



# Addressing feature selection and extreme learning machine tuning by diversity-oriented social network search: an application for phishing websites detection

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Received: 16 August 2022 / Accepted: 16 May 2023 / Published online: 28 June 2023

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## Abstract

Feature selection and hyper-parameters optimization (tuning) are two of the most important and challenging tasks in machine learning. To achieve satisfying performance, every machine learning model has to be adjusted for a specific problem, as the efficient universal approach does not exist. In addition, most of the data sets contain irrelevant and redundant features that can even have a negative influence on the model's performance. Machine learning can be applied almost everywhere; however, due to the high risks involved with the growing number of malicious, phishing websites on the world wide web, feature selection and tuning are in this research addressed for this particular problem. Notwithstanding that many metaheuristics have been devised for both feature selection and machine learning tuning challenges, there is still much space for improvements. Therefore, the research exhibited in this manuscript tries to improve phishing website detection by tuning extreme learning model that utilizes the most relevant subset of phishing websites data sets features. To accomplish this goal, a novel diversity-oriented social network search algorithm has been developed and incorporated into a two-level cooperative framework. The proposed algorithm has been compared to six other cutting-edge metaheuristics algorithms, that were also implemented in the framework and tested under the same experimental conditions. All metaheuristics have been employed in level 1 of the devised framework to perform the feature selection task. The best-obtained subset of features has then been used as the input to the framework level 2, where all algorithms perform tuning of extreme learning machine. Tuning is referring to the number of neurons in the hidden layers and weights and biases initialization. For evaluation purposes, three phishing websites data sets of different sizes and the number of classes, retrieved from UCI and Kaggle repositories, were employed and all methods are compared in terms of classification error, separately for layers 1 and 2 over several independent runs, and detailed metrics of the final outcomes (output of layer 2), including precision, recall, f1 score, receiver operating characteristics and precision–recall area under the curves. Furthermore, an additional experiment is also conducted, where only layer 2 of the proposed framework is used, to establish metaheuristics performance for extreme machine learning tuning with all features, which represents a large-scale NP-hard global optimization challenge. Finally, according to the results of statistical tests, final research findings suggest that the proposed diversity-oriented social network search metaheuristics on average obtains better achievements than competitors for both challenges and all data sets. Finally, the SHapley Additive exPlanations analysis of the best-performing model was applied to determine the most influential features.

**Keywords** Extreme learning machine · Feature selection · Metaheuristics optimization · Social network search · Hyper-parameters optimization · Diversification

## Introduction

The sphere of network research and engineering that has, in previous decades, led to the development of the world wide web (WWW) has seen a constant stream of innovations, development, and improvements. The web has moved from a niche technology to a staple of everyday life. With

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these developments came user convenience and many services migrated to hybrid and even entirely online models [1–3]. Shopping, trading, baking, business meetings, and many other operations that deal with sensitive data on an everyday basis now take place online [4, 5]. With all this in mind, it is worth noting that malicious actors exist, and they prioritize their interests over the privacy and security of others [6, 7]. Malicious actors make use of many techniques and tools during their operations.

Depending on the current goal, the methods used can vary from intrusion tools to scanning and probing tools used to evaluate systems for vulnerabilities. For example, by posing as a trustworthy entity, an attacker can use social engineering techniques which involve tricking users into disclosing sensitive information, such as login credentials or personal information. The wide range of publicly available phishing kits makes the job fairly easy even for the less technically proficient actors. Other well know and applied methods for obtaining sensitive information include using spoofing techniques to create fake websites or emails that mimic legitimate ones, or sending malicious software (malware) that can infect a user's computer and give the attacker unlimited access [8, 9]. It is also important to note that these techniques evolve along with the development of new methods used for detection and counteraction. Researchers need to constantly remain several steps ahead of malicious actors to maintain a platform secure enough to support the convinces that make the Web essential to modern life.

The field of artificial intelligence (AI) has seen many developments in recent years due to the wide adaption of computation across multiple fields, for example, business [10], finance [11], various medical [12], and many other fields [13], rely on the AI in daily operations. Accordingly, AI presents many approaches to addressing real-world problems. Various methods tackle tasks differently, and with varying degrees of success. The ability of AI to learn and adapt to a changing landscape makes it a promising candidate for addressing problems in the ever-developing field of web and network security in general. While traditional methods, such as firewalls, security certificates, blacklists, and others, exist [14–17], they require constant monitoring and maintenance to maintain an acceptable level of efficacy. By applying AI to these problems, researchers have attempted to improve existing models and provide an overall improvement in network security. Many such applications exist that tackle intrusion detection [18–20], detect attempts on exploiting users through phishing attacks [21–23], uncover embedded botnets in IoT networks [24–26], as well as tackle vectors of spread for malicious software such as spam [27–29].

The AI field in general can be roughly divided into two categories: machine learning (ML) and metaheuristics optimization algorithms. Machine learning and metaheuristics differ in terms of their objective and methodology. The ML

aims to recognize patterns and correlations in data to facilitate forecasting or decision-making, whereas metaheuristics are employed to discover effective solutions for optimization challenges. The ML algorithms are typically trained on vast data sets to enhance their precision, whereas metaheuristics do not necessitate big data sets and are usually more computationally economical. In general, ML and metaheuristics are both important tools in the field of AI, but they serve different purposes and employ different approaches to problem-solving.

A popular group of ML techniques, that models principles observed in human brains are artificial neural networks (ANN) [30]. They present a simplified model of the internal mechanisms observed in various nerve clusters. Neural networks remain popular due to their ability to tackle nonlinear approximations by processing input data. In addition, their versatility enables them to tackle a wide range of problems, that are otherwise challenging to address using traditional methods [31, 32]. However, despite many advantages, neural networks are computationally demanding, making them slower to train and evaluate. This led to many researchers developing various methods for improving their performance while preserving the positive traits that make them appealing [33–35].

One of the most efficient ANN types is the extreme learning machine (ELM) model, because it does not require traditional training, which is time and computationally consuming [36]. The ELM was originally proposed as a method for training single-hidden layer feed-forward networks (SFFN) [36]. It makes use of the Moore–Penrose (MP) generalized inverse to calculate output weights, while the input and hidden layer biases are generated randomly. The approach attempts to avoid problems present in traditional gradient-descent algorithms, e.g., getting stuck in local minima, vanishing and exploding gradients, and improve on the much slower convergence rate, providing better general performance.

However, ML like every other field suffers from some challenges and two of the most important ones are feature selection and tuning (hyper-parameters optimization). To achieve satisfying performance, every machine learning model has to be adjusted for a specific problem, as according to the no free lunch (NFL) theorem [37], the efficient universal approach for all practical challenges does not exist. In addition, most of the data sets contain irrelevant and redundant features that can even have a negative influence on the model's performance. In most cases, both above-mentioned ML challenges are NP-hard instances and since metaheuristics have proven as successful NP-hard problem solvers [38, 39], this is where these two groups of AI methods can be hybridized.

The ELMs can be tuned and adjusted for specific problems in two ways. First, the number of hidden neurons needs to be high enough to ensure good generalization, conversely, net-

work structures with only a few neurons in the hidden layer may exhibit degraded performance. Second, the model's performance, in terms of classification/regression metrics, depends to a large extent on the values of randomly initialized weights and biases. Every problem is specific and since the ELMs do not undergo traditional training, e.g., using stochastic gradient descent (SGD) based algorithms, the final output depends on initial randomly generated weights and biases values. Therefore, determining adequate hidden input weights and biases for each specific practical application presents an additional and important optimization challenge in this area.

Population-based metaheuristic algorithms have even been successfully utilized to address NP difficult problems, considered impossible to solve with traditional computational methods [40]. By mathematically modeling behaviors of individual agents, that obey simple rule sets, and with the use of an objective evaluation function, metaheuristics enable complex behaviors to manifest on a larger scale. A promising novel population metaheuristics for addressing optimization problems is the social network search (SNS) metaheuristics [41]. It simulates user interactions on social networks in a simplified manner by modeling user moods. In turn, replicating the flow of information and propagation of ideas and views. The way by which users generate popularity on social networks forms the basis of the functionality of this approach. These mechanisms make the novel algorithm an attractive option for researchers tackling various optimization problems as it shows promising results under test conditions [41].

The motivation, as the goal, behind the research proposed in this manuscript is to try to further improve phishing website detection by tuning the ELM, which utilizes the most relevant subset of features in the available phishing data sets. Such motivation stems from two facts: notwithstanding that many approaches have been devised for both, feature selection and ML tuning challenges, there is still much space for improvements, because the method that obtains satisfying accomplishments for every practical task cannot be created [37]; one of the most important challenges on the web is phishing and developing intelligent ML classifier for detecting such malicious websites is among top priorities in this domain [42–44].

A novel diversity-oriented SNS algorithm has been developed to accomplish above mentioned objective and integrated into a two-level cooperative framework for feature selection and ELM tuning. Layer 1 of devised framework performs feature selection, while the best-obtained subset of features has then been used as the input to the framework's level 2, where metaheuristics perform tuning of ELM, respecting to the number of neurons in the hidden layer and weights and biases initialization. Notwithstanding that wrapper-based feature selection can be computationally demanding [45], the level

1 of proposed framework implements wrapper feature selection approach, because compared to other approaches for this challenge it obtains better performance in terms of classification accuracy and smaller chosen subset of relevant features.

In addition, to establish metaheuristics performance for a larger scale NP-hard challenge, a second experiment, that uses only the layer 2 part of the framework, where the ELM was tuned with all available features, is also conducted. The proposed boosted SNS algorithm has been compared to six other cutting-edge metaheuristics algorithms, that were also implemented in the framework and tested under the same experimental conditions. Finally, the SHapley Additive exPlanations (SHAP) analysis was applied to the proposed model, aiming to interpret the best performing model and to discover the most influential features of two considered data sets.

Based on everything stated so far, the main contributions of this work may be summarized as the following:

1. proposal of a novel SNS algorithm based on the solution diversity adapted for feature selection and ELM tuning
2. implementation of the cooperative two-layer framework that performs feature selection (layer 1), and ELM optimization (layer 2)
3. integration of developed enhanced SNS in the framework to tackle a practical issue of phishing website detection.

The remainder of this work is structured as follows: Sect. 2 covers works related to the subject matter followed by a summary of the concepts behind ELM. Section 3 presents methods proposed in this research, followed by an overview of the experimental setup and discussion, as well as validation, of the attained results in Sect. 4. Finally, the conclusion and possible future works in the field are given in Sect. 5.

## Literature review and preliminaries

This section provides basic background information related to proposed research. First, a concept of feature selection is introduced, followed by ELM mathematical formulation and details of metaheuristics optimization methods, along with relevant literature review.

### Feature selection

The ML models frequently try to find useful patterns and connections in large data sets, packed with redundant and inessential data, that have a profound influence concerning models' accuracy and computational complexity. Frequently, the said data sets are high-dimensional, which also impedes ML model performance. This occurrence refers to the curse of dimensionality [46].

Hence, identifying essential information is crucial to tackling this issue. For this reason, the technique of dimensionality reduction [47], where the classification problem is simplified, is a main pre-processing task for machine learning. It is an action, where the data are transformed from a high-dimensional domain to a lower dimension by reducing the number of classification variables while still keeping enough meaningful attributes of the original data set. There are two approaches to dimensionality reduction: feature extraction and feature selection. While feature extraction [48] generates new variables derived from the primary set of data, feature selection chooses a subset of relevant informative variables for the desired objective.

The purpose of feature selection is to determine the relevant subset from high-dimensional data sets eliminating the insignificant features, thus enhancing the classification accuracy for ML. There are three feature selection methods: filter, wrapper, and embedded methods, as per [45].

Wrapper methods utilize learning algorithms, like ML classifiers, to evaluate feature subsets to find relevant features, i.e., the feature selection challenge is treated as search problem. Wrapper methods use a specific ML algorithm as a black-box model to evaluate the usefulness of each feature subset. This method involves evaluating each feature subset by training a machine learning model on the subset and measuring its performance. The performance of the model is then used as a criterion for selecting the best feature subset. Wrapper methods tend to provide better results than filter methods in terms of classification accuracy and smaller feature subsets, but they can be computationally expensive as they involve training and evaluating a model for each subset of chosen features [45].

Filter methods do not use a training process and instead designate a score to feature subsets using statistical or mathematical metrics that evaluate the relationship between each feature and the target variable. Filter methods consider the relevance and redundancy of features, and those with the highest scores are selected for further analysis. Due to this property, this method is not as computationally demanding as the wrapper and can be applied to a broad range of data sets, making them a popular choice for feature selection in many applications [45, 49].

Finally, the embedded method employs feature selection as a segment of the model creation process, i.e., methods perform feature selection during the model training. These methods are more accurate than filters, with the same execution speed. With computational complexity in mind, embedded methods are in between the methods mentioned above.

## Extreme learning machine (ELM)

A relatively novel learning algorithm, ELM is applied to training single-layer feed-forward network (SLFN) [50]. In the initial stage, the algorithm randomly initializes weights and biases for hidden layer neurons. This is followed by computational steps to determine output weights by applying the MP generalized inverse. Hidden neuron layer randomization presents an interesting and demanding challenge for researchers. This hidden layer transforms input values into higher dimensional ELM feature space, using nonlinear transforms. With this approach, the process of attaining a solution is simplified, since the probability of linear separability of inputs across feature space increases.

With a training set  $\aleph = (x_i, t_i) | x_i \in R^d, t_i \in R^m, i = 1, \dots, N$ , the output with  $L$  hidden neurons, using  $g(x)$  as the activation function, can be determined according to Eq. (1):

$$\sum_{i=1}^L \beta_i g(w_i \cdot x_j + b_i) = y_j, j = 1, \dots, N \quad (1)$$

where  $b$  bias and  $w_i = [w_{iqm}, \dots, w_{id}]^T$  are the weights of a hidden neuron. Output weights are represented by  $\beta_i = [\beta_{i1}, \dots, \beta_{im}]^T$ , and  $w_i \cdot x_j$  is the inner product of  $w_i$  and  $x_j$ .

Standard SLNF parameters  $\beta_i, i = 1, \dots, L$  can be approximated to Eq. (2):

$$\sum_{i=1}^L \beta_i g(w_i \cdot x_j + b_i) = t_j, j = 1, \dots, N \quad (2)$$

In addition, the parameter  $T$  can be computed according to Eq. (3):

$$T = H\beta \quad (3)$$

where  $H$  is the hidden layer output matrix seen as in Eq. (4):

$$h = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \dots & g(w_L \cdot x_1 + b_L) \\ \vdots & \dots & \vdots \\ g(w_1 \cdot x_N + b_1) & \dots & g(w_L \cdot x_N + b_L) \end{bmatrix}_{N \times L} \quad (4)$$

Furthermore,  $\beta$  and  $T$  are shown in Eq. (5):

$$\beta = \begin{bmatrix} \beta_i^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L \times m} \quad \text{and} \quad T = \begin{bmatrix} t_i^T \\ \vdots \\ t_N^T \end{bmatrix}_{N \times m} \quad (5)$$

Output weights, represented  $\beta$  are calculated using Eq. (6)

The pseudocode for the ELM method applied to SLFN can be seen in Algorithm 1.



**Algorithm 1** Pseudocode for the ELM

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With training data  $\mathfrak{N} = (x_i, t_i) | x_i \in R^d, t_i \in R^m, i = 1, \dots, N, g(x)$  as the activation function, and  $N$  the as the number of hidden nodes  
**Step 1:** Assign  $w_i$  and  $b_i$  randomly  
**Step 2:** Compute hidden layer output matrix  $H$   
**Step 3:** Compute output weight  $\beta$

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where  $\beta$  is calculated according to Eq. (6):

$$\beta = H^\dagger T \quad (6)$$

with  $H^\dagger$  representing the Moore–Penrose generalized inverse of  $H$ .

It is worth noting that many ELM applications and improved ELM approaches are presented in modern literature. Some of the more notable applications and variations include: pattern recognition, where neurons deemed irrelevant are eliminated via pruning (pruned ELM–P-ELM) [51]; a proposal of an improved method called the optimally pruned ELM (OP-ELM) [52], which constructs larger networks by applying the standard ELM algorithm, has been applied to regression and classification problems; implementation of evolutionary ELM (E-ELM) that takes advantage of differential evolution (DE) algorithm to make adequate adjustments to weights and biases within a network [53].

### Metaheuristics optimization

When dealing with optimization problems, metaheuristic algorithms are a popular choice among researchers due to their ability to address complex problems as well as higher dimensional data sets, within acceptable time periods and realistic resources. A subgroup among these is population-based algorithms, with the most prominent representative, swarm intelligence [54], that mimics a group of organisms from nature. Often nature-inspired, metaheuristics model the actions of individuals with simple rules. By following these rule sets, separate, independent agents act as a cooperative group, working towards a common goal, often aided by external objective (fitness) functions that are used to assess its performance. This mechanism allows for complex behaviors to manifest on a global scale. The exact mechanisms by which optimization is achieved depend on the details of the selected algorithm.

However, most metaheuristics rely on exploration and exploitation as primary internal mechanisms [55]. In the exploration stage, the algorithms focus on broadly covering a large area of the search space, looking for promising regions. When certain criteria are met, the algorithm transitions toward exploitation. In this stage, the primary goal is to increase the resolution of results around promising areas to gain more favorable outcomes. Due to the stochastic nature of these stages, an optimal solution is not guaranteed; however,

a satisfying solution can be generated within a reasonable time span [56, 57].

