Quasi-Reflection Learning Arithmetic Firefly Search Optimization with Deep Learning-based Cyberbullying Detection on Social Networking

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ABSTRACT

Social networks are a major medium for communicating, collaborating, and sharing knowledge, data, and ideas. However, due to anonymity preservation, incidents of cyberbullying and hate speech emerge. Cyberbullying is very common on social media, and people end up with depression and do not take action against it. Automatic identification of these situations on many social networking sites requires intelligent systems. Deep learning (DL) methods are preferred for their potential in text classification, with accurate results on various academic benchmark issues. This study develops a Quasi-reflection Learning Arithmetic Firefly Search Optimization with Deep Learning Cyberbullying Detection (QLAFSO-DLCBD) technique to detect accurately cyberbullying on social media. The proposed QLAFSO-DLCBD method undergoes an initial preprocessing stage to convert the raw data into a meaningful format. The Keras embedding layer is used for word embedding purposes. The QLAFSO-DLCBD technique applies the Attention-based Bidirectional Long Short-Term Memory (ABiLSTM) method to detect cyberbullying. The QLAFSO algorithm was employed to select optimal hyperparameters for the ABiLSTM method, enhancing detection performance. Extensive experimental and comparative results suggest a higher efficacy of the proposed QLAFSO-DLCBD method compared to other recent methods.

Keywords-metaheuristics; cyberbullying detection; natural language processing; social media; deep learning

I. INTRODUCTION

Social networks have become an essential and popular communication medium [1], providing numerous benefits to users. However, they can be used for malicious purposes. Cyberbullying is one of them, which can be described as bullying a group of people or an individual using digital technology [2]. Cyberbullying is long-lasting and has more substantial effects than other conventional bullying concepts, as it can reach more people quickly [3]. In addition, removing harmful online content can sometimes be impossible and time-consuming. Although cyberbullying does not cause direct physical harm, it can cause psychological disorders, including lack of concentration, depression, even suicide attempts, and loss of self-confidence [4]. Therefore, it is necessary to intensify the study of social network-related cyberbullying to gain insight and help advance productive methods and tools against it. Manually controlling and monitoring cyberbullying on social networking sites is impossible [5]. Furthermore, extracting social media messages to detect cyberbullying is not easy. For instance, Twitter messages are often brief and can contain emojis and gifs full of slang, making it challenging to infer individual meanings and intentions [6]. Cyberbullying is hard to detect if the bully utilizes methods such as passive-aggressiveness or sarcasm to conceal it.

Cyberbullying detection in real-time user-created content requires a higher level of semantic analysis. Previous studies on cyberbullying identification depend on manual feature extraction approaches [7]. These techniques are cumbersome, time-consuming, and sometimes capture the sentence's meaning incorrectly. Some lexicon-related methods, such as maintaining a list of hateful, offensive words, were used but were limited in scope [8]. Current studies have focused on adopting Deep Learning (DL) methods for different NLP tasks with better results. In general, deep structures are neural networks with many processing layers of neurons for a particular task [9]. DL methods minimize the need for explicit feature extraction methods, as they are fast and effective in retrieving significant patterns and features [10]. Compared to old Machine Learning (ML) methods, these methods show better results with minimal human intervention.

This study proposes a Quasi-reflection Learning Arithmetic Firefly Search Optimization with DL Cyberbullying Detection (QLAFSO-DLCBD) technique for social networks. The proposed QLAFSO-DLCBD technique undergoes the initial preprocessing stage to convert the raw data into a meaningful format. The Keras embedding layer is used for word embedding purposes. The QLAFSO-DLCBD technique applies the Attention-based Bidirectional Long Short-Term Memory (ABiLSTM) method for cyberbullying detection. Finally, the hyperparameters of the ABiLSTM technique are optimized using the QLAFSO algorithm, leading to better detection results.

