Research Article

A New Support Vector Machine Based on Convolution Product

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The support vector machine (SVM) and deep learning (e.g., convolutional neural networks (CNNs)) are the two most famous algorithms in small and big data, respectively. Nonetheless, smaller datasets may be very important, costly, and not easy to obtain in a short time. This paper proposes a novel convolutional SVM (CSVM) that has the advantages of both CNN and SVM to improve the accuracy and effectiveness of mining smaller datasets. The proposed CSVM adapts the convolution product from CNN to learn new information hidden deeply in the datasets. In addition, it uses a modified simplified swarm optimization (SSO) to help train the CSVM to update classifiers, and then the traditional SVM is implemented as the fitness for the SSO to estimate the accuracy. To evaluate the performance of the proposed CSVM, experiments were conducted to test five well-known benchmark databases for the classification problem. Numerical experiments compared favorably with those obtained using SVM, 3-layer artificial NN (ANN), and 4-layer ANN. The results of these experiments verify that the proposed CSVM with the proposed SSO can effectively increase classification accuracy.

1. Introduction

Data mining is an effective method for examining and learning from extensive compound datasets of varying quality [1] and has been broadly applied to numerous practical problems in medicine [2–4], engineering [5], time series data [6], image classification [7], speech recognition [8], handwritten recognition [9], management [10], and social sciences [11], with classification being one of the most popular topics in data mining. Numerous classifiers for data mining have been established such as support vector machines (SVMs) [3, 4, 7] and deep learning algorithms [8, 9, 12].

Deep learning based on artificial neural networks (ANNs) is made up of neurons that have learnable weights and biases such that the neural network, a special mathematical function, is connected or close to the data in dataset as much as possible [12, 13]. Deep learning techniques include convolution neural networks (CNNs) for the continuous space data types (e.g., image and speech recognition)

[7, 8, 14], recurrent neural networks (RNNs) for the time series data types (e.g., stock markets and language modeling) [12], and generative adversarial networks (GANs) for generating new examples and classifying examples [15]. Deep learning is an adequate and straightforward data-mining method for big data [12, 13]. Moreover, since deep learning techniques need big data to learn the classification rules, that is, they only work well for large datasets, they pose an enormous challenge to many applications with respect to obtaining large enough datasets [12, 13]. Furthermore, deep learning relies on good hardware, especially the graphics processing unit (GPU), to have better performance, but such hardware is still expensive [16, 17].

The SVM is another well-known and effective supervised learning model for selecting attributes and classifying data. Before the rise of deep learning, the SVM outperformed ANNs in various real-life applications in medicine [3, 4], semiconductor industry [18], online analysis [19], spectral unmixing resolution [20], imbalanced datasets [21], mining financial distress [22], data classification [23], and so forth

[24–26]. In comparison with deep learning techniques that try to connect data in terms of ANNs, the SVM separates (not to connect) different classes of data based on the kernels through mathematical optimization [27, 28]. In addition, an SVM has high accuracy with less computation power and small data, which are two shortcomings of deep learning [24–26]. Therefore, besides the original SVM, various enhanced SVMs have been developed before the development of deep learning [21, 24–26]. SVMs are discussed in detail in Section 5.1.

Small data are well-formatted data with small volumes that are accessible, understandable, and actionable for decision makers [29]. The value of data lies in the information content but not the volume of data [30]. For some cases such as the marketing strategies of targeting campaigns or delivering personalized experiences, big data might not be appropriate because they do not require full-on big data [31]. Conversely, small data extract an individual's data and provide valuable information to help decision makers formulate strategies. Moreover, the occurrence of small data is rare, with the process of collecting them being expensive and strenuous [4, 21]. Hence, if the data mining of small data is improved, it will aid in making useful, cost-efficient, and timely decisions in small data applications.

Deep learning techniques and SVMs belong to a broader family of machine learning algorithms. Deep learning techniques (e.g., convolution neural networks (CNNs)) based on neural networks are powerful for mining big data but less effective in smaller datasets. On the contrary, SVMs outperform all neural network types in smaller datasets but are less effective in mining big data. This paper proposes a novel convolutional SVM (CSVM) that has the advantages of both SVM and deep learning to enhance SVM by maximizing its prediction accuracy and tests for classifying two-class datasets.

The proposed CSVM employs a supervised learning technique that is based on simplified swarm optimization (SSO), which is another powerful machine learning algorithm [2, 6, 32–35]. Numerical experiments and comparative research with ANNs and the traditional SVM show the accuracy and effectiveness of the proposed CSVM tested on five two-class datasets.

To summarize the above, the theoretical contribution of this paper is the use of a novel convolutional SVM (CSVM) that has the advantages of both SVM and deep learning, that is, the use of SVM and the vital operation techniques of CNNs including stride and convolution, to enhance SVM

and the use of one-solution, one-filter, one-variable greedy SSO update mechanism to prevent the solutions that are near optimums to be kept away from their current positions and to reduce the runtime.

2. Proposed and Traditional Convolution Products

The major difference between the proposed CSVM and the traditional SVM is the convolution product. Hence, the traditional SVM and the proposed new convolution products are introduced and discussed in Section 2.

2.1. Convolution-Related Concept. CNNs represent some of the most significant models of deep learning, and their performance has been verified in numerous recognition research areas. Among the vital operation techniques of CNNs, we introduce some that are used in this paper [12, 13].

- (1) Padding: to prevent the reduction in data size generated by the convolution process in the next layer, we add zeros around the input image, with such action being called padding.
- (2) Stride: a kernel that is moving a horizontal or vertical distance each time is called a stride. The greater the stride is, the more independent the neighboring values in the convolution process are.
- (3) Convolution: in each operation of convolution, multiplication of the values between the input and the kernel (filter) moves through based on the given stride after padding. Then, these products are summed up and filled in the corresponding positions on the next layer.

2.2. Proposed Convolution Product with Repeated Attributes. Suppose that N_{att} , N_{sol} , N_{filter} , and N_{var} are the numbers of attributions, solutions, filters constructed in each solution, and the variables contained in each filter, respectively. Let $v_{r,a} = v_{r,a,0}$ be the value of the a th attribute in the r th record and let $v_{r,a,f}$ be the value of the a th attribute in the r th record after using the f th filter, where $a = 1, 2, \dots, N_{\text{att}}$, $s = 1, 2, \dots, N_{\text{sol}}$, and $f = 1, 2, \dots, N_{\text{filter}}$. For example, nine attributes are used in the breast cancer dataset of University of California Irvine (UCI) [36], and the vector representing the first normalized record is listed as follows:

$$I_1 = [0.50, 0.10, 0.10, 0.10, 0.20, 0.10, 0.30, 0.10, 0.10] = [v_{1,1}, v_{1,2}, v_{1,3}, v_{1,4}, v_{1,5}, v_{1,6}, v_{1,7}, v_{1,8}, v_{1,9}]. \quad (1)$$

$v_{r,a,f}$ is calculated using the convolution product in terms of $v_{r,a,f-1}, v_{r,a+1,f-1}, \dots, v_{r,a+N_{\text{var}}-1,f-1}$ and the filter $X_{s,f}$ as follows:

$$v_{r,a,f} = v_{r,a,f} \times x_{s,f,1} + \dots + v_{r,a+N_{\text{var}}-1,f-1} \times x_{s,f,N_{\text{var}}} \quad (2)$$

From equation (2), there are N_{var} attributes that are included in the a th attribute if $a + N_{\text{var}} - 1 < N_{\text{att}}$. However,

no attributes $v_r, N_{\text{att}} + 1, v_r, N_{\text{att}} + 2, \dots, v_r, N_{\text{att}} + N$ are included when we need to use equation (2) to update the last $N_{\text{var}} - 1$ attributes with $a + N_{\text{var}} - 1 > N_{\text{var}}$.

Let filter $X_{s,1} = [x_{s,1,1}, x_{s,1,2}, x_{s,1,3}] = [-1, 0, 1]$. The procedures for generating the new attributes using the convolution product are listed as follows:

$$v_{1,1,1} = v_{1,1} \times x_{s,1,1} + v_{1,2} \times x_{s,1,2} + v_{1,3} \times x_{s,1,3} = 0.50 \times (-1) + 0.10 \times 0 + 0.10 \times 1 = -0.4, \quad (3)$$

$$v_{1,2,1} = v_{1,2} \times x_{s,1,1} + v_{1,3} \times x_{s,1,2} + v_{1,4} \times x_{s,1,3} = 0.10 \times (-1) + 0.10 \times 0 + 0.10 \times 1 = 0.0, \quad (4)$$

$$v_{1,3,1} = v_{1,3} \times x_{s,1,1} + v_{1,4} \times x_{s,1,2} + v_{1,5} \times x_{s,1,3} = 0.10 \times (-1) + 0.10 \times 0 + 0.20 \times 1 = 0.1, \quad (5)$$

$$v_{1,4,1} = v_{1,4} \times x_{s,1,1} + v_{1,5} \times x_{s,1,2} + v_{1,6} \times x_{s,1,3} = 0.10 \times (-1) + 0.10 \times 0 + 0.20 \times 1 = 0.0, \quad (6)$$

$$v_{1,5,1} = v_{1,5} \times x_{s,1,1} + v_{1,6} \times x_{s,1,2} + v_{1,7} \times x_{s,1,3} = 0.10 \times (-1) + 0.10 \times 0 + 0.20 \times 1 = 0.1, \quad (7)$$

$$v_{1,6,1} = v_{1,6} \times x_{s,1,1} + v_{1,7} \times x_{s,1,2} + v_{1,8} \times x_{s,1,3} = 0.10 \times (-1) + 0.10 \times 0 + 0.20 \times 1 = 0.0, \quad (8)$$

$$v_{1,7,1} = v_{1,7} \times x_{s,1,1} + v_{1,8} \times x_{s,1,2} + v_{1,9} \times x_{s,1,3} = 0.30 \times (-1) + 0.10 \times 0 + 0.10 \times 1 = -0.10. \quad (9)$$

From the above, the first and second old attributes (i.e., $v_{1,1}$ and $v_{1,2}$) are used only once as shown in equation (3) and twice as shown in equations (3) and (4) for generating $v_{1,1,1}$ and $v_{1,2,1}$, respectively. Similarly, the last and the second last attributes in I_1 (i.e., $v_{1,9}$ and $v_{1,8}$) are only shown in equations (8) and (9), respectively. Moreover, there are no new attributes $v_{1,8,1}$ and $v_{1,9,1}$ based on equation (2).