Metaheuristic algorithms have been used to successfully tackle problems considered NP-hard which are often impossible to resolve using traditional methods [58–60]. As such, they continue to be a popular choice for researchers owing in part to their problem-solving abilities, relative simplicity, and low computational demands. Many algorithms have been developed to model various observed phenomena.

Some notable nature-inspired algorithms, that fall into the category of swarm intelligence, include the artificial bee colony (ABC) [61] algorithm, often used to improve performance through many practical applications [62–64]. Other examples include the whale optimization algorithm (WOA) [65], which models a hunting strategy unique to a species of whale. This approach is popular among researchers for its interesting search patterns and has successfully been applied to many real-world problems [39, 66, 67]. In addition, the gray wolf optimization (GWO) [68] also relies on modeling hunting techniques and has likewise proven effective when applied to real-world challenges [69–71]. Firefly algorithm (FA), introduced by [72], mimics the social behavior of fireflies, and is considered to be a very powerful optimizer, with a wide range of recent applications that include credit card fraud detection [73], intrusion detection classifier optimization [74], medical diagnostics [75], neural networks optimization [35, 76, 77], plant classification [78], and many others.

Other population-based metaheuristics have been inspired by basic mathematical principles. For example, the sine cosine algorithm (SCA) [79], relies on trigonometric formulas as its primary mechanisms for exploration and exploitation. Researchers have successfully applied the SCA in various fields with favorable results [80–82]. Another example includes the arithmetic optimization algorithm (AOA) [83], which makes use of arithmetic operations as an inspiration. This method has also been applied to various tasks with promising outcomes [84–86].

Metaheuristic algorithms inspired by social interactions form the basis of social-based metaheuristics [87]. These algorithms make use of social interaction models as the basis for their function. They sometimes draw inspiration from purely social adaptations or tactical approaches found in sports and competitions. Some notable examples include the teaching-learning-based optimization (TLBO) [88], which simulates the effect teachers have on their pupils in a school environment that is a representation of the algorithms population. When a teacher shares information with a student the quality of teaching affects the student’s grade represented in the fitness value. This approach has given promising results when applied to resolving complex problems [89–91]. One more metaheuristics example that models social interactions is league championship algorithm [92], and it also gives

promising results when applied to real-world problems [93–95].

One of the most popular research fields currently is endeavors in hybridization between population-based metaheuristics and ML. Numerous recent publications show very successful hybridization of the ANN with swarm intelligence algorithms. Some of the most representative applications include COVID-19 cases prediction [96], classification and severity estimation [97–100], brain tumor classification [31, 101], cryptocurrencies trends estimation [102], intrusion detection [103–105], and many others.

It is also worth noting that ELM has also recently been subjected to swarm intelligence optimization, as several recent research suggests [106–108]. Moreover, in the modern literature, many population-based approaches that perform feature selection using various machine learning models can be identified [109, 110].

## Proposed method and simulation framework

This section first presents the original implementation of the SNS algorithm, followed by the observed drawbacks of the basic version. Finally, the novel improved version of the SNS algorithm is provided along with details of two-level framework used for simulation and solution's encoding strategy.

### Social network search

Social behaviors are part of human nature, and in the modern communication age, these behaviors have adapted to informational technologies. Social media networks have become a part of everyday life. Just as technology adapted to human nature, humans adjusted social behaviors to emerging technologies, developing methods for interaction on social networks. The SNS algorithm models the methods users on social networks implement to gain popularity. This is done through the implementation of the user's moods in the algorithm. These moods guide the behavior of simulated users and accordingly govern the behavior of the algorithm [41].

In the algorithms model, simulated user actions are affected by the mood of those around them. These moods form simplified representations of those seen in real life and include imitation, conversation, disputation, and innovation.

Imitation models are one of the main characteristics present in social media. Users follow friends and family as well as people they like. When a user shares a new post, users following them get informed of this and are given the opportunity of perpetuating this information by sharing. If the opinions expressed in this post pose challenging concepts, users will strive to imitate their views and post similar topics. The mathematics behind this model is expressed in Eq. (7):

$$\begin{aligned} X_{i \text{ new}} &= X_j + \text{rand}(-1, 1) \times R \\ R &= \text{rand}(0, 1) \times r \\ r &= X_j - X_i, \end{aligned} \quad (7)$$

with  $X_j$  being the  $j$ th users view vector selected at random where  $i \neq j$ . Accordingly,  $X_i$  represents the view vector of the  $i$ th user. Random value selection is denoted with  $\text{rand}(-1, 1)$  and  $\text{rand}(0, 1)$ , representing the section or a random value with intervals of  $[-1, 1]$  and  $[0, 1]$  respectively. While in the imitation mood, new solutions will be created in the imitation space, using a mixture of radii of shock and popularity. The radius of shock  $R$  is proportional to the influence of the  $j$ th user, while its magnitude is based on a multiple of  $r$ . Likewise, the value of  $r$  is dependent on the popularity of the  $j$ th user and is computed according to differences in opinions of these users. The final influence of the shock is determined by multiplying the random vector value  $[-1, 1]$ , with positive component values if the shared opinions match, and negative values if they do not.

Social networks encourage communication between individual users about different issues. This is mirrored by the algorithm in the conversation mood. In this mood, simulated users learn from one another exchanging information privately. Through conversations, users gain insight into differences in their opinions. This allows them to draft a new perspective on issues. This mechanism is modeled by Eq. (8):

$$\begin{aligned} X_{i \text{ new}} &= X_k + R \\ R &= \text{rand}(0, 1) \times D \\ D &= \text{sign}(f_i - f_j) \times (X_j - X_i), \end{aligned} \quad (8)$$

in which  $X_k$  is the randomly selected issues vector,  $R$  is the chats effect based on the difference in opinions and represents the opinion change towards  $X_k$ . The difference in opinions is represented by  $D$ . A random value selection between  $[0, 1]$  is represented by  $\text{rand}(0, 1)$ . In addition, chat vectors of randomly selected users  $i$  and  $j$  are represented by  $X_i$  and  $X_j$ , respectively. It should be noted that when selecting users  $j \neq i \neq k$ . The  $\text{sign}(f_i - f_j)$  determines the direction of  $X_k$  via comparison. Should a user's opinion change through conversation it is considered a new view and is accordingly shared.

While in the disputation mood users elaborate and defend opinions among themselves. On social networks, this is usually done through a debate in comment or group chat sections, where users with differing views may be influenced by the reasoning of others. In addition, users may form friendly relations between themselves, forming additional discussion groups. The algorithms model this mood by considering a random number of users as cementers or group members. The way opinions are shaped during this process is depicted in Eq. (9):

$$\begin{aligned}
 X_{i \text{ new}} &= X_i + \text{rand}(0, 1) \times (M - AF \times X_i) \\
 M &= \frac{\sum_i^{N_r} X_i}{N_r} \\
 AF &= 1 + \text{round}(\text{rand}),
 \end{aligned}
 \tag{9}$$

with  $X_i$  representing the  $i$ th users view vector,  $\text{rand}(0, 1)$  a random vector with the interval  $[0, 1]$ ,  $M$  being the mean value of views. The admission factor  $AF$  is a random value of 1 or 2 and represents the users having their own opinions discussed among peers. The input is rounded to the nearest integer using the  $\text{round}()$  function, while  $\text{rand}$  represents a random value in the interval  $[0, 1]$ . The number of comments or members of a discussion group is depicted in  $N_r$  and is a random value between 1 and  $N_{user}$ , where  $N_{user}$  is the total number of users of the social network.

When considering an issue, occasionally users share original concepts when they can understand the nature of the problem differently. This process is modeled through the innovation mood. Sometimes a specific topic may pose different features, with each one affecting the issue as a whole. By questioning ideas behind the established norm, the fundamental way of understanding might change, resulting in a novel view. This approach is modeled by the algorithm in the innovation mood and can be mathematically expressed according to Eq. (10):

$$\begin{aligned}
 X_{i \text{ new}}^d &= t \times x_j^d + (1 - t) \times n_{new}^d \\
 n_{new}^d &= lb_d + \text{rand}_1 \times (ub_d - lb_d) \\
 t &= \text{rand}_2,
 \end{aligned}
 \tag{10}$$

where  $d$  stands for the  $d$ th randomly chosen variable withing the  $[1, D]$  interval, and  $D$  representing the number of variables available for the current problem. Additional random values in in the  $[0, 1]$  are represented by  $\text{rand}_1$  and  $\text{rand}_2$ . Minimum and maximum values for the  $d$ th value of  $n_{new}^d$  are represented by  $ub_d$  and  $lb_d$  respectfully. The current idea for the  $d$ th idea is represented by  $X_j^d$ , with the  $j$  user selected randomly, so that  $j \neq i$ . Should the  $i$ th user change their opinion, a new idea is formed and becomes  $n_{new}^d$ . Finally, a new view  $x_{new}^d$  is formed on the  $d$ th dimension as a new interpolation of the current idea.

The dimension shift in  $x_{new}^d$  introduces an overall switch in concept and may be considered a new view to share. This mechanism is modeled according to Eq. (11):

$$X_{i \text{ new}} = [x_1, x_2, x_3, \dots, x_{i \text{ new}}^d, \dots, x_D],
 \tag{11}$$

where, as in previous equations,  $x_{i \text{ new}}^d$  represents a new insight on an issue for the  $d$ th point of view, replaced with the current one  $x_i^d$ .

To construct the initial network, parameters for the number of users, maximum iterations as well as limits are set. Each

initial view is created according to Eq. (12):

$$X_0 = lb + \text{rand}(0, 1) \times (ub - lb)
 \tag{12}$$

in which  $X_0$  stands for each users initial view vector, a random value in the interval  $[0, 1]$  is represented by  $\text{rand}(0, 1)$ , and upper and lower bounds of each parameter are represented as  $ub$  and  $lb$ , respectively.

When addressing maximization problems, Eq. (13), is used by the algorithm to limit views:

$$X_i = \begin{cases} X_i, & f(X_i) < f(X_{i \text{ new}}) \\ X_{i \text{ new}}, & f(X_{i \text{ new}} \geq f(X_i) \end{cases}
 \tag{13}$$

### Deficiencies and complexity of the social network search Algorithm

The original implementation of SNS has been established as an exceptional metaheuristics with respectable performance, yet, certain drawbacks have been noticed. Due to the lack of exploration power in the early rounds of the execution, the basic SNS tends to linger in the sub-optimal areas of the search domain, as a result of premature convergence. As a consequence, the resulting solutions’ quality is not satisfactory.

According to the previous research with the SNS algorithm and additional simulations against large-scale optimization challenges for the purpose of this research (benchmark CEC bound-constrained testing suite and practical ELM tuning task), the most significant cons of the basic SNS algorithm are weak exploration mechanism and the inappropriate trade-off between exploration and exploitation [73, 111, 112]. Conversely, the SNS local search process is guided by relatively strong exploitation and population diversity condenses rapidly throughout the algorithm run.

In runs, when the algorithm can not find a proper search space part in early iterations, the whole population convergences towards sub-optimum domains, rendering final results which are too far from optimum. These scenarios are facilitated by above mentioned relatively strong SNS exploitation. However, when the algorithm ’is lucky’ and the initial random population is generated around the optimum region, guided by strong exploitation, fine-tuned search around the promising solutions is conducted even in early iterations and final rendered results are of high quality.

Concerning the complexity of the basic SNS algorithm, the original publication [41] examines it on two levels, during initialization and within the main loop of the algorithm. At the start of the algorithm execution, during initialization, a new pseudo-random population of individuals is produced, followed by the evaluation of the solutions. The complexity of producing the random individuals is  $O(NP \cdot D)$ ,  $NP$  denoting the count of users, while  $D$  represents the problem’s

dimensionality. The fitness function evaluation complexity is obtained by  $O(NP) \cdot O(F(x))$ , where  $F(x)$  marks the objective function being optimized.

The level of popularity is obtained through the main loop that iterates  $T$  times ( $T$  denotes the maximum number of iterations), producing a new solution for every user as the new view and evaluating it in every iteration. Therefore, the complexity of the main loop can be defined as  $O(T \cdot NP \cdot D)$ , and the complexity of fitness functions evaluations over the rounds can be determined as  $O(T \cdot NP) \cdot O(F(x))$ .

According to the common practice of establishing computational exhaustiveness of metaheuristics, complexity is often calculated with respect to fitness function evaluations ( $FFEs$ ), as it is the most complex computing operation [113]. Accordingly, in terms of  $FFEs$ , the complexity of SNS metaheuristics can be observed as  $O(SNS) = O(NP) + O(T \cdot NP)$ .

It can be concluded that, despite observed drawbacks and taking into account relatively low computational complexity, the SNS is a promising algorithm for solving NP-hard optimization tasks; however, there is space for its enhancements.

### Improved SNS algorithm

As it was already pointed out, the fact that SNS exhibits strong exploitation combined with weak exploration, leads to low population diversity and premature convergence. In other words, the final results at large extent depend on the solutions' positions in the initial random population.

Improved SNS algorithm proposed in this research attempts to tame the lack of exploration through the establishment of the adequate population diversity during the initialization procedure and through the entire algorithm's run. With this in mind, two modifications are introduced in the original SNS metaheuristics: novel initialization scheme and an instrument to maintain the satisfactory solutions diversity throughout the whole run of the algorithm.

#### Novel initialization scheme

The algorithm suggested in this research utilizes a traditional initialization equation for creating the solutions in the initial population:

$$X_{i,j} = lb_j + \psi \cdot (ub_j - lb_j), \quad (14)$$

where  $X_{i,j}$  denotes the  $j$ th component of  $i$ th individual,  $lb_j$  and  $ub_j$  define the lower and upper boundaries of parameter  $j$ , while  $\psi$  represents a pseudo-random value derived from the normal distribution in range  $[0, 1]$ .

Nevertheless, as demonstrated in [114], it is possible to cover wider area of the search domain if the quasi-reflection-based learning (QRL) procedure is added to the individuals

created by Eq. (14). Consequently, for each individual's parameter  $j$  ( $X_j$ ), a quasi-reflexive-opposite element ( $X_j^{qr}$ ) is obtained by

$$X_j^{qr} = \text{rnd}\left(\frac{lb_j + ub_j}{2}, x_j\right), \quad (15)$$

where the function  $\text{rnd}$  is utilized to select the pseudo-random value within  $[\frac{lb_j + ub_j}{2}, x_j]$  range.

According to the QRL, the proposed initialization scheme is not introducing the additional overhead to the algorithm in respect of  $FFEs$ , as it starts by initializing only  $NP/2$  individuals. Utilized initialization scheme is presented in Algorithm 2.

---

#### Algorithm 2 Initialization scheme based on QRL procedure pseudo-code

---

- Step 1: Generate population  $P^{init}$  of  $NP/2$  individuals by applying Eq. (14)
  - Step 2: Generate QRL population  $P^{qr}$  from the  $P^{init}$  using Eq. (15)
  - Step 3: Produce starting population  $P$  by merging  $P^{init}$  and  $P^{qr}$  ( $P \cup P^{qr}$ )
  - Step 4: Obtain fitness for each individual in  $P$
  - Step 5: Sort all solutions in  $P$  in respect of fitness
- 

According to the results presented in the experimental section, the introduced initialization scheme contributions are twofold. It enhances the diversification at the start of the algorithm's run, and it also provides an initial boost for the search procedure, because with the same number of individuals larger search space is covered.

#### Mechanism for maintaining population diversity

One way to monitor the converging/diverging extent of the algorithm's search procedure is diversification of the population, as described by [115]. The approach taken in this paper utilizes one recent definition of the population diversity metrics, the  $L1$  norm [115], which includes diversities obtained over two components—individuals in the population and the dimensionality of the problem.

The research presented in [115] also indicates the importance of data obtained from the dimensionwise component of the  $L1$  norm, that can be used to evaluate the search process of the tested algorithm.

Assuming that  $m$  represents the number of individuals in the population, and  $n$  defines the dimensionality of the problem, the  $L1$  norm is formulated as shown in Eq. (16–18):

$$\bar{x}_j = \frac{1}{m} \sum_{i=1}^m x_{ij} \quad (16)$$



$$D_j^p = \frac{1}{m} \sum_{i=1}^m |x_{ij} - \bar{x}_j| \quad (17)$$

$$D^p = \frac{1}{n} \sum_{i=1}^n D_j^p, \quad (18)$$

where  $\bar{x}$  denotes the vector with mean positions of the solutions in each dimension,  $D_j^p$  represents the solutions' position diversity vector as  $L1$  norm, and  $D^p$  marks the diversity value, as a scalar value, for the entire populace.

During the early rounds of the algorithm's execution, where the individuals in the population are produced by utilizing the common initialization equation (14), the diversity of the entire population should have a high value. Still, in later rounds, when the algorithm is converging to optimum (sub-optimum), this value should be decreased dynamically. Introduced improved SNS method uses the  $L1$  norm to manage the population's diversity during the execution of the algorithm by applying the dynamic diversity threshold ( $D_t$ ) parameter.

The mechanism for maintaining population diversity takes into account an auxiliary control parameter,  $nrs$  that denotes the number of replaced solutions. This mechanism is being executed as follows: at the start of the algorithm's run, the initial value of  $D_t$  ( $D_{t0}$ ) is obtained; in every iteration, the condition  $D^p < D_t$  is examined, where  $D^p$  represents current population diversity; if the condition is fulfilled (diversity of the population is not satisfactory),  $nrs$  of the worst individuals are substituted by the random solutions, produced analogously as in the population initialization expression.

