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An Analysis of Cyberbullying in Text Data using Deep Learning Algorithms

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Abstract

Cyberbullying is a peculiarity that unfavorably affects individuals; its casualties experience a scope of emotional wellness issues, including low confidence, uneasiness, forlornness, and sorrow. Cyberbullying is become more normal while online entertainment use is turning out to be more inescapable. Regular procedures to battle cyberbullying include the utilization of rules and guidelines, human mediators, and boycotts that rely upon hostile language. These strategies, however, are not scalable and perform poorly in social media. To automatically identify cyberbullying behaviours, a principled learning system must be created. Nonetheless, the process is difficult because of the brief, chaotic, and disorganised content material, as well as the deliberate obscuring of offensive phrases or words by those who use social media. We suggest using sentiment data to identify cyberbullying behaviours in social media by putting forth a sentiment-informed cyberbullying detection framework. Our approach has been inspired by sociological and psychological research on bullying behaviours and their relationship to emotions. Experiments conducted on two publicly accessible real-world social media datasets demonstrate the advantages of the suggested approach. Additional research confirms that using sentiment data to detect cyberbullying is beneficial.

Keywords: Sentiment analysis, Cyberbullying, Deep Neural Network, Artificial Neural Network, Radial Basis Function Network(RBFN).

I. INTRODUCTION

User-generated content (UGC) may now be published and responded to by the online community thanks to the development of technology for communication and information. Regrettably, cyberbullies have misused this ease of use, harming other people by intimidating, controlling, manipulating, threatening, or harassing tar-get victims [1]. The deliberate and persistent harm caused by using electronic devices is known as "cyberbullying" [2], [3], and [4]. A victim of cyberbullying (CB) may experience significant psychological effects, including despair and even suicide thoughts, in addition to negative feelings including anger, fear, grief, and guilt [5, 6, 7]. One of the main areas of interest in emotional computing is emotion mining, which seeks to recognise, assess, and evaluate how people feel about certain situations or experiences [8]. The stock market, customer reviews, and recommendations are just a few of the areas where emotion analysis has had a big impact [9], [10], and [11]. Researchers haven't, however, given emotion analysis much thought when it comes to identifying cyberbullying. Because there is a high correlation between cyberbullying and bad feelings, using emotion indicators into cyberbullying detection can thereby increase the accuracy of the detection.

The idea that emotion mining can enhance the identification of cyberbullying serves as the foundation for the solution put out in this paper. There are three steps to it. Getting a clear, well-balanced, and feature-rich dataset is the first step. The calibre of the data used for training datasets has a major impact on how well machine learning models work [15], [16]. Nevertheless, there aren't many datasets that address every type of cyberbullying [13], [17]. Furthermore, UGC differs in kind throughout social networking sites. For instance, Facebook posts have an entirely distinct character restriction than tweets on Twitter. Figure 1 shows the concept of cyberbullying.

Figure 1. Cyberbullying

This work investigates the extraction of emotions from text through both supervised as well as unsupervised methods. Using an emotion dataset downloaded from facebook, deep learning (DL) algorithms are applied in the supervised method. Using hashtags, the tweets are categorised into several emotional states. Three approval steps have been recommended and tried to check the programmed marking for the emotion dataset. These systems are intended to prepare feeling models with restricted, approved datasets and to affirm the opinion as well as feelings of events utilizing vocabularies. The solo technique, then again, utilizes a predefined dictionary — a catchphrase matching strategy — to distinguish the predominant feelings associated with a word. This word-level technique helps with finding unequivocal articulations inside the text. Sentiment features are also taken from text together with emotion data, and a general polarity has been given to each instance. In the third stage, Deep learning DL models are prepared to sort the information occasions into various kinds of cyberbullying or non-cyberbullying once the cyberbullying highlights have been extricated.

