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Research Article

CBDC-Net: Recurrent Bidirectional LSTM Neural Networks Based Cyberbullying Detection with Synonym-Level N-Gram and TSR-SCSOFeatures

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Abstract:

Social networks Cyber bullying has become another common problem in online social networks (OSNs) which exposes individuals to high risks of their mental health and interacting with others. Previous work in cyber bullying detection is often confronted with limitations in accurately detecting abusive behavior because of the intricacies in cyber space and evolution of cyber bullying practices. A new approach of Cyber bullying detection and classification network (CBDC- Net) for improving the effectiveness of detection of cyber bullying in OSNs based on natural language processing features, feature selection techniques, and deep learning algorithms is also presented in this study. CBDC-Net can overcome these challenges to existing detection methods of cyber bullying using innovative Natural Language Processing (NLP) and Deep Learning approaches. In the data preprocessing step, CBDC-Net filter and normalize the text data that is openly collected from OSNs. After that, CBDC-Net extracts features using a Synonym Level N-Gram (SLNG) approach and it incorporates both the word and character-based information to make the synonyms of text much better than the other method. After that, CSI of CBDC-Net applied Textual Similarity Resilient Sand Cat Swarm Optimization (TSR-SCSO) for feature selection to give an iterative value of their features' importance level to detect cyber bullying. Last, in CBDC-Net, a Recurrent Bidirectional Long Short-Term Memory (LSTM)Neural Network for classification (RBLNN) is used as classification approach is applied, which recognizes the sequential nature of textual data enabling proper distinction between cyber bullying cases. Last but not the least, the CBDC Net provides a promising solution for solving the mentioned problems of cyber bullying detection in OSNs.

1. Introduction

To the increasing extent of occurrence and severity of cyber bullying, identifying this phenomenon in OSNs has emerged as an important research issue [1]. Electronic bullying and specifically targeting and threatening those individuals through electronic means is extremely dangerous in terms of impact on the targeted person's mental health and safety Consequences of Victim Cyber Bullying are very severe, especially for youngsters and youth because nowadays, a major part of youth is active on social networks. Due to the anonymity, easiness of use and popularity of OSNs, this is even more so the case and there is a need to find good detection methods [2]. Text contains a lot of valuable information that is necessary to investigate cy berry bullying from the OSNs. Notably, while traditional bullying occurs physically and leaves little evidence, cyber bullying, often in the form of written or written based involves posts, comments, messages, chats [3]. Consequently, the evaluation of these textual data allows researchers to ascertain several patterns, linguistic features and context that helpful in determining cyber bullying behaviour. Using NLP principles [4], machine learning [5], and social network analysis [6], methods, the academicians can create elaborate techniques for the precise identification of cyber bullying cases. The main goal of detecting cyber bullying from textual data is to protect people and their mental state for being bullied, particularly prescribing to children and teenagers.

Several students become victims of cyberbullying suffer from different adverse effects such as psychological torment, depression, anxiety and social isolation and thought of suicide. Text classification of cyber bullying messages to alert the community at an early stage will help to introduce precaution measures and assistance to the victims. Moreover, it is critical to pay attention on cyber bullying as a task of promotion of safety and tolerance to everyone on the internet [7]. OSNs which refer to online social networks are virtual societies where people interact, disseminate, and exchange information. However, the use of cyber bullying hinders trust and social coherence, − hostility is created as a result making a deterioration of online communities [8].

Consequently, the positive outcomes of OSN with functional yet robust cyber bullying detection mechanisms are to address these malicious behaviours, support healthy OSN engagement, and enforce community norms. Further, research related to cyber bullying detection from textual data helps to enhance the state of the art of computational social science and digital forensic domains. The subject matter of this research cuts across psychological, sociological, linguistic, computer science, and big data analytics to propose solutions. By analysing various linguistic characteristics, attitudes, connections and behaviour in OSNs [9] the researchers can get a better understanding of the processes that take place in cyberbullying and its effects on users. Furthermore, the creation of improved detection algorithms strengthens the operations of police departments, legislation bodies, policy makers and moderators of social platforms in the fight against cyber bullying and in the implementation of regulations and policies.

Finally, research motivation for detecting cyberbullying from textual data in OSNs is due to the purpose of preventing people from being bullied, changing the current negative trends in OSNs, supporting science and creating knowledge for improving the situation, and providing useful recommendations and tools to all stakeholders who are interested in fighting against cyberbullying. What does this mean for researchers? It means that using textual data analysis they can become one of the major defenders against cyberbullying and provide safer environment within different online communities. The implications of this work are as follows

- Incorporating both word and character-based analysis, SLNG captures nuanced semantic information, enhancing the accuracy of cyberbullying detection.
- Utilizing swarm intelligence principles, TSR-SCSO efficiently selects relevant features while minimizing redundancy and overfitting, improving classification performance.
- Leveraging RBLNN's ability to capture sequential data, our model effectively analyzes textual content to distinguish cyberbullying instances with high accuracy.
- The proposed CBDC Net addresses the pressing need for effective cyberbullying detection in OSNs, promoting a safer and more positive online environment.

In the following sections, this paper reviews previous works in Section 2 features a study of the existing methodologies toward identifying cyberbullying. Section 3 considers proposed methodology including the integration of deep learning models and preprocessing the data to get improved accuracy of cyberbullying detection. After this, Section 4 provides performance comparisons of the proposed approach from experimental studies conducted. In the end, Section 5 presents an overall conclusion of the study and the importance of using deep learning to address the cyberbullying issue, and directions of possible research work in this area.

The four different DL techniques compared in Fati, et al. [10,11] while using the globally famous Twitter data set to establish their efficacy. The challenges that accompanied identification of the offending tweets were addressed using attention-based DL metrics. The Word2vec model with the help of CBOW strategy was used for making weights for the embedding layer. These weights were then passed through a convolution and pooling to reduce the feature dimensions and to also learn about the position invariance of offending words. Alqahtani et al., [12] worked on enhancing a method for categorizing six specific types of cyberbullying tweets. When applying multi-classification algorithms on the dataset that payed attention to cyberbullying, their method achieved quite good level of accuracy especially when using the TF-IDF and Bi-Gram feature extraction method. Muneer et al. [13] used an ensemble stacking learning technique to classify cases of cyberbullying in the micro blogging site, twitter.

Gattulli et al. [14] applied HAR-related models and approaches for human activity detection as subjects completed a survey using a smartphone application. Features were extracted in numerous forms, including statistical features, word N-Grams, combined n-grams, as well as BOW using TF-IDF weighting. These features were cross tested using GridSearchCV with multiple folds throughout different experimental scenarios. The detection method has been designed keeping in mind the various types of users' writing styles on social media that comprise a pool of informal and non-standard expressions.

Dewani, et al. [15] performed an in-depth analysis with the extraction of several properties such as statistical features, word N-Grams, combination n-grams, and BOW model with TF-IDF weighting. The authors experimented with GridSearchCV and cross-validation approaches in different scenarios of experiments. The detection approach was designed to consider the user's textual inputs along with his or her proper styles on social media, which are applied in informal and less formal writing modes. López-Vizcaíno et al. [16] considered textual data from comments to improve the performance of the primitive early detection models, including fixed, threshold, and dual models, with three different approaches for improvement. To start with, the authors first calculated the performance of Doc2Vec features without using MIL in early detection models and then calculated their respective performances. Time-Aware Precision (TAP) was considered as the evaluation metric to evaluate the performance of the proposed methods concerning early detection.

