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English character recognition algorithm by improving the weights of MLP neural network with dragonfly algorithm

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ABSTRACT

Character Recognition (CR) is taken into consideration for years. Meanwhile, the neural network plays an important role in recognizing handwritten characters. Many character identification reports have been publishing in English, but still the minimum training timing and high accuracy of handwriting English symbols and characters by utilizing a method of neural networks are represents as open problems. Therefore, creating a character recognition system manually and automatically is very important. In this research, an attempt has been done to incubate an automatic symbols and character system for recognition for English with minimum training and a very high recognition accuracy and classification timing. In the proposed idea for improving the weights of the MLP neural network method in the process of teaching and learning character recognition, the dragonfly optimization algorithm has been used. The innovation of the proposed detection system is that with a combination of dragonfly optimization technique and MLP neural networks, the precisions of the system are recovered, and the computing time is minimized. The approach which was used in this study to identify English characters has high accuracy and minimum training time.

Keywords: character Recognition (CR), neural network, dragonfly optimization algorithm, accuracy

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1. Introduction

In the world of machine learning, the recognition of the character (CR) represents a challenge in the research field in pattern recognition, artificial intelligence, and soft computing. In the modern world, all user data is needed digitally [1]. Digital file registration is essential because scanned data requires a vast space of storage. Another benefit of the digital data over the scanned data is the operations such as searching, editing, etc. can be performed on them. Because of these manipulations and storage problems, the scanned data should be transformed into digital forms. Digital data storage space is less than scanned images or records. The widespread availability of electronic text documents increases the importance of using automated methods to analyze the content of text documents. Handwritten recognizing characters is very difficult for a character due to the user's different writing styles in addition to a lot of font movements by users and it requires a lot of intelligence [1, 2]. Character recognition mainly contributes to human-computer interactions and improves the interface between those two. Printed documents, despite the prevalence of computer use in document processing, have a significant function in human life. Manual analysis of documents prepared with paper and pen is called handwriting identification systems, i.e. handwriting character recognition (HCR). Systems that recognize handwritten characters’ focus on identifying characters written on a sensor device, such as a touch screen, that can be converted directly to digital form. Character recognition using handwriting machines is an emerging related technology in the modern world. The evolution of character recognition is done automatically in two ways (based on information): First, handwriting character recognition (HCR), these systems use a digitizer that directly writes the characters according to strokes, speed, and type the pen records. Second, character recognition in print is also known as Character Optical Recognition (OCR), which uses an optical scanner or camera to preserve the image of data on paper and convert a text image to a bit pattern by digitally digitizing devices. Does. OCR systems/machines are utilized for applications such as document automation, authentication, and more. Currently, HCR systems could be divided into two subcategories: offline and online systems [3, 4]. Online detection systems are performed in real time while users are typing. These methods turn digital pen tip movements into a list of coordinates and are less complex because they can record time-based information such as speed, acceleration, number of strokes created, to write strokes, and so on. A lot of online systems are currently existing because they represent simple to develop and have an excellent accuracy in addition to that, they could be used to access tablets and PDAs. But offline detection systems work on static data and use characters as scanned images, which means that their input is a bitmap. Hence, the process of identifying and designing an offline HCR system is more challenging and has to deal with things like individual styles at the individual level, in different cases depending on the size, shape, thickness of the characters and so on. These limit the accuracy of offline HCR systems [3]. So, the challenging part of recognizing handwriting is the difference in people's writing patterns. Even a person's handwriting can be different at different times. For example, width, form, writing speed, width of characters and more [5]. Traditional and old machines learning approaches have long been utilized for offline HCR. The common method of machine learning to identify handwriting characters can be preprocessing, segmentation, feature extraction, and classification [6-8]. The offline HCR systems are first trained by character sets (such the scanned image) and then when the new characters images are imported as inputs, the system can accurately detect it. The usefulness and accuracy of an HCR system has been proven in lots of applications like sorting emails at the post offices, reading bank checks, digitizing old legal documents, and manually converting documents / forms. the main purpose of this research is to identify English characters with great accuracy. All the functions of a pattern recognition system depend on the performance of its constituent elements at the individual level. Therefore, this research is designed to improve the MLP neural network algorithm by focusing on the extraction and classification steps based on the dragonfly algorithm to improve the MLP neural network algorithm as a new proposal or modification of existing approaches in pattern recognition.

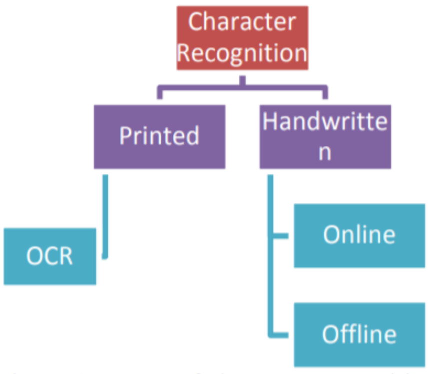

Figure 1. Types of character recognition systems

In this article, after examining the basic concepts in the introduction, in the second part, the background and background issues are described. In the third section, the principles of the proposed method and its overview are stated. The fourth section contains details on how to implement and evaluate the proposed method, and at the end of the fifth section concludes and providing the solutions for future works.

2. Related work

An HCR system includes steps such as character splitting, pre-processing of the character image, feature extraction, in addition to identifying the character class with the extracted features [9]. Character recognition methods link a symbolic identity to an image of a particular character.

