Employee reviews sentiment classification using BERT encoding and AdaBoost classifier tuned by modified PSO algorithm

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Abstract. Sentiment analysis of the employee reviews is very important to understand the satisfaction in the company, predict the engagement of the employees, identify the risk of employee retention and improve general productivity of the company. Proper analysis of these reviews may provide valuable insight into the satisfaction and moral levels among employees, and identify the potential areas where improvement is possible. Moreover, employee analysis can help in detecting the risks of employee retention and drop in satisfaction within the company prior to their escalation. Companies can then intervene to mitigate identified problems, and boost morale among employees. This manuscript suggests application of the AdaBoost classification model to execute the classification of the employee reviews sentiment. To select the appropriate values of the AdaBoost hyperparameters, an enhanced version of the particle swarm optimization algorithm was developed and applied. The simulation results were put into comparisons to the outcomes achieved by several contenting potent optimizers. The overall findings suggest that the presented model obtained accuracy of 87.2%. was superior to other regarded methods, showing considerable potential for further applications in this domain.

Keywords: Sentiment analysis · Employee reviews · BERT · AdaBoost · Stochastic optimization · Swarm intelligence · PSO.

1 Introduction

The level of success of an organization heavily depends on the engagement and happiness of the employees. Working environment where employees are not sat-

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isfied has a direct impact on the productivity and turnover. Otherwise, the organizations with good culture and healthy working environment attract a lot of potential candidates. Good company culture relies on the continuous learning and allowing the employees to self-improve, grow and advance in their careers, making the organization interesting for the potential workers [47].

In order to create a healthy work space, it is required to identify the employee dissatisfaction. Appropriate sentiment analysis of employee reviews can aid in discovering the potential domains where there is room for the improvement. Positive sentiment in reviews typically indicate a healthy working conditions, where workers are satisfied, valued and motivated. On the other hand, negative sentiments can expose underlying problems like poor management, poor communication or bad working conditions. These may allow the organization to react and implement proactive measurements that will tackle the concerns, increase morale of the employees, and prevent talented people to leave [15].

Machine learning (ML) methods are vital in sentiment analysis of employee reviews, as they allow sophisticated mechanisms that can help in gaining insight from large amount of text data. For example, ML can aid in data preprocessing, by means like tokenization, stemming or lemmatization that convert text into more suitable forms for analysis. Additionally, ML methods can perform feature extraction, like word frequency, or even complex linguistic attributes capturing the fine shades of sentiment. Finally, ML models can be deployed to perform sentiment classification of the reviews, where they classify these reviews as positive, neutral or negative sentiment. These models can then perform sentiment analysis in real-time, by continuous assessment of incoming data, and alarming the HR department to handle identified problems and enhance satisfaction.

The choice of ML model is crucial to obtain the highest possible accuracy. Another vital task is the choice of appropriate values of the selected model's hyperparameters. As these models have huge search spaces for the values of these parameters, this task is regarded as NP-hard by its nature. Stochastic algorithms, and especially the subgroup of metaheuristics algorithms are regarded as an excellent choice to deal with the complexity of this task. However, the no free lunch (NFL) [55] theorem argues that there is no universal optimizer capable to deliver superior outcomes on all optimization problems, which means that optimal algorithm does not exist [49]. This research utilizes an enhanced variant of particle swarm optimization (PSO) metaheuristics [35] to select the optimal collection of hyperparameters' values for the AdaBoost classifier for the sentiment classification challenge. BERT method is also employed to assist with the text representation.

2 Related works

The employed technologies for the presented research are given in this section, including the background on BERT, AdaBoost classifier and metaheuristics optimizers.

2.1 BERT

Bidirectional Encoder Representations from Transformers (known as BERT) [19], is based on the attention mechanism to perform text interpretation. Developed by the Google scientists, it lays foundations to numerous contemporary NLP applications, like speech recognition, search and translation. Its architecture consists of transformers, that allow focusing on various segments of input data during processing. Since transformers are capable of processing several parts of the sentence in parallel (multiple attention), data processing is very efficient.

BERT is also bidirectional, as it considers both preceding and succeeding words during encoding, opposite to traditional approaches that consider the text just in one direction (from left to right). This ability of bidirectional text understanding allows BERT to capture the context of sentences, improving its performance in discerning sentiments. Using BERT for sentiment analysis for the employee reviews enables organizations to attain precise insights into the sentiment of the employees.

