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A Novel Non-Dominated Sorting Dragonfly Optimization With Evolutionary Population Dynamics Based Multi-Objective Approach For Feature Selection Problems

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Abstract: Feature selection is a multi-objective problem which includes two contradictory objectives. It is an effective method in classification to eradicate noise, inappropriate and redundant features to maximize the classification precision and reduce the number of chosen features. In this study, meta-heuristic algorithm with multi-objective approach have been tried to explore feature selection problem with a combination of non-dominated sorting dragonfly algorithm and evolutionary population dynamics strategy. First, to enhance the value of non-dominated solutions, an evolutionary population dynamic strategy is integrated with a heuristic natural selection operators. Second, to avoid the local optimum trap and enrich the population variety, to upgrade the step size and to maintain exploration and exploitation balance, a strategy is planned to optimize these issues. Finally a Pareto optimal solutions are obtained from the non-dominated sorting strategy which makes the algorithm appropriate for handling multi-objective feature selection problems. Simulations are performed on 18 datasets from UCI repository. The proposed NDSDA, NDSDA_EPD and NDSDA_EPD_CM approaches are compared with the existing dragonfly algorithms. The proposed algorithms outperforms the other techniques by enhancing the grouping accuracy and decreasing the preferred features count.

Keywords: *Feature selection; Dragonfly optimization; Multi-objective Optimization; Evolutionary Population Dynamics; Non-dominated Sorting*

1.Introduction

Nowadays, rapid advancement in the data collection techniques makes plentiful high-dimensional datasets innumerous domains. Different research problems are involved in the analysis of multiple huge datasets from various application areas. These multiple huge datasets consists of noisy, unrelated and redundant features that disturbs the operations of classification due to ambiguous information Jiao R et.al (2023). The aim of Feature Selection (FS) is to enrich the capacity of classification by minimizing issues related to dimension of the data, develop the computational competence and ease data visualization by choosing a minor subset with appropriate features. The surge in data dimension causes a rise in challenging FS process Wang J et.al (2022).

FS is performed in an extensive range of application in research areas like remote sensing, text classification (Yang S et.al 2020); gene analysis, interruption detection and image retrieval (Kumar V &Minz S 2014). FS role in remote sensing for image classification consist of huge pixel data and diverse information (Hennessy A et.al 2020; Guo A et.al (2020). FS techniques aids in discovering vital and relevant features by minimizing the classification complexity, improving the computational competence and enhancing the accuracy.

Filter and wrapper methods are the two categories of FS approaches. A relevant score is assigned to each feature in the filter method by using statistical measures and feature ranking is performed based on the estimated score and feature subsets are selected depending on the user defined conditions Bommert A et.al (2020). In the wrapper approach, the classifier uses the FS results to perform the evaluation by learning algorithms which delivers superior outcomes than the filter approach but there is a slight increase in the consumption of computational resources when dealing with complex search space Gonzalez J et.al (2019). FS is a vital process which is considered as a combinatorial optimization issue. The three phases involved in FS challenges are the search space, N feature count and 2N feature subsets. The interaction between the features are complex. The FS is fundamentally a multi-objective problem Cheng F et.al (2022). The dual objectives of FS are to decrease the features and increase the classification capacity. The two conflicting objectives are

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handled by a commanding search techniques that forms the basis of addressing the FS problems.

For FS problem, wrapper approach is applied with swarm intelligence algorithms such as GA Alickovic E &Subasi A(2017),PSO Huda RK & Banka H (2019), ACO Kashef S &Nezamabadi-pour H (2015), BA Nakamura RYM et.al (2013), GWO Emary E et.al (2016) and its variants of swarm intelligence algorithm

for FS problems. Other meta-heuristics algorithms have been applied for FS problems are the SSA by Tubishat M et.al (2020),HHO by Hussain K et.al (2021),GWO by Ibrahim R et.al & Arora S et.al (2019), multi-objective Differential Evolution Algorithm (DEA) by Zhang Y et.al (2015) and Varghese N et.al (2020).Dragonfly Algorithm (DA)was used for solving single objective problem Mirjalili S (2016). Hybrid DA for numerical optimization was developed by KS SR&Murugan S (2017).