N. A. Samee et al. [17] used word embeddings and emotional attributes under federated learning as a solution method to overcome the drawbacks in the preceding methods as far as centralized data handling and the users' privacy is concerned. Word embeddings very effectively encapsulate the meaning or context of a text. This method enables a more profound understanding of it. This enhances the capability to identify cyberbullying by using extracted emotional elements from textual data. Chen et al. [18] combine several traditional machine learning methods, deep learning techniques, and a pre-trained language model specific to Chinese as base components. Building on this architecture, they later proposed an adapted version of BERT known as XLNet integrated with deep Bi-directional Long Short-Term Memory networks to facilitate detection in Chinese language texts. In addition to that, real-time instances of comments regarding cyberbullying are collected to augment the hate speech corpus in Chinese. Hasan et al. [19] carried out an exhaustive survey of existing literature to identify the specific gap areas. They suggested a defensive framework, which emphasizes the detection of cyberbullying using deep learning. The framework includes methods on data representation and different deep learning models. In addition, current deep learning techniques applied in cyberbullying detection were accompanied by an overall exhaustive review, recounting their significant contributions and suggesting possible future research directions.

Teoh Hwai Teng et al. [20] presented literature review of cyberbullying categorization, past and present, and concluded with 126 manuscripts. It also draws attention to text-based cyberbullying as well as multi-modal cyberbullying. An evaluation was performed on the machine learning workflow, which comprised the following four key components: assessment of dataset, pre-processing assessment, feature assessment, and method assessment. Čepulionytė et al. [21] had devised an innovative pre-processing method that used multiple layers in the detection and classification of toxic communications in social networks. This technique seeks to mitigate harm by pushing negative messages, fraudulent content, and aggressive comments in social media posts and comment threads down. Consequently, the amount of technical expertise required to assess the effects of malicious messages would be lowered. Samee et al. [22] have studied in detail the involvement of word embeddings and emotive features as well as federated learning. Additionally, they used the structure of BERT, Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), and Long Short-Term Memory (LSTM). In the process of hyperparameter and neural configuration tuning, better results are achieved, thus producing better outputs. These methods are utilized in determining incidents of cyberbullying by utilizing publicly available multi-platform data streams from social media, which are specifically based on cyberbullying incidence.

Miran et al. [23] were among those making further contributions to the continued conversation regarding creating more secure digital spaces while also reconciling the quite complex challenge of limiting hate speech but preserving free speech rights. The collaboration of academics, platform developers and stakeholders has been recognized as an essential aspect in creating effective and ethical content moderation policies on social media sites like Twitter and many more. Huang et al. [24] carried out the analysis to investigate how the variable "part of speech" impacts comments related to cyberbullying. They also did an analysis of the three classification models, viz. random forest, naïve Bayes, and support vector machine so that the posts of cyberbullying were classified into different parts of speech. The research also explored the most appropriate combinations of part-of-speech for the models. Dar et al. [25] did research about policy-based Urdu tweet spam detection. More than 1,100,000 real-time tweets were collected from different users. This was done within the Twitter limit of 100 tweets per hour. Snscrape library is used to collect the data, and this library provides an API for extracting details such as username, URL, and content of a tweet. A machine learning pipeline was created composed of TF-IDF, Count Vectorizer, and multiple classifiers such as multinomial naïve Bayes, support vector classifier with RBF kernel, logistic regression, and BERT. The extraction process for features was done according to the requirements stipulated by Twitter policy.

Khairy et al. [26] have also explored the performance of techniques in handling class imbalance in cyberbullying datasets. In this experimental study, the stage at preprocessing was further added to enhance the performance of the machine learning algorithm. Besides, the study investigated the impact of biased test sets on the accuracy of classification in four independent datasets for cyberbullying. Gamal et al. [27] made a comparative evaluation of two approaches to inappropriate language detection, including lewd comments in Chittagonian. The former relied on low-level keyword matching, whereas the latter applied high-level ML and DL. Anwar et al. [28] presented an exhaustive literature review on how sentiment analysis affects student satisfaction and online learning, especially in the context of STEM fields, based on the PRISMA framework. Allouch et al. [29] created a corpus consisting of 1,891 expressions from real situations-some textual and others audio. The films were systematically assembled and categorized into three groups: neutral, offensive and suggesting dangerous times.

2. Material and Methods

Proposed Methodology

The proposed research project introduces CBDC-Net that is composed of four fundamental stages: data preprocessing, feature extraction using SLNG, feature selection approach via TSR-SCO, and classification via RBLNN, as presented in figure 1. Integrating these phases into a single framework will be aimed at the design of a robust and efficient mechanism to detect cyberbullying incidents over online social networks. The methodology of this paper is based on some advanced techniques from natural language processing, swarm intelligence, and deep learning and overcomes the complex issues involved with cyberbullying detection. We will thus detail experimentation and testing to demonstrate the effectiveness and reliability of the proposed CBDC Net in protecting people from online harassment and building a safer online domain.

Step 1: Data Preprocessing. During very initial phase of study, preprocessing of data collected from OSNs forms the initial step that comes across to clean them and prepare them for analysis. It involves various steps such as removing duplicate records, treating missing values and making the format of the text data uniform. Therefore, we further normalize the text by ensuring that words have consistent representations. For instance, we change all the text to lowercase format and eliminate all punctuations while preprocessing the data. Data preprocessing is required for enhancing the quality of the dataset and optimizing subsequent analytical procedures.

Step 2: SLNG Feature Extraction: This stage highlights the feature extraction stage from the preprocessed text data using the SLNG approach. Unlike conventional N-Gram methods that specifically consider individual words or characters, SLNG involves synonyms and word variation for a more definite grasp of semantic content. The integration of both word and character-level analyses by SLNG enhances our ability to identify the patterns and relationships within the text effectively. This feature extraction technique allows us to capture the context and meaning of the language used in the cases of cyberbullying to allow for more accurate detection.

Step 3 TSR-SCSO Feature Selection: In this phase, we make use of a new feature selection approach known as TSR-SCSO. The algorithm intended is to identify the most significant features that are among the feature set extracted SLNG characteristics that characterize cyberbullying activity the best. TSR-SCSO systematically evaluates each feature based on its ability to distinguish cyberbullying-related instances from non-cyberbullying-related. With assistance of swarm intelligence mixing similarity resilience, TSR-SCSO can successfully make an optimal subset of relevant features that would maximally yield the performance of classification with minimal redundancy against overfitting.

Step 4: RBLNN Classification: In the final step of our developed system model, we utilize RBLNN for cyberbullying classification. RBLNN is an architecture specifically designed for deep learning suitable for sequential data processing tasks, making it the best fit for the analysis of textual data. Utilization of bidirectional connections and long short-term memory units enables extensive capture of past and future context along the text, which would lend to a more subtle understanding and stratification of instances of cyberbullying. The classification model of the selected features from TSR-SCSO could be trained to highly distinguish cyberbullying from non-cyberbullying content.