The system used for identification includes the following steps: 1. obtain the image. 2.digitization. 3.preprocessing. 4.classification. 5.feature extraction. 6.and finally a classification step to generate a digital output. The various steps that the system uses to identify are determined in Figure 2.

Images related to the HCR system can be obtained by writing directly to the computer using a pen or by taking a photo of the document, in addition to the option of scanning a handwritten document. This process is called digitization [10]. Preprocessing consists of a sequence of functions that are executed to improve it and allocates it to segmentation. The preprocessing stage includes noise removal, thinning and contouring, and more. Suitable filters such as Gaussian filters, medium filters, and maximum filters could be utilized to get rid of noise from the target image. The binary process is the part of preprocessing that transforms a gray-scale or color image into a black and white image. In addition, it may be essential to adjust the sizes of the entered document if the size is magnified to improve operations immediately. If a document is scanned, it may be tilted and should be aligned by tilting the slope. However, slope correction and size reduction may also lead to the omission of some important features for detection, so both must be done carefully. The accuracy of the exact classification of the input document depends entirely on the accuracy of the proper segmentation. Extraction is a core feature of the character recognition system [11, 12]. Feature displacement/extraction methods such as Linear Discriminants Analysis (LDA), Chain Code, Independent Components Analyses (ICA), Principal Component Analyses (PCA), Zoning, gradient-based features, Scale Invariant Feature Extraction (SIFT), and histograms are used to derive the characteristics of individual characters from these characteristics to teach the classification system.

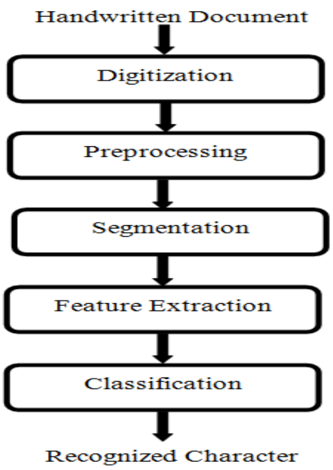

Figure 2. Different stages of characters' recognition system [9]

Neural network-based techniques are currently receiving more attention from researchers than classical techniques [13, 14]. The performance of the classical technical methods depends on the vast-amount of data utilized to define parameters of the statistical models without the flexibility to be adapted to the new limitations of handwritings. In addition, those technical ways can only be utilized if the input-data is uniform over time. While fast cognition, automatic learning, and flexibility after proper network training are the advantages of the ANN network. Therefore, in the following, we examine the neural networks as an identifier/classifier in the diagnostic systems. The history of neural networks is derived from a thorough and transparent examination of the brain in conventional computers. Neural network architecture is usually divided into two categories: feedforward neural networks and feedback neural networks [15, 16]. The structures of neural networks are made from a huge number of inner connected processing units namely neurons. Each multilayer network is defined in terms of architecture, activation functions, thresholds, and weight. When using the training algorithm to learn the network, the last two variables are used. In education, in addition to determining weight and threshold, it is necessary to optimize the number of nerve cells because the speed of the network for learning depends on this factor [17, 18]. Multilayer perceptron neural networks (MLPs) represent the most popular architecture in ANN, where neural cells are gathered in lots of layers and there is only forwards connection. In multilayer perceptron neural networks, the number of layers is limited and can be decided by the user. In each layer, several neurons process the data received from the previous layer and take the output to the next layer. A multilayer perceptron neural network in the first layer used to estimate regression uses sigmoid functions and the same function for neural cells in the output layer [19]. MLP network is widely utilized in handwriting characters identification systems because of their ease of training and is used in the decision-making process for very fast classification. MLPs generally perform well in terms of the degree of correct recognition in the classification of handwritten characters. Sadly, many limitations when using MLP in classification/recognition jobs: firstly, no theoretical relationship between the structures of MLP and the classification job does not have. The other limitations are due to the clue that MLP separates superclass spaces into attribute display spaces, which is not optimum in-terms of area margins between samples of two different classes [19]. Recently, achieving optimal detection rates, many types of research have led to the designs of classification systems using a variety of methods to combine multiple classifications. The ideas are for compensating for the weaknesses of a classification (performed by MLPs) in a particular area of the feature space after proper optimization. The hybrid methods could collect local accuracy of estimating, local learning algorithm, a fixed mix of local experts, or decisions made from separate classifiers to make statistically the best final decisions. In the offline detection system, classification/recognition techniques have been used since 1990 for identifying handwritten characters. Those methods including statistical method relayed on Bayesian decision law, neural network (ANN), the main method include support vector machine (SVM) and several hybrid classifications [20, 21]. In [22], a method for deriving hybrid features and a method based on a genetic algorithm for optimal selection of feature subsets with compatible multilayer perception (MLP) as model