Standard DA are not used for solving FS problems due to the shortcomings like insufficient exploitation abilities in the high dimensional search space. An enhanced way is essential to control the exploration and exploitation capabilities to create an optimal region. The binary form of DA is created to address the discrete problems Mafarja M et.al (2017, October). Binary DA works strong for numerous datasets but may lead to minimal exploration capabilities that suffers local optimization issues. Hence an improved version of DA is needed for FS problem. This study is proposed to combine the non-dominated sorting dragonfly optimization with evolutionary population dynamics to enhance the performance of multi-objective FS problem. The proposed method is validated using 14 datasets and equated with the former FS methods. The key contributions are listed below:

1) A combination of non-dominated sorting dragonfly optimization with evolutionary population dynamics is proposed to develop the grouping accuracy and decrease the quantity of chosen features in a multi-objective FS problem.
2) To enrich the value of non-dominated solutions, an evolutionary population dynamic strategy is integrated with a heuristic natural selection operators. This enhances the performance of multi-objective dragonfly optimization to make it suitable for FS.
3) To evade from the local optimum trap and to progress the population diversity, a strategy is proposed to optimize the search procedure. A step size upgrading strategy is introduced to retain exploration and exploitation balance, which enriches the global performance.
4) The experiments are conducted on standard UCI repository datasets and the performance is verified for FS problem. The test results are compared with other algorithms based on factors like convergence rate and selected features count.

Here, section II presents the literature review. An outline of FS problem, NDS for multi-objective optimization problem and evolutionary population dynamics strategies are presented in section III. The proposed non-dominated sorting dragonfly algorithm with problem formulation are presented in section IV. The experiment setup, parameter setup and result analysis presented in section V. Inference is presented in section VI.

2.Literature Review

Meta-heuristics approaches are one of the operational way to resolve the FS problem. The number of meta-heuristics optimization techniques to choose the features has amplified ACO (Aghdam MH &Kabiri P 2016), GA (Raman MG et.al 2017), IWD (Acharya N& Singh 2018), Firefly algorithm (Selvakumar B &Muneeswaran K 2019), a hybrid technique whale optimization with simulated annealing (Mafarja&Mirjalili S(2017),Ant lion optimization (Emary E &Zawbaa H M 2019),GWO (Alamiedy TA et.al 2020) and PSO with fruit fly optimization (Soleimanian et.al (2020).Meta-heuristic algorithms with hybridization techniques have been used to solve multiple objective optimization problem like feature selection. The subsequent subsections reviews several research ideas related to FS problem with multiple objectives to be optimized using meta-heuristic algorithms.

Zhang Y et.al (2020)presented a self-learning FS using binary differential evolution algorithm with multi-objectives. The performance is enhanced by using three operators such as mutation, one bit search and non-dominated sorting. The optimal areas are identified rapidly by based on probability differences using mutation operator. Self-learning capability is enhanced to identify optimal areas using one-bit search operator. The combination of binary mutation and one bit search operators is effective in local and global search. It is viable with meta-heuristic algorithms such as GA, DE, PSO and artificial bee colony algorithms. Sohrabi M K & Tajik A (2017) developed a novel FS approach using Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Multi-Objective PSO. Novel FS methods using NSGA-II and MOPSO were evaluated using ANN. The accuracy and precision is superior to classical methods of FS.

Wan Y et.al (2020) proposed an FS approach to pick a hyperspectral imagery using multi-objective discrete sine cosine procedure. The compromise between information conservation and redundancy sinking is obtained in the proposed framework. The designed framework is modeled to decrease the redundancy and enhance the particular feature subset relevancy. To maximize the information quantity the variance measurement is applied. The proposed method optimizes the control between local and global search space for FS. The best subset is selected by determining the effectiveness of the conducted experiments with the benchmark datasets which consists of 5 hyperspectral images and one spectral dataset of surface feature. Wang L & Zheng XL (2018) used a multi-objective fruit fly algorithm for scheduling problem. The restrained scheduling problem minimizes the make span and total cost. At first, the solutions are represented by resource and tasks. Next, cost rule is designed and at last, the search space is implemented through neighbourhood search operators which are designed for vision based searches. Non-dominated sorting approach completes the multi-objective assessment by including a search procedure to improve the exploration. The outcomes are compared with other procedures to validate the knowledge based search procedure in solving multi-objective scheduling problem.

