choice Questions, which are short and concise and can aim the basic gist needed without any further explanation. Particularly, Multiple choice questions provide multiple choices for the user and can choose a most likeable situation from the options provided. The Rating Scale Questions are similar to the rating from a scale to 0-10, which

can help statistically measure. Page 4, are Open Ended Questions, where the user describe what he/she might do in a situation, which provides qualitative and nuances which are mitigated in the quantitative questions.

Fig. 4: Page 1 (Survey)

Furthermore, we have not made each and every question mandatory to answer, we have given the user the liberty to skip a question if he/she does not feel like answering. This way, we are not forcing a user to any any question in order to reduce data biasing.

General Identification: This covers general information of the user such as 'Age', 'Gender' and 'Where do you study?'. We have specifically not asked Name or any personal details so the user does not feel cautious while answering and can answer the survey honestly. We are specifically targeting the age group 11-22. This covers middle/high school as well as college students.

Rating Scale Questions: These questions are all based on a scale from 0-10. The rationale behind these questions is to understand the mindset of the user. It covers 4 specific sections:

1) **'How would you rate the following behavior?'** : This includes 5 types of behaviors which are associated with both forms of bullying, physical and cyber-bullying. The user will provide his/her perspective regarding the behaviors, indicating the mindset of the user. Here a scale of 0 indicates *Strongly Disapprove* and scale of 10 indicates *Strongly Approve*. These behaviors are:

- Physical
- Verbal
- Cyber
- Racial
- Social

2) **'How would rate the following places based on your comfort level?':** This includes 8 most common places our targeted user would mostly access. Understanding if one does not feel safe at a particular place can be led to the deduction of him/her being a victim and on the contrary feeling comfortable indicates a superiority, a trait attributed towards a bully. Here the scale of 0 indicates *Very Uncomfortable* and scale of 10 indicates *Very Comfortable*. These 8 places are:

- Classroom

Fig. 5: Page 2.1 (Survey) Rating Scale Questions

- Restroom
- Hallway
- School/College Bus
- Gym/Sports-room
- Social Media
- Home
- Neighborhood

3) **'How would you rate your comfort level with the following people?':** This covers the relation of the user with others. It indicates the comfort level deducting if one feels safe or not with that particular person.

Fig. 6: Page 2.2 (Survey) Rating Scale Questions

A very high comfort level can indicate no tension, hence no signs of bullying, however a low comfort level can be an indication of a potential bully scenario. Here the scale 0

indicates *Very Uncomfortable* and scale 10 indicates *Very Comfortable*. The people mentioned in the question are:

- Best Friends
- Friends(Male)
- Friends(Female)
- Teachers
- Parents
- Relatives
- Neighbors

4) **'How confident are you about the following aspects of your appearance?':** This is a introspect question, which covers evaluating the physical appearance of oneself and judging if the user is confident of him/herself. As discomfort can lead to potential victim as physical complexities are the most common bully causing issues. Here the scale 0 indicates *Very Diffident* and scale 10 indicates *Very Confident*. The 3 aspects are:

- Weight
- Height
- Skin Color

Multiple Choice Questions: These questions carry 4 options which cover all possible scenarios, with a distinct differentiating range. These are all first-hand questions, whose answer only the user can provide. It covers various situations one has experienced throughout his life which are connected to the traits of a possible bully. These situations might not be applicable for all users, hence the options are made distinct. Answers of these questions, will provide a glimpse of the lifestyle of the user.

Fig. 7: Page 2.3 (Survey) Rating Scale Questions

The list of questions are:

- Have you ever carried a weapon to school?
- Have you ever hit or pushed someone?
- Have you ever insulted or threatened someone online?
- Have you ever played a prank which upset someone?
- How often do you miss school because you feel unsafe or uncomfortable
- How often do you miss school for no good reason?
- How often do you indulge in these activities?
- How often do you try to obtain money/possessions, other than the ones provided by your parent/guardian?
- How often have you had your property stolen, or deliberately damaged?
- How often have you stolen or deliberately damaged

someone's property?

- How often are you involved in a physical fight?
- How often do you experience depression?
- How often do you experience suicidal thoughts?

