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Flower Pollination Algorithm for Solving Classification Problems

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Abstract

Classification remains as a most significant area in data mining. Probabilistic Neural Network (PNN) is repeatedly used for classification problems. The main aims of this paper are to fine-tune the neural networks weights to increase the classification accuracy and to achieve speed convergence. To achieve this aim, created a hybrid model that investigate the Flower Pollination Algorithm (FPA) with PNN, where the PNN generated the initial solutions randomly and then the FPA is used to adjust the weight of the PNN, and further improvements were conducted using the FPA, which optimized the PNN weights. Experimental results using 11 benchmark datasets showed that the proposed FPA with PNN perform better than the original PNN on all data sets. After compared with another algorithm in the past work from the literature, the FPA can get improved results in regarding of the classification accuracy.

Keywords: *Optimization, Metaheuristic, Flower Pollination Algorithm, Data Mining, Classification.*

1 Introduction

The classification is considered a data analysis process, which helps to extract models that describe the principal of data classes. These are identified as classifiers models, and they can predict the class label categorical[1]. Researchers have proposed several classification techniques in the field of ML, statistics and pattern recognition [2].A majority of the algorithms are observed to be memory resident and presuming a small data size[3]. The recent researches in data mining is based on this work to develop the scalable classification and the prediction processes, which are able to handle the huge volume of the data present on disks[4]. There are many applications of the classification technique, which include fraud detection, predicting performances, targeted marketing, manufacturing and medical diagnosis [5].

Several approaches are available for solving the classification problems like the K-nearest neighbor (KNN), artificial neural network (ANN),radial basis function (RBF),logistic regression (LR),support vector machines (SVM), naive bayes (NB), and other classification technique. The main technique used for solving the classification problems includes the neural network (NN). However, the NN technique has a major limitation, i.e., it does not possess any ability for determining the optimized weights for resolving the classification` problems. Hence, a need arose to apply solutions that determined the optimal weights for the NN classification process[6].

The PNN is a type of forward neural network, that consequential from bayesian network. It was presented in the first time by D.F. Specht [7].The PNN mainly is a classifier, and it uses the supervised training set for developing the probability of density functions is presented in the pattern layer. The PNN model is based on the competitive training which has a victor takes for every type of attitude, and main idea based on the multivariate probability determination[8].

The most important and popular traditional classifier algorithms were reviewed, NN has been used as a tool for classification and it is noteworthy that using neural networks to solve classification problems has always been preferable to other methods, it has outperformed in the most cases[9]. Through the results that have been reached, it can be inferred that neural networks are considered one of the best ways to solve classification problems particularly in real word classification tasks[8]. Furthermore, more studies which has dealt with a classifier algorithm had been also provided[10]. After thoroughly understanding of the strength and limitations of many classification methods, it becomes essential to investigate the possibility of integrating two or more algorithms together to solve classification problems[11].

Over a period of time, there has been a huge interest in the hybrid meta-heuristic technique in the field of optimization[3]. The hybrid algorithms are able to obtain some best solutions for many real-life and classical optimization problems[4]. It is seen that the meta-heuristic methods are extensively used in data mining and showed impressive success[12]. As mentioned above, several of these meta-heuristic approaches have been inspired by the nature and the biological processes, e.g., genetic algorithm (GA) [13],differential evaluation (DE)[14],electromagnetism mechanism-based algorithm (EM) [15],improved bacterial chemotax is optimization (IBCO) [16],and the harmony search algorithm (HS). Also, there are many of swarm intelligence approaches have been utilized for training the NN,such as artificial fish swarm (AFS) [17], ant colony optimization (ACO) [18], artificial bee colony (ABC)[12], biogeography-based optimization (BBO) [2], cuckoo search (CS) [19], firefly algorithm (FA) [6]and particle swarm optimization (PSO) [20].

On this study, the Flower Pollination Algorithm (FPA) has been used for defining the optimal parameter value for the NN weights. The FPA technique is generally related to the pollen transfer, and this transfer is usually connected to different pollinators like the bats, bees, birds, insects etc[21]. Also, it is seen that some of the flowers and the pollinators evolve a special flower-pollinator relationship. For this case, some of the flowers attract and depend on only a very exact type of insect for their pollination[22].