Wu L et.al (2018, July) came up with a cloud model using fruit fly algorithm. It is a self-adaptive policy to adapt the dynamic search space. Pareto domination concept is introduced in the vision based search using fruit fly algorithm. A maintenance policy is incorporated to normalize the neighborhood distance. The model uses CEC2009 datasets to validate. The simulation results shows that the accuracy and distribution to meet the Pareto fronts and the performance is compared with other popular algorithms. Ma Q et.al (2016, October) developed a technique to address the point selection issue using fruit fly algorithm. A binary representation of the fruit fly indicates the number of 1s, a different position and the distance and direction of the binary string. The smell and vision search of the technique enhances the global search ability with multi-dimensional fitness function.

Du P et.al (2020) designed a forecasting model to predict air pollutants using multi-objective HHO algorithm. Earlier studies related to this problem had deficits such as eliminating the initial parameters and the stability to predict. The hybrid forecast model considers the defects of the previous studies by implementing Hawks to tune learning model parameters. The forecast accuracy and stability is high on different modes in terms of low and high frequencies. Air pollution is predicted based on time series in the optimized model. The study results of the hybrid model is stable and accurate than other models in the literature. Amoozegar M &Minaei-Bidgoli B (2018) developed a method to rank the features depending on the frequencies in the library set using multi-objective PSO. FS technique eliminates redundant, irrelevant and noisy features. The feature ranking refines the particles present in the search space. Pareto fronts visual analysis is performed based on qualitative and quantitative measures. More than hundred features are identified from the datasets used in this study.

Rodrigues D et.al (2020) came up with a single and multiple objective optimization algorithm using artificial butterfly for FS problem. To deal with high dimensional real time datasets for selecting the feature set and minimise the computational cost and classification error two approaches are proposed. The first approach optimizes the classification accuracy for each class separately and the second approach optimizes the feature set by minimizing the process. The results are compared with PSO, Firefly, black hole procedure, brainstorm and flower pollination algorithms. The results of both the approaches are better for binary single objective optimization than their counterparts. Al-Tashi Q et.al (2020) applied a GWO algorithm for FS problem. The objective is to decrease the feature count and error rate. The binary version is suitable for multi-objective FS problem. The wrapper based ANN is used to measure the selected features performance. The results are associated with NSGA-II and multi-objective PSO algorithms. A set of non-dominated solutions are produced effectively while the classification error rate and computational costs are also reduced.

Zhang Y et.al (2019) developed two novel operators for FS problem using ABC algorithm. The objectives are to maximize the classification and minimize the feature cost. The operator performs a guided search by using bees and diversified guided search for other bees. The leader and the external libraries performs an improved search ability based on different types of bees. The results obtained are robust and effective in solving the cost sensitive FS problems. A framework was created by Wang XH et.al (2020) for multi-objective FS problem using ABC algorithm to address the high computational cost. The framework reduces the computational cost by obtaining optimal results with the aid of K-means clustering strategy. A differential selection is performed to minimize the sample size in the evolutionary procedure. The ABC algorithm for FS problem is based on particle update model validated using UCI datasets. The results are compared with varied sample sizes to obtain an optimal feature subset with minimum computational time and cost.

He CL et.al (2020) creates a novel unsupervised multi-objective selection model by considering information and correlation among bands using ABC algorithm. Two operators are combined to enhance the search process which considers multi-strategy for using bees and crowding distance. Hyperspectral data are employed in this study to optimize the band selection methods. The results obtained by the proposed selection model are superior. Xue B et.al (2012) came up with a solution to optimize the feature subsets using multi-objective PSO. The first approach uses non-dominated sorting applied to PSO to handle FS problem. The second approach is to apply mutation and crowding distance concepts to control the search in Pareto front solutions. Two stage FS algorithms are applied on 12 standard datasets to validate the proposed technique. The results shows that a set of NDS solutions are produced using multi-objective PSO. The primary method overtakes the standard method which is single objective and the secondary method obtains better results than the primary and other prior methods.

Bouraoui A et.al (2018) optimizes the SVM parameters and feature subsets using kernel functions. SVM technique is efficient for pattern classification which is dependent on the kernel function and parameter values. Choosing appropriate feature based on the parameters is another factor of optimization problems. The classification accuracy, support vector count and the selected feature are the objectives to be considered. NSGA-II approach is efficient in multi-criteria selection and is validated with datasets. The results shows that the features are minimized with enhanced classification accuracy. Ghosh M et.al (2018) proposed a multi-objective GA with histogram for identifying features from high-dimensional data to enhance classification accuracy. Multi-layer classifier is applied to enhance the accuracy. 50% of the real features are represented which enhances the classification accuracy of multi-objective optimization algorithms.

