Twitter toxic comment identification in digital media and advertising using NLP and optimized classifiers

Jelena Gajic[1], Lazar Drazeta[1], Lepa Babic[1] Jelena Kaljevic[1], Dejan Jovanovic[2], and Luka Jovanovic[1]*

Singidunum University, Belgrade, Serbia
jgajic@singidunum.ac.rs, ldrazeta@singidunum.ac.rs, lbabic@singidunum.ac.rs, jkaljevic@singidunum.ac.rs, ljovanovic@singidunum.ac.rs*
College of Academic Studies "Dositej", Belgrade, Serbia
dejanjovanovic@akademijadositej.edu.rs

Abstract. Cyberbullying is a form of harassing, intimidating and harming other people through electronic media like social networks or messaging platforms. Typical forms of cyberbullying include messages containing harmful text, photos or videos that will embarrass the target, and excluding the individual from groups and chats. Unfortunatelly, it may lead to sincere psychological problems of the target, including disorders like depression, anxious behavior, lack of self-esteem, or even worse, suicidal thoughts and self-hurting. The research presented herein proposes a hybrid approach that includes natural language processing and machine learning XGBoost model optimized by an altered variant of Botox optimization metaheuristics for classification of toxic tweets on a real-world dataset. The experimental results have shown considerable prospect of application of machine learning models in solving this serious and important problem.

Keywords: Cyberbullying · Twitter · Toxic comments · Machine learning · XGBoost · Swarm intelligence · BOA metaheuristics.

1 Introduction

Cyberbullying is not a form of violence solely related to the Fourth Industrial Revolution that began with a full-scale digitalization in mid-201. It already posed a significant social problem among teenage generation [56], which originated from traditional face-to-face bullying that forced its way onto the Web in the 1990s and gain its momentum with the advent of smartphones [24]. Nowadays, it represents any form of bullying that uses digital technologies on social media, messaging or gaming platforms and smartphones in the form of: spreading lies, posting discomforting photos, sending inappropriate messages, images or videos and impersonating a victim by sending toxic messages via fake accounts [62].

N. Bacanin and H. Shaker (eds.), *Proceedings of the 2nd International Conference on Innovation in Information Technology and Business (ICIITB 2024)*,
Advances in Computer Science Research 113,
https://doi.org/10.2991/978-94-6463-482-2_12

Although cyberbullying leaves a distinct digital footprint, the self-perceived anonymity of the Web exacerbates this problem, enabling perpetrators to operate for a certain period of time without immediate repercussions. This does not apply to their victims where the consequences of harassment may range from psychological trauma to death [65]. The imperative to identify and battle any form of cyberbullying is grounded in its profound personal and social impact it has today. Hence, effective mechanism to detect malicious comments on platforms like Twitter are crucial not only to help stop the abuse of individuals but also for maintaining the integrity of digital communication spaces.

In spite of all technological advances of the modern digital world, the identification of malicious comments comes with a range of challenges. The sheer volume of data (i.e. 12 terabytes) that is generated daily on Twitter makes manual handling less suitable. Human operators can be overloaded and unable to properly inspect every comment (tweet), which may lead to erratic and unreliable handling. Along with that, the dynamic evolution of language and in particular slang and idioms that are used en masse and daily as the window of our collective psyche [63], complicates identification of nuanced forms of toxic expression in a cyber space. Traditional models that are not compliant with ever-changing linguistic landscape may fail to recognize subtle expressions of harassment via emerging derogatory terms, thus demanding more adaptive and sophisticated analytical tools.

The advent of artificial intelligence (AI), provides a new window of opportunity where the traditional models can be replaced by intelligent (i.e. cognitive) approach. By leveraging Natural Language Processing (NLP), a machine learning technology that gives computers the ability to interpret, manipulate and comprehend human language, AI can process ample quantities of data in much effective and consistent manner.

Unlike traditional methods based on simple heuristics of using predefined vocabulary with corresponding sentiment scores, AI systems can be trained on diverse datasets to understand context (nuances) of language, sarcasm, and evolving language trends. This adaptability makes AI the most promising tool in moderating vast content of comments and ensuring safer digital environments for its users. Furthermore, AI can do so without the need for explicit programming for each and every scenario, relying on learning from the very data it processes that consistently enhance its effectiveness over time. This is enabled by training machine learning models on large collections of text such as comments or reviews with labeled sentiments of the text including word choice, syntax, punctuation or tone. It can range from common type of methods using bag-of-words models that represent a text as a vector of word frequencies up to deep learning models which use multiple layers of artificial neural networks to learn complex and inconsistent features from the text.

The major advantage of NLP-based methods that can process any form of informal language, abbreviations, symbols, etc. is continuous adaptability that is based upon their own machine learning using domain-specific and new data to update the current models, thus closely resembling human intelligence. How-ever, we must also be aware of certain challenges that come with NLP method of sentiment analysis. These are: a) the high cost and efforts in setting a vast and high-quality datasets of text with labeled sentiments, which in turn determines the accuracy of the models; b) bias (systematic errors) of the machine learning models that can lead to unreliable results, and c) difficulties in proper interpretation and explanation of deep learning models.

This paper investigates capabilities of XGBoost classifier for toxic tweets identification. NLP was used to preprocess the data which is fed to the XGBoost. As it is the case with all ML models, it is necessary to adjust the hyperparameters of the model for each particular problem in hand [64]. This is an NP-hard optimization task, that necessitate application of stochastic algorithms, as traditional methods are not applicable. Metaheuristics algorithms have been very successful in the optimization of different ML structures in the past, therefore this research utilizes an altered variant of the recent Botox optimization algorithm (BOA) [27] to adjust the XGBoost structure. The obtained hybrid model has been validated on a real benchmark dataset that contains both normal and toxic tweets.

2 Related Works

Several recent studies have applied AI to the problem of cyberbullying detection. The authors in [42] utilized convolutional neural networks (CNNs) to identify bullying patterns on social media with remarkable success, demonstrating the potential of machine learning models in understanding contextual nuances. In addition, [20] employed random forests to classify toxic behavior in online gaming communities, highlighting the versatility of AI across number of different digital platforms.