II. RELATED WORKS

In [11], a multilabel dataset was developed and annotated from social media to identify toxic material, testing various ML methods, such as Stochastic Gradient Descent (SGD), Random Forrest (RF), and Naïve Bayes (NB). In [12], a unified DL algorithm was presented to detect violent conduct in cyberbullying cases, employing multichannel DL with CNN, BiGRU, and a transformer block to classify tweets. In [13], DL was combined with feature subset selection in FSSDL-CBDC for social networks, encompassing classification, preprocessing, and feature selection steps. In [14], a BiGRU model was proposed for bidirectional word learning, and a self-attention system was presented, although the evaluation was overestimated due to dataset downsampling/oversampling. In [15], a multi-faceted transformer architecture was proposed to identify hateful and aggressive remarks on social media, covering tasks such as detecting hate speech, aggression, offense type, misogynistic aggression, and offensive posts. In [16], DEA-RNN, a hybrid DL approach, was used to locate cyberbullying by fine-tuning Elman RNN variables with the optimized Dolphin Echolocation Algorithm (DEA). In [17], a hate speech identification method was developed for vulnerable minority groups on social networks, using Word2Vec, word n-grams, and GRU. In [18-20], cyberbullying detection systems (CDS) were proposed to uncover abusive behavior on social networks, comparing hybrid DL structures, such as CNN-BiLSTM and single Bi-LSTM, for various bullying types. In [21], a DL method was introduced to detect online anti-social behavior, addressing the scalability issues on online platforms.

III. THE PROPOSED METHOD

The proposed QLAFSO-DLCBD method combines NLP and DL principles to detect cyberbullying. This model encompasses data preprocessing, an embedding layer based on Keras, cyberbullying detection using ABiLSTM, and hyperparameter tuning using QLAFSO. Figure 1 shows the architecture of the proposed method.

A. Data Preprocessing and Word Embedding

The QLAFSO-DLCBD method uses the Keras embedding layer to preprocess data and embed words. Before executing the representation and transformation procedures, the data must be cleaned, removing noise, during preprocessing [18]. This includes the following steps:

- Remove punctuation and stop words from all social media posts.
- Change all capitalization to lowercase for the entire text.
- Remove unnecessary space, emojis, words, numbers, and characters from social media posts.
- Perform tokenization to separate each sentence into its component phrases, words, and other data to facilitate manageable text pieces for the model.
- Each dataset row contains a corresponding real-value vector, which is used by the DL techniques to classify all social postings as cyberbullying or not. The post-padding series technique was used to accomplish this assignment.

Word embedding is used in many text-mining tasks, and it involves creating a process vector representation of the words in the given text. To carry out text classification, text classifiers often include real-valued word vectors, containing semantic and word context relatively close in vector space and helping to detect words with similar meanings. Word2Vec contains two types of techniques for predicting the context of the word provided from the text. However, a Keras embedding layer can be used on chosen vocabularies in binary and multiclass datasets. Keras embedding is better than the pre-trained embedding techniques, as it requires less time and computing resources. The preprocessed data were transformed into a format suitable for DL models using real-valued word vectors. These vectors capture words' semantic meaning and context, which is essential for detecting nuances in language related to cyberbullying. Additionally, every text and procedure has its word vector as an input dataset for the presented methods.

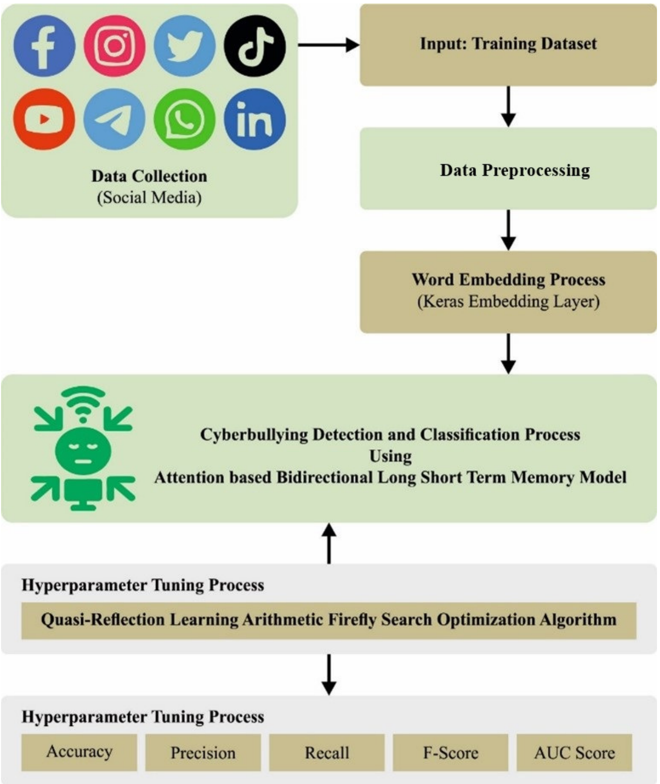

Fig. 1. Architecture of the proposed QLAFSO-DLCBD model.