The rest of this research is prepared as follows: Section 2 describes the literature reviews of FPA, and section 3 elucidates the hybridizing flower pollination algorithm with probabilistic neural network algorithm. Section 4 describes and evaluates the results of experiment on 11 benchmark datasets. Finally, section 5 accomplishes the paper.

2 Related Work

Yang [23]proposed a nature-inspired algorithm, named the FPA, to provide solutions for the one-objective optimization problems. This algorithm was based on the natural reproduction process or pollination of the flowering plants. Different pollinators bring the pollination in plants; hence the process of pollination could be local or global. The pollination can be categorized into two categories; biotic or a biotic which depends on the pollen transferring mechanism. In the case of the biotic pollination, the flowers depend on the insects or on the animal's pollinators for transferring the pollen. In the case of the a biotic process, no pollinators are required for the transfer of pollens. A majority of the plants obeys the biotic pollen transferring process. This shows that there could be pollination or a cross pollination due to the traveling or the movement of the pollinators that resulted in the global pollination. The main biological objective behind flower pollination is the optimal reproduction of a novel type of flower which possesses the fittest characteristics, which can ensure the survival of the fittest plant.

The basic flower pollination model adopts that each plant takes a single flower, and every flower product a single pollen gamete. Therefore, it is not necessary to distinguish the pollen gamete, flower or plant. In this study, 10 test functions for validating are used, and the results of FPA compared with the PSO and the GA algorithms. Simulation results indicated that the FPA was extra effective than the PSO and GA. Furthermore, the authors used the FPA for solving the nonlinear design benchmark that showed that the convergence was exponential in nature.

In a separate study, Yang et al. [24]proposed the FPA for solving the multi-objective optimization problems. The FPA was used for solving a group of multi-objective test functions and the 2 bi-objective design benchmarks. They also compared FPA with other algorithms, which showed that the FPA was very effective and had a satisfactory convergence rate.

Abdel-Raouf et al[25]proposed a novel optimization named the improved flower pollination with chaotic harmony search (FPCHS) algorithm. This process combined the FPA and the chaotic harmony search (HS) algorithm for improving the accuracy of the search process. The new FPCHS was used for solving the sudoku puzzles. The numerical results indicated that this algorithm was very accurate and effective comparing to the general harmony search (HS) algorithm.

Abdel-Raouf et al [26]developed a novel process created on the combination of FPA with the chaos theory, i.e., IFPCH for solving the definite integral. This definite integral shows many applications in computer science, operation research, physics, mechanics, mathematics, civil and mechanical engineering. The definite integral is also seen to be very useful in the field of biostatistics for evaluating the distribution function and other similar quantities. Their numerical results indicated that the new IFPCH algorithm was a very efficient method for calculating the numerical values of the definite integral, with a high accuracy, convergence rate and robust nature.

Wang and Zhou [27]suggested a dimension-by-dimension development based on FPA for solving the multidimensional function optimization problem. While iterating this algorithm, a dimension-by-dimension based on improvement and evaluation process was applied. Also, for improving the local searching ability, a local neighborhood search strategy was used in the improved algorithm. Their simulation experiments showed that the suggested strategies effectively improved the convergence speed and the solution quality.

Sharawi et al. [28]applied the flower pollination optimization algorithm (FPOA) for proposing the WSN energy aware cluster formation model, which was based on intra-cluster distance. Their objective was achieving the global optimization for the WSN lifetime. Their simulation results and the performance analysis indicated that the applying of the FPOA on the WSN clustering was very effective. It could efficiently balance the power utilization for every sensor node, and therefore, improve the WSN lifetime in the similar way of standard LEACH method.

Ku-Mahamud[29]proposed a new hybrid algorithm consisting of FPA and the ant colony for solving the optimization problems. This hybrid algorithm comprises of two hybridization levels, i.e., low level known as the ACS (FPA), and a high level, known as the ACS+FPA. The low hybridization level improves the exploration of the ACS directly, whereas the high hybridization level offers a refining technique for the solution generated by the ACS algorithm.