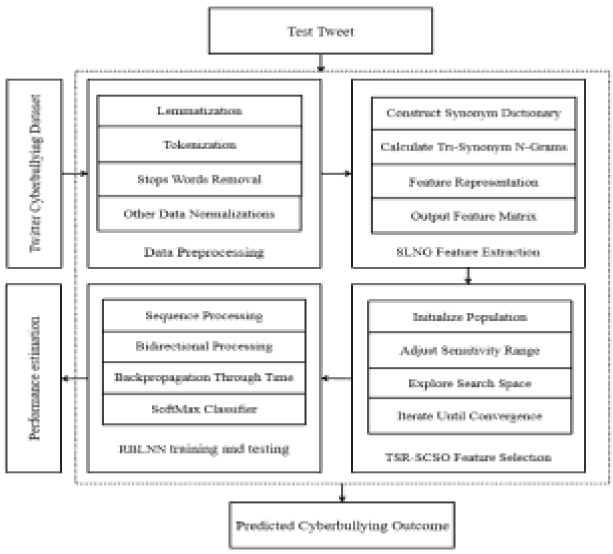

Figure 1. *Proposed CBDC-Net System Model.*

Preprocessing

Data preprocessing is an important step in the domain of NLP and text analysis, a gateway step in transforming raw textual data into something that would be suitable for later analysis and modelling work. The preprocessing step is carried out as a chain of techniques that generally clean up, standardize, and enhance the quality of the text data. Figure 2 is the suggested preprocessing steps and table 1 is algorithm for preprocessing. In the detection of cyberbullying, effective data preprocessing has taken place to handle the situation with precise and reliable results. One of the foremost ways in which data preprocessing occurs is through tokenization. Tokenization breaks text down into constituent elements known as tokens. This words, phrases, or even punctuation marks. The tokenization process helps to divide the text into significant units and allow subsequent analysis. For example, take the sentence: "The quick brown fox jumps over the lazy dog." Tokenizing this sentence would result in individual tokens for each word: ["The", "quick", "brown", "fox", "jumps", "over", "the", "lazy", "dog"]. Lowercasing is commonly used as a preprocessing step to standardize the text by transforming all letters to lowercase.

The normalization process ensures consistency in the representation of terms, treating words that consist of the same letters but are different in case as equivalent. For example, "Hello" and "hello" would be considered the same after being lowercased. This serves to eliminate the possibility of repetition of terms in further analytical work.

Another important technique is the reduction of words to their base or dictionary form, referred to as the lemma. With lemmatization, one achieves normalized variations of words that reduce redundancy while enhancing the accuracy associated with text analysis. For instance, for lemmatization, the word "running" would be reduced to "run." Different inflections of the same word are hence treated similarly in the analysis. The elimination of stop words is an important preprocessing operation that is aimed at eliminating frequently occurring words that add little to the meaning or do not sensibly alter the underlying nature of the text. Such terms, such as "the," "is," "and," and more, are ubiquitous in language but often have minimal semantic impact in analytical tasks. The removal of stop words eliminates extraneous noise and improves the efficiency of algorithms in text analysis by focusing on more meaningful content. Special character analysis identifies special characters, symbols, and punctuation marks happening in the text and handling them.

This preprocessing step involve the removal of special characters, taking care of emoticons/emojis, or dealing with any other non-standard characters that would disrupt the analysis. Handling special characters in an appropriate way during preprocessing simply means that such text data remains clean and interpretable across any other subsequent analysis tasks. Apart from the techniques, preprocessing may also involve handling numerical data, correcting spellings or typos, and dealing with encoding issues. The choice of preprocessing methods and their application may depend on the requirements of the analytical task as well as on the nature of the processed textual data.

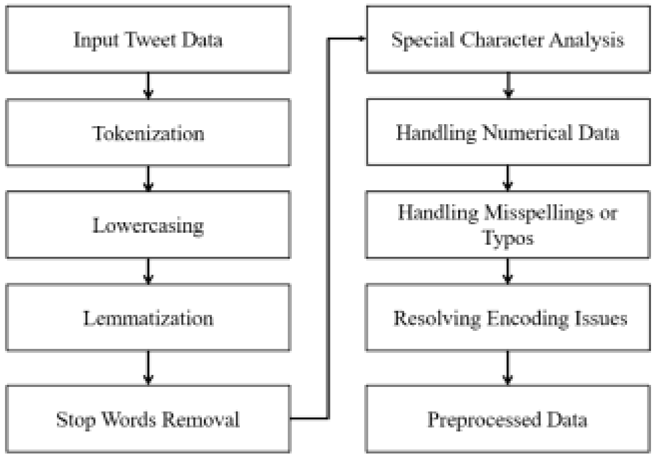

Figure 2. *Proposed Dataset Preprocessing Flowchart*

Table 1. *Proposed Data Processing Algorithm*

Input: Text Data **Output:** Preprocessed data.
Step 1: Break the text into smaller units called tokens (words, phrases, or punctuation marks).
Step 2: Convert all letters in the text to lowercase to ensure consistency in word representation.
Step 3: Reduce words to their base or dictionary form (lemma) to normalize variations and reduce redundancy.
Step 4: Eliminate common words (e.g., "the", "is", "and") that do not contribute to the overall context of the text.
Step 5: Identify and handle special characters, symbols, and punctuation marks present in the text.
Step 6: Address any numerical data present in the text, such as digits or numerical representations.
Step 7: Correct misspellings or typos in the text to ensure consistency and accuracy in subsequent analysis.
Step 8: Address any encoding issues that may arise due to different character encodings in the text data, which generates preprocessed data.

SLNG Feature Extraction

The SLNG extracts features from text data by generating n-grams based on synonyms, which gives a more substantial word representation of the text content for cyberbullying detection. Figure 3 shows

the proposed SLNG feature extraction and table 2 shows the SLNG algorithm.
It starts with preprocessed textual data available and can be at a document level, sentence-level, or paragraph-level. The actual contents of this text data could be filled with any words, phrases and punctuation. Next, synonym expansion means adding more vocabulary by taking synonyms of words from the text data. The purpose of this step is to grasp semantic changes of a word, and to expand the range of feature space semantics.
Lexical resources like WordNet or embedding-based methods can be used to obtain synonyms. Ngrams are the contiguous sequence of N tokens extracted from the text data. Feature Extraction SLNG generates both unigram (single token) and n-gram (consecutive tokens) features to overcome such text-sequence dissimilarities. If we take the sentence, "The quick brown fox jumps over the lazy dog," then the unigrams would be "The", "quick", "brown", etc, while the 2-grams would be "quick brown", "brown fox", and so on. It further means, for each word in this text, we consider the words we find in the synonym dictionary as synonyms of the word as well, so we create uni-synonym n-grams. The uni-synonym n-grams are notation as:

$$N - grams_{uni-synonym} = \{word\} \cup \{synonyms\ of\ word\} \quad (1)$$

Similarly, bi-synonym n-grams are generated by considering pairs of adjacent words along with their synonyms. Bi-synonym n-grams are represented as:

$$N - grams_{bi-synonym} = \{word1 - word2\} \cup \{synonyms\ of\ word1 - word2\} \cup \{word1 - synonyms\ of\ word2\} \cup \{synonyms\ of\ word1 - synonyms\ of\ word2\} \quad (2)$$