3.Preliminary Studies

This section presents an outline about the FS problem definition, non-dominated sorting for multi-objective optimization problem and evolutionary population dynamics strategies.

3.1 Feature Selection Problem

The feature is an attribute that denotes significant characteristics of a dataset. FS abstracts a subset of a feature. An extraction procedure that choses vital subsets of the feature that needs to be optimized. Mathematically, the dataset is $(Fe_o) = (Fe_1, Fe_2, Fe_3, Fe_{4,...}Fe_n)$ and the objective is to extract subset $(Fe_{SE}) = (Fe_1, Fe_2, Fe_3, Fe_{4,...}Fe_m)$ where Fe_1, Fe_2,…, Fe_n are the dataset features, 'm' and 'n' denotes integers where m<n. In binary representation of features, Fe_i=1, here i^{th} attribute is selected, otherwise it is not selected. The selected features determines the classifier's computational cost, if more features are chosen computational capacity is increased and classification accuracy is decreased.

3.2 Non-Dominated Sorting (NDS) for Multi-objective Optimization Problem

Multi-objective optimization problem will have numerous objectives that are conflicting. A solution set is named as Pareto optimal solutions that represents a settlement between the objectives Mirjalili&Lewis(2015). The formulation of a minimization problem is:

$$\min imize : Fe(\vec{xx}) = \{ fe_1(\vec{xx}), fe_2(\vec{xx}), ..., fe_o(\vec{xx})\} \tag{1}$$

$$conditional : g_i(\vec{xx}) \geq 0, \ i = 1,2,...,m \tag{2}$$

$$h_1(\vec{x\,x}) = 0, i = 1,2,..., p \tag{3}$$

$$L_i \leq xx_i < U_i, i = 1,2,...,n \tag{4}$$

Where, 'o' represents objectives count, 'm' denotes inequality constraints count, 'p' denotes equality constraints count and [L_i, U_i] denotes i^{th} variable boundaries.The framework of multi-objective problems are the concept of Pareto optimal dominance that equates more than two solutions in the search space. The Pareto dominance and optimality definitions are as follows:Coello CA (2009)

i) In Pareto dominance, if there are two vectors $(\vec{xx}) = (xx_1, xx_2, ...xx_k)$ and $(\vec{y}) = (y_1, y_2, ...y_k)$, vector 'xx' dominates vector 'y' represented as $x \succ y$.

$$if : \forall i \in \{1,2,...,k\}, [f(xx_i) \geq f(y_i)] \wedge [\exists i \in 1,2,...k : f(xx_i) \tag{5}$$

Here, the solution dominates other solution which is enhanced or identical values on entire objectivesNgatchou P et.al (2005, November).

ii) In Pareto optimality, $(\vec{x\,x}) \in X$ represents Pareto optimal when two solutions are non-dominating with each other represented in equation (6). In Pareto optimality neither of the solutions dominates the other. All NDS solutions in a set represents a Pareto optimal set.

$$if \ and \ only \ if : \exists \vec{y} \in X \mid F(\vec{y}) \succ F(\vec{xx}) \tag{6}$$

iii) Pareto optimal set, consists of equivalent objective values represented in equation (7). The solutions in the Pareto optimal set represents an optimal front.

$$P_s \coloneqq \{xx, y \in X \mid \exists F(y) \succ F(xx)\} \quad (7)$$

iv) Pareto front set consists of values of objective function for Pareto solutions represented in equation (8)

$$P_f \coloneqq \{F(x) \mid x \in P_s\} \quad (8)$$

3.3 Evolutionary Population Dynamics (EPD)

Evolutionary approaches are random search techniques, which creates group of solutions with random initial values. Mutation and crossover techniques are applied to the initially created solutions to modify the solutions to obtain an optimal solutions. In EPD, worst solutions are discarded from the current solution population through relocating among optimal solutions. Bak et al.1987 created a self-organized criticality using EPD.Lewis A et.al (2008) proposed changes in the population impacts the discrete population without the influence of an external force. In this study non-dominated sorting dragonfly is combined with EPD, by splitting the dragonfly swarm into two parts depending on the fitness. A part of the dragonfly swarm solutions are removed and reinitialized using EPD strategies. Here, for each worst solution in the dragonfly swarm, three finest solutions are chosen. Later, a new solution is created using the chosen three finest solutions. At last, one solutions is selected from these solutions randomly for relocating. The guided solutions are chosen based on various natural selection conditions such as crossover, mutation, tournament selection, linear ranking selection etc.