B. Cyberbullying Detection Using the ABiLSTM Model

LSTM is a common Neural Network (NN), developed to capture temporal connections in sequential datasets [22, 23]. It has memory units that accumulate past data via self-connections. All the memory units include forgetting, input, and output gates. The input gate controls the data flow as memory units, whereas forgetting and output gates regulate the data flow in memory units:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (1)$$

$$i_t = \sigma\left(W_j \cdot [h_{t-1}, x_t] + b_i\right) \quad (2)$$

$$\widetilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \quad (4)$$

$$o_t = \sigma\left(W_0 \cdot \left[h_{t-1} x_{,t}\right] + b_0\right) \quad (5)$$

$$h_t = o_t * tanh(C_t) \quad (6)$$

The f_t forget gate determines whether the data from the previous cell state must be discarded. After merging the current input x_t with the previous hidden state h_{t-1}, this gate multiplies the previous cell state c_{t-1} by the sigmoid function, which then outputs the data. This improves the layer's cell condition. Next, the output of the update gate C_t and the forget-gate f_t are used to create the most recent cell layer C_t. Then, to obtain h_t, the sigmoid layer specifies C_t data. After that, the current hidden layer combines the data from the output gates with the nonlinear *tanh* function. Figure 2 shows the ABiLSTM framework.

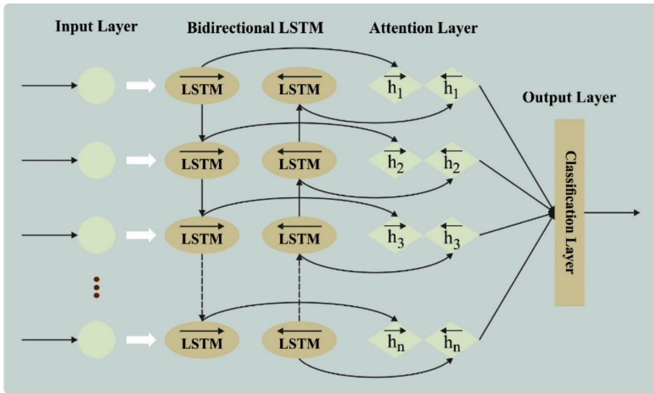

Fig. 2. ABiLSTM framework.

Despite its successful sequential data modeling, LSTM cannot encode data in both directions but only front-to-back. Bi-LSTM overcomes this restriction, as it can acquire series semantics in both directions. Problems arise when dealing with multidimensional datasets, especially when extracting useful information to improve the model's performance. The attention module attempts to replicate the brain's ability to focus on what is most important while disregarding what is less important. This can potentially improve the quality of feature extraction by removing the impact of unnecessary components. This is accomplished by progressively applying a possibility-weighted distribution when the attention module analyzes the feature vector's probability weight at each time step. Crucial information can be extracted with the help of the attention module, which can increase the model's performance. The first step involves comparing the keys of the query using a learnable matrix:

$$h_{t,t'} = tanh\left(W_t \hat{x}_t^T + W_x \hat{x}_{t'}^T + b_t\right) \quad (7)$$

$$e_{t,t'} = \sigma\left(W_a h_{t,t'} + b_a\right) \quad (8)$$

where W_t, W_x, W_a, b_t, b_a are the learnable parameters and $\hat{x}_t^T$ denotes the output of Bi-LSTM. This generates a weighted value, $a_{t\,t'}$, which is later normalized by the softmax function. Next, this value is multiplied with the weight, and the sum can be considered for generating the output:

$$a_{t,t'} = softmax\left(e_{t,t'}\right) \quad (9)$$

$$l_t = \sum t' a_{t,t'} \hat{x}_{t'}^T \quad (10)$$

In general, this model consists of an attention mechanism and Bi-LSTM. This can efficiently overcome the challenges of gradient vanishing and explosion while retaining higher accuracy, assisting in identifying pertinent data, and enhancing prediction performance. The output can be transferred to the subsequent dilated residual layer for additional refinement. The weights are adjusted during the training process, allowing the network to learn from the input dataset and optimize its prediction performance.

