A Novel Flower Pollination Algorithm for Auto-Grading of Edible Birds Nest

Wei Wen Lee
Department of Electrical and Electronics Engineering
Faculty of Engineering and Technology
Tunku Abdul Rahman University College
Kuala Lumpur, Malaysia
leeweiwen5998@gmail.com

Weng Kin Lai
Department of Electrical and Electronics Engineering
Faculty of Engineering and Technology
Tunku Abdul Rahman University College
Kuala Lumpur, Malaysia
laiwk@tarc.edu.my

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***Abstract*—Edible Bird Nest (EBN) produced by certain species of swiftlets has been known of its source of protein and vitamins that benefit the human body. This results in high demand from humanity due to the advantages of consuming the EBN. However, manual process of grading and classifying the EBN for different price range may cause drawbacks towards the production of EBN. The grading of EBN is done by observing the colour, shape, size and impurities present in the nest. Although manual process is done by trained personnel, the results obtained are often inconsistent and inaccurate due to human fatigue. Hence, this process is tedious and time consuming which may cause delay in the production of EBN. To overcome this issue, a novel Drunken Flower Pollination Algorithm (DFPA) is developed to perform auto grading on the EBN. This DFPA is also compared with the existing FPA and four other popular heuristics where the DFPA achieved better grading accuracy with an average accuracy of nearly 88%.**

Keywords—Flower Pollination Algorithm, Intoxication Model, Edible Birds Nest, Classification

I. INTRODUCTION

Edible Birds' Nest (EBN) produced by certain species of swiftlets is one of the indulgences in Chinese cuisine due to its source of proteins and vitamins that benefit the human body. This causes the EBN to be one of the most valuable food products in Southeast Asia and is named as "Caviar of the East" [1]. Furthermore, EBN is famous in Chinese traditional prescription to improve digestive system and immune system, strengthen respiratory functions and most importantly, improving skin complexion that is able to restore youthfulness. The proteins are obtained from the glutinous secretion by the salivary glands from certain species of swiftlets where the secretion is hardened on exposure after shaping it into a cup-shaped nest. The secretion also serves to glue the nest to the ceiling of the cave or building in which the birds live [2].

Malaysia is the second largest exporter of EBN after Indonesia where 11583 bird's nest farms under 7929 producers have registered with the Department of Veterinary Services [3]. Besides, Malaysia exported 5654.7 metric tonnes of EBN in 2019, which was a 345 per cent rise from 2018. Furthermore, China's high demand for raw clean EBN, raw unclean EBN and EBN products from Malaysia is expected to increase the export value to RM3 billion by the end of 2020 from RM1.15 billion in 2019 [3]. This indicates that the demand of EBN is increasing yearly.

EBN can be categorized into 4 different grades according to size, shape, impurities and colour of the nest where the grades are grade AA which has the best quality, followed by grade A, grade B and grade C [4][5]. After the EBN is harvested from the swiftlet houses or the natural caves, they are sent to the factory for grading by the experts. However, traditional methods of grading the EBN done by trained personnel are not consistent and inaccurate due to human fatigue and emotions. Furthermore, the process of training a new operator without any relevant knowledge on grading the EBN is tedious and time consuming due to the subjectivity of grading the EBN. Hence, this motivates the development of a novel Drunken Flower Pollination Algorithm (DFPA) to grade the EBN automatically.

In this paper, DFPA is introduced as the classifier to grade the EBN automatically. Literature review is done to study the methods of classification followed by the design methodology of the proposed approach. Experimental results of the proposed method are shown and discussed in detail. Finally, conclusion is made to wrap up this paper.

II. LITERATURE REVIEW

A. Concept of Grading the Edible Birds Nest

Features that are used to grade the EBN are the size, shape, impurities and colour of the nest [4][5]. The manual and traditional way of grading the EBN is done by observation and judgement from the trained operators. The methods of grading the EBN manually are explained in the following.

The size of the EBN is classified by comparing the size of the index finger, ring finger and middle finger of an adult with the EBN. This method is very subjective as the size of fingers for different operators may vary which will lead to inconsistency during the grading of the EBN. Hence, a better way is introduced to indicate the size of the EBN by measuring the height and length of the nest as shown in Fig. 1 [5].