Subsequently, tri-synonym n-grams can be developed based on triplets of consecutive words and word synonyms. Tri-synonym n-gram are like bi-synonym maintaining set of synonyms for each term in the triplet. Then there is one feature in the feature vector for each of the unique n-gram extracted from the text data. High dimensionality of the feature vector is achieved to have a binary value, 1 to represent presence of an n-gram/unigram and 0 elsewhere. The Feat/SLNG feature representations are encoded numerically using established procedures like converting to binary forms by means of one hot encoding or word frequency analysis by TF-IDF before feeding into the models.
The word level analysis apart from capturing word's meaning and function in the text, SLNG also involves character- level analysis to capture morphological and the ways orthographic features are used. Character n-grams, consecutive k characters in the text data are also extracted from text in addition to the word features. This is used to include the sub-word information into the feature vectors However, one process the feature vectors through normalization where feature values are scaled between 0 and 1 before comparing documents or data sets. Standardization procedures was performed using L2 normalization or min-max scaling to make the feature values resist in a certain range. The result of the SLNG feature extraction process is a feature matrix, here a row is an instance or document, and column is the features extracted from the textual data set. This feature matrix is used for other analysis activities including classification, clustering, and information retrieval activities.

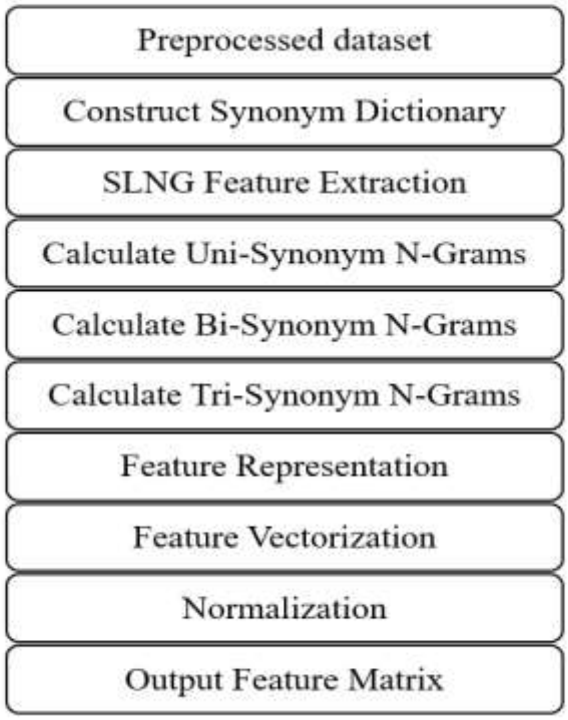

Figure 3. *Proposed SLNG Feature Extraction Flowchart*

TSR-SCSO Feature Selection
The TSR-SCSO feature selection algorithm is named after the wild behavior of sand cats and cat family more generally. Table 3 shows the proposed TSR-SCSO feature selection algorithm. Figure 4 presents the flow chart of the proposed TSR-SCSO feature selection The sand cats who are sensitive to noises below 2KHz preferably inhabit sandy and stony deserts. Nevertheless, the sand cats differ from the domestic cats in the following aspects: the bottom of their feet is hairy and cannot easily be tracked therefore its recordings. Their foraging strategy is unique with both subterranean and above ground search for prey that enables rapid prey identification. SCSO is another algorithm knitted on the hunting

style of the sand cat and is meant to maximize the opportunity finding and exploration phase as well as the exploitation phase.

The TSR-SCSO algorithm starts with the population generation whereby the search space is filled with initial solutions/Populations are initialized randomly in the search space. Each solution corresponds to a search agent that is used to model and solve a predefined problem to optimality. A merit function assesses the solutions and the way of arriving at it to provide direction towards the best solutions. During iterations, the sensitivity range of each search agent is sequentially modulated via the inverse linear reduction ($\overrightarrow{r_G}$. It regulates the surface search agent behaviour so that balance between exploration and exploitation can be achieved. Exploration phase involves search agents rapidly searching space while exploitation phase is about

***Table 2**. Proposed SLNG Feature Extraction Algorithm*

Step	Description
Preprocessing	Clean and standardize the text data through tokenization, lowercasing, lemmatization, and stop words removal.
Construct Synonym Dictionary	Create a dictionary containing synonyms or similar words for each word in the text corpus.
SLNG Feature Extraction	Generate n-grams based on synonyms at different levels and combine them to form feature representations.
Calculate Uni-Synonym N-Grams	Create n-grams by considering the word and its synonyms, capturing variations of individual words.
Calculate Bi-Synonym N-Grams	Generate n-grams for pairs of adjacent words and their synonyms, capturing combinations of synonyms.
Calculate Tri-Synonym N-Grams	Optionally, create n-grams for triplets of consecutive words and their synonyms, capturing more context.
Feature Representation	Combine the uni-synonym, bi-synonym, and optionally tri-synonym n-grams to form the SLNG feature representation.
Feature Vectorization	Convert the SLNG feature representations into numerical vectors using encoding techniques like one-hot encoding or TF-IDF.
Normalization	Apply L2 normalization to maintain the uniform range of features.
Output Feature Matrix	Incorporate the SLNG feature vectors into a cyberbullying detection model to classify instances effectively.

improvement in solutions to an optimum solution. To escape trapping in local optima, a parameter $\vec{r}$ controls the range of sensitivity of each search agent involved in the process. The probability distribution of search agents is updated in turn with reference to the best candidate position, its actual position, and the range of sensitivity. The algorithm also applies a random angle θ on the movement in circular form to facilitate examination of the search space effectively.

The sensitivity range, ($\overrightarrow{r_G}$) is calculated for each search agent using Equation (3). In textual feature selection, the sensitivity range defines how deep the search agent goes into or how much it relies on the search space. The S_M include the maximum sensitivity range, $iter_c$ is include the current iteration number. It is noted that the $iter_{max}$ has the meaning of the maximum number of iterations.

$$\overrightarrow{r_G} = S_M - \left(\frac{S_M - iter_c}{iter_{max}}\right) * SLNG_{features} \quad (3)$$

Equation (4) calculates the transition parameter ($\vec{R}$) of each search agent. The transition parameter determines how much exploration, and exploitation will be done to ensure the optimization results are achieved. Incorporating rand (0,1) into the equation enables the search agent to have geographical variability on textual feature selection tasks, complementing exploration and exploitation approaches.

$$\vec{R} = 2 \times \overrightarrow{r_G} \times rand(0,1) - \overrightarrow{r_G} \quad (4)$$

In Equation (5), $\vec{r}$ is the given parameter for sensitivity range for the search agents. The equation refers a sensitivity range with the following parameters max sensitivity range which is $\overrightarrow{r_G}$ and rand (0,1). This parameter controls the exploration and exploitation of the search agents' movements within the search space during textual feature selection.