C. Hyperparameter Tuning using QLAFSO Algorithm

The QLAFSO algorithm is employed to adjust the hyperparameter values of the ABiLSTM model. AOA exploits arithmetical operators, such as division (D), multiplication (M), subtraction (S), and addition (A) [24-30]. Initially, it arbitrarily creates a group of candidate solutions (X) as:

$$X = [x_{i,j}]_{N\times n} \quad (11)$$

This algorithm is chosen for the search phase (exploitation or exploration). There, the MOA function can be applied as follows:

$$MOA(C_{Iter}) = Min + C_{Iter}\left(\frac{Max - Min}{max_{Iter}}\right) \quad (12)$$

where C_{Iter} denotes the existing iteration and Min and Max denote the minimum and maximum values of the MOA. $MOA(C_{Iter})$ denotes the function value at t^{th} iteration, and max_{Iter} denotes the maximum number of iterations. The exploration phase exploits arithmetical operators, such as division and multiplication, since the highly distributed values make them appropriate for the exploration searching process. This exploration stage is implemented for the condition of $r_1 > MOA(C_{Iter})$, where r_1 denotes a random value.

$$x_{i,j}(C_{Iter}+1) = \begin{cases} best\,(x_j) \div (MOP+\epsilon)\cdot\left((ub_j - lb_j)\cdot\mu + lb_j\right), \\ r_2 < 0.5 \\ best\,(x_j)\cdot MOP\cdot\left((ub_j - lb_j)\cdot\mu + lb_j\right), \\ otherwise \end{cases} \quad (13)$$

where $x_i(C_{Iter}+1)$ denotes the i^{th} solution at the following iteration, $x_{i,j}(C_{Iter})$ denotes the j^{th} location of i^{th} solution at the existing iteration, $best(x_j)$ denotes the j^{th} location in the better-gained solution, e denotes a small integer number, ub_j and lb_j denote the upper and lower boundaries value of the j^{th} location, μ denotes the control variable of the search process, fixed as 0.5, and r_2 denotes a random number.

$$MOP(C_{Iter}) = 1 - \frac{C_{Iter}^{\frac{1}{\alpha_1}}}{max_{Iter}^{\frac{1}{\alpha_1}}} \quad (14)$$

where $MOP(C_{Iter})$ represents the function value at the t^{th} iteration and α_1 is a variable that describes the exploitation performance via iteration, fixed at 5. The exploitation stage uses arithmetical operators S and A since they provide highly dense outcomes, appropriate for the exploitation search mechanism. This exploitation stage can be implemented for the condition $1 \leq MOA(C_{Iter})$:

$$x_{i,j}(C_{Iter}+1) = \begin{cases} best(x_j) - MOP\cdot\left((ub_j - lb_j)\cdot\mu + lb_j\right), \\ r_3 < 0.5 \\ best(x_j) + MOP\cdot\left((ub_j - lb_j)\cdot\mu + lb_j\right), \\ otherwise \end{cases} \quad (15)$$

where r_3 denotes a random integer. In general, the exploitation search strategy aims to avoid getting stuck in local optima. This procedure assists the exploration searching strategy in attaining the optimum result while retaining diverse candidate solutions. Note that the AOA exploration is insufficient in the earlier stage of some runs, and the searching procedure is stuck in the sub-optimum domain. Furthermore, the exploitation procedure is enhanced in a later iteration to facilitate searching around the global optima area of the searching space.

This deficiency was solved by integrating two changes: the Quasi-Reflection Learning (QRL) process, which can enhance population diversity and the searching approach, and the searching approach in the Firefly Algorithm (FA), which shows more substantial intensification capabilities. QRL can be initially employed as follows: once a standard arbitrary population P of size N is produced, for every outcome $X \in P$, its quasi-reflective individual X^{qr} is produced based on (16), and population P^{qr} is generated. Fitness can be evaluated for every solution from PUP^{qr}, and the better N individuals are chosen. Thus, the first pseudo-random solution is closer to optimal. The quasi-reflected module j of the solution $X(X_j^{qr})$ is evaluated as follows:

$$X_j^{qr} = rnd\left(\frac{lb_j+ub_j}{2}, x_j\right) \quad (16)$$

where $\frac{lb_j+ub_j}{2}$ denotes the arithmetical mean (center) of the interval $[lb_j, ub_j]$, and $rnd\left(\frac{lb_j+ub_j}{2}, x_j\right)$ produces uniformly dispersed pseudo-random from the interval $\left[\frac{lb_j+ub_j}{2}, x_j\right]$.

