of two words and trigram is a twitter text data token consisting of three words.

```
#Bag of words for bigrams
def bag_of_bigrams_words(words, score_fn=BigramAssocMeasures.chi_sq, n=200):
    bigram_finder = BigramCollocationFinder.from_words(words)
    bigrams = bigram_finder.nbest(score_fn, n)
    return bag_of_words(bigrams)
#Bag of words for Trigrams
def bag_of_trigrams_words(words, score_fn=TrigramAssocMeasures.chi_sq, n=200):
    trigram_finder = TrigramCollocationFinder.from_words(words)
    trigrams = trigram_finder.nbest(score_fn, n)
    return bag_of_words(trigrams)
def bigrams_words(words, score_fn=BigramAssocMeasures.chi_sq,
n=200):
    bigram_finder = BigramCollocationFinder.from_words(words)
    bigrams = bigram_finder.nbest(score_fn, n)
    return bigrams
# In[35]:
```

Figure 6: Code Block of N-Gram Generation

4.3 RESULTS USING NAÏVE BAYES

The step taken after the pre-processing is classification using the Naïve Bayes algorithm the purpose of machine learning is to impart knowledge in a machine or computer so that computers can do work like humans. The task of the Naïve Bayes algorithm in sentiment analysis is to classify data sets into positive, negative, or neutral classes according to the knowledge implanted using training data. The data set and training data used in this study are text-type data, so pre-processing is a crucial part before classification. This research applies bulling class boundaries in classification using machine learning algorithms. This limitation is that the Naïve Bayes algorithm can only classify test data or original data into positive and negative classes. This limitation is applied because the training data used only provides data with positive and negative sentiment classes, so it is very unlikely to produce neutral sentiment classes. The following is an explanation for each stage in the pre-process and the application of the Naïve Bayes algorithms. Making Unigram and Bigram Unigram and bigram are part of n-gram, which is n-word chunks based on the sequential sequence of the text string. Unigram is Ingram where n is one (n-gram is one size), while bigram is n-gram where n is two (n-gram is two). For example, there is a text "YMCA University", then the unigram of the text is "University", "YMCA", while the bigram of the text is "YMCA University". The purpose of using n-gram is to increase the effectiveness of the Naïve Bayes sentiment classification model. The following is the program code for creating unigram and bigram, tokens that have been processed have been loaded in unigram form, so the next step is to form bigram. A bigram is formed by connecting a token with the next token by adding the character "_" (underscore) as a separator character.

```
0.944
bullying precision: 0.9053117782909931
bullying recall: 0.9631449631449631
bullying F-measure: 0.9333333333333333
not-bullying precision: 0.9735449735449735
not-bullying recall: 0.9308600337268128
not-bullying F-measure: 0.9517241379310345
```

Figure 7: Results of Naïve Bayes with N-Gram Generation

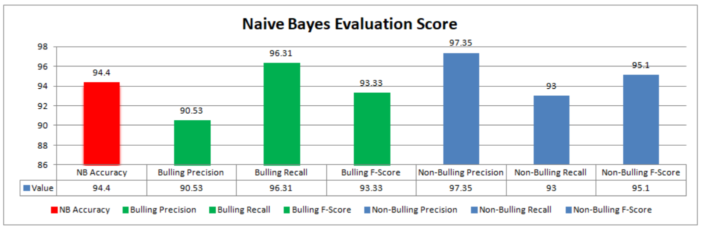

Figure 8: Results based on Naïve Bayes with Evaluation Models

For the bulling class, of the 364 copies of the validation set, 10 were misclassified. For this class, the precision of 90.53 indicates that you are very unlikely to label a bulling shows non-bullling, while the recall of 96.31 indicates that there are almost zero probabilities of labeling a bulling instance as non-bulling. Regarding the positive class, of the 157 really positive samples, 170 were erroneously classified as non-bulling. Based on precision and there call obtained for the non-bulling class, it is concluded that the classifier is unlikely to label a sample as positive negative, but at the same time unlikely to identify all the positive instances as such, that is, it could label as non-bulling a positive sample. Subsequently, the accuracy of 94.40% is achieved using Naïve Bayes.

