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Development of an enhanced hyper heuristic Firefly Algorithm based Convolutional Neural network for handwritten identification system

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Abstract
Handwritten recognition is very important especially in the area of computer vision and pattern recognition and forensic analysis where the identification of the author of a document is required for legal/tactical processing. The aim of this work is to enhance Hyper Heuristic Firefly Algorithm for any handwritten document to enhance the recognition accuracy. The Zebra Optimization Algorithm (ZOA) was then improved the HHFA for better optimization, and more accurate results in this study. Hand-written responses were obtained from employees and students of Ladoke Akintola University of Technology, Ogbomoso, Nigeria. CNN hyper parameter was optimized using the improved hyper heuristic firefly algorithm (HHZOFA). The simulated model was constructed in a MATLAB 2020. The performance of the output was compared to a hyper heuristic firefly algorithm in existence, and a hypothesis was made based on t test at p <0.5. Then we had some interesting discovery that the improved HHZOFA is of high precision and there is significant difference among HHZOFA and the traditional HHFA

Keywords: Handwritten recognition, hyper heuristic firefly algorithm (HHFA), zebra optimization algorithm (ZOA), cnn hyperparameter optimization, ladoke akintola university of technology (Data Source)

Introduction

Handwritten identification has long been recognized as a hard problem in computer vision because the handwritings in different individuals are very diverse. In addition, the handwritten of the same writer might not be the same every time (Altwaijry and Al-Turaiki, 2021) [4]. Convolutional Neural Networks is one of the approaches used to mitigate the handwritten recognition problem. However, CNNs have high accuracy rates while suboptimal selection of hyper-parameter with optimization algorithm (HHFA) and other optimization algorithms, this low parametric optimality are reported in the literature, could result in poor performance. Thus, in this research, Zebra Optimization Algorithm (ZOA) approach is utilized to overcome the drawbacks of Hyper-Heuristic Firefly Algorithm (HHFA) in achieving quality solutions of complex problem as well as the lack of low-level heuristics and slow convergence rates. Hyper-Heuristic Firefly Algorithm (HHFA) has been proved to be an efficient method to solve complex problems by obtaining good solutions and it is widely used when the classical optimization methods do not work well.

HHFA still faces difficulty in choosing and deciding on the low-level heuristics such that they increase the fitness of fireflies and fail to strike balance between exploration of the search space and exploitation, that is convergence to the best solutions slowly (Aswanandini, Deepa, 2021). The above challenges need to be addressed by proposing an improved firefly algorithm-based CNN model through incorporation of the exploitability of Zebra Optimization Algorithm (ZOA). An effective system of handwritten recognition would greatly enhance the accuracy and productivity in a wide variety of rights and processes related to handwritten documents. Convolutional Neural Networks (CNNs) have achieved incredible performance in image classification such as handwriting recognition. However, tuning the hyper parameters of the CNN is a hard and time-consuming task, thus efficient solutions have to be investigated. A derivation of Hyper-Heuristic Zebra Optimized Firefly Algorithms (HHZOFA) from HHFA was mapped and applied to optimize the hyper parameters of CNN, the model was also compared with state-of-the-art work, it is also believed to have had better performance in recognizing handwritten characters.

The aim of this research is to develop an improved Hyper Heuristic Firefly Algorithm based CNN applied to the handwritten recognition utilizing a Zebra Optimization Algorithm (ZOA). While the objectives are to enhance the Hyper-Heuristic Firefly Algorithm which includes the Zebra Optimization Algorithm to constitute the Hyper Heuristic Zebra Optimization Firefly Algorithm (HHZOFA) to deal with the trade-off of exploration and exploitation, integrate the HHZOFA with CNN to form HHZOFA-CNN model for CNN hyper parameter optimization of enhancing the overall performance, apply proposed HHZOFA-CNN model on handwritten recognition system based on MATLAB (R2020a) Software, compare the performance of HHZOFA-CNN with HHFA-CNN and CNN model in terms of sensitivity, specificity, False Positive Rate (FPR), accuracy, computation time and precision; and compare the difference in performance between HHZOFA-CNN, HHFA-CNN and model for handwritten identification system statistically.