Similarly, in an earlier ψ iteration, a quasi-reflective solution was used to improve the exploration capabilities of AOA. The $X^{*,qr}$ of the present optimum separate X^* is generated and estimated, and the best result can be retained in the population. However, in later stages, this model is no longer required, and the searching mechanism of fundamental AOA was substituted with the FA searching formula:

$$X_i^{t+1} = x_i^t + \beta_0\cdot e^{-\gamma r_{i,z}^2}(x_Z^t - x_i^t) + \alpha_2^t(\kappa - 0.5) \quad (17)$$

where κ represents an arbitrary number in Gaussian or uniform distribution, β_0 and α_2 are the typical FA search parameters, z can be an arbitrarily chosen solution in the population, and α_2 parameters can be dynamic. The QLAFSO system produces a Fitness Function (FF) to achieve superior classification performance. It resolves a positive value for characterizing the best result of candidate solutions. In this case, minimizing classifier errors can be assumed by:

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{no.of\ misclassified\ instances}{Total\ no.of\ instances} * 100 \quad (18)$$

IV. RESULTS AND DISCUSSION

The cyberbullying detection ability of the proposed QLAFSO-DLCBD system was examined using the Twitter sentiment analysis dataset in [31]. The dataset consists of 32K tweets labeled as hatred or non-hatred, as shown in Table I.

TABLE I. DATASET DETAILS

Class	No. of samples
Hatred	500
Non-Hatred	500
Total	1000

Figure 3 shows the QLAFSO-DLCBD method's confusion matrices for cyberbullying detection. The results show that the proposed QLAFSO-DLCBD system could easily distinguish between hateful and non-hateful samples. Table II and Figure 4 show the entire cyberbullying detection results of the QLAFSO-DLCBD method, indicating the proposed system reaches effective outcomes in both classes. For instance, using 80% of the dataset for training (TRP), the QLAFSO-DLCBD approach provided an average accuracy of 94.70%, precision of 94.88%, recall of 94.70%, F score of 94.74%, and AUC score of 94.70%. Meanwhile, using 20% of the dataset for testing (TSP), the QLAFSO-DLCBD method achieved an average accuracy of 96.61%, precision of 96.40%, recall of 96.61%, F score of 96.48%, and AUC score of 96.61%. Furthermore, on 70% of TRP, the QLAFSO-DLCBD approach achieved an average accuracy of 95.71%, precision of 95.84%, recall of 95.71%, F score of 95.71%, and AUC score of 95.71%. Finally, on 30% of TSP, the QLAFSO-DLCBD method achieved an average accuracy of 96.01%, precision of 96.03%, recall of 96.01%, F score of 96%, and AUC score of 96.01%.

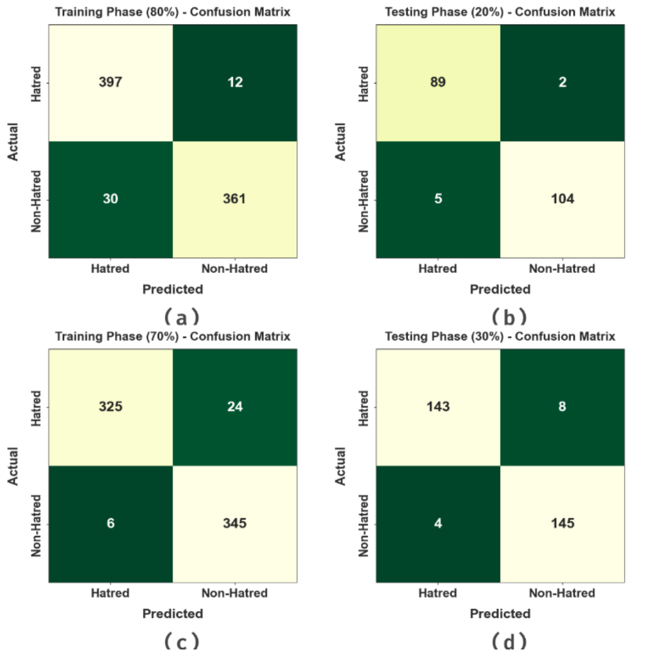

Fig. 3. Confusion matrices of QLAFSO-DLCBD system: (a-b) 80:20 TRP/TSP, and (c-d) 70:30 TRP/TSP.

