International Journal of Advanced Research in Engineering Innovation
e-ISSN: 2682-8499 | Vol. 6, No. 1, 52-60, 2024
http://myjms.mohe.gov.my/index.php/ijarei

Improved Artificial Neural Network Classification Model based Metaheuristic Optimization for Handwritten Character Recognition

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Received: 1 March 2024 | Accepted: 20 April 2024 | Published: 30 April 2024

DOI: https://doi.org/10.55057/ijarei.2024.6.1.5

Abstract: *This study addresses the concerns regarding the performance of Handwritten Character Recognition (HCR) systems, focusing on the classification stage. It is widely acknowledged that the development of the classification model significantly impacts the overall performance of HCR. The problems identified specifically pertain to the classification model, particularly in the context of the Artificial Neural Network (ANN) learning problem, leading to low accuracy in recognizing handwritten characters. The objective of this study is to improve and refine the ANN classification model to achieve better HCR. To achieve this goal, this study proposed a hybrid Flower Pollination Algorithm with Artificial Neural Network (FPA-ANN) classification model for HCR. The FPA is one of the metaheuristic approaches is utilized as an optimization technique to enhance the performance of ANN, particularly by optimizing the network training process of ANN. The experimentation phase involves using the National Institute of Standards and Technology (NIST) handwritten character database. Finally, the proposed FPA-ANN classification model is analysed based on generated confusion matrix and evaluated performance of the classification model in terms of precision, sensitivity, specificity, F-score and accuracy.*

Keywords: Metaheuristic, Machine Learning, Optimization, Flower Pollination Algorithm, Artificial Neural Network, Handwritten Character Recognition

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1. Introduction

Handwritten Character Recognition (HCR) remains a challenging task for researchers, even after nearly four decades of continuous work in this field. Although extensive research has been conducted on HCR for over five decades, it continues to be an active and demanding area with many researchers currently involved in it (Alqahtani et al., 2023; Ahmed et al., 2023; Sudarchanan, et al., 2023; Kumari et al., 2022). In this paper, the focus is on proposing a method for recognizing handwritten characters. In general, preprocessing, feature extraction, and classification phases are the typical components of an HCR system. Feature extraction can employ the clean character image produced by pre-processing directly and effectively. Selecting useful and effective characteristics for the classification step during feature extraction is necessary. Image character recognition occurs at the classification stage, which is the final step. The entire process determines the system's success rate. A good survey on HCR and its stages can be found in (Monica and Shital, 2015; Mohamad et al., 2015; Matsumoto et al., 2001).

The recognition of handwritten character is suggested in this work. Preprocessing, feature extraction, and classification phases are often present in an HCR system. However, the development of a classification model for handwritten characters is the only phase on which this work focuses. Implementing metaheuristic feature extraction techniques suggested by earlier research (Mohamad et al., 2017; Mohamad et al., 2021) is the first step in the process. These methods work as chain code extractors to get chain code characteristics that reflect the handwritten character pictures. The categorization model then incorporates these features as input. The flower pollination algorithm and an artificial neural network are incorporated in the suggested classification model for handwritten characters (FPA-ANN). This model is intended to efficiently identify and categorize handwritten characters.

Overall, this paper is organized as follows: Section 2 presents the literature review. Section 3 describes the methodology. Section 4 describes the development of proposed hybrid FPA-ANN classification model. Section 5 describes the result analysis and followed by a conclusion in Section 6.

2. Previous Work

This paper is a continuous study of previous works on chain code extraction based on metaheuristic feature extraction algorithm (Mohamad et al., 2017; Mohamad et al., 2021). After the thinning process is done against the character binary image, the chain code as feature representation of image character is extracted using a proposed metaheuristic feature extraction algorithm. In the development of metaheuristic feature extraction algorithm, chain code was used as feature representation technique and two metaheuristic algorithms which are Harmony Search Algorithm (HSA) (Mohamad et al., 2017) and Whale Optimization Algorithm (WOA) (Mohamad et al., 2021) were utilized. The purpose of both proposed algorithms is to find a continuous route of chain code which covers all the image character, which will be subsequently used in constructing the chain code as an image feature. At the end of the study, the proposed metaheuristic feature extraction algorithms are evaluated based on performances measurement of length and computation time. To end, the best metaheuristic feature extraction algorithm is selected as chain code feature extractor.

