



Dragonfly Algorithm with Gated Recurrent Unit for Cybersecurity in Social Networking

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Abstract

The advancements of information technologies and wireless networks have created open online communication channels. Inappropriately, trolls have abused the technologies to impose cyberattacks and threats. Automated cybersecurity solutions are essential to avoid the threats and security issues in social media. This paper presents an efficient dragonfly algorithm (DFA) with gated recurrent unit (GRU) for cybersecurity in social networking. The proposed DFA-GRU model aims to determine the social networking data into neural statements or insult (cyberbullying) statements. Besides, the DFA-GRU model primarily undergoes preprocessing to get rid of unwanted data and TF-IDF vectorizer is used. In addition, the GRU model is employed for the classification process in which the hyperparameters are optimally adjusted by the use of DFA, and thereby the overall classification results get improved. The performance validation of the DFA-GRU model is carried out using benchmark dataset and the results are examined under varying aspects. The experimental outcome highlighted the enhanced performance of the DFA-GRU model interms of distinct measures.

Keywords: Social media, Cyberbullying, Cybersecurity, Machine learning, Word embedding, Dragonfly algorithm.

1. Introduction

Currently, billions of people often visit millions of social media platforms to connect with their friends, share their videos, thoughts, and photos discusses with their day-to-day lives. social media platforms are traces back to the first email that is mailed in 1971 in which 2 computers are sitting near one another [1]. In 1987 Bulletin Board System exchanges information on telephone lines with another user and recently the initial copies of earlier web browsing networks are dispersed by using Usenet. Geocities was the original social website created in 1994. Theglobe.com started in 1995 and provided the capacity of communicating with other people, publish and personalize their files on the Internet. In 1997, the America on Line (AOL) Instant Messenger was launched. In 2002, Friendster was launched and within 3 months around three million peoples make use of it. In 2003, My Space was launched and in the next year's several others social media platform was launched like Twitter in 2006, etc. Facebook in 2004, [2].

There are several social media sites and social networking sites are accessible in the search engine [3]. These social media platforms have demonstrated negative and positive effects; hence several persons spend a majority of their time on these sites that leads to losing their natural social lives and families [4].

Many users, smart-users, utilize social media platforms in a positive manner; now in the Spring of Arab World! The majority of the social media platforms have members manage and create their post different types of files, personal profiles, provides facility for members to manually detect candidates with present members, and offer advanced features that developed to have user waste their most of the time website [5]. Furthermore, several researchers are functioning on innovative applications for these networking and media sites. Generally, user makes several mistakes and risks while utilizing social media facilities like misuse of corporate computers, unauthorized physical and network access, unauthorized programs, transfer sensitive information and misuse of passwords among their personal computers and works while operating at homes [6]. But, the extreme trust among users of social media platforms could be utilized for perpetrating a data leakage and different kinds of attacks [7].

There is a requirement to tackle and consider cyberbullying from different points of view involving prevention of this accident and automated detection [8]. In addition, majority of the online networks which is extensively employed by adolescents have safe centres, such as Twitter Protection and Safety, and YouTube Safety Centre provides track communications and user assistance [9].

This paper presents an efficient dragonfly algorithm (DFA) with gated recurrent unit (GRU) for cybersecurity in social networking. The proposed DFA-GRU model aims to determine the social networking data into neural statements or insult (cyberbullying) statements. Besides, the DFA-GRU model primarily undergoes preprocessing to get rid of unwanted data and TF-IDF vectorizer is used. In addition, the GRU model is employed for the classification process in which the hyperparameters are optimally adjusted by the use of DFA, and thereby the overall classification results get improved. The performance validation of the DFA-GRU model is carried out using benchmark dataset and the results are examined under varying aspects.

2. Literature Review

Sharma and Kshitiz [10] include defining methods to recognize bullying in text through experimenting and analysis using diverse approaches for finding the possible method of categorizing this comment. They projected an effective procedure to find the aggressive comments and bullying test and analyze this comment for checking the authenticity. NLP and ML methods are utilized to analyze the social comments and recognized the aggressive effects of group/ an individual. Efficient classifiers act as the essential module in the last prototype scheme which could distinguish cyberbullying on social networks. Silva et al. [11] consider an automatic method to measure and identify the amount of cyberbullying in social media platforms, and a Facebook for parentages, based upon this method, which informs them once cyberbullying takes place. This study determines the problems related to the structure of a computer method for cyberbullying detection, presents important consequences from psychology study which is utilized in this method, and mobile app developed for cyberbullying detection.

Nakano et al. [12] develop Ask.fm, a social media platform in which user creates profile and communicate with one another queries, and analyze aggressive behaviour which might possibly lead to cyberbullying events. The major reason for this aggressive behaviour and analyze how non-anonymous and anonymous users perform on social media platforms. They gathered information from Ask.fm and analyze queries posted through non-anonymous and anonymous users and answer posted through non-anonymous users. In Altay and Alatas [13], the use of NLP method and ML techniques such as BLR, RF, multi-layer sensor, J48 algorithm, and SVM were utilized to determine cyberbullying. As we know, the achievements of this method using distinct metrics within dissimilar researches were related initially.

