UNDER PEER REVIEW

Detection of Cyberbullying in the Social Media Space using Maximum Entropy and Convolutional Neural Network

ABSTRACT

Social media has proven to be a platform for information dissemination, business transactions and even for worship and political activities. This same platform have been converted for spreading hate speech and cyberbullying. Cyberbullying is a wrongdoing in which a culprit focuses on an individual with online provocation and loathe which has antagonistic, emotional, social and physical effects on the victim. These spills a lot of hate speech against individuals of different believe, selection of different opinion. To address such issues, this research develop an improved model for cyberbullying detection which is dependent on maximum entropy and deep neural network. Convolution Neural Network is utilized for the better outcomes when contrasted with the current systems. The dataset collected contained twenty-four thousand, seven hundred and eighty-three (24,783) tweets which contains 3 class labels namely “bullying language”, “non bullying language” and “neither”. In the study classification of tweets are in accordance to geo-political zones. The dataset were trained and tested during the experiment. The unigram on the model performed 96.3% accuracy, the bigram model performed accuracy of 93.8%, the trigram with an accuracy of 88.2%, and n-gram improved performance with 94.2%.The characteristic of unigram, bigram, trigram and n-grams for detection and TF-IDF (Term Frequency Inverse Document Frequency) were used as the two baseline classifiers of the tweets dataset. The result in the model during cyberbullying of the tweets will improve the bullying recall accuracy. The information from the study will provide alternate spelling and clever wording of cyberbullying in tweets.

Keywords: ***Cyberbullying, Hate Speech, Maximum Entropy, Sentiment, Word Embedding***

1. INTRODUCTION

Hate speeches are utterances, typed documents, advertorials, musicals or any form of literature that are used to attack an individual, a group – religious, social, political, business - gender or race. When this action takes place online in the social media space, we refer to it as cyberbullying. In some countries, hate speech can fall under the law of sedition, incitement to violence, verbal abuse [1] posited that "Hate speech is any speech, gesture, conduct, writing or display which could incite people to violence or prejudicial action. Essentially, such speeches rob others of their dignity".stated, "Hate speech employs discriminatory epithets to insult and stigmatize others on the basis of their race, ethnicity, gender, sexual orientation or other forms of group membership. It is any speech, gesture, conduct, writing or display which could incite people to violence or prejudicial action''.[2] defined that "Hate speech is often the gateway to discrimination, harassment and violence as well as a precursor to serious harmful criminal acts. It is doubtful if there will be hate-motivated violent attacks on any group without hate speech and the hatred it purveys." Numerous studies have been conducted about post-election violence but little has been devoted in recent time at analyzing the principal cause of this violence in relation to hate speech as well as the role they play in causing cyberbullying in social media spaces around the world. More so, given the power as well as significance of news journalism to modern society, it should come as no surprise that the discourse of newspapers has been, and continues to be, scrutinized. Sentiment analysis, also called opinion mining, is the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes. It represents a large problem space. There are also many names and slightly different tasks, e.g., sentiment analysis, opinion mining, opinion extraction, sentiment mining, subjectivity analysis, affect analysis, emotion analysis, review mining, etc. Opinions are central to almost all human activities because they are key influencers of our behaviors. Whenever we need to make a decision, we want to know others' opinions. In the real world, businesses and organizations always want to find consumer or public opinions about their products and services. Individual consumers also want to know the opinions of existing users of a product before purchasing it, and others' opinions about political candidates before making a voting decision in a political election. To tackle the negative viral effect of cyberbullying as a result of hate speech on social media platforms, this research work is intended to apply sentiment analysis to this domain with the hope of discovering and if possible, militate against the negative effect of hate speech in the Nigerian political environment. This research work does NOT propose to stop hate speech, but to discover the negative effect of viral hate speech and if possible, the possible impact of such viral effect on social media users in Nigeria with the application of sentiment analysis algorithm.