3. Methodology

This section presents the general information of proposed methodology for this study that described the whole activity in this research. The methodology is demonstrated in Figure 1. It shows the detail process involve in the methodology. In HCR, input data is defined and collected so that it can be manipulated in achieving the objective. NIST databases were used in the experiment. Therefore, character image datasets that are going to be use are identified and been selected as the input source in further progression. There are five stages in the proposed methodology which are preprocessing stage, feature extraction stage, feature vector formation stage, classification stage and evaluation stage. This paper follows the methodology accordingly. The details for each stage are explained in the next section respectively.

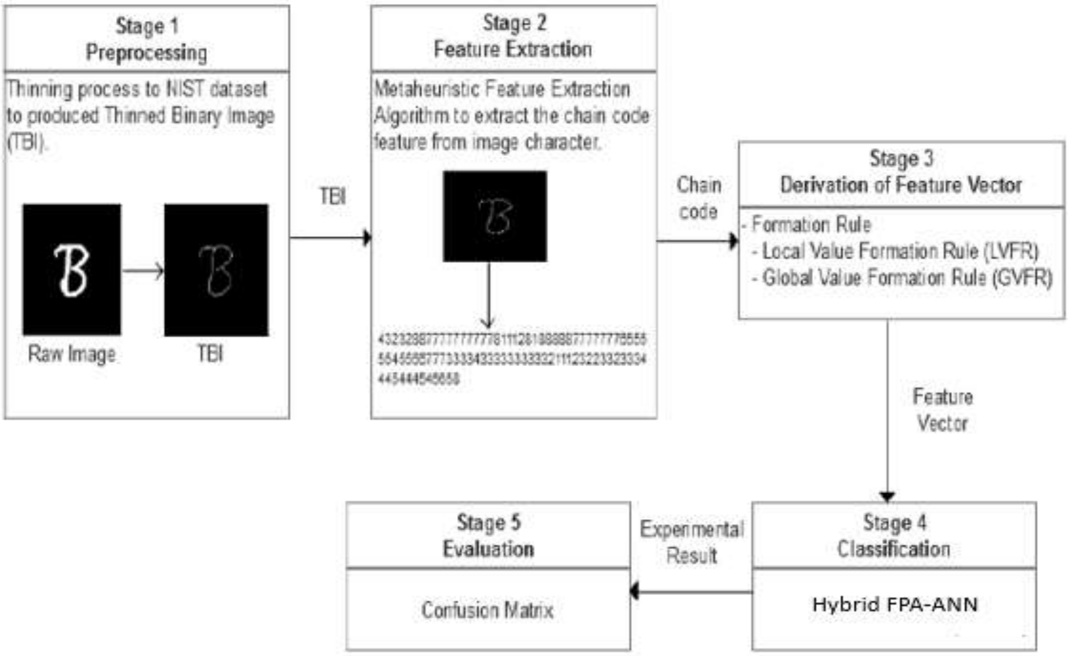

Figure 1: The Proposed Methodology

3.1 Preprocessing and Feature Extraction

Thinned Binary Image (TBI) format data that are usually been used in the development of feature extraction algorithm are applied in this research. TBI was produced in the preprocessing stage by thinning process. “Bwmorph” MATLAB function is utilized for this purpose.

After the thinning process is done against character binary image, chain code as feature representation of image character is extracted using metaheuristic feature extraction algorithm. In the development of metaheuristic feature extraction algorithm, chain code is used as a feature representation technique and the two metaheuristic algorithms; HSA and WOA were applied. The purpose of both proposed algorithms is to find a continuous route of chain code which covers all the image character, which will be subsequently used in constructing the chain code as an image feature. The metaheuristic feature extraction algorithms are evaluated based on the performances measurement of length and computation time. More details about metaheuristic feature extraction algorithm in extracting chain code of handwritten character can be referred to (Mohamad et al., 2017; Mohamad et al., 2021).

3.2 Derivation of Feature Vector

Feature vector is acted as input for the proposed FPA-ANN classification model. Feature vector was derived by proposed formation rule such as Local Value Formation Rule (LVFR) and Global Value Formation Rule (GVFR). This process produced two feature vectors: Local Feature Vector (LFV) and Local Global Feature Vector (LGFV). Details of derivation of feature vector can be referred in (Mohamad et al., 2018).

4. Proposed FPA-ANN

This section provides an overview of the process used to develop the proposed FPA-ANN classification model for handwritten characters. During the ANN classification model's network training phase, the FPA has been hybridized. At the start of the network training, the FPA is specifically incorporated into the ANN classification model. We developed an algorithm using Microsoft Visual Studio to implement this hybrid model.