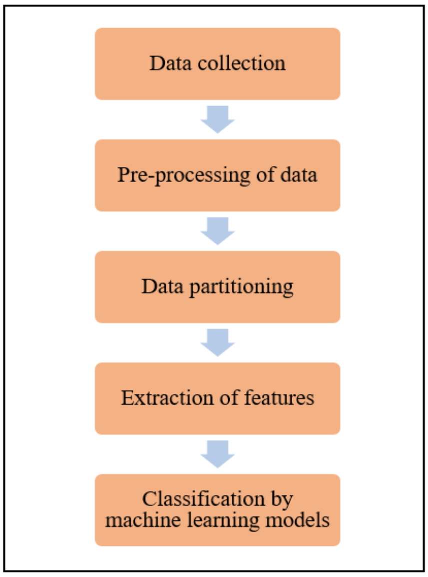

Figure 2: Architecture of this research work

Figure 2 shows the architecture of this research work, Text based data are collected from the social media then the collected data are preprocessed using the text processing techniques. The processed data is used for data partitioning, then the features are extracted and the machine learning models are used for the classification of text.

The leftover examination was organized as follows. The writing survey is shrouded in Segment II, and the materials and procedures utilized for this exploration — Deep Neural Networks (DNN), Artificial Neural Networks (ANN), Radial Basis Function Network(RBFN) for exactness — are portrayed in Segment III. In segment IV, the trial results are shown. Segment V contains the inventive data that wraps this concentrate up.

II. LITERATURE SURVEY

A mechanized cyberbullying recognizable proof framework in light of the mental attributes of Twitter clients, like characters, temperament, and feeling, was concentrated by Balakrishnan et al. [14]. The Big Five and Black Triad systems were used to discover the characters of clients, and AI calculations like NB, RF, and J48 were applied to order tweets into four gatherings: ordinary, attacker, menace, and spammer. Utilizing the hashtag #Gamergate, human experts carefully clarified 5453 messages in the Twitter data set.

In order to detect cyberbullying, Cheng et al. [15] created an organisational attention network that takes these characteristics into account. The T technique is distinguished by three primary attributes: 1) a hierarchical framework that imitates the structure of social media sessions; 2) the various attention systems that applies at the word as well as comment level, enabling the model to differentiate between different levels of attention depending on context; 3) a cyberbullying detection task that also forecasts the likelihood of cyberbullying

Singh et al. [16] claim that visual factors boost prediction outcomes and work in conjunction with textual data to identify cyberbullying.

Hence, it is basic to make mechanized techniques for distinguishing and halting cyberbullying. Despite the fact that there have been ongoing endeavors to distinguish cyberbullying and foster complex text handling calculations for this reason, visual information handling has not yet been applied to naturally identify cyberbullying. To decide whether robotized cyberbullying discovery is practical, Van Hee et al. [17] depicted the assortment and fine-grained clarifying of a cyberbullying assortment in English and Dutch, alongside a progression of paired grouping tests. With a major list of capabilities, they utilized direct SVMs to evaluate which data sources are generally valuable for the main job. Tests utilizing a hold-out testset show that it is feasible to effectively recognize presents associated on cyberbullying.Haidar et al. [18] gave strategies to recognizing cyberbullying in English and various different dialects, however nobody had at this point handled cyberbullying in Arabic. ML and NLP are two techniques that are helpful in distinguishing cyberbullying.

This article depicts a method for perceiving and halting cyberbullying, expanding on past exploration. It begins with an exhaustive examination of prior research in the space of cyberbullying discovery. Therefore, a way to deal with distinguishing cyberbullying inside Arabic text is exhibited and assessed.Agrawal et al. [19] led an itemized assessment of cyberbullying identification on various topics across various SMPs utilizing DL-based models and move learning. To lead broad tests, the analysts utilized three certifiable data sets: Wikipedia (100k posts), Twitter (16k posts), and Formspring (12k posts). Our examination delivered a few clever discoveries about the distinguishing proof of cyberbullying. Gencoglu and partners. [20] gave a model preparation technique that can assess our methodology on various information bases and maybe incorporate reasonableness requirements.

