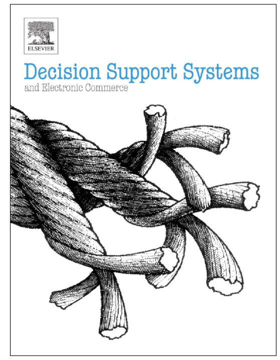

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Feature Selection Using Firefly Optimization for Classification and Regression Models

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Abstract.

In this research, we propose a variant of the Firefly Algorithm (FA) for discriminative feature selection in classification and regression models for supporting decision making processes using data-based learning methods. The FA variant employs Simulated Annealing (SA)-enhanced local and global promising solutions, chaotic-accelerated attractiveness parameters and diversion mechanisms of weak solutions to escape from the local optimum trap and mitigate the premature convergence problem in the original FA algorithm. A total of 29 classification and 11 regression benchmark data sets have been used to evaluate the efficiency of the proposed FA model. It shows statistically significant improvements over other state-of-the-art FA variants and classical search methods for diverse feature selection problems. In short, the proposed FA variant offers an effective method to

identify optimal feature subsets in classification and regression models for supporting data-based decision making processes.

Keywords: feature selection, dimensionality reduction, classification, regression, and firefly algorithm.

1. INTRODUCTION

Feature selection and dimensionality reduction are important research issues in formulating efficient classification and regression models for supporting decision making processes using data-based learning methods. A good feature subset contributes toward boosting the performance of a classification or regression model, especially when dealing with a high-dimensional feature space. Firstly, a classification or regression model with high-dimensional feature vectors (or attributes) is susceptible to the well-known “curse-of-dimensionality” problem [Xue et al., 2016]. Besides that, the original high-dimensional features may not enhance the performance of a classification or regression model for undertaking data-based decision making processes, equally, when many of the features are insignificant, irrelevant, or even redundant. In other words, classification or regression models that involve redundant features may result in performance degradation owing to the inclusion of redundant or even contradictory information. Feature selection and optimization aim to solve this problem by identifying the most discriminative features and removing redundant ones. The identified significant feature subsets constitute the optimized representations of the original problem. Indeed, feature selection has been shown to be a critical task to enhance the decision making processes in various domains [Gao et. al., 2017; Yuan et. al., 2016; Fang and Chen, 2016; Miere et. al., 2016; Dag et. al., 2016; Throckmorton et. al., 2015; Bourouis et al., 2014]. Feature selection facilitates the development of a parsimonious classification or regression model for supporting decision making processes. Many empirical studies indicate that feature selection not only accords the learned models with an efficient computational cost but also enhances their performances in tackling decision support problems [Mistry et al., 2017a; Xue et al., 2016; Zhang et al., 2016; Jothi and Inbarani, 2016].

However, identifying discriminative features is challenging owing to the large search space. Although a variety of well-known non-evolutionary feature selection methods have been widely used for dimensionality reduction, e.g. greedy search and Relief, these methods either suffer from local optimal traps, or purely conduct single feature ranking without considering feature interaction [Xue et al., 2016]. Comparatively, Evolutionary Computation (EC) techniques possess great capabilities in finding global optima, and employ a swarm-based strategy to yield multiple solutions in a single run. They also take feature interaction into account and evaluate each selected feature subset as a group using fitness evaluation. Therefore they have showed great superiority over other methods in undertaking feature selection problems. As one of the recently proposed swarm intelligence (SI) algorithms, the Firefly Algorithm (FA) [Yang, 2010] enables fireflies with low light intensities to move towards brighter ones in the neighbourhood, and possesses superior search capabilities in solving multimodal optimization problems. However the search process of FA could be further improved principally. For instance, it does not use the global optimal solutions to guide the search process explicitly. Therefore, the search process is more likely to be trapped in local optima.

This research aims to mitigate the premature convergence problem of the original FA model by proposing a modified FA model that embeds both local and global optimal signals to guide discriminative feature selection. The contributions of this research include (1) the improved attractiveness operations guided by Simulated Annealing (SA)-enhanced neighbouring and global optimal signals, (2) chaotic diversified search mechanisms, (3) diversion of weak solutions, and the cooperation of these strategies to overcome local optima traps. A total of 29 classification and 11 regression benchmark data sets are used for evaluation. It shows superior capabilities in discriminative feature selection, and outperforms other advanced FA variants, classical search methods and the original feature sets, statistically. In short, the proposed FA variant is effective to enhance classification or regression models for supporting decision making processes.

2. RELATED WORK

In this section, we introduce state-of-the-art FA variants and diverse feature selection methods. Proposed by Yang [2010], a Levy-flight FA model performs an attractiveness search operation to lead fireflies with low light intensities to move towards those with strong illuminations in the neighbourhood. This attractiveness search action is defined in Equation (1).

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_j - x_i) + \alpha \ \mathrm{sign}[\mathrm{rand} - \tfrac{1}{2}] \oplus \mathrm{Levy} \tag{1}$$

where x_i and x_j represent the positions of fireflies i and j, respectively, with the assumption that x_j has better fitness than that of x_i. γ indicates the light absorption coefficient, while r denotes the distance between two fireflies. β_0 represents the initial attractiveness at $r = 0$, while $\mathrm{sign}[\mathrm{rand} - \frac{1}{2}] \oplus \mathrm{Levy}$ indicates the random walk strategy using Levy flights with α as the randomized parameter.

Many state-of-the-art FA variants were proposed to overcome the premature convergence problem of the original FA model, e.g. FA with neighbourhood attraction (NaFA) [Wang et al., 2017a], FA with a Logistic map as the attractiveness coefficient (denoted as CFA1) [Kazem et al., 2013], opposition and dimensional FA (ODFA) [Verma et al., 2016], a modified FA (MFA) [He and Huang, 2017], FA with a variable step size (VSSFA) [Yu et al., 2015], FA with random attraction (RaFA) [Wang et al., 2016], FA with a Gauss map as the attractiveness coefficient (denoted as CFA2) [Gandomi et al., 2013], a hybrid multi-objective FA (HMOFA) [Wang et al., 2017b], and SA incorporated with both FA (SFA) and FA with Levy flights (LSFA) [Alweshah and Abdullah, 2015]. Table 1 summarizes the key characteristics of the abovementioned FA variants and our proposed FA model in this research.

Table 1 Summary of state-of-the-art FA variants in comparison with the proposed algorithm

Related work	Population initialization strategies	Adaptive parameters	Modified FA movement	Global best solution enhancement	Diversion of weak solution
LSFA [Alweshah and Abdullah, 2015]	N/A	N/A	N/A	Using SA to enhance the swarm leader	N/A
SFA [Alweshah and Abdullah, 2015]	N/A	N/A	N/A	Using SA to enhance the swarm leader	N/A
ODFA [Verma et al., 2016]	Using an opposition strategy for population initialization.	N/A	Moving each firefly towards the swarm leader.	Using a dimensional method to select the swarm leader	N/A
CFA1 [Kazem et al., 2013]	Using the Logistic map for population initialization.	Using the Logistic map as the attractiveness coefficient.	N/A	N/A	N/A
CFA2 [Gandomi et al., 2013]	N/A	Using the Gauss map as the attractiveness coefficient.	N/A	N/A	N/A

VSSFA [Yu et al., 2015]	N/A	Employing an adaptive step parameter for the randomization operation.	N/A	N/A	N/A
RaFA [Wang et al., 2016]	N/A	N/A	Using a randomly selected brighter firefly in the neighbourhood for position updating.	Employing Cauchy distribution to improve the global best solution.	N/A
MFA [He and Huang 2017]	Using the Tent chaotic map for population initialization.	N/A	Using the original FA and simple global search strategies for position updating.	N/A	N/A
NaFA [Wang et al., 2017a]	N/A	Employing an adaptive randomized step parameter and a redefined attractiveness coefficient.	Employing fireflies with strong light intensities from a predefined neighbourhood for position updating.	N/A	N/A
HMOFA [Wang et al., 2017b]	N/A	Employing an adaptive randomized step parameter and a redefined attractiveness coefficient.	Using a crossover strategy to generate two new solutions, and passing the dominating solution from two offspring fireflies to the next generation.	Using the fast non-dominated sorting method and the density estimation strategy from NSGA-II to generate Pareto fronts.	N/A
This research	Using Logistic map to initialize a firefly swarm.	Utilizing the Logistic, Gauss, Sinusoidal, Tent and Kent maps as local and global attractiveness coefficients.	Employing both local and global optimal solutions enhanced by the SA for the position updating.	Applying SA to further improve the mean of two remote swarm leaders.	Diverting weak solutions to optimal regions using the two remote swarm leaders.

Diverse FA algorithms have also been proposed for feature selection. Zhang et al. [2016] proposed a hybrid moth-firefly algorithm for facial feature selection and expression recognition. Their work embedded the spiral operation of Moth-Flame Optimization in FA to identify features pertaining to seven basic facial expressions. Jothi and Inbarani [2016] proposed a hybrid feature selection model by integrating the Tolerance Rough Set with FA for magnetic resonance imaging (MRI) brain tumor image classification. Their model identified the most significant characteristics from segmented MRI images to infer tumour classification. Kora and Krishna [2016] conducted Bundle Branch Block (BBB) detection from electrocardiogram (ECG) signals with hybrid FA-based feature selection. Their model incorporated the personal and global best solutions of Particle Swarm Optimization (PSO) with the attractiveness search mechanism in FA for BBB pattern recognition. Zhang et al. [2018] proposed a modified FA model to identity the most optimal topology for ensemble classifier/regressor construction. Their FA algorithm employed both attraction and evading mechanisms and constructed the most optimal ensemble models by removing redundant base classifiers/regressors while maintaining classification accuracy. Su et al. [2017] employed FA for optimal band selection and parameter tuning for the Extreme Learning Machine in hyperspectral image classification, while FA integrated with probability distributions was used to conduct facial feature selection in Mistry et al. [2017b]. A regression forecasting model for stock market price prediction was developed by Kazem et al. [2013], where CFA1 was used to optimize hyper-parameters of Support Vector Regression (SVR). PSO and GA-based feature selection methods were also proposed for acute lymphoblastic leukaemia classification [Srisukkham et al., 2017], skin cancer detection [Tan et al., 2016] and arousal/valence regression for bodily expression recognition [Zhang et al., 2015]. A comprehensive survey of evolutionary algorithm-based feature selection was provided by Xue et al. [2016].

3. THE PROPOSED FA VARIANT

In this research, we propose an FA variant to mitigate the premature convergence problem of the original FA model for feature selection. It employs diverse chaotic attractiveness movements, SA-enhanced local and global signals, scattering strategies of weak solutions, and the best and worst memories to increase search diversity and lead the search towards global optima. Figure 1 illustrates the pseudo-codes (Algorithm 1) and flowchart of the proposed FA variant. As shown in Algorithm 1, the Logistic chaotic map is firstly used for swarm initialization to provide more swarm diversity. In each iteration, after identifying the swarm leader, a second best solution with a competitive fitness but the lowest correlation in position to the leader is identified. This pair of promising solutions is then used to lead the weak solutions to reach optimal regions, in order to achieve fast convergence. The mean vectors of the two swarm leaders and the local promising individuals are subsequently improved by SA. The SA-enhanced local and global optimal solutions are embedded in the attractiveness search mechanism to guide the fireflies with low light intensities to move towards those with strong illuminations. The chaotic maps are exploited as the step parameters to further diversify the attractiveness behaviour. The algorithm iterates until the termination criteria are fulfilled. Overall, the SA-enhanced chaotic attractiveness mechanism and diversion strategies of weak solutions work in a collaborative manner to overcome premature convergence and to attain global optima.

Algorithm 1: Pseudo-Codes of the Proposed FA Model

Start

Initialize a firefly swarm using the Logistic map;

Evaluate each firefly using the fitness/objective function $f(x)$ and rank the fireflies;

Copy the best solution g_{best} to the **best memory;**

Copy three worst solutions to the **worst memory**;

While (termination criteria are not reached)
//maximum iterations reached, or optimal solutions found

{

  Identify the second leader, S_{best}, with similar fitness and more than 50% different in position to g_{best}.

  Improve $mean(g_{best}+S_{best})$ using SA to generate a better offspring g'_{best};

  For (each firefly i in the population && not in the worst memory) **do**

  {

    For (each firefly j in the population && not in the worst memory) **do**

    {

      If ($I_j > I_i$) // firefly j is better than firefly i

      {

        Improve firefly j using SA to generate a better offspring, x'_j;

        Replace firefly j with x'_j;

        Move firefly i towards both neighbouring and global optimal solutions using Equation (3);

      } **End If**

    } **End For**

  } End For

  Divert the three worst solutions in the **worst memory** to optimal regions using Equation (7);

  Replace g_{best} with g'_{best} if g'_{best} has better fitness than that of g_{best};

  Rank all the fireflies and update g_{best} in the **best memory** and the three worst solutions in the **worst memory**;

} End While

Output g_{best};

End

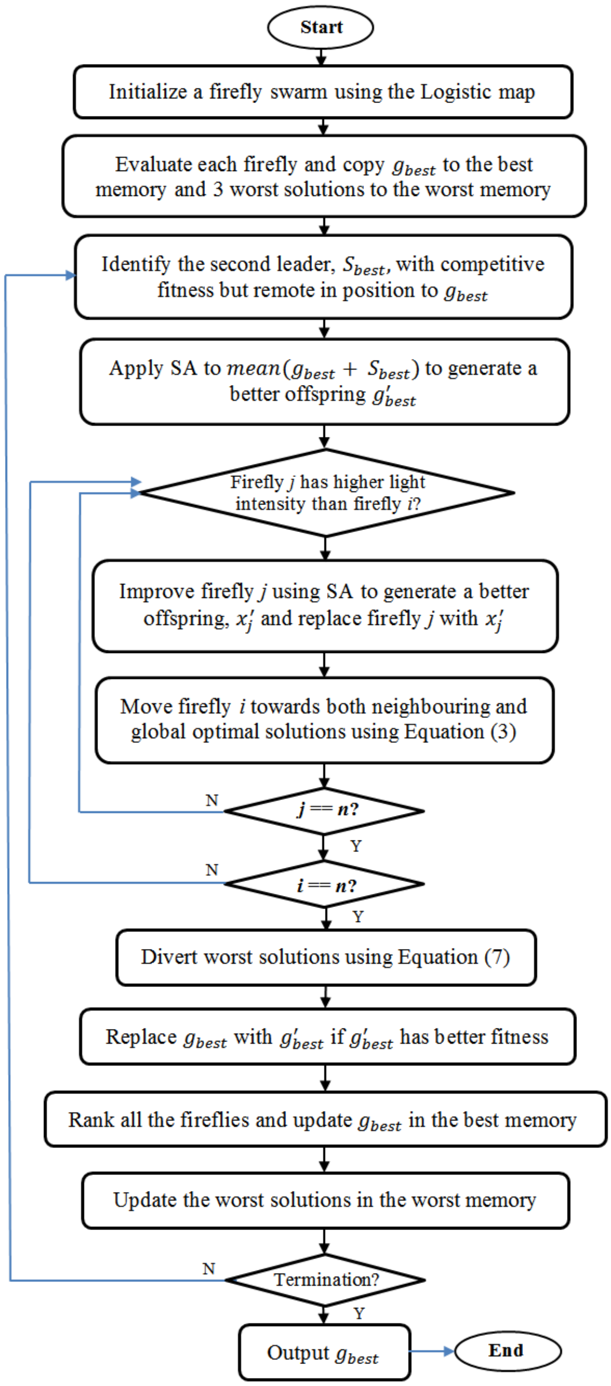

Figure 1 The pseudo-codes (left) and flowchart (right) of the proposed FA model

The objective function defined in Equation (2) is used to evaluate the fitness of each selected feature subset.

$$fitness(x) = w_1 * accuracy_x + w_2 * (number\_of\_features_x)^{-1} \tag{2}$$

where w_1 and w_2 denote the weights of classification accuracy and the number of selected features, respectively, with $w_1 + w_2 = 1$. Since classification accuracy is more important than the number of selected features, we assign $w_1 = 0.9$ and $w_2 = 0.1$ based on the recommendation of related studies [Mistry et al., 2017a; 2017b]. We introduce each key step of the proposed algorithm, as follows.

3.1 The Proposed Attractiveness Movement

The proposed FA variant employs the Logistic chaotic map for population initialization to increase swarm diversity. After ranking all fireflies according to their fitness values, the global best solution, g_{best}, is retrieved. In order to increase search diversity and overcome the local optimum traps, we also identify a second swarm leader, S_{best}, in each iteration. This secondary swarm leader possesses a comparable fitness value but with very low correlation in position to the best leader. Since both swarm leaders are more likely to explore distinctive search regions, this proposed mechanism reduces the likelihood of being trapped in local optima. Moreover, the optimal offspring of the mean position of the two leaders and the neighbouring brighter solutions are used to guide the proposed attractiveness search operation and lead the fireflies with lower light intensities to move towards the optimal regions. Equations (3)-(5) illustrate the proposed attractiveness search action.

$$x_i = x_i + \beta_0 C_k (x_j' - x_i) + C_k \varepsilon \, (g_{best}' - x_i) + \alpha' \mathrm{sign}[\mathrm{rand} - \tfrac{1}{2}] \oplus \mathrm{Levy} \quad (3)$$

$$x_j' = x_j + \lambda_1 \quad (4)$$

$$g_{best}' = mean(g_{best} + S_{best}) + \lambda_2 \quad (5)$$

where x_j' represents the fitter offspring of the brighter neighbouring firefly x_j identified by SA as defined in Equation (4), whereas g_{best}' denotes the fitter offspring of the mean of two swarm leaders generated by SA as defined in Equation (5). C_k denotes each employed chaotic map, while ε indicates a randomized vector. Moreover, we use an adaptive step parameter, α', defined as $\alpha' = \alpha' \times \left(\frac{10^{-4}}{0.9}\right)^{\frac{1}{maxi\_Gen}}$, with $maxi\_Gen$ representing the maximum number of iterations. As such, the search process utilizes a larger α' setting at the initial iterations to increase diversity of the solution vectors and a smaller α' setting at the final iterations to perform fine-tuning. According to Yang [2008], α' is initialized as 0.5. Besides that, λ_1 and λ_2 in Equations (4) and (5) denote the random search strategies of SA, such as Gaussian distribution. In SA, a fitter offspring solution is accepted directly. However, a weaker solution is accepted with a probability, p, as defined in Equation (6).

$$p = exp\left(-\frac{\Delta f}{T}\right) > \delta \tag{6}$$

where T indicates the temperature for controlling the annealing process and Δf represents the fitness difference between the new offspring and the original solutions. δ is a randomly generated vector with each element in the range of [0, 1]. The SA operator also employs a linear cooling schedule, i.e. $T = \sigma T$, to decrease the temperature by a cooling factor $\sigma \in$ [0, 1] [Yang, 2008]. When T is large, $p \rightarrow 1$, and this leads to acceptance of nearly all weak solutions. When T is small, $p \rightarrow 0$, and this implies that nearly no weak solutions are accepted. As such, a larger T setting is used at the beginning of the search process to increase exploration and a smaller T setting is used during the final iterations to perform fine-tuning of the solutions. Recommended by Yang [2008], σ is set to 0.8 and T is initialized as 1. Since the two swarm leaders have low position approximation, the offspring of the mean of their positions is more capable of guiding the search to explore distinctive search regions, in order to increase search diversity.