With respect to the empirical simulations and theoretical analysis, the expression that is used to obtain  $D_{t0}$  can be formulated in the following way:

$$D_{t0} = \sum_{j=1}^{NP} \frac{(ub_j - lb_j)}{2 \cdot NP} \quad (19)$$

Equation (19) follows the assumption that most of the individuals' components will be produced in the proximity of the mean of the lower and upper boundaries of the parameters, as given by Eq. (14) and Algorithm 2. Nevertheless, as the algorithm progresses, assuming that the population will move in the direction of the optimal domain of the search region, the  $D_t$  should decrease from the starting value  $D_t = D_{t0}$  in the following way:

$$D_{t+1} = D_t - D_t \cdot \frac{t}{T}, \quad (20)$$

where  $t$  and  $t + 1$  denote current and subsequent iterations, respectively, while  $T$  represents the maximum number of

rounds in a single run. Consequently, as the algorithm progresses, the  $D_t$  is dynamically decreasing, and at the end, above described method will not be triggered, regardless of the  $D^p$ .

### Inner workings and complexity of the proposed algorithm

With respect to the introduced modifications, novel proposed SNS metaheuristic has been named diversity oriented SNS (DOSNS). The computational complexity of the suggested DOSNS is not greater than the basic SNS in terms of  $FFEs$ . First of all, novel initialization scheme does not impose additional  $FFEs$  overhead. Similarly, mechanism for maintaining population diversity replaces  $nrs$  worst solutions regardless newly generated random individuals have better or worse fitness; therefore, its eligibility is not validated. Finally, the complexity of the DOSNS in terms of the  $FFEs$  can be expressed as:  $O(DOSNS) = O(NP) + O(T \cdot NP)$ .

The DOSNS inner-working procedures are provided in Algorithm 3. As it can be seen from the proposed pseudo-code introduced modification are additions to the original SNS algorithm [41].

### Feature selection and tuning framework

As described earlier, the proposed DOSNS algorithm was adapted to address the feature selection and ELM's hyper-parameters tuning tasks, as part of the hybrid framework between metaheuristics and ML, that has been developed. Tuning of the ELM takes into account both, determining the number of neurons in the hidden layer ( $nn$ ), and weights and biases values initialization, that link the input features with the hidden layer.

Devised framework consists of two levels—level 1 (L1), that deals with feature selection and level 2 (L2), that performs ELM tuning. Levels in two-level framework can be used independently, i.e., performing only feature selection or ELM tuning. In addition, the L1 can execute in a cooperative or individual mode. When set to cooperative mode, all metaheuristics included in the framework perform feature selection independently; however, at the end of execution (after predetermined number of runs), selected feature subset generated by best performing metaheuristics is used as the input to L2 and then all metaheuristics perform ELM tuning using the same set of selected features. Conversely, if the L1 is set to individual mode, than all metaheuristics use their own best set of selected features from L1, as an input to L2, regardless of the classifier performance with the chosen set of features.

As already emphasized in Sects. 1 and 2.1, notwithstanding that the wrapper-based feature selection can be computationally demanding [45], the L1 of proposed framework implements wrapper feature selection approach, because

**Algorithm 3** Pseudocode for the DOSNS algorithm

---

**Set** number of solutions (users),  $T, lb, ub, t = 0$   
**Initialize** starting population  $P$  of  $NP$  solutions according to Algorithm 2  
Determine values of  $D_{t0}$  and  $D_t$   
**Evaluate** each user (solution) according to objective function  
 $i = 0$   
**do**  
  **if** ( $i \geq N$ ) **then**  
     $t = t + 1$   
     $i = 0$   
  **end if**  
   $i = i + 1$   
   $Mood = rand(1, 4)$   
  **if** ( $Mood == 1$ ) **then**  
    Create new views based on Eq. (7)  
  **else if** ( $Mood == 2$ ) **then**  
    Create new views based on Eq. (8)  
  **else if** ( $Mood == 3$ ) **then**  
    Create new views based on Eq. (9)  
  **else if** ( $Mood == 4$ ) **then**  
    Create new views based on Eq. (10)  
  **end if**  
  **Limit new views** According to Eq. (13)  
  Evaluate new view based on the objective function  
  **if** (New view better than current view) **then**  
    Replace old view with new view and share it  
  **else**  
    Keep old view, don't share new view  
  **end if**  
  Calculate  $D^P$   
  **if** ( $D^P < D_t$ ) **then**  
    Replace worst  $nrs$  with solutions created as in (14)  
  **end if**  
  Asses the population  
  Find the current best  
  Update  $D_t$  by expression (20)  
**while** ( $t \leq T$ )  
**Return** Optimal Solution  
**Return** Overall and detailed optimization statistics and visualize

---

compared to other approaches for this challenge it obtains better performance in terms of classification accuracy and smaller chosen subset of relevant features [45]. In this particular case, the calculation of objective function for each metaheuristics individual involves training and testing ML classifier based on the selected features subset.

The framework is developed in Python using machine data science and ML libraries: numpy, scipy, pandas, matplotlib, seaborn and scikit-learn. The ELM was implemented from the scratch as custom library, since it is not available in scikit-learn.

Metaheuristics incorporated into the framework are encoded using flat encoding scheme (vector), and the length of the solution depends of the level of the framework. In L1 of the framework every individual in the population is represented as a vector with length  $L = nf$ , where  $nf$  represents the total number of features in the data set.

For framework L2, one individual represents the ELM's hyper-parameter  $nn$  and weights and biases values between the input features and neurons in the hidden layer. The length of the solutions depends on the tuned  $nn$  and number of selected features ( $nsf$ ) from L1. Therefore, the L2 solutions' length is given as:  $L = 1 + nn \cdot nsf + nn$ . The first parameter represents the number of neurons, which is simple scalar integer value,  $nn \cdot nsf$  are continuous parameters that encode weights values, while the  $nn$  components, which are also of a real data type, denote hidden layer biases. It is noted that all metaheuristics solutions in the L2 are of variable lengths (its length changes over iterations), because they dependent on the determined  $nn$ .

In the L1, the search is performed in the binary search space, while in the L2, the solutions' vectors consist of integer ( $nn$ ) and real parameters (weights and biases). Therefore, as the result, binary and continuous variants of DOSNS and other metaheuristics incorporated into the framework have been utilized. For feature selection task, in L1 of the framework, to map the continuous search region to binary, it is necessary to use a transfer function, that has been selected empirically, through numerous simulations with sigmoid, threshold and hyperbolic tangent function transfer functions that are common choice in recent literature [81, 116–119]. After executing experiments with a variety of transfer functions, tanh yielded the best result, and it was chosen and used in this research.

Discrete variable, that encode the  $nn$ , have been rounded up to the nearest integer value, because of the large search domain. The search equation has not been modified to match the discrete domain, as the empirical simulations indicated that there is no notable enhancement, and the simple rounding up is preserving the most of the resources.

Therefore, in the L1 of the framework, a binary tanh-based binary versions of metaheuristics are employed, e.g., bDOSNS, while in the L2 standard metaheuristics versions for real-parameters optimization are used, e.g., DOSNS.

For the L1 part of the framework, k-nearest neighbor (KNN) is chosen as the classifier with its default parameters from scikit-learn library. According to previous research [118, 120], KNN is the most common choice for feature selection tasks, because it is computationally efficient. Likewise, the most commonly used objective function for feature selection challenges [117, 118], that takes into account the KNN's classification error rate ( $err$ ) and the number of chosen features ( $nsf$ ), is used in this research:

$$F = \alpha \cdot err + \beta \cdot \frac{nsf}{nf}, \quad (21)$$

where  $\alpha$  and  $\beta$  are weight coefficients for determining the relative importance of  $err$  to  $nsf$ , and  $\beta = 1 - \alpha$ .

The objective function for the L2 framework is simply the classification error rate. Since some of the data sets are only slightly imbalanced, the error rate is viable fitness function.

Block diagram of proposed framework in cooperative mode is shown in Fig. 1. Any number of metaheuristics can be integrated into the framework; however, on the presented figure flow-chart of proposed DOSNS is shown, where other metaheuristics are represented with the general flow-chart.

## Experimental setup and results

This section first describes the data sets utilized in the experiments together with the overview of experimental setup. Later on, the outcomes of the executed experiments along with the immense comparative analysis, results discussion and statistical tests validation, are delivered.

### Data sets

The experiments were conducted over three different publicly available benchmark phishing data sets. Phishing is a type of cyber-attack where malicious user masquerades as known and trusted entity, and tries to obtain sensitive data typically through a false website that tricks the end user to enter private information such as credit card number or similar. After obtaining this data, the attacker can utilize it to access the bank accounts, steal money, data or identity, and place malware to the target's computer.

First data set is named Phishing websites Kaggle<sup>1</sup> [121], and it is publicly available from Kaggle repository. It is comprised of 48 features, derived from 5000 phishing and 5000 legit websites, collected in years 2015 and 2017. This data set is balanced, and represents a binary classification task. The class distribution and boxplot of this data set are shown in Fig. 2, while the the heat map is provided in Fig. 3.

Second data set is named phishing websites UCI data set,<sup>2</sup> proposed by [122–124], and it is publicly available on UCI Machine Learning Repository [125]. Although it is stated on the UCI repository that this data set is comprised of 2456 instances, it actually contains 11,056 instances, with 30 features. This data set is slightly imbalanced, and represents a binary classification task. The phishing websites UCI visual representation in a form of bar charts and box and whiskers diagrams are shown in Fig. 4, while the the heat map is provided in Fig. 5.

Finally, third data set is named phishing websites UCI small data set,<sup>3</sup> introduced by [126], and it is also publicly

available on UCI Machine Learning Repository [125]. It contains total of 1,353 instances, and although it is stated that it has 10 features, it actually contains 9 features with one target variable. It represents a multi-class classification task, as it contains three classes (0—normal, 1—suspicious, 2—phishing). This data set is also slightly imbalanced. The class distribution and boxplot of this data set are shown in Fig. 6, while the the heat map is provided in Fig. 7.

### Experimental setup

The performance of introduced DOSNS algorithm with respect to the converging speed and overall capabilities has been tested for feature selection and ELM optimization tasks on the above mentioned data sets. The experimental outcomes have been validated and compared to the performances of several state-of-the-art reference metaheuristics, that have been tested under the same experimental setup and simulation conditions. All metaheuristics are integrated into the devised two-level framework described in Sect. 3.3.

The set of cutting-edge metaheuristics included in comparative analysis encompasses: basic SNS [41], firefly algorithm (FA) [72], bat algorithm (BA) [127], artificial bee colony (ABC) [61], harris hawks optimization (HHO) [128] and sine cosine algorithm (SCA) [79]. This particular set of algorithms is used for comparison, because they all exhibit different exploitation and exploration abilities and in this way it was feasible to perform a robust performance validation of proposed DOSNS approach. All reference algorithms have been implemented independently in Python for the sake of this research, with the proposed control parameters values as described in their respective publications. In the sections with the experimental results, for easier understanding, for all metaheuristics the prefix FS was used for feature selection results, e.g., FS-DOSNS, FS-SNS, FS-BA, etc., while prefix ELM was utilized for ELM tuning simulations, e.g., ELM-DOSNS, ELM-SNS, ELM-BA, etc.

Prior to execution, all data sets were divided into the train and test subsets using 80–20% split rule, as it is shown in Fig. 1. Since the ELM does not employ traditional training, validation data is not used.

All experiments, for both L1 and L2 parts of the framework, have been executed by utilizing the population size of 6 ( $NP = 6$ ), maximum number of iterations was set to 10 ( $T = 10$ ) in one run, with the total number of 30 independent runs ( $runtime = 30$ ).

The DOSNS specific control parameter  $nrs$  is set to 1 because of relatively small population size, while the  $D_{t0}$  and  $D_t$  are set and updated according to Eqs. (19) and (20), respectively

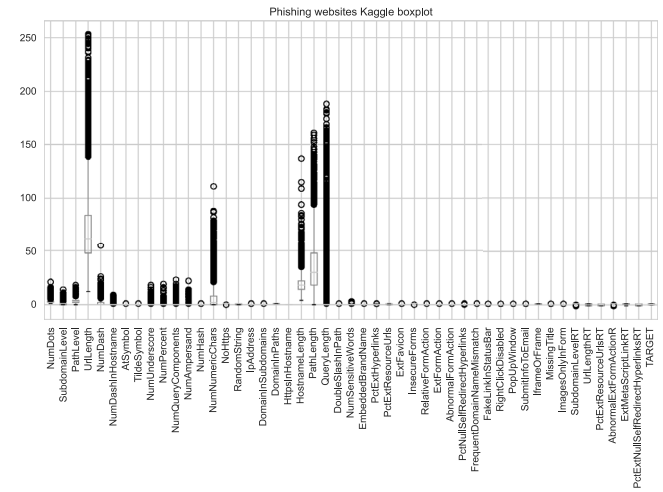
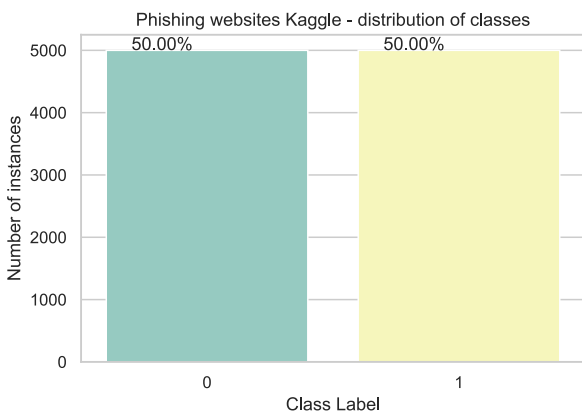
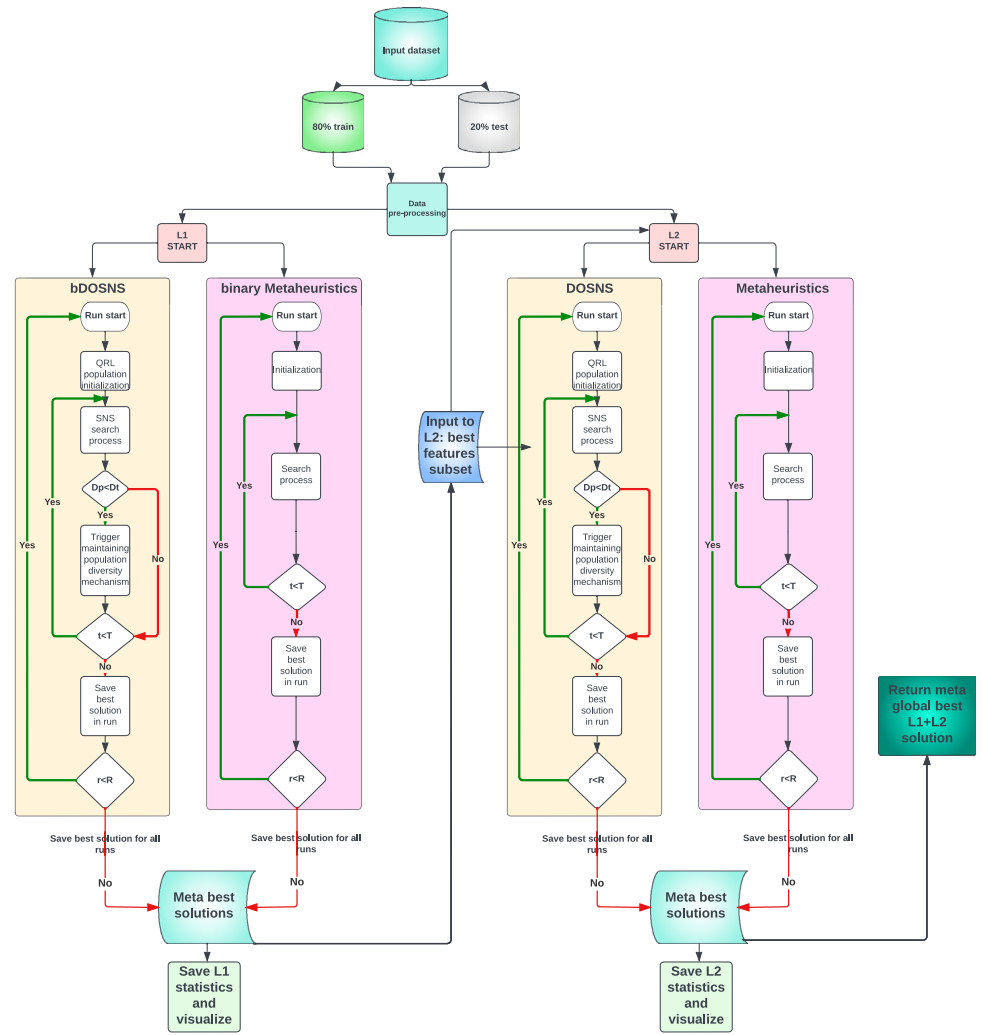
The KNN used as the classifier in the L1 is set with five neighbor solutions  $k = 5$ , while  $\alpha$  in objective function (Eq. 21) is set to 0.99. The lower and upper bounds for both

<sup>1</sup> <https://www.kaggle.com/datasets/shashwatwork/phishing-dataset-for-machine-learning>.

<sup>2</sup> <http://archive.ics.uci.edu/ml/datasets/phishing+websites>.

<sup>3</sup> <https://archive.ics.uci.edu/ml/datasets/Website+Phishing>.