classification are proposed. The adaptive nature of classification is achieved by performing a function to select the best MLP architecture in the selection and classification stages. Dinesh et al. [23] utilized horizontal or vertical types of movements and endpoints as potentials diagnostic features. and reported 90.50% diagnostic accuracy for Canadian handwritten characters. However, these methods utilize thinning processes that leads to loss of features. Paul et al. [9] presented the properties of zoning code and directionals chains code and considering feature vectors of length 100 to recognize handwritten numbers and then reports a precise accuracy of identification/recognition. However, the feature extractions processes are complicated and consume time. In the study, a diagonal features extractions scheme is proposed to recognize offline handwritten characters. This method repeats in the extractions of 54 attributes for every characteristic for all regions. These extractions of features are used for training the feed forward neural network, which is used to perform identification/classification and detection the task. Extensive simulations show that the detection systems use diagonal feature to produce better detection accuracy whereas requiring less time for training. Hamed et al. [24] have reviewed various statistical and structural features and based on the features, have recommended a unique and new perspective. The effectiveness of these features has been tested to identify English handwritten characters using the Multilayers Perceptrons (MLP) Classification and the Support Vector Machines (SVM). This research is designed by focusing on the steps of extracting and classifying preprocessing features as a new proposal or modifying existing approaches in pattern recognition. It has been found that the modified display-based feature is very efficient. Extensive evaluation test results performed with different characteristics/combinations of characteristics and classifications are presented.Rajab et al. [25] recommended the English characters recognition systems using the Markov Hidden Models (HMM). HMM uses a different feature extraction pair including global and local feature extraction. The universal feature consists of numerous features such as sloping feature, projection feature, and curvature feature in the order of 4, 6, and 4, respectively. Estimation of local properties is achieved by splitting the sample images into 9 blocks. Calculate the slope attribute of each block using four attribute vectors, which produce thirty-six total local attributes. Estimation of local properties is achieved by dividing/splitting the sample images into 9 blocks. Calculate the slope attribute of each block using four attribute vectors, which produce thirty-six total local attributes. It produces fifty attributes (local + global) for a single sample image. The features are then added to the HMM model for instruction. Post-processing information is used by this method to reduce cross-classification of different classifications. These techniques are time-consuming in training and extracting features. In addition, when many such characters are mixed in a separate image, its performance is lower at such inputs. Ganapai et al. [26] have proposed a technique used for multiscale neural networks training tailored to fit. To improve/enhance the accuracy, it uses a selective threshold that uses the calculation according to the minimum distance method. This includes the creation and developments of the GUI, which could specify the characters throughout the scanned images. Offers 85% accuracy and average training level. The program used images with huge resolution (28 × 20 pixels) to train with a reduction in time of training. Sam et al. [27] utilized the fuzzy memberships method for the improvement of the accuracy of the handwritten text identification/recognition system. Here, the text image is normalized to 10 × 20 pixels, and the next fuzzy method uses for each separate class. The junction box is built around the characters to specify horizontal and vertical text projections. Rakesh Kumar et al. [28] recommended a technique to reduce system training using a single-layer neural network, however, this slows down. The scale of the split characters is 80 to 80 pixels. The function of normalizing data on the input matrix is to improve the performance of the tutorial. The first step is to identify the characters by using the device to analyze the handwritten documents. This study[9]focuses on recognizing individual characters from English handwritten documents. The focus is on studying preprocessing and feature extraction methods. This study reviewed various statistical and structural features and based on the features, recommended a unique and new perspective. The effectiveness of these features has been tested to identify English handwritten characters using the Multilayers Perceptron (MLP) and Support Vectors Machines (SVM) classifications. It has been found the modified display-based feature is very efficient. Extensive evaluation test results performed with different characteristics/combinations of characteristics and classifications are presented. Experiments have shown that the observed features are highly accurate. By combining different features in an optimal way, the detection accuracy is 97%. Despite the work done on the problem of recognizing English characters, more research is still needed to find the optimal solution for more accurate classification and speed and accuracy. In this work, we are using MLP neural networks to solve these problems, where the task is to classify letters in the feature space. The following describes the optimization algorithms and the dragonfly algorithm and the idea of using the dragonfly algorithm in a hybrid structure to improve MLP performance.