The role of NLP in identifying toxic comments has been pivotal. Research described in [3] employed NLP techniques to analyze sentiment and detect negative tones in comments, which were indicative of bullying. Their findings showed an improved accuracy in identifying harmful posts (comments) compared to previous models. Furthermore, another study incorporated NLP with deep learning to adapt to the rapidly changing internet slang, thereby enhancing the detection of covert bullying [49]. All these studies underscore the critical role of NLP in interpreting the subtleties of human language and improving the identification of cyberbullying.

2.1 TF-IDF

Analyzing the value each word carries in a text is a useful way of classifying texts identifying keywords in a document. Term Frequency and Inverse Document Frequency (TF-IDF) [55] can be used for this purpose alongside NLP. TF-IDF is a statistical method applied to retrieval of data and text mining as explained, and is a combination of the concepts of TF and IDF [23]. The following equations

Eq 1 and Eq 2 present how TF and IDF are determined:

$$\mathrm{TF}(t,d) = \frac{\text{Count of term } t \text{ located in document } d}{\text{total number of words in document } d} \tag{1}$$

$$\mathrm{IDF}(t,D) = \log\left(\frac{\text{Number of documents in } D}{\text{Count of documents containing term } t+1}\right) \tag{2}$$

The general way TF-IDF is calculated is showcased in Eq 3:

$$\text{TF-IDF}(t,d,D) = \mathrm{TF}(t,d) \times \mathrm{IDF}(t,D) \tag{3}$$

The end values depict the significance of each word in the document in the context of the text when compared to the rest of the texts being processed. Higher scored terms are more important to the specific text at hand. This process avoids the inflation of the significance of words such as "the, and, with" and other words used in all texts on the same topic.

2.2 XGBoost

A form of ensemble learning approaches, XGBoost [21] is based on decision trees that compile predictions from weaker classifiers. The approach's success comes from methods that regulate and process parallelly, while also imploring each tree to resolve the mistakes made in previous iterations. Thus, the XGBoost model has great power to exploit complicated relationships of inputs and target patterns. One side of the models complexity is the fact that it has many hyperparameters that need to be precisely tuned for all tasks, which in itself represents an NP-hard problem.

For the most precise predictions the model should be trained in iterations. The objective function can be seen in the following Eq. 4

$$\mathrm{obj}(\Theta) \;=\; L(\theta) \;+\; \Omega(\Theta), \tag{4}$$

Θ is denoting a group of XGBoost hyperparameters, while $L(\Theta)$ stands for the loss function. Next, $\Omega(\Theta)$ is the regularization term. Lastly is shown the variable in charge of the models complexity. The specific loss function is dependant on the uniqueness of each classification task.

$$\mathrm{L}(\Theta) \;=\; \textstyle\sum_i \,(y_i \;-\; \hat{y_i})^2, \tag{5}$$

here, y_i is a symbol for the value being predicted, while $\hat{y_i}$ is congruous to the forecasted target in each i iteration.

$$L(\Theta) \;=\; \textstyle\sum_i [\, y_i \ln\,(1+e^{-\hat{y}_i}) \;+\; (1-y_i)\ln\,(1+e^{\hat{y}_i})]. \tag{6}$$

The goal of the model is separating the real and expected values. There is a need to minimization of the overall loss function in order to support classification.

2.3 Metaheuristics optimizers

Influenced by nature, swarm intelligence algorithms can be used to aid hyperparameter optimization due to their potential to solve NP-hard problems. By using decentralised independently organised systems mimicking behaviour of swarm animals the algorithms can interact with their environment and each other to search for the best solutions efficiently.

These kinds of algorithms have proved themselves invaluable in solving many realistic problems, in fields such as credit card scam detection [29, 46], medicine [41, 38, 67, 11, 33, 41, 32, 71], plant classification [15], electricity consumption [60, 6], economy [34, 57, 59, 13, 52, 47], environmental challenges [37, 31, 8, 43]. Additionally, they are also useful in cloud computing tasks [48, 9], audit opinion enhancement [61], finding software bugs [73], network and PC related challenges [69, 1, 53, 36, 51, 16, 35, 12], feature selection [7, 18, 30, 70] and optimization of IoT and WSNs [68, 5] as well as overall optimization of ML algorithms [10, 58, 14, 25, 50, 72, 4, 26, 19].

3 Methods

3.1 Basic Botox optimization algorithm

BOA is very recent population-based algorithm, introduced in 2024 [27]. Inspiration for it was found in the process of enhancing the facial beauty, where Botox injection is induced in particular facial areas to relax muscles, resulting in the smooth skin. This Botox injection procedure guides the position update of the solutions in the populace. Every individual patient that requires Botox dose denotes one solution in the populace, and the entire BOA mimics the activities doctor performs by giving injections to particular facial areas of each individual.

During the execution of BOA, the assumption is made that the count of muscles requiring Botox injection reduces over the iterations. Thus, the count of chosen muscles is decreasing over rounds as follows:

$$N_b = \left\lfloor 1 + \frac{m}{t} \right\rfloor \leq m \tag{7}$$

here, N_b corresponds to the count of muscles that require the treatment, t represents the ongoing round, while m is a count of decision variables.

The variables needing to be treated are chosen for each individual, keeping in mind that the muscles should not be treated repeatedly, as described by the following equation:

$$CBS_t = \{d_1, d_2, \ldots, d_f, \ldots, d_{N_b}\}, d_l \in \{1, 2, \ldots, m\} \text{ and } \forall h, k \in \{1, 2, \ldots, N_b\} : d_h \neq d_k \tag{8}$$

where CBS_t represents the collection of decision variables belonging to the i-th individual, being chosen for the Botox treatment, while d_j reflects the location of the j-th decision variable chosen for injection. The quantity of Botox to be injected to every individual is obtained as follows:

$$\vec{B}_i = \begin{cases} \vec{X}_{\text{mean}} - \vec{X}_i, t < \frac{T}{2}; \\ \vec{X}_{\text{best}} - \vec{X}_i, \text{ otherwise} \end{cases} \tag{9}$$

here, the amount of Botox for i-th individual is calculated as:

$$\vec{B}_i = (b_{i,1}, \ldots, b_{i,j}, \ldots, b_{i,m}) \tag{10}$$

the mean population location $\vec{X}_{\text{mean}}$ is obtained as:

$$\vec{X}_{\text{mean}} = \frac{1}{N} \sum_{i=1}^{N} \vec{X}_i \tag{11}$$

T represents the total count of rounds, and $\vec{X}_{\text{best}}$ denotes the best individual obtained so far.

