Feature Selection Using Modified Evolutionary Firefly Algorithm in Supervised Learning

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Abstract

The research idea that is presented in this paper is to find the pertinent attributes by using the Modified Evolutionary Firefly Algorithm. The proposed approach primarily works on the principle of basic "Firefly algorithm" (FFA), a modern meta-heuristic swarm optimization algorithm, along with evolutionary operations namely inversion mutation and fitness-based selection. The hybrid approach is been adopted to explore the solution space exhaustively and to help out in discovering the optimal solution. This method works on the principle of partitioning of population, Inversion mutation, and fitness-based selection. The optimal set of attributes from each sub-population will be discovered, followed by integration of the best results of each sub- population and finally performance evaluation will be performed to prove the efficiency of the approach. The performance of this work is expressed in the form of accuracy score and the size of selected attributes. Thus, the proposed approach shows a significant improvement in selecting an optimal set of pertinent attributes with good model performance.

Keywords— Feature Selection, Firefly, Accuracy, Classification, Partitioning, Mutation, Selection

1 Introduction

These days, various disciplines use big datasets which is made possible by technological advancements that involve a large number of features. Extracting knowledge from such large databases is a major challenge for most machine learning algorithms. Feature selection is the method that aims at size of input attributes to machine learning algorithms by getting rid of noisy, redundant, or inappropriate features in any other case that might worse the performance and increase the computational cost in supervised and unsupervised learning. However, conventional methods require enough adaptability to adapt to datasets having larger number of evidence or tuples and extract efficacious outcomes .There are different approaches, like statistical approach, evolutionary approach, etc., for performing feature selection.They are used for simplification of models to make them easier to interpret by researchers/users, for shorter training times and to avoid the curse of dimensionality. Swarm optimization is one, with its simple steps and efficient search methods, has become the most widely used algorithm in optimization problems focusing on performance. Particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony algorithm (ABC), Simulated Annealing (SA) algorithm, Bacterial Colony Chemo taxis (BCC), Firefly Optimization algorithm are some of them. This paper presents a methodology where feature selection is done using an evolutionary approach and swarm intelligent nature inspired Firefly algorithm.

2 Related work

A lot of exploratory study on feature extraction and selection is still going on, wherein the previous research results, survey, studies help to draw some of the required inferences.

The authors [2] have given a review of evolutionary algorithms, especially Genetic Algorithm, Particle Swarm Optimization (PSO), and Differential Evolution (DE) and also briefed other recent nature-inspired algorithms which reveal Evolutionary Algorithms are commonly used for solving optimization problems which may be of single objective type or multi-objective type. Also, different evolutionary algorithms can be used based on the nature of the problem to be solved. The study [3] looked at nature-inspired meta-heuristic techniques used in feature selection. It revealed that the relevance and redundancy of meta-heuristics techniques play a crucial role in the attribute selection process. It was found that feature selection is significantly required when processing medical field data. Similarly, the binary form of these kinds of algorithms was found to be effective.

Ajay Aditya et.al. [4] have made a study of various nature-inspired algorithms. On analysing the results of Firefly algorithm (FA) and Particle Swarm optimization (PSO), FA was found to be hypothetically dominant in handling NP-hard problems. The firefly algorithm has the scope to be modified to solve multi-objective optimization problems by combining with other algorithms.

The authors [5] have presented their knowledge and real time applications of the swarm intelligence concept and some metaheuristics like the ant colony optimization method. This study gives an idea for using the firefly algorithm, a swarm intelligence-based algorithm for solving feature selection problems.The article [6] provides a review of nature-inspired metaheuristics algorithms that use swarm intelligence, such as the Firefly algorithm, PSO algorithms, and ABC algorithm. The stimulation result shows that the Firefly algorithm is found to be effective.