4.The Proposed Multi-objective Feature Selection Approach

This segment presents the proposed non-dominated sorting dragonfly algorithm with EPD strategies and fitness formulation for multi-objective FS problem.

4.1 Dragonfly Algorithm(DA)

DA is a nature inspired technique by MirjaliliSeyedali (2016) is a stochastic population based search strategy. The swarming behaviour of the dragonflies are static and dynamic, similar to the working principle of optimization algorithms. Dragonflies create a small group and flies in various directions in search of food which is called a static swarm (exploration phase). While, dragonflies create a huge group and flies in single direction for attacking the prey or for migration to other places is called a dynamic swarm (exploitation phase). Mathematical modelling of DA are given below:

i) The separation process formulation is given in equation (9)

$$S_i = -\sum_{j=1}^{N} X - X_i \quad (9)$$

ii) The alignment process formulation is given in equation (10)

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N} \quad (10)$$

where$V_j$represents j^th neighbor's velocity vector.

iii) The cohesion process formulation is shown in equation (11)

$$Coh_i = \frac{\sum_{j=1}^{N} x_j}{N} - X \quad (11)$$

iv) The attraction approach formulation is shown in equation (12)

$$Fe_i = Fe_{loc} - X \quad (12)$$

Where, Fe_{loc} denotes position (food source).

v) The distraction process is formulation is shown in equation (13)

$$E_i = E_{loc} + X \quad (13)$$

Where, E_{loc} denotes enemy's position.

vi) The step vector formulation is shown in equation (14)

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + wX_t \quad (14)$$

where s, a, c, f, e and w denotes weighing vectors of several components.

vii) The location vectors is computed as presented in equation (15)

$$X_{t+1} = X_t + \Delta X_{t+1} \quad (15)$$

where, t denotes the iteration.

4.2 Applying Non-Dominated Sorting (NDS)

Strategy to DA

In Non-Dominated Sorting Dragonfly Algorithm (NDSDA), first, initialize the number of dragonflies by randomly generating an initial population. A matrix representation of the randomly generated dragonflies and the position vectors are presented. The dragonflies operations are estimated as shown in equations (9) - (13). Then using equation (14) and (15) the step size and position vectors are estimated. The position vector matrix is reduced over iterations due to the identification of global best solutions. The position of the dragonflies are updated using equation (15) for each iteration. Multi-objective optimization of NDSDA, consists of optimal solutions in the collation set, and it's flexible to change the solutions over iterations based on the ranking procedures. Ranking of solutions is performed by the ability of a solution. For instance, if a solution is not dominated by other solution then rank 1 is assigned to that solution. If a solution is dominated by only one solution rank 2 is assigned and the process continues. If the collection set is full then, few solutions which are non-dominated are eliminated from the collection set. Collection set retains optimal NDS. The solution are selected to develop the quality of the population based on the ranking. The solutions are updated in every iteration, the optimal position of the dragonflies are chosen according to the equation (16).

$$p_i = c / Rank_i \tag{16}$$

Where 'c' denotes a constant which is >1 and '$Rank_i$' denotes the rank number after non-dominated sorting. This procedure permits the better solutions to be included in the population. The non-dominated sorting offers a probability to dominated solutions to be chosen to enhance the exploration of NDSDA. In this procedure, after creating the solutions in each generation, the desirable solutions are selected and collected in an archive. Later, the ND solutions are archived to find suitable solutions and the solutions which are not dominating are removed. These Pareto optimality during optimization consists of convergence and coverage. An accurate Pareto optimal solution is obtained by convergence. Dispersal of Pareto optimal solutions is obtained by coverage. An optimizer identifies an accurate optimal solution with uniform dispersals through all objectives.

4.3 Applying the EPD strategy to NDSDA

The EPD methods are applied to the NDSDA to optimize the populations in the solution space. The EPD technique works by eliminating the worst solutions by splitting the population into two sections. The solutions first part in the dragonfly swarm are removed and reinitialized using EPD with random selection operators. The EPD methods are applied to the NDSDA to optimize the populations in the solution space.