Harikrishnan et al. [30]suggested a new algorithm inspired by nature, called the flower pollen localization algorithm for solving the problem of the sensor node localization. This algorithm was applied to provide solutions to the localization of the wireless sensor network. The algorithm applied the distributed localization process, wherein the computation was carried out collaboratively by a separate sensor node. Hence, this decreases the data communication to the base station. As a result; there is decrease in the energy requirement, which further increases the reliability and the life of the wireless sensor network. The flower pollen localization algorithm can be used for the minimization of the localization error of the sensor nodes in the wireless sensor networks. It has one major parameter that involves the switching with the scaling factor, making this algorithm easy to implement. The flower pollen localization algorithm shows a good performance while predicting the position information of the wireless sensor nodes along with a better convergence and accuracy.

Łukasik and Kowalski [31]studied the performance of the FPA, and also studied the properties of the FPA in the continuous optimization process. They also tried to implement these studies, by carrying out a further analysis of the parameters, and evaluating the algorithm performance with variants PSO technique.

From the FPA literature review which summarized above, the efficiency of FPA was noted in many fields. The reasons behind the success of FPA back to two reasons, long-distance pollinators and flower consistency. According to this algorithm, insects can travel distances, giving them the chance to escape any local landscape and giving it the ability to discover search space. This represents the exploration moves (local search). On the other hand, the consistency of the flower ensures is choosing one kind of the flowers (thus similar solutions) frequently ,and therefore it quickly guarantees the additional convergence, and this expresses the exploitation phase (global search). The interaction between these key components and the selection of the best solution guarantees that the algorithm is very efficient. The subordinate researches proposed the hybridization methods between the global and local search algorithms to enhance both exploration and exploitation phases.

Based on the above, FPA is more effective than some other methods, and this in turn motivated us to further investigate for its performance in classification problem. In the proposed method we describe the manner in which the FPA was applied for solving the classification problems. We have explained a basic outline of the PNN and FPA.

3 The Proposed Method

In the proposed method we describe the manner in which the FPA was applied for solving the classification problems. We have explained a basic outline of the PNN and FPA.

3.1 Probabilistic Neural Network

A PNN is a feed forward neural network, which was derived from bayesian network. it was introduced by D.F. Specht [7].The PNN is mainly a classifier. It uses the supervised training set for developing the probability of density functions which presented in the pattern layer. The PNN model is based on the competitive learning which has a winner takes for all type of attitude, and also the main idea is based on the multivariate probability determination. A typical architecture of a PNN is given in Fig.1 [7].

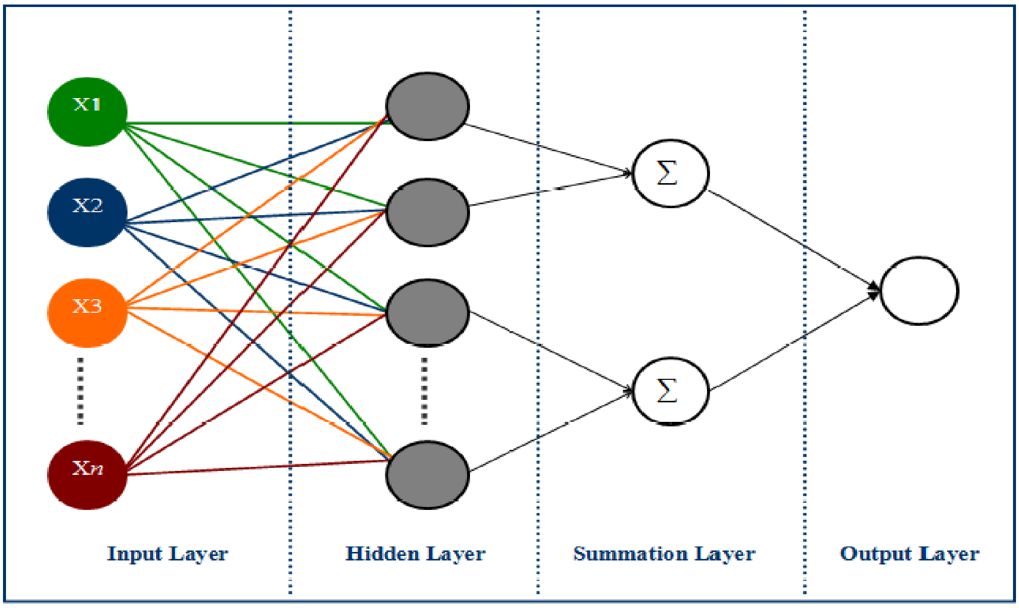

Fig.1 Architecture of the probabilistic neural network

- The input layer: In this layer, neurons and parameters number (which is needed for separable form input) has the same value.
- The hidden layer: In this phase, the training set is organized by attaching separately each input vector with hidden neuron in order to associate the vector parameter. The initiation function which are used in hidden layer is denoted as the next exponential function:

$$X_i^{t+1} = X_i^t + L(g_* - X_i^t) \quad (1)$$

The output computation of the hidden units is defined as the following equation:

$$\emptyset_j^i(x) = \frac{1}{(2\pi)^{d/2}\sigma^d} \exp\left(-\frac{(x - x_j^i)^t (x - x_j^i)}{2\sigma^2}\right) \quad (2)$$