Mohammed Abdulrazaq Kahya, .et.al [7] used a binary firefly algorithm to solve the discrete problem of selecting relevant features by using various transfer functions for exploring the solution space. The performance was evaluated and the V2 transfer function was found to have better consistency with better results.Sofiane Maza, Djaafar Zouache [8] has employed a binary encoded Firefly Algorithm (FAFS) for selecting the relevant features where both accuracy and feature reduced rate were used for evaluating the fitness of the firefly, a new calculation to find the separation value between fireflies and the attractiveness factor. The outcome of FAFS in comparison with the different classifiers and PSO algorithms clearly shows that the proposed method has outperformed.

Xiuqin Pan, Limiao Xue, and Ruixiang Li. [9] have proposed a variant of swarm intelligence algorithm named NEFA to overcome the shortcomings like slow convergence and local optimization of the algorithm by iterative dynamic updation of the moving factor of fireflies. The new NEFA approach outperformed ApFA (Adaptive FA), MFA (Memetic FA), and FA.

Abdullah A et.al [10] has developed a model hybridizing swarm intelligence Firefly Algorithm along with another meta-heuristic evolutionary operation of the Differential Evolution in estimating the parameters of non-linear biological models. The proposed model has achieved improved results because of the usage of evolutionary neighbourhood search strategy.

Zhang [11] has proposed a technique for classifying the unbalanced data by building a hybrid model for two classes and a multi-class dataset coupling one-class F-Score, improved F-Score and evolutionary GA to perform the selection of relevant attributes. The results give an idea of using an evolutionary method for feature selection.

Fan, X., Sayers, W., Zhang, S., et al. [12] reviewed some bio-inspired algorithms that try to imitate the learning mechanisms of the human brain's network of neurons called Artificial Neural Networks [ANN], Darwin's evolutionary theory based Genetic Algorithms (GA) and Genetic Programming (GP), evolutionary strategies, algorithms imitating swarm intelligence, and algorithms based on this, the authors have found that hybridization of nature inspired algorithms gives a clear view for the betterment in the iterations and seems to give promising performance. Le Wang, Yuelin Gao et al. [16] developed a variant of genetic algorithm namely asexual genetic algorithm for feature selection in Android Malware Application Detection task and found to have good results paving another way for solving Feature selection problem.

Timea Bezdan,et al.[15] had projected a modified version of firefly algorithm for the feature selection problem in which the drawbacks of basic version of FA is overcome and had obtained improved results in terms of accuracy in classification task.

2.1 Feature selection

Nowadays information rich high-dimensional datasets with hundreds of features can be easily obtained. As the dimensionality increases, other factors like time complexity, computational cost, data collection cost and lack of interpretability also increase proportionally with the chance of model getting over fitted. As a result, filtering and selecting quality features from the dataset termed as feature selecting process becomes increasingly important to modern data science to achieve a high-quality result in any machine learning task .There are four ways to determine the relevant attributes which are described below.

(i) Wrapper methods where the fitness function coupled with any of the learning for selecting the attributes

(ii) Filtering methods where the attributes are selected based on measures related to the association of the predicted attributes with target attribute, like separability or crowding.

(iii) Embedded methods where classifier dependent selection is performed with the optimal subset of features is built within the classifier model

(iv) Hybrid approach where both filter and wrapper-based methods are coupled.

2.2 METAHEURISTIC ALGORITHMS

Metaheuristics algorithms are those which are used for combinatorial optimization in discrete search-space. These are normally used for optimizing complex problems which take nondeterministic polynomial time (Non-deterministic Polynomial hard). It can be classified into categories based on the underlying principle used to solve the scenario, such as Evolution-based method based on biological evolution, Physics-based method based on physical properties, Swarm-based method based on insect swarm nature, and Human-based method based on logical reasoning. The algorithms based on the evolution principle are called evolutionary algorithms, which are widely used for solving single and multi-objective optimization problems. In this research work, a nature inspired Metaheuristics firefly algorithm [5] is modified and used for tackling feature selection problem. In this article, the feature space is binary encoded, with each bit and its vector position determining whether or not the corresponding feature can be considered. This arrangement of feature space representation allows for exploration capabilities by evolutionary algorithms.