3.2 Chaotic Accelerated Attractiveness Parameters

Because of the capability of accelerating convergence [Gandomi et al., 2013], five chaotic maps, i.e. Logistic, Gauss, Sinusoidal, Kent, and Tent, are used to fine-tune the attractiveness search parameters, respectively. Specifically, these chaotic maps are used to replace both local and global attractiveness coefficients, both denoted as C_k in Equation (3), respectively. The newly generated solution by each chaotic map is compared with one another, and the best solution is used to replace the current firefly.

3.3 Diversion of Weak Solutions

In this research, we identify a number of worst solutions in each iteration. They are guided by the mean position of the two remote swarm leaders, as defined in Equation (7), to accelerate convergence.

$$x_i^{worst} = \frac{g_{best} + s_{best}}{2} + \mu \times (x_i^{worst} - \frac{g_{best} + s_{best}}{2}) \quad (7)$$

where $\mu \in [0, 1]$ represents a uniformly distributed random number, and is implemented by a Gauss map owing to its impressive performance in comparison with other chaotic maps in our experiments. Moreover, we conduct a series of feature selection experiments using five facial expression data sets, namely CK+ [Lucey et al., 2010], MMI [Pantic et al., 2005], JAFFE [Lyons et al., 1998], Bosphorus 3D [Savran et al., 2008] and BU-3DFE [Yin et al., 2006], to determine the optimal number of diverted weak solutions in the proposed FA model (see Table 4 for data set details). We use 1-10 number of weak solutions diverted by the two remote leaders for experimentation. A total of 275 peak facial expression images from the CK+ database are used for training while a distinctive set of 175 images extracted from each of the five databases is employed for test. A set of 30 runs is conducted for each test data set. An Adaboost Support Vector Machine (SVM)-based ensemble classifier is used for 7-class expression recognition. The average results over 30 runs for the diversion of different number of weak solutions are shown in Figure 2. The results indicate that diverting three weak solutions yields the best performance for all data sets, which achieves the best trade-off between convergence speed and search diversity. Therefore, we re-allocate three worst individuals using the two leaders in the subsequent experiments. In addition, the following settings are applied to the original FA model based on empirical studies [Yang, 2010], i.e. population size=30, initial attractiveness=1.0, absorption coefficient=1.0, Levy's index=1.5, and maximum generations=500. These settings are also used by the proposed and other FA variants for evaluating diverse test data sets.

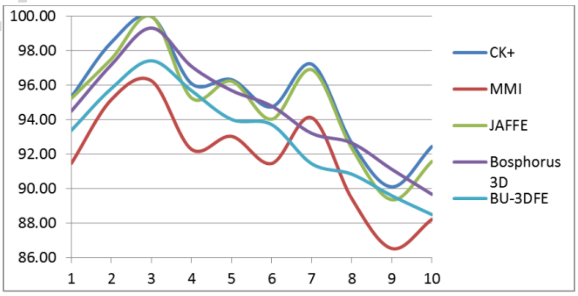

Figure 2 Performance comparison by diversion of 1-10 number of weak solutions using five facial expression databases. The *x* axis represents the 1-10 number of diverted weak solutions and the *y* axis indicates the performance accuracy rate (%)

4. EVALUATION AND DISCUSSION

To evaluate the efficiency of the proposed FA variant, we implement 11 classical search methods, i.e. PSO, Genetic Algorithm (GA), FA, Differential Evolution (DE), SA, Cuckoo Search (CS), Bat Swarm Optimization (BSO), Dragonfly Algorithm (DA), Ant-Lion Optimization (ALO), Memetic Algorithm with Local Search Chains (MA-LS) [Molina et al., 2009], and Tabu Search (TS) [Glover, 1989], and 10 advanced FA variants, i.e. SFA [Alweshah and Abdullah, 2015], LSFA [Alweshah and Abdullah, 2015], ODFA [Verma et al., 2016], CFA1 [Kazem et al., 2013], CFA2 [Gandomi et al., 2013], VSSFA [Yu et al., 2015], RaFA [Wang et al., 2016], MFA [He and Huang, 2017], NaFA [Wang et al., 2017a] and HMOFA [Wang et al., 2017b], for comparison. Motivated by Srisukkham et al. [2017], another modified FA model, AFA, is also used for comparison. It employs the mean position of neighbouring brighter fireflies to guide the attractiveness action. We evaluate the proposed algorithm using (1) benchmark functions and (2) feature selection problems.

4.1 Evaluation Using Benchmark Functions

A set of unimodal and multimodal benchmark functions is utilized for evaluation. The test functions include Dixon-Price, Rotated Hyper-Ellipsoid, Sphere, Sum of Different Powers, Sum Squares, Ackley, Griewank, and Powell. They are divided into two categories, i.e. unimodal and multimodal. The first five benchmark functions are unimodal where the search space contains a single global minimum, while the last three functions are multimodal where multiple local minima are present in the search space. For each test function, a set of 30 runs is conducted for each method. The detailed results for dimension 30 are illustrated in Table 2. The best results are marked in bold.

As indicated in Table 2, the proposed FA model outperforms all other FA variants and the classical search methods significantly for nearly all benchmark functions in dimension 30. The exception is for Dixon-Price where TS achieves the best mean global minimum. The statistical Wilcoxon rank sum test [Derrac et al., 2011] is conducted to indicate the significance level of the results. This non-parametric two-sided test is used to test the null hypothesis whether two distributions have equal medians. The test returns a *p*-value to indicate a rejection of the null hypothesis or otherwise at the 5%

significance level. The test results are provided in Table 3. All the *p*-values are lower than 0.05, indicating that the proposed FA model achieves significant improvements over 10 advanced FA variants and 11 classical methods, statistically, for most of the test cases.

Table 2 Evaluation results for benchmark functions with dimension=30

		Prop. FA	**ODFA**	**SFA**	**LSFA**	**CFA1**	**CFA2**	**AFA**	**VSSFA**	**RaFA**	**MFA**	**NaFA**
Ackley	mean	**2.88E-03**	6.11E-01	1.88E+00	1.86E+01	1.74E+01	1.51E+01	1.99E+01	1.09E+01	6.07E+00	2.03E+01	8.36E-03
	min	1.28E-03	**2.88E-05**	8.37E-03	1.73E+01	1.66E+01	1.37E+01	1.91E+01	9.59E+00	4.47E+00	2.03E+01	5.75E-03
	max	**3.91E-03**	3.58E+00	3.28E+00	2.00E+01	1.79E+01	1.59E+01	2.03E+01	1.16E+01	8.52E+00	2.03E+01	1.05E-02
	std	7.24E-04	1.03E+00	7.95E-01	9.69E-01	2.84E-01	4.77E-01	2.80E-01	4.87E-01	1.03E+00	**7.23E-15**	1.16E-03
Dixon-Price	mean	**6.67E-01**	1.17E+00	1.09E+00	2.07E+04	6.49E+05	1.80E+05	1.80E+06	1.63E+04	4.03E+01	1.62E+06	4.19E+00
	min	6.67E-01	**1.66E-01**	6.67E-01	1.84E+03	3.23E+05	7.42E+04	1.20E+06	8.07E+03	1.22E+00	1.62E+06	6.68E-01
	max	**6.68E-01**	2.49E+01	7.44E+00	5.06E+04	8.46E+05	2.64E+05	2.75E+06	2.29E+04	3.42E+02	1.62E+06	1.98E+01
	std	1.81E-04	4.50E+00	1.30E+00	1.13E+04	1.15E+05	4.71E+04	3.53E+05	3.43E+03	6.44E+01	**1.67E-10**	5.10E+00
Griewank	mean	**1.53E-05**	7.90E-01	1.24E-03	6.23E+02	3.34E+02	1.75E+02	6.36E+02	5.26E+01	2.98E+00	6.08E+02	4.64E-03
	min	**3.64E-06**	3.00E-03	1.33E-04	4.88E+02	2.68E+02	1.15E+02	5.22E+02	3.65E+01	1.09E+00	6.08E+02	2.17E-03
	max	**2.74E-05**	5.88E+00	1.03E-02	7.97E+02	4.06E+02	2.15E+02	7.30E+02	6.54E+01	8.03E+00	6.08E+02	1.70E-02
	std	5.96E-06	1.06E+00	2.80E-03	7.72E+01	3.28E+01	2.24E+01	5.33E+01	5.95E+00	1.88E+00	**2.22E-13**	3.69E-03
Rotated Hyper-Ellipsoid	mean	**2.37E-04**	9.82E+00	1.18E+01	3.20E+05	2.24E+05	1.13E+05	4.26E+05	3.37E+04	2.37E+03	4.38E+05	6.39E+01
	min	1.73E-04	**2.57E-06**	4.27E-03	2.42E+05	1.35E+05	7.19E+04	2.61E+05	2.36E+04	4.59E+02	4.38E+05	7.16E-02
	max	**3.01E-04**	9.78E+01	1.84E+02	4.04E+05	2.70E+05	1.48E+05	5.09E+05	4.34E+04	6.98E+03	4.38E+05	3.11E+02
	std	4.05E-05	2.14E+01	3.33E+01	4.15E+04	2.99E+04	1.87E+04	6.49E+04	5.01E+03	1.49E+03	**1.91E-10**	8.80E+01
Sphere	mean	**4.60E-05**	5.14E+00	5.89E-05	5.12E-02	1.06E+02	5.12E+01	1.84E+02	1.46E+01	2.18E-04	1.77E+02	1.27E-04
	min	2.43E-05	**7.26E-11**	1.34E-05	1.20E-03	8.58E+01	4.20E+01	1.30E+02	1.15E+01	2.12E-05	1.77E+02	2.12E-05
	max	**6.58E-05**	2.08E+01	1.03E-04	4.77E-01	1.22E+02	6.22E+01	2.25E+02	1.76E+01	1.88E-03	1.77E+02	4.60E-04
	std	9.00E-06	7.28E+00	2.18E-05	1.12E-01	9.62E+00	5.47E+00	2.11E+01	1.68E+00	3.96E-04	**3.54E-14**	9.54E-05
Sum of Different Powers	mean	**1.04E-08**	3.40E-05	1.62E-07	4.15E-07	1.29E-01	1.25E-02	9.42E-01	4.56E-04	6.57E-07	5.82E-01	4.49E-07
	min	**8.51E-10**	3.33E-09	2.07E-08	7.54E-08	4.64E-02	3.88E-03	4.19E-01	5.86E-05	8.45E-08	5.82E-01	7.93E-08
	max	**2.61E-08**	5.53E-04	6.55E-07	1.43E-06	2.90E-01	2.97E-02	1.75E+00	9.36E-04	1.96E-06	5.82E-01	2.00E-06
	std	7.15E-09	1.11E-04	1.35E-07	2.82E-07	5.54E-02	6.61E-03	3.54E-01	2.31E-04	5.00E-07	**1.22E-16**	4.24E-07
Sum Squares	mean	**2.54E-04**	3.51E-01	1.60E-03	5.50E-02	1.33E+03	7.04E+02	2.70E+03	2.13E+02	4.20E+00	2.77E+03	2.42E-01
	min	1.54E-04	**3.99E-12**	1.91E-04	4.00E-03	9.20E+02	4.92E+02	1.75E+03	1.54E+02	7.66E-02	2.77E+03	1.52E-03
	max	**3.72E-04**	3.48E+00	1.16E-02	8.54E-01	1.60E+03	8.83E+02	3.54E+03	2.61E+02	1.91E+01	2.77E+03	1.56E+00
	std	5.74E-05	8.58E-01	2.25E-03	1.60E-01	1.52E+02	1.05E+02	3.91E+02	2.92E+01	4.32E+00	**3.04E-13**	3.44E-01
Powell	mean	**5.77E-05**	1.41E-01	1.08E-02	6.57E-01	4.59E+03	1.70E+03	1.61E+04	3.73E+02	8.20E+00	8.71E+03	5.53E+00
	min	2.51E-05	**1.57E-11**	4.77E-03	1.54E-02	3.13E+03	1.02E+03	8.39E+03	2.16E+02	9.21E-01	8.71E+03	7.99E-01
	max	**9.15E-05**	9.12E-01	1.80E-02	4.07E+00	5.89E+03	2.31E+03	2.93E+04	4.89E+02	2.61E+01	8.71E+03	1.88E+01
	std	1.32E-05	2.81E-01	3.42E-03	1.07E+00	6.67E+02	3.61E+02	4.91E+03	7.19E+01	6.96E+00	**5.85E-13**	4.63E+00

		Prop. FA	**FA**	**SA**	**BSO**	**CS**	**PSO**	**DA**	**ALO**	**GA**	**DE**	**MA-LS**	**TS**
Ackley	mean	**2.88E-03**	4.95E-02	1.88E+01	1.68E+01	4.06E+00	1.15E+01	1.71E+01	1.90E+01	5.83E-02	6.17E-03	4.15E-02	6.43E-03
	min	**1.28E-03**	2.22E-02	1.79E+01	1.57E+01	2.99E+00	8.01E+00	9.03E+00	1.89E+01	2.90E-02	3.52E-03	2.57E-02	4.56E-03
	max	**3.91E-03**	9.96E-02	1.95E+01	1.84E+01	5.18E+00	1.55E+01	1.98E+01	1.90E+01	1.07E-01	8.95E-03	6.84E-02	8.18E-03
	std	**7.24E-04**	1.82E-02	3.51E-01	6.29E-01	5.96E-01	2.14E+00	3.27E+00	1.66E-02	4.33E-02	3.51E-03	3.29E-02	4.96E-02
Dixon-Price	mean	6.67E-01	5.42E+00	1.07E+06	2.22E+05	1.14E+01	1.41E+01	4.97E+03	1.90E+06	1.43E+00	2.40E+02	3.05E-01	**3.33E-02**
	min	6.67E-01	7.38E-01	7.86E+05	4.76E+04	2.86E+00	2.56E+00	9.21E-01	6.54E+05	1.04E+00	4.86E+02	2.06E-01	**2.45E-02**
	max	6.68E-01	2.64E+01	1.44E+06	6.11E+05	2.88E+01	1.11E+02	4.07E+04	2.55E+06	2.57E+00	6.44E+02	5.31E-01	**4.90E-02**
	std	**1.81E-04**	7.24E+00	1.71E+05	1.49E+05	6.35E+00	2.43E+01	9.33E+03	3.91E+05	4.24E-02	1.61E+04	4.49E-03	5.23E-03
Griewank	mean	**1.53E-05**	7.51E-03	4.60E+02	2.33E+02	1.07E+00	1.91E+00	9.67E+00	6.20E+02	1.80E-01	1.35E+02	1.07E-01	3.20E-02
	min	3.64E-06	3.44E-03	3.48E+02	1.43E+02	1.03E+00	4.13E-01	**0.00E+00**	5.02E+02	1.14E-01	1.00E+02	6.70E-02	1.77E-02
	max	**2.74E-05**	1.42E-02	5.48E+02	3.51E+02	1.16E+00	3.91E+00	7.90E+01	7.05E+02	3.42E-01	2.48E+02	2.31E-01	5.16E-02
	std	**5.96E-06**	2.39E-03	4.08E+01	6.15E+01	3.60E-02	7.46E-01	1.51E+01	5.41E+01	3.29E-01	5.08E+01	4.15E-01	6.60E-02
Rotated Hyper-Ellipsoid	mean	**2.37E-04**	1.06E+01	3.03E+05	1.84E+05	5.54E+01	3.42E+02	4.95E+03	4.39E+05	2.78E+01	3.73E-01	2.65E+01	2.10E+01
	min	1.73E-04	5.19E-01	1.76E+05	6.75E+04	2.29E+01	5.92E+00	**0.00E+00**	3.19E+05	1.88E+01	2.22E-01	1.35E+01	1.29E+01
	max	**3.01E-04**	5.55E+01	3.62E+05	3.76E+05	1.08E+02	4.67E+03	2.23E+04	5.51E+05	5.34E+01	6.62E-01	4.76E+01	4.08E+01
	std	**4.05E-05**	1.41E+01	4.31E+04	6.46E+04	2.17E+01	8.30E+02	6.15E+03	5.44E+04	3.41E+01	4.71E-02	5.46E+01	5.17E+01
Sphere	mean	**4.60E-05**	2.49E-03	1.34E+02	3.79E+01	2.07E-02	4.72E-01	2.71E+00	1.85E+02	5.87E+04	5.90E+04	3.00E+02	1.23E+00
	min	2.43E-05	3.85E-04	1.06E+02	1.23E+01	8.12E-03	3.66E-02	**0.00E+00**	1.43E+02	3.83E+04	3.89E+04	1.73E+02	7.90E-01
	max	**6.58E-05**	6.73E-03	1.61E+02	6.93E+01	4.88E-02	1.68E+00	1.71E+01	2.26E+02	6.70E+04	7.00E+04	6.30E+02	2.10E+00
	std	**9.00E-06**	1.51E-03	1.32E+01	1.44E+01	8.45E-03	4.13E-01	3.86E+00	2.11E+01	1.54E+04	1.88E+04	1.44E+03	2.45E+00
Sum of Different Powers	mean	**1.04E-08**	1.39E-06	3.19E-01	8.54E-07	1.86E-08	2.05E-04	2.66E-04	9.72E-01	4.08E+04	4.89E+04	2.70E+04	1.90E+02
	min	8.51E-10	1.58E-07	1.03E-01	3.86E-08	**6.96E-11**	1.22E-05	1.51E-06	1.80E-01	3.58E+04	3.03E+04	1.86E+04	1.20E+02
	max	**2.61E-08**	4.92E-06	8.26E-01	2.29E-06	2.99E-07	1.29E-03	2.55E-03	1.62E+00	5.32E+04	5.26E+04	4.29E+04	3.09E+02
	std	**7.15E-09**	1.19E-06	1.72E-01	5.71E-07	5.49E-08	2.63E-04	5.26E-04	3.76E-01	1.19E+04	1.71E+04	5.71E+04	3.49E+02
Sum Squares	mean	**2.54E-04**	8.37E-01	1.90E+03	5.66E+02	3.04E-01	2.46E+00	2.19E+01	2.74E+03	2.00E+03	1.66E+04	1.60E+02	3.00E-02
	min	1.54E-04	8.27E-02	1.55E+03	1.14E+02	1.12E-01	3.10E-01	**0.00E+00**	2.08E+03	1.27E+03	1.15E+04	1.10E+02	1.32E-02
	max	**3.72E-04**	4.90E+00	2.29E+03	1.05E+03	6.45E-01	1.32E+01	9.93E+01	3.30E+03	3.90E+03	2.39E+04	3.00E+02	6.25E-02
	std	**5.74E-05**	9.46E-01	1.64E+02	2.14E+02	1.35E-01	2.60E+00	2.38E+01	3.46E+02	4.46E+02	1.74E+03	2.24E+02	1.65E-01
Powell	mean	**5.77E-05**	1.20E+01	7.53E+03	1.28E+03	7.24E-01	3.25E+00	2.65E+02	1.35E+04	2.30E+02	1.67E+03	1.85E-03	2.25E-04
	min	**2.51E-05**	2.46E+00	4.97E+03	1.50E+02	1.60E-01	1.93E-01	5.72E-01	6.42E+03	1.06E+02	1.02E+03	1.10E-03	1.90E-04
	max	**9.15E-05**	3.02E+01	9.72E+03	3.27E+03	1.72E+00	1.34E+01	7.72E+02	1.53E+04	3.02E+02	3.72E+03	3.17E-03	6.72E-04