Chavan and Shylaja [14] developed approaches to distinguish cyberbullying with supervised learning methods. They proposed 2 novel hypotheses for feature extraction to identify aggressive comments that are perceived negatively and lead to cyberbullying. This experiment shows that the features from hypotheses besides conventional feature extraction methods such as N-gram and TF-IDF raise the precision of the method. Galán-García et al. [15] proposed a method to associate and detect false profiles on Tweet social media that is used to defamatory activities to a real profile within similar networks through examining the contents of the comment made by the profiles. Also, proposed an effective real time application where this method was employed for detecting and stopping cyberbullying scenarios in a real elementary school.

3. The Proposed DFA-GRU Model

This study has presented an effective DFA-GRU model for cybersecurity in social networking. The proposed DFA-GRU model involves preprocessing, TF-IDF vectorizer, GRU based classification, and DFA based hyperparameter optimization. The detailed working of these processes is offered in the subsequent sections.

3.1 Level I: Preprocessing

At the preprocessing stage, the proposed DFA-GRU model encompasses different subprocesses, as defined in the following.

Text cleaning

If the text has been received depending upon the execution, the data was examined to a superior degree of refinements executing and subsequent the steps required under Stop word remover, tokenization, lesser casing, sentence segmentation, and punctuation extraction. These are the steps which are received to have the data decreased to size, and so, it can also eliminate unwanted data which is established from the data. In maintenance of this manner, it can be generated a generic pre-processed that leads to the elimination of punctuation and also any non-letter character in all the documents. Eventually, the letter case of all documents is lowered. The outcome in this manner provided us sliced document text dependent upon n length by n -gram word-based tokenizers.

Tokenization

Tokenization was utilized in this procedure for addressing the condition in which provided text was divided as to lesser bits recognized as tokens. The subsequent are also considered tokens. It contains Words, numbers, and punctuation marks. Besides, other non-sensitive matching elements are exchanged with sensitive data elements without meaning or value. It can be certain that tokenization technique utilized has protected as well as tests utilizing optimum criteria significant to safety of secret information. The tokenization structure technique has utilized proposals authority and API to attaining tokens to data processing applications. It can be essential and is detokenized back to sensitive information.

Stemming

The following step when it is required away from the tokenization scheme is for transforming the token as to another typical format. Stemming, simply means, it alters the words back to their procedure in which it can be initially started from then it reduces from the amount of words types and/ or classes from the data. For instance, it can be utilized the words "Running," "Ran," and "Runner" is decreased to word "run". They demonstrate that stemming is essentially be utilized to generate classification.

Lemmatization

Similar to stemming, the resolve of lemmatization is for minimizing inflectional procedures to particular base procedure. The lemmatization doesn't essentially break of infection, before stemming. This exactly utilizes the base of lexical data for achieving the right basic kinds of vocabulary.

Stopwords

This case is utilized unimportant words as language able of generating noise as helpful feature if it can be executing text classification. As terms are named Stop words. They can find them utilized from sentences which help in linking our thinking but utilizing with manner the sentences are created. Article, preposition, and conjunction, and any pronouns, i.e., are regarded as to stop words. This technique removal general terms in the records namely "a, for, an, are, like, at, are, by, for, from, how, in, is, in, on, or, the, these, this too, was when, where, where, how, how, how," and so on. Then, it can save the document being handled and set to the next step.

3.2 Level II: TF-IDF Vectorizer

TF-IDF is the widely utilized feature extraction method for analyzing texts. The 2 significant tasks are weighting and indexing for analyzing texts, TF-IDF handles the weighting. It discovers the weight of term t in a provided document D . TF-IDF is advanced from TF and IDF that is expressed by [16]:

$$TF(t) = \frac{t_D}{N_D} \quad (1)$$

$$IDF(t) = \log \frac{d}{dt} \quad (2)$$

In which t_D , d and dt denote the overall amount of t presence in a document D , overall amount of documents and the amount of documents have term t .

The weight of all the terms with the TF-IDF is calculated as:

$$W_{t,d} = TF_{t,d} \left(\frac{t_D}{d_{f,t}} \right) \quad (3)$$

whereas $TF_{t,d}$, and $d_{f,t}$, characterizes the frequency of term t in document d and amount of documents which have t .

3.3 Level III: GRU based Classification

At this stage, the classification of social media text is done by the use of GRU model. Lately, GRU, a group of RNN models, was presented for handling gradient exploding or vanishing problems. GRU is a simple and powerful alternate to LSTM network. Like LSTM methods, GRU is developed for adoptively reset/update the memory contents with z^j update gate and r^j reset gate which is same as input forget and gates of LSTM. In comparison with LSTM, GRU doesn't have a memory cell and has 2 gates. The GRU activation h_t^j in time t is the linear interpolation of candidate activation \tilde{h}_t^j and prior activation h_{t-1}^j .

In order to calculate the states h_t^j of j -th GRU at time step t , they employ:

$$h_t^j = (1 - z_t^j) h_{t-1}^j + z_t^j \tilde{h}_t^j \quad (3)$$

Whereas \tilde{h}_t^j and h_{t-1}^j corresponds to the novel candidate and prior memory content, correspondingly. z_t^j denotes the update gate which allows the method for deciding the number of historical data (from prior time step) to be transported alongside with the upcoming and the quantity of novel memory content to be included [17]. In order to compute the update gate z_t for time step t , they utilize the prior hidden state h_{t-1} and the present input x_t as follows:

$$z_t = \sigma(W_z x_t + U_z h_{t-1}) \quad (4)$$

The novel memory content \tilde{h}_t can be estimated by:

$$\tilde{h}_t = \tanh(W_x x_t + r_t \odot U h_{t-1}) \quad (5)$$

In which \odot represent the Hadamard product (called the element-wise products) and r_t characterize the reset gate that is utilized for determining the number of data to forget from the previous. It can be expressed by:

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \quad (6)$$

GRU is quicker when compared to LSTM on training as GRU has simplified framework using less variables and thus employs lesser memory. Fig. 1 demonstrates the structure of GRU model.