There is no padding in the proposed CSVM. However, we need to guarantee that the two following situations are satisfied to fix the above problems:

- (1) Each attribute is included in the same number (i.e., N_{var}) of convolution products
- (2) The last j attributes still exist after each convolution product

The first $(N_{\text{var}} - 1)$ attributes are repeated and appended in the last attribute of the same record such that the total number of attributes is an integer multiple of N_{var} ; that is, $v_{r,N_{\text{att}}+a,f} = v_{r,a,f-1}$ for $a = 1, 2, \dots, N_{\text{var}} - 1$ and $f = 1, 2, \dots, N_{\text{filter}}$. Hence, following the same example discussed above, we have

$$\begin{aligned} v_{1,8,1} &= v_{1,8} \times x_{s,1,1} + v_{1,9} \times x_{s,1,2} + v_{1,1} \times x_{s,1,3} = 0.10 \times (-1) + 0.10 \times 0 + 0.50 \times 1 = 0.4, \\ v_{1,9,1} &= v_{1,9} \times x_{s,1,1} + v_{1,1} \times x_{s,1,2} + v_{1,2} \times x_{s,1,3} = 0.10 \times (-1) + 0.50 \times 0 + 0.10 \times 1 = 0.0. \end{aligned} \quad (10)$$

Thus, each new attribute is generated by three convolution products, and we have new I_1 accordingly.

$$I_1 \otimes X_{s,1} = [-0.4, 0.0, 0.1, 0.0, 0.1, 0.0, -0.1, 0.4, 0.0]. \quad (11)$$

Let $I_{i,j}$ be the updated i th record after using the j th filter, $I_i = I_{i,0}$. The next example demonstrates updated I_1 after two filters are used, with each having $N_{\text{var}} = 3$ variables; $X_{s,2} = [x_{s,2,1}, x_{s,2,2}, x_{s,2,3}] = [1.8, -0.9, 0.7]$.

$$\begin{aligned}
v_{1,1,2} &= v_{1,1,1} \times x_{s,2,1} + v_{1,2,1} \times x_{s,2,2} + v_{1,2,1} \times x_{s,2,3} = -0.4 \times (1.8) + 0.0 \times (-0.9) + 0.1 \times (0.7) = -0.65, \\
v_{1,2,2} &= v_{1,2,1} \times x_{s,2,1} + v_{1,3,1} \times x_{s,2,2} + v_{1,4,1} \times x_{s,2,3} = 0.0 \times (1.8) + 0.1 \times (-0.9) + 0.0 \times (0.7) = -0.09, \\
v_{1,3,2} &= v_{1,3,1} \times x_{s,2,1} + v_{1,4,1} \times x_{s,2,2} + v_{1,5,1} \times x_{s,2,3} = 0.1 \times (1.8) + 0.0 \times (-0.9) + 0.1 \times (0.7) = 0.25, \\
v_{1,4,2} &= v_{1,4,1} \times x_{s,2,1} + v_{1,5,1} \times x_{s,2,2} + v_{1,6,1} \times x_{s,2,3} = 0.0 \times (1.8) + 0.1 \times (-0.9) + 0.0 \times (0.7) = -0.09, \\
v_{1,5,2} &= v_{1,5,1} \times x_{s,2,1} + v_{1,6,1} \times x_{s,2,2} + v_{1,7,1} \times x_{s,2,3} = 0.1 \times (1.8) + 0.0 \times (-0.9) - 0.1 \times (0.7) = 0.11, \\
v_{1,6,2} &= v_{1,6,1} \times x_{s,2,1} + v_{1,7,1} \times x_{s,2,2} + v_{1,8,1} \times x_{s,2,3} = 0.0 \times (1.8) - 0.10 \times (-0.9) + 0.4 \times (0.7) = 0.37, \\
v_{1,7,2} &= v_{1,7,1} \times x_{s,2,1} + v_{1,8,1} \times x_{s,2,2} + v_{1,9,1} \times x_{s,2,3} = -0.1 \times (1.8) + 0.4 \times (-0.9) + 0.0 \times (0.7) = -0.54, \\
v_{1,8,2} &= v_{1,8,1} \times x_{s,2,1} + v_{1,9,1} \times x_{s,2,2} + v_{1,1,1} \times x_{s,2,3} = 0.4 \times (1.8) + 0.0 \times (-0.9) - 0.4 \times (0.7) = 0.44, \\
v_{1,9,2} &= v_{1,9,1} \times x_{s,2,1} + v_{1,1,1} \times x_{s,2,2} + v_{2,1,1} \times x_{s,2,3} = 0.0 \times (1.8) - 0.4 \times (-0.9) + 0.0 \times (0.7) = 0.36.
\end{aligned} \tag{12}$$

Thus, after using the two filters $X_{s,1}$ and $X_{s,2}$, we have

$$I_r^* = \otimes X_s = (I_1 \otimes X_{s,1}) \otimes X_{s,2} = [-0.65, -0.09, 0.25, -0.09, 0.11, 0.37, -0.54, 0.44, 0.36]. \tag{13}$$

The basic idea of the proposed convolution product with repeated attributes is that the first $(N_{\text{var}} - 1)$ attributes are repeated and appended in the last attribute of each (updated) record such that the total number of attributes is an integer multiple of N_{var} ; that is, $v_{r,N_{\text{att}}+a,f} = v_{r,a,f-1}$ for $a = 1, 2, \dots, N_{\text{var}} - 1$. The pseudocode of the proposed convolution product with repeated attributes is listed in Algorithm 1.

Additionally, we obtain the following properties after employing the proposed convolution product with repeated attributes.

Property 1. If $x_{s,f,1} = \alpha$ and $x_{s,f,k} = 0$ for all $k = 2, \dots, N_{\text{var}}$ and all $f = 1, \dots, N_{\text{filters}}$ then

$$v_{r,a,f} = \alpha \cdot v_{i,a,f-1} = \alpha^f \cdot v_{i,a,f-1}, \tag{14}$$

for all $a = 2, \dots, N_{\text{att}}$ and $f = 1, \dots, N_{\text{filter}}$.

3. Proposed and Traditional SSO

In the proposed CSVM, all values in filters of the proposed convolution product with repeated attributes are updated based on the proposed new SSO. The traditional SSO is introduced briefly, and the proposed SSO including the new self-adaptive solution structure with *pFilter*, the novel one-solution, one-filter, one-variable greedy update mechanism, and the fitness function are presented in Section 3.

3.1. Traditional SSO. The SSO is one of the simplest machine-learning methods [2, 6, 32–35] in terms of its update mechanism. It was first proposed by Yeh and has been tested to be a very useful and efficient algorithm for optimization problems [33, 34], including data mining [2, 6]. Owing to its simplicity and efficiency, SSO is used here to find the best values in filters of the proposed CSVM.

The basic idea of SSO is that each variable, such as the j th variable in the i th solution $x_{i,j}$, needs to be updated based on the following stepwise function [2, 6, 32–35]:

$$x_{i,j} = \begin{cases} g_j, & \text{if } \rho_{[0,1]} \in [0, C_g), \\ p_{i,j}, & \text{if } \rho_{[0,1]} \in [C_g, C_p), \\ x_{i,j}, & \text{if } \rho_{[0,1]} \in [C_p, C_w), \\ x, & \text{otherwise,} \end{cases} \tag{15}$$

where the value $\rho_{[0,1]} \in [0, 1]$ is generated randomly and the parameters $C_g, C_p - C_g, C_w - C_p$, and $1 - C_w$ are all in $[0, 1]$ and are the probabilities of the current variable that are copied and pasted from the best of all solutions, the best i th solution, the current solution, and a random generated feasible value, respectively.

There are different variants of the traditional SSO which are customized to different problems from the no free lunch theorem; for example, the four items in equation (15) are also reduced to three items to increase the efficiency; parameters C_g, C_p , and C_w are all self-adapted; special values or equations are implemented to replace $g_j, p_{i,j}, x_{i,j}$ and x ; or only a certain number of variables are selected to be updated, and so forth. However, the SSO update mechanism is always based on the stepwise function.

3.2. Fitness Function. Fitness functions help solutions learn toward optimization to attain goals in artificial intelligence, such as the proposed CSVM, the traditional SVM, and the CNN. The accuracy obtained by the SVM, based on the records transferred from the proposed convolutions, is adopted here to represent the fitness to maximize in the CSVM:

$$F(X_i) = \frac{\text{the total number of instances predicted correctly based on } X_i}{\text{the total number of instances}}. \quad (16)$$

Input: all records $I_r = [v_{r,1}, v_{r,2}, \dots, v_{r,N_{\text{att}}}]$ and the s th solution X_s for $r = 1, 2, \dots, N_{\text{rec}}$.

Output: the $F(X_s)$.

STEP F0: calculate $I_r^* = I_r \otimes X_s$ based on the pseudocode provided in Section 2.2 for $r = 1, 2, \dots, N_{\text{rec}}$.

STEP F1: classifier $\{I_1^*, I_2^*, \dots, I_{N_{\text{rec}}}^*\}$ using the SVM and let the accuracy be $F(X_s)$.