2. MATERIAL AND METHODS

Sentiment analysis has grown to be one of the most active research areas in natural language processing (NLP) [3] [4]. It is a multifaceted problem with many challenging and interrelated sub-problems, including sentence-level sentiment classification. Many researchers realized that different type of sentence need different treatment for sentiment analysis. Models of different sentence types, including subjective sentences, target-dependent sentences, comparative sentences, negation sentences, conditional sentences, sarcastic sentences, have been proposed for sentiment analysis. Subjectivity classification distinguishes sentences that express opinions (called subjective sentences) from sentences that express factual information (called objective sentences)[5] . Although some objective sentences can imply sentiments or opinions and some subjective sentences may not express any opinion or sentiment, many researchers regard subjectivity and sentiment as the same concept [6].subjective sentences express opinions and objective sentences express fact. [7] Presented a bootstrapping process to learn linguistically rich extraction patterns for subjective expressions from a large unannotated data. [8] Presented a system to detect emerging political topics on twitter and the impact on concept-level sentiment analysis. The proposal in [9] was on hybrid approach using Senti WordNet [10] and fuzzy sets to estimate the semantic orientation polarity and intensity of sentiment words, before computing the sentence level sentiments. [11] Introduced a lexicon-based sentiment classification system for social media genres, which captures contextual polarity from both local and global context[12,13]. [14] Proposed a novel approach to predict sentiment in online texts based on an unsupervised dependency parsing-based text classification method. Most previous target related works assumed targets have been given before performing sentiment classification [15]. [16] [17] [18]. Little research has been conducted on classifying sentence by the target number although there is a large body of work focusing on opinion target extraction from text. A comparative opinion sentence expresses a relation of similarities or differences between two or more entities and/or a preference of the opinion holder based on some shared aspects of the entities. [19] [20] showed that almost every comparative sentence had a keyword (a word or phrase) indicating comparison, and identified comparative sentences by using class sequential rules based on human compiled keywords as features for a naive Bayes classifier. [21] reported they were the first work for mining opinions in comparative sentences. They solved the problem by using linguistic rules and a large external corpus of Pros and Cons. from product reviews to determine whether the aspect and sentiment context were more associated with each other in Pros or in Cons. The review in [22] presented a corpus of comparison sentences from English camera reviews. [23] Proposed two linguistic knowledge-driven approaches for Chinese comparative elements extraction. Negation sentences occur fairly frequently in sentiment analysis corpus. The developed model in the research due to declination of the symbol-by-symbol restriction will ensure that a brute-force attempt outside this model when guaranteed by a hacker will fail because the system will revert to anti-brute-force to mitigate against guessing the 6-character long key in [24]. The tradeoff between the two protocols can provide a significant impact on the networks.in [25]. The prediction of incoming attacks is achieved in a timely manner which enables security professionals to install defense systems in order to reduce the possibility of such attacks [26] in Zero Day attack Prediction.

The control plane is flooded by the configuration messages thereby resulting in a trade-off between the number of configuration messages and number of permanent flow entries in the network [27].Many researchers considered the impact in [28] proposed a compositional model to detect valence shifters, such as negations, which contribute to the interpretation of the polarity and the intensity of opinion expressions. Information in [29] studied the effect of modifiers on the emotions affected by negation, intensifiers and modality. Conditional sentences are another commonly used language constructs in text. Such a sentence typically contains two clauses: the condition clause and the consequent clause. Their relationship has significant impact on the sentiment orientation of the sentence [30].First presented a linguistic analysis of conditional sentences, and built some supervised learning models to determine if sentiments expressed on different topics in a conditional sentence are positive, negative or neutral. Listed a set of interesting patterns in conditional sentences that often indicate sentiment, which was particularly useful for reviews, online discussions, and blogs about products. Sarcasm is a sophisticated form of speech act widely used in online communities. In the context of sentiment analysis, it means that when one says something positive, one actually means negative, and vice versa. The focus presented a novel semi-supervised algorithm for sarcasm identification that recognized sarcastic sentences in product reviews. The Report on a method for constructing a corpus of sarcastic Twitter messages, and used this corpus to investigate the impact of lexical and pragmatic factors on machine learning effectiveness for identifying sarcastic utterances.

3. EXPERIMENTAL DETAILS

The Order-insensitive models are insufficient to fully capture the semantics of natural language due to their inability to account for differences in meaning as a result of differences in word order or syntactic structure (e.g., “cats climb trees” vs. “trees climb cats”), hence, the adoption of the sequence model for this research work is required. The developed model for this research work is shown in figure 1.