3. Proposed method

Metaheuristic methods are a group of approximate algorithms developed that try for combining the basic principles of the heuristic method to locate a way to efficiently and effectively searching for the answering space. Innovative, nature-based algorithms find the solution for the optimization dilemmas by simulating biological and physical phenomena. Those methods fall into three categories: swarm-based, physics-based, evolution-based. The evolution-based method is inspired by the law of evolutions. The Dragonfly Algorithm, or DA for short, is a nature-inspired evolutionary algorithm that simulates the behavior of dragonflies and was introduced in 2015 [29]. As shown in Figure 3, the life-cycle of a dragonfly has only two turning points: infancy and adulthood. Dragonflies spend much of their lives in infancy and undergo metamorphosis to enter adulthood. Dragonflies have special conditions and organs of prey due to the way of life in these two stages and also the nature of hunting.

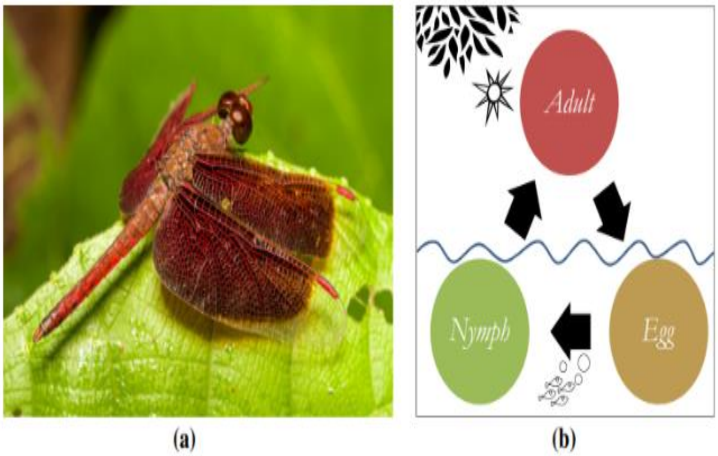

Figure 3. (a) A life dragonfly (b) The life cycle for dragonfly

The fact about dragonfly is the rare swarming and unique behavior of this insect. The mass of dragonflies is formed for two purposes only; migration and hunting. Hunting is representing feeding mass or static and migration are called migratory mass or dynamic. The static mass, dragonfly form a small group and can be flied back and forth over very smaller areas for hunting other flying prey, like mosquitoes and butterflies [4]. The local movement and sudden change in flight path are the most important features of static mass. However, in dynamic masses, it forces large numbers of dragonflies to migrate in one direction over very long distances [29]. The major inspiration for (DA algorithm) is that the dynamic and static swarming behaviors. Those two swarm behaviors were very similar to the two major stages of optimizations utilizing metaheuristic algorithms: exploitation and exploration. Dragonflies form sub masses and fly in different areas of the static mass, the main purpose of which is to find prey (exploration). However, in a static mass, dragonflies fly in larger masses in one-direction (1-D), which is desirable during the exploitation phase. The main goal of any crowd is to survive, so everyone must be attractive for a food source and distract external enemies. According to these two behaviors, there are five main factors in updating the positions of individuals in the masses, which are shown in Figure 4. As shown in Figure 4, dragonflies tend to adjust their flight to each other while keeping proper coherence and separation in the dynamic group with each other. However, in a resident population, the adaptation is very low while the cohesiveness of the prey attack is very high. Therefore, when exploration of the search spaces, dragonflies are assigned with high-level weights and low cohesion, and when exploiting the search space, they are assigned with low-level weights and high cohesion. So, dragonflies have to adapt their weights to adapt to change from explorations to exploration in the search spaces. Also assumed, as the optimization process progresses, dragonflies will try to see much more-dragonflies to modify their flight path. In other words, the neighborhood area increases and so the congestion in the last stage of optimization becomes a group to reach the global optimal. The food source and the enemy have been selected from the best and worst solutions that have been very crowded so far. This leads to converging in the promising area of the searching spaces and the divergence in non-promising areas outside the searching space.

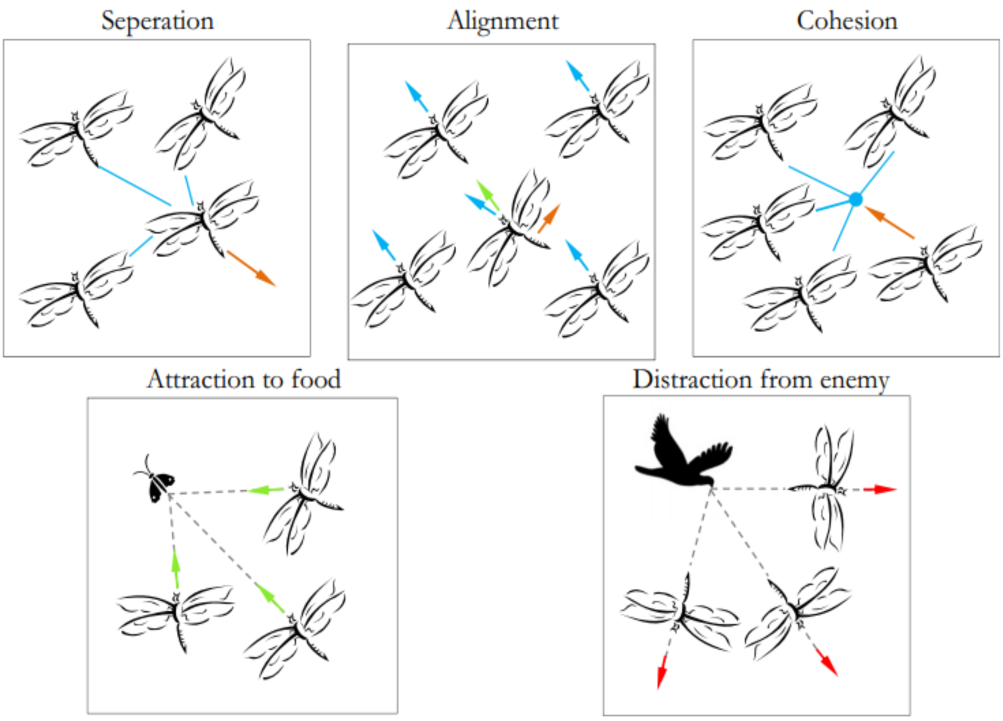

Figure 4. The early correctional pattern between the individual in the swarm

Error propagation learning (BP) algorithm represents one of the common neural networks training algorithms (MLP). The convergence of the BP algorithms relies on the selection of the initial value of network weight, bias, and some of the parameters in the training algorithm, like the number of learnings. In this research, an attempt has been made for creating a sort of automatic character recognition or identification systems for English characters with a precise recognition or identification accuracy and with a minimum classification and training time. The proposed idea is for improvement of the weights of MLP neural networks in the process of training and learning character recognition, the dragonfly optimization algorithm has been used. The method is as follows: First, with the dragonfly optimization algorithm, the optimal values for the weights and bias of the BP method, which can be used in the MLP neural networks, are obtained. The degree of convergence of algorithms of the training for neural networks is strongly influenced by initializing and causes the answers not to lead to local optimization. The performance of the optimized MLP network is then executed on the desired data set. The method is to first identify the problem parameter, here we have two parameters to optimize, including weight and bias, which we want to improve with the dragonfly algorithm. So, we randomly created an initial population of weights and biases using the Dragonfly algorithm, and the result is the optimal weight and bias as the initial values for starting network training. This process will be repeated until the optimal answer is reached. The following steps are the proposed algorithm's detailed steps. Figure 6 is showing the flow diagram of the proposed algorithm. The following steps are for the proposed method:

- ❖ Step 1: In this step, the value of the proposed problem parameters and algorithm is done randomly.