$$\vec{r} = \overrightarrow{r_G} \times rand(0,1) \quad (5)$$

In equation (6), $\overrightarrow{pos}(t+1)$ is an updated position of the search agent at time $\boldsymbol{t+1}$. The position update is quantified by the sensitivity range ($\overrightarrow{pos}(t+1)$), the difference between the best-candidate position ($\overrightarrow{pos_{bc}}(t)$) and the current position ($\overrightarrow{pos_c}(t)$), and an outlined random factor rand(0,1). Leveraging this equation, movement can take place of search agents toward favourable areas in the search space where appropriate feature selection is feasible.

$$\overrightarrow{pos}(t+1) = \vec{r}.(\overrightarrow{pos_{bc}}(t) - rand(0,1).\overrightarrow{pos_c}(t)) \quad (6)$$

In equation (7) and Equation (8), $\overrightarrow{pos_{rnd}}$ represents the distance between the best position ($\overrightarrow{pos_b}(t)$) and the current position ($\overrightarrow{pos_c}(t)$) of the search agent. The equation marks the measure, because of the displacement vector, to a probable new position in the search space. This distance measurement instructs the execution of the algorithm in determining textual features for the exploration as well as exploitation phases.

$$\overrightarrow{pos_{rnd}} = |rand(0,1).\overrightarrow{pos_b}(t) - \overrightarrow{pos_c}(t)| \tag{7}$$

$$\vec{pos}(t+1) = \overrightarrow{pos_b}(t) - \vec{r}.\overrightarrow{pos_{rnd}}.\cos\theta \tag{8}$$

The equation (9) updates the position of the search agents according to the transition parameter $\vec{R}$, the sensitivity distance $\vec{r}$, and the angle of rotation θ. There are two scenarios with regards to how the position of the search agent can be updated based on $|R|$ whose absolute value determines whether $|R|$ is less than 1 or greater than 1. When $|R| \leq 1$ for instance, an agent will proceed to switch its location towards the best position $\overrightarrow{pos_b}$(t) assuming that a random angle of orientation θ is in action. For $|R| >$ 1, however an agent will get hold of a new position determined by movement towards it through the best candidate position (($\overrightarrow{pos_c}$(t)) and its present position ($\overrightarrow{pos_{bc}}$(t)).

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{pos_b}(\mathrm{t}) - \overrightarrow{pos_{rnd}}.\cos\theta\,.\vec{r}|R| \ \leq 1; exploitation \\ \vec{r}.\left(\overrightarrow{pos_{bc}}(\mathrm{t}) - \mathrm{rand}\ (0,1).\overrightarrow{pos_c}(\mathrm{t})\right)|R| > 1; exploration \end{cases} \tag{9}$$

With regards to the context of the textual feature selection where it relates to classifiers, the fitness function determines the quality of the feature subset by measuring the class separability capability, or the text data categorization capability. This function is effective in giving value to how a specific feature set enhances the effectiveness of the text classification or sentiment analysis model being developed using a machine learning approach.

The best output textual features correlate with the optimal subset of the features selected by the TSR-SCSO algorithm after the end of the optimization procedure. These features reveal maximal significance and an ability to discriminate among the features of the analyzed texts in accordance with the set goals. Their selection stems from their contribution towards running the performance metrics that has been evaluated using a fitness function. The best output textual features assist in text related tasks of improving the accuracy and the efficiency of machine learning models.

$$Best\ Features = \mathrm{argmax}\left(FF\left(\vec{X}(t+1)\right) * SLNG_{features}\right) \tag{10}$$

The best features were the optimal subset of features where in the algorithm selected the features which maximized the combined value of the fitness function and the input SLNG features. The symbol argmax shows that what a feature subset which maximizes some quantity defined in parentheses is selected. It outputs feature subset that maximizes the value of the combinations of the objective. The value of the combined objective that maximizes the features is given by the fitness value $FF\left(\vec{X}(t+1)\right)$

Fitness function measures the quality of the feature subset regarding the problems of classification.

RBLNN Classifier

The RBLNN is widely used for sequential data processing tasks such as cyberbullying classification from textual data. Unlike traditional feedforward neural networks where each input is processed independently, RBLNN maintain a sense of memory or context by considering previous inputs while processing the current input.

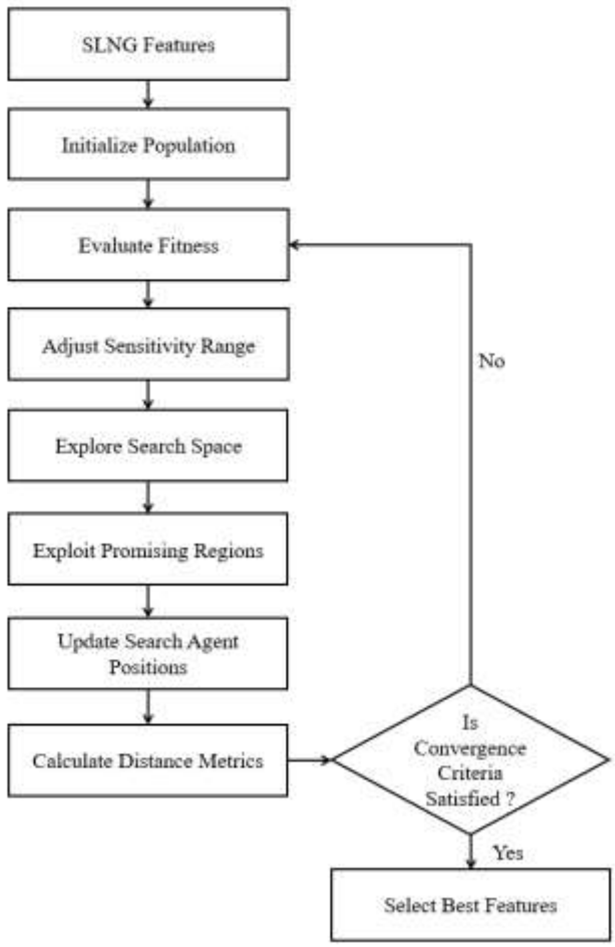

***Figure 4**. Proposed TSR-SCSO Feature Selection Flowchart*

***Table 3**. Proposed TSR-SCSO Feature Selection Algorithm*

Input: SLNG Features **Output:** TSR-SCSO Selected Optimal Features
Initialize Population: Randomly initialize search agents within the specified search space bounds. **Evaluate Fitness**: Compute the fitness function for each search agent to evaluate the quality of the solution. **Adjust Sensitivity Range**: Dynamically adjust the sensitivity range of each search agent based on the current iteration number and maximum iterations. Gradually reduce the sensitivity range to transition from exploration to exploitation. **Explore Search Space**: During the exploration phase, search agents swiftly explore the search space to identify potential solutions. **Exploit Promising Regions**: Transition to the exploitation phase to refine solutions towards the optimal solution. Balance exploration and exploitation using transition parameters. **Update Search Agent Positions**: Update the positions of search agents iteratively based on the best candidate position, current position, sensitivity range, and random factors. Use a random angle to guide movement within the search space. **Calculate Distance Metrics**: Compute distance metrics between the best position and the current position of search agents to guide exploration and exploitation phases. **Iterate Until Convergence**: Repeat steps 2-7 iteratively until convergence criteria are met or maximum iterations are reached. **Select Best Features**: Determine the optimal subset of features by maximizing the combined value of the fitness function and SLNG features. Select the feature subset that yields the highest value of the combined objective.