EBN with perfect half cup in shape without any holes that is large in size and suitable thickness is the shape that is favored the most. Basically, the shape of the nest that is similar to a 180 degrees half-cup shape after placing above a horizontal surface is categorized under grade A. Grade B EBN has similar shape with grade A EBN but covers only 135 degrees when grade B EBN is placed above a horizontal surface. However, grade C covers only 90 degrees of the half-cup shape when it is placed above a horizontal surface. The shape of different grades of the EBN is shown in Fig. 2 [5].

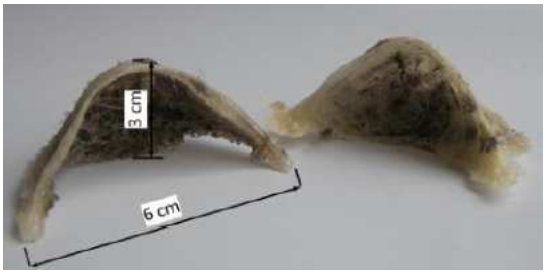

Fig. 1. Size of the Edible Birds Nest [5]

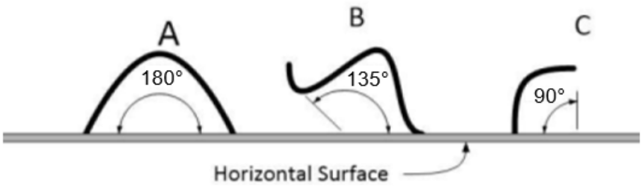

Fig. 2. Shape of Edible Birds Nest with Different Grades [5]

Impurities present in the nest is also one of the factors that contributes to different grading of the EBN. EBN that contains more impurities will have lower market value as the impurities will create a hole in the nest after the cleaning process [6]. The impurities are determined by the number of feathers and other impurities present in the nest before the cleaning process.

Usually, the colour of the EBN is white in colour where other colours of EBN is due to the added element into the original EBN. Hence, EBN with white colour will have the highest grade followed by nests that are yellowish. The existence of yellowish component in the EBN is due to high moisture environment in the swiftlet houses or the natural caves and high guano concentration which contains nitrite compound [5].

B. Related Works on Grading the EBN

There are limited works done to grade the EBN automatically due to its niche industry. An investigation was done on using the Artificial Bee Colony (ABC) as the classifier to auto-grade the EBN into three different grades including grade AA, grade A and grade B [7]. The accuracy obtained from the proposed method was compared with the results obtained from the Bat Algorithm (BA) and the popular k-Means clustering with average classification accuracies of 80.29% and 83.02% respectively. According to [7], significantly better results were obtained by the ABC compared to the BA as well as the k-Means clustering with an average accuracy of 86.29%. This concludes that the ABC classifier outperformed the BA and the k-Means clustering in grading the EBN automatically.

Another paper was written to investigate the effectiveness of using the BA to grade the EBN automatically [8]. The standard BA classifier was able to achieve an average accuracy of 80.29%. However, another method was proposed by hybridizing the k-Means clustering with the BA to obtain a new classifier known as Bat Algorithm Clustering based on k-Means (KMBA) where the KMBA achieved an average accuracy of 85.60% which is significantly better than the BA in auto-grading the EBN [8].

With these results obtained from prior works, the motivation of this paper is to develop a classifier that is able to achieve better results by using the Flower Pollination Algorithm (FPA) incorporated with the Intoxication Model to obtain a new model known as Drunken Flower Pollination Algorithm (DFPA) to auto-grade the EBN.

C. Flower Pollination Algorithm

Flower pollination is an intriguing process that occurs naturally and due to its evolutionary characteristics, the Flower Pollination Algorithm (FPA) was inspired and proposed by Xin-She Yang in 2012 which is capable to solve real-world problems [9]. Similar to every living organism, plants will reproduce to maintain their species. The method of producing offspring is through flower pollination. There are more than 250 thousand species of flowering plants throughout the world and the main strategy for these flowering plants to perform pollination is through the form of wind or pollinators such as bees, insects, birds, butterflies and bats. The basic forms of flower pollinations are biotic pollination, abiotic pollination and flower constancy. Biotic pollination also known as cross pollination is done through pollinators where this form of pollination is utilized by up to 90% of the flowering plants. This is because pollinators can move and fly with different speeds where the pollen grain can be carried to places with long distance. Abiotic pollination also known as self-pollination does not require any pollinators to perform pollination with only 10% of flowering plant utilize this method. Self-pollination is usually done by diffusion and wind where the distance travelled by the pollen grain is typically short. Flower constancy is where certain pollinators will only visit specific species of flowers without exploring new species of flowers while the flowering plants will evolve to reward the pollinators with sufficient nectar. Therefore, these characteristics of flower pollination are idealized to form the rules of FPA as stated in the following.