2.3 GENETIC ALGORITHM

Many complex optimization problems, such as NP hard problems, are solved using evolutionary concepts. One of such kind is Genetic Algorithms (GA), which was put forth by John Holland in the 1970s at the University of Michigan [1]. These algorithms provide fair solutions to various problems which are based on biological evolutionary principles like representation of solution in the form of chromosomes, inheriting solutions from parent chromosomes, and other operations such as cross-over, mutation and selection for generating newer solutions. The chromosome can be represented by a string of real numbers called a real-encoded chromosome or as a string of binary bits called a binary-coded chromosome.

2.4 FIREFLY ALGORITHM

Xin-She Yang developed a meta heuristic algorithm named Fire Fly Algorithm (FFA) inspired by the flashing pattern and the searching behaviour of the fireflies in 2008. The FFA uses fireflies' swarm behaviour in solving optimization problems having multiple optima. In this approach, the brightness and the light intensity of the firefly helps in guiding the swarm of fireflies and the randomness factor enables the exhaustive exploration in the solution space [13].

The Firefly algorithm (FA) works on swarm intelligence and has become an excellent global optimizer. It works on three ideal rules listed below:

- There is no discrimination between male and female fireflies, where a firefly will be attracted towards another brighter firefly which is based on the brightness of the light intensity.
- The attraction between fireflies is proportional to the brightness, and gets decreased as their distance increases during the movement. If there exists no brighter firefly, then the firefly will move randomly in the search space.
- The fitness/objective function value determines the brightness of a firefly.

In this method, each firefly represents an optimal set of features and will possess a brightness value proportional to fitness/objective function output. New solutions evolve as the fireflies move towards the brighter fireflies. During the evolution process, better fireflies are retained and carried over to the next successive step. The fireflies are graded based on the objective function output. The distance between the fireflies is found by using the Euclidean distance formula and the content of firefly can be updated based on the intensity and light absorption co-efficient.

Suppose there exist two fireflies, namely i, j and such that i [X_i] represents the location of the firefly in the search space at the existing iteration., and assuming the fitness function of the firefly is higher, means brighter than that of another firefly j, then the separation measure between the firefly i and j can be calculated using the (1) formula.

$r_{ij} = \sqrt{}\,(X_i - X_j)^2$ …………………………………………………………………… (1)

The Equation (1) result is used in Equation (2) to estimate the attractiveness value.

$\beta = \beta_0 * e^{-\gamma rij2}$ ………………………………………………………………………. (2)

Where β_0 represents the attractiveness value at zero separation value between firefly and normally set to 1. γ is the light absorption coefficient and normally set to 1 and rand represent the random number.

The new location in the solution space for the considered i^{th} firefly can be determined w.r.t the current generation solution of the i^{th} firefly. The method of creating the new solution is expressed in terms of two Equations (3) and (4) listed below.

$newX_{ij} = X_i + \beta$ * Random value * $\Delta X_{ij} + \alpha$ *(Random value -0.5) …..…… (3)

$\Delta X_{ij} = (X_j - X_i)$ …………………………………………………………......... (4)

Thus, in FA the evolution of solutions in terms of fireflies will repeat until the specified the termination criteria.

3 PROPOSED METHODOLOGY FOR FEATURE SELECTION USING FIREFLY ALGORITHM

This section explains about the proposed methodology of the research work which uses modified evolutionary firefly algorithm to select the optimal set of relevant variables/attributes/features from the feature space for the input dataset.

Methodology

In this approach the drawbacks for basic version of FFA [13] like less accurate solutions and long duration to converge is overcome by using the population partition strategy and by using the selection and mutation operations of GA, a evolutionary algorithm. Each partition is processed independently and the results are integrated at the end. This proposed approach involves two phases as shown in Fig.1.wherein the firefly is binary encoded [8] in which 1 indicates the selection of attribute and 0 the nonselection of attribute which is shown in the following Fig.2 .The size of the firefly relies on the count of attributes of the given input dataset. During the processing of fireflies a transfer function and a discretization/binarization method are applied to get the result in terms of 0s/1s . First the transfer function is applied to the outcome of the Equation.3 which in turn will result in a real number , then on this real number binarization method is applied so that it results in 0 or 1.