Review of Literature

Handwritten identification, Analysts in handwritten ID, evaluate different character of the handwriting (Size, shape, slant, pressure, rhythm of the writing). They also match the signature style and writing behavior of the handwritten with known handwritten samples of the suspect author. Handwritten identification has developed through the use of new technology and machine learning algorithms. Nowadays, hand written shot detection systems using artificial intelligence (AI) and neural networks are able to detect and compare handwritten samples with high accuracy (Liu and Yin, 2021; Shrivastava and Bhatia, 2019) [10].

Ahlawat *et al*. (2020) [2] introduced a manuscript to investigate design choices (layers, stride size, receptive field, kernel size, padding, and dilution) for CNN-based handwritten digit recognition. The work also aspired to consider different SGD algorithms in enhancing the HW digit recognition. Ensemble architecture improves the accuracy of a network. In this paper, the target is to obtain a CNN architecture that achieves similar accuracy without an ensemble architecture as it introduces higher computational complexity and heavy testing complexity. Therefore, the CNN architecture is introduced in order to obtain accuracy higher than even ensemble architectures but with lower operation complexities and costs. Furthermore, the work highlighted a suitable set of learning parameters when constructing a CNN, allowing us to achieve a new absolute result in classification of MNIST handwritten digits. The work conducted a lot of experiments and reported that the recognition accuracy reaches 99.87% in the case of an MNIST dataset.

The improved firefly algorithm for local trapping problem (IFLT) was suggested by Akin and Jaya (2021) [3] using convolutional neural network (CNN) for the feature extraction of the scene character. Hybrid IFLTO is the enhanced form of the firefly optimization algorithm to resolve local trapping problems. In feature extraction process, IFLT method is used to optimize the hyper parameters on CNN. Both alignment and MLP layers are also adopted over the CNN. Then, the type of the scene characters belongs to one of the classes is recognized by applying the SVM classification to the street view image. For the experiments, we used six outdoor scene character dataset SVHN, ISN, IIIT5K-words, SVT, ICDAR 2003 and ICDAR 2013 dataset. Experiments The performance of the proposed IFLT method is compared based on the metrics of standard deviation, mean, average computational time and best minimum value (MEmin). Experimental results indicate that the proposed IFLT-CNN is very appropriate for scene character recognition.

Aswadinni and Deepa 2021 proposed a hyper heuristic firefly algorithm inspired neural network for big data cyber security, they developed an Intrusion Detection model which classified both the network based and host-based intrusion without any complexity problem. an optimized Deep Learning algorithm of IDS as Hyper Heuristic Firefly Algorithm based Convolutional Neural Network (HHFA-CNN) has been presented. This proposed algorithm was evaluated using two datasets; NSL-KDD and ISCX-IDS, the result showed that the proposed HHFA-CNN model performed better than other models. where the recommended model results in an accuracy of 96.6667%.

Prashanth *et al*. (2022) [9] introduced a modified LCNN with a modification in Lenet 5 architecture CNN. The activation function of regular Lenet 5 is tanh(x). The Devangari characters are non-linear and hence non-linearity is induced in the Networks by applying Rectified Linear Unit. This overcomes the vanishing gradient problem posed by tanh(x). CNN based approach also gained a 96% accuracy on training data and 94% over testing data in the study. MLCNN achieved 99% and 94% accuracy, respectively, with cheaper computational cost. Whereas, ACNN achieved 99% and 98% recognition rate on the validation set. To validate, of course the mechanism of cross-validation was used, so the data was split in all the possible ways with 8 and 2 units/words and not mentioned split and the minimum loss was only 0.001%. This development had the effect of filling much of the enormous gulf between the real-world need and the performance of Devanagari recognizers

Abbas *et al*. (2022) [1] system which carry out pre-processing stages in order to enhance the image for the training process with a convolutional neural network. At this moment, the input document is split into fragments by line, word and character splitter. The accuracy obtained by the proposed system in character segmentation reaches up to 86%. Then, these segmented characters are fed into a neural network for recognition. The recognition and segmentation method presented the paper is yielding the most desirable accurate results over the test dataset. The result value of the proposed work is near by the accuracy of the result in convolutional neural network training is 93%, and for validation the accuracy slightly decreases with 90.42%.