After getting the treatment, the face will visually change, and the wrinkles will be removed. This is reflected by calculating the novel locations of each individual in the populace by utilizing the following equation:

$$\vec{X}_i^{\text{new}} : x_{i,d_j}^{\text{new}} = x_{i,d_j} + r_{i,d_j} \cdot b_{i,d_j} \tag{12}$$

If the fitness score of the individual is better, the novel location will replace the previous one for the given individual, as described by:

$$\vec{X}_i = \begin{cases} \vec{X}_i^{\text{new}}, F_i^{\text{new}} < F_i \\ \vec{X}_i, \text{ otherwise} \end{cases} \tag{13}$$

here, $\vec{X}_i^{\text{new}}$ corresponds to the novel location of the i-th individual after Botox treatment, x_{i,d_j} denotes the d_j dimension, F_i^{new} represents the fitness score, r_{i,d_j} represents an arbitraty value taken from the range $[0, 1]$, and b_{i,d_j} corresponds to d_j-th dimension of the Botox treatment of i-th individual. For more details about elementary BOA, interested reader is directed to the original paper [27].

3.2 Modified BOA metaheuristics

Although baseline BOA is a very recent metaheuristics, further enhancements in the converging speed may be achieved through hybridization with other methods. In this research, convergence convergence enhancements are tackled through adaptive hybridization with the firefly algorithm (FA) [66]. Search procedure of FA is depicted in Eq.14.

$$X_i(t+1) = X_i(t) + \beta e^{-\gamma r_{ij}^2} (X_j(t) - X_i(t)) + \alpha \epsilon_i(t), \tag{14}$$

here, attractiveness of individual at distance $r = 0$ is given by β_0. For practical implementations and reduced computing requirements, Eq. (15) is commonly used instead of Eq.(14).

$$\beta(r) = \frac{\beta_0}{(1 + \gamma \times r^2)} \tag{15}$$

above, $X_i(t)$ describes the i-th solution up-to-date location during t-th round, while r_{ij} describes the up-to-date location of solution j within the same round. Control variables β, γ, α, and $\epsilon_i(t)$ affect attraction of the solution, light absorbing coefficient, randomization, and stochastic vector.

During the second half of run (latter $t/2$ iterations), in every round of execution, an arbitrary number within limits $[0, 1]$ is generated for parameter ψ, alongside empirically established value $\theta = 0.5$. In case $\psi < \theta$, FA search mechanism should be used, otherwise, baseline BOA is employed. In every subsequent round, θ increases by 0.4 to improve the probability of utilizing FA in the following iterations. The adaptive procedure incorporating hybridization with FA, resulting in the Hybrid Adaptive BOA (HABOA) metaheuristics, with the pseudocode depicted in Alg 1.

Algorithm 1 HABOA metaheuristics

```
Synthesize initial collection of solutions P
Set θ = 0.5
while t < T do
    Evaluate fitness of all solutions
    if t > T/2 then
        Produce arbitrary value of ψ
        if ψ < θ then
            Utilize FA procedure
        else
            Utilize baseline BOA procedure
        end if
        θ = θ + 0.4
    else
        Utilize baseline BOA procedure
    end if
end while
```

4 Experimental Setup

A publicly available dataset, that can be obtained on `https://www.kaggle.com/datasets/saurabhshahane/cyberbullying-dataset`, was employed through simulations. It comprises of datasets collected from several social media, and this paper used Twitter data, where all entries contain textual content accompanied by a label (bully or not). A variety of forms were differentiated, like hate speech, aggressive and toxic content. Dataset has been split into 70%/30% to perform training and testing of the XGBoost, that was selected to execute classifications. The hyperparameters adjusted in this research, along with respective search domains included learning rate $[0.1, 0.9]$, minimum child weight $[1, 10]$, subsample $[0.1, 1.0]$, colsample bytree $[0.01, 1.00]$, max depth $[3, 10]$ and γ $[0, 0.8]$.

The simulations included eight different metaheuristics methods to adjust the XGBoost hyperparams, including the introduced HABOA, baseline BOA, genetic algorithm (GA) [45], particle swarm optimizer (PSO) [40], artificial bee colony (ABC) [39], baseline FA [66], whale optimization algorithm (WOA) [44] and crayfish optimization algorithm (COA) [28]. Each optimizer was allocated with $N = 10$ solutions, $T = 10$ rounds in each execution, and a total of 30 individual runs. Simulation environment has been implemented in Python, making use of a common collection of libraries like scikit-learn, pandas, scipy and seaborn.

To address the imbalance in dataset, the objective function chosen to be maximized in the simulations was the Cohen's kappa indicator κ [22], calculated in the following way:

$$\kappa = \frac{k_o - k_e}{1 - k_e} = 1 - \frac{1 - k_o}{1 - k_e} \tag{16}$$

above, arrays of observed and actual outcomes are given by k_o and k_e. Cohen's κ indicator considers class imbalance, making it a better choice than accuracy in these cases.

5 Simulation results

The outcomes of the conducted experiments are outlined in Tables **??** and 2, with respect to the objective function (Cohen's κ coefficient) and indicator function (classifying error), and the best outcome in every category is highlighted in bold text.

Table 1. Aggressive comment Cohen's kappa outcomes for each optimizer.

Approach	Best	Worst	Mean	Median	Std	Var
XG-HABOA	**.607409**	.596170	.599974	.599186	.003093	9.57E-06
XG-BOA	.604321	.599571	.601863	.601766	.001821	3.32E-06
XG-GA	.604574	.596170	.600621	.600970	.002567	6.59E-06
XG-PSO	.603802	.598386	.601268	.600941	.002066	4.27E-06
XG-ABC	.604376	.588992	.597239	.597653	.003868	1.50E-05
XG-FA	.606161	.598406	.601970	.601299	.002808	7.88E-06
XG-WOA	.606669	**.602876**	**.604808**	**.604949**	**.001042**	**1.09E-06**
XG-COA	.605038	.597531	.601088	.601326	.001934	3.74E-06

The outcomes showcase the supreme performance exhibited by the suggested HABOA, which obtained the best overall result out of all contending algorithms. Nevertheless, as it is the case with stochastic algorithms, other methods also achieved excellent outcomes, where WOA obtained the best values of worst, median and mean, as well as standard deviation and variance over thirty independent runs for the Cohen's kappa coefficient.