3.3. Self-Adaptive Solution Structure and pFilter. In the proposed CSVM, each variable of all filters in each solution is initialized randomly from $[-2, 2]$. Each filter and solution are presented by $N_{\text{var}} \times 1$ and $N_{\text{filter}} \times N_{\text{var}}$, respectively, since the number of filters may be more than one. For example, the s th solution X_s and the f th filter $X_{s,f}$ in X_s are denoted as follows:

$$X_s = \begin{bmatrix} x_{s,1,1} & x_{s,1,2} & L & x_{s,1,N_{\text{var}}} \\ x_{s,2,1} & x_{s,2,2} & L & x_{s,2,N_{\text{var}}} \\ M & M & M & M \\ x_{s,N_{\text{filter}},1} & x_{s,N_{\text{filter}},2} & L & x_{s,N_{\text{filter}},N_{\text{var}}} \end{bmatrix} = \begin{bmatrix} X_{s,1} \\ X_{s,2} \\ M \\ X_{s,N_{\text{filter}}} \end{bmatrix}, \quad (17)$$

where

$$X_{s,f} = [x_{s,f,1}, x_{s,f,2}, \dots, x_{s,f,N_{\text{var}}}] \quad (18)$$

However, overall, the number of filters is equal, that is, N_{filter} for each solution and all generations. However, a greater number of filters do not always guarantee a better fitness value. Hence, we need to record the best number of filters for each solution. Let filter j be the best filter of solution $s = 1, 2, \dots, N_{\text{sol}}$, and define $pFilter[s] = j$ if $F[X_{s,j}] \leq F[X_{s,i}]$ for all $k = 1, 2, \dots, N_{\text{filter}}$. Note that $X_{h,i}$ is the best solution for $pFilter[h] = i$ among all existing solutions if $F[X_{s,f}] \leq F[X_{h,i}]$ for all $s = 1, 2, \dots, N_{\text{sol}}$ and $f = 1, 2, \dots, N_{\text{filter}}$.

In the end, only the best solution (e.g., X_s) and its best number of filters, namely, $X_{s,1}, X_{s,2}, \dots, X_{s,j}$, where $pFilter[s] = j$, are reported. In addition, the update mechanism is based on the best filter in the proposed CSVM. Hence, the solution is self-adapted by the best number of filters.

3.4. One-Solution, One-Filter, One-Variable Greedy SSO Update Mechanism. The proposed new one-solution, one-filter, one-variable greedy SSO update mechanism is discussed in this subsection.

3.4.1. One-Solution Is Selected Randomly to be Updated in Each Generation. In the proposed CSVM, all values in filters are variables that must be determined to implement

convolution products. Without the help from the GPU, it takes a long time to update variables to deepen the SVM. Hence, instead of the traditional algorithms, including SSO, the genetic algorithm (GA), and particle swarm optimization (PSO), of which all solutions need to be updated, only one solution is selected randomly for updating in each generation of the proposed new SSO update mechanism. Let solution s be selected to be updated based on the following equations:

$$s = \begin{cases} gBest, & \text{if } p_{[0,1]} \in [0, C_{g,1}), \\ p_{[1,N_{\text{sol}}]}, & \text{if } p_{[0,1]} \in [C_{g,1}, C_{p,1}), \\ s, & \text{if } p_{[0,1]} \in [C_{p,1}, C_{w,1}), \\ 0, & \text{otherwise.} \end{cases} \quad (19)$$

where $p_{[0,1]}$ is a random floating-point number generated from interval $[0, 1]$ and $p_{[1,N_{\text{sol}}]} \in \{1, 2, \dots, N_{\text{sol}}\}$ is the index of the solution selected randomly, $gBest$ is the index of the best solution found, and the 0 is a new solution generated randomly. The new updated solution X_s will be either discarded or replaced with the old X_s based on the process described next.

3.4.2. One-Filter One-Variable Greedy Update Mechanism. All variables need to be updated, namely, the all-variable update mechanism, in the traditional SSO, and it has a higher probability of escaping the local trap compared to the updates with only some variables. However, the all-variable update mechanism may cause solutions that are near optimums to be kept away from their current positions. Additionally, its runtime is N_{sol} times that of the one-variable update, which selects one variable randomly to be updated. Hence, to reduce the runtime, only one variable in one filter in the solution selected in Section 3.4.1 is updated.

Let s be the solution selected to be updated. In the proposed new SSO, only one filter, for example, f , where $f = 1, 2, \dots, pFilter[s] = j$, in solution s is chosen randomly. Moreover, one variable, for example, $x_{s,f,k}$, where $k = 1, 2, \dots, N_{\text{var}}$, in such filter $X_{s,f}$ is also selected randomly to be updated based on the following simple process:

$$\text{Max}\{\text{Min}\{x_{s,f,k} + 0.05 \cdot p_{[-0.01,0.04]}, 2\}, -2\}, \quad (20)$$

where $p_{[-0.01,0.04]}$ is a the random number generated in the update mechanism, and subscript $[-0.01, 0.04]$ is the lower bound and upper bound for the random number ρ . The interval of ρ is derived from the optimal value of multiple randomized trial and error results. 0.05 is the step size of the local search, in order to ensure that in the local search process to find a fine enough optimal solution. After

resetting all variables in these filters $X_{s, h}$ to a random number generated from $[-2, 2]$ for all $h > f$, we have

$$x_{s,h,l}^* = \begin{cases} x_{s,h,l}, & \text{if } (h < f) \text{ or } (h = f \text{ and } l \neq k), \\ \text{Max}\{\text{Min}\{x_{s,h,l} + 0.05 \cdot \rho_{[-0.01, 0.04]}, 2\}, -2\}, & \text{if } h = f \text{ and } l = k, \\ \rho_{[-2, 2]}, & \text{otherwise.} \end{cases} \quad (21)$$

Also, $F[X_{s, l}] = F[X_{s, f-1}]$ for all $l < f$.

Moreover, the updated solutions X_s^* , including these new updated variables and filters, are all discarded, if their fitness values are not better than that of X_s ; that is,

$$X_s = \begin{cases} X_s, & \text{if } F(X_s) < F(X_s^*), \\ X_s^*, & \text{otherwise.} \end{cases} \quad (22)$$

3.5. Pseudocode of the Proposed SSO. The pseudocode of the proposed SSO based on the new self-adaptive solution structure, *pFilter*, and the new update mechanism are listed in Algorithm 2.

4. Proposed Small-Sample OA to Tune Parameters

It is important to select the most representative combination of parameters to find good results for all algorithms, such as the three parameters C_g, C_p , and C_w in SSO. To reduce the computation burden, a novel concept called small-sample orthogonal array (OA) is proposed in terms of OA test to tune parameters in Section 4.

4.1. OA. The design of experiment (DOE) adopts an array design that arranges the tests and factors in rows and columns, respectively, such that rows and columns are independent of each other, and there is only one test level in each factor level [37]. The DOE is able to select better parameters from some representative predefined combinations to reduce test numbers [2, 38].

The Taguchi OA test, first developed by Taguchi [37], is a DOE that is implemented to achieve the objective of this study. OA is denoted by $L_n(a^b)$, where $n = a^{\lceil \log a(b+1) \rceil}$, a , and b are the numbers of tries, levels of each factor, and factors, respectively. For example, Table 1 represents an OA denoted by $L_9(3^4)$.

From Table 1, we can see that the characteristics of the OA are orthogonal as follows:

- (1) The number of different levels in each column is equal; for example, numbers 1, 2, and 3 appear three times in each column in Table 1.
- (2) All ordered pairs of the two factors for the same test also appear exactly once, for example, (1, 1), (1, 2), (1,

3), (2, 1), (2, 2), (2, 3), (3, 1), (3, 2), and (3, 3) in columns 1 and 2, 1 and 3, 1 and 4, 2 and 3, 2 and 4, and 3 and 4, to ensure that each level is dispersed evenly in the complete combination of each level of factors.

4.2. Proposed Small-Sample OA. There are three major methods for tuning parameters:

- (1) The try-and-error method: It implements the tests exhaustively by trying all possible cases to find the one with the better results. It is the simplest and the most inefficient one.
- (2) The parameter-adapted method: It selects and tests some set of parameters from the existing parameters, which are already used in some applications. This method may have some issues with respect to identifying the characteristics of new problems.
- (3) The DOE: It selects the parameters from the experiment design. Compared to the two aforementioned methods, this method is the most efficient and effective one. However, this method faces an efficiency problem in large datasets or needs to be repeated very often.

Hence, to overcome these aforementioned problems, a novel method called the small-sample OA test is proposed to improve the OA method for tuning parameters. To reduce the runtime, the proposed small-sample OA test only samples few data randomly from the dataset and conducts the OA test on the subsets of such small-sample data to find the best parameters that result in the highest accuracy, the shortest runtime, and/or the largest number of solutions with the maximal number of obtained highest accuracy based on the three following rules:

Rule 1. The one with the highest accuracy among all others;

Rule 2. The one with the shortest runtime, with a big gap between such runtime and others if there is a tie based on Rule 1;

Rule 3. The one with the largest number of solutions that have the highest accuracy if there is a tie based on Rule 2.

Input: The r th record $I_r = [v_{r,1}, v_{r,2}, \dots, v_{r,N_{\text{att}}}]$ and the s th solution X_s .
Output: The $I_r \otimes X_s$.
STEP C0. Let $f=1$ and $v_{r,i,0} = v_{r,j}$ for $i=1, 2, \dots, N_{\text{att}}$.
STEP C1. Let $a=1$, $v_{r,i,f-1} = v_{r,k,f-1}$ for $i=N_{\text{att}}+1, 2, \dots, N_{\text{att}}+N_{\text{var}}-1$, $k=i-N_{\text{att}}$.
STEP C2. Let $b=0$, $i=a$, and $j=1$.
STEP C3. Let $b = b + v_{r,i,f-1} \times x_{s,f,j}$.
STEP C4. If $j < N_{\text{var}}$, let $i=i+1$, $j=j+1$, and go to STEP C3.
STEP C5. If $a < N_{\text{att}}$, let $v_{r,a,f} = b$, $a=a+1$, and go to STEP C2.
STEP C6. If $f < N_{\text{filter}}$, let $f=f+1$ and go to STEP C1.