2.2 AdaBoost

Over the past decade, a consistent rise in the adoption of different machine learning approaches may be observed. Numerous models have made considerable contributions with respect to their application areas and particular instances. Among these, AdaBoost (Adaptive Boosting) represents a pivotal tool that serves as a bridge over several optimization methods. Its primary goal is merging of weak algorithms into a cohesive set, consequently producing a robust algorithm. Initially created in 1995 by Freund and Schapire [20], AdaBoost's usage continues to expand steadily in present times. Weak classifiers' performance marginally exceeds random guess method. Over each round, AdaBoost incorporates weak classifiers into the final model, tuning their weights with respect to their individual accuracies to attain balance.

If there is a misclassification, classification weight is reduced, and vice versa, correct classification is given the increase of weight. Weak classifiers' errors are determined as follows:

$$\epsilon_t = \frac{\sum_{i=1}^{N} w_{i,t} \cdot \mathrm{I}(h_t(x_i) \neq y_i)}{\sum_{i=1}^{N} w_{i,t}} \tag{1}$$

above, ϵ_t represents the weak classifier's weighted error of the t-th iteration, N corresponds to the total amount of training samples, and $w_{i,t}$ is the weight assigned to the i-th instance during t-th round. The estimate of the weak classifier for the i-th entry during t-th iteration is given by $h_t(x_i)$. The real label of the i-th instance is indicated by the variable y_i. In this context, function $\mathrm{I}(\cdot)$ yields 0 if the conditional statement within parentheses is false, and 1 if it is true.

Once the weights have been established, novel classifiers are obtained, followed by a repetition of adjusting the weights step. Achieving accurate classifying capability necessitates a substantial ensemble of classifiers. A linear model comprises a fusion of sub-classifiers along with their outcomes. The formula for computing the weight of every classifier in the ensemble is as follows:

$$\alpha_t = \frac{1}{2} \ln \left(\frac{1 - \epsilon_t}{\epsilon_t} \right) \tag{2}$$

The weight (α_t) varies for each weak classifier within the entire collection, representing the contribution of that particular weak classifier to the ensemble model. It relies on the weighted error (ϵ_t). These weights are adjusted by the subsequent equation:

$$w_{i,t+1} = w_{i,t} \cdot \exp\left(-\alpha_t \cdot y_i \cdot h_t(x_i)\right) \tag{3}$$

in this context, y_i denotes the true label of the i-th instance, $h_t(x_i)$ signifies the forecast outcome of the i-th instance by the weak learner's t-th iteration. Finally, $w_{i,t}$ represents the weight assigned to the i-th instance during t-th iteration.

AdaBoost holds considerable importance in the machine learning domain. Its strengths lie in effective reducing bias and variance, that fosters the development of robust models. However, its drawback is found in its susceptibility to data with noise and outliers, requiring careful consideration of its applicability in particular scenarios.

2.3 Metaheuristics optimizers

Inspired by organisms flourishing in large swarms and employing collective behavioral patterns, swarm intelligence algorithms demonstrate considerable effectiveness when individual efforts alone are not sufficient to accomplish the given task. This methodology has garnered considerable success in resolving NP-hard problems.

Methods that belong to the swarm intelligence family have shown remarkable proficiency in resolving a wide array of real-life issues. Notable instances of their usage include medical applications [34, 57, 9, 29, 36, 28, 61], and detecting the scams with credit cards [25, 39]. Furthermore, swarm techniques attained considerable success in cloud computing domain [42, 7], plant classification[13], forecasting the green energy production process and delivery to consumers [53, 4], broad array of economic tasks [30, 50, 52, 11, 46, 40], improvement of the audit opinion [54], detection of defects in software modules [63], feature selection [5, 16, 26, 60], different sections of computer security [59, 1, 48, 32, 45, 14, 31, 10], Monitoring the environment and tracking pollution, [33, 27, 6, 37], different areas of wireless sensor networks and IoT tuning [58, 3] and general tuning of a variety of ML structures [8, 51, 12, 21, 44, 62, 2, 22, 17].

3 Methods

Within this section, baseline variant of PSO is explained, followed by the identified limitations of the algorithm, and suggested modifications.

