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Improved Cuckoo Search Optimization and Hybrid Firefly Artificial Neural Network Algorithm for Cyberbullying Discovery on Twitter Dataset

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Abstract

The exponential growth of SM (Social Media) and SNSs (Social Networking Sites) has seen escalations in Cyberbullying or bullying electronically making it imperative to focus researches in this area. Cyberbullying has grown into a pervasive and significant problem, impacting Internet users. TMTs (Text Mining Techniques) can help identify Cyberbullying while addressing many such similar concerns. However, proposed algorithms have certain issues on the Twitter dataset while identifying Cyberbullying texts or mining such texts. Hence this study proposes the use of ECSOs (Enhanced Cuckoo Search Optimizations) along with HFANNs (Hybrid Firefly Artificial Neural Networks) to overcome aforesaid hurdles. This work follows three steps namely pre-processing, feature subset selections, and classifications in order. K-Means clustering is a pre-processing step in this work and is used on the Twitter dataset to reduce processing record counts where k-means centroid values and min max normalisations manage missing and redundant features. K-Means used in this work improves categorization accuracy. The dataset features are pre-processed for obtaining more information and then used in the feature selection process where ECSOs compute a feature's importance based on fitness values and given by an objective function. The proposed HFANN subsequently classifies the selected features by training on the features to learn and use this learning to predict in tests. The best firefly is used to classify features accurately. This work's experimental result demonstrates the effectiveness of the proposed method. ECSO+HFANN algorithm provides better classification performance in terms of lower time complexity, higher precision, recall, f-measure and accuracy than the existing algorithms.

Keywords: Cyberbullying detection, Twitter dataset, k-means algorithm, Enhanced Cuckoo Search optimization (ECSO), Hybrid Firefly Artificial Neural Network (HFANN)

1. Introduction

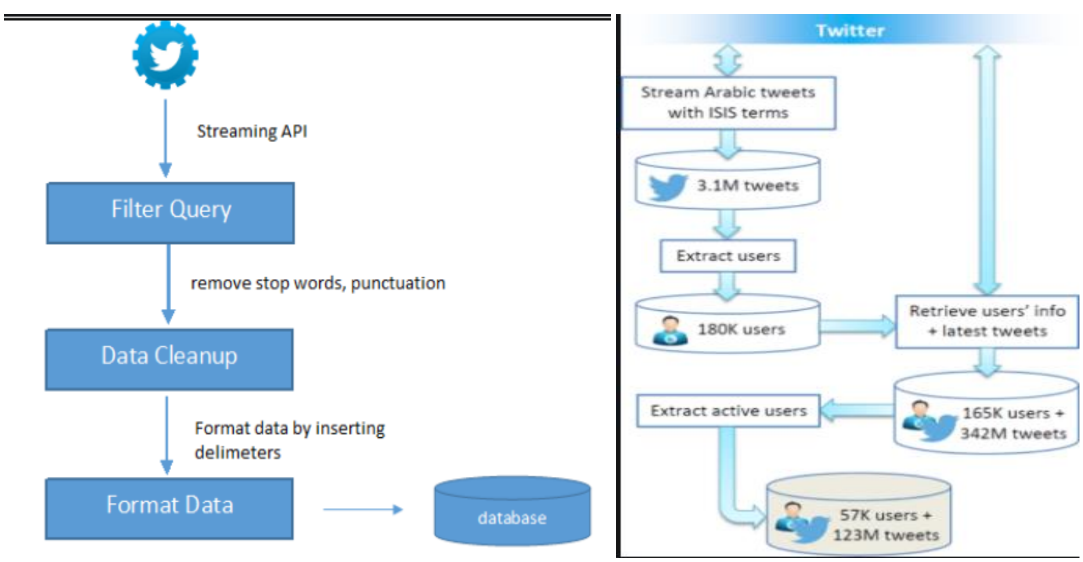
TMTs have grown in importance as a study area, revealing previously unknown information from diverse data sources. Connecting extracted data to produce new facts or hypotheses for further investigations is a crucial component of research. TMTs are not similar to web searches [1]. In most cases, searches happen for known information, but the issue is in identifying unwanted information that comes along with results. The purpose of using TMTs is to discover unknown and hidden information in vast sources of data.

Cyberbullying can be described as intentional aggressive, activities using digital communication means like sending messages or posting comments that go against victims. Cyberbullying sources can be individuals or groups [2] [3]. Cyberbullying contrasts traditional bullying as they can occur anywhere and anytime using the medium of internet, Traditional bullying occurs in known places or known people while Cyber Bullies hide behind the Internet screen and youngsters who are continuously connected to the Internet or social media become victims of Cyberbullying as they are easily exposed to harassments.

Twitter, a SNS has millions of users who share their thoughts on a variety of topics including politics, businesses, goods, and celebrities. It is a popular micro-blogging platform where users communicate using 140-character messages called tweets [4]. About 100 million daily active users can be found on Twitter with approximately 200 million tweets per day. Tweet contents have hashtags/mentions which are Twitter-specific elements used in studies. Other Twitter variables used include age of accounts, tweets quantity, and follower-followee. These Twitter-specific traits, when combined with URL-based features can prove to be a part of powerful systems which detect phishing tweets.