Where is the j[th] pattern of training vector from patterns in class C_i and d is the input space dimensions.

- The output layer: This is too labeled as the integration layer. In the output layer, the number of elements and the current classes has the same value. Each unit is linked to every neuron in the pattern layer denote samples which go to this class. Each neuron output in current layer describes for the input probability of vector X that belongs to class Ci. subsequently:

equals $P(C_i \backslash x) = \frac{1}{(2\pi)^{d/2}\sigma^d} \frac{1}{N_i} \sum_{j=1}^{N_i} \exp\left(-\frac{(x-x_j^i)^t (x-x_j^i)}{2\sigma^2}\right)$ (3)

Where N_i represents training patterns number from class C_i.

In some cases, if the input vectors are not already normalized, additional layer is added to normalize them [26], and that because, the input vector must be normalized to make the hidden layer perfectly separation .

Used the rule of bayes decision to give the classification decision for the input vector X

$$\bar{C}(x) = \underset{i=1, \ ,m}{\arg max} \left\{ \frac{1}{(2\pi)^{d/2}\sigma^d} \frac{1}{N_i} \sum_{j=1}^{N_i} exp\left(-\frac{(x - x_j^i)^t (x - x_j^i)}{2\sigma^2}\right) \right\} \quad (4)$$

where m represents the presented classes number in the training set [27].

The units of radial hidden in the training process are directly copied from the training set, where a Gaussian function is centered on a training sample for each hidden node. In the summation layer, every class has an output unit which the hidden units belonging to the same class are associated to it, without connections Bascil and Oztekin neurons [28]. Here, the outputs can be proportional to the density functions of each different class, and they are also normalized to get a sum equal to 1.

The following Gaussian activation function for the hidden layer neurons is used:

$$f(x) = e^{-}(w_i - x_i)^t (w_i - x_i)/2\sigma^2 \quad (5)$$

Where w_i is the weights, x_i represents the model variables, and is a smoothing parameter.

3.2 Probabilistic Neural Network

Nature is capable for solving many complex problems. As a result, there are ingenuous solutions for the biological systems, which display a great efficiency while carrying out their activities like reproduction. Hence, based on the successful traits displayed by the biological systems, there are several nature-inspired algorithms which have been developed recently [32, 33] .In the earlier studies, the GA was based on the 'survival of the fittest' theory, which was Darwinian evolution theory for the biological systems[34], while the PSO based on swarmed behaviors of the fish and the birds[35, 36] . Also, the BAT algorithm are based on the sonar behavior of the micro bats [34], on the other hand, the firefly algorithm had its basis on flashing light pattern of tropical fireflies[37, 38]. All the above-mentioned algorithms have wide applications and are very popular.

Biologists have estimated that the Earth contains more than quarter million flowering plants, and approximately 80% of the plants are flowering. The flowering plants have been evolving for 125 million years. Flowers are essential component of the plant kingdom, and it is very difficult to imagine plants without the flowers. The major purpose of flowers is to help in reproduction by the pollination mechanism. The pollination of the flowers is related to the pollen transfer, and this transfer is generally associated with the pollinators, which include the birds, bees, insects, bats etc. It is seen that many flowering plants and the insects have co-evolved from very special flower-pollinator relationships. It is seen that some of the flowers attract and depend on only one particular type of pollinator for its pollination [39].The pollination of flowers takes place in two ways: biotic and a biotic. Around 90% of the flowering plants undergo biotic pollination, wherein the transfer of pollen takes place using a pollinator like an insect or an animal. Meanwhile, 10% of the flower pollination takes place a biotically, wherein the pollen transfer does not need any pollinator. In such cases, wind and water diffusion bring about pollination of the plants. The grass is an example of the a biotic pollination [39].The pollinators or the pollen vectors are quite diverse. It has been estimated that there are minimal of 200,000 pollinators like bats, insects, birds, etc. in nature.