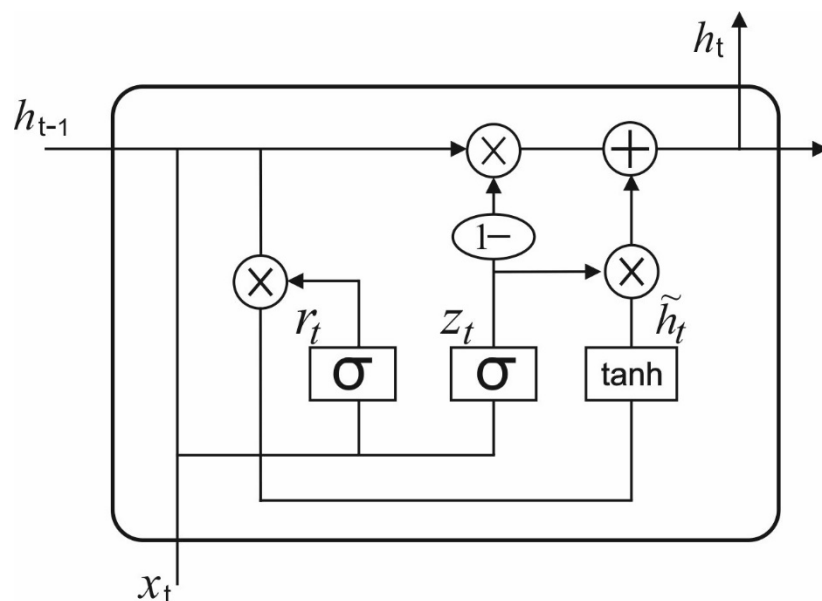


Fig. 1. GRU framework

3.4 Level IV: DFA based Hyperparameter Optimization

The hyperparameter tuning of the GRU model takes place through DFA. Recently, DFA method is a proposed bio inspired optimization algorithm. Mainly, it is advanced from static and dynamic efficiency of dragonflies swarming behaviour. The DFA method is made of Migration (dynamic swarm) and Hunting (static swarm). In the event of static swarm, dragonfly makes small groups and move backward within a chosen place to hunt the flying victims. A flying way feature of static swarm is local movements and immediate changes. Thus, the feature varies from dynamic swarm, as larger dragonflies, amount of migrating on longer distance creates the swarm to move in single direction. It is grown from emerging sub-swarms and flies on several regions in a dynamic swarm which focuses on exploration stage where static swarm tries to move in big swarms as determined in exploitation stage [18]. Fig. 2 illustrates the process flow of DFA.

In DFA method, 3 common methods of swarming behaviour are given below:

- Separation: It implies the removal of individual static collisions from one another.
- Alignment: It implies the individual velocity corresponds to another neighbourhood.
- Cohesion: it represents individual ability to neighbourhood' mass centre.

The survival rate is the main objective of swarm in which all the individuals are dispersed outside and attracting towards the food position. Due to this behaviour, 5 significant characteristics that impact the individual's upgrade position are Attraction, Separation, Alignment, Cohesion towards Distraction of enemy, and food source. These features are determined as follows.

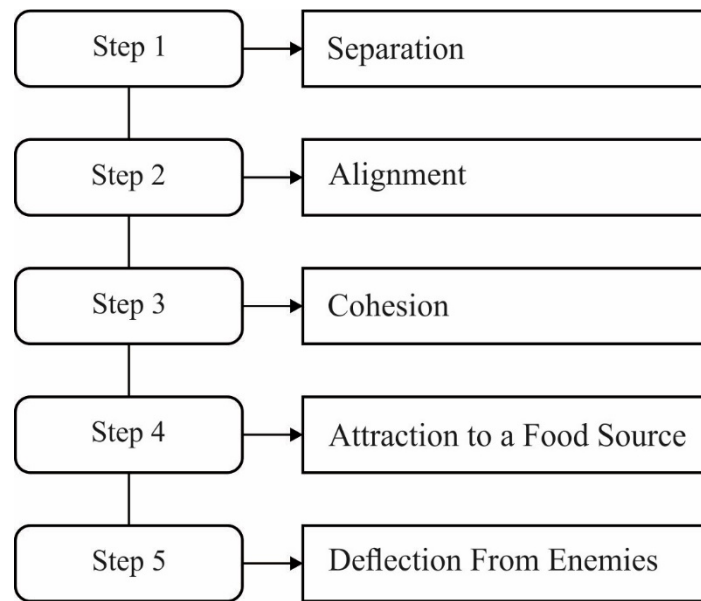


Fig. 2. Process of DFA

Separation: This variable can be evaluated as:

$$S_i = - \sum_{k=1}^M Y - Y_k, \quad (7)$$

In which Y represents the individual position, Y_k indicates the position of k -th neighbouring individuals and M determines the total amount of neighbouring separations.