Phase-1

In Phase -1 the pool of fireflies is partitioned into two parts resulting into a small sized sub-population of fireflies which are processed separately. Each part is processed two times with fitness-based selection along with inversion- mutation and without inversion mutation. The effect of inversion-mutation is retained only if it results with better performance in accuracy value and lesser or equal number of selected attributes than the original firefly , avoiding the algorithm being getting trapped to local minima.

Based on the number and position of 1's in each firefly the dimensionality of the dataset will be reduced and each firefly will be evaluated to determine the light intensity by the use objective function. The objective function will output the accuracy of the classifier model generated which will be based on the reduced dataset having the selected attributes with respect to each firefly. The selection and sorting of fireflies relies on the fitness value .

Fitness of Firefly

The fitness of each firefly is found by considering the number of selected attributes along with accuracy score of the classifier by considering the reduced dataset with selected attributes .

Phase -2

In this phase the results of each sub-population is integrated to a single optimal solution by considering the fitness . The global best firefly from each population is sorted to find the final best firefly. Thus, this optimal solution will be the input for the evaluation step. The outcome of the proposed evolutionary firefly method is evaluated against other feature selection methods like Univariate selection method (SelectKBest) and Principal Component Analysis by taking into account the count of selected features. The outcomes obtained after experimenting with different datasets show that modified evolutionary firefly algorithm selects better set of features compared to other methods.

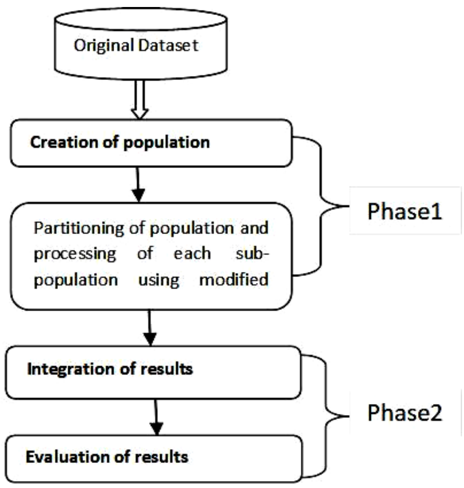

Fig.1. Outline of Proposed Methodology

1	0	………………	1	1

Fig.2. Representation of a firefly

A. Transfer Function

The binary coded firefly requires a function that transforms continuous search space into the discrete binary search space called transfer functions , which plays vital role in all binary swarm processing algorithms [14].This transfer function that converts the elements of position vector into the interval from 0 to 1 can make the fireflies to wander in the binary space. For a binary space which deals with only two numbers ("0" and "1"), the position updating process, toggling between "0" and "1" values cannot be done by using Equation (3). This kind of toggling in a firefly algorithm should be done depending on distance and Intensity measure between the fireflies. There are V-Shaped and S-Shaped transfer functions. In this proposed work a V-Shaped transfer function is used for updating the positions of the fireflies as it is proved that the v-shaped family of transfer functions are capable of finding the best solution with good convergence rate for multimodal benchmark functions using swarm optimization algorithms namely BPSO[17] . The V shaped transfer function used is described below.

$T = X / \sqrt{(1+(X^2)}$ ……………………...…………………………………… (5)

Where X represents a position in the firefly and gets updated by the following rule

$$Xnew = \begin{cases} 1 & \text{if } T > \text{rand}(0, 1) \\ 0 & \text{otherwise} \end{cases} \qquad \text{(6)}$$

By using the equations 3,5 and 6 every bit in the firefly will be updated for better exploration and exploitation.