1-1: Determining the replication counter of the algorithm, determining the number of dragonflies in the populations, and determining the number of weight and bias and the number of inputs, hidden and output layers.

1-2: Determining the maximum number of iterations of the proposed method and the maximum number of rounds for MLP network training.

1-3: Determining fixed values for the parameters in the dragonfly algorithm such as s which represents the weight of separation, a weight of alignment, c represents the weight of coherence. f is the factor of the food source, e is the factor of the enemy, w is the weight of inertia.

- ❖ Step 2: In this step, play the dragonflies, each of which indicates the implicit position of the weight and the biases that are randomly in the problem space.

- ❖ Step 3: In this step, we enter the training sample into the network. Input can be given in reverse, but pre-processing must be done before entering the network.

- ❖ Step 4: This step is that first the image that represents an English character, if it is colored, turns gray, and then becomes the values 0 and 1 (binary) or you can enter the desired character from the beginning as 0 and 1. For better recognition, we created a box for accurate implementation. Therefore, we resize the photos to a resolution of 15 x 15 pixels. This size significantly reduces training time; Because the number of nodes decreases and as a result, the number of weights to be updated will decrease.

- ❖ Step 5: Calculate the parameters S, A, C, F, and E in the dragonfly algorithm according to the relations (1), (2), (3), (4), (5)

- ❖ Step 6: In this step, the calculation of the step vector and the new position vector of each dragonfly is done according to relations (6) and (7).

- ❖ Step 7: In this step, the target function (network error values) of every single dragonfly in the populations is calculated and the best dragonfly in each repetition in terms of having the lowest values of the goal function is thrown into a variable.

- ❖ Step 8: This step checks if the weight values and biases are optimized enough, if yes answer jumps to step 9 else jump to step 5.

- ❖ Step 9: In this step, the optimal values of weights and biases are taken from the dragonfly algorithm and used as the optimal values in the MLP neural network.

- ❖ Step 10: Formation of the MLP neural networks architecture and select the BP-algorithm for the network training process. Our training data includes 26 English alphabet characters in five variant fonts including Georgia, Arial, and Times New Romance, Verdanas, and Courier with a font size of 12 pt. Here we have a 15 * 15-pixel box to recognize each letter; Therefore, the length of each vector is 225 = 15 * 15 (forming a row by row matrix from left to right and from bottom to top) in the form of cells 0 and 1. White cells are coded with 0 and black cells with 1. Our neural network consists of one input-layer, 2 hidden-layers, and one output-layer. The neurons in the input layer are set to be 225 and the number of neurons in each of the hidden layers is 10 and in the output layer is 52 (depending on the case of uppercase and lowercase letters). Figures (2-3) and (3-3) show examples of characters in the dataset. It should be noted that we considered the transfer function for the tensing hidden-layers and for the purlin output-layer. We have considered the number of network trainings as 1000 times and the learning rate as 0.1.

- ❖ Step 11: In this step, the BP training error is calculated.

- ❖ Step 12: In this step, the network weights and biases are updated.

- ❖ Step 13: The training stops when the difference between the mean error obtained in two consecutive periods (EPOCH) is small enough, otherwise the move to step 11 is done.

- ❖ Step 14: In this step, the test image is entered and the new converted binary image is compared with the trained data.

- ❖ Step 15: The binary output is converted to a character and displayed.

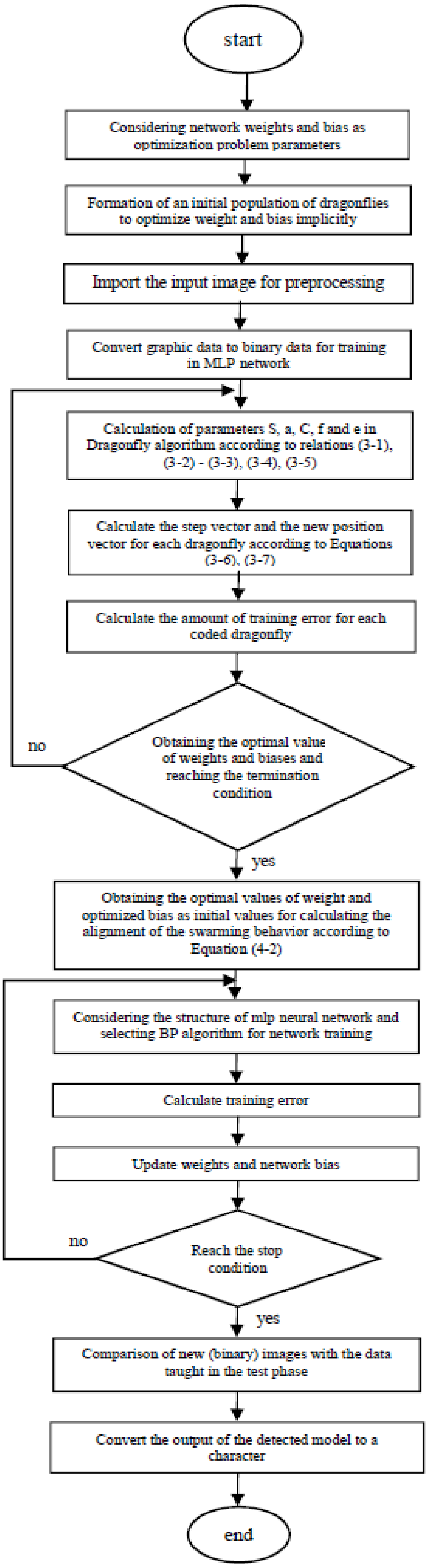

Figure 5. Flowchart Proposed Method - Optimization of BP Algorithm by Dragonfly Algorithm