The visualizations of the metaheuristics algorithms' performance are given in Fig. 1, showcasing the violin diagrams of the objective function and box plots of the classification error across thirty separate runs.

Furthermore, converging graphs of Cohen's kappa and classification error within the best execution of each metaheuristics are presented in Fig. 2. HABOA

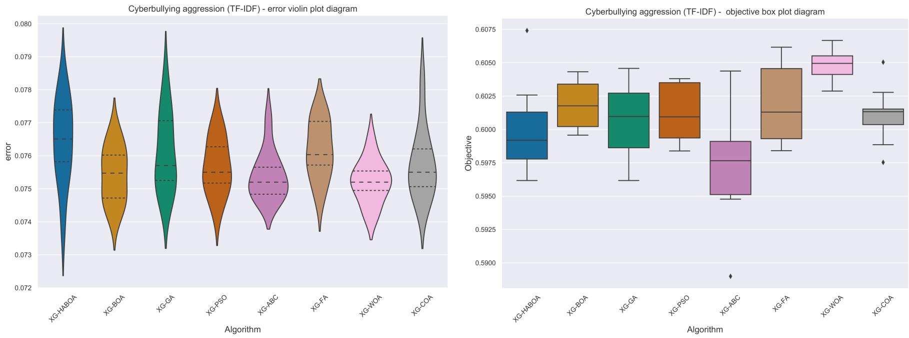

Fig. 1. Objective and indicator function outcome distributions.

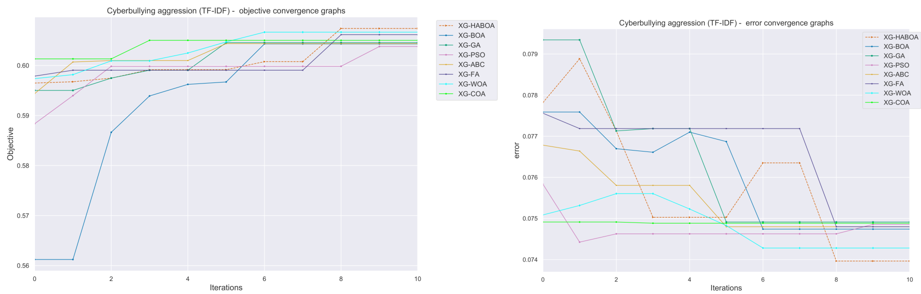

Fig. 2. Objective and indicator function convergence graphs.

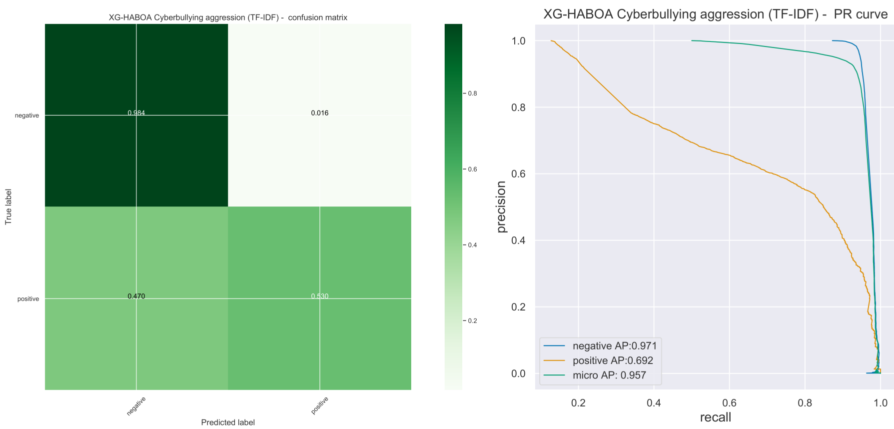

Fig. 3. Best performing model confusion matrix and PR curve.

Table 2. Aggressive comment detection indicator function outcomes for each optimizer.

Method	Best	Worst	Mean	Median	Std	Var
XG-HABOA	**.073964**	.078280	.076447	.076510	.001202	1.45E-06
XG-BOA	.074741	**.074626**	.075423	.075475	.000793	6.29E-07
XG-GA	.074914	.078280	.076096	.075705	.001121	1.26E-06
XG-PSO	.074856	.075604	.075667	.075503	.000796	6.34E-07
XG-ABC	.074799	.074827	.075403	.075201	.000704	4.96E-07
XG-FA	.074799	.077244	.076177	.076036	.000818	6.69E-07
XG-WOA	.074281	.075201	**.075216**	.075201	**.000621**	**3.85E-07**
XG-COA	.074885	.075489	.075762	.075503	.001017	1.03E-06

Table 3. Aggressive comment detailed metrics for each optimizer best constructed model.

Method	Metric	harassment	non-harassment	Accuracy	Macro avg.	Weighted avg.
XG-HABOA	recision	.934716	.828400	.926036	.881558	.921151
	ecall	.983941	.530101	.926036	.757021	.926036
	1-score	.958697	.646501	.926036	.802599	.918864
XG-BOA	precision	.934606	.821042	.925259	.877824	.920116
	recall	.983116	.529651	.925259	.756383	.925259
	f1-score	.958248	.643914	.925259	.801081	.918142
XG-GA	precision	.934867	.817111	.925086	.875989	.919842
	recall	.982589	.531905	.925086	.757247	.925086
	f1-score	.958134	.644359	.925086	.801247	.918100
XG-PSO	precision	.934571	.820119	.925144	.877345	.919968
	recall	.983017	.529425	.925144	.756221	.925144
	f1-score	.958182	.643464	.925144	.800823	.918027
XG-ABC	precision	.934684	.819798	.925201	.877241	.920026
	recall	.982951	.530327	.925201	.756639	.925201
	f1-score	.958210	.644031	.925201	.801120	.918124
XG-FA	precision	.935230	.815400	.925201	.875315	.919941
	recall	.982292	.534837	.925201	.758564	.925201
	f1-score	.958183	.645969	.925201	.802076	.918348
XG-WOA	precision	.934830	.824064	.925719	.879447	.920697
	recall	.983413	.531229	.925719	.757321	.925719
	f1-score	.958506	.646010	.925719	.802258	.918635
XG-COA	precision	.934978	.816517	.925115	.875747	.919863
	recall	.982490	.532807	.925115	.757648	.925115
	f1-score	.958145	.644836	.925115	.801490	.918170
	support	30325	4435			

method attained supreme converging speed and successfully avoided local optimums, that could negatively affect the results if a premature convergence happens, visible on the converging graphs of ABC and PSO.