One such example of the pollinators is the honey bees that develop flower constancy. The flower constancy of the bees refers to the fact that the bees visit a particular species of the flower while neglecting the other species of flowers[40]. This type of flower constancy has evolutionary advantages, as it can maximize the pollen transfer to nonspecific or the same flowering plants, thereby improving the reproduction of the species. Flower constancy can prove to be beneficial for the pollinators too, as they are ensured of a regular supply of nectar within their limited amount of memory and also, the flower constancy decreases the exploring and searching for new flower species[41]. Instead of focusing on the unpredictable but ultimately more advantageous new species of flower, the flower constancy requires a minimal cost of investment and assures the pollinators with the nectar supply [42].

The pollination takes place by cross pollination. The cross pollination or the Allegany refers to the pollination that occurs from the transfer of pollen from the flowers of another plant, whereas self-pollination refers to fertilization from the pollen transfer from the same or different flowers belonging to the same plant. The self-pollination usually occurs in the absence of a reliable pollinator[43].

The biotic cross pollination can take place over long distances, and the pollinators like the bats, bees or birds can fly these distances, hence, it is called as global pollination. Additionally, the pollinators use the Levy flight behavior [44], with jumps and flight of the step length obeying the Levy distribution. Moreover, the flower constancy is used as the incremental step based on the similarities or the differences of the 2 flowers.

The above-mentioned traits of the pollination mechanism have been idealized, flower constancy and the pollinator behavior as follows:

- The biotic cross pollination is said to be a global pollination phenomenon where the pollinators perform the Levy flights.
- The biotic self-pollination represents a local pollination phenomenon.
- The flower constancy refers to the reproduction probability which is seen to be proportional to the similarities of the flowers involved in the process.
- The local and the global pollination may be measured by the switch probability, p € [0,1].

Because of the physical closeness and additional parameters similar to wind, the local pollination has the significant fraction, p, in the general pollination process. For the formulation and updating the formulas, the above-mentioned rules must be converted in appropriate equations. For instance, during global pollination, the pollinators like the insects carry the gametes and the pollen is transported over long distances as insects fly and travel in a long-distance range. Hence, the first rule and the flower constancy rule, i.e., rule 3, are mathematically represented as follows:

$$X_i^{t+1} = X_i^t + L(g_* - X_i^t) \quad (6)$$

Wherein, refers to the pollen, *i*, or the solution vector, x_i at the iteration, t; while g_*refers to the best current solution observed amongst all the solutions for the present generation/ iteration; parameter L refers to the pollination strength, which is mainly the step size. As the pollinator insects can travel long distances with varied steps, the Levy flight has been used for efficiently mimicking this trait [45]. The L > 0 has been derived using the Levy distribution, as follows:

$$L \sim \frac{\lambda\Gamma(\lambda)\sin\left(\frac{\pi\lambda}{2}\right)}{\pi} \cdot \frac{1}{s^{1+\lambda}}\ , \ (S \gg S_0 > 0) \quad (7)$$

Where the Lévy exponent was the general gamma function, and the distribution was valid for the large steps, s>0.

Also, the local pollination process (Rule 2) and the flower constancy is represented as follows:

$$X_i^{t+1} = X_i^t + \epsilon(X_j^t - X_k^t) \quad (8)$$

Wherein and refer to the pollen since dissimilar flowers which belongs to the similar plant gender. This simulates the flower constancy rule in a small neighborhood. Mathematically, if the X_j^t and X_j^t arise from one plant class or are choice from equivalent flower population, this results in a random walk, if ϙ is dragged from unchanging distribution from [0,1]. A majority of the pollination takes place at the local and the global level.

Practically, the adjoining flowering patches or the flowers within a smaller distance have a higher probability of being pollinated by the local pollination process as compared to the distant flowers. For this purpose, the switch probability has been used (i.e., Rule 4) or the proximity probability, p, for switching between the more popular global pollination processes to the more demanding local pollination process. To begin with, the p = 0.5 was used as the initial value and thereafter carried out a parametric study for determining the proper parameter range. Based on the simulation results, observing that the p = 0.8 was better for a popular of the applications[46].