B. ***Algorithm***

The Phase1 of the proposed methodology involves the following algorithm

Pseudo code:

1. Set the Parameters
2. Create Initial Population of fireflies
3. Partition the population
4. Apply twice Firefly algorithm to each subpopulation
    a) First time FFA using Inversion Mutation
    b) Second time FFA without using Inversion Mutation
    c) Integrating the results of Step a and Step b
5. Integrating the results of each sub-population from Step4

Firefly Algorithm for Feature Selection – with Inversion Mutation

Input: Dataset Output: Global best firefly

Initialization: Attractiveness at zero distance $\beta_0=1$; Light absorption coefficient $\gamma=1$
Objective Function f(x): $x=<x_1,x_2,..x_d>$ [d denotes no. of attributes of dataset]
f(x) is represented in Fig. 3
Max_Iterations=<Integer value> ; Number of fireflies: n=<Integer value>

Step: 1 Create a pool of " n" fireflies

Step: 2 Evaluate the light Intensity of fireflies using f(x)

Step: 3 Loop till Max_Iterations

Step: 3a. Loop for i=1 till n

Loop for j=1 till n

i. Construct the Inverse of i^{th} firefly

j. Find the best firefly among i^{th} firefly and its inverse mutant

k. If the Inverse is better than original by using Fitness based selection
Make that mutant as i^{th} firefly

Else

Ignore the Inverse

If(Intensity(j) > Intensity(i))

Step: 3b Move i^{th} firefly towards jth using Eq. (3) using the transfer function

Step: 3c Vary the attractiveness using Eq. (2)

Step: 3d Evaluate the fireflies and update light intensity

Step: 3e Select the local best and compare with global best and update the global best

Step: 3f Record the progress of the best firefly

Step: 4 Output the global best firefly

Firefly Algorithm with Inversion uses the concept of reversing the firefly, and choosing the best between the original and reverse based on the fitness value and number of selected features. Firefly Algorithm without Inversion does not construct the inverse.

Termination Condition : The proposed algorithm terminates after the specified number of iterations is completed.

Objective function: f(x)

Step1: Scanning the firefly to select those attributes which are set by the corresponding position in the firefly

Step2: Based on selected attributes transform the dataset resulting in reduced dimension

Step3: Generating a Classifier model using reduced dataset

Step4: Calculating the accuracy score of the classifier

Fig.3. Objective Function outline

The sorting of fireflies is done based on the objective function output and count of selected features. During every iteration locally best firefly is identified and checked with the global best firefly for similarity. If the locally best is found to improved solution than global then global best firefly is updated to local.

4 EXPERIMENTAL RESULTS AND DISCUSSION

The proposed methodology is implemented using python language in Anaconda3 Jupyter Notebook. Using four dataset as described in Table I , the performance of the algorithm is evaluated. All the datasets used were assumed to be noise free and with no missing values. In the experiments conducted the execution time was not found to be too varying because of the size of the dataset was not too big but showed better results in terms of accuracy.

The Decision tree classifier model is used in proposed algorithm with the train-test split ratio 70:30 and random State = 10.

TABLE I. DATASET DESCRIPTION

S.No	Dataset Information		
	Name	***Instances***	***Attributes***
1	MobilePrice.csv ; Source : https://www.kaggle.com	1400	21+1
2	Winequality-white.csv ; Source : https://www.kaggle.com	4898	11+1
3	WDBC.csv; Source : https://www.kaggle.com/uciml/breast-cancer-wisconsin-data	569	32
4	spambase.csv ; Source : https://archive.ics.uci.edu/ml/datasets/spambase	4601	58

In this article SelectKBest available in scikit-learn library in Python is used which scores the features against the target variable using Chi-squared statistics. Principal Component Analysis (PCA) is a another dimensionality-reduction method is used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information found in the large set where data is projected into a subspace (principal components). The fraction of variance is way to measure performance of PCA. The count of selected features from proposed algorithm will be taken as input to PCA which indicates the number of principal components to be generated from original feature space. Then based on the principal components the dataset would be transformed and fit into a Decision Tree Classifier model to check its performance in terms of accuracy score and explained variation.Thus the accuracy score of SelectKBest, Principal Component Analysis and the proposed algorithm is compared and modified firefly is found to be superior.The proposed algorithm has some parameters to be set which controls the movement of fireflies in exploring and exploiting the search space as specified in Table II.