Step 1 : Handwritten character dataset declaration
Step 2 : ANN parameter declaration
Step 3 : FPA parameter declaration
Step 4 : FPA Optimization in Network Training
Step 5: Generate initial population of flowers
Step 6: Train the Network
Step 7: Calculate the fitness function. MSE is utilized as fitness function.
Step 8: Select Best Solution in Population.
Step 9: for each solution, do Pollination
Step 10: Evaluate new solution.
Step 11: Update the population.
Step 12: Repeat Step 8 to step 11 until the maximal number of iterations is met.
Step 13 : Find the best current solution
Step 14 : Network Testing

Figure 1: The FPA-ANN Classification Algorithm

A dataset of handwritten characters taken from the NIST database is used for the FPA-ANN experiment. A collection of feature vectors serves as the input to the proposed FPA-ANN classification model, while the character class labels serve as the output. The architecture is specified with layers for input, hidden, and output for the ANN parameter declaration. Kolmogorov's Theorem, which recommends employing $2n+1$ node, where n is the number of nodes in the input layer, is used to calculate the number of nodes in the hidden layer. The definition and configuration of the ANN parameters are shown in Table 1.

Table 1: ANN Parameter Setting

Parameters	Setting Value
Input (n)	Feature Vector (69)
Output (character class)	Class label (62)
No of hidden node	$2n+1$
Network Structure (I-H-O)	69-139-62
Network Algorithm	Feed Forward BP
Transfer Function	*Sigmoid*
Performance Function (MSE)	0.05
Learning Rate	0.50
Momentum Constant	0.95
Max Number of Epochs	10000

The third step of the proposed FPA-ANN, the FPA parameters are declared. These parameters include the number of flowers (n), pollination rate (p), and maximum number of iterations. The declaration of FPA parameter values is based on previous research (Yang, 2012). The researcher has suggested parameter values within a specific range to reduce the time needed for trial and error while still ensuring favorable results in optimizing the algorithm. Table 2 shows the FPA parameters declaration for this study. To provide a better understanding of the

FPA terminology and basic processes used in this study, Table 3 presents the equivalent terminologies employed.

Table 2: FPA Parameter Setting

Parameters	Setting Value
Number of flowers in population	100
Pollination Rate	0.9
Max number of iterations	10000

Table 3: Main Terminology of FPA based on this study

Terminology of FPA	Equivalent Terminology
Flower	Weight and biases of ANN as solution vector
Population of Flower	Population of solution
Fitness Function	Means Square Error (MSE) as error of ANN Network
Best Solution	Best solution according to Fitness Function
Termination Criterion	Minimum value of MSE and maximum number of iterations
Number of iterations	Number of Epoch in ANN

Step 4 of the proposed algorithm involves using the FPA for optimization during the network training process. The network training approach used here is supervised training, with FPA employed as the optimization approach. The network training process in the FPA-ANN algorithm consists of signal propagation through each layer, starting from the input layer, passing through the hidden layer, and finally reaching the output layer. Each node in one layer is connected to every node in the subsequent layer with specific weights. The input is processed by the network, and the obtained output results are compared to the desired outputs. Based on the comparison, errors are calculated and propagated through the system to adjust the weights, which control the network's behavior. After the training phase, the resulting map contains the winning neurons and their associated weight vectors. The weight vectors are further optimized using the FPA optimization approach. This iterative process is repeated until the error reaches the minimum level or a maximum number of iterations (stopping conditions) are reached. The Mean Square Error (MSE) is monitored during training, and the process stops when the MSE reaches a value lower than the defined minimum error (0.05) or after a maximum number of iterations (10,000). Throughout the iterations, the algorithm records the best error convergence rate achieved, which allows for the investigation of the network's behavior. Figure 3 provides an illustration of the FPA optimization process during the network training, covering Step 5 to Step 13 of the FPA-ANN algorithm. To design the FPA for training the network, several terms need to be highlighted and defined.

i. The weights and biases of the network are presented as flowers in the population of FPA.
ii. The fitness function is defined as minimum error of MSE of the network.