The flowchart for the FPA has been presented in Fig.2, and in Fig.3, the pseudo code for the FPA has been shown as following:

1) Set the values of the population size n (pollen gametes), a switch probability p, where p϶[0,1] and maximum number of generations MGN.
2) for (*i* = 1; *i*<= n; *i*++) do
3) Create initial population $x_i$by the randomly initialization.
4) Evaluate the result of fitness function f(x_i) for all solutions in the population
5) end for{ Initialization }
6) set t = 0
7) repeat
8) for (*i* = 1; *i*<= n; *i*++) do
9) Generate random number r { r is a uniform distribution in [0,1] }
10) if r < p then
11) Generate a step vector L, which obeys a Lévy distribution
12) Set { Global pollination }
13) else
14) Choose j and k solutions among all the solutions.
15) Generate a parameter ε, ε ϵ [0,1]
16) Set { Local pollination }
17) end if
18) end for
19) for (*i* = 1; *i*<= n; *i*++) do
20) Evaluate the result of fitness function f(x_i) for all solutions in the population
21) end for
22) if<then
23) Set
24) else
25) Set
26) end if
27) Rank the solutions and save the greatest solution g^* found so far in the population
28) t = t + 1
29) until t < MGN
30) Produce the optimal solution.

Fig.2 The FPA pseudo code

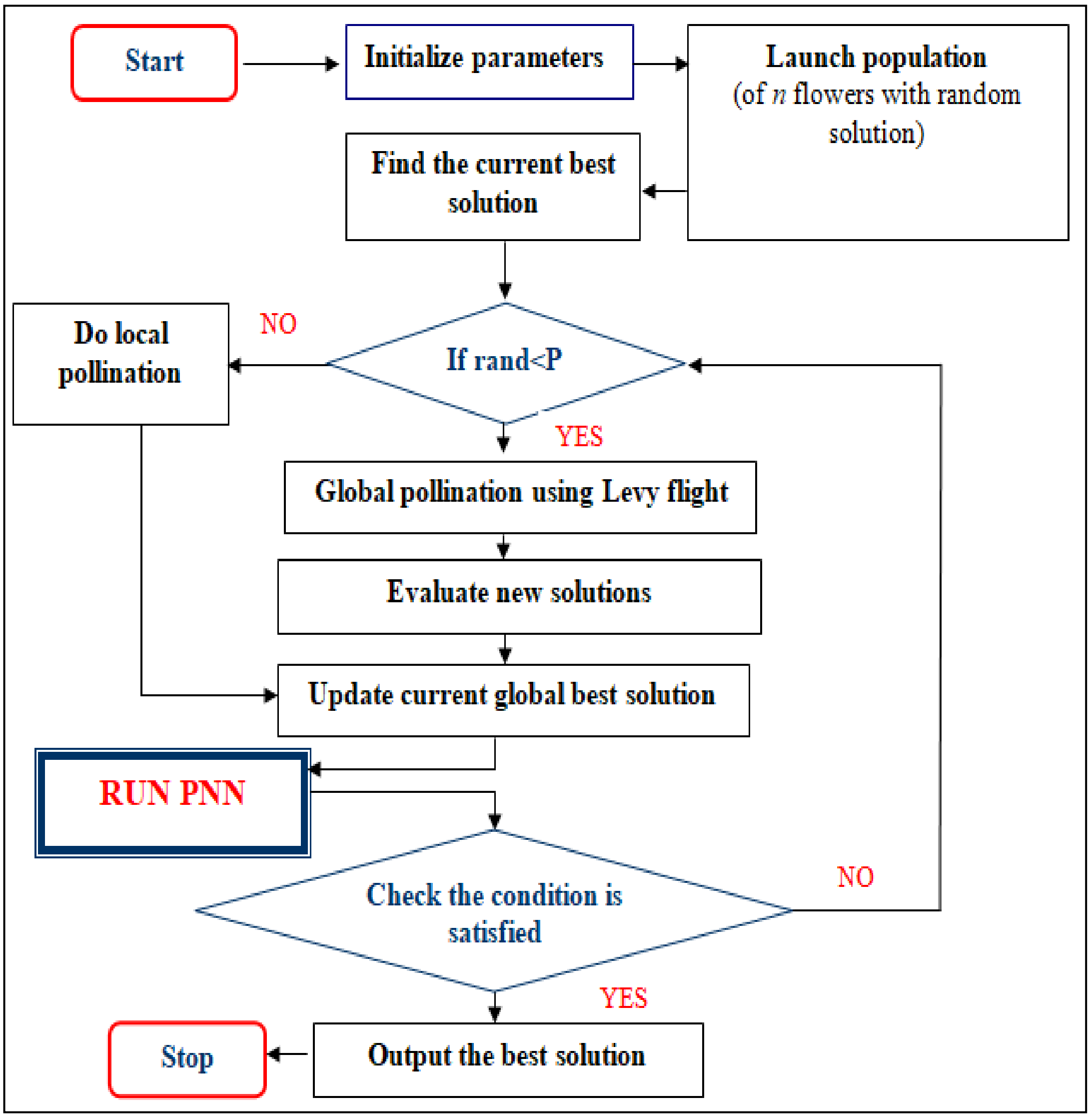

Fig.3 Flowchart for the FPA

4 Experimental Results

The proposed FPA was implemented on MATLAB R2010a programming package and the simulations were carried out on the Xeon® CPU E6-1630 3.70 GHz computer. 30 independent runs were executed for every dataset. The different parameters and the settings of the parameter for the FPA algorithm have been shown as in Table 2, determined after the preliminary experimentation. As already mentioned, solving the classification problems is essential, which can improve the data mining performance. This research study focuses on using the FPA technique for resolving the classification problems. We carried out this work using 11 datasets, which were downloaded free from the following reference: (https://archive.ics.ucr.edu/ml/datasets.html).Training sets and the training size were used from the reference mentioned above. Table 1 has been summarized all the features of the 11 datasets used.