Twitter endeavours to provide a space for people to express themselves freely. Additionally, provides a medium for users to report any sort of abusive content on the platform. The user can include multiple tweets in the same report, helping Twitter to improve its context, while inspecting the problems to get them resolved sooner. In addition, a user can block, mute or unfollow other unwanted users. Cyberbullying was detected by Ozel et al. In [5]. They acquired data from Twitter and Instagram in Turkish and used DTs (Decision Trees) C4.5, SVM, Multinomial Nave Bayes, and KNNs (K Nearest Neighbors). According to their findings, accuracy improved when both words and emoticons in text messages were included as characteristics. In their experimental testing, Nave Bayes surpassed all other algorithms in detections with an accuracy of 84 percent.. Figure 1 depicts Twitter data Example

Figure 1. Example of Twitter Data



The features selection process is an important stage finding efficient features (more discriminant) and improving the quality of datasets (better and faster results). Different features are extracted from the given datasets have been evaluated to achieve better representation. Cyberbullying classifier accuracy is based on both its feature selection method and classification algorithm. Irrelevant and improper features cause classifier to output inaccurate results. Feature selections are optimization-based solutions to this issue and involve eliminating irrelevant and redundant characteristics in datasets [6]. Methods classify data attributes for predictions or categorize labels (Classification) using training sets and values. SVMs are supervised pattern classifications and were used to categorise data from Twitter. SVMs translate data into a higher-dimensional feature spaces and separate classes sing a maximum margin hyper plane, SVMs can also discover a non-linear decision functions in the input space. They use a subset of informative points known as support vectors which form a sparse linear combination or represent the separating hyper plane [7].

The main problem of this research work is the Cyberbullying detection on Twitter dataset. Though several studies and techniques have been proposed, the accuracy of predictions using the Twitter dataset has been found to be wanting. Existing methods have drawbacks like increased time consumptions and inaccuracies in identifying Cyberbullying. To overcome this issue, this work proposes ECSO+ HFANN with the aim of increasing overall system performance. The primary contribution of this research work is pre-processing, feature selection using ECSO algorithm and Cyberbullying detection using HFANN. The proposed method is used to provide more accurate results using effective algorithms for the given Twitter dataset.

2. Related Work

In [8], Al-Garadi et al (2016) introduced a set of unique features derived from Twitter; network, activity, user, and tweet content, based on these features. The scheme was a supervised machine learning solution for detecting Cyberbullying in Twitter. Their evaluations demonstrated that detection models based on their proposed features, achieved an area under the ROC (Receiver-Operating Characteristic) curve of 0.943 and an f-measure of 0.936, thus indicating that their proposed model based on the study’s considered features provides a feasible solution to detecting Cyberbullying in online communication environments. Finally, the results from the study’s suggested features with two baseline features were compared where outputs demonstrated the importance of proposed features.

In [9], León-Paredes et al (2019) presented SPC (Spanish cyberbullying Prevention System) based on NLPs (Natural Language Processing) and MLTs (Machine Learning Techniques) including (Naive Bayes, SVMs and LRs (Logistic Regressions) using Twitter data. The scheme trained with a variety of precision metrics and different corpus data sizes. Their learning resulted in a maximum accuracy of 93 percent..

In [10], Zhang et al (2019) using several MLTs on Twitter data. They extracted different textual characteristics and investigated their impacts on the Japanese text to build an optimum model for automatic detection of Cyberbullying. Their best model using predictive textual characteristics achieved an accuracy of above 90%, according to the testing results.

In [11], Balakrishnan et al (2020) in their study proposed an automatic cyberbullying detection method that tapped psychological characteristics of Twitter users like personalities, mood, and emotion. Big Five and Dark Triad models were employed to identify user personalities, while MLTs like Nave Bayes, RFs (Random Forests), and J48 were used to categorise tweets into one of four categories: bully, aggressor, spammer, and normal. The Twitter dataset of 5453 messages was manually annotated by human specialists and obtained using the hashtag #Gamergate. As a baseline algorithm, selected Twitter-based characteristics like text, user, and network-based features were employed. Their results revealed that when personalities and feelings were utilised, cyberbullying detection increased; however, there was no such impact for emotions. Extraversion, agreeableness, neuroticism, and psychopathy were found to have larger impacts in identifying online bullying when compared to other personality characteristics. Using a dimensionality reduction approach, key characteristics were discovered and incorporated into a single model that gave the study greater detection accuracy. The study also suggested on using their results to mitigate Cyberbullying.

In [12], Dash et al (2010) proposed K-means partitioning for discovering specific number of clusters based on centroid values. Since, the outputs depended heavily on the starting cluster centre locations and distance computations increased exponentially for voluminous data, the study used PCAs (Principal Component Analysis) for dimensionality reduction before K-means clustering. The study could visualize multi-dimensional data easier. The scheme also presented a novel approach for locating the initial cluster centroids for improving the scheme's effectiveness and efficiency. The experimental evaluations of the study obtained better accurate when compared to other existing approaches.

In [13], Salesi et al (2017) introduced a pseudo-binary mutation neighbourhood search method and integrated it with a binary version of CSO to overcome their scheme's shortcomings. The suggested Extended Binary CSO selected features and retained only the best as a feature subset. The study developed a new objective function by taking into account the feature counts and classification accuracy while framing its optimal subset of features. SVM classifications in this generated set of candidate features showed that the proposed Extended Binary CSO outperformed other nature-inspired algorithms like Binary ACOs, Binary GAs and Binary PSOs on biomedical datasets. The scheme also inferred that by utilising their suggested function, greater classification accuracy could be achieved with lesser number of features.

In [14], Abd El Aziz et al (2018) proposed a modified CSO for data with more number of features. The study used rough sets while mimicking natural behaviour of cuckoo's parasite and flying behaviours. The fitness function of the proposed scheme used rough sets theory to reduce the amount of features and better classification quality. The proposed method was benchmarked on multiple UCI repository datasets for experimentations while being evaluated with Variance test analysis. The study also compared their scheme with other algorithms on on discrete datasets where the suggested technique was compared with KNNs and SVMs based learning where it was demonstrated that the scheme considerably improved classification performance.