Alignment: It shows the mean of velocities which is determined by given expression:

$$A_i = \frac{\sum_{k=1}^M V_k}{M}, \quad (8)$$

whereas V_k represent the velocity of k -th neighbouring individuals.

Cohesion: In this feature can be estimated by:

$$C_i = \frac{\sum_{k=1}^M Y_k}{M} - Y \quad (9)$$

Attraction towards a food source: It indicates a distance amongst location of present individuals and position of food source (Y^+) as follows:

$$F_i = Y^+ - Y \quad (10)$$

Distraction outwards an enemy: It implies a distance amongst location of present individuals and location of an enemy (Y^-) as:

$$E_i = Y^- - Y \quad (11)$$

In dragonfly, nature is a union of 5 parameters. Next, 2 vectors are used to upgrade dragonfly position in a searching space, like position vector (Y) and step vector (ΔY). It can be expressed as:

$$\Delta Y_{t+1} = (aA_i + sS_i + cC_i + eE_i + fF_i) + w \Delta Y_t, \quad (12)$$

whereas a represent the alignment weight, A_i denotes the alignment of i -th individuals, s means the separation weight, S_i indicates the difference of i -th individuals, c describes the cohesion weight, C_i characterizes the cohesion of i -th individuals, e portrays enemy weight, E_i describes the position of enemy in i -th individuals, f implies the food weight, F_i indicates a food source of i -th individuals, w showcases the inertia weight, and t displays the iteration number. It is expressed by:

$$Y_{t+1} = Y_t + \Delta Y_{t+1} \quad (13)$$

In the event of optimization method, dissimilar exploitative and explorative behaviours are attained through three variables ($a, s, c, e,$ and f). In addition, this parameter is applied in handling exploitation and exploration stages.

4. Experimental Validation

This section examines the cybersecurity performance analysis of the DFA-GRU technique on the test Kaggle dataset applied. The dataset contains 12,729 samples with 11,661 samples under non-cyberbullying class and 1068 samples under cyberbullying class.

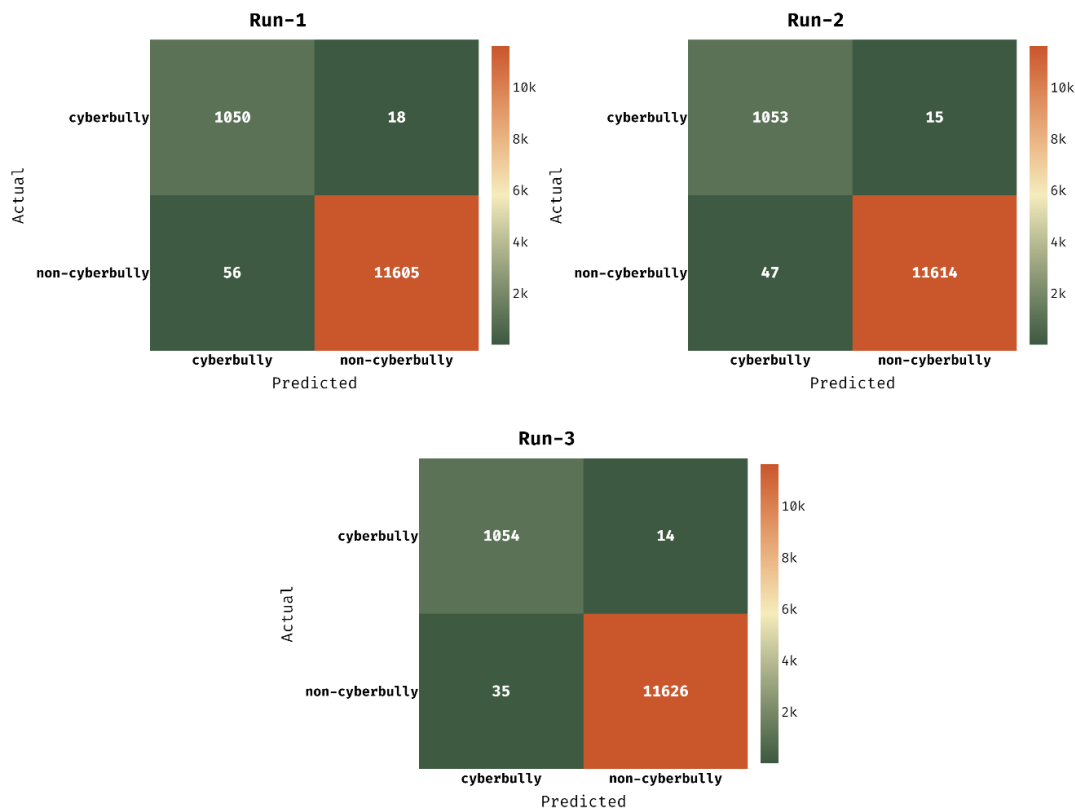


Fig. 3. Confusion matrix of DFA-GRU model with three runs

Fig. 3 demonstrates the confusion matrix generated by the DFA-GRU technique on the classification of cyberbullying under three runs. With the test run-1, the DFA-GRU technique has classified 1050 instances into cyberbullying and 11605 instances into non-cyberbullying. Moreover, with the test run-2, the DFA-GRU technique has classified 1053 instances into cyberbullying and 11614 instances into non-cyberbullying. Furthermore, with the test run-3, the DFA-GRU technique has classified 1054 instances into cyberbullying and 11626 instances into non-cyberbullying.