ALGORITHM 1: Proposed convolution product.

Input: A random selected solution (e.g., X_s) with its $pFilter$.

Output: The updated X_s .

STEP U0. Generate a random number $\rho_{[0,1]}$ from $[0, 1]$ and select a solution, say X_s where $s \in \{1, 2, \dots, N_{\text{sol}}\}$ based on equation (19).

STEP U1. Select a filter, say $X_{s,j}$ where $j \in \{1, 2, \dots, pFilter[s]\}$.

STEP U2. Update X_s to X^* based on equation (21).

STEP U3. Based on equation (22) to decide to let $X_s = X^*$ or discard X^* .

STEP U4. If $X_s = X^*$, let $pFilter[s] = f$, where $F(X_i^*) \leq F(X_f^*)$ for all $i=1, 2, \dots, N_{\text{filter}}$. Otherwise, halt.

STEP U5. If $F(X_{gBest}, pFilter[gBest]) \leq F(X_s, pFilter[s])$, let $gBest = s$.

ALGORITHM 2: Proposed SSO.

TABLE 1: An experiment of four factors with three levels using an OA.

Try ID	Factor 1	Factor 2	Factor 3	Factor 4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Then, this selected parameter set is applied to the rest of the unsampled dataset. The example for this proposed test is provided in Section 6.

5. Proposed CSVM and Traditional SVM

The proposed CSVM is a convolutional SVM modified by employing a new convolution product, which is updated based on the proposed new SSO. The traditional SVM is introduced briefly, and then the proposed pseudocode of the proposed CSVM is presented.

5.1. Traditional SVM. SVMs are excellent machine learning tools for binary classification cases [27, 28]. The purpose of an SVM is to maximize the margin between two support hyperplanes to separate two classes of data. Let $X = \{z_1 = (x_1, y_1), z_2 = (x_2, y_2), \dots, z_n = (x_n, y_n)\}$ be a two-class dataset for training. For example, in a linear SVM, a hyperplane is a line, and we want to find the best hyperplane $W^T X + b = 0$ to separate these two classes of data in X , where W is the weight

vector and b is the bias perpendicular to such hyperplane such that $\|W\|$ is as large as possible. The above linear SVM is a constrained optimization model and it can be written as follows [27, 28]:

$$\begin{aligned} & \text{Max} \|W\|, \\ & \text{s.t. } y_i (W^T x_i + b) \geq 1. \end{aligned} \quad (23)$$

After applying the Lagrange multiplier method to the constrained optimization model, the SVM problem is a convex quadratic programming problem that can be presented as follows [27]:

$$\begin{aligned} & \text{Min} \frac{\|W\|^2}{2} - \sum_{i=1}^l \lambda_i y_i (W^T x_i + b) + \sum_{i=1}^l \lambda_i \\ & \text{s.t. } \lambda_i > 0 \text{ for all } i = 1, 2, \dots, n, \end{aligned} \quad (24)$$

where λ_i is the Lagrange multiplier.

For these high-dimensional data, it is very difficult to find a single linear line to separate two different sets. Hence, these data are mapped into a higher-dimensional space using a function

that is called the kernel in SVM. Then, a hyperplane can be found to separate the mapped data. Here, we list some popular kernel functions [27, 28]:

$$\begin{aligned} K(z_i, z_j) &= (z_i^T z_j + 1)^p, \\ K(z_i, z_j) &= \exp\left[\frac{-\|z_i - z_j\|^2}{(2\sigma^2)}\right], \\ K(z_i, z_j) &= \tanh(kz_i^T z_j - \delta). \end{aligned} \quad (25)$$

For more details of SVM and its development, the reader is referred to [25, 26].

5.2. Pseudocode of the Proposed CSVM. The pseudocode of the proposed CSVM is described below together with the integration of the proposed convolution product discussed in Subsection 2.2, the proposed SSO introduced in Section 3, and the proposed small-sample OA presented in Section 4.2 (Algorithm 3).

6. Experimental Results and Summary

There are two experiments, Ex1 and Ex2, in this study. Ex1 is based on the proposed small-sample OA concept to find the parameters C_g , C_p , C_w , N_{gen} , N_{filter} , and N_{var} in the proposed CSVM. Then, these parameters are employed in Ex2 to conduct an extension test to compare these results with those obtained from the DSCM, SVM, 3-layer ANN, and 4-layer ANN, respectively.

6.1. Simulation Environment. Four algorithms are developed and adapted in this study including the proposed CSVM, SVM, the 3-layer ANN, and the 4-layer ANN. The proposed CSVM is implemented using Dev C++ Version 5.11 C/C++, and the SVM part is integrated by calling the libsvm library [28] with all default setting parameters. The codes of both the 3-layer and 4-layer ANNs are modified using the source code provided in [39], which is coded in Python and run in Anaconda with `epochs=150`, `batch_size=10`, `loss="binary_crossentropy"`, `optimizer="Adam"`, `activation="ReLU"` and 12 neurons in the first hidden layer, and `activation="sigmoid"` in the second hidden layer of the 4-layer ANN. The test environment is Intel (R) Core (TM) i9-9900K CPU @ 3.60 GHz, 32.0 GB memory, and 64-bit Windows 10.

To validate the proposed CSVM, the proposed CSVM was compared with the traditional SVM and the 3-layer and 4-layer ANNs on five well-known datasets: "Australian Credit Approval" (A), "breast-cancer" (B), "diabetes" (D), "fourclass" (F), and "Heart Disease" (H) [34] based on a tenfold cross-validation in Ex2. Summary of the five datasets is provided in Table 2. A brief introduction of the datasets is as follows:

"Australian Credit Approval" (A): this file concerns credit card applications. This database exists elsewhere in the repository (Credit Screening Database) in a

slightly different form. This dataset is interesting because there is a good mix of attributes-continuous, nominal with small numbers of values, and nominal with larger numbers of values. There are also a few missing values.

"breast-cancer" (B): the term "breast cancer" refers to a malignant tumor that has developed from cells in the breast. It is the most common cancer among women in almost all parts of the world. The used dataset consists of 699 instances that were classified as benign and malignant. Also, the dataset has 11 integer-valued attributes.

"diabetes" (D): diabetes mellitus is one of the most serious health challenges in both developing and developed countries. Diabetes dataset that we used contains 8 categories and 768 instances and records on diabetes patients (several weeks to months worth of glucose, insulin, and lifestyle data per patient and a description of the problem domain), gathered from larger databases belonging to the National Institute of Diabetes and Digestive and Kidney Diseases.

"fourclass" (F): the dataset has irregular spreads over the space including disconnected regions and they are not linearly separable. A four-class nonlinearly separable dataset consists of 862 pieces of data and 2 dimensions.

"Heart Disease" (H): heart attack diseases remain the main cause of death worldwide, including South Africa, and possible detection at an earlier stage will prevent the attacks. This database contains 76 attributes, but all published experiments refer to using a subset of 14 of them. In particular, the Cleveland database is the only one that has been used by ML researchers to this date.

Let Φ , T , G , f , and N be the highest accuracy levels obtained in the end, the runtime, the earliest generation that obtained Φ , the number of filters generating Φ , and the number of solutions that have Φ , respectively. To be easily recognized, the subscripts 25, 50, 75, 100, avg, max, min, and std represent the related values obtained at the end of the 25th, 50th, 75th, and 100th generations, the average, the maximum, minimum, and the standard deviation, respectively.

6.2. Ex1: Small-Sample OA Test. The orthogonal array used in this study is called $L_9(3^4)$ as shown in Table 3.

In $L_9(3^4)$, there are nine tries and four factors: $C = (C_g, C_p, C_w, C_r)$, N_{sol} , N_{var} , and N_{filter} ; each factor has three levels as shown in Table 4. The higher the level, the larger related values with the exception of C ; for example, in level 1, $N_{\text{sol}}=25$ is smaller than that in level 2. The most distinguishable difference among all three levels in C of Table 3 is that level 2 has higher c_r which is to increase the global search ability, while level 3 has the lower value of c_r to enhance the local search ability.

The results obtained from the proposed CSVM in terms of the proposed small-sample OA test are listed in Table 5, in which each try is run fifteen times, where the larger N_{filter}

PROCEDURE CSVMO

Input: A dataset.**Output:** The accuracy of the classifier CSVMO.**STEP 0.** Separate the dataset into k folds randomly, and then select one-fold (e.g., the k *th fold of the dataset); for the small-sample OA, it has N tries.**STEP 1.** Implement CSVMO (i, k *) using the i th parameter setting on the k *th fold of the dataset for $i = 1, 2, \dots, N$, and then let the parameter setting of the try (e.g., i *) with the highest accuracy among all N tries.**STEP 2.** Implement CSVMO (i *, j) on the j th fold of the dataset using the parameter setting of the i *th try for $j = 1, 2, \dots, k$.**PROCEDURE CSVMO** (α, β)**Input:** The parameter setting in the α th try of the small-sample OA and the β th fold of the dataset.**Output:** The accuracy.**STEP W0.** Generate solutions X_s randomly, then calculate $F(X_s, f)$ based on the proposed convolution product and the SVM. Find $pFilter[s]$ and $gBest$ such that $F(X_{gBest}, pFilter[gBest]) \geq F(X_s, f)$, where $s = 1, 2, \dots, N_{sol}$ and $f = 1, 2, \dots, N_{filter}$.**STEP W1.** Let $t = 1$.**STEP W2.** Update a randomly selected solution based on the pseudocode of the new SSO provided in Subsection 3.5 and the parameter setting in the α th try of OA.**STEP W3.** Increase the value of t by 1, that is, let $t = t + 1$, and then go to STEP W2 if $t < N_{gen}$.**STEP W4.** Halt, $F(X_{gBest}, pFilter[gBest])$ is the accuracy, and $X_{gBest}, pFilter[gBest]$ is the classifier.