In [15], Emary et al (2015) proposed feature selections using flash lighting mechanism of fireflies inspired FFA (FireFly Algorithms) optimizations. Since, datasets may contain useless or redundant data thus increasing the search space and impairing classification accuracies, the study aimed at attribute reductions and chose a subset of useful traits from a large number of accessible attributes in order to achieve classification accuracy. The study's feature selection method was based on a modified FFA optimizations where it quickly discovered the best solution by adaptively up[dating FFA with balanced explorations and exploitations. FFA was found to swiftly search feature spaces for generating feature subsets and minimized by a fitness function as the function considered classification accuracy and feature reductions. The study tested their proposed method in 18 datasets where it scored better in terms of accuracy when compared to PSOs and GAs.

In [16], Ghiassi et al (2013) proposed a method for developing a Twitter-specific vocabulary utilising n-grams and statistical analysis for SAs (Sentiment Analysis) based on supervised feature reductions. For brand-related tweets, the study supplemented Twitter-specific lexicons with brand-specific words. The work proved that even with reduced features (187), the lexicon set reduced modelling complexity while retaining a high degree of coverage on Twitter corpus, and improved sentiment classification performances. The study's sentiment model using Twitter-specific vocabulary when compared with SVM and standard sentiment lexicons in classifications illustrated the scheme's efficiency. In terms of recall and accuracy measures, Twitter-specific vocabulary was much more effective. The study's use of DAN2 machine learning technique proved to be effective in overcoming other text classification issues. Thus, the study's Twitter-specific vocabulary and DAN2 machine learning approach delivered better accuracy than SVMs in sentiment classifications.

3. Proposed Methodology

In this research work, the ECSO+ HFANN algorithm is proposed to improve the Cyberbullying detection results on the Twitter dataset. The proposed system contains preprocessing using k-means clustering algorithm, feature selection using ECSO algorithm and Cyberbullying detection process using HFANN algorithm.

3.1 Preprocessing using k-means Algorithm

To improve the accuracy of Cyberbullying detection, pre-processing using k-means clustering technique was done in this research work. Twitter data is generally noisy as it includes banned emoticons, folksonomies, slangs, and phrases [24]. The short message of Twitter was used to extract useful information with K-means clustering and by dividing data into categories based on cluster's initial centroids [17]. The centroids of the clusters are computed using the Euclidean distances. Algorithm I computes current cluster centres (i.e. the average vector of each cluster in the data space) while the second reassigns each data item to the cluster whose centre is closest to it, starting with a random partitioning. The procedure stops when there are no more reassignments. The intra-cluster variance, or the sum of squares of differences between data features and their associated cluster centres, is reduced locally in this proposed approach. k-means is used as it is easy to implement and its runtime runs linearly with the amount of data items. The cluster class couts are kept equal in this work.

Algorithm 1: k-means Algorithm

1. Select the clusters count k from the Twitter Dataset
2. Pass initial values to cluster centers µ1,… µk
3. Select k data points (tweets) and cluster centers for these data points
4. Assign points randomly to clusters and compute the mean of clusters
5. Calculate the distance measure for identifying the missing values for each data point by computing the cluster centre it is closest to using the formula below.

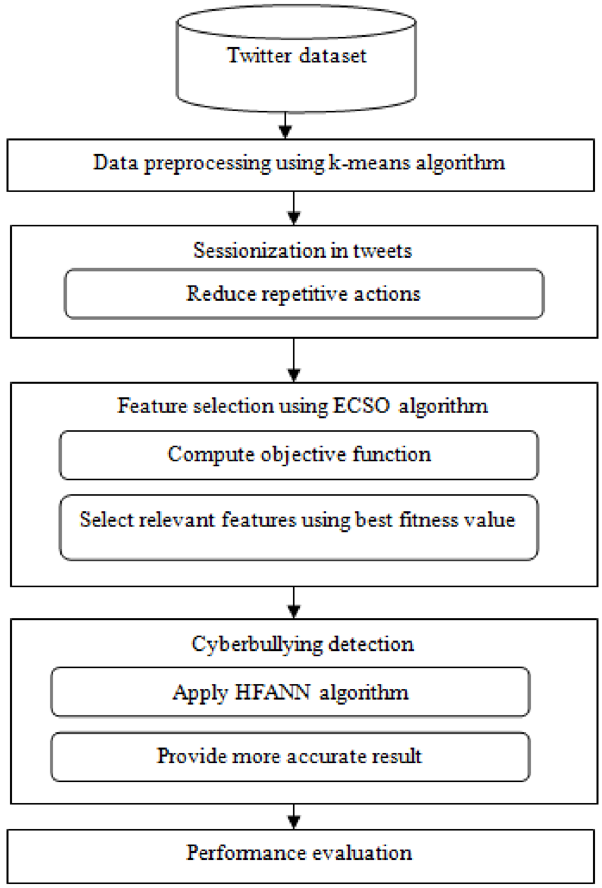
   $$d(i, j) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (1)$$

   Where x_i and y_i are two points in Euclidean n-space
6. Assess redundant features using min-max normalization $v' = \frac{v - \min(D)}{\max(D) - \min(D)}$ (2)

   Where min and max is minimum and maximum values for the features in the D
7. Assign data points to clusters
8. Re-calculate cluster centers based on cluster's mean values
9. End the process when there no new re-assignments

The instances in the original Twitter dataset that had missing values were removed from the dataset and the dataset was split into two sets, one with full instances and no missing values while the other had incomplete instances with missing values. K-means clustering was used to produce clusters with full examples. Each instance was processed one by one and missing attributes were filled with their potential values. From the generated clusters, K-means clustering verified newly added instances and checked its grouping in the proper class. If the cluster was accurate, the given value was made permanent, and the operation was repeated. In the case of incorrect instances the next potential value was allocated and compared until the value proper cluster value was identified. Min-max normalisation determined and reduced redundant values [18]. K-means pre-processing included Uppercase to lowercase conversions, URL replacements, removal of punctuation marks/ hashtags, conversion of emoticons into the most suitable words, stop words removal, and stemming of words. The pre-processing approach was aimed at increasing Cyberbullying classification accuracy. Figure 2 depicts the overall structure of the proposed system.