The options have been created keeping in mind all types of users. The options are:

- Never
- Sometimes (1 or 2 times a month)
- Regularly(1 or 2 times a week)
- Every day

Open Ended Questions: The reason behind these questions, was to get a deeper understanding of the user, giving him/her a platform to elaborate his feelings in a situation. Though, these questions do not have a direct connection with the algorithm used, they do provide a support to the final output of the algorithm. Tallying the result with these answers can be a good way to evaluate the algorithm. There are particularly two types of questions in here, first, they have specific options as well as an extra option to elaborate and second, they are solely situation based questions, where the user needs to pin down his/her thoughts. An example of first type of questions: *Q) Your friends start calling you names, sending you nasty text messages and forcing you to give them things. You don't feel good when these things happen. What should you do?*

- Nothing. You must have done something wrong to make your friends act like that.
- Start calling them names in return and threaten them.
- Speak to your parents or teacher and tell them what is happening.
- Other:

An example of second type of questions: *Q)You're invited to a party but your friend is not. At the party, some of the kids make jokes about your friend and laugh at him. What would you do?*

B. Algorithmic Process

We are going to employ the basic Data Mining Algorithm as our base method to analyze data and convert it into meaningful information[6]. We will be following the five process method as follows:

- **Data Collection:** Our prime source of data collection is from the Online Survey. We have secured a collection of over 3500 Survey answers. The results are obtained via google forms stored in excel file, converted in '.csv' file.

- **Data Cleaning:** As we have given an option to leave questions unanswered, so our data-set will need cleaning. This process consists of eradicating duplicate data, an examination of inconsistent data and correct data errors, for example missing or null values. We accumulated exactly 3756 user entries, but out of those many contained missing values. After cleaning the data, we reduced it to a round figure of 3000 entries for simplicity. The processing and storing of this data was in '.csv' file.

- **Data Labeling:** According to each and every feature we have included in the survey, we labeled the data according to it in '.csv' using a python-script. We employed 'Binary Classification' (0-1), with two prominent labels 'Possible Bully' and 'Not a Bully'. As per our survey questions and features mentioned above, we divided the data-set into 4 groups.

The first group consisted of the 5 major behaviors mentioned in 'How would you rate the following behavior?'. We took the average of all 5 factors and here we utilised a scale of [14]:

$$<= 0.4: NotaBully; > 0.4 : Bully$$

The following three groups employed the same scale, with the average of each group factors independently. The three groups factors were the ones mentioned in the questions above with 8, 7, 3 factors respectively, 'How would you rate the following

places based on your comfort level?', 'How would you rate your comfort level with the following people?' and 'How confident are you about the following aspects of your appearance?'. The scale utilised is[14]:

$$<= 0.7: PossibleVictim; > 0.7: NotaVictim$$

- **Data Mining:** The process of looking for patterns or interesting information in the selected data with the use of a particular technique or method is known as Data Mining. We narrowed down on essential features from the data-set that led to an output decision of BULLY/NOT A BULLY. Here we scrapped out the usage of Open- Ended questions as it being a qualitative measure did not serve a place in our algorithm. Under the guidance of a psychologist, we assessed the data-set and finalised the ranges of measurement for our predictive algorithm. With the output decision of BULLY/NOT BULLY, we got 2 Outputs based on 1st group and a combination of 2nd, 3rd, 4th group. The second output consisted of an average of those three groups, as they had the same scale used with the same parameter.

$$Output\ 1: Average of Group 1$$

$$Output\ 2: Averages of Groups 2, 3, 4$$

We now had a cross combination of 4 possible outcomes, from which we divided it into 2 possible cases with an equal chance for both, Bully/Not a Bully. The outcomes were as follows:

$$PossibleBully + PossibleVictim = Bully$$
$$PossibleBully + NotaVictim = Bully\ NotaBully +$$
$$PossibleVictim = NotaBully\ NotaBully + NotaVictim =$$
$$NotaBully$$

- **Interpretation/Evaluation:** Data Mining generates information and patterns which can only be useful if displayed in a way which can be easily understood. Here we analyzed the outcomes and the statistical figures of our data-set after the labelling and mining. Out of the 3000 entries, we secured 2730 as 'Not a Bully', which is 91 percentage of the data-set. On the other hand, 270 were 'Bully', a mere 9 percentage of the data-set. Keeping this in mind, we have employed SMOTE process, explained in detail below as part of our Data Augmentation[10].
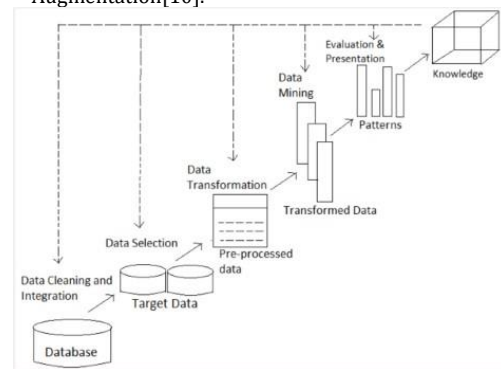
Fig. 8: Data Mining Flow Chart [15]