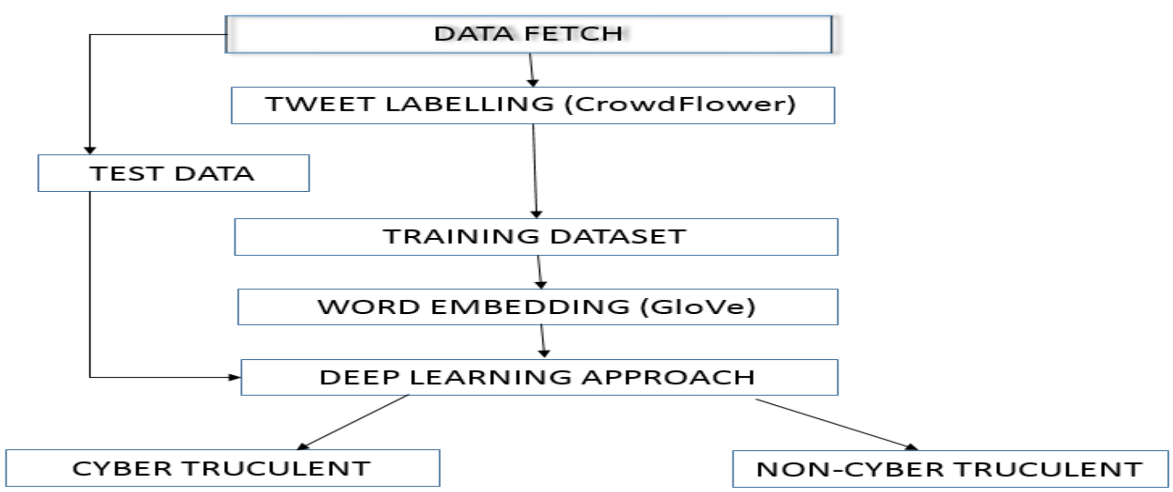


Figure 1: Developed Model

Data Collection

In the first step, data was collected from cloud media or social media by extracting reviews and data regarding reviews from sources such as websites and micro-blogging platform (Twitter). However, to manually copy and paste all the reviews from the considered websites into a document would be time-consuming and inefficient; hence this process will be automated by using a data scraping script that was developed in the research. The collected dataset contained twenty-four thousand, seven hundred and eighty-three (24,783) tweets which contains 3 class labels namely “bullying language”, “non bullying language” and “neither”. In the study classification of tweets according to geo-political zones (SE,SW,SS,NC,NE,NW) was conducted. Where tweets were labelled as hate speech based on the definition of bullying or abusive speech, tweets labelled as none bullying language do not contain abusive words and hence do not meet the bullying or truculent speech definition and finally tweets labelled as neither contained neither bullying or abusive words. The dataset also has a count column that indicates the annotator vote of decision on that tweet when classifying.

The dataset was split up for downstream tasks into 80% for training (20% of the 80% was used to validate the trained model while 60% was used for the actual training) and 20% for testing performance. The first important deficiency in the data set is the huge number of redundant records. Analyzing train and test sets, the research found that about 78% and 75% of the records are duplicated in the train and test set, respectively. This large amount of redundant records in the train set will cause learning algorithms to be biased towards the more frequent records, and thus prevent it from learning unfrequent records. Another issue with the data set which was noticed was is a high level of class imbalance with the hate speech class label sample size, the Figure 2 shows a bar chart indicating this class imbalance,