Figure 2. Overall Flow of the Proposed System



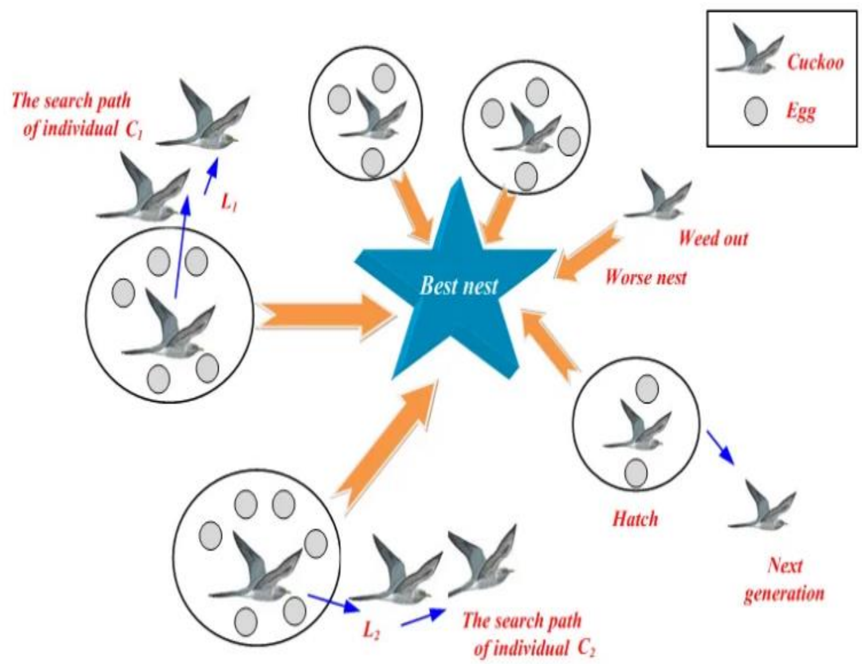
3.2 Sessionization

Because cyber bullying generally entails repeated behaviours, it seeks to track users' tweets over a period of time. [19], Considering a lower threshold of comments for media sessions as derived from Instagram in annotations, this work produced sets of time-sorted tweets (sessions) for each user by grouping tweets posted near to each other in time. Initially, inactive users or users who haven't tweeted more than five times in the last three months are filtered. Subsequently, a session-based approach in which the inter-arrival time between tweets for each session Si does not exceed a specified time threshold ti is employed. For the hate-related dataset, lowest, median, and maximum lengths of the resultant sessions (in terms of tweets count included) were 12, 22, and 2.6k tweets, respectively where 5, 44, and 1.6 thousand tweets existed in the baseline collection.

3.3 Feature Selection using Enhanced Cuckoo Search Pptimization (ECSO)

Feature selection is done by using ECSO algorithm which chooses relevant features from the tweets. By using ECSO algorithm, optimal feature selection is done through best fitness values. In this section, the feature selection is performed by using ECSO algorithm for selecting important and more informative features from the given Twitter dataset. Cuckoo search is a recently developed nature-inspired metaheuristic method for finding optimum solutions. Cuckoos are appealing birds due to their exquisite vocalisations and aggressive reproductive tactics. Several species of cuckoos, such as the Ani and Guira, lay their eggs in communal nests and may remove other people's eggs to enhance the chances of their own eggs hatching. CSO is based on a few cuckoo species' brood parasitism, in which they lay their eggs in the nests of other host birds. The Levy flights, rather than isotropic random walks, improve the CSO method. If a host bird recognises the eggs as not being its own, it will either discard them or quit its nest and build a new one somewhere [20]. Each cuckoo egg indicates a fresh solution, and each egg in the nest represents a solution. If the new solution (cuckoo) is better than the old, it will take the place of the current solution in the nest. The Levy flights, rather than isotropic random walks, improve the CSO method. The Cuckoo's Habitat is depicted in Figure 3.

Figure 3. Cuckoo’s Habitat



The following rules have been used to describe cuckoo search in this study.

- Each cuckoo lays one egg at a time and deposits it in a randomly selected nest
- Only best nests with high-quality eggs are passed down to future generations.
- The number of available host nests is determined, and the cuckoo's egg is located by the host bird with a high likelihood of belonging to one of them (0,1). The host bird has the option of either removing the egg or abandoning the nest and starting over.

A fraction pa of n host nests are replaced by new nests approximated based on the last assumption (new random solutions). CSOs are easy to use and offer a large search area as they employ levy flights instead of normal random walks of global search, allowing CSO to explore search space more effectively and quickly.

Different forms of host nests with many eggs increase CSO outputs [21]. In general, cuckoos lay their eggs in one of three types of nests. The common cuckoo chooses a group of host nests that produce eggs that are identical to their own. Other cuckoos choose a group of host nests with eggs that are different from their own. Other cuckoo species lay cryptic eggs, which are dark in colour when their host birds' eggs are light. This technique evolved in cuckoos that parasitize hosts with dark, domed nests in order to hide the eggs from the host.

Initial Population

Each egg in this work represents a possible collection of characteristics that are chosen and utilised to accurately classify tweets. The top-m rated features derived using statistical measures across the Twitter dataset are used to pick the tweets (features).

Finding new solutions and Levy flight

For discovering novel solutions from Equation, the ECSO-based feature selection technique use levy flight of Equation (4). A short stroll around the best solution discovered thus far should create some new solutions, speeding up the local search. The novel solution employs Levy flying to produce $x_i^{(t+1)}$ for cuckoo i and as given below

$$x_i^{(t+1)} = x_i^{(t)} + C \oplus \text{Levy}\ (s, \lambda) \tag{3}$$

t is the step size. The step length follows the Levy distribution

$$\text{Levy}\ (S, \lambda) \sim s^{-\lambda}, \quad 1 < \lambda \leq 3 \tag{4}$$

Crossover and Mutation

- If the cuckoo is a common cuckoo, crossover is utilised to produce two eggs in the nest and select the best one.
- The European cuckoo breeds two eggs and selects the best of them utilising the crossover with uniform mutation operator.
- Otherwise, random solution is used to generate eggs (cryptic).