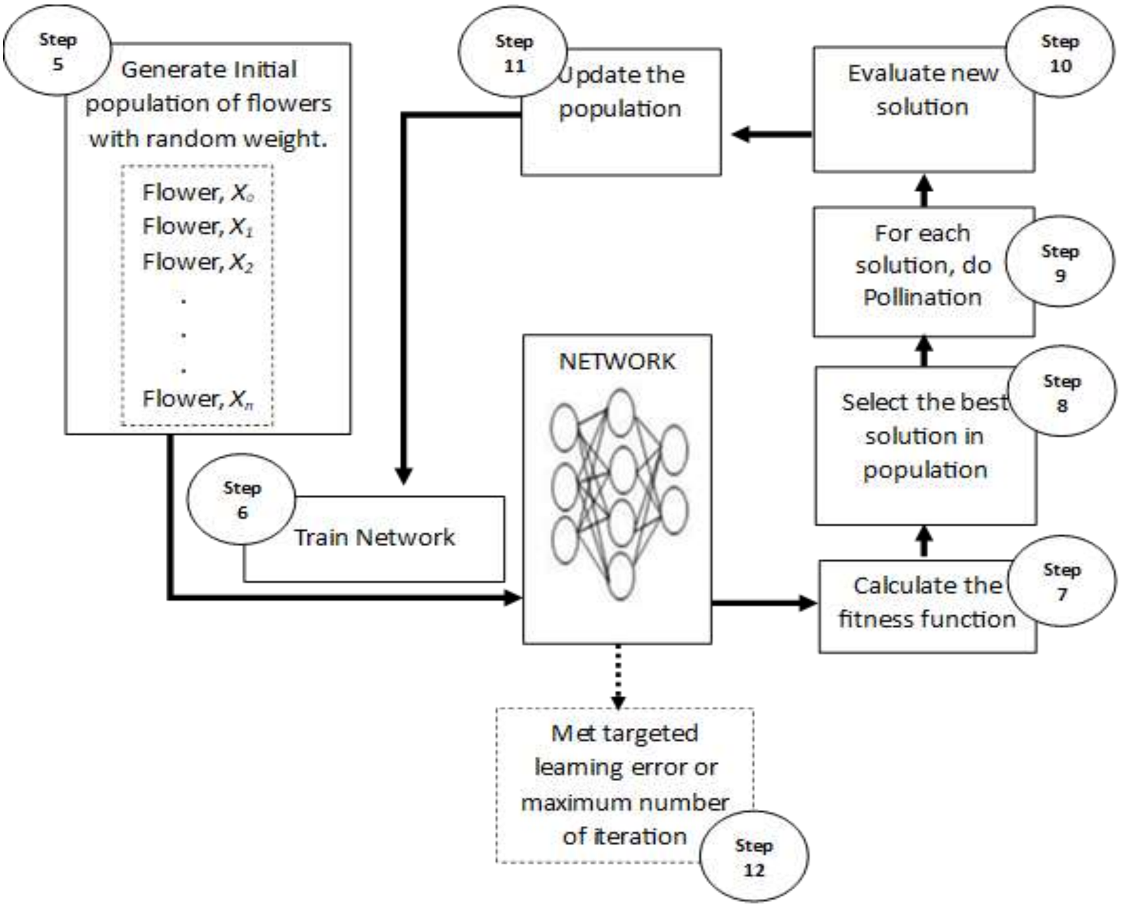

Figure 3: Illustration of Flower Pollination Algorithm Optimization in ANN Network Training

5. Result Analysis and Evaluation

This section presents the analysis results of the proposed FPA-ANN classification model for handwritten characters. The performance of the FPA-ANN model in classifying the handwritten characters is evaluated, and a confusion matrix is used to gain a clear understanding of the model's findings for each character class. The confusion matrix is constructed as a 62x62 matrix to assess the model's performance on the testing dataset. In the confusion matrix, four possible outcomes are considered: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These outcomes provide insights into how well the model correctly identifies positive and negative instances for each character class.

To evaluate the proposed FPA-ANN classification model, a comparison is made with a previous single ANN classification model [11] based on performance measurements. Precision, sensitivity, and specificity are used as performance metrics to assess the classification models' performance for handwritten characters. Precision is defined as the proportion of true positive (TP) results against all positive results (both TP and FP). It indicates how well the model correctly identifies positive instances among the predicted positive ones. Similarly, specificity measures the proportion of true negatives (TN) correctly identified, indicating how well the model recognizes negative instances. In terms of precision, sensitivity, and specificity, if the proportion is closer to 1, it means the margin of error is smaller, indicating better performance of the classification model.