Table 1: Datasets properties

Number	Name of Dataset	Data Testing	Data Training	Classes	Attributes number
1	PIMA Indian diabetes (PID)	192	518	2	8
2	Haberman Surgery Survival (HSS)	77	206	2	3
3	The Appendicitis (AP)	27	71	2	7
4	Breast Cancer (BC)	72	193	2	10
5	Liver Disorder (LD)	86	233	2	6
6	Heart dataset (Heart)	68	182	2	13
7	German Credit data set (GCD)	250	675	2	20
8	Parkinson’s	49	131	2	23
9	SPECTF	67	180	2	45
10	Australian Credit Approval (ACA)	173	465	2	14
11	Fourclass	216	581	2	2

Table 2: Settings of the parameter

Name of the parameter	The value of parameter
Population size(Pollen gametes)	50
Number of iterations	200
Switch probability	0.8

4.1 Results for Classification Quality

The rating quality of the proposed method depends on their generation of enhancing the desired solution. Table 3 presents a comparison of the proposed FPA approach performance when creating a randomized initial solution.

Table 3: Classification accuracy, accuracy mean, accuracy standard deviation, sensitivity and specificity (%) for the FPA with the PNN.

Dataset	TP	FN	FP	TN	Accuracy	Accuracy S.D.	Accuracy Mean	Specificity	Sensitivity
1-PID	39	14	24	115	80.21	0.85	78.94	89.15	61.90
2-HSS	51	7	5	14	84.42	0.85	83.51	66.67	91.07
3-AP	24	1	0	2	96.30	1.65	93.52	66.67	100.00
4.BC	19	8	4	41	83.33	0.93	81.46	83.67	82.61
5-LD	22	4	11	49	82.56	0.87	81.22	92.45	66.67
6-Heart	32	10	0	26	85.29	1.12	83.09	72.22	100.00
7-GCD	161	30	18	41	80.80	1.03	78.58	57.75	89.94
8-Parkinsons	39	2	0	8	95.92	1.54	94.70	80.00	100
9-SPECTF	52	4	1	10	92.54	1.02	91.64	71.43	98.11
10-ACA	69	5	5	94	94.22	0.58	93.35	94.95	93.24
11-Fourclass	78	0	0	138	100.00	0.00	100.00	100.00	100.00

As shown in Table 3, the proposed FPA method shows an improved performance compared to the PNN, where the results showed the ability of the FPA to give better results in the different datasets used.