Fitness function

In the selection process, the fitness function is quite important. Notable tweets (features) from the Twitter dataset are successfully picked by utilising best fitness function values. In the process of Twitter categorization utilising significant characteristics from feature vectors, classification accuracy is significant. Since, fitness function of ECSO assesses classification accuracy of the Minimum distance classifier, the fitness function includes both relevance and redundancy to help ECSO choose the best feature as represented by the following Equation.

$$\text{fitness (f)} = \text{accuracy (f)} \tag{5}$$

Accuracy(f) is the test accuracy of testing data f in a classifier developed with training data feature selection. Equation (6) gives the minimal distance classifier's classification accuracy.

$$\text{Accuracy (f)}=\frac{s}{t} * 100 \tag{6}$$

Where, s – KNN’s correctly classified samples using minimum distance in test data, t - Total test data samples

As a result, the significant and necessary characteristics are picked more effectively from the provided dataset utilising ECSO.

Parameter Pa

In ECSO P_a value changes dynamically given by Equation (7)

$$P_a = P_a \max - \frac{P_a \max - P_a \min}{\text{iter\_max}} * \text{iter} \tag{7}$$

Algorithm 2: ECSO

Generate an initial population of n host nests with m eggs (tweets);

while (t<MaxGeneration) or (stop criterion)

for every nest

Get a cuckoo type randomly (say i)

Check the type of the cuckoo

If cuckoo_type=common_cuckoo

Create two eggs through crossover with two best eggs in the nest (solution) and choose the best one among them

Else if cuckoo_type = European cuckoo

Create two eggs through crossover with uniform mutation operator with any two eggs in the nest

Select the best one among them

Else

Create egg with random solution (cryptic egg)

End if

Evaluate its fitness fi using (5)

Select an egg with the worst solution in the nest (say j)

If (fi>fj)

Replace j by new solution i

End if

Based on the solution, assign a score to the egg.

Among the m eggs in the nest, choose the optimal solution.

Build additional eggs utilising levy flight (3) and abandon a portion of the eggs in the nest that have the worst solutions (4)

Calculate the accuracy value by using (6)

Use Pa to update the parameter Pa. (7)

Keep the most effective solutions.

End of Rank the eggs in all nests based on fitness value and determine the current best

Select the more relevant and important tweets

End while

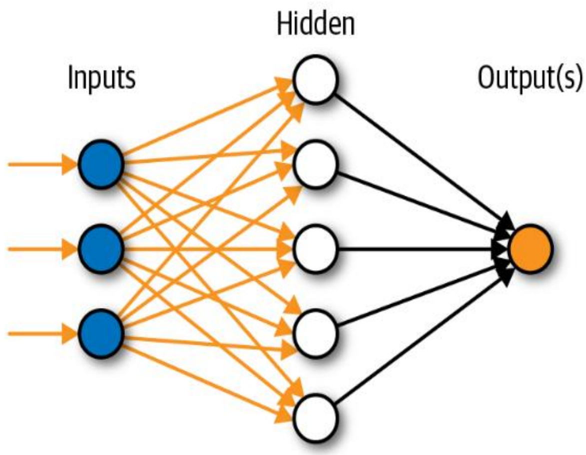
The algorithm describes that the Tweets (features) are selected by using best fitness values of objective function. The levy flight is built the new best solutions and unnecessary features are reduced significantly. Thus the ECSO optimization algorithm is used to increase the more informative features for the given Twitter dataset.

3.4 Cyberbullying Detection by using Hybrid Firefly Artificial Neural Network (HFANN) Algorithm

In this work, Cyberbullying detection is performed by using Hybrid Firefly Artificial Neural Network (HFANN) algorithm. Because cyber bullying is a classification problem (classifying an incident as offensive or non-offensive), HFANN is used in this study to improve classification accuracy and performance in detecting cyber bullying on Twitter. It is utilised to offer more reliable results for the identification of cyber bullying. ANNs (Artificial Neural Networks) are another biologically inspired technology that mimics the human brain. An ANN is meant to mimic the behaviour of brain neurons and is made up of nodes, neurons, dendrites, and synapses connected by arcs, exactly like a biological nervous system. Every arc has a weight connected with it. After applying inputs, an activation function is applied to these arcs to change the weights in order to obtain the appropriate set of outputs. A neural network is essentially a computer model that implements machine learning [22].

ANN can execute perceptual and recognition tasks in a shorter period of time than humans. In this study, ANN is used to determine if a tweet constitutes cyber bullying or not. A neural network takes use of a problem's non-linearity to define a set of preferred inputs. The construction of ANN is depicted in Figure 4. It has three layers and is made up of three components.

Figure 4. Structure of ANN



Input Layer - The information that is fed into the network is carried by the input layer. Initially, this information is rather raw.

Hidden Layer - The primary function of the hidden layer is to convert the raw data received from the input layer into something that the output layer can use. One or more hidden layers can be present in an ANN architecture.

Output Layer - The output layer receives information from the hidden layer and processes it to generate the desired results.

ANNs include adaptable weights along pathways between neurons that may be fine-tuned using a learning algorithm that learns from observed data to enhance the model. In addition to the learning algorithm, an acceptable cost function must be chosen. They utilised word embedding to identify cyberbullying by creating a list of pre-defined offensive phrases and assigning weights to them.