std	**1.32E-05**	6.53E+00	1.36E+03	8.25E+02	4.64E-01	3.18E+00	2.17E+02	2.59E+03	5.53E+02	5.36E+03	4.25E-03	3.64E-04

Table 3 The Wilcoxon rank sum test results for all benchmark functions with dimension=30

	ODFA	SFA	LSFA	CFA1	CFA2	AFA	VSSFA	RaFA	MFA	NaFA
Ackley	3.99E-04	3.02E-11	2.80E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.21E-12	3.02E-11
Dixon	1.11E-06	5.49E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.67E-11	3.02E-11
Griewank	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.15E-12	3.02E-11
Rotated Hyper-Ellipsoid	5.57E-10	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	6.32E-12	3.02E-11
Sphere	6.77E-05	6.67E-03	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	9.21E-05	1.07E-11	8.20E-07
Sum of Different Powers	1.70E-08	4.98E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.36E-11	3.02E-11
Sum Squares	2.52E-08	4.62E-10	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.67E-11	3.02E-11
Powell	3.11E-09	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.15E-12	3.02E-11

	FA	SA	BSO	CS	PSO	DA	ALO	GA	DE	MA-LS	TS
Ackley	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.72E-12	3.02E-11	3.02E-11	3.02E-11	3.02E-11
Dixon	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
Griewank	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	1.10E-06	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
Rotated Hyper-Ellipsoid	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	8.48E-09	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
Sphere	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	5.57E-10	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
Sum of Different Powers	3.02E-11	3.02E-11	3.02E-11	8.99E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
Sum Squares	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	8.48E-09	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11
Powell	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11	2.11E-11	3.02E-11	3.02E-11	3.02E-11	3.02E-11

4.2 Evaluation Using UCI and Other High-dimensional Data Sets

We evaluate the proposed FA model using a total of 40 feature selection problems. They are grouped into 29 classification and 11 regression problems. Specifically, 33 data sets are extracted from UCI repository [Lichman, 2013], along with 1 blood cancer, 5 facial expression, and 1 bodily expression data sets. Table 4 presents the data set details. The performances obtained using the entire feature set for each data set are recorded for comparison. SVM, neural networks (NN), Decision Tree Learning (DT), Random Forest, Rotation Forest [Rodriguez et al., 2006], the NN-based and SVM-based Adaboost ensemble classifiers, are used to perform classification using the optimal feature subsets identified by each method. The NN-based and SVM-based ensemble classifiers are built using the Adaboost strategy with three single NN and SVM classifiers embedded, respectively.

The feature selection process is conducted as follows. Each firefly in the population is represented by an *n*-dimensional vector in the search space. In other words, each firefly has *n* elements, where *n* represents the dimension of the original feature set. The search strategy of each algorithm drives the swarm towards the optimal regions in the *n*-dimensional search space. Therefore, each element in an *n*-dimensional vector has a continuous value representing the position of a firefly in a specific dimension. For fitness evaluation using Equation (2), we convert the continuous value in each dimension of each firefly into a binary value (i.e. 0 or 1), with ‘1’ and ‘0’ indicating the selection and non-selection of that dimension. The swarm leader identified during the search process is regarded as the most optimal solution. After converting to a binary string, it represents the most optimal feature subset. For each data set, a total of 30 runs are conducted to generate 30 feature subsets using the above process. The average result of the 30 generated feature subsets is used for comparison.

Table 4 Details of the test data sets

		Data sets	Instances	Attributes	Classes	Training	Test
Classification	**1.**	**CK+**	593	625	7	275	175
	2.	**MMI**	175	625	7	275 (CK+)	175
	3.	**JAFFE**	213	625	7	275 (CK+)	175
	4.	**Bosphorus 3D**	4652	625	7	275 (CK+)	175
	5.	**BU-3DFE**	2500	625	7	275 (CK+)	175
	6.	**ALL-IDB2**	180	80	2	90	90
	7.	**Sonar**	208	60	2	140	68
	8.	**Ozone**	2536	72	2	600	300
	9.	**Secom**	1567	591	2	350	200
	10.	**Libras**	360	91	15	210	150
	11.	**Arcene**	900	10000	2	500	300
	12.	**DrivFace**	606	6400	3	300	300
	13.	**Daily & Sports Activities**	9120	5625	19	4000	2000
	14.	**Human Activity Recognition**	10299	561	6	6000	3000
	15.	**Music Analysis (FMA)**	106574	518	163 (genres)	5000	2000
	16.	**Semeion Handwritten Digit**	1593	256	10	700	400
	17.	**Arrhythmia**	452	279	16	250	200
	18.	**Breast Cancer Wisconsin**	198	34	2	100	90
	19.	**Heart Disease**	303	75	5	200	100
	20.	**Isolated Letter Speech Recognition (ISOLET)**	7797	617	26	3000	2000
	21.	**MicroMass**	931	1300	20	500	300
	22.	**Weight Lifting Exercises monitored with Inertial Measurement Units**	39242	152	5	5000	3000
	23.	**Gas Sensor Array Drift**	13910	129	6	5000	2000
	24.	**LSVT Voice Rehabilitation**	126	309	2	60	50
	25.	**Geographical Original of Music**	1059	68	33	600	400
	26.	**Grammatical Facial Expressions**	27965	100	2	10000	5000
	27.	**Mice Protein Expression**	1080	82	8	500	300
	28.	**Detect Malacious Executable**	373	513	2	200	100
	29.	**Epileptic Seizure Recognition**	11500	179	2	3000	1000
Regression	**30.**	**Bodily Expression**	45000	54	arousal & valance	40000	5000
	31.	**Communities and Crime**	1994	128	number of violent crimes	1000	500
	32.	**Relative Location of CT Slices on Axial Axis**	53500	386	the relative location of the CT slice on the axial axis	10000	5000
	33.	**UJIIndoorLoc**	21048	529	actual longitude and latitude estimation	10000	3000
	34.	**Greenhouse Gas Observing Network**	2921	5232	the optimal values of the weights	1000	500
	35.	**PM2.5 Data of Five Chinese Cities**	52854	86	cumulated precipitation	10000	5000
	36.	**BlogFeedback**	60021	281	the number of comments in the next 24 hours	20000	10000
	37.	**ElectricityLoadDiagrams 2011-2014**	370	140256	electricity consumption	170	150
	38.	**Gas Sensor Array Drift**	13910	129	gas concentration level	5000	2000
	39.	**NoisyOffice**	216	216	cleaning (or binarization) and enhancement of noisy grayscale printed text images	120	90
	40.	**YearPredictionMSD**	515345	90	the release year of a song	20000	10000

4.2.1 Evaluation of Classification Data Sets

We first employ the facial expression data sets, i.e. CK+, MMI, JAFFE, Bosphorus 3D and BU-3DFE, for evaluation. Each facial image is represented by a 625-dimensional feature vector extracted by Local Binary Patterns. Table 5 shows the evaluation results with the best performances marked in bold. Our algorithm outperforms all other FA variants and classical search methods significantly. As shown in Table 5, a total of 35-65 features are selected by the proposed model for the facial expression data sets, which are significantly lower than those extracted by all classical methods and the majority of FA variants (e.g. 50-100 for LSFA). Figure 3 shows the features selected by the proposed model for the 7 facial expressions. The image sub-regions selected by the proposed FA model associate strongly with the characteristics provided by Facial Action Coding System (FACS) [Ekman et al., 2002] for emotional expressions. As an example, for happiness, the features associated with Lip Corner Puller (AU12) and Cheek Raiser (AU6) are selected by the proposed model. Characteristics of the Inner Brow Raiser (AU1), Brow Lowerer (AU4) and Mouth Stretch (AU27) are extracted for fear. Such discriminating features contribute significantly to the robust recognition of different emotion categories. While other methods tend to extract more features, some of such FACS-related significant characteristics are not embedded. This degrades their performances especially for the recognition of subtle negative emotions, owing to the missing of crucial discriminative information. A similar scenario applies to the original feature sets where insignificant features (e.g. forehead) are used, resulting in performance degradation.

Another evaluation is conducted using the acute lymphoblastic leukaemia (ALL) data set, i.e. ALL-IDB2 [Labati et al., 2011]. In our previous research [Srisukkham et al., 2017], a set of 80 features was extracted including 16 shape, 54 textural, and 10 CIELAB colour descriptors from the segmented nucleus and cytoplasm sub-images. They are used as the input to the proposed FA model for feature selection. As shown in Table 5, our algorithm selects the minimum feature subsets (e.g. 11-16) as compared with those of other methods (e.g. 27-33 for LSFA), and outperforms all other methods. Moreover, our selected features include clinically significant characteristics for ALL diagnosis, such as cytoplasm and nucleus areas, ratio of nucleus to cytoplasm, filled area, eccentricity, convex area, form factor, and entropy [Labati et al., 2011; Neoh et al., 2015]. Some of these features have not been selected, or co-exist, in the feature subsets selected by other methods, although they tend to select comparatively larger feature subsets, therefore leading to inferior performance.

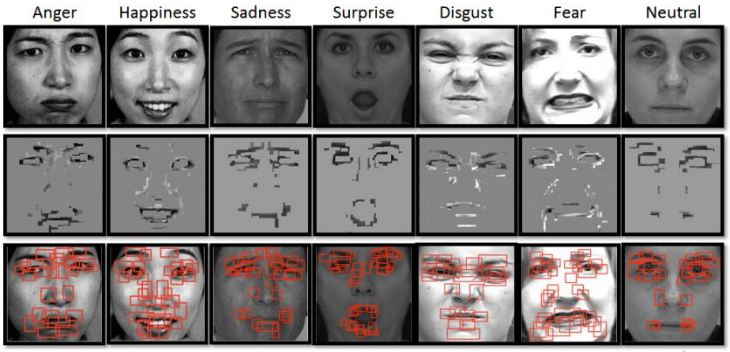

Figure 3 Facial features and sub-regions selected by the proposed algorithm for a number of facial expression images extracted from JAFFE (anger and happiness), BU-3DFE (sadness), Bosphorus 3D (surprise), CK+ (disgust and fear), and MMI (neutral) databases, respectively

In addition, a total of 23 UCI data sets [Lichman, 2013] are randomly selected for evaluation (see Table 4 for data set details). As indicated in Table 5, the proposed model outperforms all other methods for nearly all 23 UCI data sets in combination with all classification models. It also extracts the smallest number of features as compared with those of other methods in most of the test cases. The Wilcoxon rank sum test is conducted for each method integrated with the SVM-based ensemble classifier. As shown in Table 6, the majority of the *p*-values are lower than 0.05, except for four cases where the proposed model , RaFA, and NaFA achieve an accuracy rate of 100%, therefore leading to *p*-value=1. This indicates that our proposed model outperforms all other methods statistically for nearly all classification problems. The results obtained using the proposed FA variant are also significantly better, statistically, than those obtained using the original feature sets.

4.2.2Evaluation of Regression Data Sets

A total of 11 regression data sets are used for evaluation (see Table 4 for data set details). It includes 10 UCI data sets and a Bodily Expression data set [Zhang et al., 2015]. SVR, Logistic Regression (LR) and SVR-based Adaboost ensemble regressor, are employed for regression analysis. The average Mean Squared Error (MSE) over 30 runs is used for evaluation of each method. As illustrated in Table 7, for the prediction of diverse continuous variables, the proposed FA variant achieves the smallest average MSE over 30 trials through the integration with diverse regression models in comparison with those of all other methods. It also identifies the smallest discriminative feature subsets for all regression analyses. For the Bodily Expression data set, the original feature set has 54 (25 static and 29 dynamic) features. Our proposed model extracts 18-25 features for arousal, with approximately similar numbers of static and dynamic features, whereas for valence, it extracts 16-23 features, with more static features than dynamic ones. These findings are consistent with the theoretical studies in Zhang et al. [2015], which indicate that arousal is associated with both static and dynamic characteristics while valence is associated more strongly with static features. As an example, both thrilled and furious bodily expressions may involve unconscious waving of arms fiercely, therefore dynamic features could be less informative for valence interpretation.

Moreover, for all 11 regression problems, the statistical results shown in Table 8 indicate that our proposed model outperforms all other methods statistically, with all *p*-values lower than 0.05. A theoretical analysis of the proposed FA model is provided, as follows. First of all, the proposed model employs the Logistic map to initialize the swarm, which provides more population diversity than that generated using a randomization method as in the original FA model. The proposed model employs both SA-enhanced neighbouring and global optimal signals to guide the attractiveness operation, whereas the original FA model purely relies on the neighbouring optimal indicators to lead the search process. Therefore, the search of the proposed model is better guided in comparison with that of the original FA model. In particular, the global optimal signals in the proposed model are derived from two remote leaders, in order to reduce the probability of being trapped in local optima. Since SA has better global search capability as compared with other random walk strategies and the weak solutions are accepted subject to a probability threshold, the proposed FA variant explores a wider search space in comparison with all other FA variants, and has better chances of finding global optima. Five chaotic maps are also used to diversify the proposed attractiveness operation and to avoid stagnation. The proposed model is able to accelerate convergence by diverting the weak solutions to optimal regions, which is missing in the original FA model. Overall, the proposed search mechanisms account for the superiority of our FA variant over other methods in undertaking diverse feature selection tasks.

5. CONCLUSIONS

In this research, we have proposed a modified FA model for feature selection. Evaluated with 29 classification and 11 regression problems, the proposed FA model shows superior discriminative capabilities and outperforms other state-of-the-art FA variants, classical methods and experiments using the entire feature sets, statistically, for diverse feature selection problems. The statistical test results ascertain the effectiveness of the proposed FA variant in enhancing classification and regression models for supporting decision making processes. Future research directions have been identified to improve the proposed FA model. The current search process purely depends on the attractiveness driven mechanism. Other alternative velocity updating strategies such as scattering or evading operations could be embedded. As such, when the attractiveness action stagnates, other complementary search mechanisms are able to increase search diversity and lead the search towards unexploited optimal regions. Motivated by animal survival tactics, diverse attraction and escaping coefficients illustrating erratic movement trails could also be utilized to diversify the search process.