3.1 Particle swarm optimization algorithm

The baseline PSO is one of the oldest metaheuristics, developed and proposed in 1995 [35], and drawing inspiration by the flocking behavior demonstrated by birds and fish. Particles form the population and correspond to the search agents. PSO has been successfully used to address both discrete and continuous optimization tasks.

The inner-workings of the baseline method are defined as follows. Each particle is given an initial velocity, and over iterations, the individuals change their locations aiming to find a better one. Particle's speed is described by the weight coefficient, comprised of the old velocity, the best attained so far, accompanied by the best attained by the particles in the neighborhood as described by Eq. 4.

$$\begin{cases} \overrightarrow{v_i} \leftarrow \overrightarrow{v_i} + \overrightarrow{U}(0,\phi_1) \bigotimes (\overrightarrow{p_i} - \overrightarrow{x_i}) + \overrightarrow{U}(0,\phi_2) \bigotimes (\overrightarrow{p_g} - \overrightarrow{x_i}) \\ \overrightarrow{x_i} \leftarrow \overrightarrow{x_i} + \overrightarrow{v_i}, \end{cases} \tag{4}$$

where $\bigotimes$ denotes the component-wise multiplication, the components of v_i are ranging between $[-V_{max}, +V_{max}]$, while the vector marked $\overrightarrow{U}(0,\phi_1)$ denotes each solution arbitrarily produced with a univorm distribution ranging in $[0,\phi_i]$. The best solution of the individual i is denoted by p_i, and the global best solution is given by pg. Each individual particle correspond to the potential solution within D-dimensional space, with the location described by Eq. 5, the best location attained so far before position updating given by Eq. 6, and the velocity set defined by Eq. 7.

$$X_i = (x_{i1},\ x_{i2},\ ...,\ x_{iD}) \tag{5}$$

$$P_i = (p_{i1},\ p_{i2},\ ...,\ p_{iD}) \tag{6}$$

$$V_i = (v_{i1},\ v_{i2},\ ...,\ v_{iD}) \tag{7}$$

The optimal solutions, both globally (p_i) and within the group (p_g), are acknowledged. The particle considers both pieces of information when determining its next move based on the current distance between its position and p_i and p_g. By employing the inertia weight method, it can be mathematically described as shown in Eq 8.

$$v_{id} = W * v_{id} + c_1 * r_1 * (P_{id} - X_{id}) + c_2 * r_2 * (P_{gd} - X_{id}) \tag{8}$$

The Eq. 8 illustrates the inertia factors' relative impact, labeled as w, while c_1 and c_2 are utilized for cognitive and social components. Here, r_1 and r_2 denote arbitrary values, while the particle's velocity and its present location are respectively provided by v_{id} and x_{id}. Furthermore, p_{id} and p_{gd} correspond to p_i and p_g, respectively.

Inertia factor itself is described by the Eq. 9. The starting weight is given by w_{max}, and the final weight is marked as w_{min}. Maximum count of iterations in the run is given by T, while the ongoing iteration is denoted as t.

$$w = w_{max} - \frac{w_{max} - w_{min}}{T} \cdot t \tag{9}$$

3.2 Accelerated Guided best PSO

Despite being one of the first metaheuristics, PSO is still heavily in use, as it is known of its powerful optimization capabilities. However, as any other metaheuristics, it has some known limitations, exposed with extensive simulations on the benchmark functions. These drawbacks include tendency to get stuck in the areas with local optima in case of problems with a high count of dimensions, and slow converging velocity in certain runs.

This manuscript proposes a couple of alterations to the baseline method, to specifically tackle the constraints described above. First modification is based on the quasi-reflection-based learning procedure (QRL) which is incopropated in the initialization stage of the metaheuristics. This mechanism is renowned of its capability to enhance the covering of the search realm [43]. The procedure is applied to each component j of the particle X_j, by synthesizing a quasi-reflexive-opposite parameter denoted as X_j^{qr} in the following way:

$$X_j^{qr} = \text{rand}\left(\frac{lb_j + ub_j}{2}, x_j\right) \tag{10}$$

above, $rand$ is an arbitrary value within $\left[\frac{lb_j + ub_j}{2}, x_j\right]$. The tweaked PSO initialization procedure begins by synthetizing $NP/2$ individuals by employing the QRL mechanism, without rising the complexity of the method in $FFEs$ (fitness function evaluation). This procedure is listed within Algorithm 1.