4.4 RESULTS USING LOGISTIC REGRESSION

This step is the analysis using the Logistic Regression method is to define the Y (response variable) and X (predictor variable) data used. Following this, a simultaneous and partial test will be carried out on twitter data and its predictor variables with the data used as an example of testing which is the data that has the highest classification performance value using unigram, bigram, trigram and N-Gram. Based on the data obtained from grams, it can be seen that the value of bulling tweets are abusive eywords based on sentiwords dictionary which means it can be decided can be concluded that there is a significant influence between the keyword variables on the classification variable for bulling and non-bulling sentiments. Furthermore, based on the results of the parameter significance test, the decision was made that the auxiliary variable based on accuracy precision and recall.

```
The accuracy of Logistic Regression is  0.92
Bulling precision: 0.1141552511415525
Bulling recall: 0.18427518427518427
Bulling F-measure: 0.14097744360902256
Non-Bulling precision: 0.8858447488584474
Non-Bulling recall: 0.9814502529510961
Non-Bulling F-measure: 0.9312
```

Figure 9: Results using Logistic Regression

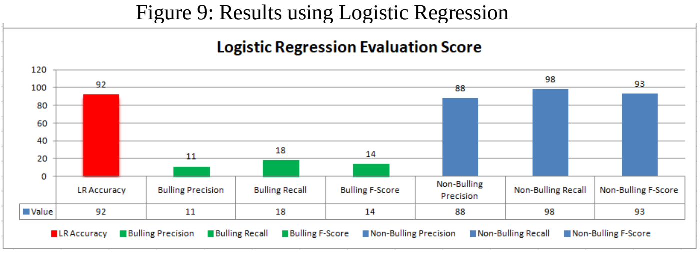

Figure 10: Results based on Logistic Regression

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 11 Issue 09, September 2022

Using the above approach of the total of 364 copies of the non-bulling class, 34 were classified erroneously by Logistic Regression. For this class, the model obtained the values of 88 in precision and 98 in recall. these are very good results, very close to 1.00 (perfect performance), which indicates that for the class managed to find most of the copies and that what is labeled is of very good quality (level of certainty when labelling). Regarding its performance for the bulling class, of the total of 157 were incorrectly labeled. This allows reaching the assertion that the bulling class performed worse than the non-bulling for all the models used, for which 2 possible causes are postulated: the first, which is the class with the least representation in the training data, so the model has less data to learn from; the second, that at be two classes represented in one (bulling and non-bulling), there may be difficult the task of associating the features to the class, because it could be given the relationship of more features in fewer samples. Furthermore, consider that some features could apply to both the bulling and non-bulling class, which that usually generates difficulties in the field of machine learning.

4.5 RESULTS USING DECISION TREE

Decision Tree technique steps in the form of sentence with a limited number of words, but structured logically and systematic using UniGram, BiGram, TriGram and N-Gram. Apart from that the algorithm is a clear procedure to solve a problem using steps and is limited in number.

1. Algorithms have a beginning and an end, an algorithm must quit after working on a series of tasks. With words have finite steps using N-Gram.
2. Each step must be precisely defined so that it is not has a double meaning, not confusing with the help of UniGram, BiGram, TriGram and N-Gram.
3. Having input (input) or initial conditions.
4. Has an output (output) or final condition. The algorithm must be effective, if it is followed absolutely it will be solve the problem of Bulling and Non-Bulling Data.

```
0.711
bullying precision: 0.8010204081632653
bullying recall: 0.3857493857493858
bullying F-measure: 0.5207296849087895
non-bullying precision: 0.6890547263681592
non-bullying recall: 0.9342327150084317
non-bullying F-measure: 0.7931281317108089
```

Figure 11: Results using Decision Tree

The objective of this task is to identify aspects that generate results within the same context, selecting those characteristics that are frequently mentioned and the associated bulling or non-bulling scenario. To identify these characteristics or aspects, the simplest solution is to use a classification with one independent variable with allows us to obtain the nominal phrases of the tweets using decision tree and taking into account that most of the aspects are substantive as mentioned in result below.