Table 5 Average performance of each algorithm over 30 runs for 29 classification data sets

Data set	Methods	No. of features	DT	Ran. Forest	Rot. Forest	NN	SVM	NN-based Ensemble	SVM-based Ensemble
CK+	GA	100-200	72.61	74.73	74.72	75.10	75.75	77.50	78.00
	PSO	110-200	75.37	74.47	75.86	77.00	77.45	79.33	81.95
	FA	55-90	76.26	77.40	79.19	79.55	80.25	83.66	85.00
	SA	150-235	71.14	71.46	72.26	75.06	73.73	76.14	77.33
	DE	145-230	72.39	73.54	74.20	75.55	75.28	76.25	78.23
	MA-LS	95-125	74.30	74.82	75.00	76.79	76.94	78.67	80.50
	TS	90-150	75.27	75.42	75.95	77.20	77.64	79.55	81.00
	BSO	75-90	76.76	77.26	78.19	81.35	79.78	81.82	83.65
	CS	70-89	79.54	78.87	80.30	82.13	81.75	84.59	85.71
	DA	70-90	80.02	81.78	82.04	84.24	83.19	85.59	86.93
	ALO	75-85	81.15	83.51	82.89	84.41	84.74	85.99	87.33
	LSFA	50-100	77.13	78.45	79.03	80.00	80.50	82.60	85.50
	CFA1	50-90	87.56	88.84	88.62	89.00	90.00	93.75	96.88
	CFA2	49-85	87.71	89.23	90.17	90.22	91.34	94.00	96.90
	VSSFA	55-88	86.79	88.10	88.77	90.00	90.00	92.57	95.35
	RaFA	50-80	89.46	89.49	89.86	90.25	91.50	94.88	97.20
	AFA	35-60	87.65	89.00	89.35	90.15	90.65	95.55	96.54
	MFA	50-70	88.54	89.14	89.24	90.50	91.00	94.66	95.98
	NaFA	45-70	90.10	91.26	92.02	92.60	93.71	98.90	**100.00**
	HMOFA	55-68	89.27	90.19	90.66	91.96	91.97	93.93	95.60
	Entire set	625	69.83	70.67	70.55	70.84	72.24	72.83	74.43
	Prop. FA	**35-65**	**92.42**	**92.45**	**93.43**	**93.15**	**94.51**	**99.10**	**100.00**
MMI	GA	100-200	71.16	71.55	71.89	71.19	72.86	73.97	75.20
	PSO	110-200	71.55	74.14	73.42	73.52	75.12	75.33	77.21
	FA	55-90	77.01	78.13	77.67	78.65	79.15	80.51	81.87
	SA	150-235	70.69	71.15	71.51	71.81	71.52	73.81	75.06
	DE	145-230	70.88	70.29	71.70	72.09	73.22	74.28	75.55
	MA-LS	95-125	71.64	73.70	73.38	72.14	74.18	75.59	76.79
	TS	90-150	72.63	73.03	74.09	72.89	74.93	75.40	77.20
	BSO	75-90	75.50	75.94	76.51	77.68	78.48	79.95	81.35
	CS	70-89	77.70	78.87	78.35	78.65	79.48	80.45	82.13
	DA	70-90	79.07	80.94	80.82	79.52	81.27	82.66	84.24
	ALO	75-85	79.88	78.75	79.42	80.28	82.25	83.34	84.41

	LSFA	50-100	77.04	78.91	78.83	77.55	78.69	80.92	82.00
	CFA1	50-90	83.77	85.48	85.75	85.99	86.18	87.77	89.65
	CFA2	49-85	86.06	87.03	86.82	87.42	87.53	90.32	91.33
	VSSFA	55-88	86.01	84.68	85.65	86.10	86.90	89.38	90.40
	RaFA	50-80	87.84	86.33	87.22	87.30	88.87	90.20	92.00
	AFA	35-60	85.16	84.41	85.71	85.86	86.18	88.83	90.00
	MFA	50-70	86.11	86.20	85.54	86.99	86.65	88.71	90.50
	NaFA	45-70	89.55	90.78	90.44	90.90	91.93	92.55	94.21
	HMOFA	55-68	87.00	88.59	88.67	88.83	89.13	90.65	91.96
	Entire set	625	68.79	69.86	68.60	69.59	69.82	71.53	73.50
	Prop. FA	**35-65**	**91.60**	**92.65**	**92.63**	**91.69**	**93.87**	**95.45**	**96.69**
JAFFE	GA	100-200	69.16	70.17	70.01	70.02	70.46	73.91	75.00
	PSO	110-200	74.52	73.43	75.93	74.56	74.31	78.02	79.22
	FA	55-90	80.18	78.66	79.67	79.50	78.74	82.53	83.56
	SA	150-235	69.78	69.67	71.22	69.48	69.50	73.04	74.33
	DE	145-230	71.73	70.78	70.22	70.18	70.69	73.17	75.00
	MA-LS	95-125	75.27	75.42	75.56	75.46	75.50	78.58	80.45
	TS	90-150	77.99	75.18	76.99	76.72	76.98	79.43	81.10
	BSO	75-90	76.45	78.14	77.21	76.93	76.87	80.41	81.55
	CS	70-89	78.90	79.31	79.56	78.49	78.18	81.45	82.61
	DA	70-90	78.39	78.54	79.57	78.85	77.99	81.68	82.93
	ALO	75-85	80.83	78.82	80.54	79.18	79.77	82.14	84.00
	LSFA	50-100	80.43	81.44	81.01	80.23	80.51	83.03	85.00
	CFA1	50-90	89.62	87.69	89.20	88.09	88.08	91.04	93.00
	CFA2	49-85	89.94	89.28	90.21	88.55	88.79	91.68	93.55
	VSSFA	55-88	87.03	87.34	88.26	87.76	87.72	90.89	91.98
	RaFA	50-80	88.50	89.38	88.13	88.61	88.36	91.66	93.10
	AFA	35-60	87.66	88.82	88.58	88.53	88.66	91.46	92.70
	MFA	50-70	87.50	86.63	88.15	87.63	87.82	90.65	92.50
	NaFA	45-70	94.36	94.38	93.77	93.85	93.65	96.87	98.33
	HMOFA	55-68	87.65	87.85	87.89	87.78	87.25	91.03	92.20
	Entire set	625	67.23	67.04	67.65	66.52	66.78	69.36	71.00
	Prop. FA	**35-65**	**95.94**	**95.03**	**95.82**	**95.42**	**95.13**	**98.77**	**100.00**
Bosphorus 3D	GA	100-200	70.58	71.60	71.54	72.98	72.93	74.37	76.51
	PSO	110-200	74.65	74.03	74.64	75.43	74.74	76.76	78.65
	FA	55-90	78.33	78.46	78.90	79.65	79.52	81.46	82.97
	SA	150-235	71.06	71.99	72.27	73.42	73.47	73.93	76.57
	DE	145-230	72.28	73.10	72.97	74.04	73.89	74.15	77.14
	MA-LS	95-125	74.55	74.37	73.82	75.22	75.35	76.36	78.76
	TS	90-150	73.22	74.33	74.16	75.17	74.85	77.01	78.81
	BSO	75-90	78.62	78.84	78.31	79.86	80.06	81.76	83.16
	CS	70-89	78.84	78.89	78.73	80.36	80.40	81.98	83.65
	DA	70-90	80.44	81.54	81.44	82.90	82.77	84.33	86.19
	ALO	75-85	80.70	81.46	81.27	81.92	81.65	82.68	85.56
	LSFA	50-100	77.89	78.29	78.43	79.99	79.33	81.69	83.26
	CFA1	50-90	86.52	86.65	87.21	87.69	87.66	90.21	91.47
	CFA2	49-85	86.84	88.16	88.44	88.78	89.12	91.47	92.48
	VSSFA	55-88	87.51	87.38	87.37	88.92	88.62	91.10	92.30
	RaFA	50-80	89.24	88.62	89.26	90.03	90.37	92.30	93.56
	AFA	35-60	85.63	87.01	87.09	88.05	88.31	88.96	91.60
	MFA	50-70	87.97	87.96	88.03	88.49	89.27	90.73	92.45
	NaFA	45-70	90.09	91.31	91.00	92.36	92.28	93.27	95.37
	HMOFA	55-68	88.43	89.78	89.89	90.90	90.75	91.62	93.90
	Entire set	625	70.85	70.12	70.34	71.30	71.49	73.27	75.06
	Prop. FA	**35-65**	**93.49**	**93.63**	**93.51**	**94.48**	**94.06**	**95.01**	**97.74**
BU-3DFE	GA	100-200	69.75	71.88	71.98	72.10	71.69	74.93	76.52
	PSO	110-200	74.86	75.62	76.10	75.91	77.27	79.23	80.43
	FA	55-90	77.69	78.39	78.89	79.94	78.53	82.17	83.20
	SA	150-235	68.55	71.38	70.43	71.81	70.94	74.20	75.42
	DE	145-230	71.76	71.79	71.23	72.36	73.30	75.12	76.89
	MA-LS	95-125	72.75	73.50	73.53	75.16	75.57	77.10	78.97
	TS	90-150	72.51	74.30	73.63	74.88	75.65	77.06	79.04
	BSO	75-90	76.19	78.00	77.19	78.33	78.67	80.95	82.58
	CS	70-89	78.41	80.17	78.63	80.66	80.43	82.74	84.56
	DA	70-90	78.60	80.42	79.73	81.23	82.47	84.14	85.48
	ALO	75-85	80.58	81.69	80.73	81.07	82.16	83.78	85.72
	LSFA	50-100	76.74	78.55	79.05	79.25	80.30	82.38	83.62
	CFA1	50-90	88.85	91.09	90.09	92.02	92.17	94.01	95.25
	CFA2	49-85	90.24	90.79	90.26	91.22	90.31	94.04	95.26
	VSSFA	55-88	87.43	89.19	87.83	89.88	89.39	92.24	93.74
	RaFA	50-80	90.08	91.43	89.90	92.13	91.11	93.70	95.63
	AFA	35-60	89.82	89.61	90.93	90.64	91.23	93.78	95.26
	MFA	50-70	87.77	89.53	89.22	90.06	89.62	92.73	94.56
	NaFA	45-70	91.51	**93.39**	93.03	93.54	**95.05**	96.42	98.30
	HMOFA	55-68	88.50	89.09	88.27	89.95	90.14	91.87	93.81

	Entire set	625	67.61	68.69	67.15	69.54	69.61	71.55	72.91
	Prop. FA	**35-65**	**92.90**	92.88	**93.79**	**94.56**	94.12	**97.44**	**98.44**
ALL-IDB2	GA	32-39	73.19	73.62	73.49	74.81	75.44	76.05	77.44
	PSO	30-38	74.96	75.52	75.57	77.01	76.90	77.78	79.40
	FA	28-35	80.28	79.94	80.56	81.56	81.23	82.24	83.60
	SA	34-41	74.01	73.27	73.50	74.81	74.51	75.33	77.04
	DE	36-43	73.72	73.99	73.56	74.97	75.27	76.12	77.36
	MA-LS	33-40	74.53	75.95	76.15	77.05	76.44	78.11	79.28
	TS	35-40	75.95	75.28	75.99	76.44	76.23	77.61	79.19
	BSO	31-39	79.15	80.58	79.77	80.93	81.66	82.07	83.70
	CS	27-34	80.77	80.10	80.86	81.35	81.10	82.61	83.86
	DA	26-33	83.76	84.11	83.71	85.12	84.57	85.68	87.12
	ALO	25-31	81.41	82.44	82.54	83.92	83.90	84.68	86.25
	LSFA	27-33	80.07	79.87	80.11	80.94	81.05	81.62	83.36
	CFA1	21-27	84.82	84.50	84.49	86.23	86.23	86.93	88.48
	CFA2	21-25	87.38	86.91	86.99	87.80	88.04	89.32	90.52
	VSSFA	21-26	85.84	87.25	86.44	87.40	87.95	88.46	90.32
	RaFA	16-22	88.52	88.13	88.75	89.44	89.84	90.49	91.94
	AFA	19-24	86.83	88.12	87.82	88.33	88.21	89.51	91.14
	MFA	20-25	86.55	87.37	87.43	88.20	88.00	89.41	90.50
	NaFA	15-20	88.92	89.16	89.04	90.77	90.12	91.84	92.93
	HMOFA	20-24	87.09	86.63	86.69	87.62	87.74	88.30	90.26
	Entire set	80	72.60	74.28	74.33	74.73	74.99	76.21	77.57
	Prop. FA	**11-16**	**90.62**	**90.96**	**91.63**	**92.38**	**92.54**	**93.06**	**94.80**
Sonar	GA	45-50	80.20	80.84	82.25	81.17	81.39	83.33	85.00
	PSO	40-45	81.67	82.93	83.97	82.88	83.60	84.97	86.50
	FA	30-37	86.32	85.44	87.19	86.11	86.65	88.67	89.75
	SA	50-60	78.86	79.60	81.14	80.65	80.89	82.12	83.33
	DE	50-60	78.61	79.00	79.74	80.00	79.15	81.18	83.00
	MA-LS	40-50	80.82	81.65	83.58	83.18	82.01	83.72	85.70
	TS	40-50	83.19	82.04	83.93	83.34	84.46	85.39	86.73
	BSO	38-50	83.76	84.76	86.05	85.36	85.83	86.90	88.55
	CS	40-48	84.15	85.25	85.12	85.68	86.17	87.55	88.93
	DA	35-40	84.61	85.44	86.64	85.47	86.12	87.78	89.43
	ALO	33-37	88.28	88.42	89.66	90.00	89.63	91.02	92.65
	LSFA	20-30	88.41	89.20	89.62	89.15	89.61	91.15	92.50
	CFA1	15-35	89.38	89.91	91.55	91.65	90.57	92.47	94.24
	CFA2	20-30	91.17	91.18	91.41	92.19	91.00	92.91	94.75
	VSSFA	15-25	92.60	91.19	93.51	93.23	92.37	94.07	95.66
	RaFA	15-25	92.08	91.16	93.58	93.53	92.18	94.66	96.00
	AFA	20-30	89.99	89.51	91.36	91.37	90.76	92.93	94.50
	MFA	24-30	86.00	85.75	87.84	86.87	86.31	88.16	90.12
	NaFA	13-23	93.11	93.74	94.09	94.31	94.25	95.51	96.77
	HMOFA	20-25	87.43	88.23	88.22	89.12	89.44	90.71	92.00
	Entire set	60	82.40	80.73	81.80	81.66	81.65	83.92	85.60
	Prop. FA	**15-20**	**95.28**	**96.21**	**95.47**	**95.90**	**96.98**	**97.40**	**99.22**
Ozone	GA	40	76.51	77.18	77.10	78.02	78.14	80.66	81.00
	PSO	37-41	76.21	76.89	77.04	78.98	78.24	80.41	81.00
	FA	25-28	84.97	85.81	86.32	87.50	86.69	89.47	89.50
	SA	45-50	77.92	77.44	78.22	79.35	79.63	81.39	82.02
	DE	43-47	76.49	77.76	77.80	78.94	79.17	81.21	81.38
	MA-LS	36-40	80.35	81.42	81.29	82.66	82.10	84.31	84.94
	TS	35-40	80.75	80.61	82.01	82.59	83.02	84.23	85.10
	BSO	33-38	82.47	81.97	82.82	84.22	83.90	86.14	86.76
	CS	32-39	83.09	84.21	84.13	84.75	84.58	86.40	87.35
	DA	30-36	82.74	82.96	84.10	85.01	85.47	86.88	87.67
	ALO	30-35	83.81	83.45	84.69	85.59	86.01	87.85	88.43
	LSFA	20-35	86.54	86.72	87.88	88.79	88.62	90.75	91.45
	CFA1	20-33	87.47	88.23	88.81	89.29	89.30	91.38	92.00
	CFA2	25-40	85.44	85.15	86.77	87.28	87.28	89.39	90.09
	VSSFA	23-38	86.33	86.16	86.99	88.59	88.42	90.15	90.88
	RaFA	25-35	86.32	87.67	87.21	87.70	87.86	89.99	90.67
	AFA	20-33	85.31	85.56	86.56	87.35	87.16	89.11	90.00
	MFA	30-34	82.17	83.76	83.56	84.87	84.99	86.20	87.14
	NaFA	20-26	88.77	89.60	89.45	90.62	90.89	92.75	93.00
	HMOFA	28-33	81.59	82.41	82.42	83.21	83.19	86.01	86.12
	Entire set	72	79.56	79.22	80.05	81.80	81.06	83.23	83.94
	Prop. FA	**18-25**	**91.52**	**91.66**	**92.23**	**93.16**	**92.96**	**95.37**	**95.70**
Libras	GA	60-65	81.62	80.83	81.70	81.86	82.35	83.76	85.75
	PSO	55-58	83.91	83.46	84.34	84.89	84.40	87.15	88.30
	FA	50-55	86.12	85.95	86.77	86.91	86.55	88.40	90.25
	SA	70-85	81.53	81.75	83.15	83.22	82.44	84.67	86.33
	DE	70-80	81.11	80.85	82.40	82.15	81.93	83.83	85.62
	MA-LS	63-69	85.04	84.31	85.98	86.02	86.09	87.66	89.29
	TS	60-70	85.34	85.84	84.92	86.55	86.28	88.23	89.89