ALGORITHM 3: Proposed CSVMO.

TABLE 2: Information and characteristics of the five datasets.

ID	Full name	Record number	Attribute number	Attribute characteristics
A	Australian Credit Approval	690	14	Integer, real
B	breast-cancer	699	10	Integer, real
D	Diabetes	768	8	Integer, real
F	fourclass	862	2	Integer, real
H	Heart Disease	270	13	Integer, real

TABLE 3: L_9 (3^4).

Try	N_{filter}	N_{sol}	N_{var}	(C_g, C_p, C_w, C_r)
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	3	2	1
5	2	3	3	2
6	2	1	1	3
7	3	2	3	1
8	3	3	1	2
9	3	1	2	3

TABLE 4: Levels of all-factor test for selecting the parameters.

Level code	N_{filter}	N_{sol}	N_{var}	$C = (C_g, C_p, C_w, C_r)$
1	1	25	$\lceil N_{att}/4 \rceil$	(0.40, 0.30, 0.20, 0.10)
2	3	50	$\lceil 2N_{att}/4 \rceil$	(0.35, 0.25, 0.15, 0.25)
3	4	75	$\lceil 3N_{att}/4 \rceil$	(0.45, 0.30, 0.20, 0.05)

N_{sol} , N_{var} , and/or N_{gen} , the longer the runtime. However, it is not necessary to have better fitness values from Table 5. For example, the best fitness value has already been found in G_{25} , namely, $F_{25} = F_{50} = F_{75}$, in all datasets except Dataset D whose best fitness value is found in G_{75} .

Adhering to Rule 1 listed in Section 4, only the try with the highest accuracy ϕ is selected to be used for the rest of the unsampled dataset. In this case, Try 7 is selected for Dataset D, since the greatest accuracy is obtained from Try 7 in G_{75} .

From Rule 2, the runtime T must be considered if there are two tries tied in accuracy. For example, both Try 5 and Try 9 have the highest accuracy in Dataset A, but Try 5 is selected, since its runtime is only 43.43, which is considerably less than the runtime (149.28) of Try 9. Similarly, Try 7 and Try 1 are selected for Datasets B and H, respectively. The parameter setting for the rest of datasets, namely, Dataset F, is based on Rule 3, and Try 5 is selected in accordance with Rule 2.

Hence, we obtain the parameter settings listed in Table 6.

In Dataset *F*, there are only two attributes resulting in also two variables in each filter of Table 6. Another observation is that the values N_{filter} , N_{var} , N_{sol} , and N_{gen} are always the smallest, since all the best final fitness values are equal to 88.00000 regardless of the generation number. Then, the parameter setting with less runtime is selected, which is reasonable. This is similar to Dataset B whose solution number is only 25, with less local search ability.

In Table 5, the accuracy levels obtained from SVM for the first fold of each dataset are listed in the last second column named $100F_{\text{SVM}}$. From Table 5, all values in $F_{N_{\text{gen}}}$ are better than those in the corresponding F_{SVM} . Moreover, also from Table 5, all fitness values obtained from G_{25} , namely, F_{25} , are already at least equal to F_{SVM} ; that is, $F_{\text{SVM}} \leq F_{25} \leq F_{50} \leq F_{75} \leq F_{100}$. Hence, the proposed CSVM outperforms the traditional SVM in the small-sample OA, and the wide discrepancy between the final performances of the CSVM and the SVM is further reinforced in Subsection 6.3 using the parameters setting from the proposed small-sample OA.

6.3. *Ex2*. The results for G_{100} are collected to evaluate the effectiveness of the concept of the proposed small-sample OA and verify any possible effects on the average and the best fitness values of higher generation numbers. The complete data including the average, best, worst, and standard deviation of fitness of each fold for each dataset are listed in Tables 7–11.

6.3.1. *Boxplots of the Experimental Results from Ex2*. Both results obtained from the 3-layer and 4-layer ANNs are the least favorable with a big gap between the proposed CSVM and the traditional SVM. Hence, these two ANN-based methods are not discussed further, and we only focus on the proposed CSVM and the traditional SVM.

We determined that the higher the generation number, the better average fitness value. However, it can be observed that the best fitness value remains unchanged from G_{75} to G_{100} except for the 8th fold in Dataset A, the 1st and 10th folds in Dataset B, and the 5th fold in Dataset F. Therefore, $N_{\text{gen}} = 75$ is acceptable and there is no need for $N_{\text{gen}} = 100$ to increase the fitness value of the best solution. The position (the fitness values obtained) and the length (the range of the fitness values) of box in G_{100} are frequently higher and shorter than those of G_{25} in most boxplots. Hence, a larger generation number has a higher probability of enhancing the average solution quality under the cost of the longer runtime but ultimately does little to improve the best fitness value.

6.3.2. *Number of Folds for Finding the Final Best Fitness Values*. Table 12 lists the number of folds that have found the final best fitness values. The subscripts of dataset ID in the first column of Table 12 indicate the generation number used in Ex 2; for example, B_{25} indicates that 25 generations are used for Dataset B based on the parameters obtained with small-sample OA in Ex 1. Folds 7, 8, 10, 8, and 10 (see bold

numbers in Table 12) under G_{25} , G_{25} , G_{75} , G_{25} , and G_{25} in Datasets A, B, D, F, and H, respectively, have found the best final fitness values.

The folds written as subscripts indicate the final best fitness values that have failed to be found. For example, $7_{1,4,7}$ in G_{25} , A_{25} represents that there are seven folds (from the ten folds) that have already found the best fitness values after 25 generations with the remaining three folds 1, 4, and 7 failing to do so in Dataset A.

To calculate the probability of the best final fitness value in Table 12, we add the folds ($7 + 8 + 10 + 8 + 10$) and divide the product by the total number of folds (50) in Table 6 to get 86%, which informs us that the probability of finding the best final fitness value without reaching G_{100} , which entails a significantly longer runtime, is 86%.

Hence, the proposed small-sample OA is effective in setting parameters to increase the efficiency and solution quality of the proposed CSVM. The above observation further confirms that having better parameters ultimately negates the need for a greater generation number to increase the fitness of the best solution.

6.3.3. *ANOVA of the Experimental Results*. To investigate the small-sample OA, the Analysis of Variance (ANOVA) is carried out to test the average fitness obtained from the proposed CSVM in terms of the parameters set by the small-sample OA, as shown in Table 13. The cells marked with “v” indicate that there is a significant gap between the pair of distinctive generation numbers listed in their respective rows in the fold denoted by the column. This is reinforced through the distinct difference between the average fitness values obtained from G_{25} and G_{75} in all folds of Dataset A.

From Table 13, the minimal generation numbers should be 75 and 50 for only Datasets A and F, respectively, with an insignificant gap between the fitness values in each fold. Hence, the proposed small-small OA is still effective in determining the generation number to reduce the significant difference among all fitness values; even it focuses only on the best fitness value and not the average fitness value that we found.

6.3.4. *MPI of the Experimental Results*. To further investigate the development of the proposed CSVM, two other indices, the average maximum possible improvement ($\text{MPI}_{\text{avg}}\%$) and the best maximum possible improvement ($\text{MPI}_{\text{max}}\%$), are introduced and defined as

$$\text{MPI}_{\text{avg}}\% = \frac{(\text{the average fitness obtained} - F_{\text{SVM}})}{1 - F_{\text{SVM}}}, \quad (26)$$

$$\text{MPI}_{\text{max}}\% = \frac{(\text{the best fitness obtained} - F_{\text{SVM}})}{1 - F_{\text{SVM}}}.$$

The $\text{MPI}_{\text{avg}}\%$ and $\text{MPI}_{\text{max}}\%$ results are listed in Tables 14 and 15, respectively, where the cells marked “*” indicate that both the related F_{svm} and the average and/or the best fitness obtained are 100% correct, for example, the 2nd, 4th, and 5th folds in Dataset B in Table 14. The bold numbers denote the

TABLE 5: Levels of all-factor test for selecting the parameters.