The cost function is used to discover the best solution to the situation at hand. This entails figuring out the optimum values for all of the adjustable model parameters, with neuron path adaptive weights being the main focus, as well as algorithm tuning parameters like learning rate. It's usually done through optimization techniques such as gradient descent or stochastic gradient descent.

In the hidden layer, the features from the input layer are calculated by a linear function (8) and a transfer function (9) to generate the output feature of a hidden node

$$N_i = \sum_{p=1}^{P} w_{i,p} I_P + B_i \quad (8)$$

where N_i is the value of the i^{th} feature; $w_{i,p}$ and B_i are the weight of the p^{th} input to the i^{th} hidden node and the bias parameter of the i^{th} hidden node, respectively; I_P is the value of the p^{th} input node.

The transfer function is defined as:

$$y_i = f(N_i) = \frac{1}{1+\exp(-N_i)} \quad (9)$$

Where the transfer function in this study is a sigmoid function and y_i is the output signal of the i^{th} hidden node

During the learning process, ANN uses the Mean Square Error (MSE), to evaluate the performance of the model as follows:

$$\mathrm{MSE} = \frac{1}{NN_{out}} \sum_{n=1}^{N} \sum_{o=1}^{N_{out}} (e_{n,o})^2 \quad (10)$$

where N and $N_{out}$are the number of instances and the number of outputs, respectively; $e_{n,o}$is the training error at the o^{th} output with n^{th} instance; y is the actual output and $\bar{y}$ is the predicted output by ANN. FFA is used with ANN to minimise error rates and improve accuracy. The optimization approach aims to get the ANN solution nearer to the optimal solution, which implies that if it succeeds, the ANN will be able to handle the issue with high performance. To increase the convergence speed and accuracy for the provided Twitter dataset, the firefly method is coupled with the ANN algorithm in this study.

The physiological and sociological characteristics of actual fireflies inspired the Firefly algorithm [23]. Real fireflies emit a brief, rhythmic light that aids in attracting (communicating) their mating partners as well as serving as a defensive warning mechanism. The objective function optimizes to design FFA's flashing behaviour. For the fundamental formulation of FFA, the following three rules are idealised. (3) All fireflies are unisex, which means that they will attract each other regardless of gender. (2) Attractiveness is related to the brightness of the flies, which diminishes as the distance between them grows. As a result, the one that is less brilliant will migrate towards the one that is brighter. If it cannot identify a brighter one, it will travel at random. (3) The landscape of the objective function determines the brightness of a firefly..

$$x_i = x_i + \beta_o \times e^{-\gamma r^2 ij} \times (x_j - x_i) + \alpha \times (\mathrm{rand} - 0.5) \quad (11)$$

Where the first part of (1) represents the movement of attraction between two fireflies, the second part represents the attraction. β_0 is the initial attractiveness which is always set to 1, and γ is the absorption coefficient which controls the speed of convergence between fireflies. The third part of (1) is randomization, where α is a constant randomization parameter defined between [0, 1], it represents the noise of the environment that be used to provide more diversity of solutions, rand is a random number generated from a uniform distribution [0, 1] and adjusted to range between [– 0.5, 0.5] by expression (rand – 0.5). The proposed method in Twitter is analyzed as positive opinion tweets and negative opinion tweets

Algorithm 3: HFANN

Input: Twitter dataset, training data, testing data

Objective function: Assign the Cyberbullying detection accuracy as fitness function

Output: Cyberbullying or Non Cyberbullying Tweets

1. Start
2. For each training data $\{(x(i), d(i)), i = 1, \ldots p$
3. Compute weight value and bias for every feature in input data
4. Adjust weight value and bias value for every feature
5. Objective function f(x), x = (x1,……x4) T
6. Generate initial population of fireflies xi (i=1,2,...n)
7. Light intensity Ii at xi is determined by f(xi)
8. Define light absorption coefficient γ
9. for i=1:n all n fireflies
10. for j=1:i all n fireflies
11. if (Ij>Ii),
12. end if
13. Evaluate new solution and update light intensity
14. end for j
15. end for i
16. Rank the fireflies and find the current best
17. Compute best fitness values using (11)
18. Update weight and bias value(8)
19. End for
20. ANN = ANN(Input, Hidden, Output)
21. Train model = Accuracy (train feature)

22. Test model = Accuracy (test feature)

23. Calculate error rate (MSE) using (10)

24. MSE(train and test tweets)

25. Return more accurate results (cyberbullying or non-cyberbullying tweet)

By achieving the higher accuracy, this method improves cyberbullying detection to help people to use social media safely. It is used for detecting cyberbullying pattern for the large size of training data.

4. Experimental Result

4556 tweets from diverse subjects including demonetisation, kids, mobile phones, sachin, and whatsapp are searched and evaluated as good and negative opinion tweets in the Twitter dataset. Table 1 lists tweets that were examined. Precision, accuracy, recall, f-measure, and time complexity are among the performance measures examined. On the Twitter dataset, the current SSVM, v, and new ECSO+HFANN algorithms are assessed for performing the above stated metrics.

Table 1: Tweets Collected using different w Search Terms

File Name	**Total No. of Tweets**	**Actual**	
		Positive Opinion Tweets	**Negative Opinion Tweets**
demonetisation.txt	1003	498	505
kids.txt	984	402	582
mobilephones.txt	783	599	184
sachin.txt	994	483	511
whatsapp.txt	792	599	193

- True Positive (TP) → Correctly identified as positive opinion tweets
- False Positive (FP) → Incorrectly identified as positive opinion tweets
- True Negative (TN) → Correctly identified as negative opinion tweets
- False Negative (FP) → Incorrectly identified s negative opinion tweets