The evaluation results of the proposed FPA-ANN and single ANN models in terms of precision, sensitivity, and specificity for each character are illustrated in Figure 4,5 and 6 respectively. The illustrations clearly shows that the FPA-ANN model outperforms the ANN model in classifying handwritten characters, as it achieves smaller margin errors with precision and sensitivity values closer to 1 for all characters compared to the single ANN model. In terms of specificity, both classification models show similar distribution results, indicating that they successfully recognize negative or non-character instances accurately.

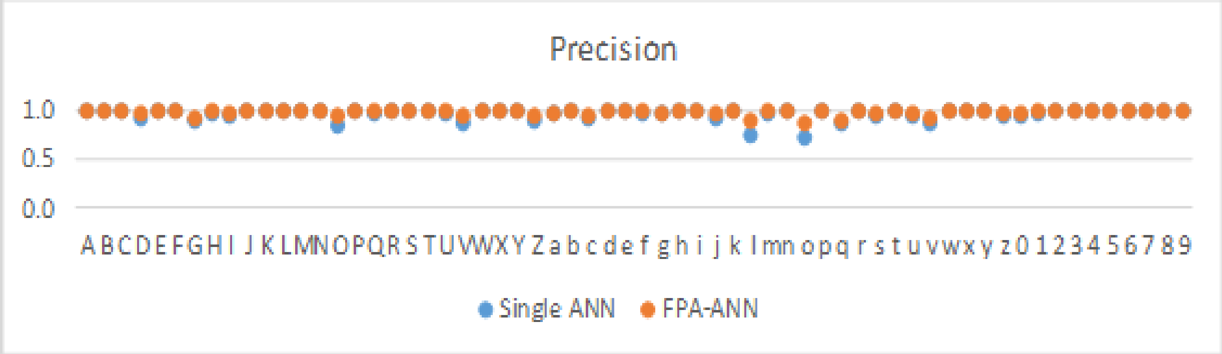

Figure 4: Comparison of Proposed FPA-ANN and Single ANN in term of Precision

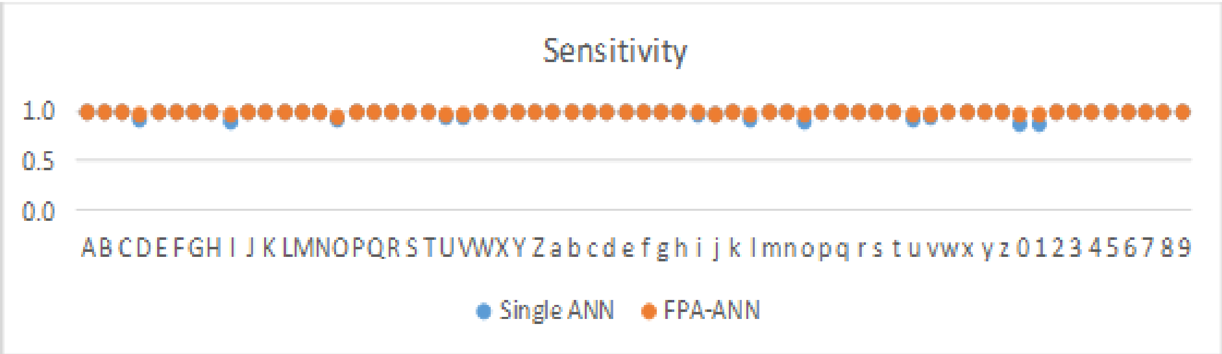

Figure 5: Comparison of Proposed FPA-ANN and Single ANN in term of Sensitivity

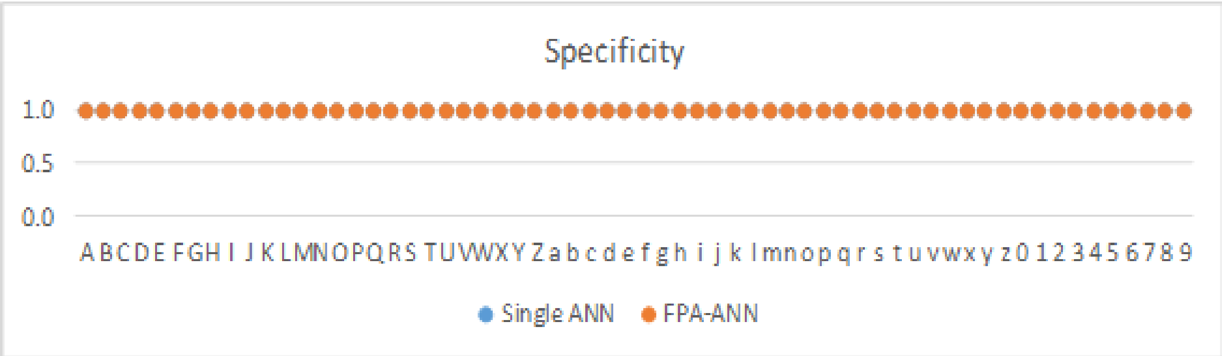

Figure 6: Comparison of Proposed FPA-ANN and Single ANN in term of Specificity

In conclusion, the overall performances of the proposed FPA-ANN classification model for handwritten characters are summarized using common performance measurements: accuracy and error rate. The accuracy of the model represents the percentage of correctly classified instances among all instances in the dataset. A higher accuracy indicates better performance in recognizing the characters. The error rate, on the other hand, is the complement of accuracy and shows the percentage of incorrectly classified instances. Lower error rates indicate better performance. In addition to accuracy and error rate, the F-score is also utilized as a performance measurement. The F-score is the harmonic mean between precision and sensitivity, serving as a balanced measure of the model's performance. It considers both the ability to correctly identify positive instances (precision) and the ability to capture all positive instances (sensitivity) in its calculation. The F-score provides a more comprehensive evaluation of the model's capabilities. The summarized results, including accuracy, error rate, and F-score, are illustrated in Figure 7. This representation gives a clear understanding of the overall performance of the proposed FPA-ANN classification model for handwritten character recognition.