- Rule 1: Global pollination that involves cross pollination or biotic pollination where the pollen carried by the pollinators are based on Levy flights.
- Rule 2: Local pollination that involves self-pollination or abiotic pollination.
- Rule 3: Flower constancy that is similar to the reproduction probability is proportional to two similar flowers involved.
- Rule 4: The switch probability, P ε [0,1] is used to control the switching or interaction of global pollination and local pollination.

With these rules, the mechanism of the FPA can be explained in three key steps. Global search of the FPA which mimics the biotic pollination ensures the diversity of the pollination for reproduction. Hence, the first rule and the third rule are implemented in global search. Local search of the FPA which mimics the abiotic pollination implements the second rule and the third rule. Although the biotic pollination and abiotic pollination have been considered, the frequency and percentage of each type of pollination are not considered. Hence, rule 4 is implemented to mimic this feature where p indicates whether the modification of solution follows either the global pollination or the local pollination. With the explanation of the mechanism of the FPA, the pseudocode of the FPA is shown in Fig. 3 [10].

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```
Initialize parameters with switching probability p ∈ [0,1] ;
Generate initial population of flowers randomly;
Evaluate initial population and find the current best solution gbest;
while (stopping criterion not satisfied) do
    For each flower
        if rand() < p
            Global pollination : x_i^{t+1} = x_i^t + L(x_i^t − gbest) ; // Based on Lévy step
        else
            Select two random solutions x_j^t and x_k^t ;
            Local pollination : x_i^{t+1} = x_i^t + ϵ(x_j^t − x_k^t);
        end if
        Evaluate new solutions;
        Update solutions with better new ones;
    end for
    Keep the current best solution;
end while
```

Fig. 3. Pseudocode of the Flower Pollination Algorithm [10]

```
INTOXICATION MODEL

TOTAL_DISTANCE(t) = TOTAL_DISTANCE(t - dt) +
(ABS_STEP_SIZE) * dt
INIT TOTAL_DISTANCE = 0
INFLOWS:
ABS_STEP_SIZE = ABS(STEP_SIZE)

X(t) = X(t - dt) + (MOVE_X) * dt
INIT X = 0
INFLOWS:
MOVE_X = STEP_SIZE*COS(CHOSEN_ANGLE)

Y(t) = Y(t - dt) + (MOVE_Y) * dt
INIT Y = 0
INFLOWS:
MOVE_Y = STEP_SIZE*SIN(CHOSEN_ANGLE)