Here are the math relationships for the fifth and sixth steps:

$$S_i = -\sum_{j=1}^{N} X - X_j \tag{1}$$

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N} \tag{2}$$

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - X \tag{3}$$

$$F_i = X^+ - X \tag{4}$$

$$E_i = X^- + X + a \tag{5}$$

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_t \tag{6}$$

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{7}$$

4. Evaluate the Proposed Method

In this section, we will simulate the proposed method on 26 English letters. We will also compare the proposed method with the Bayesian naïve and random weighting methods [4] that have solved this problem. In this article, we have considered the number of different neurons for the hidden layer and the different training rates. We considered 70 and 80 for the hidden layer and 0.6, 0.8, 1, 1.2, and 1.4 for the training rate. You can see the settings of the previous methods and comparable to our proposed method, the number of hidden layers 70 and 80 and the training rate of 0.6, 0.8, 1, 1.2, and 1.4, as well as the considered weight range h in the following figures.

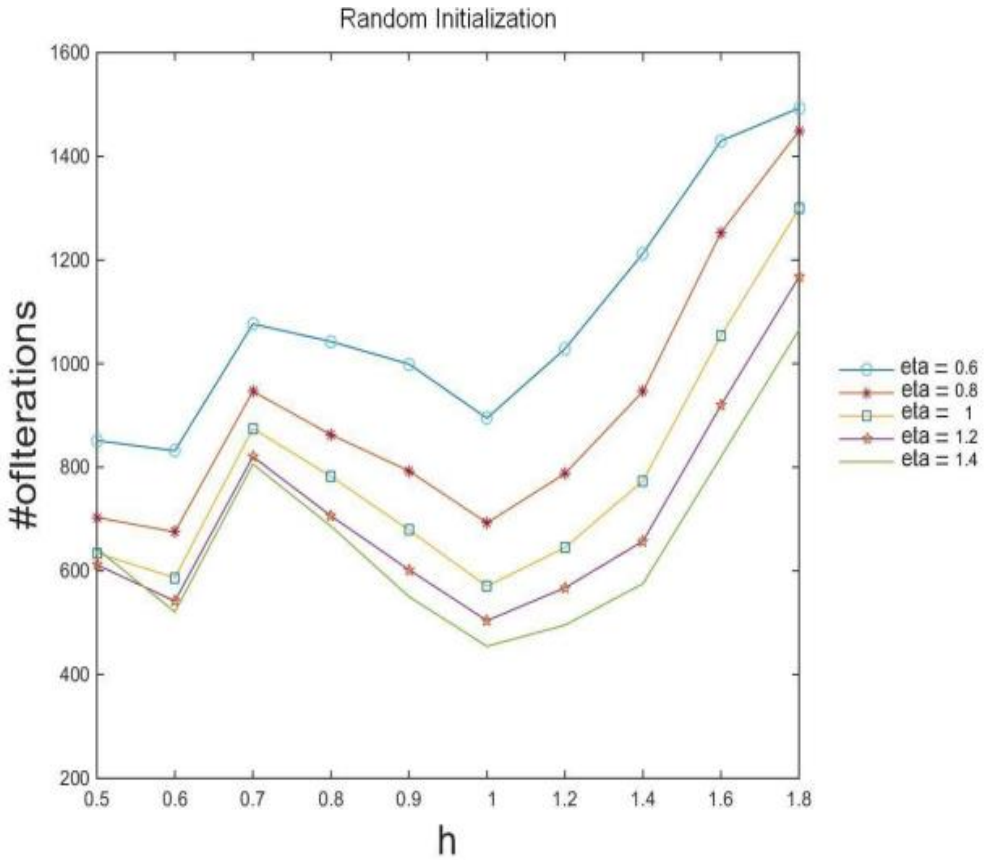

Figure 6. BP convergence rate with random weighting with 70 neurons in the hidden-layer