Table 1 and Fig. 4 provide a brief classification results analysis of the DFA-GRU technique under three runs. For instance, with run-1, the DFA-GRU technique has gained a precision, recall, accuracy, and F-Score of 0.9494, 0.9831, 0.9942, and 0.9660 respectively. Eventually, with run-1, the DFA-GRU method has reached a precision, recall, accuracy, and F-Score of 0.9573, 0.986, 0.9951, and 0.9714 correspondingly. Meanwhile, with run-3, the DFA-GRU approach has gained a precision, recall, accuracy, and F-Score of 0.9679, 0.9869, 0.9962, and 0.9773 correspondingly.

Table 1 Result analysis of DFA-GRU model with different measures

No. of Runs	Precision	Recall	Accuracy	F-Score
Run-1	0.9494	0.9831	0.9942	0.9660
Run-2	0.9573	0.986	0.9951	0.9714
Run-3	0.9679	0.9869	0.9962	0.9773
Average	0.9582	0.9853	0.9952	0.9716

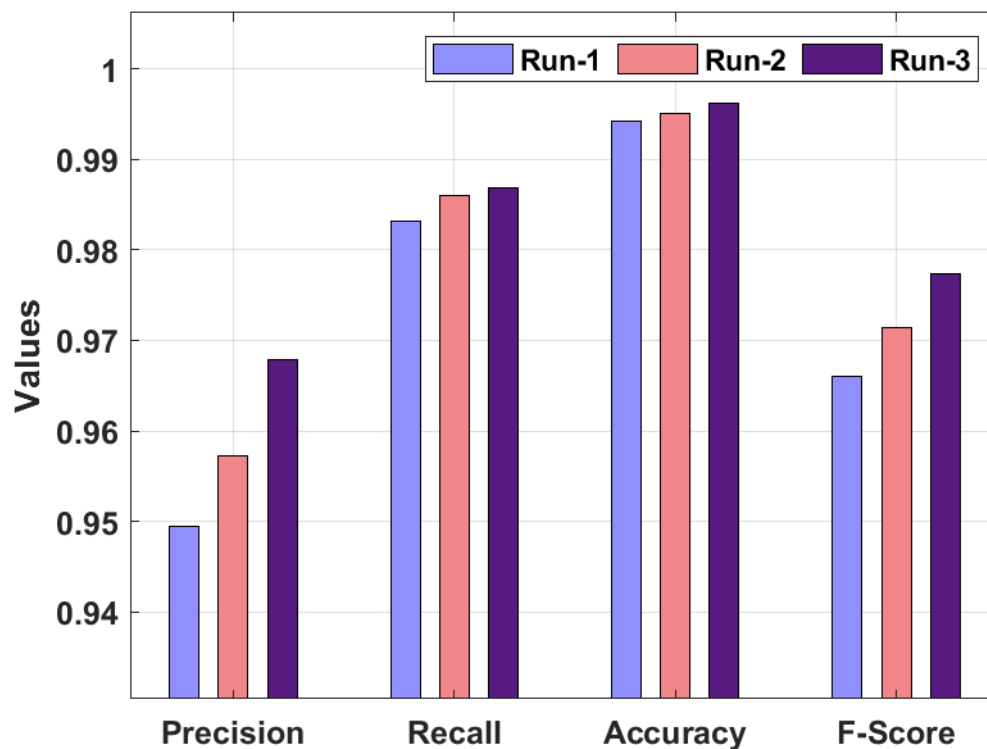


Fig. 4. Result analysis of DFA-GRU model with varying measures

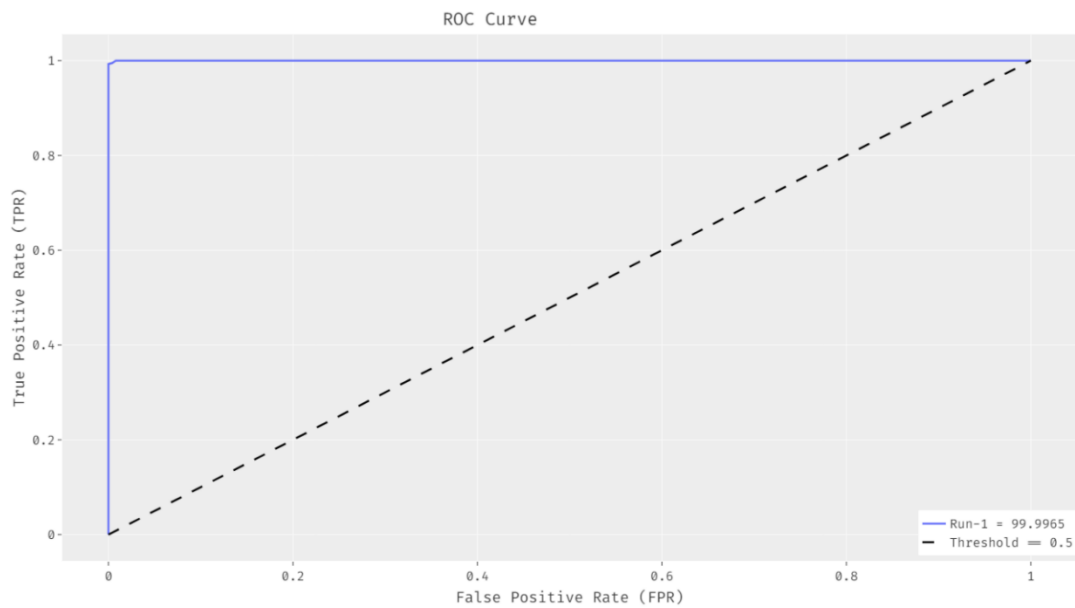


Fig. 5. ROC analysis of DFA-GRU model under run-1

Fig. 5 depicts the ROC analysis of the DFA-GRU technique on the classification of two classes. The figure portrayed that the DFA-GRU technique has resulted in an increased ROC of 99.9965 on the classification of two classes.