**Fig. 1** Block diagram of devised two-layer feature selection and ELM tuning framework in cooperative mode with flow-chart of proposed DOSNS metaheuristics



**Fig. 2** Phishing websites Kaggle data set class distribution and boxplot



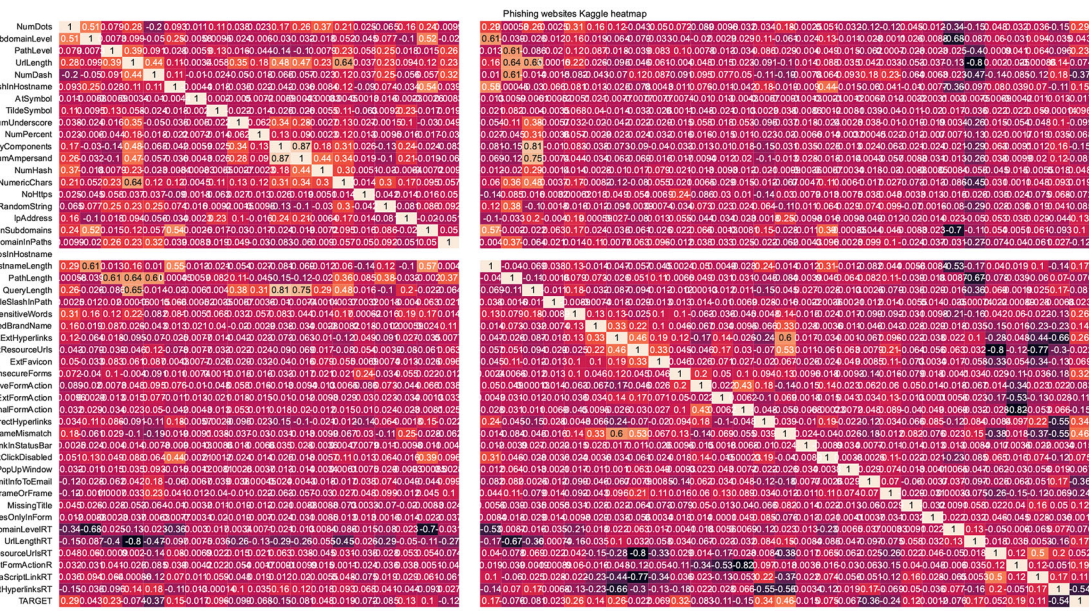


Fig. 3 Phishing websites Kaggle data set heat map

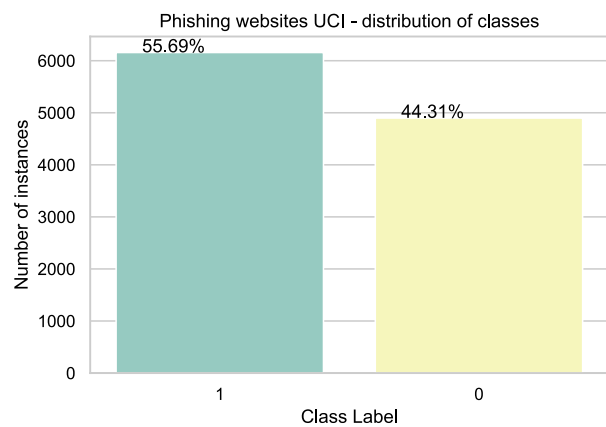
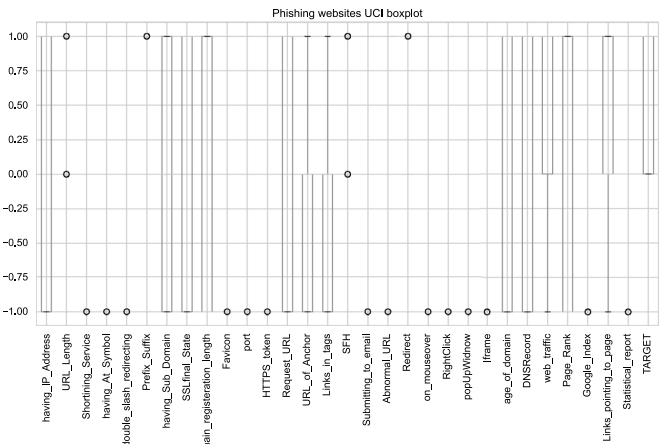


Fig. 4 Phishing websites UCI data set class distribution and boxplot



weight and bias variables in the L2 for ELM are defined by the interval  $[-1, 1]$ . The search space limits for the  $nn$  variable are specified in the range  $[nsf \cdot 3, nsf \cdot 15]$ . All these values are determined empirically. It is noted that prior to rendering final decision regarding the L1 classifier, experiments with support vector machine (SVM) were also executed and similar results are obtained. However, due to the faster execution, the KNN is utilized instead of SVM.

### Experimental findings

Two sets of experiments were executed in this research. First experiment utilizes both L1 and L2 of the proposed optimization framework. The L1 is set to cooperative mode and in this way, the best obtained set of features for all metaheuristics is used as the input to L2, i.e., in the L2 part of the framework, all methods tune ELM with the same set of input features.

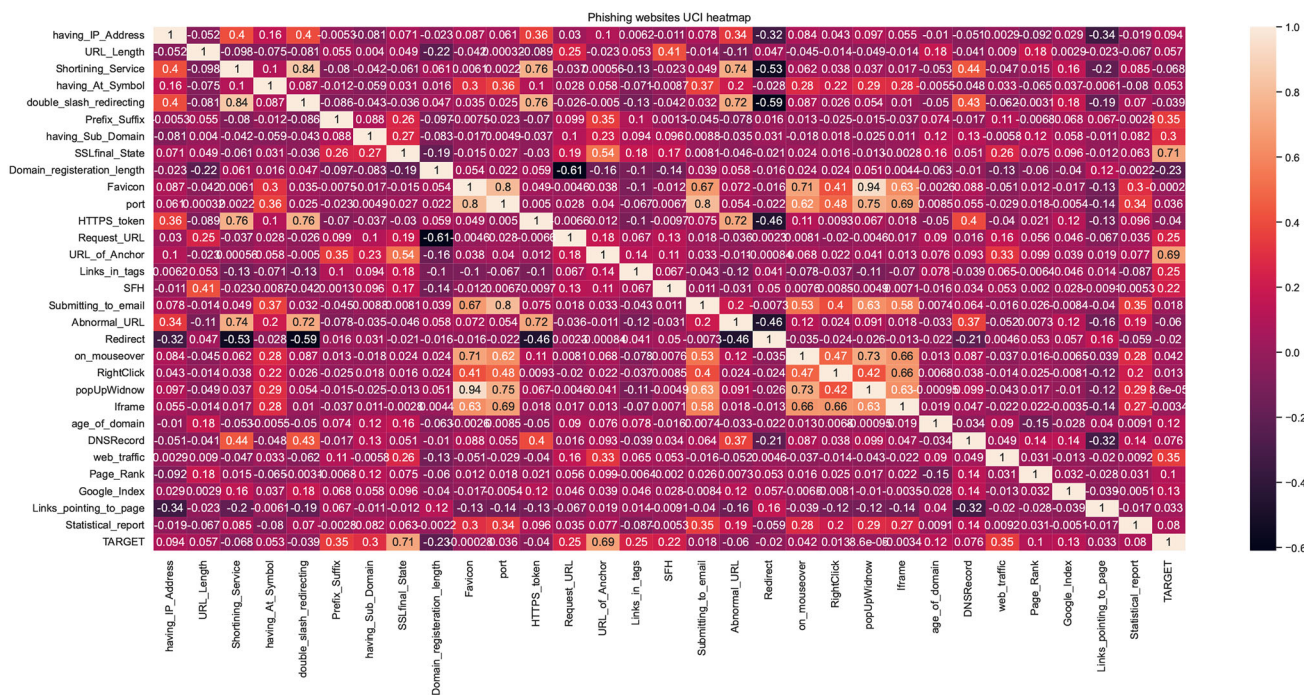


Fig. 5 Phishing websites UCI data set heat map

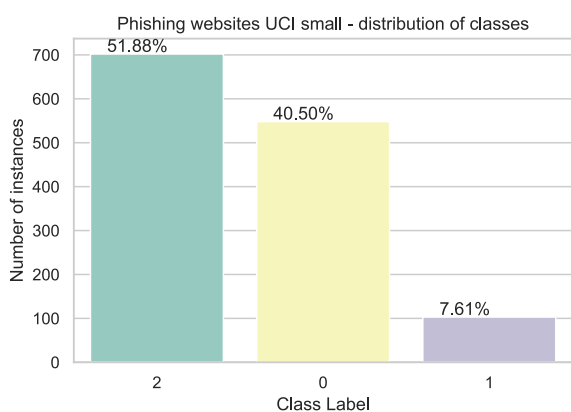
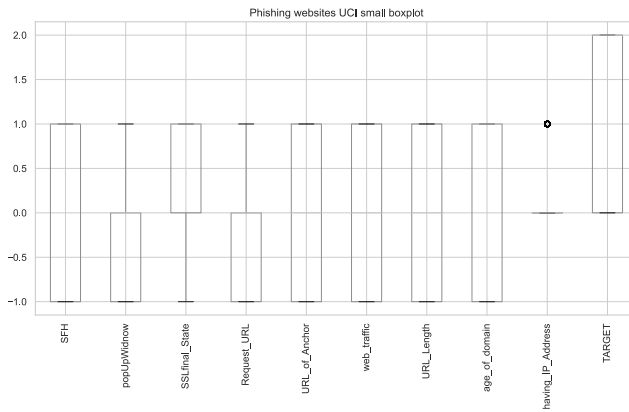


Fig. 6 Phishing websites UCI small data set class distribution and boxplot



Second simulation is focused only on tuning the ELM with all employed features (without the feature selection), using only L2 part of the framework. The goal of this simulation is to test performance of suggested DOSNS for large-scale global optimization tasks with many parameters (components).

For both experiments, two different group of metrics were presented. First, overall metrics, that summarize average values obtained over 30 runs, include best, worst, mean, median, standard deviation for objective in L1 and classification error in L2. In addition, number of selected features for best obtained objective in L1, and the number of neurons for the best performing ELM in L2 are also shown.

Detailed performance indicators were also provided for simulations with L2 part of the framework and this set include the following metrics for the best generated solution of each metaheuristics: accuracy, precision, recall and f1 score per each class and micro-averaged over all classes. Metrics for receiver operating characteristic (ROC) and precision recall (PR) area under the curve (AUC) are shown visually.

Findings for both experiments are shown in Sects. 4.3.1 and 4.3.2 and best obtained results for each category of metrics is marked with bold style in the tables with reported results.

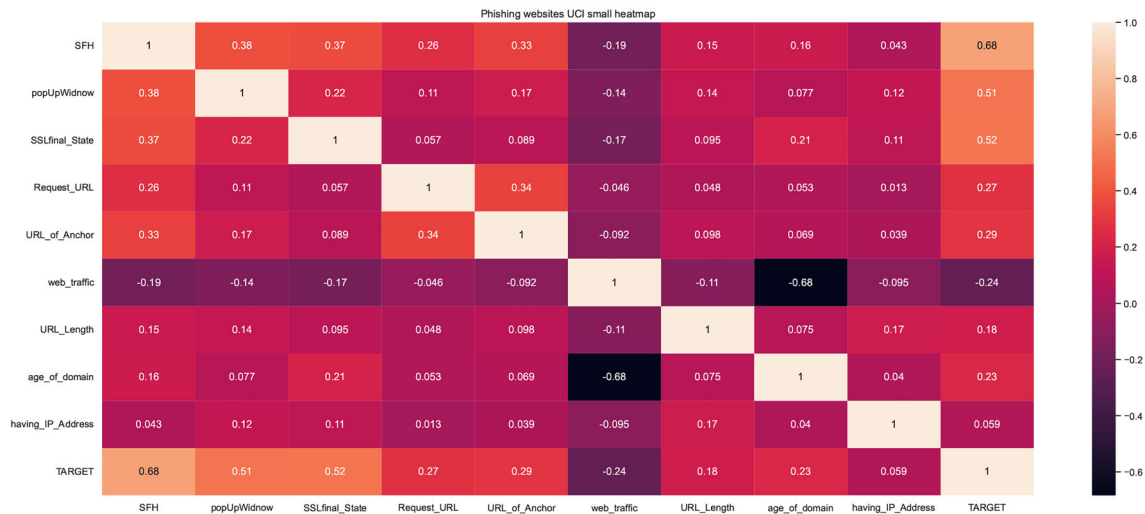


Fig. 7 Phishing websites UCI small data set heat map

Table 1 Experiment I—overall metrics for L1 results (feature selection) with respect to objective function

Method	FS-DOSNS	FS-SNS	FS-FA	FS-BA	FS-ABC	FS-HHO	FS-SCA
<i>Kaggle dataset</i>							
Best	<b>0.038530</b>	0.040980	0.045330	0.051478	0.050175	0.050045	0.040302
Worst	<b>0.048977</b>	0.066615	0.061092	0.073180	0.064868	0.078885	0.074822
Mean	<b>0.045316</b>	0.050902	0.051420	0.062082	0.055203	0.061156	0.051322
Median	<b>0.046358</b>	0.049473	0.050593	0.061300	0.054722	0.058655	0.049616
Std	<b>0.003067</b>	0.007689	0.004276	0.006315	0.004063	0.010100	0.010862
Var	<b>0.000009</b>	0.000059	0.000018	0.000040	0.000017	0.000102	0.000118
Best error	<b>0.034500</b>	0.039500	0.042000	0.048000	0.045000	0.045500	0.036500
Best no. feat	21	9	18	19	27	24	20
<i>UCI dataset</i>							
Best	<b>0.056274</b>	0.057836	0.057388	0.057617	0.056597	0.068020	0.062104
Worst	<b>0.067458</b>	0.080109	0.075413	0.108204	0.076537	0.109547	0.072622
Mean	<b>0.062618</b>	0.071968	0.067185	0.076603	0.068676	0.081738	0.067400
Median	<b>0.063261</b>	0.071721	0.067348	0.074012	0.068015	0.079142	0.067239
Std	0.003676	0.006546	0.005327	0.016053	0.006475	0.012600	<b>0.002857</b>
Var	0.000014	0.000043	0.000028	0.000258	0.000042	0.000159	<b>0.000008</b>
Best error	0.052465	0.053370	0.052917	0.053822	<b>0.051108</b>	0.063320	0.059701
Best no. feat	13	15	15	13	18	16	9
<i>UCI small dataset</i>							
Best	0.099106	0.116261	0.099106	0.119914	0.117372	0.135638	0.114830
Worst	<b>0.127220</b>	0.192185	0.163752	0.287167	0.190754	0.212673	0.191866
Mean	<b>0.112568</b>	0.148941	0.137782	0.179993	0.154480	0.176994	0.147670
Median	<b>0.116261</b>	0.154063	0.146597	0.165023	0.164467	0.172329	0.144930
Std	<b>0.011258</b>	0.027886	0.021520	0.047198	0.027404	0.029065	0.029909
Var	<b>0.000127</b>	0.000778	0.000463	0.002228	0.000751	0.000845	0.000895
Best error	0.092251	0.110701	0.092251	0.114391	0.110701	0.129151	0.107011
Best no. feat	7	6	7	6	7	7	8



### Simulation I—L1 and L2 (feature selection and ELM tuning)

This section shows the result of the first experiment, that utilized both L1 and L2 of the proposed cooperative framework. The best obtained subset of features at L1 that performs the feature selection is used as the input to the L2 that conducts the ELM tuning process.

Table 1 presents the overall metrics for L1 results (feature selection task) in terms of objective function, defined in Eq. (21). In addition, best rendered classification error for the best objective is also presented.

From Table 1, it is clear that the proposed FS–DOSNS method obtains superior results on Kaggle and UCI data sets, in terms of best, worst, mean and median values. In the case of UCI small data set, FS–DOSNS shares the first place with FS–FA for the best result, while other metrics are clearly in favor of the proposed FS–DOSNS.

As the conclusion for L1 simulations, the FS–DOSNS establishes the best balance between the number of features (complexity) and classification performance (error).

Table 2 presents the overall metrics for ELM tuning (L2 of the framework), where the best obtained subset of features (from all algorithms in L1) was used as the input. The proposed FS–DOSNS achieved the best accuracy on the Kaggle data set, and shares the first place on UCI data set (with FS–SCA) and UCI small data set (again with FS–SCA). Concerning other metrics, the best worst and mean results on Kaggle data set were obtained by FS–SCA, while FS–HHO obtained the best median and standard deviation. In case of UCI data set, the best worst and mean results were achieved by the proposed FS–DOSNS approach, FS–SCA obtained the best median result, while FS–ABC obtained the best standard deviation. Finally, on the UCI small data set, the best worst value was achieved with the proposed FS–DOSNS and FS–SCA approaches that shared the first place. The proposed FS–DOSNS also obtained the best mean and median values, while the FS–ABC obtained the best standard deviation.

Table 3 shows the detailed metrics on the Kaggle, UCI, and UCI small data sets, for the best solutions after the execution of the complete framework (L1 + L2). In case of Kaggle data set, the proposed ELM–DOSNS approach obtained the best accuracy of 95.65%, while the ELM–FA approach finished second with 95.50%. For the UCI data set, the proposed ELM–DOSNS method obtained the best accuracy of 93.94%, together with the ELM–SCA approach that obtained the same accuracy. Finally, the detailed metrics on the UCI small data set, show that the proposed ELM–DOSNS approach share the first place with ELM–SCA, where both methods accomplished an accuracy of 90.78%. All other performance metrics included in Table 3, precision, recall and f1 score, on average prove superiority of ELM–DOSNS.