CHOSEN_ANGLE =
NORMAL(DESIRED_ANGLE,INTOXICATION_INDEX)
CLOSE = IF (X<=.5) AND (100-Y <= .25) THEN PAUSE
ELSE 0
DESIRED_ANGLE = IF X < 0 THEN ARCTAN((Y-100)/(X)) ELSE
ARCTAN((Y-100)/(X)) + PI
INTOXICATION_INDEX = 0
STEP_SIZE = NORMAL(1,INTOXICATION_INDEX)
```

Fig. 4. Intoxication Model [11]

D. *Intoxication Model*

Intoxication model mimics the behavior of a inebriated person drunk at certain degrees that is trying to walk towards the destination from an initial position [11]. Usually, a normal person is able to walk in a straight line. Conversely, a drunk person will reel and unable to walk like a normal person. Hence, the inebriated person will always resight the goal prior to taking another step after each step. The chosen direction of each step should have a normally distributed variation around the desired direction. Similarly, the step size of a intoxicated person should have a normally distributed variation around the step size of a normal person. The standard deviations of the step size and step direction are assumed to be similar and is known as intoxication index. In order words, the lower the intoxication index, the lesser the person is intoxicated. The mean of the direction chosen by the intoxicated person is the desired direction towards the destination whereas the mean of the step size is 1, which is the step size of a normal person.

After the indication of step size and chosen angle, the actual movement towards the destination is determined by (1).

$$Move\ Y = Step\ Size\ \times Sin(Chosen\ Angle) \tag{1}$$

The horizontal movement of the intoxicated person is determined by (2).

$$Move\ X = Step\ Size\ \times Cos(Chosen\ Angle) \tag{2}$$

The total distance walked by the intoxicated person is the accumulation of all the steps taken. The complete intoxication model is shown in Fig. 4 [11].

III. Proposed Methodology

A. *Data Normalization*

Since there are different ranges of values for each feature including colour, size, impurities and shape in the dataset of the EBN, normalization is required to standardize the ranges of each features in order to ease the process of classifying the EBN. Hence, min-max normalization technique is used as it ensures that all features in the dataset will be in the same scale.

Min-max normalization, also known as min-max scaling is one of the methods of feature scaling where the range of features or variable of data is normalized. Furthermore, Min-max normalization will rescale the range of values in each feature from 0 to 1 by determining the maximum value and minimum value of each features. Finally, min-max normalization is done by (3).

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

There are 63 pieces data in the dataset of the EBN with 3 grades where the grades are Grade AA, Grade A and Grade B. The values of each features in the dataset are normalized using min-max normalization. The normalized data will then be distributed into training dataset and testing dataset randomly where 70% of the dataset (44 pieces of data) are allocated for training whereas 30% of the dataset (19 pieces of data) are allocated for testing. The testing set will not be revealed to the system during the training process as this set of data is used to determine the accuracy of the classifier.

B. *Flower Pollination Algorithm (FPA)*

In FPA, the user defined parameters are switch probability p, scale factor γ, population size n and Lévy distribution index λ [10]. Regarding the switch probability that determines the percentage of global pollination and local pollination, the suitable probability that applies to most of the applications is 0.8 [12]. To prevent the pollen from flying too far away in global search or global pollination, the scale factor, γ is determined as 0.01 where this value is the factor of the returned value from Lévy distribution during the global search [12]. The Lévy distribution is shown in (4).

$$L \sim \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda/2)}{\pi} \frac{1}{s^{1+\lambda}}, \quad (s \gg s_0 > 0) \tag{4}$$

The value of Lévy distribution index, λ is proved to be best within 0.75 to 1.95 [10]. Hence, the Lévy distribution index, λ for this paper is set to be 1.5. In short, the parameters defined for the FPA to grade the EBN are 0.8 for switch probability p, 0.01 for scale factor γ and 1.5 for Lévy distribution index λ. However, the most suitable population size, n is determined according to the application where different applications will have different values of population size [13]. Hence, the population size is determined by experimenting the relationship between the population size and the average accuracy obtained from the classification. The value of the population size that provides the best average accuracy will be used.

C. A Novel Drunken Flower Pollination Algorithm (DFPA)

Although FPA is successfully developed by mimicking the behavior of flower pollination with results of high convergence rate, further improvement can be done by modifying the algorithm to improve the performance of the FPA [9]. Hence, this motivates the modification of the FPA to the novel DFPA by incorporating the intoxication model into the FPA. Since the intoxicated person in the intoxication model is walking in a staggered manner, this inspired the manipulation of the Lévy distribution of the FPA to the intoxication model for the global pollination in the DFPA. The pseudocode of the DFPA is shown in Fig. 5.

Since Lévy distribution in the FPA is removed and replaced with the intoxication model for the DFPA, the parameters of scale factor, γ and Lévy distribution index, λ under the Lévy distribution are removed. However, they are replaced with new parameter in the intoxication model which is the intoxication index, I. The initial intoxication index is set at 2.5 which is highly intoxicated to perform the global search. Furthermore, the drunkenness of the global search is designed to be decreasing at a factor of e for every occurrence of global search to stabilize the global search function. Hence, the initial intoxication index, I is assigned with a value of 2.5 whereas the reduction factor, e of the intoxication index for every occurrence of global search is assigned with a value of 1.005. The intoxication index, I for every occurrence of global search can be calculated as shown in (5). The number of population, n and the switch probability, p for DFPA will remain unchanged and are similar to the n and p determined in the FPA.

$$I_{new} = \frac{I_{current}}{e} \tag{5}$$