TABLE II. CB DETECTION RESULTS OF QLAFSO-DLCBD WITH DISTINCT MEASURES

Class	Accuracy	Precision	Recall	F score	AUC score
Training Phase (80%)					
Hatred	97.07	92.97	97.07	94.98	94.70
Non-Hatred	92.33	96.78	92.33	94.50	94.70
Average	94.70	94.88	94.70	94.74	94.70
Testing Phase (20%)					
Hatred	97.80	94.68	97.80	96.22	96.61
Non-Hatred	95.41	98.11	95.41	96.74	96.61
Average	96.61	96.40	96.61	96.48	96.61
Training Phase (70%)					
Hatred	93.12	98.19	93.12	95.59	95.71
Non-Hatred	98.29	93.50	98.29	95.83	95.71
Average	95.71	95.84	95.71	95.71	95.71
Testing Phase (30%)					
Hatred	94.70	97.28	94.70	95.97	96.01
Non-Hatred	97.32	94.77	97.32	96.03	96.01
Average	96.01	96.03	96.01	96.00	96.01

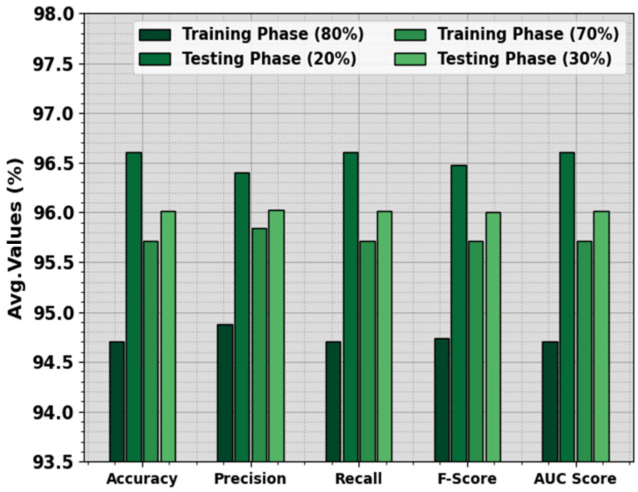

Fig. 4. Average results of the QLAFSO-DLCBD approach with distinct measures.

Figure 5 shows the training and validation accuracy and loss of the QLAFSO-DLCBD method for different training/testing ratios. The QLAFSO-DLCBD method achieves its maximum accuracy at later epochs and demonstrates effective learning on the test dataset, as seen by the greater validation than training accuracy. The results also show that the QLAFSO-DLCBD method achieved lower validation and training loss values for an 80:20 train/test split than for 70:30. Figure 6 shows the QLAFSO-DLCBD method's results at 80:20 and 70:30 training/testing ratios. It should be noted that the QLAFSO-DLCBD method achieves improved ROC values in all classes.

Table III and Figure 7 show a brief comparative study of QLAFSO-DLCBD with recent methods [32], indicating that the proposed method achieves enhanced results. The QLAFSO-DLCBD method achieved better accuracy, precision, and recall compared to the SVM, NB, RF, and LR models. These results show the remarkable performance of the QLAFSO-DLCBD approach in cyberbullying detection.