Convergence graphs of the objective function for the L1, and error for the L2 experiments, for all observed metaheuristic

and all three utilized data sets, are shown in Fig. 8. Box and whiskers diagrams, that display the dispersion of the objective function for L1, and error for L2 framework simulations, over 30 independent runs for all observed methods are depicted in Fig. 9.

Confusion matrices for output of framework L1 with feature selection, for all observed algorithms and all three data sets, are shown in Fig. 10, while Fig. 11 shows the ROC AUC curves with micro and macro averages for the best solutions (output) of the framework L2, for all observed algorithms over all three utilized data sets.

### Simulation II—L1 (ELM tuning)

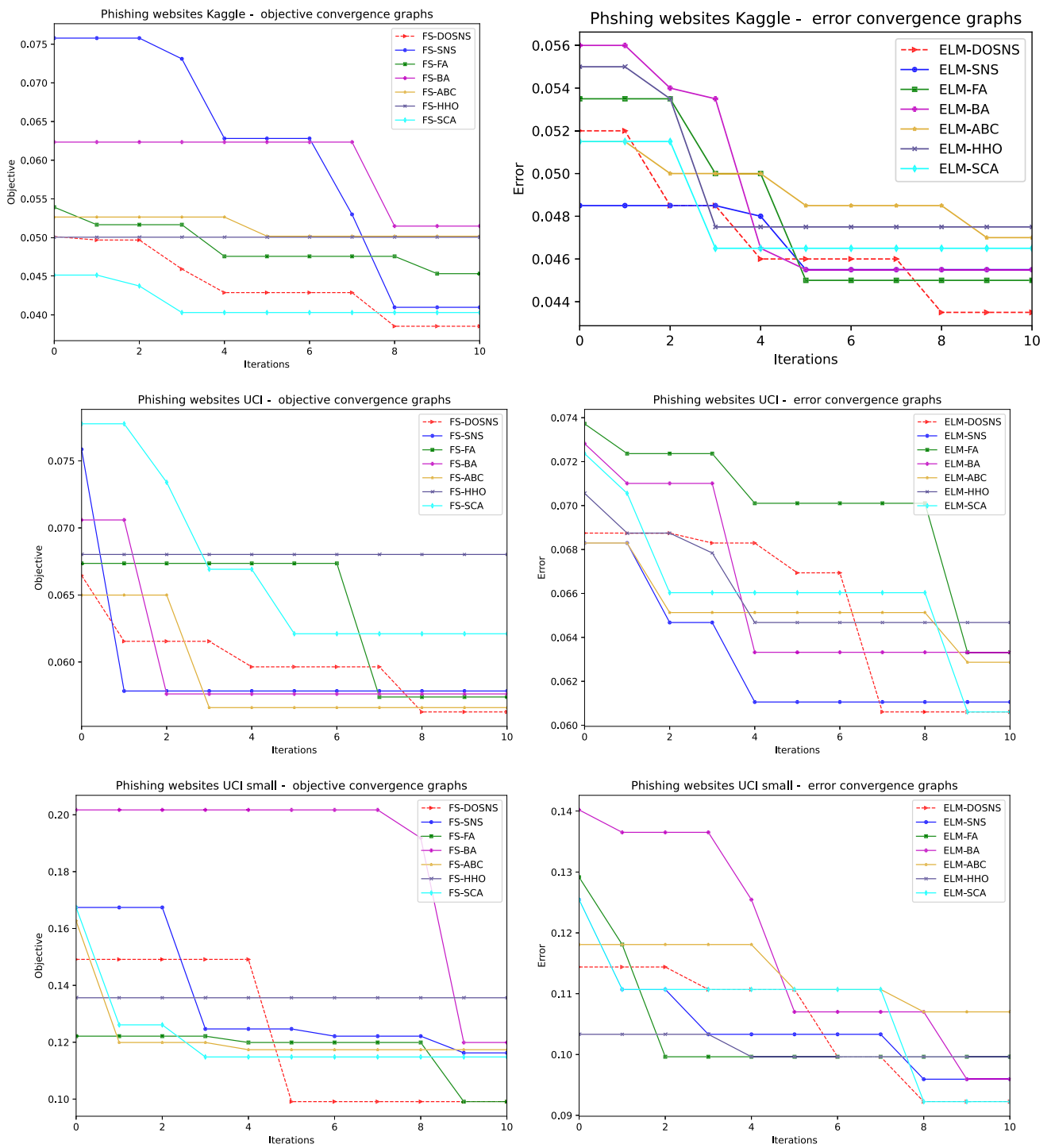
In the second set of the experiments, all algorithms were tested for the task of ELM tuning, without feature selection (meaning that all features were used by the models), and in this case only L2 of the framework was utilized. Table 4 shows the overall metrics for this scenario, and it can be noticed that the proposed ELM–DOSNS obtained superior results on all three used data sets, by achieving the first place in terms of best, worst, mean and median results. It is also noticed that the ELM–DOSNS managed to establish good results' quality with relatively simple ELM (small number of neurons in the hidden layer).

Table 5 shows the detailed metrics on the Kaggle, UCI, and UCI small data sets, for the best solutions without feature selection. In case of Kaggle data set, the proposed ELM–DOSNS approach obtained the best accuracy of 97.25%, in front of the ELM–FA and ELM–BA approaches that obtained the accuracy of 97.00%. Similarly, in case of UCI data set, the proposed ELM–DOSNS approach again obtained the best accuracy of 94.75%, in front of the ELM–SCA that obtained the accuracy of 94.57%. Finally, also for the UCI small data set, proposed ELM–DOSNS obtained the best accuracy of 90.04%, followed by the ELM–SCA and ELM–FA that managed to establish an accuracy of 89.93%. Similarly as in the previous experiment, all other metrics are on average in favor to ELM–DOSNS.

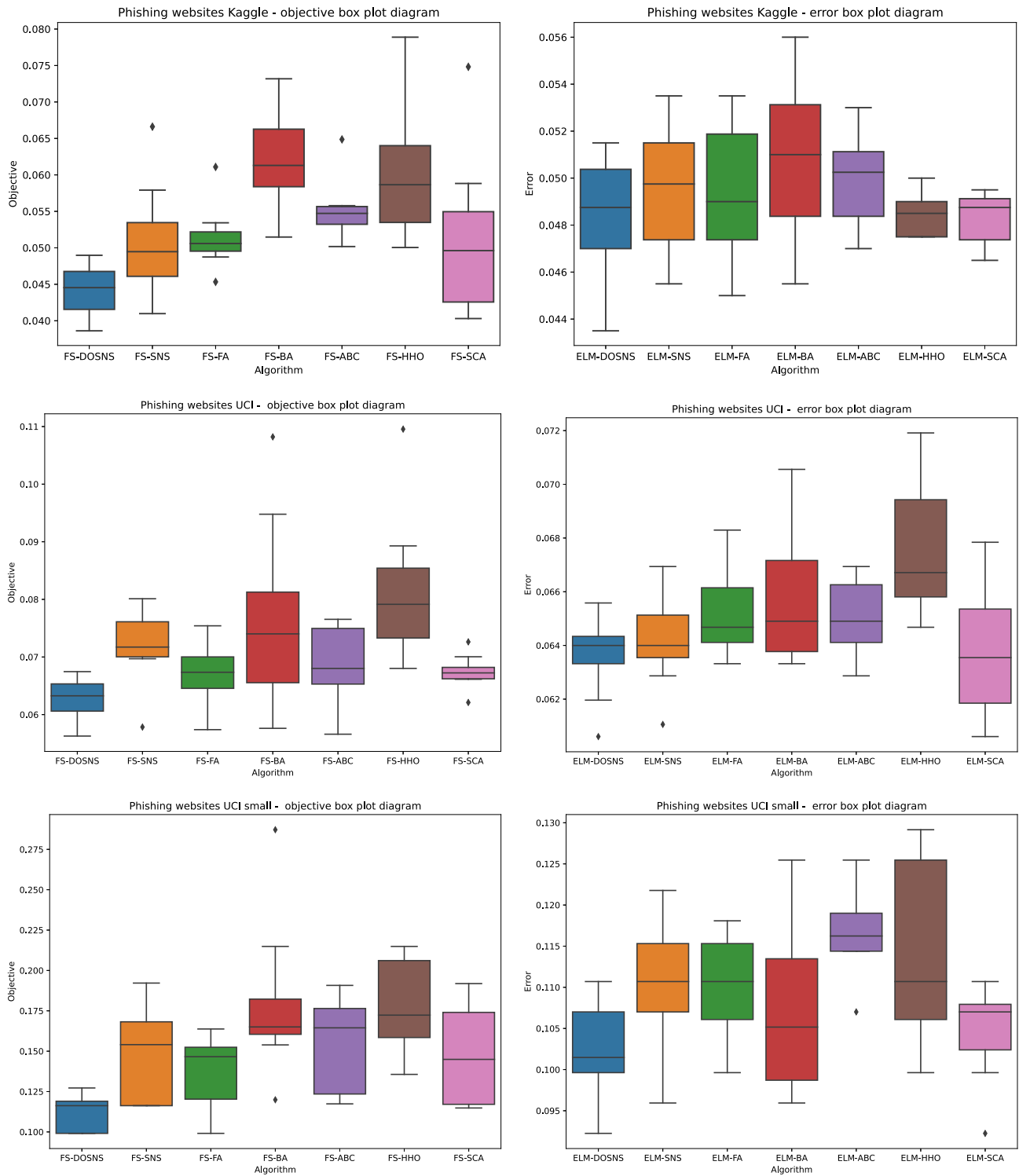
Convergence graphs and box plots of the error (as this experiment is executed with just L2 framework without feature selection), for all observed methods and all three data sets are given in Fig. 12.

The PR AUC curves for the best generated solution of all metaheuristics, where only ELM hyper-parameters tuning was performed without feature selection, are shown in Fig. 13. In addition, to visualize performance of the classifier with more details, one vs rest (OvR) ROC curves are visualized in Fig. 14, for all observed methods and all three data sets, in case of ELM tuning with all features (no feature selection). The relation of each class to other classes, together with their distribution, can be seen on histograms that are also provided in Fig. 14.



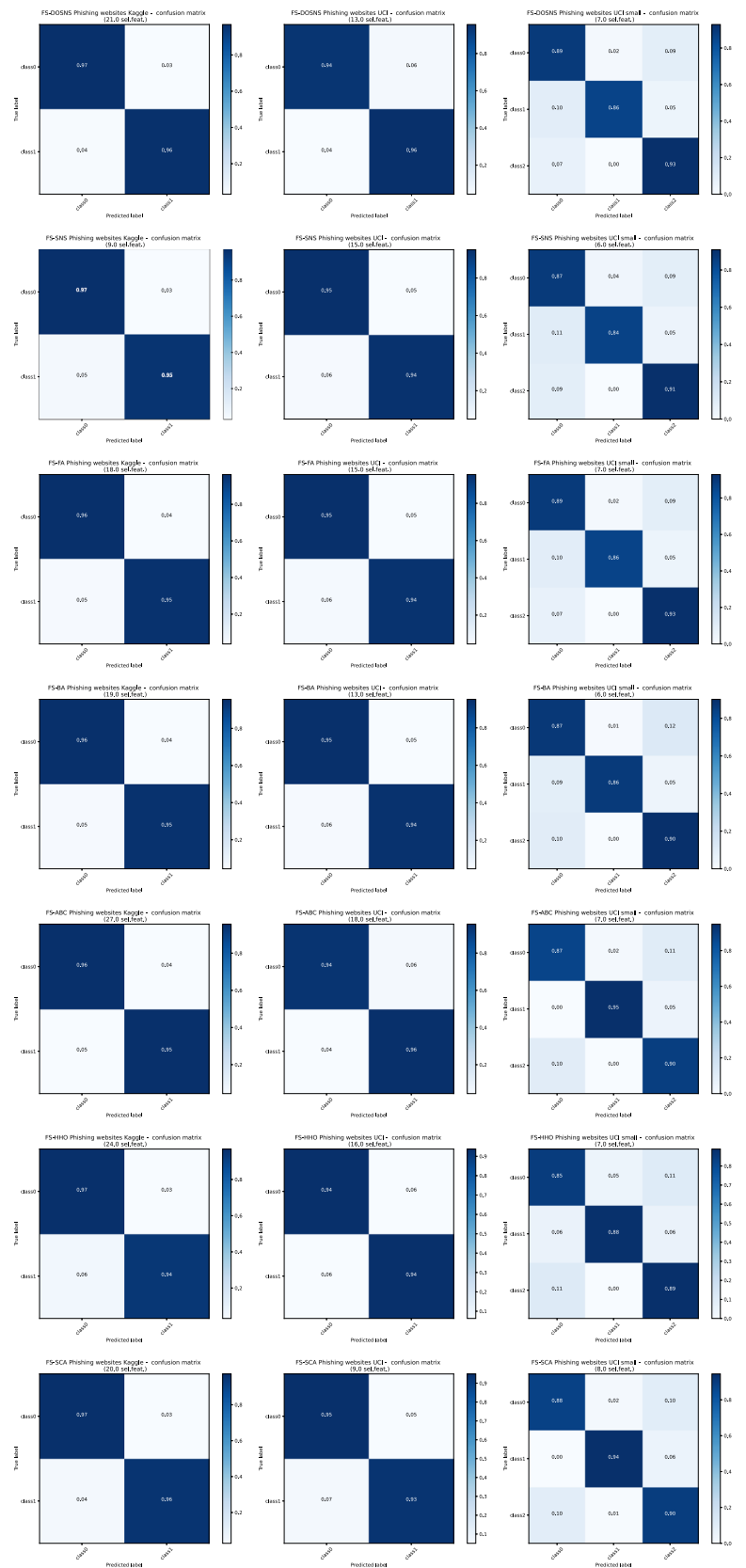


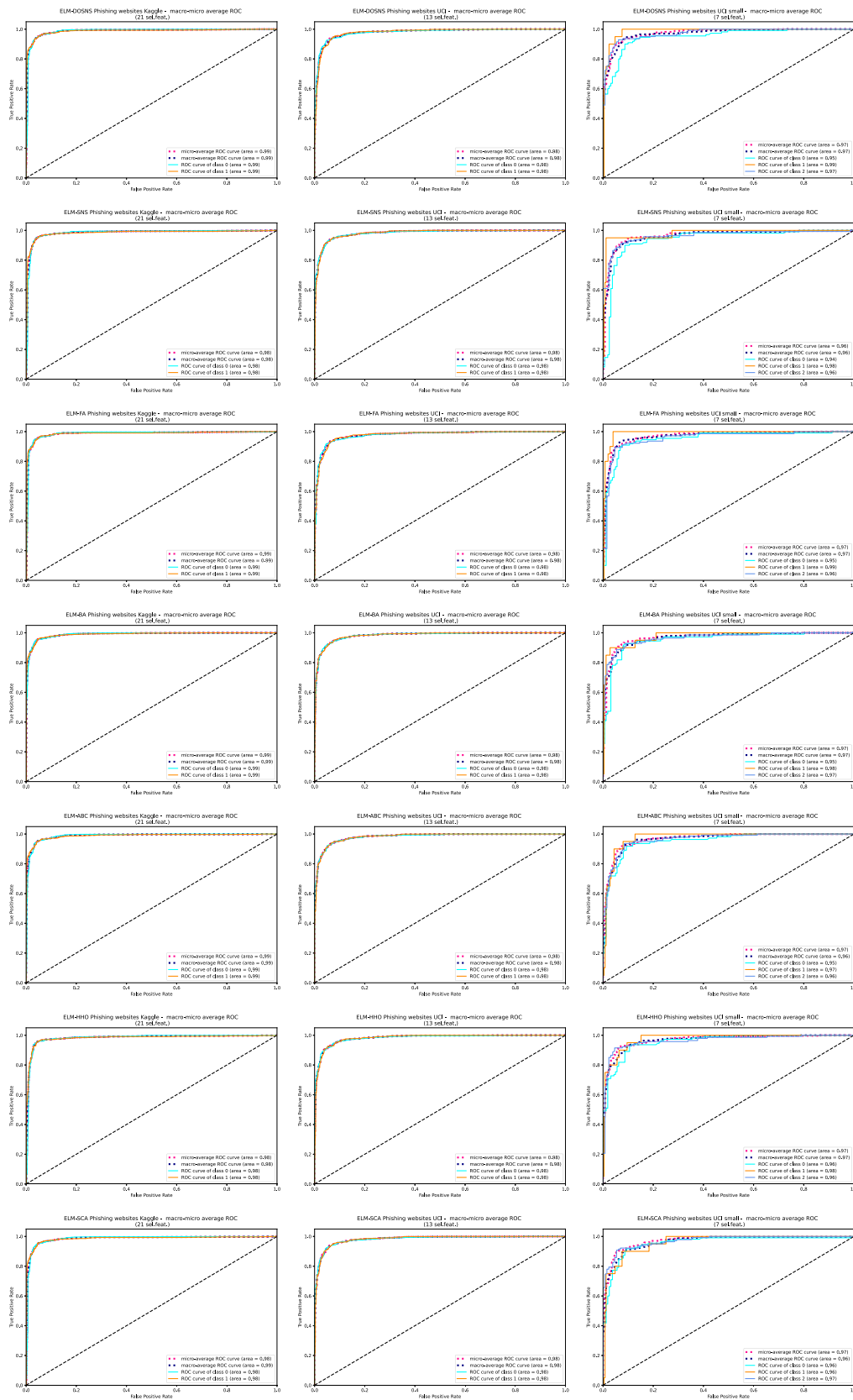
**Fig. 8** Experiment I—convergence graphs of objective function for L1 simulations, and error for L2 experiments, for all observed methods and all three data sets