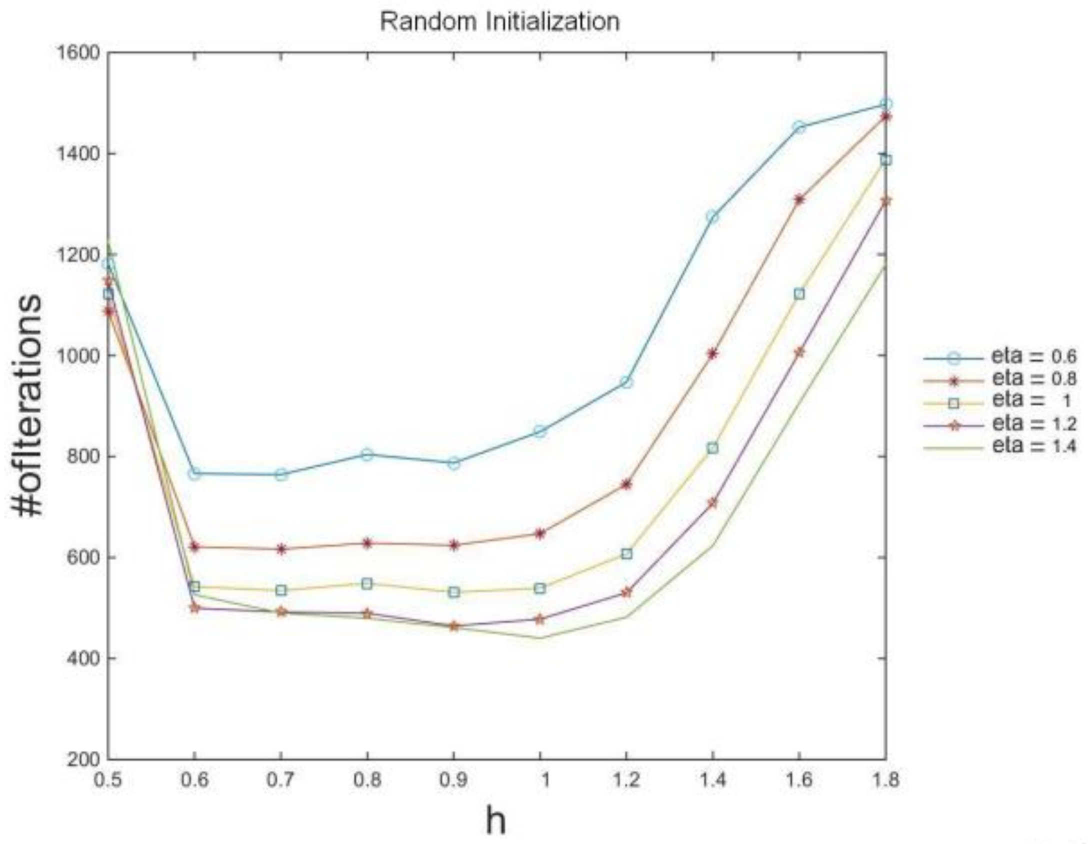

Figure 7. BP convergence rate with random weighting with 80 neurons in the hidden-layer

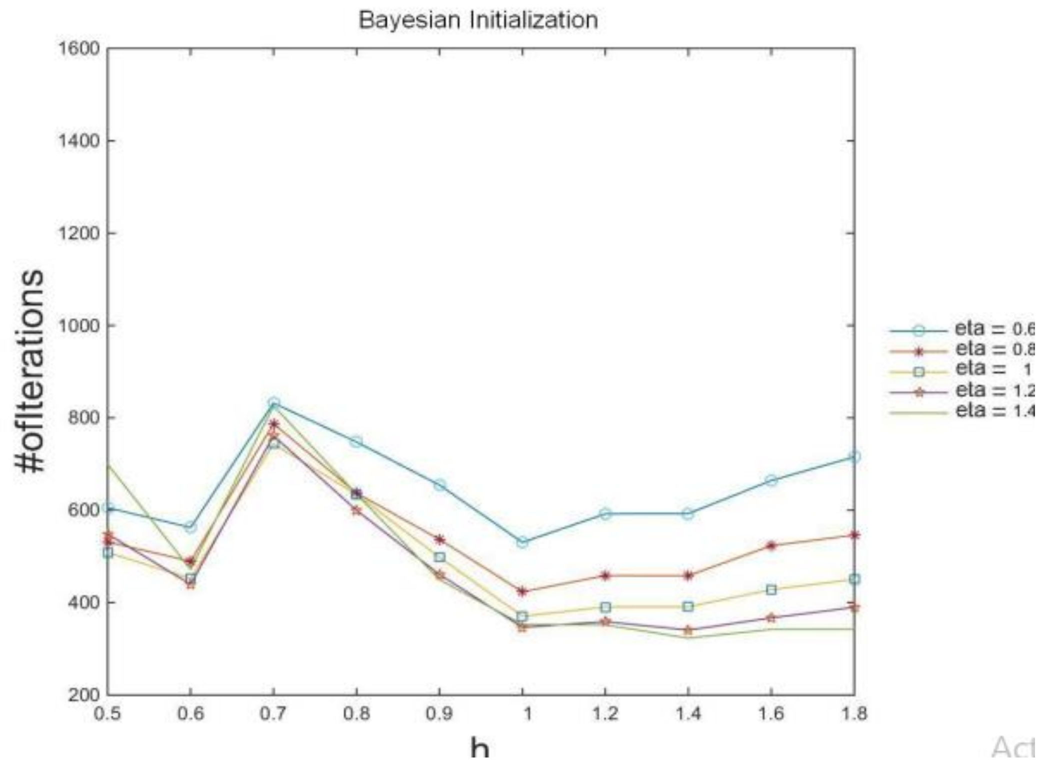

Figure 8. BP convergence rate with initialization of weights with Bayesian with 70 neurons in the hidden-layer