	BSO	58-65	86.19	86.10	86.28	87.59	87.32	89.29	90.93
	CS	60-65	87.04	86.81	87.59	88.45	88.17	90.61	91.80
	DA	52-60	87.69	88.41	88.69	88.67	89.51	91.47	92.52
	ALO	50-55	88.56	88.11	88.12	89.61	89.20	91.45	93.08
	LSFA	45-55	88.26	88.52	88.28	89.69	89.30	91.16	93.05
	CFA1	45-50	91.09	90.78	90.21	91.70	91.48	93.32	95.20
	CFA2	40-50	88.85	88.96	88.41	89.03	89.44	91.97	93.00
	VSSFA	45-50	87.92	88.38	89.20	88.71	88.65	91.38	92.50
	RaFA	40-55	89.14	89.19	90.42	90.16	89.87	92.79	93.85
	AFA	40-60	89.32	89.73	89.37	90.78	90.33	92.69	94.00
	MFA	45-55	87.17	87.47	88.21	88.47	88.54	90.21	92.00
	NaFA	38-45	91.10	91.01	91.75	91.37	92.07	93.80	95.11
	HMOFA	43-50	86.02	86.65	86.50	87.28	87.80	88.96	90.94
	Entire set	91	83.91	84.50	84.90	85.20	85.01	86.82	88.66
	Prop. FA	**35-40**	**92.66**	**92.98**	**93.15**	**93.84**	**93.34**	**96.11**	**97.15**
Secom	GA	300-400	81.50	82.37	82.73	83.06	83.93	85.50	87.50
	PSO	300-360	81.81	83.46	83.15	83.28	83.75	86.72	88.00
	FA	250-280	84.96	84.06	84.65	86.98	86.22	88.27	90.00
	SA	320-450	78.21	80.01	79.17	80.27	81.72	83.62	84.96
	DE	350-450	77.76	78.91	79.59	80.62	81.00	82.41	84.41
	MA-LS	280-360	80.70	81.80	81.95	83.05	84.10	86.33	87.59
	TS	275-340	81.30	83.43	83.31	84.86	84.03	86.54	88.10
	BSO	260-300	83.11	84.94	84.45	85.52	84.69	87.72	89.66
	CS	210-270	83.82	86.09	86.20	86.86	86.12	88.29	90.27
	DA	200-270	85.47	85.46	85.75	85.87	86.36	89.02	90.58
	ALO	190-245	87.22	89.98	89.77	90.41	90.08	92.38	94.08
	LSFA	200-300	87.07	89.71	88.58	90.93	90.70	92.35	94.00
	CFA1	150-170	89.90	90.58	90.60	91.74	91.34	93.11	95.10
	CFA2	120-167	86.18	86.08	87.03	87.64	87.33	90.03	92.00
	VSSFA	120-160	85.65	86.27	85.90	88.68	87.19	90.00	91.78
	RaFA	115-150	87.83	87.95	87.64	90.15	88.22	91.80	93.15
	AFA	110-145	86.61	87.53	87.47	88.36	89.35	91.01	92.45
	MFA	140-167	88.24	89.97	89.97	89.55	90.89	92.95	94.33
	NaFA	112-155	91.89	91.22	92.44	92.67	92.47	95.47	97.21
	HMOFA	125-176	88.02	88.55	88.17	88.79	90.18	92.45	93.56
	Entire set	591	81.25	82.85	82.45	82.11	82.26	85.15	86.89
	Prop. FA	**100-150**	**93.44**	**93.58**	**95.30**	**95.09**	**96.27**	**98.31**	**99.31**
Arcene	GA	2500-4000	67.76	68.22	71.93	69	70	75.5	77.8
	PSO	2400-4000	71.37	72.30	75.98	72.35	73.66	77.65	80.1
	FA	2000-3000	71.09	71.65	74.82	73	73	76.75	79.3
	SA	4000-6000	67.66	67.61	70.53	68	69.33	71.45	72
	DE	4000-6000	67.68	67.79	70.95	68.4	69.71	72	73.2
	MA-LS	2500-3500	68.27	69.39	73.18	70.1	70.5	74.5	76
	TS	2300-3120	70.29	70.09	72.41	71	71.33	75.6	76.85
	BSO	2150-3200	69.24	70.47	74.84	72	72	76.55	77.21
	CS	2200-3000	71.58	71.07	76.42	71.56	72.98	76.77	77.75
	DA	2000-3100	73.47	73.34	76.66	72.3	74.55	78.1	78.33
	ALO	2500-2700	71.76	71.48	75.44	73	73.15	78.9	80.66
	LSFA	1800-2400	77.31	78.93	81.31	80	80	84.33	85.7
	CFA1	1100-2000	80.30	80.97	85.12	82.5	82.75	87.45	88.33
	CFA2	900-1500	81.99	82.24	86.12	83.26	83.76	88	88.76
	VSSFA	850-1250	82.46	83.36	88.97	84.56	85	87.76	88.59
	RaFA	600-1000	84.03	84.68	89.13	86	86.19	90.5	91
	AFA	750-1000	83.85	84.89	89.51	86.43	86.55	91.9	92.1
	MFA	800-1400	85.35	85.37	89.23	87	87	92	92.05
	NaFA	570-710	89.43	88.44	**94.05**	89.33	90.43	94.54	95.5
	HMOFA	800-1050	86.74	86.21	91.02	86.75	88	90.73	91.66
	Entire set	10000	67.18	66.49	70.81	66.9	68.35	71	71.33
	Prop. FA	**450-650**	**90.57**	**89.90**	93.50	**91.23**	**91.79**	**96**	**96.67**
DrivFace	GA	1250-2400	73.14	73.77	73.71	75.00	75.66	79.46	80.10
	PSO	1240-2400	74.15	75.55	75.28	75.35	76.75	80.50	81.21
	FA	1200-2300	74.74	75.20	75.28	77.00	77.00	82.67	82.90
	SA	2000-3100	70.05	71.28	71.31	73.10	73.00	77.33	78.50
	DE	2100-3220	70.86	70.66	72.07	72.70	73.10	77.45	77.93
	MA-LS	1100-1500	74.75	75.36	75.65	76.90	77.00	81.21	82.40
	TS	1100-1550	73.92	75.21	75.42	75.44	76.50	79.98	80.65
	BSO	1070-1350	75.48	75.49	77.12	77.50	78.33	82.69	83.21
	CS	1000-1300	75.78	76.60	76.86	77.00	78.10	83.75	84.00
	DA	1000-1300	75.49	77.34	76.74	77.35	78.45	82.76	83.98
	ALO	1055-1275	76.06	76.46	76.94	78.00	78.33	83.75	85.45
	LSFA	1180-2240	76.39	76.89	76.51	77.93	78.43	85.88	86.40
	CFA1	1110-2200	79.04	79.40	79.52	81.50	81.20	89.05	89.25
	CFA2	920-1150	82.27	83.38	82.69	82.60	84.50	90.00	90.45
	VSSFA	810-1125	84.88	84.27	85.84	86.10	86.90	92.21	93.00
	RaFA	660-1100	87.28	87.85	88.59	90.33	90.25	95.45	96.20

	AFA	715-1100	86.77	88.26	88.12	88.75	89.67	92.50	93.70
	MFA	680-840	85.22	85.61	86.38	87.56	88.00	91.12	91.45
	NaFA	450-900	88.70	89.14	89.05	91.00	91.00	96.00	96.77
	HMOFA	600-1400	84.77	85.38	85.99	87.33	87.47	91.70	92.55
	Entire set	6400	71.05	72.32	71.78	72.50	73.66	78.60	79.73
	Prop. FA	**389-790**	**90.18**	**90.31**	**90.85**	**92.35**	**92.50**	**97.98**	**98.76**
Daily and Sports Activities	GA	1000-1800	78.62	79.25	80.01	81.20	81.60	89.26	89.78
	PSO	990-1700	80.04	81.45	80.51	81.60	82.50	90.00	90.33
	FA	1000-1675	80.84	80.65	82.50	82.40	83.50	89.90	90.83
	SA	1900-2300	77.82	78.97	79.24	80.00	80.33	86.55	87.00
	DE	1850-2300	78.33	79.07	78.66	80.50	80.66	86.00	86.33
	MA-LS	1000-1400	79.84	80.32	80.98	81.45	82.33	87.98	88.21
	TS	975-1450	80.43	81.84	81.05	82.10	83.00	88.56	88.90
	BSO	990-1500	81.04	82.29	81.74	82.50	83.71	89.30	90.43
	CS	900-1300	79.69	80.26	81.04	81.59	82.68	90.21	90.50
	DA	950-1400	80.88	81.16	82.45	83.00	83.60	90.50	91.00
	ALO	900-1600	80.68	81.77	82.16	82.83	83.51	89.78	90.33
	LSFA	940-1625	84.05	85.41	85.14	86.50	86.98	92.47	93.33
	CFA1	900-1570	85.57	85.54	86.03	87.10	87.90	93.21	93.87
	CFA2	900-1500	84.89	85.77	85.95	86.98	87.00	92.50	93.10
	VSSFA	800-1395	88.63	88.76	90.16	90.53	91.25	94.45	94.90
	RaFA	688-1050	88.47	89.64	90.09	91.40	91.33	95.76	96.25
	AFA	600-900	84.81	86.05	85.86	87.60	87.75	91.33	92.45
	MFA	600-1000	84.70	85.41	85.49	87.33	87.45	91.50	93.00
	NaFA	565-798	94.17	95.30	94.98	96.00	96.50	99.00	**100.00**
	HMOFA	780-1100	88.36	88.28	89.29	89.00	90.43	96.09	96.23
	Entire set	5625	78.66	78.38	79.06	80.55	81.00	85.33	86.11
	Prop. FA	**500-729**	**97.28**	**98.53**	**98.45**	**99.45**	**99.60**	**100.00**	**100.00**
Human Activity Recognition	GA	100-180	85.40	85.82	86.38	87.60	87.75	93.21	93.87
	PSO	90-172	85.73	84.67	86.80	87.10	87.90	93.50	94.00
	FA	100-150	87.74	88.40	89.66	90.33	91.47	94.20	94.66
	SA	200-300	81.60	81.11	83.51	85.00	85.00	89.33	90.10
	DE	190-300	81.63	83.95	83.55	85.21	85.50	90.33	90.75
	MA-LS	98-135	87.68	85.99	88.54	88.56	89.81	94.55	95.63
	TS	95-140	86.55	86.66	89.33	90.10	90.43	95.70	96.00
	BSO	90-114	88.14	88.96	89.52	89.98	91.00	96.21	96.50
	CS	92-110	86.41	87.04	88.54	90.00	90.11	96.50	96.50
	DA	100-110	88.69	88.50	89.68	91.23	91.50	96.87	97.10
	ALO	89-106	87.90	90.15	89.98	90.55	91.22	97.21	97.33
	LSFA	94-151	89.22	89.44	91.13	92.50	93.10	95.20	95.50
	CFA1	90-130	92.06	92.68	93.42	94.45	94.90	96.11	96.43
	CFA2	80-110	94.00	93.84	94.89	95.70	96.55	97.50	98.10
	VSSFA	80-112	93.09	95.54	95.62	96.00	96.89	97.45	98.90
	RaFA	64-79	95.28	95.74	96.72	97.75	98.00	**100.00**	**100.00**
	AFA	72-97	93.75	94.33	94.47	94.88	95.90	97.33	97.45
	MFA	80-86	92.17	92.82	94.97	96.23	96.00	98.50	99.00
	NaFA	56-64	**96.81**	96.26	97.54	99.25	99.10	**100.00**	**100.00**
	HMOFA	60-75	91.98	94.29	94.45	95.33	95.50	98.09	98.23
	Entire set	561	82.78	82.28	83.20	84.75	85.10	89.00	89.33
	Prop. FA	**45-56**	96.21	**97.96**	**98.60**	**99.80**	**100.00**	**100.00**	**100.00**
Music Analysis	GA	90-130	69.36	70.25	69.80	70.10	71.55	73.45	75.50
	PSO	90-127	68.50	71.05	73.55	71.25	72.20	76.00	77.41
	FA	93-115	73.11	74.18	76.57	74.70	75.25	78.90	79.87
	SA	110-175	66.70	68.20	68.62	70.00	70.00	72.50	73.87
	DE	115-160	68.10	68.76	67.72	69.21	70.10	71.50	72.50
	MA-LS	92-109	68.74	70.58	72.81	71.33	72.00	76.40	77.00
	TS	95-125	68.87	69.86	71.39	70.33	71.20	75.33	75.93
	BSO	90-123	73.27	74.82	76.13	75.70	76.33	79.00	79.20
	CS	95-130	73.10	75.59	75.13	75.93	76.88	78.23	79.23
	DA	85-114	75.04	77.45	78.83	77.35	78.45	81.00	81.80
	ALO	82-106	75.73	76.42	78.06	77.90	78.33	80.45	81.37
	LSFA	88-107	76.85	78.24	77.41	79.00	79.45	81.00	81.90
	CFA1	85-102	79.59	80.12	81.26	81.10	81.67	84.50	86.65
	CFA2	80-95	79.69	81.64	84.63	82.00	83.35	86.76	88.00
	VSSFA	80-100	81.25	83.38	86.06	84.25	84.88	88.45	90.00
	RaFA	48-71	84.03	85.84	87.88	86.67	87.00	90.33	94.45
	AFA	81-99	83.16	83.92	86.92	84.75	85.50	89.44	92.10
	MFA	63-77	83.94	84.63	88.16	86.23	86.00	90.50	91.00
	NaFA	45-51	86.40	88.85	92.88	90.25	90.10	95.78	96.33
	HMOFA	68-70	81.64	84.19	87.62	85.33	85.50	91.09	91.45
	Entire set	518	67.29	68.14	69.29	69.50	70.00	72.33	73.00
	Prop. FA	**40-49**	**89.87**	**91.31**	**93.75**	**91.80**	**92.33**	**97.45**	**98.12**
Semeion Handwritten Digit	GA	60-65	78.29	78.77	79.01	80.15	80.50	83.85	85.75
	PSO	55-58	80.12	81.06	81.05	82.40	83.00	86.98	87.30
	FA	50-55	83.32	84.48	83.74	84.00	85.71	88.30	90.25

	SA	80-100	76.92	78.31	77.52	79.10	79.50	83.00	83.50
	DE	79-95	76.43	76.61	77.92	78.50	79.00	82.21	83.11
	MA-LS	75-85	80.22	81.69	81.69	82.50	83.00	88.73	89.21
	TS	75-90	80.94	82.01	81.62	82.75	83.50	89.66	90.65
	BSO	61-69	81.93	82.02	82.68	83.00	84.37	90.54	91.00
	CS	53-65	81.60	82.08	82.01	83.21	83.77	89.93	91.50
	DA	50-60	82.56	82.33	83.50	82.79	84.75	91.56	92.00
	ALO	51-58	81.54	81.78	82.08	83.00	83.90	92.00	92.81
	LSFA	45-55	86.38	85.68	86.72	87.80	88.66	91.50	92.05
	CFA1	45-50	86.38	86.34	87.02	88.75	89.00	92.33	93.20
	CFA2	40-47	86.81	86.75	87.73	89.00	89.35	92.76	94.00
	VSSFA	41-50	88.40	89.87	89.34	90.25	90.88	95.45	96.00
	RaFA	37-44	90.67	90.15	91.56	92.67	93.00	96.33	97.45
	AFA	40-46	90.33	90.83	90.77	92.75	92.50	94.44	96.10
	MFA	37-50	88.99	88.05	89.43	90.23	91.00	94.50	95.00
	NaFA	35-41	92.82	93.08	93.44	94.25	95.10	98.78	99.33
	HMOFA	40-50	87.76	87.65	88.89	90.33	90.50	95.09	94.45
	Entire set	256	78.14	77.91	78.53	79.00	80.21	86.54	87.33
	Prop. FA	**33-38**	**93.65**	**93.43**	**95.01**	**95.80**	**96.33**	**99.45**	**100.00**
Arrhythmia	GA	85-100	65.00	67.10	68.50	70.00	71.45	75.33	76.00
	PSO	83-101	66.50	68.50	70.33	72.20	73.30	76.50	77.20
	FA	80-95	67.30	69.63	71.45	74.00	75.00	78.00	78.80
	SA	100-123	65.10	66.82	69.50	70.00	70.00	72.50	73.87
	DE	102-110	64.40	65.00	67.10	68.50	69.33	70.00	70.40
	MA-LS	91-104	67.71	68.45	69.00	69.70	70.10	72.70	73.50
	TS	90-100	67.00	67.33	69.50	70.33	71.20	74.20	74.93
	BSO	87-95	68.33	70.96	73.85	75.70	76.33	79.00	79.20
	CS	88-100	68.90	71.00	74.00	75.93	76.88	78.23	79.23
	DA	80-95	69.50	72.44	75.10	77.35	78.45	81.00	81.80
	ALO	80-88	70.00	73.10	75.63	77.90	78.33	80.45	81.37
	LSFA	70-80	69.00	72.23	75.33	76.00	77.20	79.33	80.10
	CFA1	69-80	71.45	74.55	76.31	78.90	79.00	83.20	83.97
	CFA2	68-82	72.75	76.98	78.90	79.85	80.45	84.15	85.50
	VSSFA	56-70	73.00	77.00	78.98	80.20	81.00	85.45	86.17
	RaFA	40-53	77.98	80.00	83.50	85.00	85.70	89.00	89.07
	AFA	50-60	75.00	78.65	80.66	82.00	82.93	86.44	88.23
	MFA	50-60	72.00	76.33	79.50	80.10	80.78	84.93	85.50
	NaFA	38-45	79.43	81.50	84.00	85.33	86.50	90.20	90.50
	HMOFA	50-57	72.33	75.81	77.79	79.00	79.98	83.50	84.50
	Entire set	279	61.20	65.00	66.45	66.90	67.33	71.50	72.00
	Prop. FA	**30-42**	**81.66**	**84.45**	**86.71**	**87.50**	**88.45**	**91.30**	**92.97**
Breast Cancer Wisconsin	GA	30	66.10	67.33	67.75	68.00	68.70	70.20	71.07
	PSO	29	67.00	67.50	68.30	69.20	69.50	71.05	72.50
	FA	20-23	68.50	69.40	70.00	70.00	70.40	72.30	73.93
	SA	33	64.61	65.33	65.98	66.00	66.00	68.00	69.10
	DE	34	64.00	64.77	65.20	65.00	66.10	68.50	69.50
	MA-LS	20-24	67.40	68.21	69.33	69.90	70.00	72.00	72.60
	TS	19-25	66.45	67.33	68.00	68.83	69.10	71.00	71.47
	BSO	20	67.50	67.98	68.56	70.10	70.40	72.45	73.60
	CS	20-22	66.32	67.51	68.20	68.70	69.60	71.60	72.33
	DA	19-23	69.31	70.00	70.50	71.33	71.45	74.70	75.87
	ALO	18-20	69.33	70.50	71.67	72.50	73.00	76.35	77.33
	LSFA	20-21	70.20	70.45	71.00	71.50	71.00	74.10	75.00
	CFA1	18-24	72.41	72.98	73.33	74.55	75.33	77.40	78.87
	CFA2	17-21	75.87	76.21	77.01	77.12	78.43	80.00	80.50
	VSSFA	18-25	75.33	76.10	76.98	77.05	77.76	80.56	81.20
	RaFA	10-14	77.45	78.00	78.70	79.56	80.00	83.98	84.73
	AFA	13-15	76.10	76.89	77.50	78.88	79.00	82.00	82.63
	MFA	14-16	74.33	75.23	76.50	76.93	77.10	81.75	82.50
	NaFA	9- to 13	78.68	79.55	80.00	82.33	83.45	86.00	86.63
	HMOFA	13-16	75.50	77.00	78.57	79.60	80.43	83.00	83.77
	Entire set	34	64.10	64.70	65.33	65.55	66.00	68.00	69.00
	Prop. FA	**7-10**	**80.45**	**81.67**	**83.50**	**85.00**	**85.45**	**88.50**	**89.67**
Heart Disease	GA	60-63	62.67	66.25	67.38	68.98	68.40	72.10	74.50
	PSO	60-65	66.15	68.84	70.21	71.50	71.45	72.33	75.70
	FA	56-57	67.75	70.54	69.92	72.00	72.50	73.20	76.50
	SA	64-68	65.20	66.87	65.77	69.33	68.70	71.00	73.50
	DE	66-70	63.01	65.28	65.96	67.89	69.00	70.33	73.83
	MA-LS	55-59	67.72	70.03	68.60	72.25	71.98	73.20	74.60
	TS	55-62	65.56	69.33	66.96	70.50	69.87	73.10	74.10
	BSO	54-63	73.50	74.69	73.58	76.10	76.50	77.00	78.40
	CS	55-60	67.73	71.46	71.56	73.33	72.79	76.50	78.00
	DA	55-60	66.13	68.91	67.67	72.10	70.75	74.30	78.00
	ALO	53-61	66.39	70.22	74.27	73.20	76.57	77.60	79.60
	LSFA	57-63	68.47	70.79	70.22	72.30	72.85	74.67	75.97