TABLE II. PARAMETERS USED IN MODIFIED FIREFLY ALGORITHM

S.No	Parameter	INITIALI VALUE
1	Number of Fireflies	10
2	MAX_ITERATION	20
3	Beta0	0.2
4	Gamma	1
5	Alpha	0.5

The following tables and graphs depicts the evaluation of the proposed methodology with other methods with respect to each dataset depicting the progress of firefly algorithm along the iterations in terms of accuracy score , accuracy obtained using SelectKBest and the selected attributes, accuracy obtained using Principal Component Analysis – (PCA) method and the explained variance and Accuracy of Decision Tree classifier considering all the features (i.e., without feature selection)

TABLE III ACCURACY COMPARISON - : WINEQUALITY-WHITE.CSV

Methods	Dataset : winequality-white.csv		
	No. of Features	Accuracy %	Inference
Decision Tree Classifier	11	58.02	All the features were considered
SelectKBest	6 / 11	59.86	**Selected Attributes Indices** [1, 2, 4, 5, 6, 10]
PCA	6 PC	58.70	**Variance of PCs** [9.11312392e-01 7.73858874e-02 1.04363597e-02 5.13705969e-04 3.26074596e-04 8.75115973e-06]
Modified Firefly	6 / 11	61.29	**Selected Attributes Indices** [0 1 3 5 6 10]

Table III depicts the performance of the suggested method experimented on winequality-white dataset and compared with other feature selection methods. It is inferred that performance is near to the method when all features of dataset are considered.

TABLE IV ACCURACY COMPARISON - MOBILEPRICE DATASET

Methods	Dataset : MobilePrice.csv		
	No. of Features	*Accuracy %*	Inference
Decision Tree Classifier	21	80.23	All the features were considered
SelectKBest	9 / 21	80.95	**Selected Attributes Indices** [0 1 7 9 12 13 14 16 17]
Principal Component Analysis	9 PC	84.52	**Variance of PCs** [6.15630930e-01 1.50304460e-01 1.02199334e-01 8.21454322e-02 4.88303712e-02 6.52398618e-04 1.70246904e-04 2.39451178e-05 1.59354488e-05]
Modified Firefly	9 / 21	84.047	**Selected Attributes Indices** [1, 4, 5, 7, 11, 12, 13, 14, 15]

Table IV depicts the performance of the suggested method experimented on MobilePrice dataset and compared with other feature selection methods. It is inferred that performance is near to the method when all features of dataset are considered.

TABLE V ACCURACY COMPARISON - SPAMBASE DATASET

Methods	**Dataset :** spambase.csv		
	No. of Features	***Accuracy %***	Inference
Decision Tree Classifier	57	90.51	All the features were considered
SelectKBest	34 / 57	90.15	**Selected Attributes Indices** [3 4 5 6 7 8 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 32 34 36 41 43 44 45 51 52 54 55 56]
PCA	34 PC	86.38	**Variance of Principal Components** [9.68278064e-01 3.06877420e-02 9.50108548e-04 2.70412368e-05 1.02334109e-05 6.56532010e-06 3.97609637e-06 3.41298123e-06 2.95145271e-06 2.81139523e-06 2.58740802e-06 2.19156268e-06 2.02497787e-06 1.94133447e-06 1.74100535e-06 1.41179790e-06 1.30353275e-06 1.05294082e-06 9.99237080e-07 9.44644356e-07 8.90522489e-07 7.68671938e-07 7.13870623e-07 6.34628759e-07 6.13453225e-07 5.92131080e-07 5.68607015e-07 4.87057264e-07 4.66427083e-07 4.26988579e-07 3.85059062e-07 3.58275120e-07 3.46110219e-07 3.18809109e-07]
Modified Firefly	34/57	93.26	**Selected Attributes Indices** [4, 5, 6, 8, 9, 10, 12, 13, 15, 17, 19, 20, 22, 24, 25, 26, 27, 30, 33, 34, 35, 36, 37, 39, 41, 44, 45, 46, 47, 49, 52, 53, 55, 56]