4.3.1.Non-Dominated Sorting Dragonfly Algorithm Evolutionary Population Dynamics (NDSDA_EPD)

In NDSDA_EPD approach, selection operator choses the solutions randomly. Here, top three individual solutions are nominated. Each worst half solutions are repositioned depending on random selection. A random number is created $X_{rn}$for each epoch and then repositioning the worst solution. For instance, $X_{rn} \in [0, 0.20]$ represents first best solution,$X_{rn} \in [0.20, 0.7]$ represents second best solution, $X_{rn} \in [0.7, 0.55]$ represents third best solution, $X_{rn} \in [0.55, 1]$ represents a random solution. The repositioning of worst solutions in each step enhances the population of the search space and produces premature meeting of the solution. Hence local search strategy avoids the local optima trap. Figure 1 represents the pseudo code NDSDA_EPD approach.

```
The swarm is initialized as Xi (i =1,2,…,n);
Initialize Δ Xi(i =1,2,…,n);
While do;
Estimate the fitness of all the dragonflies;
Sort the solutions according to the fitness value;
Update 'F'(food) and 'E'(enemy);
Reinitialize individuals in 2nd half population using EPD_CM;
Update (i, s, a, c, f, e and w) ;
For i=1 to n do
Calculate S, A, C, F and E
Update the step vectors (Δ Xt+1);
Update Xt+1 ;
End;
End;
Return the best position;
```

Figure 1. Pseudo code of NDSDA_EPD

4.3.2 Non-Dominated Sorting Dragonfly Algorithm Evolutionary Population Dynamics with Crossover & Mutation (NDSDA_EPD_CM)

The NDSDA_EPD_CM is similar to NDSDA_EPD, here the modification is the inclusion of crossover and mutation operators. One solution is chosen from the generated random number which is related to the NDSDA_EPD. The chosen resolution is altered to enrich algorithm's exploration. Crossover operation is performed on the mutated and the poor solution. The EPD_CM algorithm is shown in figure 2

Initialize and define original solution X^{DA}, solutions from
EPD mechanisms X^{EPD},solution dimension N;
Estimate mutation and crossover rate;
for$j$ = 1 *to N* **do**
Alter *jth*aspect of X^{EPD};
Reinitialize the *jth*dimension of X^{EPD} by crossing
The *jth*dimensions of X^{DA} and X^{EPD};
end
Return X^{EPD};
//XEPD ***is the relocated solutions***

Figure 2 EPD_ CM Algorithm

4.4Fitness Formulation

FS is a multi-objective problem, aims to choose a feature subset from the entire set with an objective to minimize the chosen feature count and maximize the grouping accuracy. To achieve the objective concurrently the following fitness function is applied.

$$f_{fitness} = \alpha.CER + \beta.\frac{F_S}{F_T} \tag{17}$$

where CER denotes the classification error rate, F_S denotes selected features count, F_T denotes total number of features. $\alpha \in [0,1]$ and $\beta = (1-\alpha)$ are the weighting factors of the dual objectivesMafarja M et.al (2017, October). Set α = 0.99 and β = 0.01to enrich accuracy of classification as specified in Hammouri AI et.al (2020). The first part assurances accuracy while the subsequent part aids in reducing the selected feature count. A linear weighted function combines these two parts. This study uses k-nearest neighbor (KNN) classifier since it is easy, effective and suitable to implement in a wrapper approach Altman, N. S. (1992).

5. Experimental Results

This section discusses the test results obtained to validate the performance of the proposed NDSDA, NDSDA_EPD and NDSDA_EPD_CM approaches for the FS problem. Benchmark datasets and system for performing the experiments are presented. Test results of NDSDA_EPD, NDSDA_EPD_CM approaches are presented and compared with the existing algorithms and are analyzed. Finally, the efficacy of the proposed approach enhanced aspects are assessed.

5.1 Setups for Experiment, UCI benchmark datasets and Parameter tuning

The experiments are performed using Intel Core i7 7th generation processor, 2.7 GHz, 500GB hard disk, 16 GB RAM, and Microsoft Windows 10 OS. The proposed model is evaluated using Python 3.9 language and its additional libraries. This study uses 18datasets selected from the UCI MLR(Blake and Merz 1998)to perform the experiments. The dataset information are presented in Table 1. These datasets are taken from different fields like biology, medical, physics, games, chemistry and politics with diverse dimensions. Each algorithm is independently implemented 10 times and the average fitness value is considered for evaluation. Parameter values are vital in obtaining optimal solutions in meta-heuristic algorithms. Table 2 presents the tuned parameter values.