**Fig. 9** Experiment I—box and whiskers diagrams of objective function for L1 simulations, and error for L2 experiments, for all observed methods and all three data sets

**Fig. 10** Experiment I—confusion matrices for L1 output for feature selection, for all observed methods and all three data sets





**Fig. 11** Experiment I—ROC AUC with micro and macro averages for the best solutions (output) of L2 for all observed methods and all three data sets



**Table 2** Experiment I—overall metrics for L2 results (ELM tuning) with respect to classification error

Method	FS–DOSNS	FS–SNS	FS–FA	FS–BA	FS–ABC	FS–HHO	FS–SCA
<i>Kaggle</i>							
Best	<b>0.043500</b>	0.045500	0.045000	0.045500	0.047000	0.047500	0.046500
Worst	0.051500	0.053500	0.053500	0.056000	0.053000	0.050000	<b>0.049500</b>
Mean	0.048500	0.049375	0.049438	0.050938	0.049938	0.048438	<b>0.048313</b>
Median	0.048750	0.049750	0.049000	0.051000	0.050250	<b>0.048500</b>	0.048750
Std	0.002500	0.002701	0.002822	0.003340	0.001861	<b>0.000845</b>	0.001088
Var	0.000006	0.000007	0.000008	0.000011	0.000003	0.000001	0.000001
Best no. feat	21	21	21	21	21	21	21
Best no. neurons	313	315	315	291	298	313	315
<i>UCI</i>							
Best	0.060606	0.061058	0.063320	0.063320	0.062867	0.064677	0.060606
Worst	<b>0.065581</b>	0.066938	0.068295	0.070556	0.066938	0.071913	0.067843
Mean	<b>0.063602</b>	0.064224	0.065185	0.065751	0.065072	0.067673	0.063885
Median	0.063998	0.063998	0.064677	0.064903	0.064903	0.066712	<b>0.063546</b>
Std	0.001482	0.001766	0.001541	0.002349	<b>0.001384</b>	0.002588	0.002475
Var	0.000002	0.000003	0.000002	0.000006	0.000002	0.000007	0.000006
Best no. feat	13	13	13	13	13	13	13
Best no. neurons	195	188	118	181	181	189	195
<i>UCI small</i>							
Best	0.092251	0.095941	0.099631	0.095941	0.107011	0.099631	0.092251
Worst	0.110701	0.121771	0.118081	0.125461	0.125461	0.129151	0.110701
Mean	<b>0.102399</b>	0.110701	0.110240	0.107472	0.116697	0.113930	0.104705
Median	<b>0.101476</b>	0.110701	0.110701	0.105166	0.116236	0.110701	0.107011
Std	0.005458	0.007380	0.006240	0.010508	<b>0.005198</b>	0.010508	0.005816
Var	0.000030	0.000054	0.000039	0.000110	<b>0.000027</b>	0.000110	0.000034
Best no. feat	7	7	7	7	7	7	7
Best no. neurons	105	105	94	105	105	104	105

The visualization of results clearly indicates the superior performance of the proposed ELM–DOSNS method. However, it is required to execute additional statistical tests to prove that the results are statistically significantly better than the results obtained by other considered approaches.

It is also interesting to compare results from Table 3, that shows detailed findings with feature selection employed, to the results from Table 5, where all features have been utilized. From this side-by-side comparison, it can be seen that in majority of cases the obtained accuracy is better when all features are used (no feature selection), however, with drastically higher computational costs. Therefore, it is justified to perform the feature selection and reduce the computational complexity. For example, the proposed ELM–DOSNS achieves the best accuracy of 95.65% on the Kaggle data set, 93.94% on UCI data set, and finally, 90.78% on UCI small data set when the feature selection is utilized. The same approach achieves accuracy of 97.25%, 94.75%, and 90.04%, respectively, with all features used (no feature selection).

Therefore, the same approach delivers better accuracy on the Kaggle and UCI data sets without feature selection (second experiment), while on the UCI small data set the accuracy is better when feature selection is used (first experiment). The same conclusion applies for all utilized approaches on these three particular data sets. From these findings, a conclusion that the UCI small data set contains noisy features, which disrupt classification, can be derived.

### Findings validation and best models interpretation

Reported findings from experiments I and II, showed in Sects. 4.3.1 and 4.3.2, respectively, prove that in average proposed DOSNS showed better results' quality and convergence speed than other opponent cutting-edge metaheuristics. However, the experimental results are not sufficient to determine if one algorithm has significantly better performance compared to the others and there is an urge to conduct statistical tests.

**Table 3** Experiment I—detailed metrics for the best solutions with feature selection and ELM tuning (L1+L2)

	ELM–DOSNS	ELM–SNS	ELM–FA	ELM–BA	ELM–ABC	ELM–HHO	ELM–SCA
<b>Kaggle dataset</b>							
Accuracy (%)	<b>95.65</b>	95.45	95.50	95.45	95.30	95.25	95.35
Precision 0	0.957874	0.959555	0.959596	<b>0.961421</b>	0.953000	0.953862	0.952144
Precision 1	<b>0.955135</b>	0.949555	0.950495	0.947783	0.953000	0.951147	0.954865
M.Avg. Precision	<b>0.956504</b>	0.954555	0.955046	0.954602	0.953000	0.952504	0.953504
Recall 0	0.955000	0.949000	0.950000	0.947000	0.953000	0.951000	0.955000
Recall 1	0.958000	0.960000	0.960000	<b>0.962000</b>	0.953000	0.954000	0.952000
M.Avg. Recall	<b>0.956500</b>	0.954500	0.955000	0.954500	0.953000	0.952500	0.953500
F1 Score 0	<b>0.956435</b>	0.954248	0.954774	0.954156	0.953000	0.952429	0.953570
F1 Score 1	<b>0.956565</b>	0.954749	0.955224	0.954839	0.953000	0.952571	0.953430
M.Avg. F1 Score	<b>0.956500</b>	0.954499	0.954999	0.954497	0.953000	0.952500	0.953500
<b>UCI dataset</b>							
Accuracy (%)	93.94	93.89	93.67	93.67	93.71	93.53	93.94
Precision 0	0.936017	0.928862	0.940189	<b>0.944857</b>	0.934783	0.938155	0.939646
Precision 1	0.942029	<b>0.947025</b>	0.934022	0.930599	0.938956	0.933174	0.939200
M.Avg. Precision	0.939367	0.938983	0.936753	0.936912	0.937108	0.935380	<b>0.939398</b>
Recall 0	0.926456	<b>0.933606</b>	0.915220	0.910112	0.922370	0.914198	0.922370
Recall 1	0.949675	0.943182	0.953734	<b>0.957792</b>	0.948864	0.952110	0.952922
M.Avg. Recall	0.939394	0.938942	0.936680	0.936680	0.937133	0.935323	0.939394
F1 Score 0	0.931211	<b>0.931228</b>	0.927536	0.927159	0.928535	0.926022	0.930928
F1 Score 1	0.945837	0.945100	0.943775	0.944000	0.943884	0.942547	<b>0.946011</b>
M.Avg. F1 Score	<b>0.939361</b>	0.938957	0.936585	0.936543	0.937087	0.935230	0.939333
<b>UCI small dataset</b>							
Accuracy (%)	90.77	90.41	90.04	90.41	89.3	90.04	90.77
Precision 0	0.877193	0.883929	0.877193	0.883929	0.873874	0.869565	<b>0.885965</b>
Precision 1	<b>0.928571</b>	0.875000	0.823529	0.833333	0.812500	0.866667	0.812500
Precision 2	0.930070	0.923077	0.928571	0.929078	0.916667	0.929078	<b>0.936170</b>
M.Avg. Precision	<b>0.908496</b>	0.903638	0.899965	0.903686	0.891609	0.900316	0.906665
Recall 0	0.909091	0.900000	0.909091	0.900000	0.881818	0.909091	<b>0.918182</b>
Recall 1	0.650000	0.700000	0.700000	<b>0.750000</b>	0.650000	0.650000	0.650000
Recall 2	<b>0.943262</b>	0.936170	0.921986	0.929078	0.936170	0.929078	0.936170
M.Avg. Recall	0.907749	0.904059	0.900369	0.904059	0.892989	0.900369	0.907749
F1 Score 0	0.892857	0.891892	0.892857	0.891892	0.877828	0.888889	<b>0.901786</b>
F1 Score 1	0.764706	<b>0.777778</b>	0.756757	0.789474	0.722222	0.742857	0.722222
F1 Score 2	<b>0.936620</b>	0.929577	0.925267	0.929078	0.926316	0.929078	0.936170
M.Avg. F1 Score	0.906169	0.903078	0.899675	0.903681	0.891572	0.899022	<b>0.906424</b>

Various statistical tests are available to establish whether or not rendered improvements by referenced approach are statistically significant. In this paper, 7 methods (including proposed DOSNS) were compared with respect to measure taken as fitness (objective function and error in case of L1 and L2 tests, respectively), which falls into the domain of multiple-approaches multi-problem analysis [129].

Following related literature recommendations [129–131], to conduct statistical tests, a results sample for each approach is constructed by taking average values of measured objec-

tives over multiple independent runs for each problem. The downside of this approach can be observed in cases when the measured variable has outliers, not following a normal distribution and in such scenarios, misleading results can be generated. Whether the average objective function value should be taken for the purpose of statistical tests when comparing stochastic methods still remains an open question [129].

Therefore, to check whether or not it is safe to use the mean objective value as the base for statistical tests, Shapiro–

**Table 4** Experiment II—overall metrics for L2 results (ELM tuning) without feature selection

Method	ELM–DOSNS	ELM–SNS	ELM–FA	ELM–BA	ELM–ABC	ELM–HHO	ELM–SCA
<b>Kaggle dataset</b>							
Best	<b>0.027500</b>	0.030000	0.030000	0.030000	0.037500	0.040000	0.037500
Worst	<b>0.037500</b>	0.047500	0.042500	0.042500	0.045000	0.045000	0.045000
Mean	<b>0.033125</b>	0.038750	0.037500	0.039375	0.041563	0.042188	0.041250
Median	<b>0.033750</b>	0.037500	0.037500	0.041250	0.042500	0.042500	0.041250
Std	0.002997	0.005449	0.004146	0.004098	0.002142	<b>0.001952</b>	0.002165
Var	0.000009	0.000030	0.000017	0.000017	0.000005	<b>0.000004</b>	0.000005
Best no. feat	48	48	48	48	48	48	48
Best no. neurons	225	552	317	259	452	292	216
<b>UCI dataset</b>							
Best	<b>0.052465</b>	0.055631	0.054726	0.054726	0.056536	0.059249	0.054274
Worst	<b>0.054274</b>	0.059249	0.057440	0.058345	0.059249	0.062415	0.057440
Mean	<b>0.053068</b>	0.057440	0.056008	0.056234	0.057892	0.060681	0.056008
Median	<b>0.052917</b>	0.057214	0.056083	0.056083	0.057892	0.060380	0.056083
Std	<b>0.000622</b>	0.001454	0.000920	0.001422	0.000977	0.001025	0.000991
Var	<b>0.000000</b>	0.000002	0.000001	0.000002	0.000001	0.000001	0.000001
Best no. feat	30	30	30	30	30	30	30
Best no. neurons	418	411	450	450	391	395	446
<b>UCI small dataset</b>							
Best	<b>0.099631</b>	0.114391	0.110701	0.110701	0.114391	0.118081	0.110701
Worst	<b>0.114391</b>	0.132841	0.132841	0.125461	0.129151	0.177122	0.136531
Mean	<b>0.107011</b>	0.122386	0.121771	0.118696	0.121771	0.143296	0.123001
Median	<b>0.107011</b>	0.121771	0.121771	0.119926	0.119926	0.142066	0.121771
Std	<b>0.004764</b>	0.006876	0.009286	0.004958	0.005637	0.019341	0.008159
Var	<b>0.000023</b>	0.000047	0.000086	0.000025	0.000032	0.000374	0.000067
Best feature size	9	9	9	9	9	9	9
Params	135	135	116	135	127	133	135

Wilk [132] test for single-problem analysis [129] was first performed in the following way: for each algorithm and every problem, a data sample is constructed by taking the results obtained in each run, and respective  $p$  values are calculated for every method—problem pair. Such generated  $p$  values are shown in Table 6.

As can be seen from the test results, all  $p$  values are higher than the threshold significance level  $\alpha = 0.05$ ; therefore, the null hypothesis, which states that the data samples come from normal distribution, cannot be rejected. Therefore, data samples for all method—problem pairs are originating from a normal distribution, and it is safe to use average objective in the statistical tests.

Afterwards, multi-problems multiple-methods statistical analysis was conducted and the data sample for each method was constructed by taking the average objective function value over 30 independent runs for each problem instance. First, requirements for safe use of the parametric tests conditions, including independence, normality, and homoscedas-

ticity of the variances of the data, were checked [133]. Each run was executed independently starting with unique pseudo-random number, confirming that the condition of independence was satisfied. By again using the Shapiro–Wilk test [132], the normality condition was checked and the results for compared methods are shown in Table 7.

To check homoscedasticity based on means, Levene’s test [134] is applied, and the  $p$  value of 0.64 is obtained, which leads to a conclusion that the homoscedasticity is satisfied.

On the other hand, the calculated  $p$  values from the Shapiro–Wilk test for all methods are smaller than  $\alpha = 0.05$  (Table 7), providing the conclusion that the safe use of parametric tests is not satisfied; therefore, it was proceeded with non-parametric tests, where the proposed DOSNS was designated as the control method.

To determine the significance of the proposed algorithm performance over other algorithms, the Friedman test [135, 136] and a two-way variance analysis by ranks were conducted, as suggested in [130]. The Friedman test results are

**Table 5** Experiment II—detailed metrics for the best solutions of ELM tuning without feature selection (L2)

	ELM–DOSNS	ELM–SNS	ELM–FA	ELM–BA	ELM–ABC	ELM–HHO	ELM–SCA
<i>Kaggle dataset</i>							
Accuracy (%)	<b>97.25</b>	97.00	97.00	97.00	96.25	96.00	96.25
Precision 0	<b>0.984615</b>	0.937824	0.965347	0.974747	0.955665	0.964646	0.960199
Precision 1	0.960976	0.908213	<b>0.974747</b>	0.965347	0.969543	0.955446	0.964824
M.Avg. Precision	<b>0.972795</b>	0.923018	0.970047	0.970047	0.962604	0.960046	0.962512
Recall 0	0.960000	0.905000	<b>0.975000</b>	0.965000	0.970000	0.955000	0.965000
Recall 1	<b>0.985000</b>	0.940000	0.965000	0.975000	0.955000	0.965000	0.960000
M.Avg. Recall	<b>0.972500</b>	0.922500	0.970000	0.970000	0.962500	0.960000	0.962500
F1 Score 0	<b>0.972152</b>	0.921120	0.970149	0.969849	0.962779	0.959799	0.962594
F1 Score 1	<b>0.972840</b>	0.923833	0.969849	0.970149	0.962217	0.960199	0.962406
M.Avg. F1 Score	<b>0.972496</b>	0.922476	0.969999	0.969999	0.962498	0.959999	0.962500
<i>UCI dataset</i>							
Accuracy (%)	<b>94.75</b>	94.44	94.53	94.53	94.35	93.94	94.57
Precision 0	<b>0.954689</b>	0.951477	0.947808	0.952532	0.944792	0.939646	0.951630
Precision 1	0.942155	0.939034	<b>0.943336</b>	0.939826	0.942446	0.939200	0.941270
M.Avg. Precision	<b>0.947705</b>	0.944544	0.945316	0.945452	0.943485	0.939398	0.945857
Recall 0	0.925434	0.921348	<b>0.927477</b>	0.922370	0.926456	0.922370	0.924413
Recall 1	<b>0.965097</b>	0.962662	0.959416	0.963474	0.956981	0.952922	0.962662
M.Avg. Recall	<b>0.947535</b>	0.944369	0.945274	0.945274	0.943464	0.939394	0.945726
F1 Score 0	<b>0.939834</b>	0.936170	0.937532	0.937208	0.935534	0.930928	0.937824
F1 Score 1	<b>0.953488</b>	0.950701	0.951308	0.951503	0.949658	0.946011	0.951846
M.Avg. F1 Score	<b>0.947442</b>	0.944267	0.945208	0.945173	0.943404	0.939333	0.945637
<i>UCI small dataset</i>							
Accuracy (%)	<b>90.04</b>	88.56	88.93	88.93	88.56	88.19	88.93
Precision 0	<b>0.883929</b>	0.868421	0.900000	0.857143	0.852174	0.866071	0.867257
Precision 1	1.00000	0.800000	0.727273	1.00000	0.846154	0.733333	0.833333
Precision 2	0.90411	0.908451	0.893333	0.910345	<b>0.916084</b>	0.909722	0.910959
M.Avg. Precision	<b>0.902995</b>	0.884199	0.883784	0.895367	0.884982	0.878987	0.887491
Recall 0	0.900000	0.900000	0.9	0.927273	0.890909	0.881818	0.890909
Recall 1	<b>0.650000</b>	0.600000	0.400000	0.350000	0.550000	0.550000	0.50000
Recall 2	0.93617	0.914894	<b>0.950355</b>	0.93617	0.929078	0.929078	0.943262
M.Avg. Recall	<b>0.900369</b>	0.885609	0.889299	0.889299	0.885609	0.881919	0.889299
F1 Score 0	0.891892	0.883929	<b>0.900000</b>	0.89083	0.871111	0.873874	0.878924
F1 Score 1	<b>0.787879</b>	0.685714	0.516129	0.518519	0.666667	0.628571	0.625000
F1 Score 2	0.919861	0.911661	0.920962	0.923077	0.922535	0.919298	<b>0.926829</b>
M.Avg. F1 Score	<b>0.898768</b>	0.883729	0.882577	0.880131	0.882779	0.879404	0.885109