```
1:  Initialize parameters with switching probability p ∈ [0,1]
2:  Generate initial population of flowers randomly
3:  Evaluate initial population and find the current best
    solution gbest
4:  while (stopping criterion not satisfied) do
5:    For each flower
6:      if rand() < p
7:        Global pollination: x_i^{t+1} = x_i^t + D(x_i^t − gbest)
          //Based on Intoxication Model
8:      else
9:        Select two random solutions x_j^t and x_k^t
10:       Local pollination: x_i^{t+1} = x_i^t + ϵ(x_j^t − x_k^t)
11:     end if
12:     Evaluate new solutions
13:     Update solutions with better new ones
14:   end for
15:   Keep the current best solution
16: end while
```

Fig. 5. Pseudocode of Drunken Flower Pollination Algorithm

D. Grading Accuracy

Since the dataset of the EBN is randomly partitioned into training data and testing data, each simulation will run for 100 iterations where the dataset will be partitioned and the classifier will be trained and evaluated for every iteration to consider different combinations of training data and testing data. After the training process, the test data are classified by calculating the Euclidean distance between the test data and the centroids obtained from the training process. The test data that has the smallest distance with the centroids will be categorized under the centroid's class or grade. The results for every classification are evaluated to measure the performance of the method used. The accuracy of the classification can be calculated using (6).

$$Grading\ Accuracy = \frac{\sum Graded\ Test\ Data\ with\ Correct\ Grades}{Total\ Test\ Data} \tag{6}$$

To compare the performance of the proposed methods, the average accuracies obtained from the simulations of different methods will be compared to evaluate their performances. The flowchart of the proposed classification system is shown in Fig. 6.

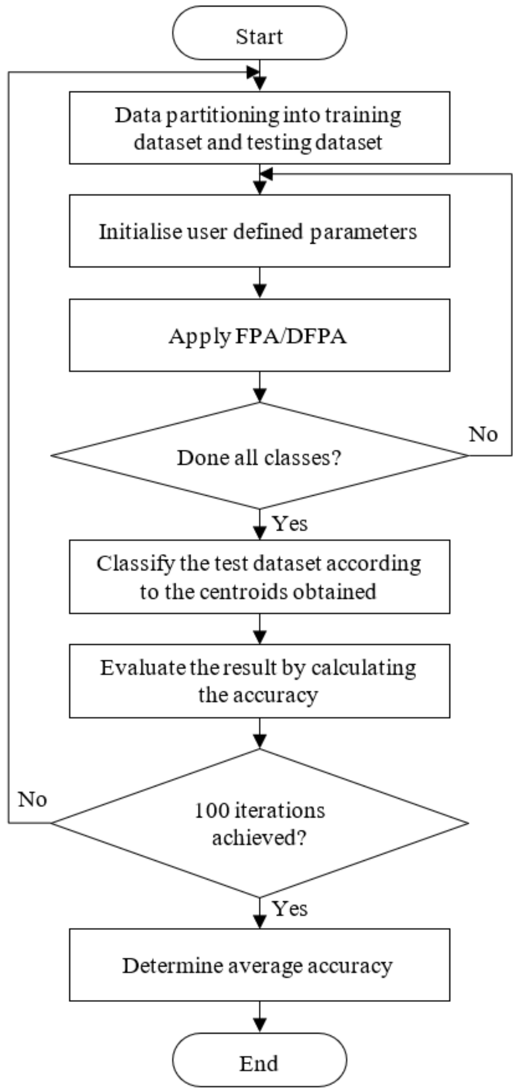

Fig. 6. Flowchart of the Proposed Classification System

IV. RESULTS AND DISCUSSIONS

The population size, *n* of the original FPA classifier is experimented to determine the best population size that will produce the best results on classifying the EBN. The normalized dataset of the EBN is partitioned randomly into training dataset and testing dataset for every iteration. After 100 iterations, the accuracies are recorded and statistical analysis is done. The number of populations is set at 5 initially and is incremented with an interval of 5. Hence, the population size is manipulated where the average accuracies for each population size and the standard deviation of the accuracies are tabulated in table I. To visualize the trend of the average accuracy and the standard deviation of the accuracy in grading the EBN for different population size in the FPA classifier, the results tabulated in table I are plotted into graphs in Fig. 7 and Fig. 8 for average accuracy and standard deviation respectively.