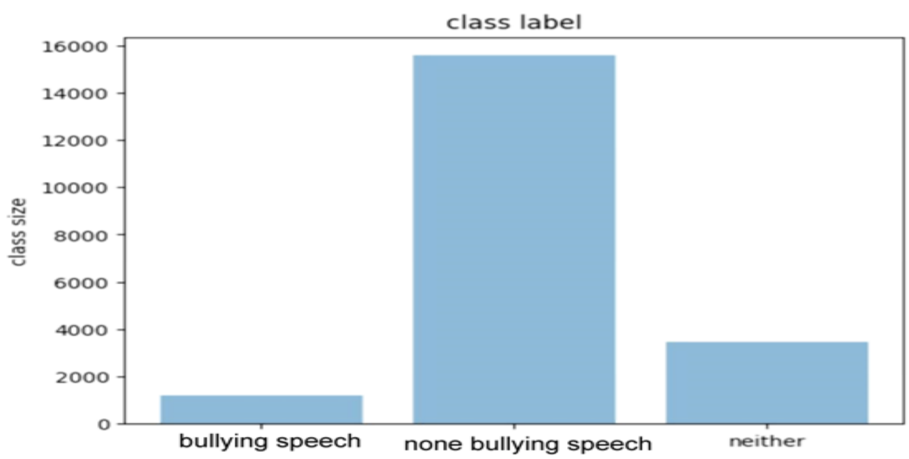


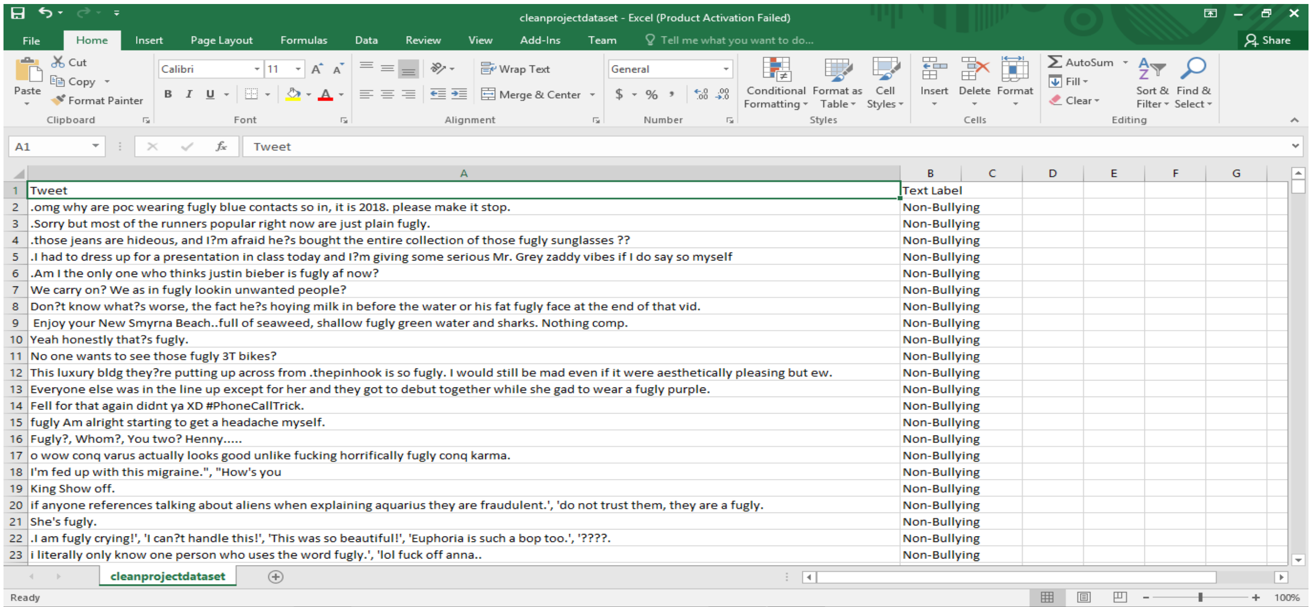
Figure 2: Class imbalance in the Dataset Sentiment Analysis

Table 1 present details showing the hate speech of class label that occupies only 5.7% of the entire dataset, the table also points out that there was a high level of disagreement on whether that tweet was a bullying speech or not, compared to other class labels such as none bullying language and neither, the annotators were more in uniform.