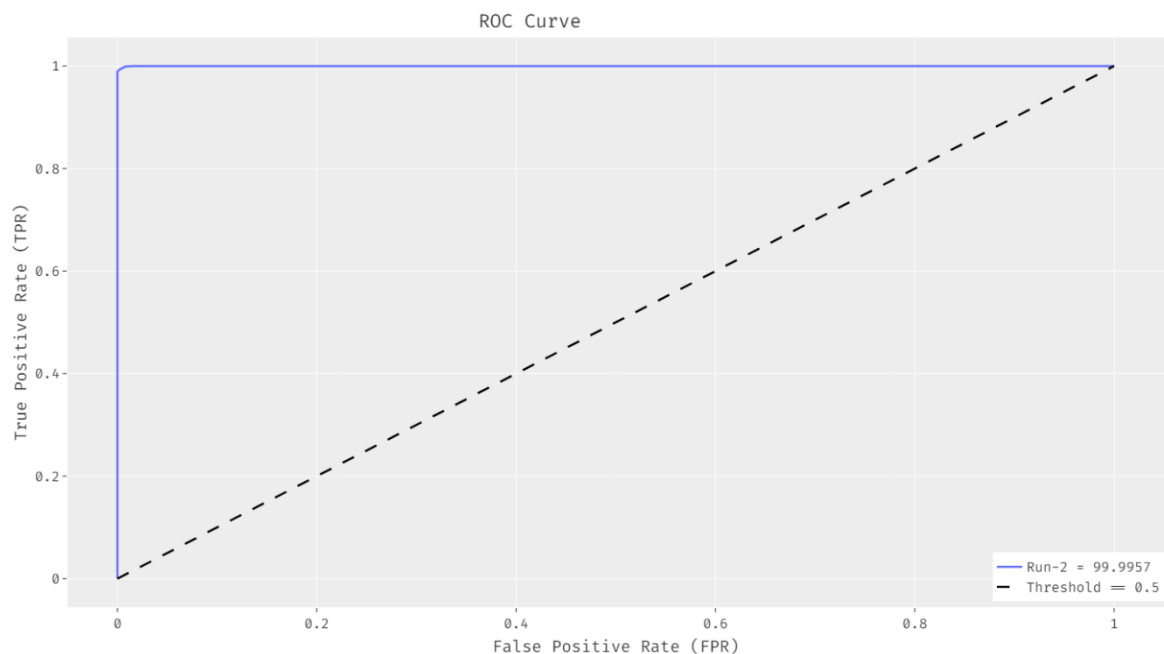


Fig. 6. ROC analysis of DFA-GRU model under run-2

Fig. 6 showcases the ROC analysis of the DFA-GRU system on the classification of two classes. The figure portrayed that the DFA-GRU manner has resulted in a higher ROC of 99.9957 on the classification of two classes.

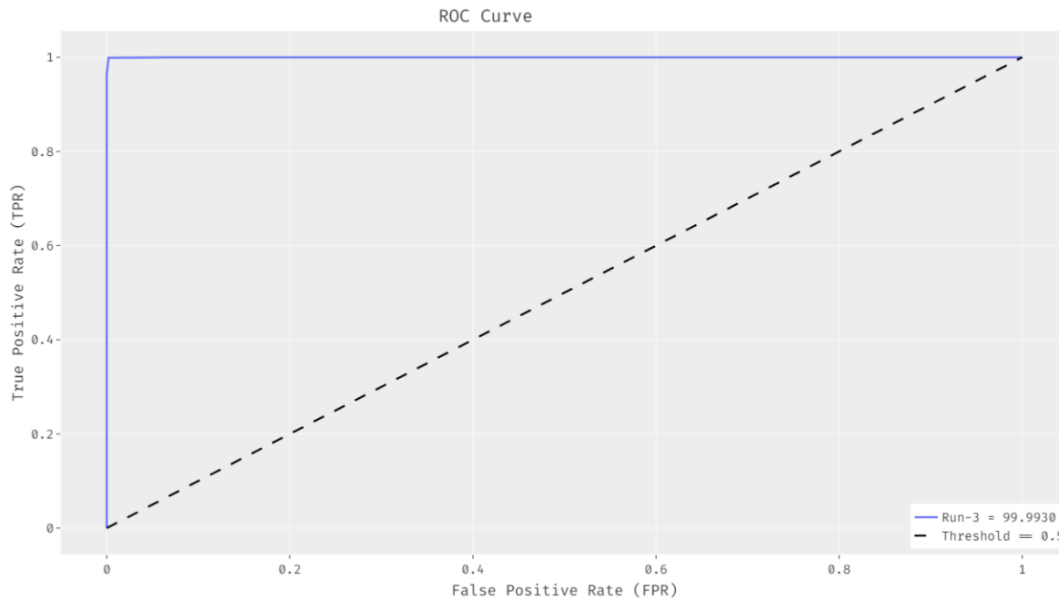


Fig. 7. ROC analysis of DFA-GRU model under run-3

Fig. 7 showcases the ROC analysis of the DFA-GRU method on the classification of two classes. The figure portrayed that the DFA-GRU algorithm has resulted in a superior ROC of 99.9930 on the classification of two classes.