4.2 Comparison with approaches on the state-of-the-art

It must be noted that none of the approaches mentioned in Table 4, were tested for all the datasets used in this study except firefly algorithm (FA). Hence, the result for every dataset has been compared with the help of different approaches, as described in Table 5. The best results have been highlighted in bold. It was observed that five datasets out eleven datasets which have been tested, the FPA showed the best performance. On the SPECTF dataset the FPA and FA showed the best performance. The FPA is ranked second on the PID, BC, GCD and LD (with regards to the classification accuracy). Furthermore, the FPA could classify the Fourclass dataset with no misclassification (100% accuracy).

Table 4: Compared methods (acronyms)

The Acronym	Approach name	The reference number
1.M_1	Neutral's Fuzzy Inference System.	[40].
2.M_2	Fuzzy NNs.	[41].
3.M_3	BP.	[42].
4.M_4	ANNs.	[43].
5.M_5	CBA.	[44].
6.M_6	FA.	[2].

Table 5: The comparison the results between using FPA and approaches on the state-of-the-art.

Dataset names	Approach's	Accuracies
1-PID	FPA	**80.21**
	M5	76.70
	M6	76.04
2-HSS	FPA	**84.42**
	M5	72.70
	M6	83.12
3-AP	FPA	**96.30**
	M5	91.40
	M6	92.59
4.BC	FPA	83.33
	M_8	73.50
	M5	**84.30**
	M6	80.88
5-LD	FPA	**82.56**
	M_{12}	70.97
	M6	79.07
6-Heart	FPA	**85.29**
	M5	77.90
	M6	80.88
7-GCD	FPA	80.80
	M5	**86.40**
	M6	78.40
8-Parkinsons	FPA	**95.92**
	M_9	81.30
	M5	85.70
	M6	89.79
9-SPECTF	FPA	**92.54**
	M5	83.60
	M6	**92.54**

10-ACA	FPA	**94.22**
	M5	69.90
	M6	91.91
11-Fourclass	FPA	**100.00**
	M_3	99.80
	M5	94.60
	M6	**100.00**

4.3 Validation and Analysis of Results

Validation and analysis are done to know if there is a statistically different from the FA with FPA. This will be made by trial one sample T-Test with interval significance of 95% this indicate that ($\alpha = 0.05$) on the sensitivity, specificity and accuracy, Table 6 represents the obtained p-values acheived ,and the statistical information presented in Table IV shows that the results for the FPA are statisticallysignificance different (the p-value < 0.01) from FA (except Fourclass).For sensitivity, also it seen in Table VI that the FPA is statistically different from FA (except Fourclass).From Table 6 , it can be observed that the FPA is statistically significancedifferent compared with FA algorithm.

Table 6: P-Values of the t-test for FPA with FA

Dataset	Sensitivity	Specificity	Accuracy
1-PID	0.0	0.0	0.0
2-HSS	0.0	0.0	0.0
3-AP	0.0	0.0	0.0
4.BC	0.0	0.0	0.0
5-LD	0.0	0.0	0.0
6-Heart	0.0	0.0	0.0
7-GCD	0.0	0.0	0.0
8-Parkinsons	0.0	0.0	0.0
9-SPECTF	0.0	0.0	0.0
10-ACA	0.0	0.0	0.0
11-Fourclass	1.0	1.0	1.0

The results indicated that the proposed FPA approach was a very suitable methodology that could be used for solving the classification problems as it could show a good performance with regards to the convergence speed and the classification accuracy. In general, the results obtained confirmed the effective performance of the proposed algorithm, where it is able to (i) enhance the search space exploration capability and the exploitation capability, (ii) ensure efficient convergence speed and (iii) find high-quality classification solutions. One of the main shortcomings of the FPA can be found on a set of parameters, which can affect the performance of the algorithm. A subject of the future work could be the tuning of these parameters during the search (automatically) to contribute in finding optimal solutions.

5 Conclusion and Discussion

The final objective of this research is to adjust the neural networks weights in order to increase the accuracy of the classification and to achieve high speed of the convergence. In this work the use of the flower pollination algorithm (FPA) with probabilistic neural network (PNN) was investigated, where the FPA was used to adjust the weight of the PNN. To obtain the objectives of the research, the original PNN has been implemented for classification accuracy for the classification problems, and in order to compare this result, with a hybrid approach based on PNN and FPA for classification problems. The initial solutions were generated randomly using the PNN and further improvements were conducted using the FPA, which optimized the PNN weights. Experimental results using 11 benchmark datasets showed that the proposed FPA with PNN perform better than the original PNN on all data sets.

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