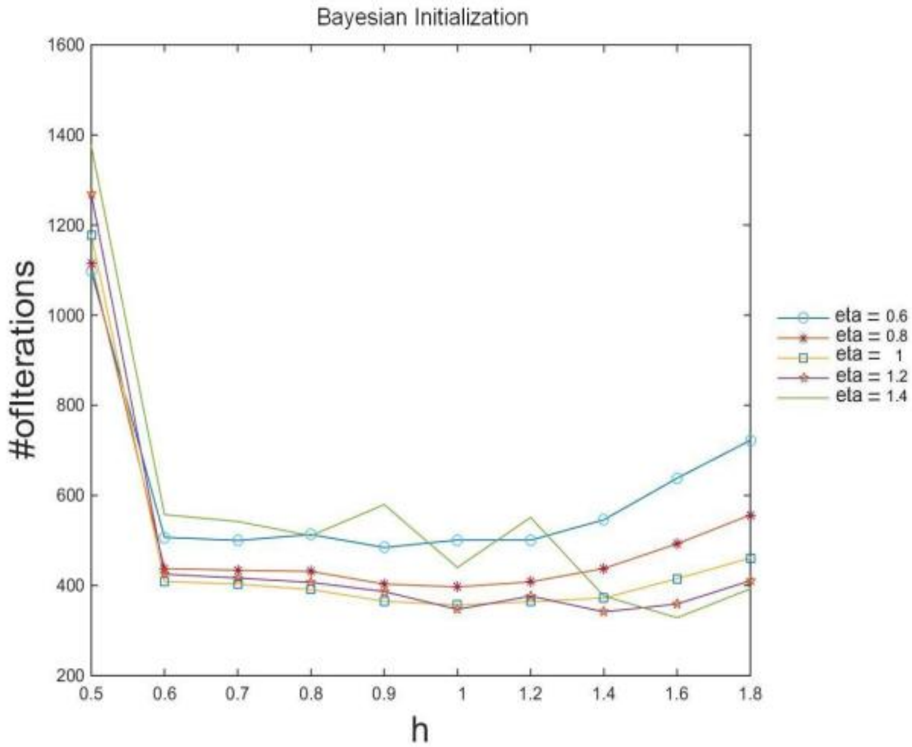

Figure 9. BP convergence rate with initialization of weights with Bayesian with 80 neurons in the hidden-layer

As shown in Figures 7 and 8, when h is in the range 0.5 to 1, the convergence rate in the BP algorithm decreases. In Figures 9 and 10, when h is greater than 1, the convergence rate in the BP algorithm increases; However, in Figure 10, when the convergence rate is 1.4, the convergence rate fluctuates. The convergence rate in Bayesian method is more resistant than the random weighting method due to the growth of η learning rate. Random weighting method causes the convergence speed of BP algorithm to decrease with increasing values of weights.

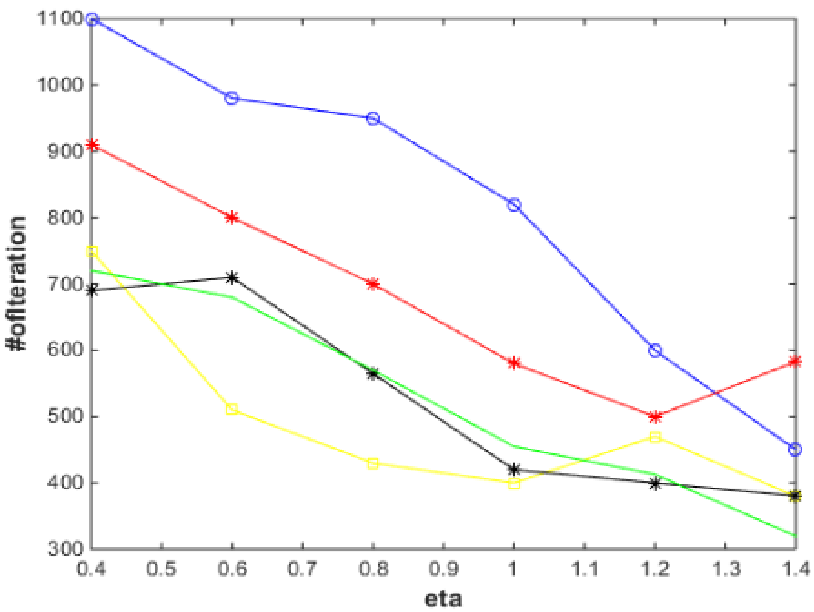

Figure 10. BP convergence rate with the proposed algorithm and weights improved with the dragonfly algorithm with 80 neurons in the hidden-layer

As we can see in Figure 10, as the eta value increases, the number of repetitions is still decreasing and has its own resistance in reducing the learning time compared to the Bayesian method due to the growth of the value of η. The proposed method also continues to reduce the amount of error as the learning rate increases.

According to the values obtained in the above figures for the proposed method in comparison with the previous methods, it can be concluded that our proposed method in terms of speed and accuracy of diagnosis in most cases was better than other previous methods. Also, using the proposed method, we were able to improve network performance and reduce computational complexity and reduce network training time compared to descending gradient and least squares methods.

5. Conclusion

Character recognition is the process of associating a symbolic meaning with objects (letters, symbols, and numbers) drawn on an image. One of the most important challenges of existing diagnostic systems is that they have a large number of training samples and therefore a large volume of calculations; Because when training each character, it requires several training examples of that character. Also, if these systems are developed to recognize characters with a greater variety of fonts, the detection error will increase. Therefore, we need a diagnostic system that is able, in addition to the small number of training samples, to be resistant to font change, and its detection error in exchange for adding new fonts, not change it so much. In this article, we have used MLP neural network with BP method for its training process. In MLP neural network, the selection of initial weight values plays a very important role in the network training process, which is not easily possible using classical methods in the network, and they have highly complex calculations, as a result of meta-heuristic algorithms to improve Network performance and acceleration of convergence are used. also, we have used the Dragonfly algorithm to improve the network performance due to its high accuracy and low number of adjustment parameters. As can be seen, the proposed algorithm is better than other previous methods.

The promising results of this research can be used to continue work for other researchers interested in this field. Therefore, researchers interested in this field of research are recommended to use the KNN classification to select more effective features and reduce network and memory learning time to data processing.

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