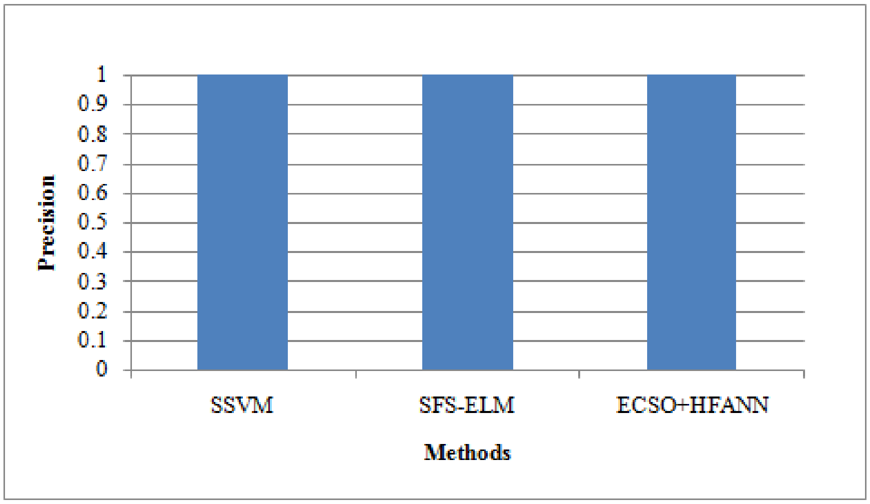
Precision

The precision is calculated as follows:

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive+False positive}} \quad (12)$$

Precision is a measure of completeness, whereas recall is a calculation of correctness or quality. In general, high precision means that an algorithm produced many more relevant results than irrelevant ones. The accuracy of a class is the number of genuine positives divided by the total number of items identified as belonging to the positive class in a classification job.

Figure 5. Precision



In terms of accuracy, the comparison measure is assessed using both current and suggested methods, as shown in Fig 5. The techniques are displayed on the x-axis while y-axis shows precision values. Existing algorithms like SSVM and SFS-ELM have lesser precision, but the suggested ECSO+HFANN approach has a better precision for the provided Twitter dataset. Thus, the suggested ECSO+HFANN increases Cyberbullying detection accuracy by the optimal selection of features, according to the results.

Recall

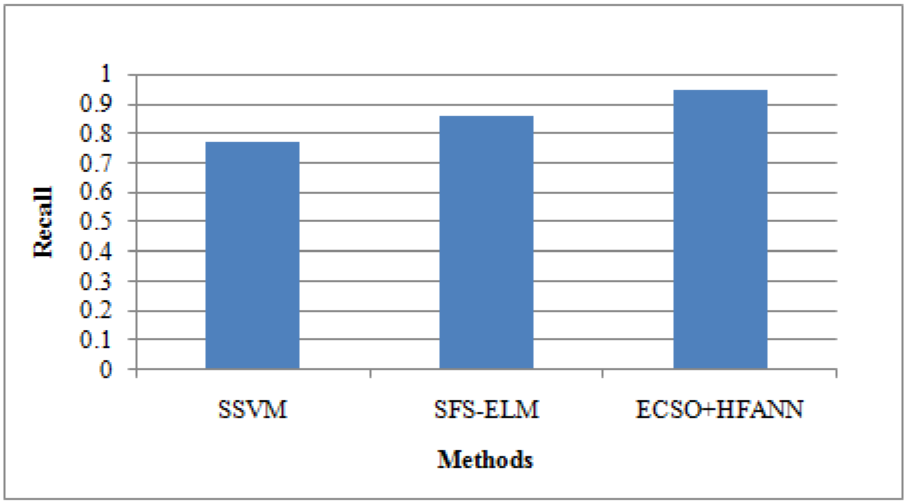
The calculation of the recall value is done as follows:

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive+False negative}} \tag{13}$$

The comparison graph is depicted as follows:

The number of relevant documents recovered by a search divided by the total number of existing relevant documents is known as recall, whereas the number of relevant documents retrieved by a search divided by the entire number of documents obtained by that search is known as precision.

Figure 6. Recall



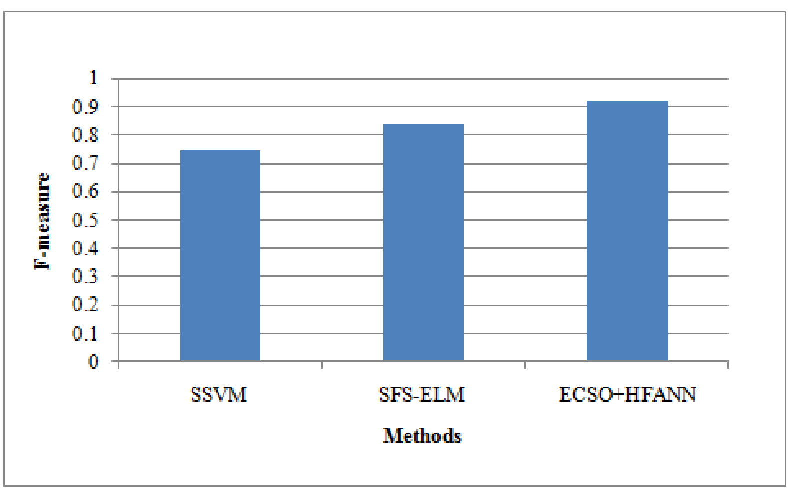
In terms of recall, the comparison measure is assessed using both current and new methods, as shown in Fig 6. The techniques are displayed on the x-axis, while the recall value is plotted on the y-axis. For the provided Twitter dataset, current techniques such as SSVM and SFS-ELM algorithms provide lesser recall, but the suggested ECSO+HFANN algorithm gives higher recall. Thus, the suggested ECSO+HFANN increases Cyberbullying detection accuracy by the optimal selection of features, according to the results.