	CFA1	50-55	71.73	72.81	72.90	76.00	76.30	80.50	81.40
	CFA2	50-53	71.92	75.08	76.05	78.75	79.21	81.60	82.67
	VSSFA	50-55	69.19	71.66	72.17	74.61	74.50	77.50	81.57
	RaFA	40-45	77.27	79.37	82.36	82.00	83.60	84.10	86.13
	AFA	48-54	72.61	74.82	76.16	78.00	79.98	81.00	83.53
	MFA	46-55	78.46	79.47	75.38	80.50	78.45	82.40	84.77
	NaFA	35-40	81.17	83.43	80.67	85.33	83.20	87.00	89.87
	HMOFA	45-55	78.37	79.84	80.15	82.10	83.70	84.67	85.87
	Entire set	75	62.93	63.99	65.73	67.00	67.33	68.50	70.50
	Prop. FA	**30-36**	**82.68**	**84.43**	**86.75**	**87.56**	**89.51**	**91.33**	**93.27**
ISOLET	GA	200-250	68.98	68.09	68.48	70.50	69.60	72.02	73.50
	PSO	190-205	67.70	66.67	69.51	70.28	69.75	72.38	74.30
	FA	180-195	70.54	70.60	71.83	72.54	70.87	73.61	76.03
	SA	250-300	64.14	63.80	66.69	67.20	67.04	69.66	71.27
	DE	300-350	65.23	63.42	68.35	67.08	67.98	69.84	71.50
	MA-LS	170-200	71.84	69.69	71.32	73.48	73.42	74.89	76.50
	TS	175-190	67.72	67.60	71.18	71.57	71.43	73.40	76.00
	BSO	160-170	71.05	70.19	72.93	74.01	73.55	75.61	78.33
	CS	165-180	71.21	71.90	72.92	73.35	72.54	75.34	77.50
	DA	150-164	73.57	74.55	76.60	76.48	76.69	78.07	80.03
	ALO	153-172	71.85	72.27	75.35	74.64	75.83	77.21	78.87
	LSFA	162-177	71.60	69.28	74.66	73.07	73.99	75.96	77.00
	CFA1	127-140	75.65	74.25	79.48	77.97	79.51	80.94	82.90
	CFA2	120-133	80.49	78.74	81.75	81.77	81.30	83.09	84.93
	VSSFA	125-140	76.82	76.45	79.20	79.49	79.96	82.31	83.50
	RaFA	90-102	84.30	84.88	87.64	88.12	87.42	90.41	91.70
	AFA	100-110	76.44	78.62	79.85	79.90	79.57	82.44	85.17
	MFA	99-114	78.88	76.77	80.30	80.17	80.91	82.03	84.03
	NaFA	70-89	84.63	84.34	85.79	86.09	86.25	87.57	90.50
	HMOFA	105-130	79.18	81.11	83.00	82.50	83.73	85.01	86.93
	Entire set	617	63.27	63.59	64.07	64.65	65.13	66.91	67.53
	Prop. FA	**60-75**	**87.77**	**88.61**	**90.64**	**91.58**	**90.15**	**93.05**	**94.50**
MicroMass	GA	400-500	69.84	71.95	74.15	72.55	75.02	76.52	77.27
	PSO	400-480	72.16	72.97	74.97	73.66	74.42	76.67	78.33
	FA	380-470	75.88	73.83	77.09	75.46	76.71	78.91	80.00
	SA	500-800	70.31	71.39	74.01	71.74	74.39	75.69	75.70
	DE	500-850	69.21	70.16	73.79	74.10	74.43	76.33	76.50
	MA-LS	350-460	73.61	76.66	76.23	77.74	79.02	80.54	81.10
	TS	350-450	78.20	79.84	79.96	79.58	82.00	83.08	83.17
	BSO	300-410	77.94	75.37	79.67	78.59	79.51	82.19	83.23
	CS	320-420	76.73	79.77	79.57	80.70	83.15	84.23	84.30
	DA	300-390	75.91	79.24	79.30	80.32	81.34	83.64	85.50
	ALO	290-400	79.82	83.52	83.75	83.22	85.62	86.73	87.00
	LSFA	350-400	82.09	80.73	83.42	83.44	81.91	84.54	85.57
	CFA1	250-340	81.92	82.88	86.30	84.86	86.10	88.23	89.20
	CFA2	225-297	83.88	84.54	88.11	87.76	88.56	89.92	91.00
	VSSFA	245-288	85.56	83.77	86.85	87.35	87.12	88.38	89.50
	RaFA	178-212	88.09	88.45	90.10	89.72	90.84	92.41	93.40
	AFA	200-250	84.05	84.43	88.12	88.36	88.71	89.82	91.50
	MFA	200-245	83.37	84.21	86.01	85.73	87.33	88.70	89.50
	NaFA	151-179	90.57	90.60	**94.64**	**95.07**	93.13	96.09	96.57
	HMOFA	200-350	84.95	85.62	89.04	88.64	88.31	90.92	91.50
	Entire set	1300	64.22	66.03	66.25	67.22	69.30	70.77	72.33
	Prop. FA	**123-155**	**91.93**	**91.90**	93.73	93.76	**94.16**	**96.74**	**97.50**
Weight Lifting Exercises	GA	70-77	71.20	74.09	73.75	72.43	72.99	76.30	76.40
	PSO	70-80	73.98	74.61	74.48	73.48	73.09	75.16	76.77
	FA	65-73	74.93	73.42	75.61	74.34	76.52	77.52	77.57
	SA	80-100	65.59	67.61	67.92	68.68	68.39	70.77	71.43
	DE	80-105	69.79	67.73	70.59	70.13	68.43	71.58	71.97
	MA-LS	70-75	74.02	71.91	74.86	75.48	74.34	76.83	77.27
	TS	70-80	74.42	72.37	75.47	74.34	76.98	76.60	78.33
	BSO	65-70	80.72	81.90	80.65	83.06	81.96	82.43	84.07
	CS	65-75	79.07	80.39	80.79	80.67	83.40	83.72	84.50
	DA	65-75	80.91	83.94	83.30	85.36	83.85	85.57	86.50
	ALO	60-70	80.81	80.42	81.87	81.13	82.82	84.43	84.57
	LSFA	65-74	75.35	77.97	78.93	80.07	78.59	80.85	81.13
	CFA1	55-67	83.16	81.23	84.53	83.65	83.47	85.21	86.13
	CFA2	55-60	81.40	81.79	85.81	84.79	85.15	84.92	86.90
	VSSFA	50-65	84.31	85.88	87.65	85.61	85.10	87.32	88.67
	RaFA	40-50	86.42	89.15	89.41	87.55	88.22	89.94	91.33
	AFA	55-60	86.50	83.73	86.79	84.76	86.79	88.20	88.63
	MFA	50-60	88.13	84.71	88.10	88.14	88.29	89.23	90.20
	NaFA	35-44	**90.89**	88.76	91.94	91.08	91.45	92.88	93.00
	HMOFA	50-61	86.97	87.09	88.00	86.64	85.48	88.80	89.37
	Entire set	152	64.75	66.11	67.79	67.23	68.49	68.17	69.50

	Prop. FA	**30-42**	90.32	**92.25**	**92.31**	**93.82**	**92.96**	**94.03**	**95.87**
Gas Sensor Array Drift	GA	70-75	69.65	70.69	70.55	70.72	71.52	74.13	74.17
	PSO	70-85	71.61	72.83	74.47	73.34	74.74	76.60	76.97
	FA	60-73	73.52	71.42	73.91	73.06	75.67	76.31	78.27
	SA	70-90	67.98	66.54	67.63	68.30	69.37	70.75	72.03
	DE	80-90	65.05	66.16	67.64	66.99	67.74	70.96	71.30
	MA-LS	60-70	73.89	72.42	73.61	73.89	75.09	77.17	79.07
	TS	60-80	71.78	72.26	73.32	72.66	73.44	76.56	76.70
	BSO	60-70	78.16	78.31	79.17	79.93	79.87	82.86	83.03
	CS	65-75	76.73	77.62	78.91	79.76	80.53	82.31	83.70
	DA	65-70	78.72	79.57	81.51	81.73	82.07	83.96	84.33
	ALO	60-70	82.78	80.87	82.18	83.21	83.79	85.75	85.87
	LSFA	65-70	77.35	78.67	78.98	79.32	79.45	81.98	82.37
	CFA1	55-63	79.89	79.55	82.25	82.22	82.73	84.31	85.33
	CFA2	55-60	81.46	84.56	84.56	84.55	85.23	88.12	89.07
	VSSFA	50-60	82.70	82.23	83.93	83.04	83.82	86.31	87.07
	RaFA	40-47	87.26	87.80	88.82	88.16	88.37	91.13	91.27
	AFA	55-60	84.96	84.85	84.48	84.53	86.42	88.37	89.60
	MFA	50-60	85.57	83.59	86.21	84.68	87.07	88.54	89.17
	NaFA	35-40	88.35	88.73	89.75	90.07	91.30	92.29	93.40
	HMOFA	50-55	85.92	84.14	86.32	85.98	88.08	89.03	90.20
	Entire set	129	62.79	63.73	63.58	64.98	66.05	67.44	69.10
	Prop. FA	**28-35**	**89.81**	**90.91**	**91.69**	**91.73**	**93.71**	**95.53**	**96.03**
LSVT Voice Rehab.	GA	130-155	68.66	72.00	70.16	71.44	72.83	74.11	75.30
	PSO	130-150	70.08	72.45	72.65	73.25	73.45	74.79	76.30
	FA	125-140	70.21	72.73	73.94	74.54	74.54	76.33	78.37
	SA	160-200	66.54	65.45	66.46	69.04	68.95	68.76	71.27
	DE	165-200	66.46	66.77	66.09	68.22	68.84	69.45	71.90
	MA-LS	120-150	70.37	73.65	72.74	72.92	72.83	75.76	76.80
	TS	125-145	76.11	76.70	76.36	76.56	78.43	79.02	80.50
	BSO	120-130	76.83	79.84	80.24	80.71	81.03	82.78	83.90
	CS	120-135	77.24	78.06	77.20	79.38	79.34	80.12	81.80
	DA	115-133	81.42	81.38	81.17	84.40	83.61	84.98	86.50
	ALO	110-140	76.40	79.46	79.45	80.65	79.39	82.00	83.30
	LSFA	120-150	75.16	76.76	76.42	78.39	78.69	79.32	81.10
	CFA1	110-125	79.76	79.75	81.34	82.01	81.92	83.74	85.13
	CFA2	105-120	82.17	82.04	82.86	84.89	84.61	84.97	87.47
	VSSFA	110-115	81.75	83.23	82.81	84.87	84.42	86.08	88.33
	RaFA	90-99	83.60	86.92	85.53	87.65	88.49	89.44	91.30
	AFA	100-110	80.70	84.66	83.82	84.60	84.77	87.18	88.47
	MFA	99-106	84.36	85.97	85.84	87.99	88.00	88.12	90.90
	NaFA	78-91	88.86	**91.21**	89.70	90.99	91.34	93.61	94.63
	HMOFA	100-120	81.73	83.95	83.02	86.99	85.35	86.50	89.20
	Entire set	309	63.47	65.93	67.26	66.26	67.07	69.82	70.00
	Prop. FA	**67-75**	**89.86**	90.42	**91.28**	**93.71**	**93.98**	**93.62**	**96.53**
Geographical Origin of Music	GA	40-45	70.35	71.38	71.58	72.92	73.90	74.18	75.17
	PSO	40-45	69.14	70.61	73.81	72.31	72.44	75.47	76.20
	FA	38-44	70.78	70.58	74.48	75.06	74.41	77.73	77.87
	SA	50-55	66.64	66.59	68.34	68.62	69.08	71.34	72.37
	DE	50-55	63.65	65.27	67.07	67.77	67.21	69.21	71.10
	MA-LS	40-45	72.70	74.40	76.31	77.60	76.51	77.93	79.80
	TS	40-46	70.71	71.94	70.89	74.02	73.07	74.76	76.60
	BSO	35-45	79.30	81.62	80.93	81.77	82.79	82.55	84.33
	CS	35-45	78.57	79.65	79.33	81.48	81.27	83.12	83.87
	DA	36-40	79.47	80.59	82.26	83.89	82.44	83.27	85.20
	ALO	35-40	79.61	82.06	82.40	81.23	83.10	83.56	84.93
	LSFA	35-40	78.36	77.29	77.54	80.88	80.52	80.62	82.60
	CFA1	30-40	81.12	82.14	82.24	81.60	83.22	84.01	85.20
	CFA2	30-35	81.83	83.35	86.80	85.39	85.58	88.08	88.53
	VSSFA	30-40	79.13	79.10	84.00	84.91	82.71	85.68	86.67
	RaFA	20-29	85.53	87.32	87.87	89.08	89.04	89.69	91.60
	AFA	30-35	84.61	83.29	88.58	88.67	86.52	89.68	89.97
	MFA	26-33	85.36	84.48	84.16	86.63	87.90	87.74	89.43
	NaFA	18-24	86.03	88.37	89.34	90.23	89.65	92.71	93.00
	HMOFA	29-34	84.43	84.14	86.28	88.60	87.46	88.44	90.13
	Entire set	68	66.33	66.81	67.02	68.33	69.09	69.57	71.20
	Prop. FA	**15-20**	**88.02**	**90.90**	**93.11**	**93.54**	**92.00**	**95.04**	**95.73**
Grammatical Facial Expressions	GA	60-70	67.72	68.07	70.58	71.38	71.55	73.87	75.20
	PSO	55-65	72.66	71.01	73.03	73.76	74.84	76.28	77.13
	FA	50-55	71.24	73.87	73.07	74.57	73.63	76.72	78.60
	SA	70-90	62.13	66.25	66.85	66.42	65.87	68.81	70.77
	DE	70-90	65.68	66.11	67.71	67.72	67.74	70.45	71.60
	MA-LS	50-60	72.17	72.06	70.90	73.56	73.64	75.82	76.80
	TS	55-65	72.57	73.55	74.82	72.52	75.77	77.16	78.83
	BSO	50-55	78.28	78.41	78.89	80.87	80.06	83.96	84.30