This makes them particularly suitable for tasks where the sequence of inputs carries important information, as is often the case with text data. Figure 5 shows the proposed RBLNN architecture with layer wise details. The operation of RBLNN involves several key components. Let's break down its operation:

Input Layer: In cyberbullying classification, textual data is preprocessed and represented as numerical TSR-SCSO vectors. Each word or token in the text is converted into a vector representation.

Bi-LSTM Layer with Sequence Processing: The RBLNN, in the second phase, takes in the input stream in a sequential manner focusing on the word sequence of the text. At a certain instant, the network utilizes a current input token (X_t) and a previous hidden state (h_{t-1}) to determine a current hidden state (h_t). This computation is represented by the equation:

$$h_t = f(h_{t-1}, X_t) \tag{11}$$

Where f is the activation function and h_t is the hidden vector containing the neuron information now t in the time series data.

Bi-LSTM Layer with Bidirectional Processing: The importance, as it is used in conjunction with the RBLNN, is that this layer makes bidirectional processing possible, allowing one part of the RBLNN to process inputs X_i at a specific xi and the other half of the network to any x_i in the future such as X_i. Such mechanisms are beneficial to the neural network model-level comprehension, allowing it to assimilate critical contextual information from both past and future time slots.

Output Layer: An activation function (for example, ReLU, sigmoid or tanh) is used on the hidden state h_t to add non-linearity and control the information. The hidden state is dotted with a weight matrix and together with the factors W_{h_t} this weight matrix will compute the output y_t:

$$y_t = W_{h_t} \cdot h_t \tag{12}$$

During the training phase, the RBLNN is trained to update the values of its parameters such as weights and biases through optimization techniques including gradient descent. This is done to achieve a set target where the predicted output is close to the actual target labels and the known output. Since RLNNs are rolled out across time, back propagating the error involves propagating the error across time steps and since the error propagates across time steps, the BPTT algorithm can be used to enable learning from a past time step to modify parameters to be used for future iterations of the model. In the classification of cyberbullying text instances, the RBLNN will determine the cyberbullying or non-cyberbullying class to which the text sequence belongs as determined by features expected from the text sequence using the TSR-SCSO algorithm. Constructing the input from the sequence of words together with their context, the RBLNN can detect words which exhibit the characteristics of cyberbullying behaviour.

3. Results and Discussions

Based on the Twitter-Cyberbullying Datasets, the effectiveness of various methods and measurement indicators is contrasted in this section. Different methods of machine learning and methods of evaluating the results are compared to analyze which of them work better in terms of detecting cyberbullying incidents. The evaluation intends to

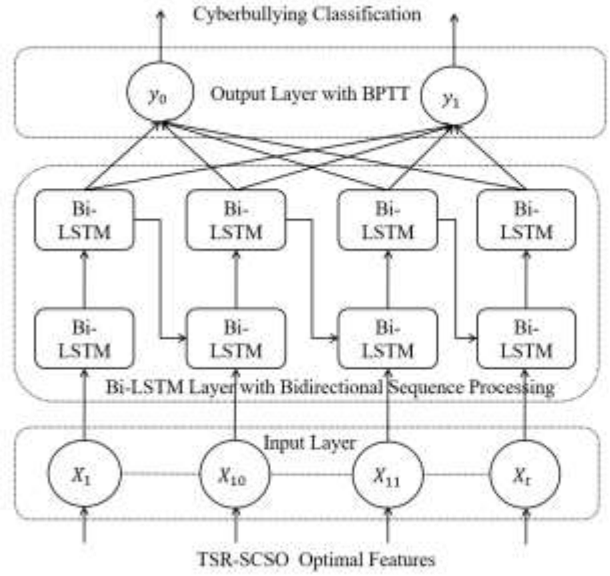

***Figure 5**. Proposed RBLNN Architecture*

determine the best approach of detecting cyberbullying from the tweets in Twitter.

3.1 Dataset

This researching employed the streaming feature of the Twitter Application Programming Interface to collate a vast sample of tweets in cyberbullying. Since then, thirty-two key characters related to cyberbullying were identified, used to establish the input dataset. The analyzed dataset constitutionally includes 130K + tweets and are sorted under categories such as racism, insult, sexism, and profanity from a total sample of 435,764 tweets. Many of these tweets were shocking or obscene in some way, so I had to scan the tweets carefully. Only those tweets that were written in a language other than English and which had English words were not included in the dataset. Moreover, retweet only option was checked to control the content proper, although the analysis involved only English language tweets. The variables 'reliable', 'tweet relevance' and 'language consistency' allowed for the removal of 57,027 of the initial tweets while the remaining 10,323 tweets were randomly selected for the final dataset, which was approximately 10,000 in size. All these steps were performed in a fully automated manner to optimize time and make the preprocessing procedures of datasets more efficient. To this end, this study employed a comprehensive data collection and preprocessing technique to establish a robust dataset that could enable accurate analysis as well as identifying cyberbullying cases in the Twitter platform.

3.2 Ablation Study

An ablation study is a method employed in testing the impact or value of specific components or features of a system or model within the general research framework. The term "ablation" concern with their removal or elimination and the consequent-testing of how this impacts overall performance or behavior. In its simplest form, an ablation study means that a part of a system is systematically removed or altered in some way and the effects on the performance or behaviour of the new are investigated. The main goal of an ablation study is to investigate the components of a system on a more detailed level by investigating the influence of the individual parts. In this way, if one or several components are either eliminated or made unavailable, and other components of the system are maintained constant, researchers will be able to examine how much of an impact these components have to the system's performance.

Table 4 and figure 6 show the results of an ablation study performed to evaluate CBDC-Net, a model that the authors have developed for cyberbullying identification. The first column of the table having the title of "CBDC-Net with only RBLNN Classifier" demonstrates the performance of the model when RBLNN classifier is only implemented without using SLNG feature extractor or TSR-SCSO feature selector. In this setup, the model yields an accuracy of 96.301%, and a precision of 95.424% together with a recall of 96.835% and an F1-Score of 96.316%, and a sensitivity of 96.814%. The second row, CBDC-Net without SLNG Feature Extraction, shows performance when no use has been made of SLNG feature extraction while TSR-SCSO feature selection, and RBLNN classifier are used. Nevertheless, the model developed in this study achieves higher accuracy than the model in the control study across the board as summarized in table 6 where the accuracy of the model is 97.937%, whereas the precision is 97.535%, the recall is 97.398%, the F1-measure is 97.615%, and the sensitivity is 97.892%. Likewise, the third bar titled, 'CBDC-Net without TSR-SCSO Feature Selection', shows the result of CBDC-Net when TSR-SCSO feature selection is excluded while the SLNG feature extraction and/or the RBLNN classifier is included. The results are still higher with an accuracy of 98.141%, for a precision of 97.153%, recall of 97.006%, F1-score of 98.688% and sensitivity of 98.236%.

Finally, the last column, "Overall CBDC-Net," represents the performance of the complete CBDC-Net model, incorporating all components including SLNG feature extraction, TSR-SCSO feature selection, and the RBLNN classifier. As expected, this configuration yields the highest performance across all metrics, with an accuracy of 99.75%, a precision of 99.98%, a recall of 99.58%, an F1-score of 99.34%, and a sensitivity of 99.55%.