F-measure

F1-score is defined as:

$$\mathrm{F1-score} = \frac{2\times\mathrm{precision}\times\mathrm{recall}}{\mathrm{precision}+\mathrm{recall}} \tag{14}$$

Figure 7. F-measure



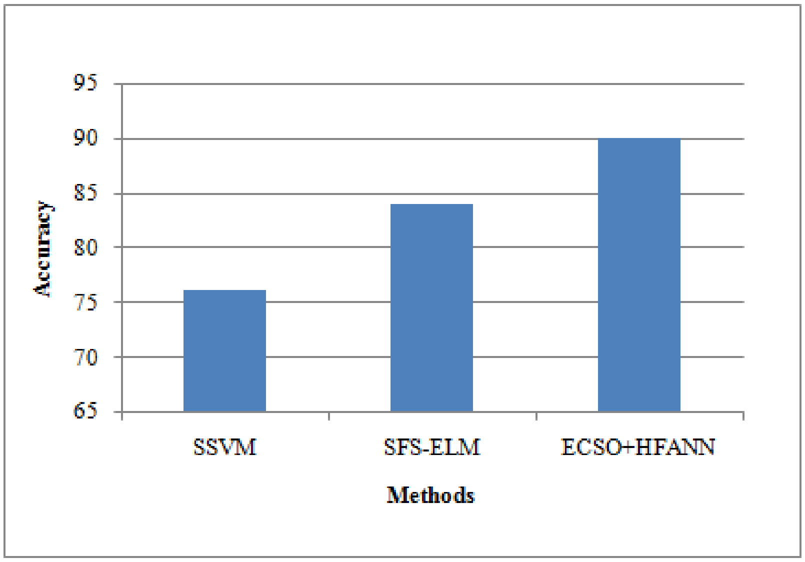
In terms of F-measure, the comparison metric is assessed using both current and suggested methods, as shown in Fig 7. The techniques are displayed on the x-axis, and the F-measure value is plotted on the y-axis. For the provided Twitter dataset, current techniques such as SSVM and SFS-ELM algorithms provide lower F-measure, but the suggested ECSO+HFANN algorithm gives greater F-measure. Thus, the suggested ECSO+HFANN increases Cyberbullying detection accuracy by the optimal selection of features, according to the results.

Accuracy

Accuracy is determined as the overall correctness of the model and is computed as the total actual classification parameters $(T_p + T_n)$ which is segregated by the sum of the classification parameters $(T_p + T_n + F_p + F_n)$. The accuracy is computed as like :

$$\text{Accuracy} = \frac{T_p+T_n}{(T_p+T_n+F_p+F_n)} \tag{15}$$

Figure 8. Accuracy

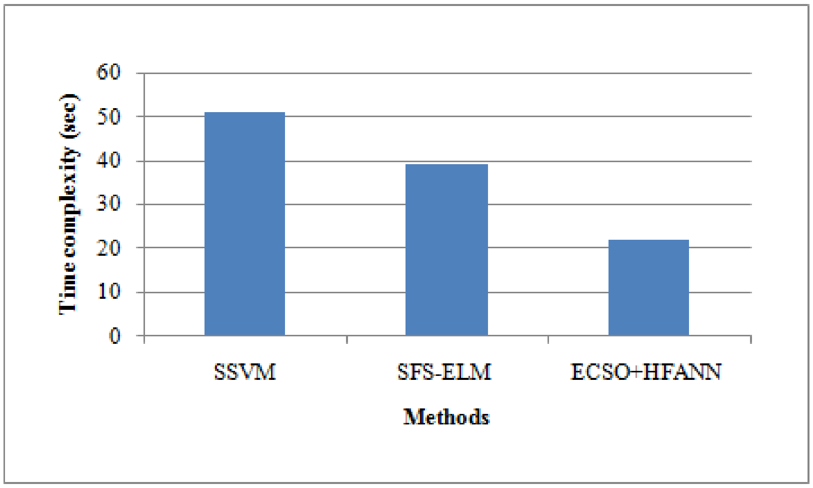


In terms of accuracy, the comparison measure is assessed using both current and suggested methods, as shown in Fig 8. The techniques are displayed on the x-axis, and the accuracy value is plotted on the y-axis. Existing algorithms like SSVM and SFS-ELM have lesser accuracy, but the suggested ECSO+HFANN approach has a better accuracy for the provided Twitter dataset. As a consequence, the suggested ECSO+HFANN enhances Cyberbullying detection accuracy by the optimal selection of characteristics, according to the findings.

Time Complexity

The system is better when the proposed algorithm executes in less time consumption.

Figure 9. Time Complexity Comparison



In terms of temporal complexity, the comparison measure is assessed using both current and new methods, as shown in Fig 9. The techniques are displayed on the x-axis, while the time complexity value is plotted on the y-axis. Existing algorithms like SSVM and SFS-ELM have a greater time complexity, but the suggested ECSO+HFANN approach has a reduced time complexity for the provided Twitter dataset. As a consequence, the suggested ECSO+HFANN improves Cyberbullying detection performance by accurately categorising results in the Twitter dataset.

Conclusion

The ECSO+HFANN method has been suggested in this study to significantly enhance the Cyberbullying detection accuracy outcomes on Twitter dataset. Pre-processing in this study was with k-means clustering which improved the accuracy of Cyberbullying detection. In pre-processing missing values and redundant characteristics were eliminated from a Twitter dataset for enhancing data's quality. Subsequently stop words, additional characters, and hyperlinks were removed before feature selections. ECSO approach used in this work to choose a subset of characteristics from features using the best fitness function of cuckoos has resulted in most significant and relevant characteristics of Twitter data. The HFANN method used to classify Twitter data improves Cyberbullying detection accuracy as shown in results. The proposed ECSO+HFANN algorithm has fared better in Cyberbullying detections when compared to SSVM and SFS-ELM algorithms in terms of precision, recall, f-measure, and accuracy. Further, the proposed study reduces time complexity of processing large datasets. In the future, an optimization-based fuzzy clustering technique for managing massive Twitter dataset might be created.

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