Table 1: Hate Speech Class Label

Class	Data Size (%)	Disagreement (Agreement)
Bullying Speech	1.430 Sample (5.77%)	87.4% (12.6%)
None Bullying Language	19.190 Sample (77.43%)	22.1% (77.9%)
Neither	4.163 Sample (16.79%)	28.8 %(71.2%)
Total	24.783 (100%)	

For training maximum entropy classification model for target extraction and sentence type classification, the study used the tweeter comment dataset since it contains a diverse range of sentences with various numbers of opinion targets. It contains 14,492 sentences from a wide variety of user sources who commented on topics of interest for sentiment classification with maximum entropy model as presented below.



	A	B
1	Tweet	Text Label
2	.omg why are poc wearing fugly blue contacts so in, it is 2018. please make it stop.	Non-Bullying
3	.Sorry but most of the runners popular right now are just plain fugly.	Non-Bullying
4	.those jeans are hideous, and I?m afraid he?s bought the entire collection of those fugly sunglasses ??	Non-Bullying
5	.I had to dress up for a presentation in class today and I?m giving some serious Mr. Grey zaddy vibes if I do say so myself	Non-Bullying
6	.Am I the only one who thinks justin bieber is fugly af now?	Non-Bullying
7	We carry on? We as in fugly lookin unwanted people?	Non-Bullying
8	Don?t know what?s worse, the fact he?s hoying milk in before the water or his fat fugly face at the end of that vid.	Non-Bullying
9	Enjoy your New Smyrna Beach..full of seaweed, shallow fugly green water and sharks. Nothing comp.	Non-Bullying
10	Yeah honestly that?s fugly.	Non-Bullying
11	No one wants to see those fugly 3T bikes?	Non-Bullying
12	This luxury bldg they?re putting up across from .thepinhook is so fugly. I would still be mad even if it were aesthetically pleasing but ew.	Non-Bullying
13	Everyone else was in the line up except for her and they got to debut together while she gad to wear a fugly purple.	Non-Bullying
14	Fell for that again didnt ya XD #PhoneCallTrick.	Non-Bullying
15	fugly Am alright starting to get a headache myself.	Non-Bullying
16	Fugly?, Whom?, You two? Henny.....	Non-Bullying
17	o wow conq varus actually looks good unlike fucking horrifically fugly conq karma.	Non-Bullying
18	I'm fed up with this migraine.", "How's you	Non-Bullying
19	King Show off.	Non-Bullying
20	if anyone references talking about aliens when explaining aquarius they are fraudulent.', 'do not trust them, they are a fugly.	Non-Bullying
21	She's fugly.	Non-Bullying
22	.I am fugly crying!', 'I can?t handle this!', 'This was so beautiful!', 'Euphoria is such a bop too.', '????.	Non-Bullying
23	i literally only know one person who uses the word fugly.', 'lol fuck off anna..	Non-Bullying

Fig 3: Cleaning of the Dataset for Classification

The training in the research was rule-based subjective sentence detector. Since the clues have orientations to the opinionated, arguing, and polarizing topics, they are suitable for our sentimental based problem. To build the cyber bullying lexicon, the study begin by extracting from the subjective sentences semantic word features that render a sentence subjective. Since our domain of cyber bullying is heavily laden with domain dependence and context specific lexicon that need to augment the subjective semantic lexicon with corpus generated lexicon. Using bootstrapping and WordNet we add into our lexicon, bullying-related verbs and dependency-type generated grammatical patterns relating to the three thematic areas identified. Based on the lexicon, the creation of a cyber bullying detection application with three levels of: “Bullying”, “None Bullying” and “Neutral”. The model test the application using our annotated corpus 750 labeled paragraphs was gathered. The summarize process was carried out in four main steps:

Step 1: use a rule-learning approach to extract subjective sentences.

Step 2: Using subjective sentences identified in step 1 above, extract semantic and subjective word features was obtain.

Step 3: Using bootstrapping, we augment the lexicon in step 2 with noun patterns based on the semantic classes of religion, ethnicity and race and bullying-related verbs.

Step 4: Then build and test the classifier with the annotated corpus based on the features identified in Step 2 and Step 3.

The target is to use the contextual information of the document (unigrams, bigrams, other characteristics within the text) in order to categorize it to a given class (positive/neutral/negative, objective/subjective etc). Following the standard bag-of-words framework that is commonly used in natural language processing and information retrieval, let $\{w_1,\ldots,w_m\}$ be the m words that can appear in a document require optimization. To solve optimization problem the Lagrangian multipliers was introduced, then unconstrained dual problem to estimate the lamda free variables $\{\lambda_1,\ldots,\lambda_n\}$ with the Maximum Likelihood Estimation was obtained in below.