Table 2 Average analysis of DFA-GRU model under 2 classes

2 Classes	Average
DFA-GRU	0.9952
SVM-Linear	0.9904
SVM-Poly	0.9941
SVM-rbf	0.6377
SVM-Sigmoid	0.9904
Naïve Bayes	0.9698

Table 2 and Fig. 8 showcases the average accuracy analysis of the DFA-GRU technique on the classification of two classes. The figure indicated that the SVM-rbf technique has attained poor outcomes with the least average accuracy of 0.6377. At the same time, the NB, SVM-Sigmoid, SVM-Poly, and SVM-Linear models have obtained moderately closer average accuracy of 0.9698, 0.9904, 0.9941, and 0.9904. However, the proposed DFA-GRU technique has accomplished maximum performance with a higher average accuracy of 0.9952.

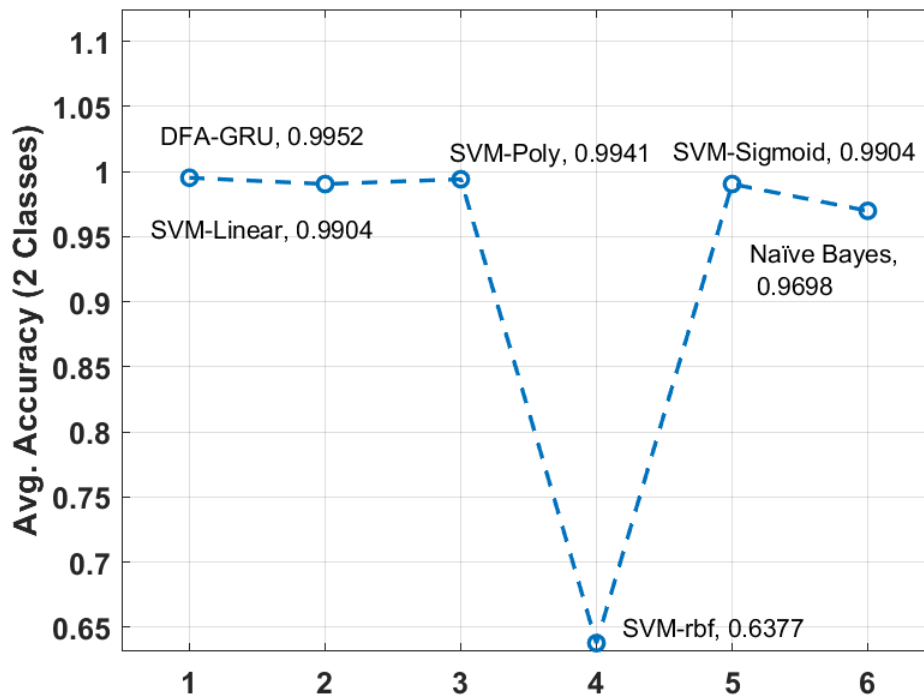


Fig. 8. Average accuracy analysis of DFA-GRU model under 2 classes

Table 3 Average analysis of DFA-GRU model under 4 classes

4 Classes	Average
DFA-GRU	0.9826
SVM-Linear	0.9521
SVM-Poly	0.9781
SVM-rbf	0.8190
SVM-Sigmoid	0.9521
Naïve Bayes	0.9237

Table 3 and Fig. 9 demonstrated the average accuracy analysis of the DFA-GRU technique on the classification of four classes. The figure indicated that the SVM-rbf technique has attained poor outcomes with the minimum average accuracy of 0.8190. Also, the NB, SVM-Sigmoid, SVM-Poly and SVM-Linear techniques have obtained moderately closer average accuracy of 0.9237, 0.9521, 0.9781, and 0.9521. But, the proposed DFA-GRU technique has accomplished maximal performance with a higher average accuracy of 0.9826.