The best-produced XGBoost structures synthesized by each contending metaheuristics are analyzed in detail within Table 3. The suggested HABOA obtained highest classification accuracy of around 92.6%, while other optimizers also exhibited respectable levels of accuracy. The top-produced XGBoost structures synthesized by every optimizer are listed in Table 4. Lastly, Fig. 3 provides insights into the PR curve and confusion matrix of the XG-HABOA.

6 Conclusion

The importance of digital harassment cannot be underestimated, both at work and in private life. It is shown that cyberbullying and social overload induce considerable distress and personal exhaustion, which result in leaving a social network, while social exclusion and particularly verbal harassment induce a negative emotional state that affect victims' wellbeing [2]. More severe cases may

Table 4. Parameter selections made by each optimizer for the respective best performing models.

Method	Learning Rate	Min Child W.	Subsample	Col by Tree	Max depth	Gamma
XG-HABOA	.900000	9.978990	.472872	1.000000	10	.235927
XG-BOA	.900000	1.000000	.416978	1.000000	10	.000000
XG-GA	.900000	9.736952	.731480	1.000000	10	.345499
XG-PSO	.896924	9.452084	.459394	1.000000	10	.783611
XG-ABC	.826650	1.200439	.428363	.900105	10	.800000
XG-FA	.900000	1.000000	.559239	1.000000	10	.800000
XG-WOA	.900000	6.349483	.439112	.994262	10	.504256
XG-COA	.900000	4.505191	.506069	1.000000	10	.000000

involve mental health issues, post-traumatic stress symptoms, insomnia, low self-esteem, anti-social behaviour [17], and finally suicidal attempts of a victim of abuse [54].

Our paper provides a conceptual understanding of the current landscape in cyberbullying detection using AI and NLP technologies, outlining both the significant challenges and the innovative approaches that are being developed to tackle this growing worldwide issue. XGBoost adjusted by the introduced HABOA metaheuristics was utilized classify toxic tweets, preprocessed by the TF-IDF method. The proposed approach achieved respectable accuracy of approximately 92.6%. Future endavours in this area will include experimentation with other metaheuristics algorithms, aiming to obtain even higher classification accuracy.

Acknowledgment

This research was supported by the Science Fund of the Republic of Serbia, Grant No. 7373, Characterizing crises-caused air pollution alternations using an artificial intelligence-based framework - crAIRsis and Grant No. 7502, Intelligent Multi-Agent Control and Optimization applied to Green Buildings and Environmental Monitoring Drone Swarms - ECOSwarm.

References

1. Nadheera AlHosni, Luka Jovanovic, Milos Antonijevic, Milos Bukumira, Miodrag Zivkovic, Ivana Strumberger, Joseph P Mani, and Nebojsa Bacanin. The xgboost model for network intrusion detection boosted by enhanced sine cosine algorithm. In *International Conference on Image Processing and Capsule Networks*, pages 213–228. Springer, 2022.
2. Ashraf Alhujailli, Waldemar Karwowski, Thomas TH Wan, and Peter Hancock. Affective and stress consequences of cyberbullying. *Symmetry*, 12(9):1536, 2020.
3. Jalal Omer Atoum. Cyberbullying detection through sentiment analysis. In *2020 International Conference on Computational Science and Computational Intelligence (CSCI)*, pages 292–297. IEEE, 2020.
4. Nebojsa Bacanin, Milos Antonijevic, Nikola Vukobrat, Timea Bezdan, and Miodrag Zivkovic. Enhanced seagull optimization algorithm adapted for artificial neural network training. In *ICT with Intelligent Applications: Proceedings of ICTIS 2021, Volume 1*, pages 753–761. Springer, 2022.

5. Nebojsa Bacanin, Uros Arnaut, Miodrag Zivkovic, Timea Bezdan, and Tarik A Rashid. Energy efficient clustering in wireless sensor networks by opposition-based initialization bat algorithm. In *Computer Networks and Inventive Communication Technologies: Proceedings of Fourth ICCNCT 2021*, pages 1–16. Springer, 2022.
6. Nebojsa Bacanin, Luka Jovanovic, Miodrag Zivkovic, Venkatachalam Kandasamy, Milos Antonijevic, Muhammet Deveci, and Ivana Strumberger. Multivariate energy forecasting via metaheuristic tuned long-short term memory and gated recurrent unit neural networks. *Information Sciences*, 642:119122, 2023.
7. Nebojsa Bacanin, Aleksandar Petrovic, Miodrag Zivkovic, Timea Bezdan, and Milos Antonijevic. Feature selection in machine learning by hybrid sine cosine metaheuristics. In *International Conference on Advances in Computing and Data Sciences*, pages 604–616. Springer, 2021.
8. Nebojsa Bacanin, Marko Sarac, Nebojsa Budimirovic, Miodrag Zivkovic, Ahmad Ali AlZubi, and Ali Kashif Bashir. Smart wireless health care system using graph lstm pollution prediction and dragonfly node localization. *Sustainable Computing: Informatics and Systems*, 35:100711, 2022.
9. Nebojsa Bacanin, Vladimir Simic, Miodrag Zivkovic, Melfi Alrasheedi, and Aleksandar Petrovic. Cloud computing load prediction by decomposition reinforced attention long short-term memory network optimized by modified particle swarm optimization algorithm. *Annals of Operations Research*, pages 1–34, 2023.
10. Nebojsa Bacanin, Catalin Stoean, Miodrag Zivkovic, Dijana Jovanovic, Milos Antonijevic, and Djordje Mladenovic. Multi-swarm algorithm for extreme learning machine optimization. *Sensors*, 22(11):4204, 2022.
11. Nebojsa Bacanin, Miodrag Zivkovic, Fadi Al-Turjman, K Venkatachalam, Pavel Trojovskỳ, Ivana Strumberger, and Timea Bezdan. Hybridized sine cosine algorithm with convolutional neural networks dropout regularization application. *Scientific Reports*, 12(1):6302, 2022.
12. Nebojsa Bacanin, Miodrag Zivkovic, Milos Antonijevic, K Venkatachalam, Jinseok Lee, Yunyoung Nam, Marina Marjanovic, Ivana Strumberger, and Mohamed Abouhawwash. Addressing feature selection and extreme learning machine tuning by diversity-oriented social network search: an application for phishing websites detection. *Complex & Intelligent Systems*, 9(6):7269–7304, 2023.
13. Nebojsa Bacanin, Miodrag Zivkovic, Luka Jovanovic, Milica Ivanovic, and Tarik A Rashid. Training a multilayer perception for modeling stock price index predictions using modified whale optimization algorithm. In *Computational Vision and Bio-Inspired Computing: Proceedings of ICCVBIC 2021*, pages 415–430. Springer, 2022.
14. Nebojsa Bacanin, Miodrag Zivkovic, Mohamed Salb, Ivana Strumberger, and Amit Chhabra. Convolutional neural networks hyperparameters optimization using sine cosine algorithm. In *Sentimental Analysis and Deep Learning: Proceedings of ICSADL 2021*, pages 863–878. Springer, 2022.
15. Nebojsa Bacanin, Miodrag Zivkovic, Marko Sarac, Aleksandar Petrovic, Ivana Strumberger, Milos Antonijevic, Andrija Petrovic, and K Venkatachalam. A novel multiswarm firefly algorithm: An application for plant classification. In *International Conference on Intelligent and Fuzzy Systems*, pages 1007–1016. Springer, 2022.
16. Nebojsa Bacanin, Miodrag Zivkovic, Catalin Stoean, Milos Antonijevic, Stefana Janicijevic, Marko Sarac, and Ivana Strumberger. Application of natural language processing and machine learning boosted with swarm intelligence for spam email filtering. *Mathematics*, 10(22):4173, 2022.