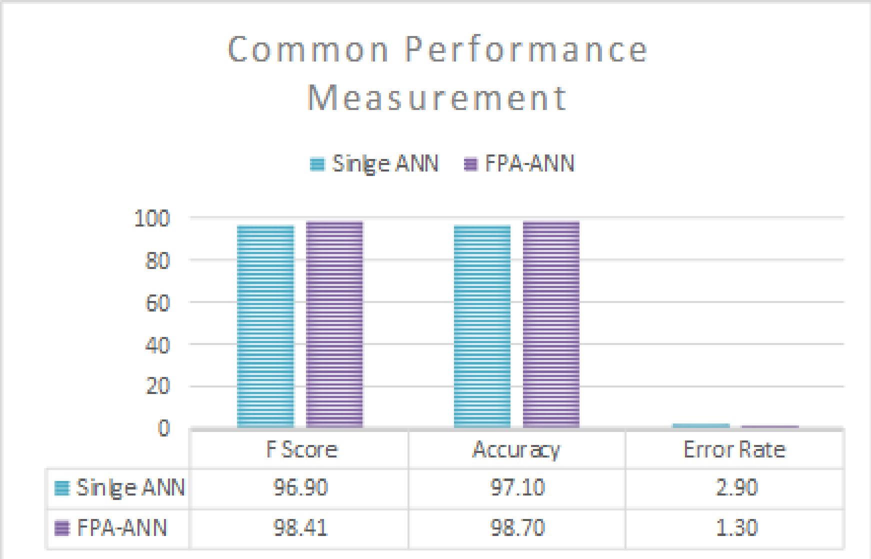

Figure 7: Comparison of Proposed FPA-ANN and Single ANN in term of F-Score, Accuracy and Error Rate

6. Conclusion

This paper presents the development and evaluation of a hybrid Flower Pollination Algorithm-Artificial Neural Network (FPA-ANN) classification model for handwritten character recognition. The goal is to enhance the performance of the ANN using the metaheuristic approach, the FPA. The development of the hybrid FPA-ANN model consists of three main processes, which are outlined in an algorithm comprising thirteen steps. These processes involve optimizing the network's learning process through the FPA, which modifies the weights of interconnections to minimize the network's error and improve its performance in recognizing handwritten characters. In the evaluation phase, the proposed hybrid FPA-ANN model is compared to a single ANN in terms of several performance metrics, including precision, sensitivity, specificity, F-score, and accuracy. The results demonstrate that the hybrid FPA-ANN model achieves a 1.59 percent improvement in accuracy compared to the single ANN model. As a significant contribution, this paper highlights the enhancement of the ANN classification model through the optimized network learning process using the Flower Pollination Algorithm. The proposed hybrid FPA-ANN classification model demonstrates better performance in classifying handwritten characters, showing promising results for character recognition tasks.

Acknowledgement
The authors would like to express their sincere gratitude to the Soft Computing and Optimization Research Group (SCORE) for their valuable support throughout the research process. Their support and contribution have been instrumental in the successful development and evaluation of the proposed hybrid FPA-ANN classification model for handwritten character recognition.

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