III. The creators exhibit how to actually decrease incidental inclinations of numerous sorts without forfeiting the precision of the model. The work, as indicated by the analysts, upgrades the chase after fair-minded, open, and moral AI ways to deal with cybersocial health.Balakrishnan et al. [21] utilized both the Big Five and Dark Triad of three techniques to foster a calculation for distinguishing cyberbullying in light of client brain research. In view of relationship between character attributes and cyberbullying, the calculation searches for tormenting designs inside Twitter people group. RF, a notable ML strategy, was utilized related to a beginning stage technique that included seven Twitter factors (number of notices, supporters and following, acknowledgment, most loved count, status count, number of hash labels) to order cyberbullying (for example attacker, spammer, menace, typical).

IV. MATERIALS AND METHODS

A. Deep Neural Network (DNN)

In recent years, deep learning has achieved tremendous success in a variety of application fields. The science of machine learning is rapidly expanding and has found application in both traditional and novel fields. Based on many learning categories, including supervised, semi-supervised, and unsupervised learning, numerous ways have been created. A subset of machine learning known as deep learning (DL) was created utilizing deep learning architectures or hierarchical learning techniques. Estimating model parameters to enable the trained model to complete a task is the process of learning. For example, in an artificial neural network (ANN), the parameters that need to be estimated are the weight matrices. DL, on the other hand, has several layers between the layers of input and output in its design [29] [30]. Pattern recognition and feature learning can benefit from the multi-stage nonlinear information processing made possible by this hierarchical structure design. In this context, representation learning refers to a data-driven learning approach. Figure 3 shows architecture of DNN algorithm.

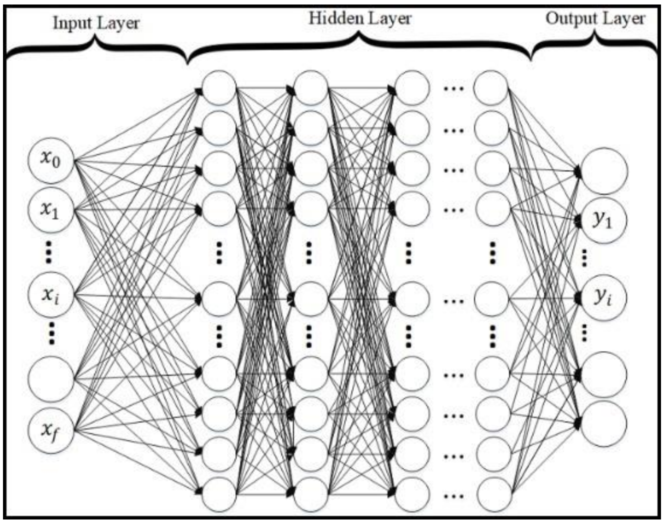

Figure 3: Architecture of DNN algorithm

Pseudo code for DNN

Step 1: Initialize Parameters: Set the neural network's weights and biases to either random or present values.

Step 2: Loop over Epochs: Continue iterating until convergence or for a predetermined number of epochs.

Step 3: Forward Propagation: To determine the expected output for every input sample, carry out forward propagation over the network.

Step 4: Compute Cost Function: To determine the difference within the expected and actual output, compute the cost function, also known as the loss function.

Step 5: Backward Propagation: To calculate the change in slope of the cost functions with respect to the network's parameters.

Step 6: Update Parameters: Using an optimization approach like gradient descent, update the network's parameters (weights and biases).

Step 7: Utilize Trained Model for Predictions: After the model has been trained, apply it to new or untested data to generate predictions.

Step 8: Examine the Model: You can choose to use measures like exactness, accuracy, review, or F1-score to survey how well the prepared model performed.