17. Suhans Bansal, Naval Garg, Jagvinder Singh, and Freda Van Der Walt. Cyberbullying and mental health: past, present and future. *Frontiers in Psychology*, 14:1279234, 2024.
18. Timea Bezdan, Dusan Cvetnic, Luka Gajic, Miodrag Zivkovic, Ivana Strumberger, and Nebojsa Bacanin. Feature selection by firefly algorithm with improved initialization strategy. In *7th conference on the engineering of computer based systems*, pages 1–8, 2021.
19. Milos Bukumira, Miodrag Zivkovic, Milos Antonijevic, Luka Jovanovic, Nebojsa Bacanin, and Tamara Zivkovic. The extreme gradient boosting method optimized by hybridized sine cosine metaheuristics for ship vessel classification. In *International Conference on Advances in Data-driven Computing and Intelligent Systems*, pages 255–270. Springer, 2023.
20. Alessandro Canossa, Dmitry Salimov, Ahmad Azadvar, Casper Harteveld, and Georgios Yannakakis. For honor, for toxicity: Detecting toxic behavior through gameplay. *Proceedings of the ACM on Human-Computer Interaction*, 5(CHI PLAY):1–29, 2021.
21. Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '16, page 785–794, New York, NY, USA, 2016. Association for Computing Machinery.
22. Jacob Cohen. A coefficient of agreement for nominal scales. *Educational and psychological measurement*, 20(1):37–46, 1960.
23. Mamata Das, PJA Alphonse, et al. A comparative study on tf-idf feature weighting method and its analysis using unstructured dataset. *arXiv preprint arXiv:2308.04037*, 2023.
24. Richard Donegan. Bullying and cyberbullying: History, statistics, law, prevention and analysis. *The Elon Journal of Undergraduate Research in Communications*, 3(1):33–42, 2012.
25. Masa Gajevic, Nemanja Milutinovic, Jelena Krstovic, Luka Jovanovic, Marina Marjanovic, and Catalin Stoean. Artificial neural network tuning by improved sine cosine algorithm for healthcare 4.0. In *Proceedings of the 1st international conference on innovation in information technology and business (ICIITB 2022)*, volume 104, page 289. Springer Nature, 2023.
26. Luka Gajic, Dusan Cvetnic, Miodrag Zivkovic, Timea Bezdan, Nebojsa Bacanin, and Stefan Milosevic. Multi-layer perceptron training using hybridized bat algorithm. In *Computational Vision and Bio-Inspired Computing: ICCVBIC 2020*, pages 689–705. Springer, 2021.
27. Marie Hubálovská, Štěpán Hubálovskỳ, and Pavel Trojovskỳ. Botox optimization algorithm: A new human-based metaheuristic algorithm for solving optimization problems. *Biomimetics*, 9(3):137, 2024.
28. Heming Jia, Honghua Rao, Changsheng Wen, and Seyedali Mirjalili. Crayfish optimization algorithm. *Artificial Intelligence Review*, 56(Suppl 2):1919–1979, 2023.
29. Dijana Jovanovic, Milos Antonijevic, Milos Stankovic, Miodrag Zivkovic, Marko Tanaskovic, and Nebojsa Bacanin. Tuning machine learning models using a group search firefly algorithm for credit card fraud detection. *Mathematics*, 10(13):2272, 2022.
30. Dijana Jovanovic, Marina Marjanovic, Milos Antonijevic, Miodrag Zivkovic, Nebojsa Budimirovic, and Nebojsa Bacanin. Feature selection by improved sand cat swarm optimizer for intrusion detection. In *2022 International Conference on Artificial Intelligence in Everything (AIE)*, pages 685–690. IEEE, 2022.