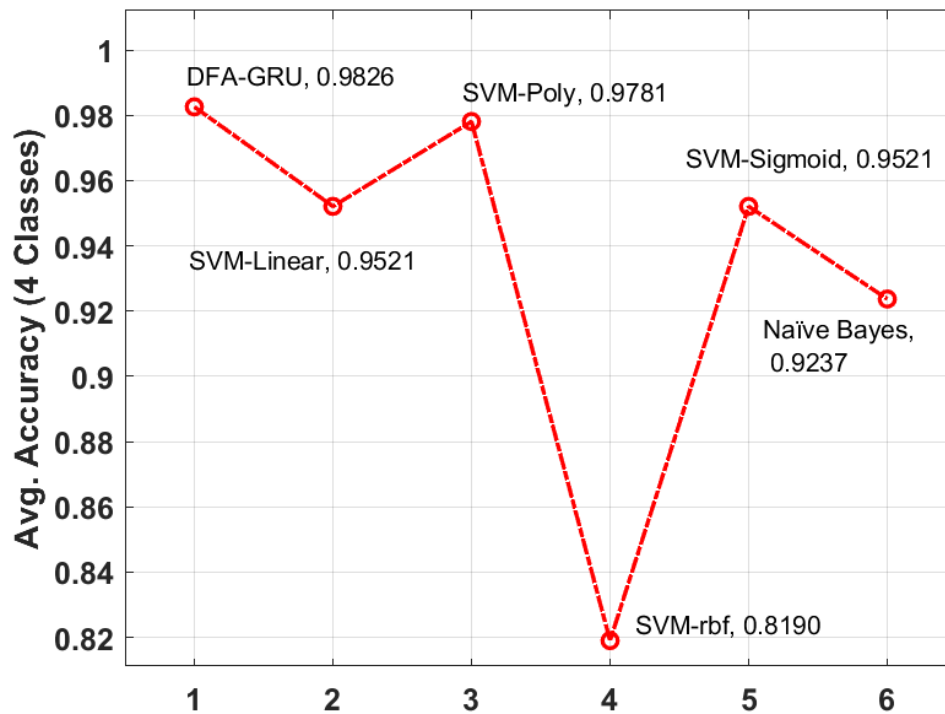


Fig. 9. Average accuracy analysis of DFA-GRU model under 4 classes

Table 4 Average analysis of DFA-GRU model under 11 classes

11 Classes	Average
DFA-GRU	0.9657
SVM-Linear	0.9348
SVM-Poly	0.9412
SVM-rbf	0.8673
SVM-Sigmoid	0.9348
Naïve Bayes	0.8909

Table 4 and Fig. 10 illustrate the average accuracy analysis of the DFA-GRU approach on the classification of 11 classes. The figure has shown that the SVM-rbf technique has gained worse outcomes with lower average accuracy of 0.8673. Besides, the NB, SVM-Sigmoid, SVM-Poly and SVM-Linear manners have gained moderately closer average accuracy of 0.8909, 0.9348, 0.9412, and 0.9348. At last, the presented DFA-GRU technique has accomplished maximal performance with higher average accuracy of 0.9657.

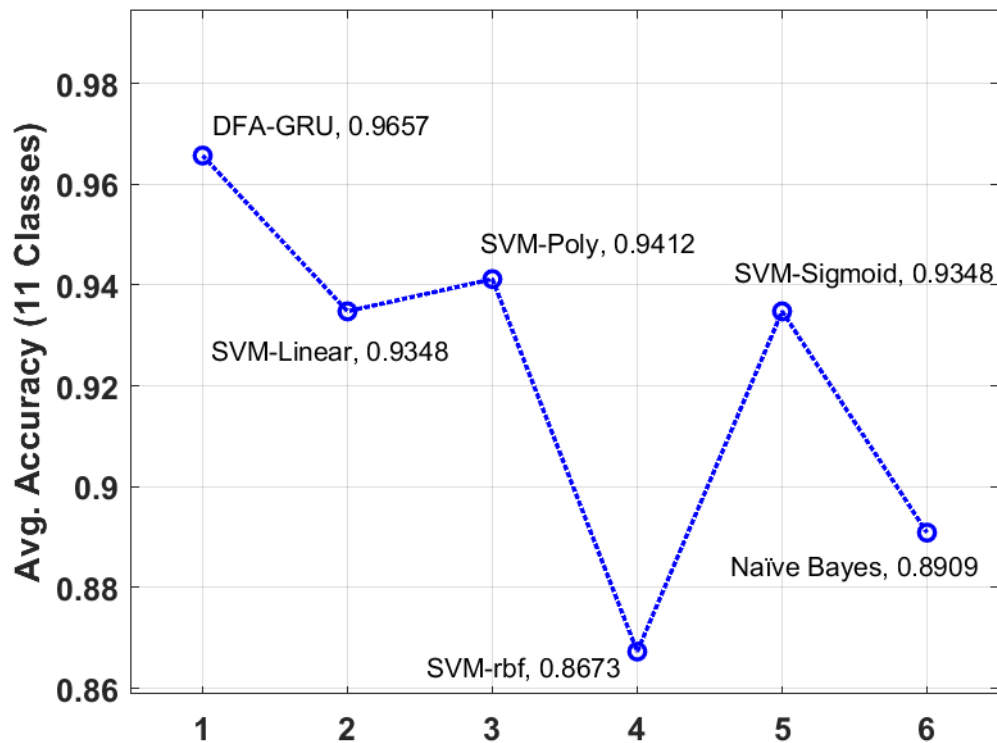


Fig. 10. Average accuracy analysis of DFA-GRU model under 11 classes

5. Conclusion

This paper has developed an effective DFA-GRU model for cybersecurity in social networking. The proposed DFA-GRU model aims to determine the social networking data into neural statements or insult (cyberbullying) statements. Besides, the DFA-GRU model primarily undergoes preprocessing to get rid of unwanted data and TF-IDF vectorizer is used. In addition, the GRU model is employed for the classification process in which the hyperparameters are optimally adjusted by the use of DFA, and thereby the overall classification results get improved. The performance validation of the DFA-GRU model is carried out using benchmark dataset and the results are examined under varying aspects. The experimental outcome highlighted the enhanced performance of the DFA-GRU model interms of distinct measures.

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