Algorithm 1 QRL init stage

Turn 1: Formulate an initial populace, denoted as P^{init}, by applying the conventional PSO initialization mechanism to synthesize $NP/2$ individuals in Eq. (**??**)
Turn 2: Project the QRL population P^{qr} starting from P^{init} with help of the Eq. (10)
Turn 3: Finalize the overal starting populace P by fusing P^{init} and P^{qr} ($P \cup P^{qr}$)
Turn 4: Establish the fitness value of each particle inside P
Turn 5: Organize all solutions within set P based on their respective fitness scores.

Following the initialization phase, throughout the entire run of the altered metaheuristics, the poorest individual is removed in each round and substituted by the QRL opposite of the top-performing particle (guided best approach). The proposed modification doesn't elevate the complexity of the baseline algorithm computed in $FFEs$, as the fitness values of particles are not assessed.

Additional modification integrated into PSO draws inspiration from GA [38]. As the algorithm progresses and convergence nears, emphasis should be placed on refining the best individuals discovered thus far. Acceleration occurs during the final $max_iter/2$ rounds by replacing the particle with the second poorest fitness value with a novel particle produced as a hybrid of the pair of best particles. This synthesis employs a uniform crossover operator with a per-gene crossover probability set to $p_c = 0.1$. This adjustment improves exploitation, thereby accelerating the metaheuristics. Once again, this change doesn't entail additional fitness value computations, therefore keeping the complexity in terms of $FFEs$. Finally, the complexity of the altered PSO remains identical to the baseline PSO. This adapted variant of PSO is dubbed Accelerated Guided best Adaptive PSO (AGbAPSO), with the pseudocode presented in Algorithm 2.

Algorithm 2 AGbAPSO pseudocode

```
Generate starting populace P by QRL mechanism shown in Algorithm 1
while (t < T) do
    Arrange individuals P according to their fitness values
    for every individual X within P do
        Use PSO search
        Create novel particle as QRL opposite of the currently best particle
        Substitute the worst particle in P with new particle
        if (t > max_iter/2) then
            Synthesize novel particle as the hybrid of the best two particles, using the uniform crossover operator
            with p_c = 0.1
            Substitute the second-poorest particle by this fresh hybrid solution
        end if
    end for
end while
return The best individual from P
```

4 Experimental setup

Dataset for the employee reviews sentiment classification employed in the experiments presented in this paper is publicly accessible at `https://www.kaggle.com/datasets/davidgauthier/glassdoor-job-reviews`. It is comprised of job descriptions and ranks from different industries in the United Kingdom, covering different criteria like income, work-life trade-off, culture etc. The reviews are labeled as positive, mild, negative or no opinion. Dataset was partitioned into 70% utilized for training, and remaining 30% saved for testing purposes. Classification was executed by AdaBoost, where the hyperparameters opted for tuning, accompanied by their appropriate search limits were count of estimators $[10, 50]$, depth $[1, 10]$ and learning rate $[0.1, 2]$.

The AdaBoost classifier has been optimized by the described AGbAPSO metaheuristics. The simulations were implemented in Python, making use of the standard collection of ML libraries, such as scikit-learn, scipy, pandas, numpy and seaborn. To evaluate the results attained by suggested AdaBoost tuned by AGbAPSO (shortly labeled AB-AGbAPSO) were put into comparisons to the outcomes of potent optimizers like baseline PSO, GA [38], FA [56], RFO [41], COA [24] and COLSHADE [23]. Each metaheuristics was allocated with populace size of 6, 8 rounds per execution, and 30 individual runs.

As the Glassdoor dataset is imbalanced, Cohen's kappa measure κ was chosen as the objective function for maximization [18], described as:

$$\kappa = \frac{k_o - k_e}{1 - k_e} = 1 - \frac{1 - k_o}{1 - k_e} \tag{11}$$

above, observed and expected outcomes vectors are marked as k_o and k_e. Cohen's κ considers the class imbalance, therefore it is able to deliver more robust forecasts in comparison to accuracy, that can be deceiving under this circumstances.

5 Simulation outcomes

Tables 1 and 2 summarize the experimental outcomes with respect to the Cohen's kappa (fitness function) and error rate (selected as indicator function). The superior results for each category is presented in bold text. The most supreme AdaBoost configuration was synthesized by the introduced AGbPSO algorithm, that obtained the best outcome for the best result (for both fitness and indicator). The stochastic behavior of metaheurisics methods is visible by observing other categories, where other algorithms performed better. For instance, elementary PSO attained the best score of the mean and median values of κ, and COLSHADE had the best scores for the worst metric, std and variance.