Table 1. Description of datasets from UCI data repository

Dataset Name	Attributes count	Objects count
Breastcancer	9	699
BreastEW	30	569
CongressEW	16	435

Exactly	13	1000
Exactly2	13	1000
HeartEW	13	270
IonosphereEW	34	351
KrvskpEW	36	3196
Lymphography	18	148
M-of-n	13	1000
PenglungEW	325	73
SonarEW	60	208
SpectEW	22	267
Tic-tac-toe	9	958
Vote	16	300
WaveformEW	40	5000
WineEW	13	178
Zoo	16	101

Table 2. Parameter Tuning

Parameter Name	**Value**
Search space size	20
Iteration count	150
Dimension	Features count
Number of epochs	10
K-NN Classifier (K)	5

5.2 Results and Analysis

Table 3 compares the average classification accuracy attained by the proposed NDSDA, NDSDA_EPD and NDSDA_EPD_CM approaches with the existing approaches. The results of NDSDA_EPD achieves greater accuracy on most datasets compared to NDSDA, while NDSDA_EPD_CM steadily outperforms NDSDA in accuracy on entire datasets. Additionally, for 5 datasets the average accuracy is same for all the proposed approaches. NDSDA_EPD_CM proves better robustness than NDSDA, which indicates the capacity to handle differences in the datasets more successfully. The optimum results highlighted in bold. The results of NDSDA_EPD_CM are compared with the existing BDA-DDO, IBDA and SBDA approaches which uses DA based algorithms. Multi-objective DA algorithms with EPD methods proved to be enhance the search ability. Therefore, NDSDA_EPD_CM achieves better results by employing the EPD strategies, which enriches the algorithm's search ability.

Table 3. Comparison of average classification accuracy of NDSDA, NDSDA_EPD &NDSDA_EPD_CM approaches with existing approaches

Dataset Name	**NDSDA**	**NDSDA_EPD**	**NDSDA_EPD_CM**	**BDA-DDO** Chen Y et.al (2023)	**IBDA** Li J et.al (2020)	**SBDA** Hammouri AI et.al (2020)
Breastcancer	0.951	0.983	**1**	0.999	0.9786	0.993
BreastEW	0.927	0.945	**0.998**	0.993	0.9614	0.975
CongressEW	0.969	0.986	**1**	1	0.9784	0.975
Exactly	**1**	**1**	**1**	0.987	-	1
Exactly2	0.832	0.834	**0.838**	-	-	0.757
HeartEW	0.893	0.925	**0.963**	0.919	0.8593	0.867
IonosphereEW	0.927	0.986	**0.997**	0.968	0.9172	0.984
KrvskpEW	0.977	**0.989**	**0.989**	0.974	0.9801	0.966
Lymphography	0.964	0.969	**0.972**	1	0.4333	0.954
M-of-n	**1**	**1**	**1**	-	-	1

PenglungEW	**1**	**1**	**1**	1	-	1
SonarEW	0.991	0.995	**0.998**	0.964	0.9210	0.993
SpectEW	0.891	0.896	**0.925**	0.929	0.7352	0.925
Tic-tac-toe	0.822	0.843	**0.854**	-	0.8521	0.832
Vote	0.979	**0.981**	**0.981**	-	-	0.972
WaveformEW	0.776	0.776	**0.836**	0.834	0.8417	0.776
WineEW	**1**	**1**	**1**	1	0.9556	1
Zoo	**1**	**1**	**1**	1	0.9409	1

Table 4 compares the selected features count attained by NDSDA, NDSDA_EPD and NDSDA_EPD_CM approaches with the existing approaches on the 18 datasets. The optimum results emphasized in bold. Table 4 specify that NDSDA_EPD_CM steadily choses lesser features than NDSDA and NDSDA_EPD LBDA across all 18 datasets. Furthermore, NDSDA_EPD proves a lesser features count compared to NDSDA. The NDSDA_EPD_CM results are compared with the existing BDA-DDO, IBDA and SBDA approaches which uses DA based algorithms. The capacity of the NDSDA_EPD_CM minimize the chosen features count effectively in comparison to NDSDA_EPD, thus removing noisy or unrelated features. The NDSDA_EPD method may have chosen these features.

Figure 5 illustrates the convergence rates of NDSDA, NDSDA_EPD and NDSDA_EPD_CM based algorithms on two datasets. The x-axis and y-axis represents the epoch count and the fitness function value. The convergence rate is similar to the convergence performance on all datasets.