B. Artificial Neural Networks (ANN)

The amazing capacities of the human brain have inspired the development of an intriguing computer paradigm known as artificial neural networks, or ANNs. Because of their superior performance on tasks like pattern recognition, regression, classification, and clustering, these networks—the foundation of machine learning—have transformed a number of fields . Artificial neurones, sometimes referred to as nodes or units, are coupled to form ANNs. An info layer, various hidden layers, with a result layer make up the layers that these neurons are organized into. Each neuron learns, changes it utilizing an actuation capability, and afterward produces a result that is utilized as a contribution by neurons in the layer above. Weighted associations connect neurons inside adjoining layers . Each relationship has a weight that compares to its solidarity or importance. These loads are changed during preparing to diminish the disparity between the anticipated and genuine results of the organization. Figure 4 shows engineering of ANN calculation.

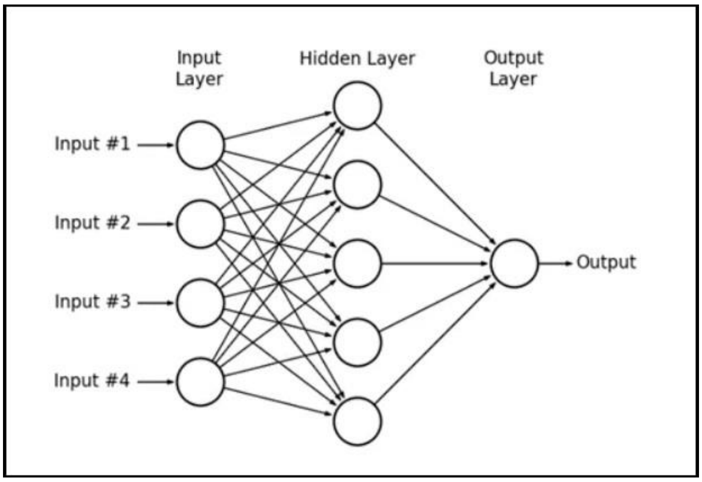

Figure 4: Architecture of ANN algorithm

Pseudo code for ANN

Step 1: Randomly or with predetermined settings, establish the weights and biases.

Step 2: Give definitions to the derivative and activation function. The derivative ofthe sigmoid activation function is one example.

Step 3: Establish the loss function.
Mean squared error (MSE) and cross-entropy loss are two examples.

Step 4: Establish the amount of epochs and the learning rate.

Step 5: Continue around the epochs: Repeat for every training case:

- Carry out forward diffusion and Determine the input and bias weights, weighted collectively, for every neuron in every layer. To obtain each neuron's output, apply the stimulation function to the scaled aggregate.
- Determine the amount of loss that exists between the expected and actual output.
- Carry out backward propagation by utilizing the chain rule to calculate the gradient of the loss with regard to the biases and weights.

- Apply gradient descent to modify the weights and biases: Using the gradient and learning rate of each weight, update the bias.

Step 6: The artificial neural network (ANN) model is trained following the predetermined number of epochs.

Step 7: To forecast: Implement forward propagation with the biases and weights that have been trained and Determine each layer's neuron's output. Give the forecast back as the last layer's output.

C. Radial Basis Function Network (RBFN)

In the field of artificial neural networks, the Radial Basis Function Network (RBFN) algorithm is a potent tool that offers a distinctive architecture and learning methodology apart from conventional feedforward networks . Regression tasks, pattern recognition applications, and function approximation are areas where RBFNs excel. The three primary layers that make up an RBFN's layered structure are the input, hidden, and output layers. Each neuron in the input layer represents an area of the input space, acting as the data entry point. The unique quality of RBFNs appears in the concealed layer. Each neuron in it is linked to a radial basis function (RBF). These RBFs calculate how similar the input data is to a set of centroids, or reference vectors. The Gaussian function, that determines the separation between the input value and centroid in a space with multiple dimensions, is a popular option for RBFs . Figure 5 shows the architecture of RBFN algorithm.