TABLE I. AVERAGE ACCURACIES AND STANDARD DEVIATION FOR DIFFERENT POPULATION SIZE IN FLOWER POLLINATION ALGORITHM

Population Size, *n*	**Accuracy (%)**	
	Average Accuracy	***Standard Deviation***
5	82.2105	9.4559
10	85.2105	7.3561
15	85.1053	6.6933
20	86.0526	6.8715
25	86.0000	6.3573
30	86.2105	6.5975
35	85.2632	6.9776
40	86.0000	6.7832
45	87.2632	6.2669
50	85.6316	5.5908
55	85.0526	6.7625
60	85.8421	7.2796
65	85.3684	7.0008
70	86.4737	5.9496
75	85.4211	7.2857
80	86.3684	6.4393
85	84.2632	8.0046
90	86.9474	6.6692
95	85.6842	6.6524
100	84.6842	6.9007

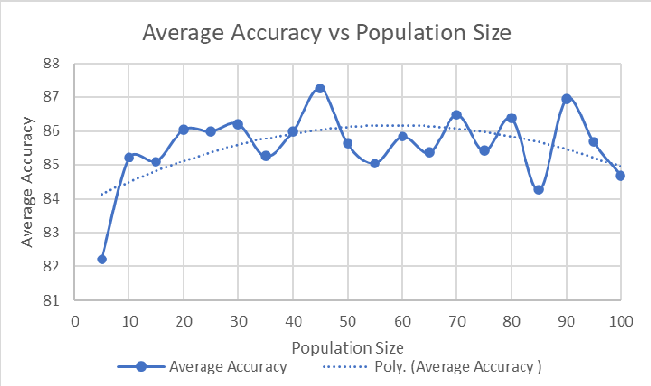

Fig. 7. Graph of Average Accuracy vs Population Size

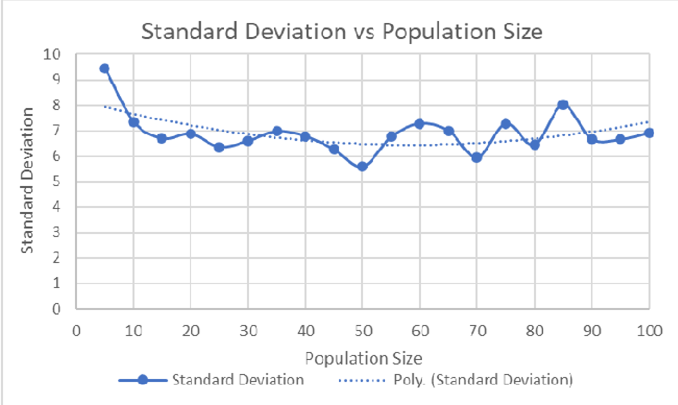

Fig. 8. Graph of Standard Deviation vs Population Size

Second order polynomial interpolation is plotted on the graphs of mean accuracy and standard deviation vs the population size to visualize the trends of the plotted graphs. Second order polynomial interpolation is used as this technique is able to trace the quadratic curve of the plotted graphs and determine the peak and trough of the graphs. According to Fig. 7, the trendline reaches the peak at population size of 40 to 70. Furthermore, the FPA classifier achieved the highest accuracy of 87.26% when the population size is 45. However, the average accuracy does not ensure the consistency of the results obtained from the FPA classifier. Hence, the standard deviation of the accuracies obtained from the classifier is plotted as shown in Fig. 8 to study the consistency of the FPA classifier with respect to the population size of the FPA. Referring to Fig. 8, it can be seen that the trendline reach the trough at population size of 40 to 70. The minimum point of the graph of standard deviation is 5.5908 at population size of 50. However, the population size of 45 is still chosen in this case as the standard deviation for population size of 45 is 6.2669 which is very close to the standard deviation at population size of 50. Conversely, the mean accuracy for population size of 50 is much lower than the mean accuracy with population size of 45. Therefore, the most suitable population size for auto-grading the EBN is 45.

A novel Drunken Flower Pollination Algorithm (DFPA) is developed after the process of experimenting the relationship between the population size of the FPA and the performance of the FPA classifier. With the parameters defined in design methodology, the novel DFPA classifier is able to achieve an average accuracy of 87.68% which is relatively high. The average accuracies obtained from the FPA and the DFPA and the classifiers studied in the literature review to auto-grade the EBN are tabulated in table II to compare the performances of different classifiers.