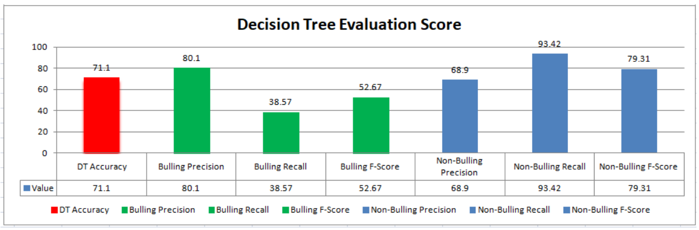

Figure 12: Results based on Decision Tree with Evaluation Models

Regarding the bulling class, of the 353 truly negative specimens, 41 were misclassified. The precision worth 80.1 is a good sign, considering that it is closer to 1.00 than to 0.5, indicating that it is unlikely to identify a positive negative sample. A very similar case is presented for the recall who got the same value of 38.57, indicating that there is the same low probability of identify a negative sample as positive as to identify a positive as negative. According to what was obtained for the positive class, of the 168 samples, 73 were misclassified. As expected, according to analyzed for the negative class, this model also delivered very similar to recall and precision for the positive class, taking the values 68.9 and 93.42 respectively, so the conclusions between the ratios of both classes is maintained as expressed in the analysis on the class negative of this model. Consequently, 71.1% of accuracy is achieved using decision tree.

4.6 RESULTS USING SUPPORT VECTOR MACHINE

This approach proposes the Support Vector Machine method for the classification process on the cyber bulling sentiment review. The result dataset from initial data processing that has been applied to three types of N-Gram is then classified using the proposed method with processed and labeled tweets and tests Model validation allows you to cross validate the different amounts of data using N-Gram to determine accuracy with precision and recall, below is results achieved using Support Vector Machine.

```
Accuracy using SVM  0.949
Bulling precision: 0.9013761467889908
Bulling recall: 0.9656019656019657
Bulling F-measure: 0.9323843416370107
Non-Bulling precision: 0.9429037520391517
Non-Bulling recall: 0.9747048903878583
Non-Bulling F-measure: 0.9585406301824211
```

Figure 13: Results using Support Vector Machine

The condition imposed on our function will be replaced by the conditions of the Lagrange multipliers, which will be easier to handle. With which, the saddle point of the following Lagrangian function must be found. Where $(wx_1 + b = +1) - (wx_2 + b = -1) \Rightarrow w(H_1 - H_2)$ is the class associated with the point x_i. By imposing this restriction, the SVM will place all the points that have the class associated $y_i = 1$ above hyperplane H_{11} and to the points that have the class associated $y_i = -1$ will place them below hyperplane H_{12}. Consequently, the results are elaborated as under.