31. Gordana Jovanovic, Mirjana Perisic, Nebojsa Bacanin, Miodrag Zivkovic, Svetlana Stanisic, Ivana Strumberger, Filip Alimpic, and Andreja Stojic. Potential of coupling metaheuristics-optimized-xgboost and shap in revealing pahs environmental fate. *Toxics*, 11(4):394, 2023.
32. Luka Jovanovic, Nebojsa Bacanin, Miodrag Zivkovic, Milos Antonijevic, Aleksandar Petrovic, and Tamara Zivkovic. Anomaly detection in ecg using recurrent networks optimized by modified metaheuristic algorithm. In *2023 31st Telecommunications Forum (TELFOR)*, pages 1–4. IEEE, 2023.
33. Luka Jovanovic, Marko Djuric, Miodrag Zivkovic, Dijana Jovanovic, Ivana Strumberger, Milos Antonijevic, Nebojsa Budimirovic, and Nebojsa Bacanin. Tuning xgboost by planet optimization algorithm: An application for diabetes classification. In *Proceedings of fourth international conference on communication, computing and electronics systems: ICCCES 2022*, pages 787–803. Springer, 2023.
34. Luka Jovanovic, Dejan Jovanovic, Nebojsa Bacanin, Ana Jovancai Stakic, Milos Antonijevic, Hesham Magd, Ravi Thirumalaisamy, and Miodrag Zivkovic. Multistep crude oil price prediction based on lstm approach tuned by salp swarm algorithm with disputation operator. *Sustainability*, 14(21):14616, 2022.
35. Luka Jovanovic, Dijana Jovanovic, Milos Antonijevic, Bosko Nikolic, Nebojsa Bacanin, Miodrag Zivkovic, and Ivana Strumberger. Improving phishing website detection using a hybrid two-level framework for feature selection and xgboost tuning. *Journal of Web Engineering*, 22(3):543–574, 2023.
36. Luka Jovanovic, Dijana Jovanovic, Milos Antonijevic, Miodrag Zivkovic, Nebojsa Budimirovic, Ivana Strumberger, and Nebojsa Bacanin. The xgboost tuning by improved firefly algorithm for network intrusion detection. In *2022 24th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC)*, pages 268–275. IEEE, 2022.
37. Luka Jovanovic, Gordana Jovanovic, Mirjana Perisic, Filip Alimpic, Svetlana Stanisic, Nebojsa Bacanin, Miodrag Zivkovic, and Andreja Stojic. The explainable potential of coupling metaheuristics-optimized-xgboost and shap in revealing vocs' environmental fate. *Atmosphere*, 14(1):109, 2023.
38. Luka Jovanovic, Miodrag Zivkovic, Milos Antonijevic, Dijana Jovanovic, Milica Ivanovic, and Hothefa Shaker Jassim. An emperor penguin optimizer application for medical diagnostics. In *2022 IEEE Zooming Innovation in Consumer Technologies Conference (ZINC)*, pages 191–196. IEEE, 2022.
39. Dervis Karaboga and Bahriye Basturk. A powerful and efficient algorithm for numerical function optimization: artificial bee colony (abc) algorithm. *Journal of global optimization*, 39:459–471, 2007.
40. James Kennedy and Russell Eberhart. Particle swarm optimization. In *Proceedings of ICNN'95-international conference on neural networks*, volume 4, pages 1942–1948. ieee, 1995.
41. Stanislava Kozakijevic, Mohamed Salb, Ali Elsadai, Joseph Mani, Kanchana Devi, Anni Dasho Sharko, and Suresh Muthusamy. Seizure detection via time series classification using modified metaheuristic optimized recurrent networks. *Theoretical and Applied Computational Intelligence*, 1(1):82–94, 2023.
42. Nijia Lu, Guohua Wu, Zhen Zhang, Yitao Zheng, Yizhi Ren, and Kim-Kwang Raymond Choo. Cyberbullying detection in social media text based on character-level convolutional neural network with shortcuts. *Concurrency and Computation: Practice and Experience*, 32(23):e5627, 2020.
43. Joseph Mani, Hotefa Shaker, Luka Jovanovic, et al. Sunspot occurrence forecasting with metaheuristic optimized recurrent neural networks. *Theoretical and Applied Computational Intelligence*, 1(1):15–26, 2023.

44. Seyedali Mirjalili and Andrew Lewis. The whale optimization algorithm. *Advances in engineering software*, 95:51–67, 2016.
45. Seyedali Mirjalili and Seyedali Mirjalili. Genetic algorithm. *Evolutionary algorithms and neural networks: Theory and applications*, pages 43–55, 2019.
46. Aleksandar Petrovic, Nebojsa Bacanin, Miodrag Zivkovic, Marina Marjanovic, Milos Antonijevic, and Ivana Strumberger. The adaboost approach tuned by firefly metaheuristics for fraud detection. In *2022 IEEE World Conference on Applied Intelligence and Computing (AIC)*, pages 834–839. IEEE, 2022.
47. Aleksandar Petrovic, Luka Jovanovic, Miodrag Zivkovic, Nebojsa Bacanin, Nebojsa Budimirovic, and Marina Marjanovic. Forecasting bitcoin price by tuned long short term memory model. In *1st International conference on innovation in information technology and business (ICIITB 2022)*, pages 187–202. Atlantis Press, 2023.
48. Bratislav Predić, Luka Jovanovic, Vladimir Simic, Nebojsa Bacanin, Miodrag Zivkovic, Petar Spalevic, Nebojsa Budimirovic, and Milos Dobrojevic. Cloud-load forecasting via decomposition-aided attention recurrent neural network tuned by modified particle swarm optimization. *Complex & Intelligent Systems*, pages 1–21, 2023.
49. Mitushi Raj, Samridhi Singh, Kanishka Solanki, and Ramani Selvanambi. An application to detect cyberbullying using machine learning and deep learning techniques. *SN computer science*, 3(5):401, 2022.
50. Mohamed Salb, Nebojsa Bacanin, Miodrag Zivkovic, Milos Antonijevic, Marina Marjanovic, and Ivana Strumberger. Extreme learning machine tuning by original sine cosine algorithm. In *2022 IEEE World Conference on Applied Intelligence and Computing (AIC)*, pages 143–148. IEEE, 2022.
51. Mohamed Salb, Luka Jovanovic, Nebojsa Bacanin, Milos Antonijevic, Miodrag Zivkovic, Nebojsa Budimirovic, and Laith Abualigah. Enhancing internet of things network security using hybrid cnn and xgboost model tuned via modified reptile search algorithm. *Applied Sciences*, 13(23):12687, 2023.
52. Mohamed Salb, Miodrag Zivkovic, Nebojsa Bacanin, Amit Chhabra, and M Suresh. Support vector machine performance improvements for cryptocurrency value forecasting by enhanced sine cosine algorithm. In *Computer Vision and Robotics: Proceedings of CVR 2021*, pages 527–536. Springer, 2022.
53. Nikola Savanović, Ana Toskovic, Aleksandar Petrovic, Miodrag Zivkovic, Robertas Damaševičius, Luka Jovanovic, Nebojsa Bacanin, and Bosko Nikolic. Intrusion detection in healthcare 4.0 internet of things systems via metaheuristics optimized machine learning. *Sustainability*, 15(16):12563, 2023.
54. Ariel Schonfeld, Dale McNiel, Takeo Toyoshima, and Renée Binder. Cyberbullying and adolescent suicide. *The journal of the American Academy of Psychiatry and the Law*, pages JAAPL–220078, 2023.
55. Julia Silge and David Robinson. Term frequency and inverse document frequency (tf-idf) using tidy data principles. *CRAN–R project. URL: https://cran. rproject. org/web/packages/tidytext/vignettes/tf_ idf. html*, 2018.
56. Peter K Smith, Jess Mahdavi, Manuel Carvalho, Sonja Fisher, Shanette Russell, and Neil Tippett. Cyberbullying: Its nature and impact in secondary school pupils. *Journal of child psychology and psychiatry*, 49(4):376–385, 2008.
57. Marko Stankovic, Nebojsa Bacanin, Miodrag Zivkovic, Luka Jovanovic, Joseph Mani, and Milos Antonijevic. Forecasting ethereum price by tuned long short-term memory model. In *2022 30th Telecommunications Forum (TELFOR)*, pages 1–4. IEEE, 2022.