	CS	45-55	76.84	78.61	78.41	79.99	80.71	82.55	83.23
	DA	50-65	78.83	82.24	83.30	81.85	83.09	84.65	86.33
	ALO	45-60	78.40	77.53	81.62	80.52	80.52	83.23	85.13
	LSFA	50-55	76.44	74.74	77.03	75.27	78.17	80.14	80.60
	CFA1	44-50	81.05	79.79	81.37	82.60	81.37	85.05	85.60
	CFA2	45-50	82.51	81.91	81.56	84.15	83.15	86.45	86.93
	VSSFA	50-55	82.38	83.35	83.97	82.79	84.19	87.77	87.97
	RaFA	40-50	84.71	86.80	87.00	86.63	87.87	91.00	91.10
	AFA	45-50	80.91	85.25	83.36	83.08	84.96	87.27	88.33
	MFA	45-55	84.41	84.01	87.00	87.60	86.42	89.94	90.43
	NaFA	30-45	87.26	86.67	90.19	88.53	89.13	91.72	93.33
	HMOFA	45-60	84.96	87.26	87.30	87.88	88.25	90.46	90.53
	Entire set	100	65.82	65.71	66.62	66.57	66.86	67.02	68.93
	Prop. FA	**25-35**	**89.40**	**91.31**	**90.65**	**91.60**	**92.19**	**95.98**	**96.33**
Mice Protein Expression	GA	50-55	69.97	71.40	72.10	72.59	73.02	75.13	75.77
	PSO	48-55	70.57	69.15	71.04	73.61	74.72	74.83	76.07
	FA	43-49	70.35	70.78	70.89	73.30	75.89	75.96	77.40
	SA	70-75	68.41	67.60	66.88	70.87	70.69	72.41	72.63
	DE	70-75	66.28	65.27	66.02	69.31	69.50	70.63	70.73
	MA-LS	42-46	74.44	76.08	73.71	77.27	78.48	79.68	79.70
	TS	41-47	72.42	72.10	71.37	74.50	76.41	76.42	77.53
	BSO	43-50	76.93	76.25	77.99	79.05	81.49	81.78	82.67
	CS	40-45	78.61	78.90	80.43	81.63	83.87	83.86	85.17
	DA	40-45	76.59	78.22	77.95	78.77	81.57	81.65	82.83
	ALO	42-45	79.23	80.95	80.81	82.92	83.82	84.20	85.20
	LSFA	45-50	76.78	76.21	77.25	77.84	78.90	80.50	81.47
	CFA1	36-41	78.87	80.58	80.01	83.36	83.68	84.38	85.93
	CFA2	33-40	83.02	84.84	84.05	85.62	86.07	88.06	88.67
	VSSFA	35-40	80.62	82.18	80.93	83.86	84.87	85.95	86.00
	RaFA	27-31	87.66	85.65	86.59	89.73	89.33	91.04	91.23
	AFA	30-35	83.63	82.49	84.82	85.77	87.96	88.35	89.80
	MFA	30-35	84.04	82.39	82.19	86.31	86.97	88.00	88.93
	NaFA	20-25	86.63	85.85	88.29	89.40	91.91	91.43	93.40
	HMOFA	30-35	82.77	81.11	83.17	84.67	85.48	86.61	88.27
	Entire set	82	63.26	65.70	64.38	66.34	68.04	69.23	70.50
	Prop. FA	**16-24**	**90.98**	**91.17**	**91.61**	**91.97**	**93.21**	**94.90**	**95.23**
Detect Malacious Executable	GA	200-250	68.44	70.57	71.13	71.72	71.53	74.32	74.50
	PSO	190-205	69.32	70.56	71.34	71.76	72.64	75.53	76.63
	FA	180-195	69.53	72.97	74.34	73.26	73.04	76.66	77.67
	SA	250-300	65.74	67.40	67.88	68.74	69.49	71.63	71.97
	DE	300-350	64.40	68.87	68.81	68.68	67.43	71.23	72.00
	MA-LS	170-200	70.21	72.55	73.58	72.31	73.08	75.83	76.27
	TS	175-190	72.65	73.79	73.54	74.30	75.10	77.86	79.33
	BSO	160-170	76.96	79.44	81.28	80.67	80.75	84.32	84.53
	CS	165-180	75.49	79.36	78.24	79.11	78.60	82.09	83.80
	DA	150-165	79.60	83.49	80.65	83.08	81.73	85.55	86.37
	ALO	150-160	75.43	79.00	81.50	81.33	80.38	83.73	84.37
	LSFA	162-177	76.00	77.87	80.30	79.95	79.14	82.76	83.10
	CFA1	127-140	77.35	79.71	81.80	80.81	81.70	84.27	84.80
	CFA2	120-135	80.27	82.76	81.81	82.86	83.61	85.88	87.67
	VSSFA	125-140	80.94	83.06	83.97	84.61	83.87	87.61	87.77
	RaFA	90-105	84.20	86.43	86.70	87.20	88.50	91.11	91.13
	AFA	100-110	83.35	85.87	85.53	85.08	85.49	88.75	89.07
	MFA	95-115	81.92	85.98	84.53	86.07	86.10	88.45	89.67
	NaFA	70-90	86.66	89.48	89.84	88.11	89.34	92.02	93.93
	HMOFA	105-130	80.96	85.24	86.09	86.28	84.83	88.48	89.57
	Entire set	513	66.05	69.49	67.61	69.63	68.81	71.94	72.00
	Prop. FA	**60-75**	**89.98**	**91.57**	**91.83**	**92.11**	**93.95**	**96.07**	**96.33**
Epileptic Seizure Recognition	GA	70-76	68.54	69.28	69.71	72.64	72.25	74.15	74.70
	PSO	70-80	71.32	71.57	72.06	75.19	74.98	76.42	76.73
	FA	65-75	72.76	71.54	72.85	74.00	75.06	75.88	77.60
	SA	80-100	67.03	67.97	66.89	69.07	69.98	70.92	72.03
	DE	80-105	65.87	66.05	65.66	67.03	68.55	69.74	70.80
	MA-LS	70-75	77.77	74.52	74.56	76.22	78.88	78.59	80.20
	TS	70-80	72.68	71.54	71.35	73.13	75.01	75.14	76.30
	BSO	65-70	78.56	78.68	79.51	80.16	81.25	81.89	82.70
	CS	65-75	78.12	77.50	78.53	79.46	80.22	81.81	83.13
	DA	65-75	77.74	80.53	78.66	80.70	81.22	82.81	83.50
	ALO	60-70	79.87	80.28	83.24	82.29	83.39	85.25	86.17
	LSFA	65-77	77.69	77.80	78.13	78.23	79.79	81.11	81.60
	CFA1	55-65	79.15	79.12	79.87	81.83	82.63	83.66	85.53
	CFA2	55-60	83.34	85.97	85.22	86.52	86.26	88.16	88.57
	VSSFA	50-65	80.68	81.88	83.16	83.91	83.39	85.96	86.00
	RaFA	40-50	87.46	86.42	86.16	88.50	90.01	90.13	91.50
	AFA	55-60	86.21	85.71	86.66	88.07	89.92	90.10	91.20

	MFA	50-60	86.09	84.61	85.21	86.48	87.27	87.59	88.33
	NaFA	35-46	88.44	89.16	88.82	90.23	91.66	91.96	93.73
	HMOFA	50-63	84.87	84.17	86.95	86.78	87.68	89.10	90.20
	Entire set	179	68.91	67.56	69.23	70.06	70.91	71.37	72.10
	Prop. FA	**30-38**	**90.86**	**92.85**	**92.24**	**93.12**	**92.81**	**95.69**	**95.77**

Table 6 The *p*-values of the Wilcoxon rank sum test for all classification data sets

Data sets	**LSFA**	**CFA 1**	**CFA 2**	**VSSFA**	**RaFA**	**AFA**	**MFA**	**NaFA**	**HMOFA**
CK+	1.17E-12	1.07E-12	7.21E-13	1.15E-12	1.86E-09	6.06E-10	1.15E-12	1.00E+00	1.17E-12
MMI	3.32E-11	6.73E-09	1.87E-08	8.35E-09	1.72E-05	1.99E-08	5.43E-09	1.77E-05	3.32E-11
JAFFE	1.11E-12	1.17E-12	1.09E-12	1.14E-12	4.42E-12	1.17E-12	1.06E-12	3.82E-12	1.14E-12
Bosphorus 3D	1.11E-12	1.12E-12	1.00E-12	1.13E-12	4.34E-12	1.11E-12	1.02E-12	3.73E-12	1.11E-12
BU-3DFE	1.19E-12	1.20E-12	1.13E-12	1.21E-12	4.49E-12	1.21E-12	1.14E-12	3.85E-12	1.15E-12
ALL-IDB2	1.13E-12	1.20E-12	1.18E-12	1.22E-12	4.45E-12	1.18E-12	1.13E-12	3.85E-12	1.18E-12
Sonar	1.21E-12	1.19E-12	1.10E-12	1.22E-12	4.43E-12	1.20E-12	1.08E-12	3.84E-12	1.21E-12
Secom	1.13E-12	1.18E-12	1.14E-12	1.23E-12	4.46E-12	1.20E-12	1.12E-12	3.91E-12	1.23E-12
Libras	1.12E-12	1.17E-12	1.14E-12	1.15E-12	4.48E-12	1.23E-12	1.15E-12	3.88E-12	1.17E-12
Ozone	1.21E-12	1.25E-12	1.18E-12	1.17E-12	4.46E-12	1.20E-12	1.14E-12	3.84E-12	1.20E-12
Arcene	3.43E-11	2.80E-11	8.99E-10	2.64E-08	1.89E-05	3.00E-08	3.82E-07	7.58E-03	7.76E-07
DrivFace	3.83E-11	3.55E-11	9.04E-10	2.64E-08	2.54E-05	3.00E-08	3.82E-07	7.51E-03	7.76E-07
Daily & Sports Act.	3.36E-11	2.77E-11	9.02E-10	2.64E-08	7.21E-03	3.00E-08	3.82E-07	1.00E+00	7.76E-07
Human Activity Rec.	3.68E-11	2.88E-11	9.00E-10	2.64E-08	1.00E+00	3.00E-08	3.82E-07	1.00E+00	7.76E-07
Music Analysis	3.58E-11	3.26E-11	8.97E-10	2.64E-08	2.11E-05	3.00E-08	3.82E-07	7.60E-03	7.76E-07
Handwritten Digit	3.53E-11	3.34E-11	8.99E-10	2.64E-08	2.10E-05	3.00E-08	3.82E-07	7.25E-03	7.76E-07
Arrhythmia	3.78E-11	3.54E-11	9.07E-10	2.64E-08	2.00E-05	3.00E-08	3.82E-07	8.16E-03	7.76E-07
Breast Cancer	3.67E-11	3.07E-11	9.03E-10	2.64E-08	1.82E-05	3.00E-08	3.82E-07	8.17E-03	7.76E-07
Heart Disease	3.72E-11	3.42E-11	9.05E-10	2.64E-08	1.88E-05	3.00E-08	3.82E-07	8.12E-03	7.76E-07
ISOLET	3.46E-11	3.21E-11	9.04E-10	2.64E-08	2.00E-05	3.00E-08	3.82E-07	8.16E-03	7.76E-07
MicroMass	3.69E-11	3.35E-11	9.05E-10	2.64E-08	1.89E-05	3.00E-08	3.82E-07	8.05E-03	7.76E-07
Weight Lifting	3.64E-11	3.52E-11	9.02E-10	2.64E-08	1.90E-05	3.00E-08	3.82E-07	7.94E-03	7.76E-07
Gas Sensor	4.05E-11	3.60E-11	9.08E-10	2.64E-08	2.18E-05	3.00E-08	3.82E-07	8.20E-03	7.76E-07
LSVT Voice Rehab.	3.96E-11	3.95E-11	9.11E-10	2.64E-08	2.15E-05	3.00E-08	3.82E-07	8.36E-03	7.76E-07
Geographical Origin of Music	3.85E-11	3.64E-11	9.11E-10	2.64E-08	2.02E-05	3.00E-08	3.82E-07	8.45E-03	7.76E-07
Grammatical Facial Exp.	4.04E-11	3.81E-11	9.10E-10	2.64E-08	2.37E-05	3.00E-08	3.82E-07	7.80E-03	7.76E-07
Mice Protein Exp.	3.73E-11	3.20E-11	9.05E-10	2.64E-08	2.05E-05	3.00E-08	3.82E-07	8.07E-03	7.76E-07
Detect Malacious Exe.	3.36E-11	3.18E-11	9.04E-10	2.64E-08	2.52E-05	3.00E-08	3.82E-07	7.98E-03	7.76E-07
Seizure Recog.	3.34E-11	3.19E-11	9.06E-10	2.64E-08	2.18E-05	3.00E-08	3.82E-07	8.15E-03	7.76E-07

Data sets	**GA**	**PSO**	**FA**	**SA**	**DE**	**MA-LS**	**TS**	**BSO**	**CS**	**DA**	**ALO**
CK+	1.19E-12	1.17E-12	1.19E-12	1.19E-12	1.19E-12	1.19E-12	1.19E-12	1.19E-12	1.16E-12	1.17E-12	1.19E-12
MMI	2.79E-11	2.81E-11	4.81E-11	2.78E-11	2.75E-11	2.81E-11	2.81E-11	4.54E-11	4.70E-11	4.81E-11	3.95E-11
JAFFE	1.18E-12	1.12E-12	1.1E-12	1.18E-12	1.18E-12	1.14E-12	1.12E-12	1.10E-12	1.30E-12	1.10E-12	1.10E-12
Bosphorus 3D	1.09E-12	1.11E-12	1.03E-12	1.16E-12	1.14E-12	1.11E-12	1.05E-12	1.02E-12	1.27E-12	1.05E-12	1.01E-12
BU-3DFE	1.24E-12	1.18E-12	1.17E-12	1.23E-12	1.24E-12	1.16E-12	1.21E-12	1.14E-12	1.39E-12	1.17E-12	1.20E-12
ALL-IDB2	1.22E-12	1.17E-12	1.10E-12	1.19E-12	1.24E-12	1.22E-12	1.12E-12	1.11E-12	1.34E-12	1.18E-12	1.16E-12
Sonar	1.22E-12	1.20E-12	1.17E-12	1.27E-12	1.25E-12	1.23E-12	1.16E-12	1.14E-12	1.36E-12	1.18E-12	1.11E-12
Secom	1.21E-12	1.18E-12	1.15E-12	1.21E-12	1.21E-12	1.20E-12	1.18E-12	1.17E-12	1.38E-12	1.17E-12	1.19E-12
Libras	1.26E-12	1.15E-12	1.15E-12	1.28E-12	1.24E-12	1.19E-12	1.13E-12	1.11E-12	1.37E-12	1.10E-12	1.18E-12
Ozone	1.22E-12	1.16E-12	1.15E-12	1.19E-12	1.27E-12	1.15E-12	1.16E-12	1.14E-12	1.34E-12	1.20E-12	1.15E-12
Arcene	2.42E-11	2.47E-11	2.40E-11	2.02E-11	2.21E-11	2.09E-11	2.08E-11	2.01E-11	2.22E-11	9.69E-10	6.16E-11
DrivFace	2.97E-11	2.96E-11	3.01E-11	3.15E-11	2.84E-11	3.11E-11	2.69E-11	3.04E-11	2.90E-11	9.78E-10	6.79E-11
Daily & Sports Act.	2.37E-11	2.41E-11	2.15E-11	2.11E-11	1.97E-11	2.40E-11	2.22E-11	2.29E-11	2.20E-11	9.69E-10	6.05E-11
Human Act. Rec.	1.97E-11	2.38E-11	2.36E-11	2.25E-11	2.41E-11	2.36E-11	2.18E-11	2.07E-11	2.42E-11	9.72E-10	6.28E-11
Music Analysis	2.24E-11	1.96E-11	1.97E-11	2.03E-11	2.48E-11	2.42E-11	2.23E-11	2.48E-11	2.23E-11	9.67E-10	6.31E-11
Handwritten Digit	2.10E-11	1.90E-11	2.25E-11	2.02E-11	2.27E-11	2.12E-11	1.98E-11	2.20E-11	2.51E-11	9.67E-10	6.17E-11
Arrhythmia	2.69E-11	2.75E-11	2.78E-11	2.75E-11	2.65E-11	2.75E-11	2.67E-11	2.73E-11	2.75E-11	9.75E-10	6.65E-11
Breast Cancer	2.49E-11	2.59E-11	2.69E-11	2.33E-11	2.33E-11	2.31E-11	2.48E-11	2.39E-11	2.30E-11	9.73E-10	6.33E-11
Heart Disease	2.20E-11	2.74E-11	2.69E-11	2.30E-11	2.49E-11	2.49E-11	2.30E-11	2.56E-11	2.74E-11	9.74E-10	6.18E-11
ISOLET	2.55E-11	2.74E-11	2.60E-11	2.56E-11	2.39E-11	2.60E-11	2.64E-11	2.32E-11	2.36E-11	9.74E-10	6.45E-11
MicroMass	2.23E-11	2.59E-11	2.42E-11	2.70E-11	2.42E-11	2.43E-11	2.48E-11	2.47E-11	2.69E-11	9.72E-10	6.53E-11
Weight Lifting	2.35E-11	2.31E-11	2.42E-11	2.36E-11	2.52E-11	2.57E-11	2.44E-11	2.55E-11	2.62E-11	9.70E-10	6.56E-11
Gas Sensor Array Drift	3.13E-11	3.16E-11	3.17E-11	3.23E-11	3.00E-11	3.16E-11	2.73E-11	3.04E-11	3.23E-11	9.79E-10	7.03E-11
LSVT Voice Rehab.	2.90E-11	2.82E-11	2.88E-11	2.99E-11	2.67E-11	2.87E-11	2.80E-11	2.79E-11	3.22E-11	9.76E-10	6.97E-11
Geographical Origin of Music	2.95E-11	2.88E-11	3.07E-11	3.15E-11	2.67E-11	3.11E-11	3.00E-11	3.14E-11	2.81E-11	9.76E-10	7.03E-11
Grammatical Facial Exp.	2.89E-11	3.07E-11	2.94E-11	3.04E-11	3.04E-11	2.99E-11	3.10E-11	3.21E-11	3.19E-11	9.78E-10	6.79E-11
Mice Protein Exp.	2.54E-11	2.60E-11	2.33E-11	2.55E-11	2.44E-11	2.28E-11	2.52E-11	2.59E-11	2.43E-11	9.71E-10	6.64E-11
Detect Malacious Exe.	2.50E-11	2.28E-11	2.53E-11	2.59E-11	2.32E-11	2.28E-11	2.43E-11	2.47E-11	2.59E-11	9.75E-10	6.45E-11
Seizure Recog.	2.24E-11	2.69E-11	2.34E-11	2.30E-11	2.61E-11	2.44E-11	2.48E-11	2.71E-11	2.55E-11	9.75E-10	6.64E-11

Table 7 Average performance of each algorithm over 30 runs for 11 regression data sets

Data sets	**Methods**	**No. of features**	**LR (MSE)**	**SVR (MSE)**	**SVR-based Ensemble (MSE)**
Communities and Crime	GA	70-80	0.105	0.103	0.101