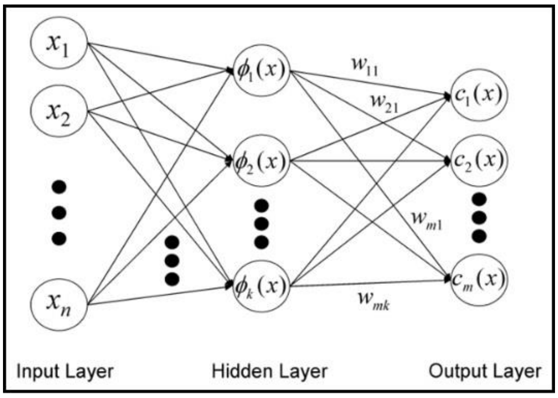

Figure 5: Architecture of RBFN algorithm

Pseudo code for RBFN

Step 1: Set the length parameter (sigma) and the total amount of centers (num_centers) to initial values.

Step 2: Initialize the centers at random.

Step3: Educate the RBFN: Determine each RBF neuron's activity for the given input data.

- Calculate the output of the radial base function based on the input data point (x) and center (c) for each.
- Save the result as the relevant RBF neuron's activation.

- Give the activations a bias term. Utilizing least squares regression, determine the weights: Join the activations together with a bias column of ones.
- To determine the weights that minimizes the error between the expected and actual outputs, use least squares regression.

Step 4: With the trained RBFN, forecast:

- Determine how much each and every RBF neuron is activated given the input data
- Give the activations a bias term.
- Multiply the activations by the weights to calculate the predictions.

Step 5: Present the forecasts.

V. EXPERIMENTAL RESULTS

The objective of this research work is to use text datasets (categorical data) to forecast heart disease. Numerous techniques are employed to identify problems in the healthcare industry, such as medical data sets, and to forecast patient illness risks and individual costs. Preprocessing the data and making predictions are the two primary processes in this research project. During preprocessing, the duplicate record, data that is missing, and noise in the reliable information will be eliminated from the database. In order to predict the attitudes and viewpoints in the kind of textual data, the dataset was used in the prediction process using Deep Neural Network, Artificial Neural Network, Radial Basis Function Network.

A. Data Set

The text-based dataset used in this study was downloaded as a.csv file from the Kaggle repository. The dataset's filename is text_data.csv. This research project has around 5000 records, of which 500 text records were taken and examined.

id	text	malignant	highly_ma	rude	threat	abuse	loathe
00009979	Explanati	0	0	0	0	0	0
000103f0	D'aww! He	0	0	0	0	0	0
000113f07	Hey man,	0	0	0	0	0	0
0001b41b	"	0	0	0	0	0	0
0001d958	You, sir, ar	0	0	0	0	0	0
00025465	"	0	0	0	0	0	0
0002bcb3	COCKSUCK	1	1	1	0	1	0
00031b1e	Your vand	0	0	0	0	0	0
00037261	Sorry if the	0	0	0	0	0	0
00040093	alignment	0	0	0	0	0	0
00053000	"	0	0	0	0	0	0
00054a5e	bbq	0	0	0	0	0	0
0005c987	Hey...	1	0	0	0	0	0
0006f16e	Before	0	0	0	0	0	0
00070ef9	Oh, and th	0	0	0	0	0	0
00078f8c	"	0	0	0	0	0	0
0007e25b	Bye!	1	0	0	0	0	0
00089788	REDIRECT	0	0	0	0	0	0
0009801b	The Mitsu	0	0	0	0	0	0
0009eaea	Don't	0	0	0	0	0	0
000b08c4	"	0	0	0	0	0	0
000bfd08	"	0	0	0	0	0	0
000c0dfd	"	0	0	0	0	0	0
000c6a3f	"	0	0	0	0	0	0

Figure 6: Sample Dataset

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The dataset used in this research project is in.CSV format. There are five attributes in the dataset, and 500 entries are examined. The text was categorised as abuse, highly malignant, malignant, threat, and loathe in this regard. Figure 6 displays the dataset sample. The characteristics vary throughout texts.