Table 1. Objective function overall outcomes for sentiment classifiers.

Method	Best	Worst	Mean	Median	Std	Var
AB-AGbPSO	**0.744904**	0.718571	0.732307	0.733681	0.008678	7.53e-05
AB-PSO	0.743398	0.727532	**0.736786**	**0.736970**	0.004774	2.28e-05
AB-GA	0.742902	0.730489	0.735677	0.734434	0.004529	2.05e-05
AB-FA	0.743398	0.698131	0.730701	0.735435	0.014882	2.21e-03
AB-RFO	0.744403	0.712147	0.731566	0.734921	0.010038	1.01e-04
AB-COA	0.743446	0.728896	0.735612	0.735951	0.004446	1.98e-05
AB-COLSHADE	0.742358	**0.731449**	0.736754	0.736925	**0.003904**	**1.52e-05**

Table 2. Indicator function overall outcomes for sentiment classifiers.

Method	Best	Worst	Mean	Median	Std	Var
AB-AGbPSO	**0.127490**	0.140687	0.133798	0.133093	0.004348	1.89e-05
AB-PSO	0.127988	0.136703	0.132885	0.132844	0.002874	8.26e-06
AB-GA	0.128486	0.134711	0.132097	0.132719	0.002267	5.14e-06
AB-FA	0.128237	0.150896	0.134587	0.132221	0.007452	5.55e-05
AB-RFO	0.127739	0.143924	0.134172	0.132470	0.005039	2.54e-05
AB-COA	0.128237	0.135458	0.132138	0.131972	**0.002212**	**4.89e-06**
AB-COLSHADE	0.128735	**0.134213**	0.131557	0.131474	0.001964	3.86e-06

Violin plot of the Cohen's κ and box plots of the error rate over 30 individual executions are presented in Fig. 1. Additionally, Fig. 2 gives insights into the convergence plots of the fitness (κ) and error rate for the best execution of all considered metaheuristics. It is clearly visible that the AGbPSO achieves supreme converging capability by avoiding local optima, that may affect the results by premature converging to unfavourable regions, which is evident by other methods (most obviously RFO and COA).

Detailed analysis of the outcomes achieved by the best-performing AdaBoost classifiers synthesized by each algorithm observed in the comparative analysis are provided in Table 3. Introduced AB-AGbPSO exhibited supreme outcomes, attaing the best scores for the majority of the regarded metrics, most notably the accuracy of 87.25%. Nevertheless, it should be mentioned that other metaheuristics also achieved respectable accuracy levels. To further facilitate the replication studies, the determined set of AdaBoost parameters of each metaheuristics is given in Table 4.

Finally, PR curve (prec-recall) and confusion matrix of AB-AGbPSO classifier are provided in Fig. 3. To conclude the general experimental results, it

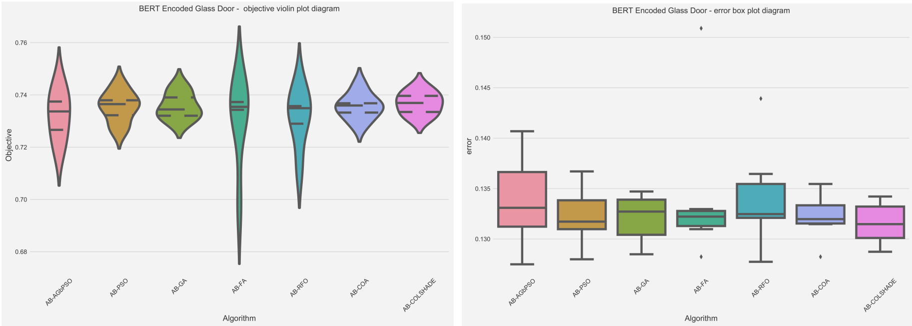

Fig. 1. Distributions for objective and indicator functions.