	PSO	70-80	0.102	0.102	0.099
	FA	65-75	0.099	0.098	0.095
	SA	80-100	0.108	0.108	0.105
	DE	80-105	0.111	0.108	0.106
	MA-LS	70-75	0.098	0.098	0.096
	TS	70-80	0.097	0.097	0.095
	BSO	65-70	0.097	0.095	0.093
	CS	65-75	0.094	0.094	0.092
	DA	65-75	0.095	0.095	0.093
	ALO	60-70	0.094	0.094	0.091
	LSFA	65-74	0.098	0.094	0.093
	CFA1	55-67	0.094	0.092	0.089
	CFA2	55-60	0.092	0.090	0.088
	VSSFA	50-65	0.094	0.089	0.088
	RaFA	40-50	0.074	0.073	0.071
	AFA	55-60	0.082	0.083	0.079
	MFA	50-60	0.083	0.083	0.080
	NaFA	35-45	0.077	0.076	0.074
	HMOFA	50-63	0.087	0.085	0.083
	Entire set	128	0.112	0.112	0.110
	Prop. FA	**30-45**	**0.070**	**0.071**	**0.067**
Relative Location of CT Slices on Axial Axis	GA	85-100	0.111	0.109	0.107
	PSO	81-105	0.107	0.106	0.104
	FA	80-95	0.103	0.102	0.100
	SA	100-130	0.114	0.112	0.110
	DE	100-110	0.114	0.113	0.111
	MA-LS	91-105	0.105	0.104	0.101
	TS	90-100	0.104	0.104	0.101
	BSO	86-95	0.099	0.100	0.097
	CS	88-100	0.101	0.101	0.098
	DA	80-95	0.101	0.100	0.098
	ALO	80-90	0.099	0.098	0.095
	LSFA	70-80	0.102	0.101	0.098
	CFA1	70-80	0.096	0.096	0.094
	CFA2	65-80	0.098	0.097	0.094
	VSSFA	56-70	0.097	0.097	0.094
	RaFA	40-58	0.079	0.078	0.075
	AFA	50-60	0.086	0.087	0.084
	MFA	50-60	0.090	0.088	0.086
	NaFA	40-45	0.082	0.081	0.079
	HMOFA	50-57	0.091	0.090	0.088
	Entire set	386	0.117	0.117	0.114
	Prop. FA	**30-45**	**0.074**	**0.074**	**0.071**
UJIIndoorLoc	GA	200-230	0.107	0.105	0.104
	PSO	185-205	0.103	0.103	0.101
	FA	180-196	0.098	0.098	0.096
	SA	260-300	0.108	0.109	0.107
	DE	320-350	0.111	0.110	0.108
	MA-LS	175-200	0.100	0.100	0.099
	TS	170-190	0.100	0.100	0.098
	BSO	160-170	0.097	0.097	0.095
	CS	160-180	0.097	0.096	0.095
	DA	150-167	0.097	0.098	0.096
	ALO	150-160	0.096	0.095	0.093
	LSFA	160-174	0.098	0.097	0.096
	CFA1	125-140	0.092	0.091	0.090
	CFA2	120-135	0.094	0.092	0.091
	VSSFA	125-140	0.092	0.092	0.091
	RaFA	90-105	0.075	0.074	0.073
	AFA	100-110	0.082	0.081	0.080
	MFA	95-115	0.084	0.084	0.082
	NaFA	70-90	0.077	0.078	0.076
	HMOFA	105-130	0.088	0.087	0.086
	Entire set	529	0.112	0.112	0.111
	Prop. FA	**60-70**	**0.070**	**0.069**	**0.068**
Greenhouse Gas Observing Network	GA	850-1000	0.114	0.113	0.112
	PSO	830-1010	0.109	0.110	0.108
	FA	800-950	0.105	0.105	0.103
	SA	1000-1230	0.117	0.117	0.115
	DE	1020-1100	0.116	0.116	0.114
	MA-LS	910-1040	0.109	0.108	0.107
	TS	900-1000	0.106	0.106	0.105
	BSO	870-950	0.105	0.105	0.103
	CS	880-1000	0.105	0.105	0.103
	DA	800-950	0.107	0.106	0.105

	ALO	800-880	0.101	0.102	0.100
	LSFA	700-800	0.107	0.106	0.104
	CFA1	690-800	0.098	0.098	0.097
	CFA2	680-820	0.101	0.101	0.100
	VSSFA	560-700	0.102	0.101	0.100
	RaFA	420-570	0.082	0.081	0.080
	AFA	500-600	0.089	0.089	0.088
	MFA	500-600	0.091	0.091	0.089
	NaFA	380-450	0.084	0.084	0.082
	HMOFA	500-570	0.094	0.093	0.092
	Entire set	5232	0.123	0.123	0.122
	Prop. FA	**300-480**	**0.078**	**0.077**	**0.076**
PM2.5 Data of Five Chinese Cities	GA	50-55	0.101	0.100	0.099
	PSO	45-55	0.100	0.099	0.098
	FA	41-47	0.095	0.095	0.093
	SA	70-75	0.105	0.105	0.104
	DE	70-75	0.108	0.107	0.105
	MA-LS	40-45	0.096	0.094	0.093
	TS	40-48	0.096	0.095	0.093
	BSO	45-50	0.093	0.093	0.092
	CS	40-45	0.092	0.092	0.090
	DA	40-45	0.093	0.092	0.091
	ALO	40-45	0.092	0.091	0.090
	LSFA	45-50	0.092	0.092	0.091
	CFA1	37-41	0.089	0.089	0.088
	CFA2	35-40	0.089	0.088	0.087
	VSSFA	35-40	0.089	0.087	0.086
	RaFA	23-30	0.072	0.071	0.069
	AFA	30-35	0.077	0.078	0.076
	MFA	30-35	0.080	0.080	0.078
	NaFA	19-25	0.073	0.073	0.072
	HMOFA	30-35	0.083	0.083	0.081
	Entire set	86	0.111	0.110	0.109
	Prop. FA	**15-22**	**0.067**	**0.066**	**0.065**
BlogFeedback	GA	90-105	0.107	0.104	0.102
	PSO	85-105	0.106	0.105	0.101
	FA	83-100	0.102	0.102	0.098
	SA	104-130	0.111	0.110	0.107
	DE	107-126	0.113	0.111	0.109
	MA-LS	94-100	0.103	0.101	0.098
	TS	91-99	0.101	0.101	0.097
	BSO	85-97	0.099	0.098	0.096
	CS	84-98	0.098	0.096	0.094
	DA	79-94	0.098	0.098	0.094
	ALO	76-85	0.099	0.097	0.094
	LSFA	72-83	0.099	0.098	0.095
	CFA1	65-77	0.096	0.095	0.092
	CFA2	62-75	0.095	0.094	0.091
	VSSFA	63-71	0.093	0.093	0.090
	RaFA	41-50	0.076	0.075	0.073
	AFA	50-60	0.084	0.083	0.081
	MFA	50-60	0.086	0.085	0.082
	NaFA	33-40	0.079	0.079	0.075
	HMOFA	50-60	0.090	0.088	0.086
	Entire set	281	0.116	0.116	0.113
	Prop. FA	**29-38**	**0.072**	**0.071**	**0.068**
ElectricityLoadDiagrams 2011-2014	GA	30000-31000	0.119	0.117	0.113
	PSO	29900-30000	0.119	0.117	0.114
	FA	26000-28900	0.113	0.114	0.108
	SA	70000-90000	0.124	0.124	0.119
	DE	70000-90000	0.125	0.124	0.120
	MA-LS	25000-26000	0.115	0.113	0.111
	TS	25000-26000	0.116	0.116	0.111
	BSO	25000-26000	0.111	0.109	0.107
	CS	25000-26000	0.112	0.109	0.106
	DA	25000-26000	0.110	0.110	0.106
	ALO	25000-26000	0.112	0.113	0.108
	LSFA	25400-26000	0.112	0.110	0.107
	CFA1	17800-19300	0.110	0.109	0.105
	CFA2	17000-18400	0.110	0.111	0.105
	VSSFA	17100-19000	0.108	0.107	0.103
	RaFA	13700-14300	0.091	0.090	0.086
	AFA	16000-18500	0.099	0.100	0.095
	MFA	15550-19005	0.099	0.099	0.093
	NaFA	10000-13456	0.093	0.092	0.088

	HMOFA	16000-18000	0.102	0.102	0.098
	Entire set	140256	0.130	0.131	0.126
	Prop. FA	**9000-11050**	**0.085**	**0.085**	**0.080**
Gas Sensor Array Drift	GA	70-75	0.097	0.098	0.096
	PSO	70-85	0.096	0.096	0.094
	FA	60-73	0.094	0.091	0.090
	SA	70-90	0.102	0.102	0.100
	DE	80-90	0.105	0.103	0.101
	MA-LS	60-70	0.094	0.092	0.091
	TS	60-80	0.093	0.093	0.091
	BSO	60-70	0.090	0.091	0.089
	CS	65-75	0.091	0.090	0.088
	DA	65-70	0.092	0.090	0.089
	ALO	60-70	0.090	0.089	0.087
	LSFA	65-70	0.090	0.090	0.088
	CFA1	55-63	0.087	0.085	0.084
	CFA2	55-60	0.086	0.085	0.084
	VSSFA	50-60	0.084	0.084	0.082
	RaFA	40-47	0.068	0.068	0.066
	AFA	55-60	0.076	0.077	0.075
	MFA	50-60	0.077	0.077	0.074
	NaFA	35-40	0.071	0.071	0.068
	HMOFA	50-55	0.081	0.080	0.078
	Entire set	129	0.107	0.107	0.105
	Prop. FA	**28-35**	**0.063**	**0.064**	**0.062**
NoisyOffice	GA	75-90	0.095	0.093	0.092
	PSO	73-91	0.094	0.094	0.090
	FA	70-85	0.087	0.088	0.084
	SA	90-117	0.099	0.098	0.095
	DE	100-130	0.101	0.098	0.096
	MA-LS	83-95	0.088	0.089	0.085
	TS	80-90	0.089	0.088	0.086
	BSO	87-95	0.088	0.086	0.084
	CS	73-81	0.087	0.085	0.084
	DA	70-85	0.088	0.086	0.083
	ALO	69-75	0.086	0.086	0.084
	LSFA	70-83	0.089	0.088	0.085
	CFA1	65-70	0.085	0.083	0.081
	CFA2	65-70	0.082	0.083	0.080
	VSSFA	63-74	0.081	0.079	0.077
	RaFA	44-50	0.064	0.064	0.062
	AFA	51-58	0.074	0.073	0.071
	MFA	50-55	0.076	0.075	0.071
	NaFA	33-40	0.067	0.064	0.063
	HMOFA	51-65	0.077	0.078	0.075
	Entire set	216	0.105	0.104	0.101
	Prop. FA	**28-37**	**0.062**	**0.060**	**0.058**
YearPredictionMSD	GA	60-70	0.100	0.099	0.098
	PSO	55-65	0.099	0.097	0.096
	FA	50-55	0.093	0.093	0.091
	SA	70-90	0.105	0.104	0.102
	DE	70-90	0.106	0.105	0.103
	MA-LS	50-60	0.095	0.093	0.092
	TS	55-65	0.094	0.094	0.092
	BSO	50-55	0.093	0.093	0.090
	CS	45-55	0.091	0.091	0.089
	DA	50-65	0.091	0.090	0.089
	ALO	45-60	0.090	0.090	0.088
	LSFA	50-55	0.093	0.092	0.089
	CFA1	44-50	0.087	0.089	0.086
	CFA2	45-50	0.088	0.088	0.085
	VSSFA	50-55	0.087	0.086	0.085
	RaFA	40-50	0.071	0.071	0.068
	AFA	45-50	0.077	0.077	0.075
	MFA	45-55	0.080	0.080	0.077
	NaFA	30-45	0.072	0.072	0.071
	HMOFA	45-60	0.082	0.082	0.080
	Entire set	90	0.109	0.110	0.108
	Prop. FA	**25-35**	**0.065**	**0.065**	**0.063**
Bodily Expression - Arousal	GA	30-50	0.106	0.108	0.104
	PSO	40-45	0.103	0.102	0.100
	FA	35-45	0.094	0.093	0.091
	SA	50-54	0.113	0.112	0.110
	DE	50-54	0.115	0.114	0.112
	MA-LS	38-45	0.096	0.096	0.092

	TS	40-50	0.094	0.095	0.092
	BSO	30-49	0.094	0.091	0.090
	CS	31-48	0.093	0.092	0.089
	DA	32-50	0.093	0.092	0.089
	ALO	30-45	0.090	0.091	0.088
	LSFA	35-50	0.091	0.091	0.089
	CFA1	30-45	0.078	0.077	0.075
	CFA2	30-40	0.078	0.077	0.074
	VSSFA	23-31	0.070	0.070	0.068
	RaFA	20-30	0.064	0.065	0.061
	AFA	20-28	0.063	0.064	0.060
	MFA	32-41	0.073	0.072	0.070
	NaFA	19-30	0.058	0.057	0.055
	HMOFA	35-45	0.073	0.072	0.069
	Entire set	54	0.117	0.118	0.114
	Prop. FA	**18-25**	**0.050**	**0.049**	**0.047**
Bodily Expression - Valence	GA	30-45	0.102	0.100	0.098
	PSO	40-42	0.099	0.100	0.096
	FA	35-37	0.093	0.093	0.090
	SA	50-54	0.104	0.104	0.102
	DE	50-54	0.106	0.106	0.103
	MA-LS	38-45	0.096	0.096	0.092
	TS	40-50	0.094	0.094	0.092
	BSO	30-49	0.094	0.092	0.090
	CS	31-48	0.093	0.093	0.089
	DA	32-50	0.092	0.093	0.089
	ALO	30-45	0.091	0.090	0.088
	LSFA	36-35	0.089	0.088	0.086
	CFA1	30-40	0.083	0.084	0.080
	CFA2	30-40	0.082	0.082	0.080
	VSSFA	25-33	0.078	0.078	0.074
	RaFA	21-29	0.075	0.074	0.073
	AFA	25-27	0.072	0.073	0.070
	MFA	32-41	0.082	0.080	0.078
	NaFA	19-28	0.072	0.073	0.069
	HMOFA	35-45	0.083	0.084	0.081
	Entire set	54	0.109	0.106	0.105
	Prop. FA	**16-23**	**0.069**	**0.069**	**0.065**

Table 8 The *p*-values of the Wilcoxon rank sum test for all regression data sets

Data sets	**LSFA**	**CFA 1**	**CFA 2**	**VSSFA**	**RaFA**	**AFA**	**MFA**	**NaFA**	**HMOFA**
Arousal	2.73E-11	2.80E-11	2.78E-11	2.75E-11	2.71E-11	2.73E-11	2.76E-11	2.70E-11	2.73E-11
Valence	2.80E-11	2.70E-11	2.83E-11	2.75E-11	6.05E-11	1.79E-09	2.78E-11	6.08E-11	2.72E-11
Communities and Crime	2.75E-11	2.66E-11	2.79E-11	2.71E-11	6.02E-11	1.79E-09	2.75E-11	6.05E-11	2.68E-11
Relative Location of CT	2.87E-11	2.78E-11	2.94E-11	2.80E-11	6.15E-11	1.79E-09	2.84E-11	6.10E-11	2.72E-11
UJIIndoorLoc	2.83E-11	2.72E-11	3.00E-11	2.81E-11	6.22E-11	1.79E-09	2.85E-11	6.12E-11	2.89E-11
Greenhouse Gas	2.69E-11	2.56E-11	2.66E-11	2.73E-11	5.88E-11	1.79E-09	2.58E-11	5.92E-11	2.59E-11
PM2.5 Data	2.82E-11	2.70E-11	2.88E-11	2.77E-11	6.06E-11	1.79E-09	2.83E-11	6.11E-11	2.74E-11
BlogFeedback	2.74E-11	2.66E-11	2.82E-11	2.75E-11	6.01E-11	1.79E-09	2.77E-11	6.03E-11	2.71E-11
ElectricityLoadDiagrams	2.52E-11	2.50E-11	2.60E-11	2.47E-11	5.92E-11	1.79E-09	2.49E-11	6.00E-11	2.64E-11
Gas Sensor Array Drift	3.00E-11	2.99E-11	2.89E-11	2.84E-11	6.37E-11	1.79E-09	2.92E-11	6.28E-11	2.86E-11
NoisyOffice	1.97E-11	2.64E-11	2.67E-11	2.18E-11	5.46E-11	1.79E-09	2.59E-11	5.53E-11	1.95E-11
YearPredictionMSD	2.40E-11	2.64E-11	2.73E-11	2.54E-11	6.02E-11	1.79E-09	2.67E-11	5.93E-11	2.39E-11

Data sets	**GA**	**PSO**	**FA**	**SA**	**DE**	**MA-LS**	**TS**	**BSO**	**CS**	**DA**	**ALO**
Arousal	2.78E-11	2.76E-11	2.81E-11	2.79E-11	2.80E-11	2.75E-11	2.78E-11	2.81E-11	2.76E-11	2.74E-11	2.78E-11
Valence	2.88E-11	2.81E-11	2.86E-11	2.87E-11	2.83E-11	2.86E-11	2.86E-11	2.85E-11	2.86E-11	2.86E-11	2.87E-11
Communities and Crime	2.78E-11	2.76E-11	2.76E-11	2.81E-11	2.77E-11	2.86E-11	2.85E-11	2.75E-11	2.84E-11	2.83E-11	2.81E-11
Relative Location of CT	2.96E-11	2.81E-11	2.86E-11	2.88E-11	2.85E-11	2.93E-11	2.91E-11	2.92E-11	2.95E-11	2.92E-11	2.88E-11
UJIIndoorLoc	3.06E-11	2.90E-11	3.03E-11	2.93E-11	2.94E-11	2.90E-11	2.96E-11	2.88E-11	3.02E-11	2.98E-11	3.02E-11
Greenhouse Gas	2.73E-11	2.70E-11	2.81E-11	2.71E-11	2.63E-11	2.72E-11	2.84E-11	2.81E-11	2.66E-11	2.81E-11	2.80E-11
PM2.5 Data	2.89E-11	2.86E-11	2.92E-11	2.88E-11	2.86E-11	2.86E-11	2.90E-11	2.92E-11	2.93E-11	2.89E-11	2.90E-11
BlogFeedback	2.82E-11	2.78E-11	2.83E-11	2.85E-11	2.77E-11	2.80E-11	2.82E-11	2.83E-11	2.81E-11	2.80E-11	2.84E-11
ElectricityLoadDiagrams	2.81E-11	2.69E-11	2.63E-11	2.59E-11	2.54E-11	2.70E-11	2.82E-11	2.56E-11	2.82E-11	2.60E-11	2.70E-11
Gas Sensor Array Drift	2.93E-11	3.06E-11	2.92E-11	2.99E-11	2.97E-11	2.92E-11	2.92E-11	3.12E-11	3.00E-11	3.21E-11	2.90E-11
NoisyOffice	2.20E-11	2.19E-11	2.84E-11	2.43E-11	2.74E-11	2.01E-11	2.07E-11	2.30E-11	2.83E-11	2.77E-11	2.51E-11
YearPredictionMSD	2.72E-11	2.56E-11	2.73E-11	2.51E-11	2.55E-11	2.71E-11	2.79E-11	2.80E-11	2.48E-11	2.84E-11	2.70E-11

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Highlights

- We propose a variant of the Firefly Algorithm for feature optimization.
- SA-enhanced local and global optimal solutions are used to lead the search process.
- The attractiveness search action is also further diversified using chaotic maps.
- Swarm leaders divert weak solutions to optimal regions to accelerate convergence.
- It outperforms other methods statistically for the evaluation of 40 data sets.