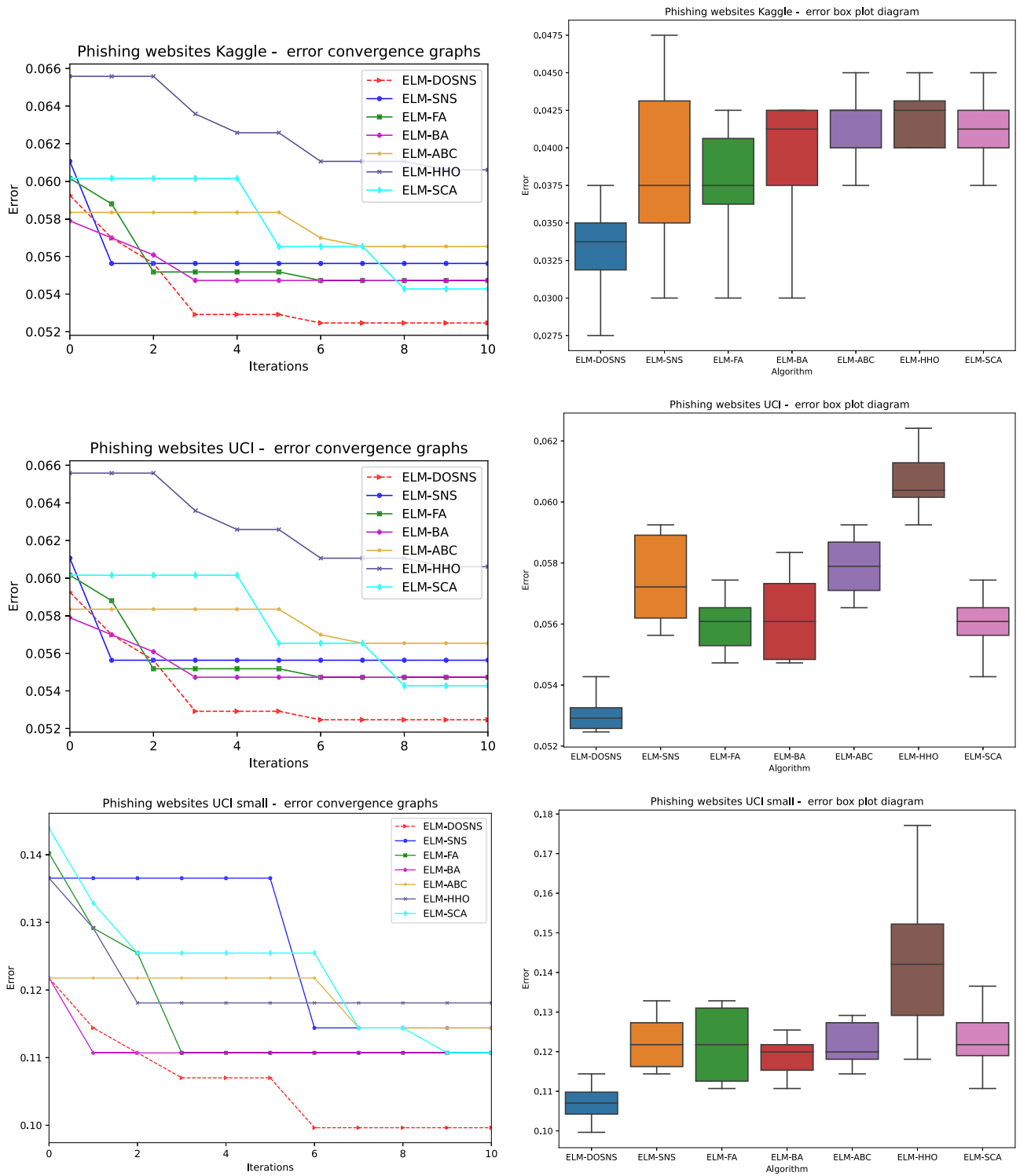
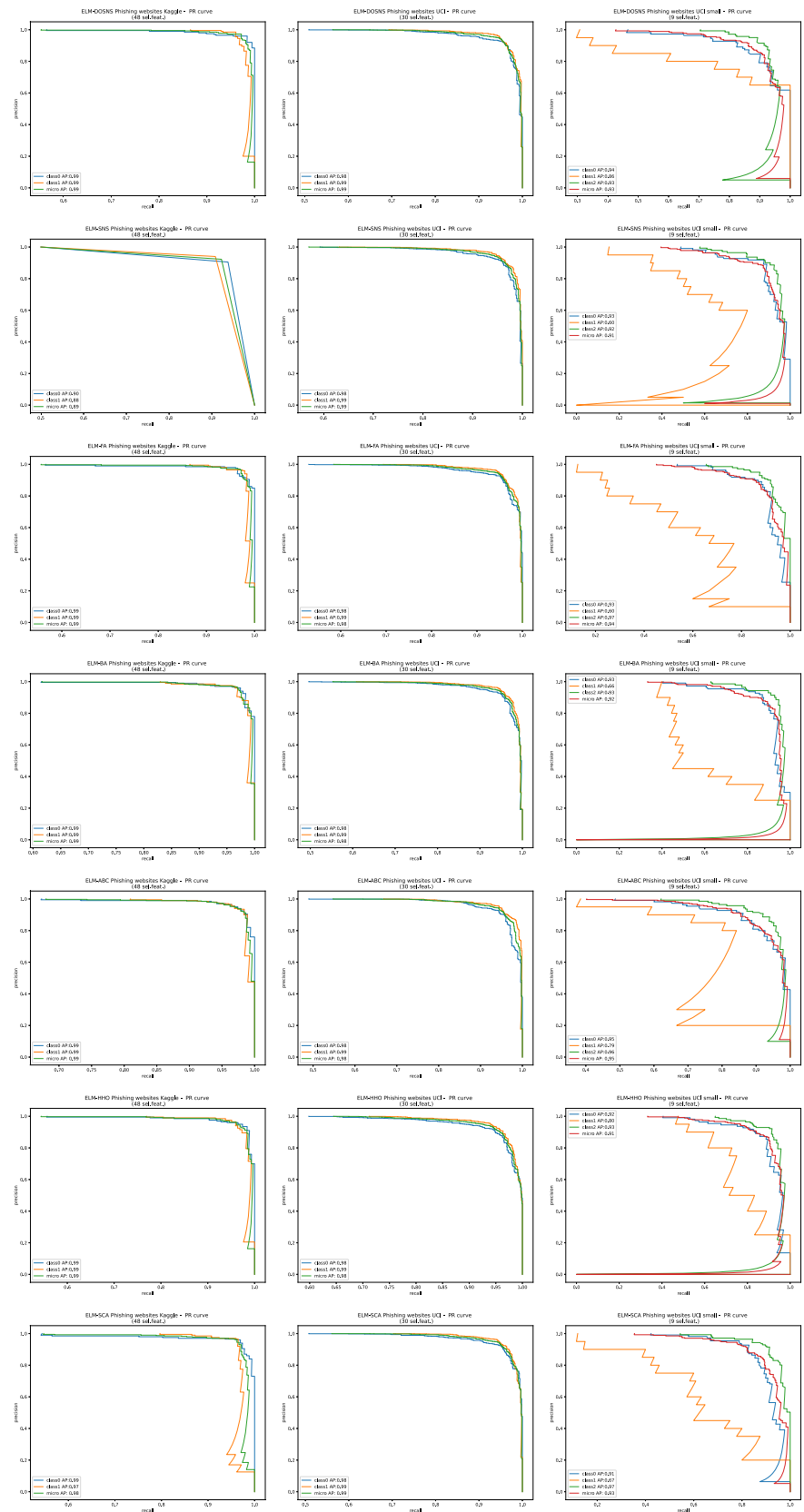
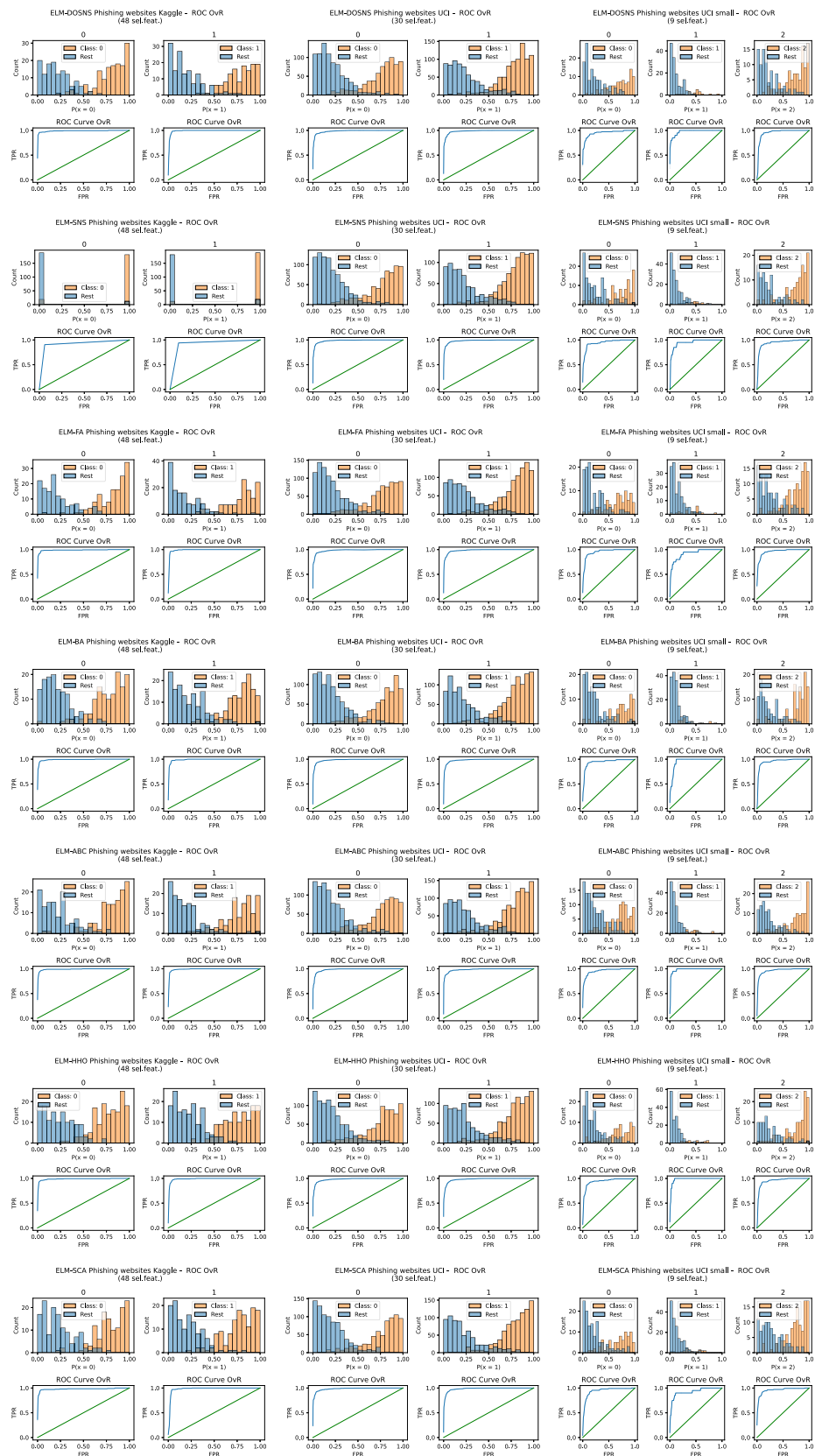


Fig. 12 Experiment II—convergence graphs and box plots of the error for all observed methods and all three data sets

**Fig. 13** Experiment II—the PR AUC curves for the best solutions (smallest error) of L2 without feature selection for all observed methods and all three data sets



**Fig. 14** Experiment II—OvR  
 ROC curves for the best solutions (smallest error) of L2 without feature selection for all observed methods and all three data sets



**Table 6** Shapiro–Wilk test results for single-problem analysis

Problem	DOSNS	SNS	FA	BA	ABC	HHO	SCA
PW Kaggle FS	0.6753	0.3256	0.2743	0.4561	0.3234	0.4562	0.5283
PW UCI FS	0.4511	0.3335	0.2152	0.4052	0.1236	0.2567	0.5183
PW UCI small FS	0.0975	0.0825	0.1743	0.3561	0.1221	0.3252	0.0945
PW Kaggle FS+HT	0.1742	0.2237	0.1805	0.2465	0.0974	0.3462	0.1285
PW UCI FS+HT	0.1251	0.2357	0.3210	0.5592	0.1245	0.2574	0.2456
PW UCI small FS+HT	0.5552	0.0821	0.1844	0.2564	0.1253	0.2764	0.4253
PW Kaggle HT	0.2751	0.2254	0.1642	0.3564	0.4256	0.1925	0.5281
PW UCI HT	0.3551	0.2275	0.1845	0.2569	0.1936	0.2590	0.1251
PW UCI small HT	0.4752	0.0988	0.1725	0.1554	0.2251	0.1599	0.4241

**Table 7** Shapiro–Wilk test results for multi-problems multiple-methods analysis

DOSNS	SNS	FA	BA	ABC	HHO	SCA
0.0129	0.0162	0.0127	0.0213	0.0318	0.0133	0.0325

reported in Table 8. Moreover, the Friedman aligned test was also utilized, and these findings are shown in Table 9.

The results from Tables 8 and 9 statistically indicate that the proposed DOSNS method obtained superior performance in comparison with other algorithms by achieving an average rank value of 1. The second-best result was achieved by FA, with an average rank of 3. The original SNS accomplished an average ranking of 3.94; therefore, the superiority of the proposed DOSNS over original method is also proven. Furthermore, the Friedman statistics,  $\chi_r^2 = 21.27$ , is greater than the  $\chi^2$  critical value, with 6 degrees of freedom (12.59), at significance level  $\alpha = 0.05$ , and the Friedman  $p$  value is  $2.22 \times 10^{-16}$ , inferring that significant differences in results between different methods exist. Consequently, it is possible to reject the null hypothesis ( $H_0$ ) and state that the proposed DOSNS obtained performance were significantly different from other competitors. Similar conclusions can be derived from the Friedman aligned test results.

As indicated in [137], the Iman and Davenport's test [138] could give results with more precision than the  $\chi^2$ . The Iman and Davenport's test result is  $3.25 \times 10^0$ , which is significantly larger than the critical value of the  $F$ -distribution ( $2.09 \times 10^0$ ). In addition, the Iman and Davenport  $p$  value is  $6.73 \times 10^{-2}$ , which is smaller than the level of significance. Finally, it is concluded that this test also rejects  $H_0$ .

Finally, the non-parametric post-hoc Holm's step-down procedure was applied based on the fact that both conducted tests rejected the null hypothesis. These findings are reported in Table 10. In this test, the observed algorithms are sorted in respect of their  $p$  values and evaluated to  $\alpha/(k-i)$ , where  $k$  and  $i$  represent the degree of freedom ( $k = 6$  for this research) and the algorithm number, respectively, after sorting accord-

ing to the  $p$  value in ascending order (corresponding to rank). In this research  $\alpha$  values of 0.05 and 0.1 are used in this experiment. The outcomes from Table 10 clearly indicate that the suggested DOSNS significantly outperformed all competing algorithms at both significance levels.

To comprehend the modeling process and identify the most effective model, the explainable artificial intelligence method called SHAP was employed. This approach overcomes the usual trade-off between accuracy and interpretability by offering a precise and significant explanation of the model's choices. By utilizing a game-theory approach that evaluates the influence of individual features on predictions, the SHAP technique determines feature importance through Shapley values [139]. These values distribute the disparity between predictions and the mean predictions among the features and represent a just allocation of payouts to collaborating features with respect to their individual contributions to the combined payout.

SHAP can interpret the impact of a feature in relation to a model's prediction by assigning each feature an importance measure that indicates its contribution to a particular prediction, compared to the prediction in case that feature was set to the baseline value. By generalizing Shapley values and preserving local faithfulness, this technique offers insights into the model's behavior and solves the significant issue of inconsistency while reducing the likelihood of undervaluing a feature with a specific attribution value. It also accounts for interactions between features and enables the interpretation of the model's overall behavior [140].

Aiming to interpret the model and determine the influence features have on the outcome, SHAP diagrams were generated for Kaggle and UCI small data sets. The results from the experiment 1—overall metrics for L2 results (described in Sect. 4.3.1) were used, where the features were chosen by L1 framework, and the best performing ELM–DOSNS model was subjected to the SHAP analysis.