Estimating Lamda Parameters

Input : *Feature functions* $f_1, f_2, \cdots f_n$; *empirical distribution* $\tilde{p}(x, y)$

Output : *Optimal parameter values* Λ_i^*; *optimal model* p^*

1. *Start with* $\lambda_i = 0$ *for all* $i \in \{1, 2, \cdots, n\}$
2. *Do for each* $i \in \{1, 2, \cdots, n\}$:
   a. *Let* $\Delta\lambda_i$ *be the solution to*

   $$\sum_{x,y} \tilde{p}(x) p(y \mid x) f_i(x, y) \exp\left(\Delta\lambda_i f^{\#}(x, y)\right) = \tilde{p}(f_i)$$

   where $f^{\#}(x, y) = \sum_{i=1}^{n} f_i(x, y)$

   b. *Update the value of* λ_i *according to* : $\lambda_i \leftarrow \lambda_i + \Delta\lambda_i$
3. *Go to step 2 if not all the* λ_i *have converged*

The $f^{\#}(x,y)$ is the total number of features which are active for a particular (x, y) pair. If this number is constant for all documents then the $\Delta\lambda_i$ can be calculated in closed-form:

$$\Delta\lambda_i = \frac{1}{C} \log \frac{\tilde{p}(f_i)}{p(f_i)} \quad where C = f^{\#}(x, y)$$

Deep Learning: The 1d-CNN takes sentences of varying lengths as input and produces fixed-length vectors as outputs. Before training, word embedding for each word in the glossary of all input sentences are generated. All the word embedding's are stacked in a matrix M. In the input layer, embedding of words comprising current. training sentence are taken from M. The maximum length of sentences that the network handles is set. Longer sentences are cut; shorter sentences are padded with zero vectors. Then, dropout regularization is used to control over-fitting.

In the convolution layer, multiple filters with different window size move on the word embedding to perform one-dimensional convolution. As the filter moves on, many sequences, which capture the syntactic and semantic features in the filtered n-gram, are generated. Many feature sequences are combined into a feature map. In the pooling layer, a max-overtime pooling operation is applied to capture the most useful local features from feature maps. Activation functions are added to incorporate element-wise non-linearity. The outputs of multiple filters are concatenated in the merge layer. After another dropout process, a fully connected *softmax* layer output the probability distribution over labels from multiple classes.

CNN is one of most commonly used connectionism model for classification. Connectionism models focus on learning from environmental stimuli and storing this information in a form of connections between neurons (figure 5). The weights in a neural network are adjusted according to the training data by some learning algorithm.

That is, the greater the difference in the training data, the more difficult for the learning algorithm to adapt the training data, and the worse classification results it will produce. Dividing opinionated sentences into different types according to the number of targets expressed in them can reduce the differences of training data in each group, therefore, improve overall classification accuracy s deduce in figure 4 below.