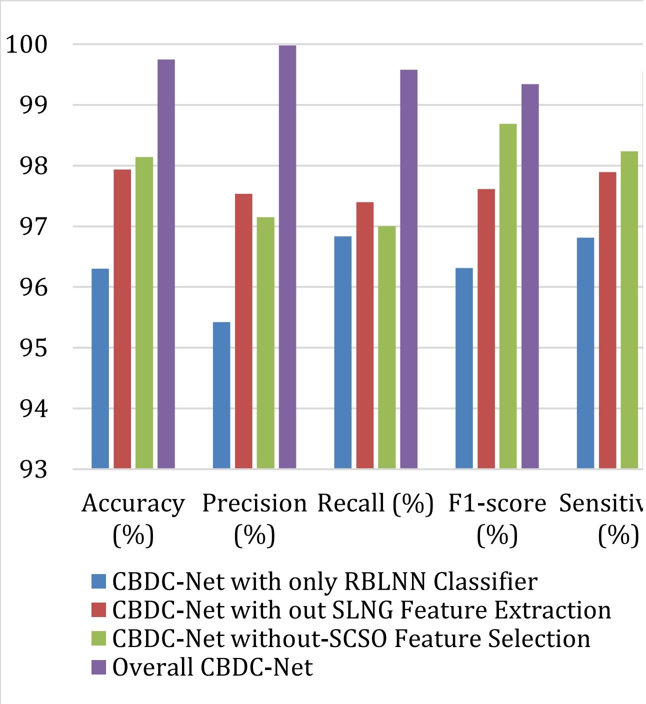

***Figure 6**. Ablation study of CBDC-Net Graphical Representation.*

***Table 4**. Ablation study of CBDC-Net*

Metric	CBDC-Net with only RBLNN Classifier	CBDC-Net with out SLNG Feature Extraction	CBDC-Net without-SCSO Feature Selection	Overall CBDC-Net
Accuracy (%)	96.301	97.937	98.141	99.75
Precision (%)	95.424	97.535	97.153	99.98
Recall (%)	96.835	97.398	97.006	99.58
F1-score (%)	96.316	97.615	98.688	99.34
Sensitivity (%)	96.814	97.892	98.236	99.55

3.3 Performance Evaluation

Table 5 and figure 7 include the comparative analysis of the performance of the word-based cyberbullying detection models: CBOW-DL [11], TF-IDF [12], BERT-M [13], as well as the proposed CBDC-Net. As for accuracy, CBDC-Net outperforms the CBOW-DL [11], TF-IDF [12], and BERT-M [13]. CBDC-Net is significantly more accurate than models CBOW-DL [11] with a difference of 4.55%, TF-IDF with a difference of 2.10%, and BERT-M [13] with a difference of 1.50%. This suggests that CBDC-Net has a higher overall correct classification rate for instances of cyberbullying. Concerning the accuracy of the outcomes, the average precision achieved by CBDC-Net is 3.54%, 2.26%, 0.84% more than CBOW-DL, TF-IDF, and BERT-M, respectively. This suggests that, out of all the positive predictions, CBDC-Net suggests a better recall rate for true positive cases than the other models. Taking calculations from the tables above, we can detect that CBDC-Net has slightly higher recall rates from CBOW-DL [11] by about 1.10%, from TF IDF [12] about 2.24%, and from BERT-M [13] at about 0.45 This means that CBDC-Net has a way better performance in identifying a higher number of actual positive instances than false negatives Finally, the F1-score, which is the harmonic mean of precision and recall showed the better performance of CBDC-Net than CBOW-DL[11], TF-IDF[12], and BERT-M[13].

***Table 5**. Word Based Cyberbullying Detection Models Performance Comparison*

Metric	CBOW-DL [11]	TF-IDF [12]	BERT-M [13]	Proposed CBDC-Net
Accuracy (%)	95.204	97.652	98.252	99.75
Precision (%)	96.441	97.723	99.140	99.98
Recall (%)	95.642	97.342	99.123	99.58
F1-score (%)	96.492	97.262	98.319	99.34
Sensitivity (%)	95.163	97.863	99.182	99.55

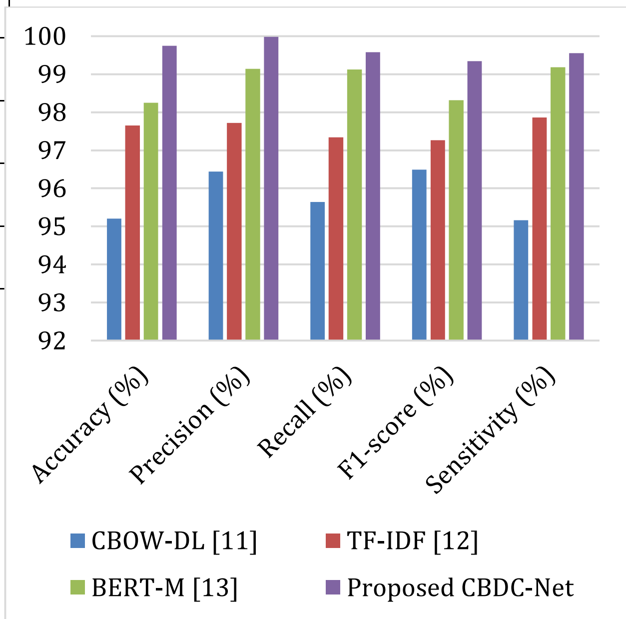

***Figure 7**. Word Based Cyberbullying Detection Models Performance Comparison*

By comparing the results of the experiment, the proposed CBDC-Net model has higher F1-scores by around 3.00%, 2.08%, and 1.02% than the CBOW-DL [11], TF-IDF [12], and BERT-M [13] models, respectively. The bigger value of F indicates that there is comparatively equal precision and recall, implying probable better identification of cyberbullying. Besides, the sensitivity level of CBDC- Net is higher than CBOW-DL [11], TF-IDF [12], and BERT-M, [13] by 0.41%, 1.69%, and 0.37%, respectively. This hints at a horribly high level of accuracy for true positive representation through CBDC-Net but relatively less sensitivity to false negatives which makes it better placed to detect cyberbullying behaviour. The performance comparison of the different character-based cyberbullying detection models is shown in table 6 and figure 8 where BOW-TF-IDF[15], MIL-TAP[16], XLNet [18], and CBDC-Net proposed in this paper is compared. In terms of accuracy, the proposed CBDC-Net perform better than BOW-TF-IDF [15], MIL-TAP [16], and XLNet [18]. The experiments show that CBDC-Net has an average accuracy of 99.75% which is an enhancement approximately 4.18% higher than BOW-TF-IDF [15], 2.98% higher than MIL-TAP [16], and 0.58% than XLNet [18]. Specifically, as for the precision, we obtain the better result than BOW-TF-IDF [15], MIL-TAP [16], and XLNet [18]. Table 5 reveals that CBDC-Net has achieved accuracy of 99.98% which is slightly higher than BOW-TF-IDF [15] by 3.00%, MIL-TAP [16] by 2.63%, and XLNet [18] by 1.56% respectively. CBDC-Net achieves higher recall rate of 99.58% compared to BOW-TF-IDF [15] by 3.44%, MIL-TAP [16] by 2.43%, and XLNet [18] by 0.48%. The F1 score that takes both precision and recall into account also shows that the proposed CBDC-Net outperforms BOW-TF-IDF [15], MIL-TAP [16], and XLNet [18]. Compared with the methods of BOW-TF-IDF achieving of 96.5%, MIL-TAP of 98.89%, and XLNet of 99.15%, CBDC-Net obtains higher value with 99.34%. Moreover, CBDC-Net achieves higher sensitivity rates than BOW-TF-IDF [15], MIL-TAP [16], and XLNet [18]. Although no statistical differences can be claimed when comparing the sensitivity of CBDC-Net with BOW-TF-IDF [15], MIL-TAP [16], and XLNet [18], with rate of 99.55% the proposed method outperforms the others by 3.35%, 2.12% and 0.41% respectively. Table 7 and figure 9 presents the similarities between different models of cyberbullying detection based on the synonym approach that comprise the Federated Learning [17], CNN-DNN [22], RBF-BERT [25], and the proposed CBDC-Net. CBDC-Net has the highest accuracy, recall, F-measure and lowest error rate of all the models developed to identify cyberbullying behaviour in text data. The correctness of the proposed model is higher than the others where the