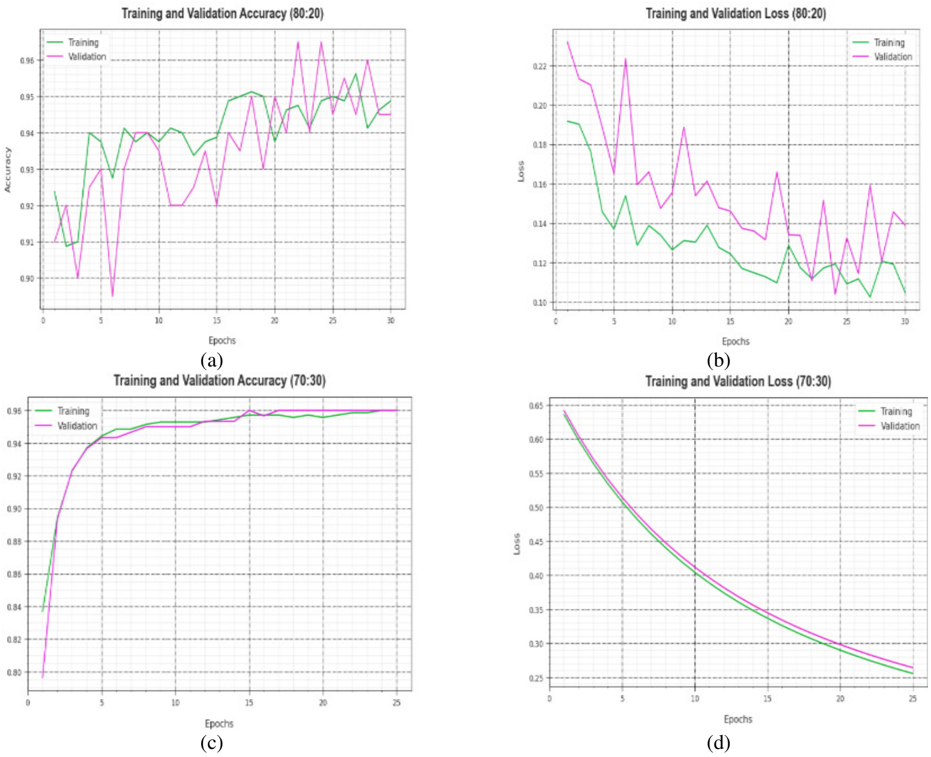

Fig. 5. Accuracy and loss curves different training/testing ratios.

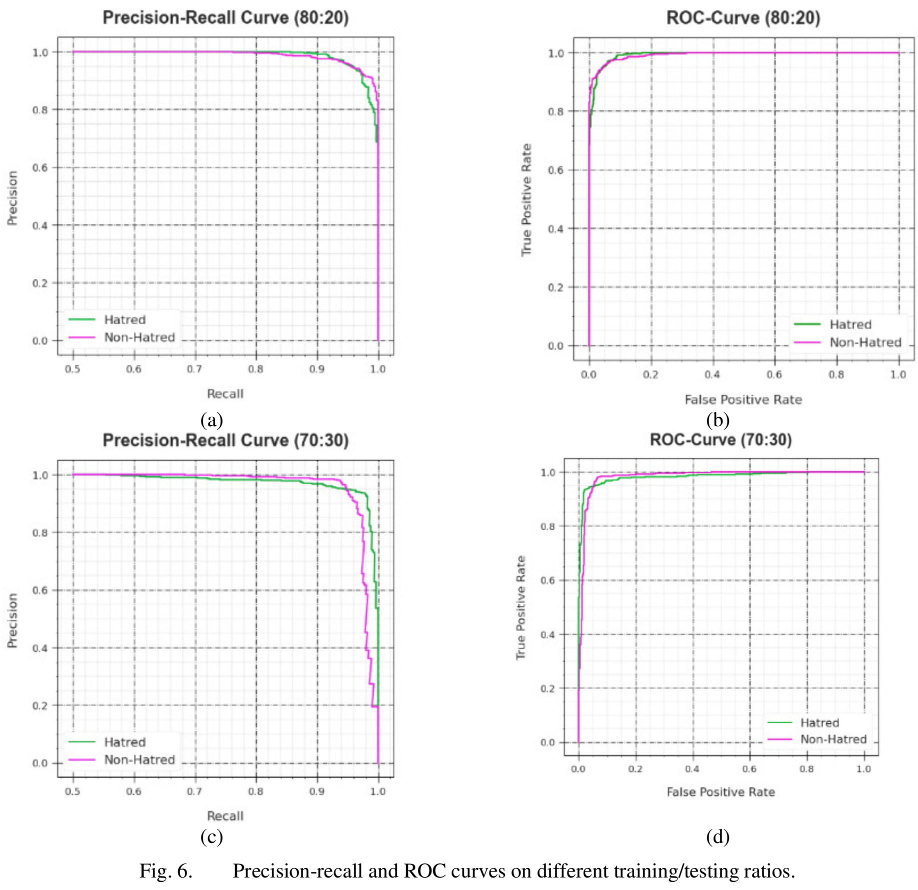

Fig. 6. Precision-recall and ROC curves on different training/testing ratios.