ID	Try	T_{25}	G_{25}	f_{25}	N_{25}	100F ₂₅	T_{50}	G_{50}	f_{50}	N_{50}	100F ₅₀	T_{75}	G_{75}	f_{75}	N_{75}	100F ₇₅
A ²	1	13.09	7	1	12	85.00000	26.11	19	1	1	86.66666	39.07	19	1	1	86.66666
	2	27.68	9	1	1	88.33334	55.33	13	1	1	88.33334	82.59	28	1	2	88.33334
	3	42.81	4	1	4	88.33334	86.04	11	1	5	88.33334	128.39	26	1	6	88.33334
	4	130.54	6	3	13	88.33334	260.18	11	3	15	88.33334	389.33	11	3	15	88.33334
	5	43.44	6	3	1	90.00000	87.39	14	3	1	90.00000	131.20	14	3	1	90.00000
	6	84.35	7	3	15	86.66666	168.38	13	3	2	88.33334	252.73	27	3	3	88.33334
	7	149.28	8	5	4	90.00000	298.47	15	5	6	90.00000	447.50	24	5	7	90.00000
	8	215.83	9	5	14	88.33334	427.65	9	5	14	88.33334	637.65	21	5	1	88.33334
	9	113.32	9	5	8	88.33334	225.84	18	5	11	88.33334	337.70	25	5	15	88.33334
B ²	1	16.03	6	1	13	97.05882	31.99	6	1	13	97.05882	47.83	26	1	14	97.05882
	2	33.41	5	1	15	97.05882	67.26	5	1	15	97.05882	101.45	5	1	15	97.05882
	3	51.63	6	1	15	97.05882	103.01	6	1	15	97.05882	155.17	6	1	15	97.05882
	4	160.82	0	3	15	97.05882	324.22	0	3	15	97.05882	485.32	0	3	15	97.05882
	5	53.08	2	3	15	97.05882	106.13	2	3	15	97.05882	159.76	2	3	15	97.05882
	6	103.51	0	3	15	97.05882	209.98	0	3	15	97.05882	316.64	0	3	15	97.05882
	7	185.49	0	5	15	97.05882	372.27	17	5	1	98.52941	558.38	17	5	1	98.52941
	8	271.51	9	5	1	98.52941	542.93	9	5	1	98.52941	815.96	9	5	1	98.52941
	9	91.88	5	5	1	98.52941	184.50	17	5	2	98.52941	276.67	17	5	2	98.52941
D ¹	1	22.70	0	1	15	78.08219	45.41	0	1	15	78.08219	68.09	0	1	15	78.08219
	2	45.36	8	1	8	80.82191	90.93	19	1	11	80.82191	136.65	21	1	12	80.82191
	3	68.45	4	1	2	82.19178	137.29	13	1	2	82.19178	206.65	27	1	4	82.19178
	4	207.15	8	3	2	82.19178	416.77	19	3	5	82.19178	624.94	29	3	6	82.19178
	5	68.42	9	3	3	82.19178	137.33	17	3	5	82.19178	206.86	29	3	6	82.19178
	6	136.61	9	3	7	80.82191	274.81	15	3	10	80.82191	412.70	23	3	12	80.82191
	7	232.55	6	5	6	82.19178	464.95	18	4	10	82.19178	696.72	25	5	1	83.56165
	8	345.07	4	5	15	80.82191	691.15	4	5	15	80.82191	1037.06	4	5	15	80.82191
	9	114.58	9	5	1	82.19178	230.88	18	5	2	82.19178	347.32	29	5	5	82.19178
F ³	1	19.82	0	1	15	80.23256	39.71	0	1	15	80.23256	59.61	0	1	15	80.23256
	2	39.97	0	1	15	80.23256	80.54	0	1	15	80.23256	121.10	0	1	15	80.23256
	3	61.63	9	1	12	83.72093	123.97	19	1	14	83.72093	186.52	22	1	15	83.72093
	4	181.25	0	1	15	80.23256	364.80	0	1	15	80.23256	548.34	0	1	15	80.23256
	5	62.05	6	3	15	83.72093	124.67	6	3	15	83.72093	187.85	6	3	15	83.72093
	6	120.07	0	1	15	80.23256	242.21	0	1	15	80.23256	364.72	0	1	15	80.23256
	7	211.59	2	5	15	83.72093	424.27	2	5	15	83.72093	637.24	2	5	15	83.72093
	8	303.38	0	1	15	80.23256	610.26	0	1	15	80.23256	918.33	0	1	15	80.23256
	9	100.15	0	1	15	80.23256	202.20	0	1	15	80.23256	304.68	0	1	15	80.23256
H ²	1	12.58	8	1	10	88.00000	26.11	19	1	11	88.00000	39.67	24	1	13	88.00000
	2	26.09	9	1	10	88.00000	54.12	19	1	14	88.00000	81.41	26	1	15	88.00000
	3	40.98	9	1	5	88.00000	82.38	16	1	7	88.00000	124.00	28	1	9	88.00000
	4	122.50	6	3	14	88.00000	244.67	6	3	14	88.00000	366.86	6	3	14	88.00000
	5	39.94	8	3	10	88.00000	80.13	8	3	10	88.00000	122.23	24	3	12	88.00000
	6	79.05	5	3	12	88.00000	160.39	16	3	15	88.00000	241.89	16	3	15	88.00000
	7	136.33	8	5	12	88.00000	273.14	15	5	13	88.00000	409.73	21	5	14	88.00000
	8	203.64	7	5	15	88.00000	407.86	7	5	15	88.00000	612.67	7	5	15	88.00000
	9	68.08	9	5	8	88.00000	135.69	17	5	9	88.00000	203.97	25	5	12	88.00000

¹Select the setting based on Rule 1. ²Select the setting based on Rule 2. ³Select the setting based on Rule 3.

best values among all folds for each dataset under the same generation number. Note that a value of 100, as in the 7th fold of Dataset B in Table 15, indicates that the related accuracy is 100%.

As shown in Tables 14 and 15, the results obtained from the proposed CSVM are at least 14.96% and 20.17%, with at most a 50.68% and 63.10% improvement in MPI_{avg}% and

MPI_{max}%, respectively. The results shed light on the effectiveness of the proposed CSVM in comparison with the traditional SVM. It can be also observed that the more attributes, the greater the results obtained from the proposed CSVM regardless of the number of records. Ultimately, compared to the traditional SVM, the proposed CSVM is more suitable for small data.

TABLE 6: Parameters used in the proposed CSVM.

ID	Try ID	N_{rec}	N_{att}	N_{filter}	N_{sol}	N_{var}	(C_g, C_p, C_w, C_r)	N_{gen}	100F _{SVM}	100F _{Ngen}	T
A	5	690	14	3	75	$[3N_{\text{att}}/4] = 11$	(0.35, 0.25, 0.15, 0.25)	25	81.666664	90.00000	43.44
B	9	699	10	4	25	$[2N_{\text{att}}/4] = 5$	(0.45, 0.30, 0.20, 0.05)	25	95.588234	98.52941	91.88
D	7	768	8	4	50	$[3N_{\text{att}}/4] = 6$	(0.40, 0.30, 0.20, 0.10)	75	76.712326	83.56165	696.72
F	5	862	2	3	75	$[3N_{\text{att}}/4] = 2$	(0.35, 0.25, 0.15, 0.25)	25	80.232559	83.72093	62.05
H	1	270	13	1	25	$[N_{\text{att}}/4] = 4$	(0.40, 0.30, 0.20, 0.10)	25	80.000000	88.00000	12.58

TABLE 7: The results obtained based on the Australian Credit Approval dataset.

Fold	Index	SVM	F ₂₅	F ₅₀	F ₇₅	F ₁₀₀
1	AVG	81.666664	90.222222	90.722221	90.944444	91.277776
	MAX	81.666664	91.666664	93.333336	93.333336	93.333336
	MIN	81.666664	88.333336	88.333336	90.000000	90.000000
	STDEV	0.000000	1.048015	1.043436	1.043437	0.947201
2	AVG	92.156860	96.732025	97.254901	97.516339	97.647058
	MAX	92.156860	98.039215	98.039215	98.039215	98.039215
	MIN	92.156860	96.078430	96.078430	96.078430	96.078430
	STDEV	0.000000	0.940124	0.977006	0.881915	0.797722
3	AVG	83.116882	92.987014	93.463204	93.982685	94.112555
	MAX	83.116882	96.103897	96.103897	96.103897	96.103897
	MIN	83.116882	90.909088	90.909088	90.909088	90.909088
	STDEV	0.000000	1.430810	1.426060	1.543568	1.552959
4	AVG	92.187500	93.750000	93.802083	93.802083	93.958333
	MAX	92.187500	93.750000	95.312500	95.312500	95.312500
	MIN	92.187500	93.750000	93.750000	93.750000	93.750000
	STDEV	0.000000	0.000000	0.285272	0.285272	0.540228
5	AVG	87.878792	93.787877	94.090907	94.242422	94.292928
	MAX	87.878792	95.454544	95.454544	95.454544	95.454544
	MIN	87.878792	92.424240	92.424240	93.939392	93.939392
	STDEV	0.000000	0.728274	0.728274	0.616422	0.651793
6	AVG	80.701752	87.076024	87.602340	87.660820	87.719299
	MAX	80.701752	87.719299	87.719299	87.719299	87.719299
	MIN	80.701752	84.210526	85.964912	85.964912	87.719299
	STDEV	0.000000	0.975533	0.445102	0.320306	0.000000
7	AVG	82.278481	91.308018	91.856540	91.983121	92.151897
	MAX	82.278481	92.405060	93.670883	93.670883	93.670883
	MIN	82.278481	88.607597	91.139244	91.139244	91.139244
	STDEV	0.000000	1.037095	0.719390	0.691987	0.697290
8	AVG	85.135132	90.405406	90.720722	90.810812	91.126127
	MAX	85.135132	91.891891	91.891891	91.891891	93.243240
	MIN	85.135132	89.189186	89.189186	90.540543	90.540543
	STDEV	0.000000	0.740167	0.586719	0.549780	0.768000
9	AVG	86.419754	93.333334	93.744858	93.991772	94.156381
	MAX	86.419754	95.061729	95.061729	95.061729	95.061729
	MIN	86.419754	92.592590	92.592590	92.592590	93.827164
	STDEV	0.000000	0.695363	0.555281	0.536015	0.555279
10	AVG	85.185188	90.370371	90.617285	90.823046	91.028807
	MAX	85.185188	91.358025	91.358025	92.592590	92.592590
	MIN	85.185188	88.888885	88.888885	90.123459	90.123459
	STDEV	0.000000	0.753404	0.695360	0.701629	0.720113

TABLE 8: The results obtained based on the breast-cancer dataset.