***Table 6**. Character Based Cyberbullying Detection Models Performance Comparison*

Metric	BOW-TF-IDF [15]	MIL-TAP [16]	XLNet [18]	Proposed CBDC-Net
Accuracy (%)	95.574	97.769	99.172	99.75
Precision (%)	95.979	97.354	98.416	99.98
Recall (%)	96.138	97.146	99.102	99.58
F1-score (%)	96.495	97.886	99.143	99.34
Sensitivity (%)	96.206	97.438	99.145	99.55

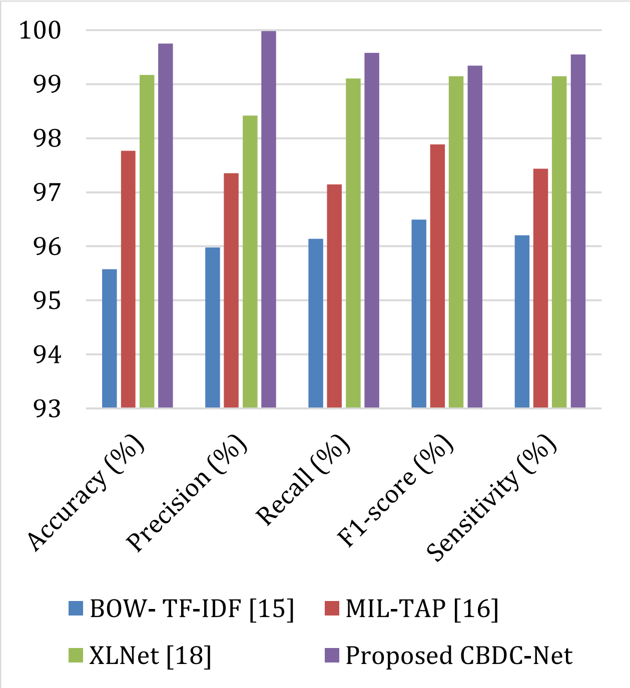

***Figure 8**. Character Based Cyberbullying Detection Models Performance Comparison*

correctness rate is 99.75% which outperforms Federated Learning [17], CNN-DNN [22], and RBF-BERT [25] by about 4.56%, 2.34%, and 1.42%, respectively. The proposed model of CBDC-Net yields a precision rate of 99.98%. This compared to Federated Learning [17], CNN-DNN [22], or RBF-BERT [25] improves by about 4.68%, 2.03% and 1.14% respectively. This simply shows that CBDC-Net can identify true positive instances with less instances of false positive. The proposed model, the CBDC-Net, shows higher recall rates versus Federated Learning [17] (93.47%), CNN-DNN [22] (92.5%), and RBF-BERT [25] (93.68%) of 99.58%. In addition, CBDC-Net is more effective in capturing a higher percentage of the true positive compared to the false negatives by 3.38%, 2.42%, 0.49% higher than these models, respectively. Moreover, for the biological model, our work excels in F1 scores compared to Federated Learning [17], CNN-DNN [22], and RBF-BERT [25] at a 99.34 It outperforms these models by approximately by 4.15%, 2.32%, and 0.83% respectively and the diagram shows how the proposed CBDC-Net has also done well in the precision/recall balance. This outperforms Federated Learning [17], CNN-DNN [22], and RBF-BERT [25] by an accuracy of 2.74%., 2.21% and 0, 38% respectively which proves that our approach is efficient in correctly classifying true positives.

Table 7. *Synonym Based Cyberbullying Detection Models Performance Comparison*

Metric	Federated Learning [17]	CNN-DNN [22]	RBF-BERT [25]	Proposed CBDC-Net
Accuracy (%)	95.188	97.410	98.331	99.75
Precision (%)	95.316	97.952	98.841	99.98
Recall (%)	96.178	97.162	99.064	99.58
F1-score (%)	95.183	97.018	98.508	99.34
Sensitivity (%)	96.814	97.337	99.173	99.55

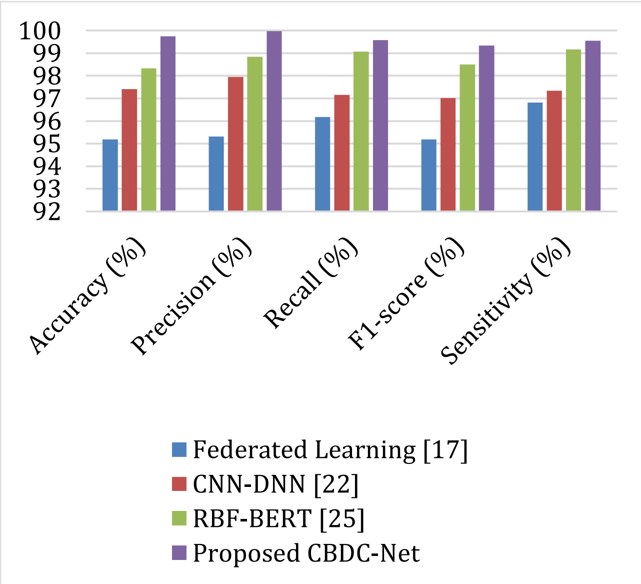

Figure 9. *Synonym Based Cyberbullying Detection Models Performance Comparison*

4. Conclusions

Therefore, with the help of the CBDC-Net developed in this paper, we have a solution to the complex problem of cyberbullying detection in OSN. SLNG feature extraction can extract features from the text, TSR-SCSO can select relevant features, and RBLNN can classify the input; collectively, the proposed model can improve the reliability of the detection system. The CBDC Net's potential implies that there are certain directions in which subsequent research can be advanced: Exploring the incorporation of more than one data modality, including multimedia features, to enhance the precision of detecting cyberbullying in various online settings, From developing methods to quickly identify and provide interventions and solutions for ongoing cyberbullying occurrences, Working with Explainable Artificial Intelligence to interpret the detection outcomes, which will be critical for users' trust and understanding of the technology. Machine learning is a popular methods and used in different applications in the literature [30-42].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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