TABLE III. COMPARATIVE RESULTS OF QLAFSO-DLCBD WITH OTHER RECENT SYSTEMS [32]

Method	Accuracy	Precision	Recall	F score
SVM	94.97	69.40	48.10	56.80
Naïve Bayes (NB)	93.10	51.10	40.00	44.90
Random Forest (RF)	94.66	52.20	48.60	50.30
Logistic Regression (LR)	95.00	81.90	37.30	51.00
QLAFSO-DLCBD	96.61	96.40	96.61	96.48

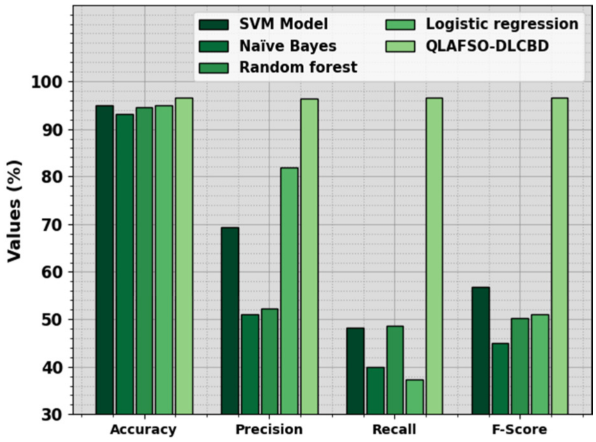

Fig. 7. Comparative results of QLAFSO-DLCBD approach with other algorithms [32].

V. CONCLUSION

This paper describes a new QLAFSO-DLCBD method to automatically detect cyberbullying on social media sites, combining the principles of NLP and DL. The steps used are data preprocessing, an embedding layer based on Keras, cyberbullying detection using ABiLSTM, and hyperparameter tuning using QLAFSO. The QLAFSO algorithm improved cyberbullying detection by optimizing the hyperparameters of the ABiLSTM approach. A comprehensive evaluation showed that the proposed QLAFSO-DLCBD technique outperformed other current systems in various metrics. Consequently, a reliable cyberbullying detection procedure can be implemented using the QLAFSO-DLCBD method.

The novel contributions of this study are:

- Quasi-reflection Learning Arithmetic Firefly Search Optimization (QLAFSO): This algorithm introduces a hybrid optimization technique that combines the strengths of quasi-reflection learning and arithmetic operations with the Firefly algorithm. This method significantly improves the balance between exploration and exploitation, preventing the model from converging to local optima and enhancing overall performance.
- Attention-based Bidirectional LSTM (ABiLSTM): This algorithm allows for the incorporation of attention mechanisms, which enable the model to focus on the most relevant parts of the input sequences. This dual-directional context capture leads to a more accurate understanding and classification of complex text patterns associated with cyberbullying.

The importance of this work stems from its:

- Enhanced Detection Capabilities: Integration of QLAFSO with ABiLSTM results in a highly accurate cyberbullying detection system. This system addresses the growing concern about cyberbullying on social networks by providing a reliable early detection and intervention tool, contributing to safer online environments.
- Optimization Efficiency: QLAFSO's ability to efficiently fine-tune hyperparameters reduces the computational cost and time required for model training, making it feasible for deployment in real-world applications where resources may be limited.
- Scalability and Adaptability: The proposed approach is designed to be scalable and adaptable to various social media platforms, ensuring that it can handle diverse datasets and evolving patterns of cyberbullying language.

Finally, the comparison with existing methods can be summarized as follows:

- Superior Performance: Comparative results demonstrate that the proposed QLAFSO-DLCBD method consistently outperformed existing methods in key metrics such as accuracy, precision, recall, and F1-score. This highlights the effectiveness of the proposed approach in capturing the nuanced language of cyberbullying more accurately than traditional models.
- Innovative Optimization Strategy: Unlike conventional optimization techniques, QLAFSO's innovative combination of quasi-reflection learning and arithmetic operations with the Firefly algorithm offers a more robust solution for hyperparameter tuning, leading to better model performance and reliability.

DECLARATIONS OF INTEREST

The authors declare no conflict of interest.

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