Fold	Index	SVM	F ₂₅	F ₅₀	F ₇₅	F ₁₀₀
1	AVG	95.588234	98.529411	98.529411	98.529411	98.578431
	MAX	95.588234	98.529411	98.529411	98.529411	100.000000
	MIN	95.588234	98.529411	98.529411	98.529411	98.529411
	STDEV	0.000000	0.000000	0.000000	0.000000	0.268492
2	AVG	100.000000	100.000000	100.000000	100.000000	100.000000
	MAX	100.000000	100.000000	100.000000	100.000000	100.000000
	MIN	100.000000	100.000000	100.000000	100.000000	100.000000
	STDEV	0.000000	0.000000	0.000000	0.000000	0.000000
3	AVG	95.588234	97.303921	97.499999	97.598038	97.745097
	MAX	95.588234	98.529411	98.529411	98.529411	98.529411
	MIN	95.588234	97.058823	97.058823	97.058823	97.058823
	STDEV	0.000000	0.557425	0.685429	0.720783	0.746201
4	AVG	100.000000	100.000000	100.000000	100.000000	100.000000
	MAX	100.000000	100.000000	100.000000	100.000000	100.000000
	MIN	100.000000	100.000000	100.000000	100.000000	100.000000
	STDEV	0.000000	0.000000	0.000000	0.000000	0.000000
5	AVG	100.000000	100.000000	100.000000	100.000000	100.000000
	MAX	100.000000	100.000000	100.000000	100.000000	100.000000
	MIN	100.000000	100.000000	100.000000	100.000000	100.000000
	STDEV	0.000000	0.000000	0.000000	0.000000	0.000000
6	AVG	94.117645	97.058823	97.058823	97.058823	97.058823
	MAX	94.117645	97.058823	97.058823	97.058823	97.058823
	MIN	94.117645	97.058823	97.058823	97.058823	97.058823
	STDEV	0.000000	0.000000	0.000000	0.000000	0.000000
7	AVG	95.588234	97.892156	98.039215	98.284313	98.333333
	MAX	95.588234	100.000000	100.000000	100.000000	100.000000
	MIN	95.588234	97.058823	97.058823	97.058823	97.058823
	STDEV	0.000000	0.920680	0.891880	0.870726	0.840216
8	AVG	98.529411	98.529411	98.529411	98.529411	98.529411
	MAX	98.529411	98.529411	98.529411	98.529411	98.529411
	MIN	98.529411	98.529411	98.529411	98.529411	98.529411
	STDEV	0.000000	0.000000	0.000000	0.000000	0.000000
9	AVG	94.117645	98.529411	98.529411	98.529411	98.529411
	MAX	94.117645	98.529411	98.529411	98.529411	98.529411
	MIN	94.117645	98.529411	98.529411	98.529411	98.529411
	STDEV	0.000000	0.000000	0.000000	0.000000	0.000000
10	AVG	97.183098	97.183098	97.183098	97.183098	97.230046
	MAX	97.183098	97.183098	97.183098	97.183098	98.591553
	MIN	97.183098	97.183098	97.183098	97.183098	97.183098
	STDEV	0.000000	0.000000	0.000000	0.000000	0.257148

TABLE 9: The results obtained based on the Diabetes dataset.

Fold	Index	SVM	F ₂₅	F ₅₀	F ₇₅	F ₁₀₀
1	AVG	76.712326	83.515981	83.926940	84.018263	84.018263
	MAX	76.712326	84.931503	84.931503	84.931503	84.931503
	MIN	76.712326	80.821915	80.821915	80.821915	80.821915
	STDEV	0.000000	1.271038	1.133810	1.156413	1.156413
2	AVG	76.811592	82.512076	82.946859	83.140096	83.236714
	MAX	76.811592	85.507248	85.507248	85.507248	85.507248
	MIN	76.811592	79.710144	81.159416	81.159416	81.159416
	STDEV	0.000000	1.314764	1.054974	1.041153	0.983928
3	AVG	82.022469	86.404494	86.666666	86.891385	86.891385
	MAX	82.022469	87.640450	87.640450	87.640450	87.640450
	MIN	82.022469	85.393257	85.393257	85.393257	85.393257
	STDEV	0.000000	0.743555	0.765669	0.681437	0.681437

TABLE 9: Continued.

Fold	Index	SVM	F ₂₅	F ₅₀	F ₇₅	F ₁₀₀
4	AVG	76.470589	79.558825	79.705884	79.803923	79.852943
	MAX	76.470589	80.882355	80.882355	80.882355	80.882355
	MIN	76.470589	79.411766	79.411766	79.411766	79.411766
	STDEV	0.000000	0.448719	0.598292	0.661436	0.685429
5	AVG	71.232880	71.278542	71.324203	71.369865	71.369865
	MAX	71.232880	72.602737	72.602737	72.602737	72.602737
	MIN	71.232880	71.232880	71.232880	71.232880	71.232880
	STDEV	0.000000	0.250101	0.347544	0.417983	0.417983
6	AVG	68.292686	71.138209	71.910567	72.154470	72.154470
	MAX	68.292686	73.170731	73.170731	73.170731	73.170731
	MIN	68.292686	69.512192	70.731705	70.731705	70.731705
	STDEV	0.000000	0.924510	0.815458	0.852356	0.852356
7	AVG	82.558144	82.558144	82.596903	82.596903	82.635663
	MAX	82.558144	82.558144	83.720932	83.720932	83.720932
	MIN	82.558144	82.558144	82.558144	7.000000	82.558144
	STDEV	0.000000	0.000000	0.212295	0.212295	0.295009
8	AVG	71.428574	74.025972	74.329003	74.632034	74.805194
	MAX	71.428574	75.324677	75.324677	75.324677	75.324677
	MIN	71.428574	71.428574	72.727272	72.727272	72.727272
	STDEV	0.000000	1.023167	0.881703	0.742010	0.731485
9	AVG	80.519478	83.246752	83.679652	83.852811	83.939391
	MAX	80.519478	84.415581	84.415581	84.415581	84.415581
	MIN	80.519478	81.818184	81.818184	81.818184	83.116882
	STDEV	0.000000	0.859431	0.738077	0.738077	0.636534
10	AVG	78.378380	84.009009	84.594594	84.909910	85.000000
	MAX	78.378380	87.837837	87.837837	87.837837	87.837837
	MIN	78.378380	82.432434	82.432434	82.432434	82.432434
	STDEV	0.000000	1.378265	1.610712	1.590385	1.677734

TABLE 10: The results obtained based on the fourclass dataset.

Fold	Index	SVM	F ₂₅	F ₅₀	F ₇₅	F ₁₀₀
1	AVG	80.232559	86.240310	87.015504	87.248062	87.403101
	MAX	80.232559	88.372093	88.372093	88.372093	88.372093
	MIN	80.232559	83.720932	83.720932	84.883720	84.883720
	STDEV	0.000000	1.674868	1.262130	1.201573	1.104529
2	AVG	79.000000	81.133333	81.333333	81.433333	81.533333
	MAX	79.000000	82.000000	82.000000	82.000000	82.000000
	MIN	79.000000	81.000000	81.000000	81.000000	81.000000
	STDEV	0.000000	0.345746	0.479463	0.504007	0.507416
3	AVG	75.862068	81.072795	81.417622	81.494250	81.570878
	MAX	75.862068	82.758621	82.758621	82.758621	82.758621
	MIN	75.862068	78.160919	78.160919	78.160919	80.459770
	STDEV	0.000000	0.839420	0.744504	0.698190	0.367634
4	AVG	81.818184	83.863637	84.166668	84.356062	84.659091
	MAX	81.818184	86.363632	86.363632	86.363632	86.363632
	MIN	81.818184	82.954544	82.954544	82.954544	82.954544
	STDEV	0.000000	0.811801	0.891949	0.879379	0.882748
5	AVG	82.857140	84.285713	84.285713	84.285713	84.333332
	MAX	82.857140	84.285713	84.285713	84.285713	85.714287
	MIN	82.857140	84.285713	84.285713	84.285713	84.285713
	STDEV	0.000000	0.000000	0.000000	0.000000	0.260821
6	AVG	81.914894	82.978722	83.014183	83.049644	83.085105
	MAX	81.914894	82.978722	84.042557	84.042557	84.042557
	MIN	81.914894	82.978722	82.978722	82.978722	82.978722
	STDEV	0.000000	0.000000	0.194229	0.269904	0.324607

TABLE 10: Continued.

Fold	Index	SVM	F ₂₅	F ₅₀	F ₇₅	F ₁₀₀
7	AVG	85.897438	85.897438	85.897438	85.897438	85.897438
	MAX	85.897438	85.897438	85.897438	85.897438	85.897438
	MIN	85.897438	85.897438	85.897438	85.897438	85.897438
	STDEV	0.000000	0.000000	0.000000	0.000000	0.000000
8	AVG	71.428574	77.752811	77.940077	74.632034	78.127343
	MAX	71.428574	78.651688	78.651688	75.324677	78.651688
	MIN	71.428574	77.528091	77.528091	72.727272	77.528091
	STDEV	0.000000	0.457122	0.550711	0.742010	0.570131
9	AVG	80.519478	84.573643	85.155038	83.852811	85.465115
	MAX	80.519478	86.046509	86.046509	84.415581	86.046509
	MIN	80.519478	81.395348	82.558144	81.818184	83.720932
	STDEV	0.000000	1.363349	1.043759	0.738077	0.732235
10	AVG	78.378380	89.285713	89.285713	84.909910	89.285713
	MAX	78.378380	89.285713	89.285713	87.837837	89.285713
	MIN	78.378380	89.285713	89.285713	82.432434	89.285713
	STDEV	0.000000	0.000000	0.000000	1.590385	0.000000

TABLE 11: The results obtained based on the Heart Disease dataset.