In case of Phishing websites Kaggle data set, 21 features were chosen and this data set was used in SHAP analysis. Details about this data set and description of each feature

**Table 8** Friedman statistical test results

Functions	DOSNS	SNS	FA	BA	ABC	HHO	SCA
PW Kaggle FS	1	2	4	7	5	6	3
PW UCI FS	1	5	2	6	4	7	3
PW UCI small FS	1	4	2	7	5	6	3
PW Kaggle FS+HT	1	3.5	2	3.5	6	7	5
PW UCI FS+HT	1	3	5	6	4	7	2
PW UCI small FS+HT	1	5	4	3	7	6	2
PW Kaggle HT	1	3	2	4	6	7	5
PW UCI HT	1	5	2.5	4	6	7	2.5
PW UCI small HT	1	5	3.5	2	3.5	7	6
Average ranking	1	3.94	3	4.72	5.17	6.67	3.5
Rank	1	4	2	5	6	7	3

**Table 9** Friedman aligned statistical test results

Functions	DOSNS	SNS	FA	BA	ABC	HHO	SCA
PW Kaggle FS	4	14	16	59	47	57	15
PW UCI FS	5	43	10	56	19	60	13
PW UCI small FS	1	18	3	63	53	62	12
PW Kaggle FS+HT	17	32.5	27	32.5	45	48	41
PW UCI FS+HT	22	24	36	40	35	51	23
PW UCI small FS+HT	6	46	42	20	58	55	8
PW Kaggle HT	7	31	21	37	50	52	49
PW UCI HT	11	39	28.5	30	44	54	28.5
PW UCI small HT	2	34	25.5	9	25.5	61	38
Average ranking	8.33	31.28	23.22	38.5	41.83	55.56	25.28
Rank	1	4	2	5	6	7	3

**Table 10** Holm’s step-down procedure statistical test results

Comparison	<i>p</i> _values	Ranking	Alpha = 0.05	Alpha = 0.1	H1	H2
DOSNS vs HHO	0.000000	0	0.0083	0.0167	True	True
DOSNS vs ABC	0.000021	1	0.01	0.02	True	True
DOSNS vs BA	0.000129	2	0.0125	0.025	True	True
DOSNS vs SNS	0.001918	3	0.0167	0.0333	True	True
DOSNS vs SCA	0.007045	4	0.025	0.05	True	True
DOSNS vs FA	0.024767	5	0.05	0.1	True	True

are available on official Kaggle repository<sup>4</sup> [121]. SHAP diagrams by default show 20 features that are the most influential, and as such are provided in this section. Figure 15 brings forward the summary plot of all classes and waterfall chart for class 1 (phishing), while Fig. 16 presents the summary plots for class 0 and class 1 (phishing).

Looking at the SHAP waterfall chart for class 1 (phishing) from Fig. 15, it can be noted that the PctExtHyperlinks attribute is the most influential, followed by the features NumNumericChars and NumQueryComponents. Analyzing

the summary plot for class 1, shown in Fig. 16, it is possible to note that PctExtHyperlinks attribute is in direct correlation with class 1, as the increased amount of the external hyperlinks will highly likely indicate that the particular website is phishing. In addition, probability of classification as class 1 increases with the increase of properties PctNullSelfRedirectHyperlinks, FrequentDomainNameMismatch and InsecureForms, as well as NumNumericChars feature. All these observations are in line with the practice, where the phishing websites typically have large number of external links, insecure forms, and large numbers of numeric characters.

<sup>4</sup> <https://www.kaggle.com/datasets/shashwatwork/phishing-dataset-for-machine-learning>.



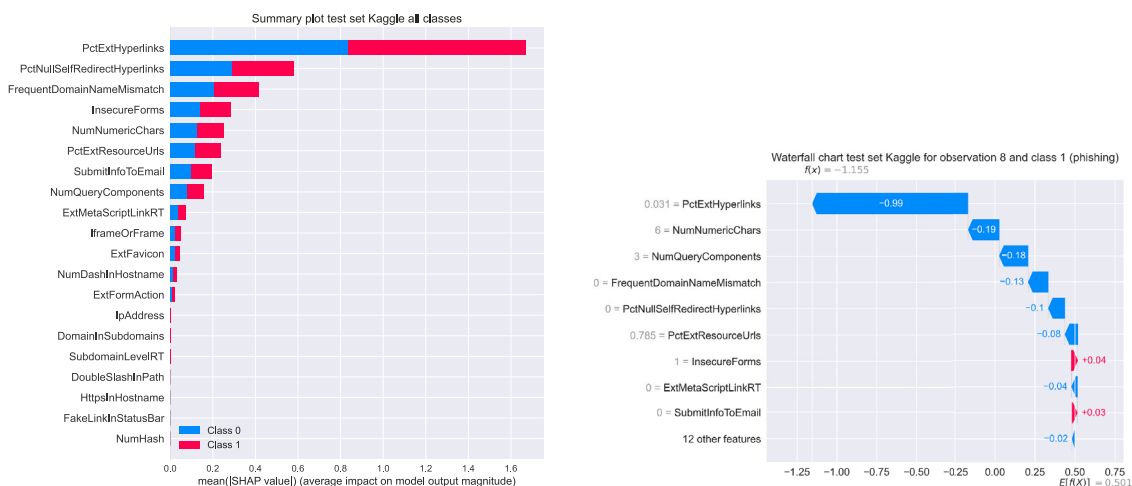


Fig. 15 SHAP summary plot (left side) and waterfall chart for Kaggle data set (right side)

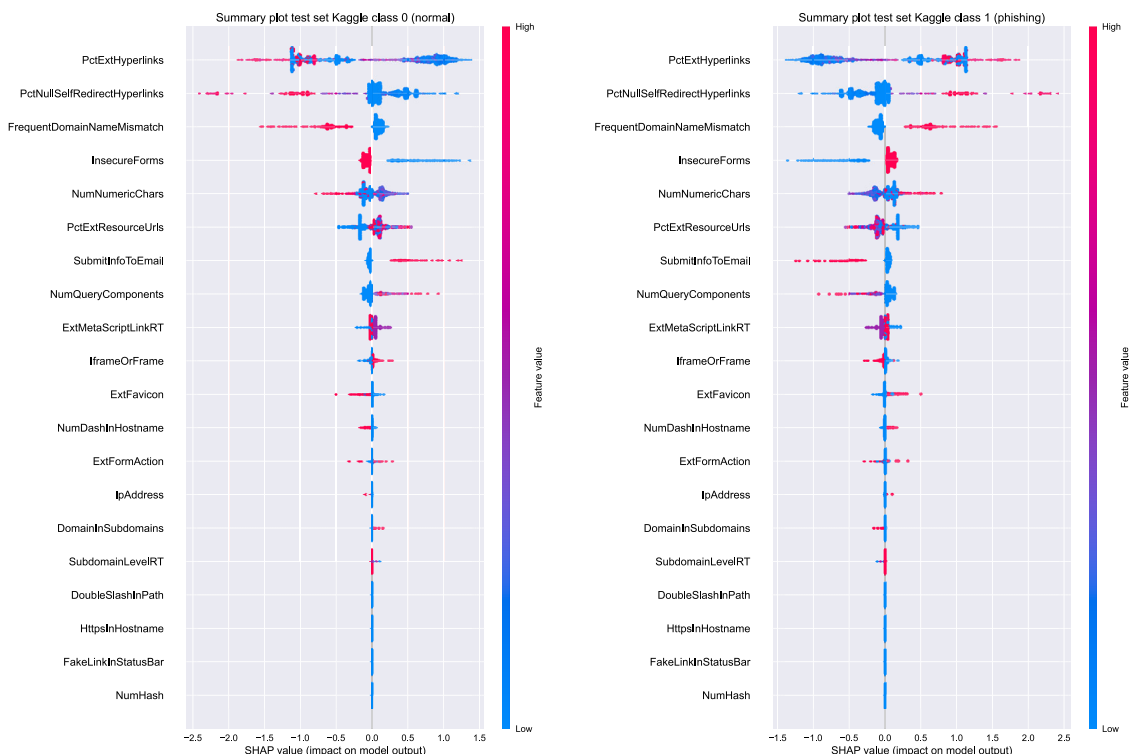


Fig. 16 SHAP summary plots for class 0 (left side) and class 1 of Kaggle data set (right side)

In case of UCI small data set, 7 features were chosen and this data set was used in SHAP analysis. Details about this data set and description of each feature are available on UCI Machine Learning Repository<sup>5</sup> [125, 126]. Figure 17 brings forward the summary plot of all classes and waterfall chart for class 1 (phishing), while Fig. 18 presents the summary plots for class 0 (normal), class 1 (suspicious) and class 2 (phishing) for the UCI small data set.

<sup>5</sup> <https://archive.ics.uci.edu/ml/datasets/Website+Phishing>.

According to the waterfall diagram shown in Fig. 17, it is possible to observe that the most important features regarding the UCI small data set are SFH (server form handler), URL\_of\_Anchor and Request\_URL, followed by popUpWindow, URL\_Length and SSL final state. All these features are in direct correlation with the classification as class 2 (phishing), as the increase of these features will also increase the probability of the web site being classified as phishing. Once again, these observations are confirmed in the practical

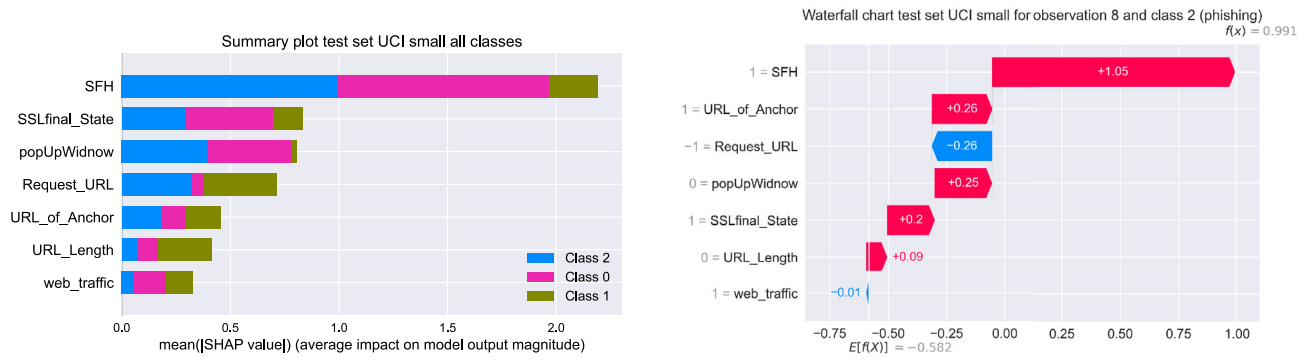


Fig. 17 SHAP summary plot (left side) and waterfall chart for UCI small data set (right side)

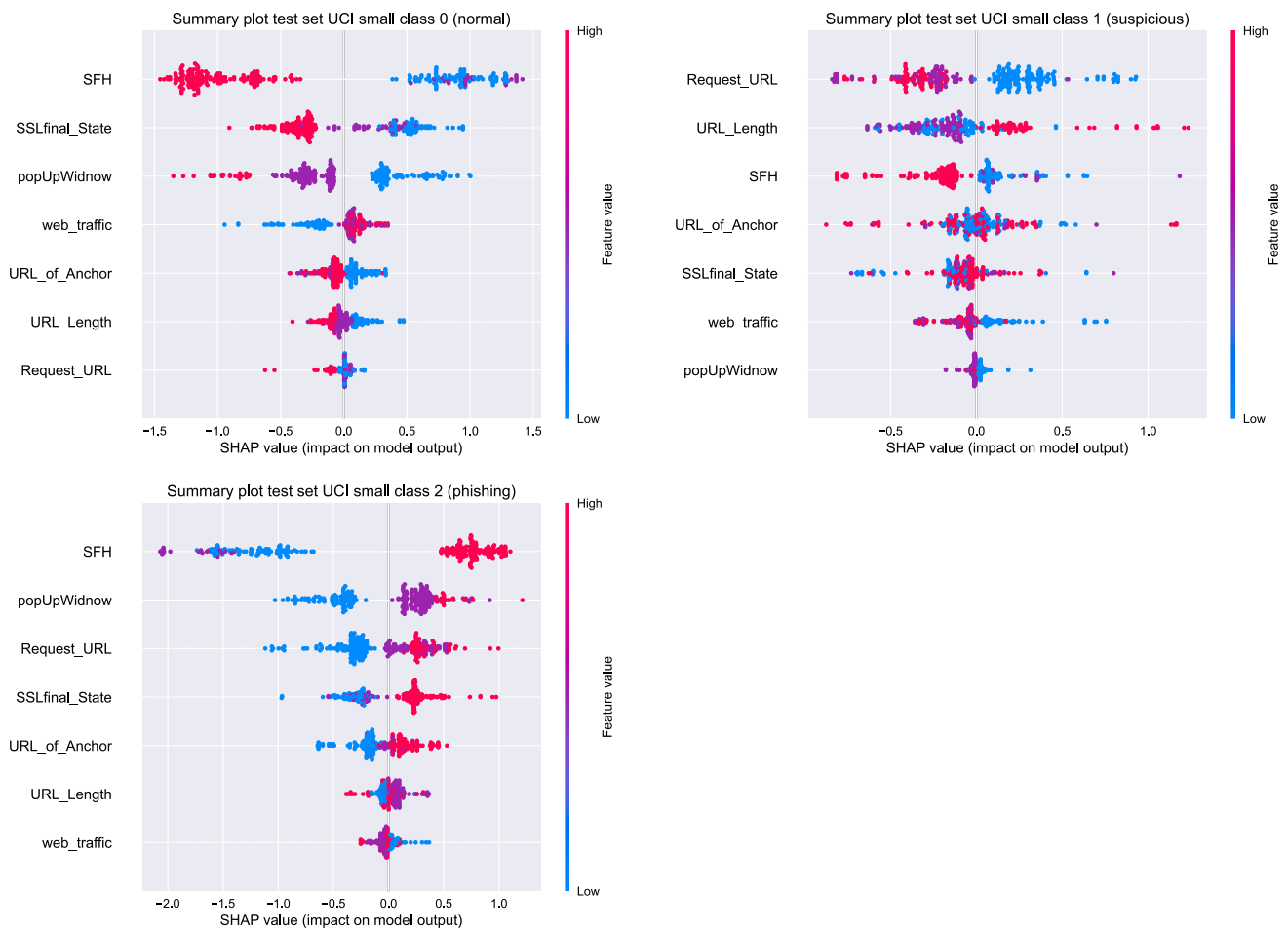


Fig. 18 SHAP summary plots for class 0, class 1 and class 2 of UCI small data set

applications, as data phishing sites commonly have indicators as URL length, request a URL, the URL of anchor, SFH, submitting to email, SSL final state and abnormal URL, as observed by [141].

## Conclusion

The research proposed in this manuscript addresses two of the most important ML challenges, feature selection, and

hyper-parameters optimization. The presented study tried to improve phishing website detection by tuning ELM that utilizes the most relevant subset of phishing website data sets features.

To accomplish this goal, a novel DOSNS has been developed and incorporated into devised two-level cooperative framework. The framework consists of two levels—L1, which deals with feature selection, and L2, which performs ELM tuning. Levels in the two-level framework can be used independently, i.e., performing only feature selection or ELM tuning. In addition, the L1 can execute in a cooperative or individual mode. When set to cooperative mode, all metaheuristics included in the framework perform feature selection independently; however, at the end of execution (after the predetermined number of runs), the selected feature subset generated by best-performing metaheuristics is used as the input to L2 and then all metaheuristics perform ELM tuning using the same set of selected features. Conversely, if the L1 is set to individual mode, then all metaheuristics use their own best set of selected features from L1, as an input to L2, regardless of the classifier performance with the chosen set of features.

The proposed DOSNS has been validated against 6 cutting-edge metaheuristics, that were also incorporated into the devised framework, over two experiments. The first experiment utilized both L1 and L2 of the proposed optimization framework, where the L1 was adjusted in cooperative mode. The second simulation is focused only on tuning the ELM with all employed features (without the feature selection), using only the L2 part of the framework. The goal of this simulation was to test the performance of the suggested DOSNS for large-scale global optimization with many parameters (components).

All methods were validated against three challenging phishing websites data sets, which represent one of the most important challenges in the web security domain. Data sets are available publicly and they were retrieved from UCI and Kaggle repositories. All methods were compared with respect to objective and error, separately for layers 1 and 2 over several independent runs, and detailed metrics of the final outcomes (output of layer 2), including precision, recall, f1 score, receiver operating characteristics, and precision recall area under the curves.

The rigid statistical tests that were conducted for reported experimental findings suggest that the proposed DOSNS is an efficient and robust optimizer, achieving on average better results than other state-of-the-art metaheuristics.

Some limitations of the proposed research refer to the fact that the DOSNS still hasn't been validated against tuning other ML models and that further investigation is required with different transformation functions for feature selection challenge. In addition, for handling moderately and highly imbalanced data sets, investigation with more promising fit-

ness functions is required. Therefore, these domains will be included as part of the future work in this promising area.

**Acknowledgements** This work was supported by the Korea Technology and Information Promotion Agency (TIPA) for SMEs grant funded by the Korea government (Ministry of SMEs and Startups) (No.S3271954) and This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2022H1D8A3038040), and the Soonchunhyang University Research Fund.

**Author Contributions** N.B. and M.Z. implemented methods and performed simulations. M.M. and M.A. performed results' visualization. K.V. and J.L. analysed the results. Y.N. wrote original draft. M.A. revise and editing. All authors reviewed the manuscript.

**Data availability** The data sets used and/or analysed during the current study available from the corresponding author on reasonable request.

## Declarations

**Conflict of interest** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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