B. Data Preprocessing

We can pre-process data with the help of natural language processing (NLP) libraries. The preprocessing steps involved are as follows:

a) Converting all text to lowercase (for uniformity)

b) Stop word removal

c) Hashtag and URL removal

d) Tokenization of text

e) Punctuation removal

f) Lemmatization and stemming

B. Performance Metrics

Performance metrics provide information about the dataset's performance. The evaluation criteria used to evaluate the suggested scheme's presentation are Precision, Recall, F-measure and Accuracy. Here, conventional count values are taken advantage of, including True Positive (Tp), True Negative (Tn), False Positive (Fp), and False Negative (Fn).

$$\Pr ecision = \frac{T_p}{T_p + F_p} \times 100 \quad (1)$$

$$Fmeasure = 2 * \frac{\Pr ecision * recall}{precision + recall} \quad (3)$$

$$\operatorname{Re} call = \frac{T_p}{T_p + F_n} \times 100 \quad (2)$$

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \quad (4)$$

These estimations are unequivocally taken to decide the calculations' presentation in light of the assessment of the informational index chose for the review.

C. Results and Discussions

This part gives a full report on the results of the cyberbullying calculations, which are implicit the Python scripting language. The calculations incorporate DNN, ANN, RBFN. All the calculation viability is assessed utilizing f-measure, exactness, accuracy, and review. The figure 8 shows the extent of accuracy, review and f-measure for every one of the three techniques.

Figure 7 shows the consequences of the exhibition investigation of each of the three calculations before information Pre-handling. The DNN calculation accomplishes the most noteworthy accuracy (84.80%), review (82.24%), and F-measure (83.01%) values. The accuracy worth of 80.29%, review worth of 81.30%, and F-measure worth of 81.25% are accomplished utilizing DNN. The ANN Calculation is accomplished with accuracy of 81.58%, review of 80.37%, and F-proportion of 82.29%.

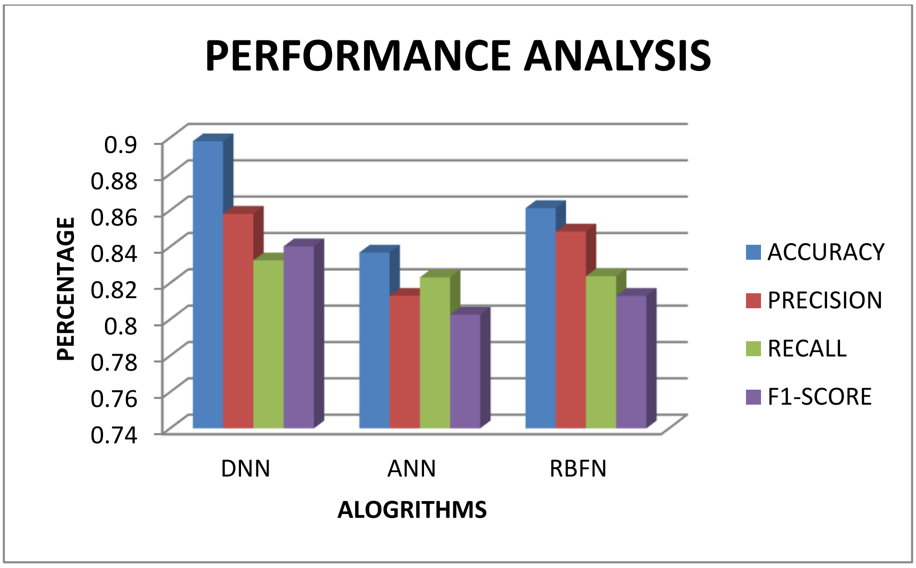

Figure 7: Performance Analysis of algorithm before preprocessing

As demonstrated in Figure 7, the accuracy of the comparison measure is assessed using methods that are currently available and advised. The algorithm is shown on the x-axis, while the accuracy numbers are shown on the y-axis.