Fold	Index	SVM	F ₂₅	F ₅₀	F ₇₅	F ₁₀₀
1	AVG	80.000000	88.400000	88.533333	88.933333	89.066667
	MAX	80.000000	92.000000	92.000000	92.000000	92.000000
	MIN	80.000000	88.000000	88.000000	88.000000	88.000000
	STDEV	0.000000	1.220514	1.382984	1.720732	1.799106
2	AVG	82.758621	96.321842	96.436785	96.551727	96.551727
	MAX	82.758621	96.551727	96.551727	96.551727	96.551727
	MIN	82.758621	93.103447	93.103447	96.551727	96.551727
	STDEV	0.000000	0.874857	0.629567	0.000000	0.000000
3	AVG	82.758621	89.655174	89.770117	89.770117	89.770117
	MAX	82.758621	89.655174	93.103447	93.103447	93.103447
	MIN	82.758621	89.655174	89.655174	89.655174	89.655174
	STDEV	0.000000	0.000000	0.629566	0.629566	0.629566
4	AVG	88.235291	92.745096	93.235292	93.431371	93.431371
	MAX	88.235291	94.117645	94.117645	94.117645	94.117645
	MIN	88.235291	91.176468	91.176468	91.176468	91.176468
	STDEV	0.000000	1.492401	1.370858	1.265245	1.265245
5	AVG	100.000000	100.000000	100.000000	100.000000	100.000000
	MAX	100.000000	100.000000	100.000000	100.000000	100.000000
	MIN	100.000000	100.000000	100.000000	100.000000	100.000000
	STDEV	0.000000	0.000000	0.000000	0.000000	0.000000
6	AVG	80.000000	93.500000	94.666667	94.833333	95.000000
	MAX	80.000000	95.000000	95.000000	95.000000	95.000000
	MIN	80.000000	90.000000	90.000000	90.000000	95.000000
	STDEV	0.000000	2.330458	1.268541	0.912871	0.000000
7	AVG	82.608696	95.652176	95.797103	95.797103	95.797103
	MAX	82.608696	100.000000	100.000000	100.000000	100.000000
	MIN	82.608696	91.304352	95.652176	95.652176	95.652176
	STDEV	0.000000	1.141795	0.793800	0.793800	0.793800
8	AVG	89.285713	89.880951	90.476189	90.714284	91.071426
	MAX	89.285713	92.857140	92.857140	92.857140	92.857140
	MIN	89.285713	89.285713	89.285713	89.285713	89.285713
	STDEV	0.000000	1.353746	1.712368	1.779545	1.816240
9	AVG	75.000000	86.203707	86.388892	86.481484	86.481484
	MAX	75.000000	88.888885	88.888885	88.888885	88.888885
	MIN	75.000000	86.111115	86.111115	86.111115	86.111115
	STDEV	0.000000	0.507149	0.847577	0.960403	0.960403

TABLE 14: The $100 \times \text{MPI}_{\text{avg}}\%$.

		1	2	3	4	5	6	7	8	9	10	Avg
A	F ₂₅	46.67	58.33	58.46	20.00	48.75	33.03	50.95	35.46	50.91	35.00	43.76
	F ₅₀	49.39	65.00	61.28	20.67	51.25	35.76	54.05	37.58	53.94	36.67	46.56
	F ₇₅	50.61	68.33	64.36	20.67	52.50	36.06	54.76	38.18	55.76	38.06	47.93
	F ₁₀₀	52.42	70.00	65.13	22.67	52.92	36.36	55.71	40.30	56.97	39.44	49.19
B	F ₂₅	66.67	*	38.89	*	*	50.00	52.22	0.00	75.00	0.00	40.40
	F ₅₀	66.67	*	43.33	*	*	50.00	55.56	0.00	75.00	0.00	41.51
	F ₇₅	66.67	*	45.56	*	*	50.00	61.11	0.00	75.00	0.00	42.62
	F ₁₀₀	67.78	*	48.89	*	*	50.00	62.22	0.00	75.00	1.67	43.65
D	F ₂₅	29.22	24.58	24.37	13.12	0.16	8.97	0.00	9.09	14.00	26.04	14.96
	F ₅₀	30.98	26.46	25.83	13.75	0.32	11.41	0.22	10.15	16.22	28.75	16.41
	F ₇₅	31.37	27.29	27.08	14.17	0.48	12.18	0.22	11.21	17.11	30.21	17.13
	F ₁₀₀	31.37	27.71	27.08	14.37	0.48	12.18	0.44	11.82	17.56	30.62	17.36
F	F ₂₅	30.39	10.16	21.59	11.25	8.33	5.88	0.00	13.91	36.83	18.18	15.65
	F ₅₀	34.31	11.11	23.02	12.92	8.33	6.08	0.00	14.64	39.21	18.18	16.78
	F ₇₅	35.49	11.59	23.33	13.96	8.33	6.27	0.00	15.07	40.00	18.18	17.22
	F ₁₀₀	36.27	12.06	23.65	15.63	8.61	6.47	0.00	15.36	40.48	18.18	17.67
H	F ₂₅	42.00	78.67	40.00	38.33	*	67.50	75.00	5.56	44.81	26.67	46.50
	F ₅₀	42.67	79.33	40.67	42.50	*	73.33	75.83	11.11	45.56	28.33	48.81
	F ₇₅	44.67	80.00	40.67	44.17	*	74.17	75.83	13.33	45.93	30.00	49.86
	F ₁₀₀	45.33	80.00	40.67	44.17	*	75.00	75.83	16.67	45.93	32.50	50.68

TABLE 15: The $100 \times \text{MPI}_{\text{max}}\%$.

		1	2	3	4	5	6	7	8	9	10	Avg
A	F ₂₅	54.55	75.00	76.92	20.00	62.50	36.36	57.14	45.45	63.64	41.67	53.32
	F ₅₀	63.64	75.00	76.92	40.00	62.50	36.36	64.29	45.45	63.64	41.67	56.95
	F ₇₅	63.64	75.00	76.92	40.00	62.50	36.36	64.29	45.45	63.64	50.00	57.78
	F ₁₀₀	63.64	75.00	76.92	40.00	62.50	36.36	64.29	54.55	63.64	50.00	58.69
B	F ₂₅	66.67	*	66.67	*	*	50.00	100.00	0.00	75.00	0.00	51.19
	F ₅₀	66.67	*	66.67	*	*	50.00	100.00	0.00	75.00	0.00	51.19
	F ₇₅	66.67	*	66.67	*	*	50.00	100.00	0.00	75.00	0.00	51.19
	F ₁₀₀	100.00	*	66.67	*	*	50.00	100.00	0.00	75.00	50.00	63.10
D	F ₂₅	35.29	37.50	31.25	18.75	4.76	15.38	0.00	13.64	20.00	43.75	22.03
	F ₅₀	35.29	37.50	31.25	18.75	4.76	15.38	6.67	13.64	20.00	43.75	22.70
	F ₇₅	35.29	37.50	31.25	18.75	4.76	15.38	6.67	13.64	20.00	43.75	22.70
	F ₁₀₀	35.29	37.50	31.25	18.75	4.76	15.38	6.67	13.64	20.00	43.75	22.70
F	F ₂₅	41.18	14.29	28.57	25.00	8.33	5.88	0.00	17.39	42.86	18.18	20.17
	F ₅₀	41.18	14.29	28.57	25.00	8.33	11.76	0.00	17.39	42.86	18.18	20.76
	F ₇₅	41.18	14.29	28.57	25.00	8.33	11.76	0.00	17.39	42.86	18.18	20.76
	F ₁₀₀	41.18	14.29	28.57	25.00	16.67	11.76	0.00	17.39	42.86	18.18	21.59
H	F ₂₅	60.00	80.00	60.00	50.00	*	75.00	100.00	33.33	55.56	50.00	60.43
	F ₅₀	60.00	80.00	60.00	50.00	*	75.00	100.00	33.33	55.56	50.00	62.65
	F ₇₅	60.00	80.00	60.00	50.00	*	75.00	100.00	33.33	55.56	50.00	62.65
	F ₁₀₀	60.00	80.00	60.00	50.00	*	75.00	100.00	33.33	55.56	50.00	62.65

7. Conclusions and Future Work

Classification is of utmost importance in data mining. The proposed new classifier, CSVM, is a convolutional SVM modified with a new repeated-attribute convolution product, in which all variables in each filter are updated and trained based on the proposed novel SSO. Equipped with a self-adaptive structure and *pFilter*, this greedy SSO is a one-resolution, one-filter, one-variable type and its parameters are delineated by the proposed small-sample OA.

According to the experiment results for the five UCI datasets, namely, Australian Credit Approval, breast-cancer, Diabetes, fourclass, and Heart Disease [36], from Ex2 in Section 6, the proposed CSVM with the parameter setting selected from Ex1 outperforms the traditional SVM, the 3-layer ANN, and the 4-layer ANN with an improved accuracy of at least 14.96% and up to 50.68% in $\text{MPI}_{\text{avg}}\%$. Hence, the proposed small-sample OA discussed in Subsection 4.2 enables the CSVM to improve its overall performance, while the proposed CSVM ultimately serves as a successful

concoction of the advantages of SVM, the convolution product, and SSO.

The classifier design method is a crucial element in the provision of useful information in the modern world. Through comparisons of the results of experiments, it can be determined whether further research will be conducted on the proposed CSVM, which will be applied to multiclass datasets based on several references [40, 41] with more attributes, classes, and records, and amalgamated with particular feature selections.

Data Availability

To validate the proposed CSVM, it was compared with the traditional SVM and the 3-layer and 4-layer ANNs on five well-known datasets, “Australian Credit Approval” (A), “breast-cancer” (B), “Diabetes” (D), “fourclass” (F), and “Heart Disease” (H), at <http://archive.ics.uci.edu/ml/>.

Disclosure

This article was once submitted to arXiv as a temporary submission that was just for reference and did not provide the copyright.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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