C. Algorithms

We explored several Machine Learning Algorithms. As Machine Learning Algorithms fall into two major categories, Supervised and Unsupervised. According to our data-set we narrowed down on 4 Supervised Learning Algorithms, explained in detail below. The rationale behind using Supervised over Unsupervised was that we had labelled data associated with an output, based on which the algorithm we imply is trained on. Supervised was a more realistic and efficient approach for our already existing labeled data-sets and was the best fit[11]. The 4 algorithms we have a look in detail are:

1) K-Nearest-Neighbor
2) SVM (Support Vector Machine
3) Random Forest Regression

4) Logistic Regression

D. KNN

K-Nearest-Neighbor Algorithm is a supervised algorithm which can be used for regression as well as classification problems[16]. In simple words, it estimates things which are similar in nature based on its proximity. Similar things are closer to each other. Let us have a look at the advantages of KNN:

- Lazy Learner: Based on instances
- Addition of new data is simplified
- Easy to implement(Using Euclidean Distance)

We tested this algorithm on our data-set and secured an accuracy percentage of 93.5. The output is shown below:

E. SVM

SVM (Support Vector Machine) is a discriminative classifier which formally separates a hyper-plane [17]. In basic terms, it is used for separation of classes. It can be used to differentiate amongst ton of data, by creating a margin of separation.
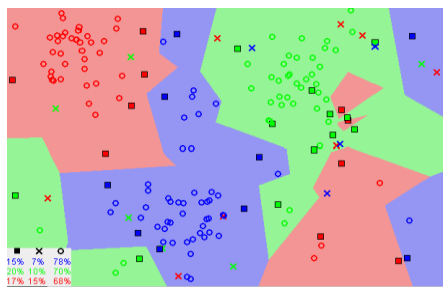

Fig. 9: K-Nearest Neighbor Process [16]

```
K Nearest Neighbours
0.9350282485875706
[[154   1]
 [ 22 177]]
              precision    recall  f1-score   support

           0       0.88      0.99      0.93       155
           1       0.99      0.89      0.94       199

    accuracy                           0.94       354
   macro avg       0.93      0.94      0.93       354
weighted avg       0.94      0.94      0.94       354
```
Fig. 10: Accuracy Output for KNN

Fig. 11: SVM graph [17]

```
SVM
0.9463276836158192
[[157   0]
 [ 19 178]]
              precision    recall  f1-score   support

           0       0.89      1.00      0.94       157
           1       1.00      0.90      0.95       197

    accuracy                           0.95       354
   macro avg       0.95      0.95      0.95       354
weighted avg       0.95      0.95      0.95       354
```
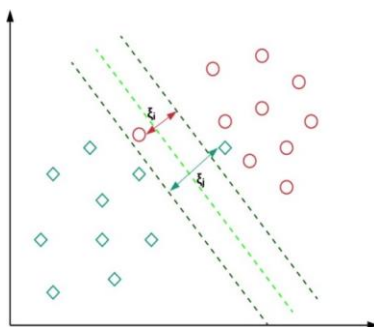**Fig. 12: Accuracy Output for SVM**

It will determine the amount of generalisation required amongst the classes formed of the data sets[7]. Let us have a look at the advantages of SVM:

- Efficient for data-set with clear margin of separation
- Memory efficient
- Works well when dimensions are greater than samples
  We tested this algorithm on our data-set and secured an accuracy percentage of 94.6. The output is shown below:

F. Random Forest Regression Algorithm

Random Forest is a supervised learning algorithm. As we contain a labeled data-set from which it infers set of training examples. Random forest couples both regression and classification by using ensemble learning method. Ensemble learning is the grouping of various features/decision trees to obtain an enhanced predictive performance.

$$g(x) = f0(x) + f1(x) + f2(x) + ...$$

here, g= final model; fi= simple base models/decision trees.

Ensemble Learning has 2 basic types, Boosting and Bootstrap Aggregation also known as Bagging. Random Forest is a type of Bagging as all the decision trees function independently, with no interaction amongst one another[18]. Connecting this to our data set, we also have several features which embody this mechanism. Bagging also helps reduce the variance and understand the bias, eventually aggregating all the outputs at the end[12].