TABLE II. GRADING ACCURACIES OF DIFFERENT CLASSIFIERS

Classifier	**BA**	**k-Means**	**KMBA**	**ABC**	**FPA**	**DFPA**
Average Accuracy (%)	80.29	83.02	85.60	86.29	87.26	87.68

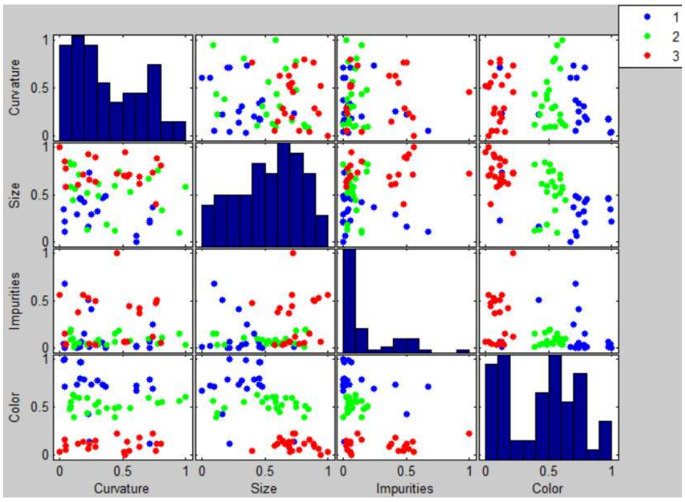

Fig. 9. Scatter Plot Matrix of Normalized EBN Dataset

Table II tabulates the grading accuracies of different classifiers classifying the EBN. The results of using the Bat Algorithm (BA) and the k-Means Bat Algorithm (KMBA) to auto-grade the EBN are 80.29% and 85.60% respectively [8]. Besides, the results of using the k-Means and the Artificial Bee Colony (ABC) to auto-grade the EBN are 83.02% and 86.29% respectively [7].

There are 63 pieces of data in the dataset of EBN where 70% of the dataset will be used to train the classifier whereas the rest of the dataset will be used to evaluate the performance of the classifier. Hence, there are only 14 pieces of data in the testing dataset where one misclassification on the testing dataset will be very significant with reduction of 7.14% in the accuracy. Furthermore, the data of the EBN are not separated nicely as shown in Fig. 9 where some of the data are mixed with different classes which may confuse the classifier. However, the FPA is still able to obtain an average accuracy of 87.26%, which is significantly better than the BA, k-Means, KMBA and ABC. Furthermore, the novel DFPA proposed in this paper where the Lévy distribution in the FPA is substituted with the Intoxication Model associated with reduction factor has even better results. The average accuracy obtained by the DFPA classifier is the highest among the classifiers which is 87.68%. Thus, the novel DFPA has the best performance among the classifiers in terms of auto-grading the EBN.

V. Conclusion and Future Development

All in all, population size of 45 provides the best performance for the FPA to grade the EBN automatically where the issue of grading the EBN inconsistently through manual method is overcame. Furthermore, a novel Drunken Flower Pollination Algorithm (DFPA) is developed in this paper where the performance of the DFPA outperforms the FPA and other classifiers used to auto-grade the EBN. The accuracy obtained by the DFPA to auto-grade the EBN is highest among all the classifiers with accuracy of up to 88%.

The performance of the DFPA can be further enhanced by exploring methods to converge the searching results during the process of determining the centroids for each class. This intend will increase the accuracy of the classifier. Besides, the procurement of dataset of the EBN is suggested in the future to increase the amount of data available for training and evaluating the performance of the classifier which will increase the consistency and accuracy of the DFPA classifier.

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