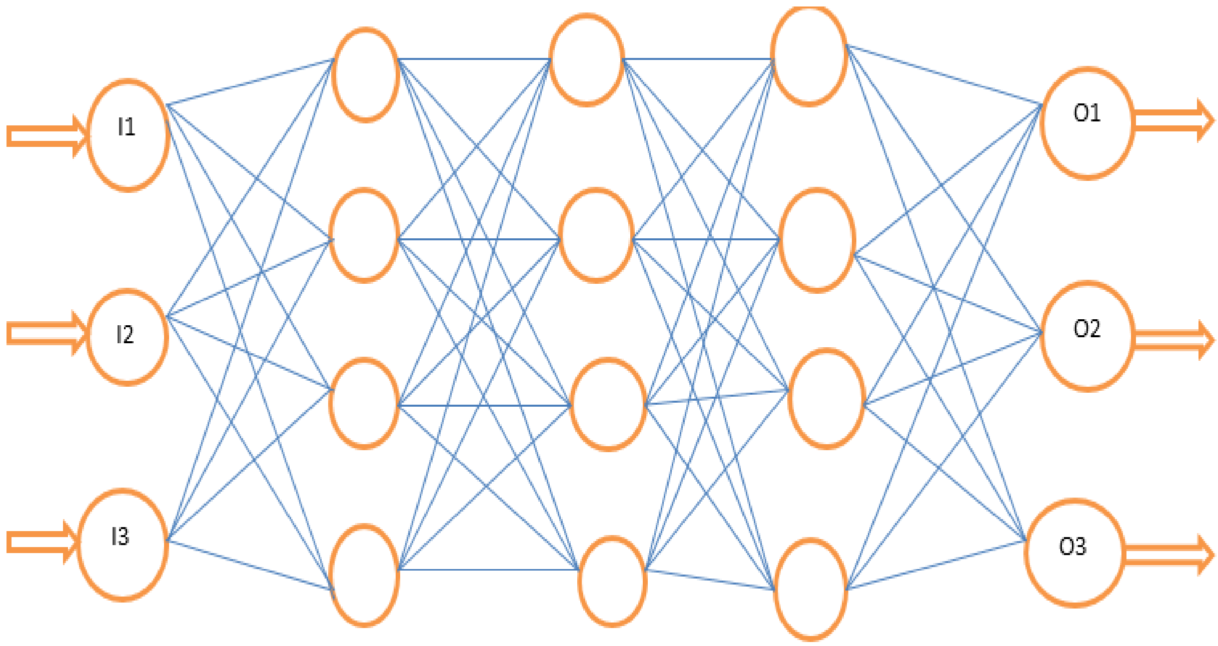
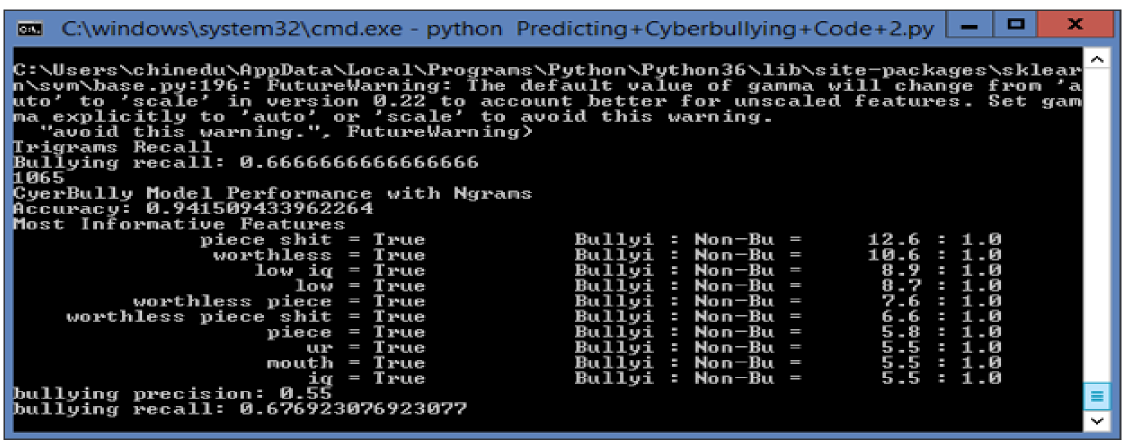