Let us have a closer look at the features and advantages of Random Forest:

- Estimates the most important variables in classification
- Can generate an unbiased estimate for missing data
- Maintains accuracy with missing data in data-set

We tested this algorithm on our data-set and secured an accuracy percentage of 91.8. The output is shown below:

G. Logistic Regression Algorithm

Logistic Regression Algorithm, specifically the binary classification is a predictive analysis algorithm used for classification based on probability[13].
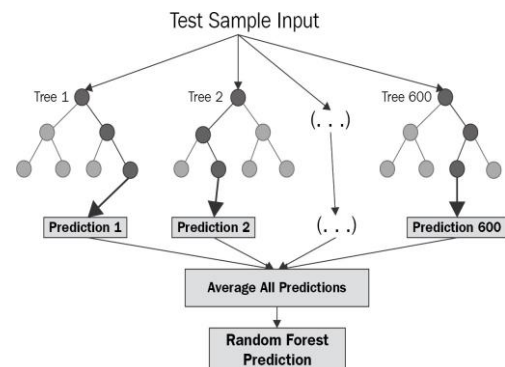

Fig. 13: Random Forest Regression Flow Diagram [18]

```
Random Forest
0.9180790960451978
[[148   1]
 [ 28 177]]
             precision    recall  f1-score   support

          0       0.84      0.99      0.91       149
          1       0.99      0.86      0.92       205

   accuracy                           0.92       354
  macro avg       0.92      0.93      0.92       354
weighted avg       0.93      0.92      0.92       354
```

Fig. 14: Accuracy Output for Random Forest Regression

Logistic Regression uses the 'Sigmoid Function' whose range varies from 0 to 1. (PHOTO2) Let us have a look at the advantages of Logistic Regression:

- Go to method for binary classification
- Functions well with Linearly separable data-set
- Easy to implement and train (PHOTO3)

After a detailed scrutiny of various algorithms, such as SVM, Random Forest Regression, K-Means, we have finalised Logistic Regression Algorithm as the most suitable for our data-set as it provides the highest accuracy output of 95.1 percentage.

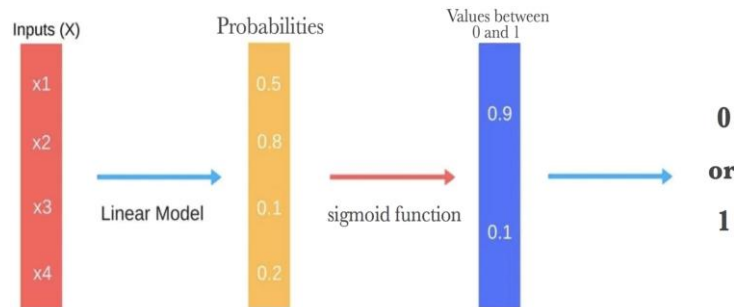$$f(x) = \frac{1}{1 + e^{-(x)}}$$

Fig. 15: Sigmoid Function [19]

Fig. 16: Steps in Logistic Regression [19]

```
Logistic Regression
0.9519774011299436
[[162   3]
 [ 14 175]]
             precision    recall  f1-score   support

          0       0.92      0.98      0.95       165
          1       0.98      0.93      0.95       189

   accuracy                           0.95       354
  macro avg       0.95      0.95      0.95       354
weighted avg       0.95      0.95      0.95       354
```

Fig. 17: Accuracy Output for Logistic Regression

H. SMOTE Process

SMOTE was used in Data Augmentation, while the classification of data, we have utilised SMOTE(Synthetic Minority Over-Sampling Technique). SMOTE is used to increase the minority in a more rationale way rather than simply duplicating the data[10]. It is mostly employed to imbalanced data-sets. Here the minority cases are increased in a balanced way. It works by generating newer instances from the present minority cases in the input you provide. SMOTE does not affect the number of majority cases. The new instances generated are not duplicates of the existing one, in-fact it utilises the feature space of each neighbour along with target class and generates an instance based on their features[20].