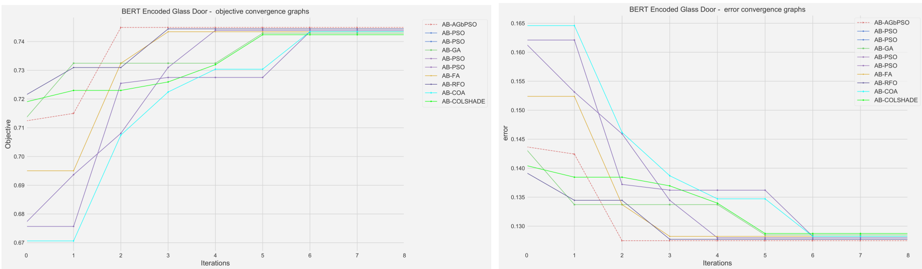

Fig. 2. Convergence plots for objective and indicator functions.

Table 3. Detailed metrics comparisons between best-performing sentiment classifiers.

Method	Metric	Satisfied	Dissatisfied	Accuracy	Macro avg.	Weighted avg.
AB-AGbPSO	precision	0.874104	0.870999	**0.872510**	**0.872552**	**0.872525**
	recall	0.865248	0.879530	**0.872510**	**0.872389**	**0.872510**
	f1-score	**0.869654**	**0.875244**	**0.872510**	**0.872449**	**0.872496**
AB-PSO	precision	0.874295	0.869376	0.871763	0.871835	0.871794
	recall	0.863222	0.880020	0.871763	0.871621	0.871763
	f1-score	0.868723	0.874665	0.871763	0.871694	0.871744
AB-GA	precision	0.873846	0.869313	0.871514	0.871579	0.871541
	recall	0.863222	0.879530	0.871514	0.871376	0.871514
	f1-score	0.868502	0.874391	0.871514	0.871446	0.871496
AB-FA	precision	0.874295	0.869376	0.871763	0.871835	0.871794
	recall	0.863222	0.880020	0.871763	0.871621	0.871763
	f1-score	0.868723	0.874665	0.871763	0.871694	0.871744
AB-RFO	precision	0.874040	0.870577	0.872261	0.872308	0.872279
	recall	0.864742	0.879530	0.872261	0.872136	0.872261
	f1-score	0.869366	0.875030	0.872261	0.872198	0.872246
AB-COA	precision	0.870117	**0.873350**	0.871763	0.871733	0.871761
	recall	**0.868794**	0.874633	0.871763	0.871714	0.871763
	f1-score	0.869455	0.873991	0.871763	0.871723	0.871761
AB-COLSHADE	precision	**0.877657**	0.865357	0.871265	0.871507	0.871403
	recall	0.857649	**0.884427**	0.871265	0.871038	0.871265
	f1-score	0.867538	0.874788	0.871265	0.871163	0.871224
	support	1974	2042			

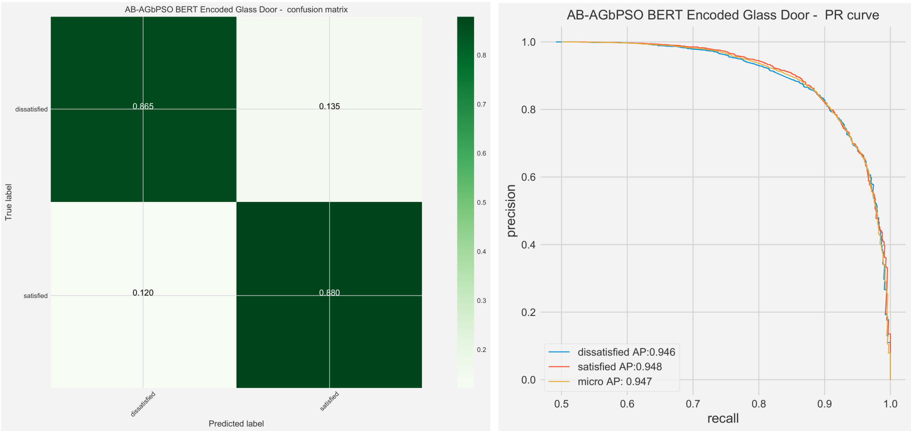

Fig. 3. AGbPSO optimized sentiment classifier PR curve and confusion matrix.

Table 4. Best constructed Arabist classifier parameters selected by optimizers.

Methods	Number of estimators	Depth	Learning rate
AB-AGbPSO	5	5	0.396655
AB-PSO	5	5	0.294675
AB-GA	5	5	0.421371
AB-FA	5	5	0.422030
AB-RFO	5	5	0.399369
AB-COA	5	5	0.454070
AB-COLSHADE	5	5	0.401295

should be mentioned that AB-AGbPSO could be an excellent solution to classify employee reviews. Additionally, the competitor algorithms have also attained respectable performance levels for this particular task.