Table 4. Comparison of average selected features of NDSDA, NDSDA_EPD &NDSDA_EPD_CM approaches with existing approaches

Dataset Name	NDSDA	NDSDA_EPD	NDSDA_EPD_CM	**BDA-DDO** Chen Y et.al (2023)	**IBDA** Li J et.al (2020)	**SBDA** Hammouri AI et.al (2020)
Breastcancer	5.09	5.14	**4.96**	5.07	6.00	5.00
BreastEW	11.84	11.92	**11.79**	13.17	2.00	12.20
CongressEW	6.29	6.12	**5.76**	5.10	6.20	5.40
Exactly	6.96	6.72	**6.05**	6.77	-	6.13
Exactly2	5.31	4.93	**4.87**	-	-	5.03
HeartEW	4.92	3.87	**2.92**	4.80	3.00	6.03
IonosphereEW	7.72	8.92	**5.82**	12.37	6.80	12.67
KrvskpEW	18.59	**17.64**	17.92	18.63	18.60	19.57
Lymphography	7.84	7.99	**6.39**	7.73	7.20	6.83
M-of-n	6.89	6.77	**5.90**	-	-	6.07
PenglungEW	107.97	107.91	**106.85**	108.47	-	117.53
SonarEW	23.92	**22.17**	22.84	23.73	19.30	24.33
SpectEW	10.84	9.83	**7.92**	9.00	11.70	8.57
Tic-tac-toe	3.96	3.76	**2.97**	-	9.00	6.93
Vote	3.27	**3.92**	**3.92**	-	-	4.00
WaveformEW	20.29	20.38	**19.58**	20.50	23.33	21.83
WineEW	3.99	3.92	**3.17**	3.23	5.40	4.40
Zoo	2.27	1.96	**1.68**	4.13	7.80	1.97

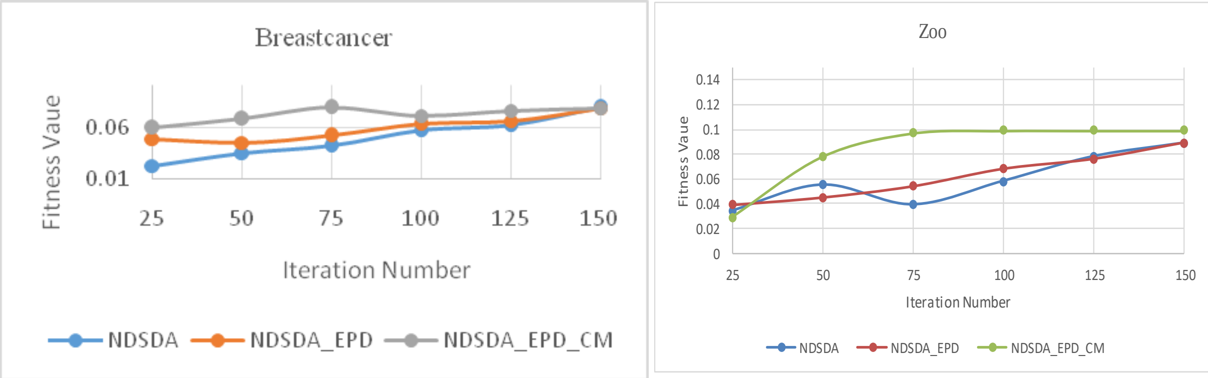

Figure 3 Convergence rates for NDSDA, NDSDA_EPD and NDSDA_EPD_CM

6.Conclusion

A multi-objective FS problem is investigated with an aim to maximize the classification accuracy and minimize the chosen features count by eliminating the noise, irrelevant and redundant features. A meta-heuristic algorithm with a combination of NDS dragonfly procedure and evolutionary population dynamics strategy is proposed. The problem is formulated to handle multiple contradictory objectives. NDSDA, NDSDA_EPD and NDSDA_EPD_CM are the three proposed variants for handling the feature selection problem. A non-dominated algorithm with evolutionary population dynamic strategy is integrated for a heuristic natural selection. A strategy is proposed to handle the local optimum trap, enhance the population diversity, to upgrade the step size and to maintain a balance between exploration and exploitation. A Pareto optimal solutions are obtained from the proposed algorithm which is appropriate for handling multi-objective feature selection problems. The results of the proposed NDSDA, NDSDA_EPD and NDSDA_EPD_CM approaches are compared with the existing dragonfly algorithms. The algorithm parameters are well tuned to attain the optimum results. The proposed NDSDA_EPD_CM algorithm outperforms the other techniques by maximizing the classification accuracy and minimizing the chosen features count.

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