58. Marko Stankovic, Jelena Gavrilovic, Dijana Jovanovic, Miodrag Zivkovic, Milos Antonijevic, Nebojsa Bacanin, and Milos Stankovic. Tuning multi-layer perceptron by hybridized arithmetic optimization algorithm for healthcare 4.0. *Procedia Computer Science*, 215:51–60, 2022.
59. Marko Stankovic, Luka Jovanovic, Nebojsa Bacanin, Miodrag Zivkovic, Milos Antonijevic, and Petar Bisevac. Tuned long short-term memory model for ethereum price forecasting through an arithmetic optimization algorithm. In *International Conference on Innovations in Bio-Inspired Computing and Applications*, pages 327–337. Springer, 2022.
60. Catalin Stoean, Miodrag Zivkovic, Aleksandra Bozovic, Nebojsa Bacanin, Roma Strulak-Wójcikiewicz, Milos Antonijevic, and Ruxandra Stoean. Metaheuristic-based hyperparameter tuning for recurrent deep learning: application to the prediction of solar energy generation. *Axioms*, 12(3):266, 2023.
61. Mihailo Todorovic, Nemanja Stanisic, Miodrag Zivkovic, Nebojsa Bacanin, Vladimir Simic, and Erfan Babaee Tirkolaee. Improving audit opinion prediction accuracy using metaheuristics-tuned xgboost algorithm with interpretable results through shap value analysis. *Applied Soft Computing*, 149:110955, 2023.
62. UNICEF et al. Cyberbullying: What is it and how to stop it. unicef, 2022.
63. Tippabhotla Vyomakesisri, Thigulla Sonu, and Doballi Srikanth. Pop culture: Interaction of and influence on the youth. *International Journal of English Literature and Social Sciences (IJELS)*, 5(1):8–12, 2020.
64. David H Wolpert and William G Macready. No free lunch theorems for optimization. *IEEE transactions on evolutionary computation*, 1(1):67–82, 1997.
65. Bin Yang, Bo Wang, Nan Sun, Fei Xu, Lianke Wang, Jiajun Chen, Shiwei Yu, Yiming Zhang, Yurui Zhu, Ting Dai, et al. The consequences of cyberbullying and traditional bullying victimization among adolescents: Gender differences in psychological symptoms, self-harm and suicidality. *Psychiatry research*, 306:114219, 2021.
66. Xin-She Yang. Firefly algorithm, stochastic test functions and design optimisation. *International journal of bio-inspired computation*, 2(2):78–84, 2010.
67. Miodrag Zivkovic, Nebojsa Bacanin, Milos Antonijevic, Bosko Nikolic, Goran Kvascev, Marina Marjanovic, and Nikola Savanovic. Hybrid cnn and xgboost model tuned by modified arithmetic optimization algorithm for covid-19 early diagnostics from x-ray images. *Electronics*, 11(22):3798, 2022.
68. Miodrag Zivkovic, Nebojsa Bacanin, Tamara Zivkovic, Ivana Strumberger, Eva Tuba, and Milan Tuba. Enhanced grey wolf algorithm for energy efficient wireless sensor networks. In *2020 zooming innovation in consumer technologies conference (ZINC)*, pages 87–92. IEEE, 2020.
69. Miodrag Zivkovic, Luka Jovanovic, Milica Ivanovic, Nebojsa Bacanin, Ivana Strumberger, and P Mani Joseph. Xgboost hyperparameters tuning by fitness-dependent optimizer for network intrusion detection. In *Communication and intelligent systems: Proceedings of ICCIS 2021*, pages 947–962. Springer, 2022.
70. Miodrag Zivkovic, Luka Jovanovic, Milica Ivanovic, Aleksa Krdzic, Nebojsa Bacanin, and Ivana Strumberger. Feature selection using modified sine cosine algorithm with covid-19 dataset. In *Evolutionary computing and mobile sustainable networks: Proceedings of ICECMSN 2021*, pages 15–31. Springer, 2022.
71. Miodrag Zivkovic, Catalin Stoean, Aleksandar Petrovic, Nebojsa Bacanin, Ivana Strumberger, and Tamara Zivkovic. A novel method for covid-19 pandemic information fake news detection based on the arithmetic optimization algorithm. In *2021 23rd international symposium on symbolic and numeric algorithms for scientific computing (SYNASC)*, pages 259–266. IEEE, 2021.

72. Miodrag Zivkovic, Ana Vesic, Nebojsa Bacanin, Ivana Strumberger, Milos Antonijevic, Luka Jovanovic, and Marina Marjanovic. An improved animal migration optimization approach for extreme learning machine tuning. In *International Conference on Intelligent and Fuzzy Systems*, pages 3–13. Springer, 2022.
73. Tamara Zivkovic, Bosko Nikolic, Vladimir Simic, Dragan Pamucar, and Nebojsa Bacanin. Software defects prediction by metaheuristics tuned extreme gradient boosting and analysis based on shapley additive explanations. *Applied Soft Computing*, 146:110659, 2023.