6 Conclusion

This paper investigated the capability of AdaBoost classifier optimized by metaheuristics optimizers to handle employee reviews sentiment classification task. Appropriate classification of these reviews can help in evaluating the employee satisfaction within the organization, and identify the potential risks where the organization should intervene. AdaBoost classifier was tuned by an altered version of PSO algorithm, and the outcomes were put into comparisons to the AdaBoost tuned by other potent optimizers. Proposed AB-AGbPSO syntesized the top-performing mode, that achieved the accuracy of 87.25%.

The constraints of this research are correlated to the extremely high hardware requirements for the experiments, which resulted in reduced count of individuals and iterations per execution, and also limited number of contending algorithms. Additionally, search areas for the hyperparameters were also been limited. These constraints should be addressed in the future, if supplementary computing power is available.

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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. 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.
3. 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.
4. 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.
5. 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.
6. 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.
7. 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.
8. 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.
9. Nebojsa Bacanin, Miodrag Zivkovic, Fadi Al-Turjman, K Venkatachalam, Pavel Trojovský, Ivana Strumberger, and Timea Bezdan. Hybridized sine cosine algorithm with convolutional neural networks dropout regularization application. *Scientific Reports*, 12(1):6302, 2022.
10. 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.
11. 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.
12. 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.
13. 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.
14. 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.
15. Sandra Baroudi, Rana Tamim, and Zeina Hojeij. A quantitative investigation of intrinsic and extrinsic factors influencing teachers' job satisfaction in lebanon. *Leadership and policy in schools*, 21(2):127–146, 2022.
16. 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.
17. 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.
18. Jacob Cohen. A coefficient of agreement for nominal scales. *Educational and psychological measurement*, 20(1):37–46, 1960.
19. Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.
20. Yoav Freund and Robert E Schapire. A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences*, 55(1):119–139, 1997.
21. 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.
22. 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.
23. Javier Gurrola-Ramos, Arturo Hernàndez-Aguirre, and Oscar Dalmau-Cedeño. Colshade for real-world single-objective constrained optimization problems. In *2020 IEEE congress on evolutionary computation (CEC)*, pages 1–8. IEEE, 2020.

24. Heming Jia, Honghua Rao, Changsheng Wen, and Seyedali Mirjalili. Crayfish optimization algorithm. *Artificial Intelligence Review*, 56(Suppl 2):1919–1979, 2023.
25. 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.
26. 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.
27. 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.
28. 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.
29. 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.
30. 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.
31. 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.
32. 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.
33. 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.
34. 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.
35. 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.
36. 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.

37. 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.
38. Seyedali Mirjalili and Seyedali Mirjalili. Genetic algorithm. *Evolutionary algorithms and neural networks: Theory and applications*, pages 43–55, 2019.
39. 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.
40. 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.
41. Dawid Połap and Marcin Woźniak. Red fox optimization algorithm. *Expert Systems with Applications*, 166:114107, 2021.
42. 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.
43. S. Rahnamayan, H. R. Tizhoosh, and M. M. A. Salama. Quasi-oppositional differential evolution. In *2007 IEEE Congress on Evolutionary Computation*, pages 2229–2236, 2007.
44. 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.
45. 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.
46. 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.
47. Yunia Sari et al. Improving employee satisfaction and performance through motivation, organizational culture, and employee competency in pekanbaru city health office. *Journal of Applied Business and Technology*, 3(1):1–16, 2022.
48. 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.
49. Ashish Sharma. Stochastic nonparallel hyperplane support vector machine for binary classification problems and no-free-lunch theorems. *Evolutionary Intelligence*, 15(1):215–234, 2022.
50. 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.

51. 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.
52. 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.
53. 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.
54. 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.
55. David H Wolpert and William G Macready. No free lunch theorems for optimization. *IEEE transactions on evolutionary computation*, 1(1):67–82, 1997.
56. Xin-She Yang. Firefly algorithm, stochastic test functions and design optimisation. *International journal of bio-inspired computation*, 2(2):78–84, 2010.
57. 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.
58. 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.
59. 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.
60. 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.
61. 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.
62. 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.
63. 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.