Table 2: Performance analysis of algorithm

Algorithms	Accuracy	Precision	Recall	F-measure
DNN	86.25	83.80952	82.24299	83.01887
ANN	82.25	80.29412	81.30841	81.25359
RBFN	84.76	81.58333	80.37383	82.29064

The results demonstrate that, in comparison to the other two available approaches, the DNN performs better. The performance analysis is displayed in Table 2.

Figure 8 shows the consequences of the exhibition investigation of each of the three calculations after information Pre-handling. The DNN calculation accomplishes the most elevated accuracy (85.80%), review (83.24%), and F-measure (83.24%) values. The accuracy worth of 81.29%, review worth of 82.30%, and F-measure worth of 80.25% are accomplished utilizing DNN. The ANN Calculation is accomplished with accuracy of 84.83%, review of 82.37%, and F-proportion of 81.29%.

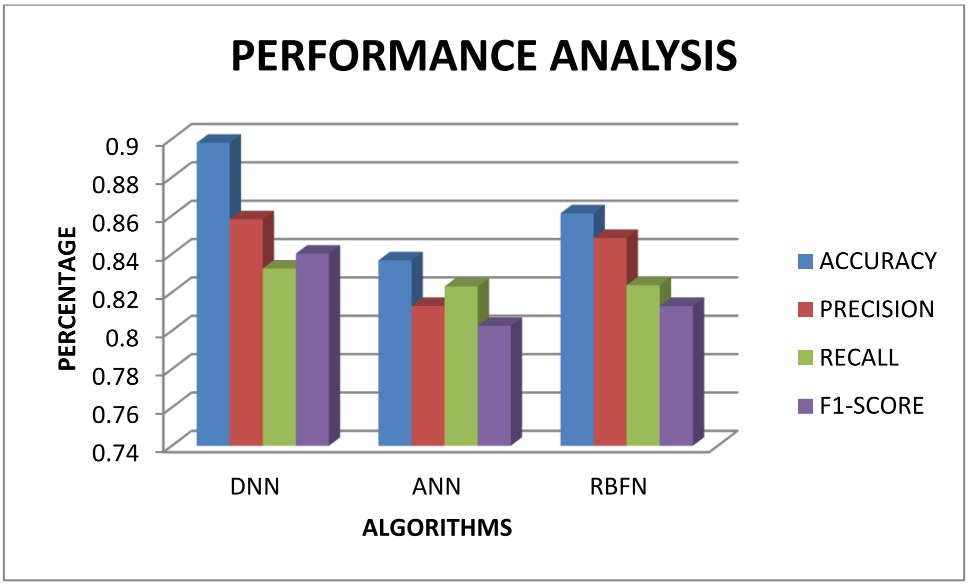

Figure 9: Performance Analysis of algorithm after preprocessing

As demonstrated in Figure 9, the accuracy of the comparison measure is assessed using methods that are currently available and advised. The algorithm is shown on the x-axis, while the accuracy numbers are shown on the y-axis.

Table 3: Performance analysis of algorithm

Algorithms	Accuracy	Precision	Recall	F-measure
DNN	89.80	85.80952	83.24299	84.01887
ANN	83.67	81.29412	82.30841	80.25359
RBFN	86.12	84.83333	82.37383	81.29064

The results demonstrate that, in comparison to the other two available approaches, the DNN performs better. The performance analysis is displayed in Table 3.

VI. CONCLUSION

It was observed that the most investigated subject in the climate of online entertainment was the ID of cyberbullying. Making a framework to recognize cyberbullying is fundamental for safeguarding individuals from provocation and guaranteeing wellbeing. In this work, the DNN is utilized to accomplish this. In this examination exertion, the accentuation, urls, html labels, and feelings from the info tweet messages are dispensed with first. Preprocessing is followed by sentiment feature extraction to increase classification accuracy. The study's test results demonstrate the effectiveness of the recommended strategy. The DNN outperforms in terms of classification performance when it comes to decreased better precision, recall, fmeasure, and accuracy.

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