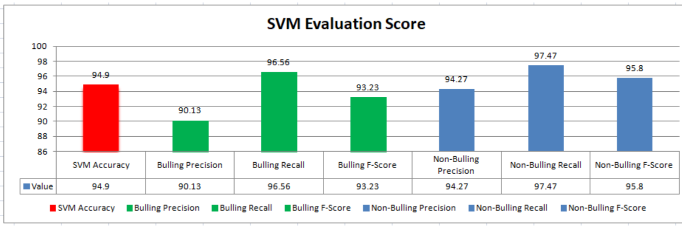

Figure 14: Results based on SVM with Evaluation Models

Regarding the performance over the bulling class, SVM mislabeled 38 samples of the total of 317 truly negative specimens. With a precision of 90.13 and a recall of 96.56 this model indicates that, for the class bulling, has greater certainty than uncertainty at the time of labeling. On the other hand, for the positive class, of the 166 truly bulling samples, 26 were wrongly labeled. Although the model had worse performance for the bulling class than the non-bulling one, it is possible to appreciate that there is a correlation between the performances of the different classes, since, being dichotomous classes, it makes sense that the strengths and weaknesses to identify one class are reflected in the strengths and weaknesses of its opposite class. Applied to this specific case (model and class), it is verified that if in the class negative the precision> recall, in its opposite class the opposite occurs (recall> precision) under the SVM. Consequently, 94.9% of accuracy is achieved using SVM.

5. CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

Based on the results of research conducted that:-
When classical pre-processing is done and using a NLP techniques like CBOW and N-Gram, results are obtained in accordance with the literature, sufficing only with taking unigrams despite the fact that they are few messages coupled with the vague writing style, In addition, the baseline has been exceeded. Initially it was thought that by including stop words to help bigram and trigrams would have a better performance in the classifiers, but it has been verified that the n-gram is more effective approach with cbow. Based on experimentation, it was found that by not including the two characteristics pre-processing (eliminate stop words and do stemming) the results may come out with a lower value.

The bulling and non-bulling messages or tweets captured by the tweet extractor correspond to a common language and colloquial, so these messages contain quite a few misspellings, terms coined on the fly and erroneous grammar. This makes it difficult to model language and have common characteristics in different messages that serve as help the classifier. There were also small annotated corpora compared to others given in tweets and this influenced the learning of the classifiers. Other messages required more contexts because the extractor might return a message from a group that belonged therefore this lack of information further complicated the fact of being able to classify a message. Subsequently, the different models of representation of the words, it was possible to appreciate that the best is that of grams, and the best classifier are that of Naïve Bayes, Decision Tree and Support Vector Machine. When the labeled tweets for bulling and non-bulling were analyzed and based on the results it is possible to say that if the fact of having these tweets in a messages will improve or worsen the results without the cbow and gram model. So these results indicate that if it is preferable to use grams and cbow and add them as features to the training vectors of a classifier.

The justification for this is that using only symbols we have a value higher than the baseline. It can also be seen that the top line for these symbols is around 90% using unigrams/bigrams/trigrams and n-grams and as value of the cbow features. Finally in this particular analysis of tweets we have that the best values are generated when the model is of trigrams, this reinforces the idea that the more bulling tweets together, the more intensifies the gravity of the message (bulling or non-bulling) by lemmatization, stemming and applying the same models, as well as the same sorter.

Finally, when the combination of classifiers was analyzed, it was found that the Naive Bayes with the accuracy of 94.4%, Logistic Regression with the accuracy of 92.0%, Support Vector Machine with accuracy of 94.9% classifiers presented a excellent results when it was used with combining the cbow and n-gram collectively, whereas the decision tree is with 71.1% accuracy acting as the average classifier used. Therefore, the combination of cbow and grams with classifiers helps when choosing a method of weighting on the best classifiers for detecting bulling and non-bulling under the cyberbulling model.

At the end of the development of this thesis it was possible to see that it is possible to detect cyber-bulling automatically with few messages using robust techniques. Despite some limitations, based on the results obtained, we consider that the objectives of studying different processing techniques of the natural language, as well as apply machine learning techniques to meet the task of detecting cyber-bulling in the messages of the social network Twitter.

5.2 Future Work

The following are some suggestions that can be used in developing better future research.
1. Attempt to balance the proportion of data used between each class so that it is balanced and can affect the increase in the value of accuracy.
2. Voluminous Dataset can be integrated with Big-Data
3. Perform other pre-processing steps such as Map-Reduce algorithm
4. Experiments in changing the proportion of use of training data and test data along with Deep Learning Models.

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