Figure 4: Convolutional Neural Network

RESULTS AND DISCUSSION

Cyberbullying Model for performance with Ngram, Trigrams recall, bullying Precision, bullying recall and accuracy is shown in the above figure. The most informative features were obtained for performance Evaluation. The developed model was able to predict the cyberbullying performance as shown in fig 5 below.



```
C:\windows\system32\cmd.exe - python  Predicting+Cyberbullying+Code+2.py
C:\Users\chinedu\AppData\Local\Programs\Python\Python36\lib\site-packages\sklear
n\svm\base.py:196: FutureWarning: The default value of gamma will change from 'a
uto' to 'scale' in version 0.22 to account better for unscaled features. Set gam
ma explicitly to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
Trigrams Recall
Bullying recall: 0.6666666666666666
1065
CyerBully Model Performance with Ngrams
Accuracy: 0.9415094339622264
Most Informative Features
              piece shit = True          Bullyi : Non-Bu =     12.6 : 1.0
               worthless = True          Bullyi : Non-Bu =     10.6 : 1.0
                  low iq = True          Bullyi : Non-Bu =      8.9 : 1.0
                     low = True          Bullyi : Non-Bu =      8.7 : 1.0
         worthless piece = True          Bullyi : Non-Bu =      7.6 : 1.0
    worthless piece shit = True          Bullyi : Non-Bu =      6.6 : 1.0
                   piece = True          Bullyi : Non-Bu =      5.8 : 1.0
                      ur = True          Bullyi : Non-Bu =      5.5 : 1.0
                   mouth = True          Bullyi : Non-Bu =      5.5 : 1.0
                      iq = True          Bullyi : Non-Bu =      5.5 : 1.0
bullying precision: 0.55
bullying recall: 0.676923076923077
```

Fig 5: Predict the Cyberbullying Performance

The result of the precision, f-score and recall is given in table 3 below: Table 2 result of precision, f - score and recall for the developed model was presented below.

Table 2: Evaluation of Cyberbullying the Model

DATASET	ACCURACY	PRECISION	RECALL	F-SCORE
Unigram	96.3%	95.5%	73.7%	83.2%
Bigrams	93.8%	93.7%	67.6%	84.7%
Trigrams	88.2%	92.3%	85.7%	88.9%
Ngrams	94.2%	92.9%	67.7%	78.3%
Final	**97.9%**	**93.6%**	**73.7%**	**83.8%**

The primary threat to external validity for this study involves the representativeness of the dataset, both training and test cases. It is obvious that the systems may exhibit different behaviors, during the test cases. The study compare the proposed solution with a similar work of Banerjee et al method. The result of the comparison is presented in figure 5 below:

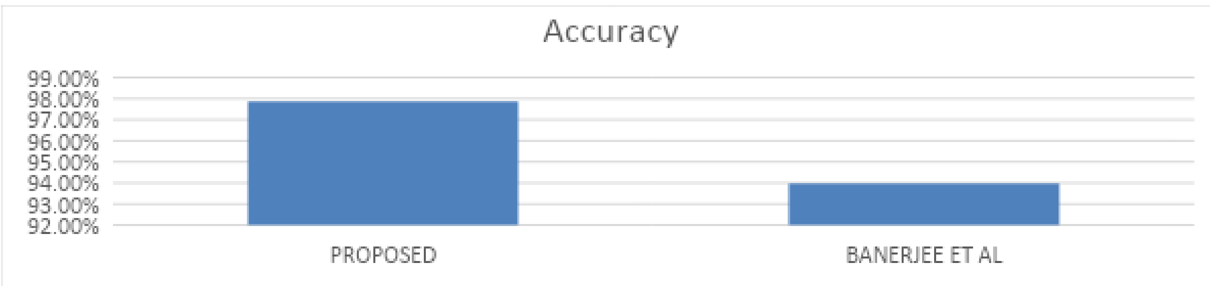


Fig 6: Graph of Accuracy Result

4. Conclusion

WordNet with character unigram, bigram, trigram and n-grams known for detection of rare and TF-IDF (Term Frequency Inverse Document Frequency) were used to create the data representations used in training the two baseline classifiers over a 50,000 augmented tweets dataset. The developed ensemble model based on maximum entropy and convolutional neural network. Performed better than the individual models on their own in detecting OOV word, alternate spelling and clever wording of cyberbullying in tweets which satisfies the aim of the research work while improving on the bullying recall accuracy. The unigram on the model performed fairly well with 96.3% accuracy while the bigram with the model performed well with an accuracy of 93.8%, the trigram however dropped the performance with an accuracy of 88.2%, and the n-gram improved performance with 94.2%, finally with the combination of the model, best-gram produced an accuracy of 97.9% but on closer investigation it was observed that the proposed model, which is a combination of maximum entropy and convolutional neural network, performed better than the individual models on their own in detecting OOV word, alternate spelling and clever wording of cyberbullying in tweets which satisfies the aim of this research work.

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