TABLE VI ACCURACY COMPARISON - WDBC DATASET

Methods	**Dataset :** WDBC.csv		
	No. of Features	Accuracy %	Inference
Decision Tree Classifier	31	92.39	All the features were considered
SelectKBest	10 / 31	91.22	Selected Attributes Indices [0 1 3 4 13 14 21 22 23 24]
PCA	10 PCs	94.15	**Variance of PCs** [1.00000000e+00 2.47308925e-11 4.42650282e-13 4.73483824e-14 2.93772913e-15 2.23365907e-15 1.86190927e-16 1.02637986e-16 2.26307710e-17 9.56742320e-18]
Modified Firefly	10 / 31	97.6	Selected Attributes Indices [7, 10, 11, 15, 18, 21, 24, 25, 26, 28]

Table V, V1 depicts the performance of the suggested method experimented on spambase and WDBC datasets and compared with other feature selection methods. It is inferred that performance is near to the method when all features of dataset are considered

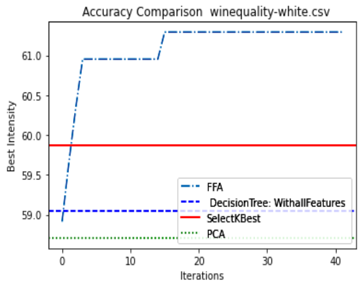

FIG.4 ACCURACY COMPARISON CHART- WINEQUALITY-WHITE.CSV

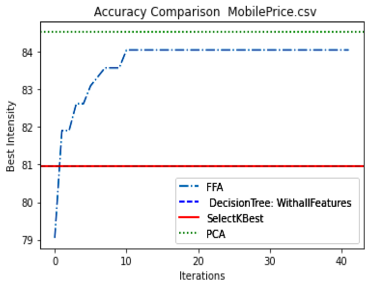

FIG 5. ACCURACY COMPARISON CHART- MOBILEPRICE DATASET

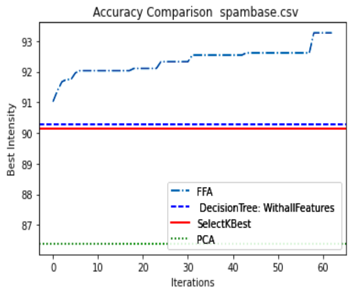

FIG 6. ACCURACY COMPARISON CHART - SPAMBASE DATASET

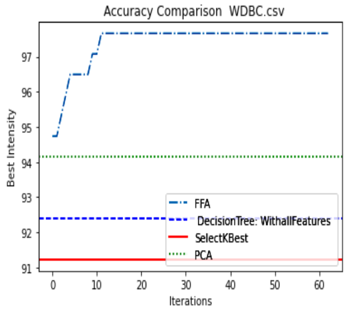

FIG 7. ACCURACY COMPARISON CHART - WDBC DATASET

In Fig 4,5,6,7 the graph represents the progress of proposed modified firefly algorithm with respect to the iterations representing the direction of searching for optimal solution and compared with the accuracy obtained It is evident that the proposed method is superior when compared to using SelectKBest and Principal Component Analysis(PCA).

Conclusion

In this research work, a Metaheuristics algorithm – evolutionary firefly algorithm is applied to determine a set of persistent features for the given dataset which exploits the benefits of swarm intelligence along with the evolutionary algorithmic mutation and selection techniques. To demonstrate the success of the algorithm's performance, four different datasets were used for testing and found to outperform in selecting features leading to the same/better accuracy when considered with all the features. Therefore, it can be considered as a better tool for high-dimensional data reduction problems. It is observed during experimentation that results fluctuate given the stochastic nature of the algorithm or evaluation procedure, or differences in numerical precision. Therefore, to get a consistent output , to discover optimal solution and to exploit the solution space in a better way the algorithm has to incorporate larger number of iteration and fireflies overcoming the time complexity issue, providing a scope for further research.

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