In our data-set this works like a gem as the number of 'bully' are the minority cases with only 9 percent of data and 'not bully' are the majority with 91 percent. This feature helps to train the Algorithm by increasing the available features and create a more general and balanced sample.
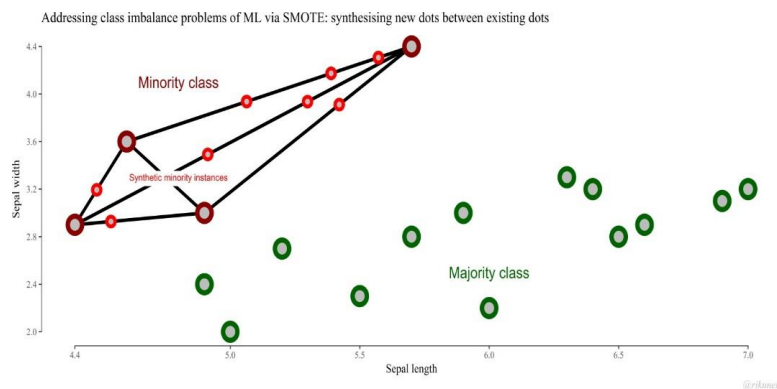

Fig. 18: SMOTE Process [20]

I.   Discussions

The output of this tool is to identify a potential bully. Comparing and analysing it with the characteristics of a bully and with the use of Algorithms, we can identify a bully. We have chosen this as it along with all the advantages mentioned above, it is the most accurate algorithm, with the highest success rate after trying it out several times with the same amount of data and determine which provides the most reliable output on various algorithms, we have chosen Logistic Regression coupled with SMOTE[13].

To showcase our survey results we have showcased it by 2D plots. The main reason for using them is an effective way to represent the data. As our plan is to provide the results back to the school. This way of representation will help them have a simpler overview of the results and can comprehend the data in a more efficient manner. Usage of gender is a key feature while making comparisons, specifically aimed at our target audience (teachers/guardian), which will help them incorporate future steps in their school. The figures utilise the most effective representation format comprising of the groups(as mentioned above) we utilised in our algorithm. We have shown a visual comparisons of:

1)Gender vs. Rating Scale 2)Gender vs. Appearance 3)Gender vs. Comfort Level Figure 19 shows "Other" (transgender) being the mostlikely to bullying with a higher value as a higher value indicates a mindset of approval of that behavior. With "Male" having an higher average value compared to "Females", tending Males to have a more tendency to be bullies. Figure 20 here also shows "Other" and "Male" gender having a higher value showcases they are confident with their appearance, and will have a natural tendency to not be insecure and likely to be bullies compared to "Females".

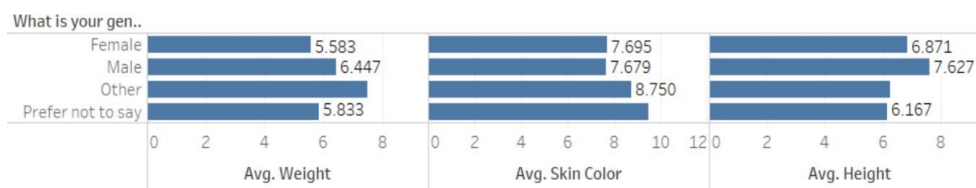**Fig. 19: Gender vs. Rating Scale**

Fig. 20: Gender vs. Appearance

Figure 21 bifurcates the Genders in separate groups, with the peak (higher scale value) showcasing the trend for comfort level. Higher indicates comfortable, with the lower values being the sign of concern.

CONCLUSION

We are aiming to utilise our tool for the benefit of the society. The plan is to provide the results to the parents/guardian/teachers and help them understand the child better. Further on, this can be supplied to educational institutes and they can take appropriate actions based on the results.
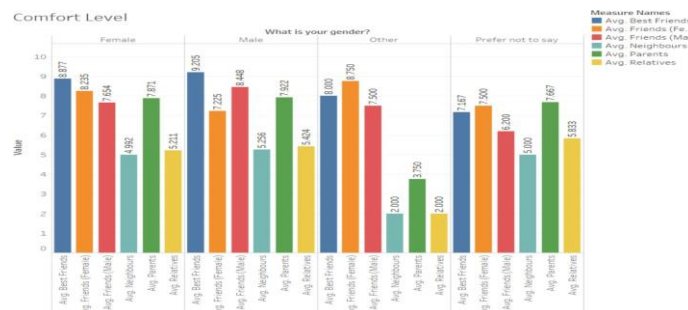

Fig. 21: Gender vs. Comfort Level

We can add additional information, where the parents/guardian can contact a reliable source, like a psychiatrist or a child service which deals with cases regarding bullying and guide the parents/guardian to step-by-step action plan.

This tool can do a lot good to the society, as it can encounter a potential bully and if rights steps are taken to reverse that action, it can destroy the root cause from childhood itself. It can act as a barrier or prevention to a worst case scenario of someone doing harm to the society.

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