Singh *et al*. (2022) [11] proposed a CNN-based model for the recognition of the Gurumukhi month names. The architecture is de- signed with five convolutional and three pooling layers. The authors also constructed a dataset with 24,000 images of size 50× 50. The dataset was written by 500 distinct writers from various age groups and occupations. The developed approach yielded training accuracy of around 97.03% and validation accuracy of medium of 99.50% for the proposed dataset.

Ullah and Jamjoom (2022) [12] introduced an intelligent model for automatic recognition of handwritten Arabic letters. Their method adopted a CNN model in recognizing handwritten Arabic letters. The model is regularized by batch normalization and dropout. Side That Model was trained and tested with and without dropout, and behaves very differently. So, the model overfitting is overcome by using dropout regularization. The developed model is confirmed for the popular publicly available Arabic Handwritten characters (AHCD) dataset of 16,800 letters and the performance is computed with the various evaluation measures. Experimental results indicated the superiority of the presented model with higher accuracies that reached 96.78%, and other evaluation criteria compared to the prominent domain-related existing approaches in the literature.

Nayef *et al.* (2022) [7] proposed an optimized leaky ReLU to retain more negative vectors using a CNN architecture with a batch normalization layer. To evaluate the proposed method, four datasets are used: Arabic Handwritten Characters Dataset (AHCD), self-collected, Modifed National Institute of Standards and Technology (MNIST), and AlexU Isolated Alphabet (AIA9K). The proposed method shows significant performance in terms of accuracy, precision, and recall measures compared to the state-of-art methods. The results showed outstanding improvement over the known leaky ReLU as follows: 99% for AHCD, 95.4% for self-collected data, 90% for HIJJA dataset and 99% for Digit MNIST. The proposed CNN architecture with the proposed optimized leaky ReLU showed a stable accuracy performance and error rates between the training, validation, and testing phases. This indicates that most samples are trained and classified correctly.

Niharmine *et al*. (2022) [8] developed an efficient model, namely CNN-Grad-GLCM, for handwritten character recognition. This proposed model of CNN is a multilayer architecture that is a kind of feed forward neural network receiving features and characteristics directly from the input images. It is built on a latest deep learning open source Keras Python library. The novelty of the model was in building up the OCR system for best performance both in terms of accuracy and execution time. The proposed OCR system is evaluated using a novel customized data derived from the Amazigh handwritten character database. The experimental results demonstrate that the performance of system (99.27%) are encouraging and the classification time is the lowest among the existing works.

Jindal and Ghosh (2023) [6] has presented an optimized convolution neural network (CNN) based OCR system to recognize all the characters of the ancient document handwritten in Grantha script. The deep hierarchical feature vectors are obtained from the input character image by a set of convolutional layers in the proposed system. These feature vectors have been classified into its correct class by two Fully Connected Neural Network (FCNN) layers. The hyper parameters in CNN architecture including the number of filters in each convolution layer, the size of the filter in each convolution layer, the number of FCNN layers, and neurons in each FCNN layer were tuned through Bayesian optimization. The key contribution of this paper is the introducing of an optimized CNN structure for OCR of ancient documents for the Grantha script. Experimental results show that the proposed OCR is superior to other existing state-of-the-art ones.

HHFA and Its Challenges

The HHFA is derived from the hybrid of hyper-heuristics and multi-objective firefly algorithm. The hyper-heuristic optimization solution increases the optimization function of the firefly optimization algorithm based on high and low-level strategies. At a more fundamental level, the problem is scrutinized and the criterion by which solutions are chosen is defined. They update a solution or a solution set to produce a number of new potential solutions. Based on the guidelines obtained from the low-level strategy, the high-level one triggers the heuristic search in order to extract solutions from the candidate solutions (Aswanandini and Deepa, 2021). The rule set that solves the combinatorial part of the problem, namely one that specifies rules which solves the problem space on every instance of a space that is selected from, falls under the regulations of the low heuristic level. One or more solutions, combining or altering them through a series of search methods, form a new set. Another of the search modes developed by some of the search modes in this paper is an FA-based search method which is used to generate fresh solutions. The higher-level strategic policy is modeled as the selection mechanism after the innovative solutions have been generated. The high-level strategy automatizes the heuristic selection, i.e., where every heuristic is selected individually and the solutions are worked with it. Online Heuristic Selection: A heuristic selection process is performed online to choose the heuristics from the set of heuristics being generated by the rules generated by the low-level strategy. The empirical reward and the confidence level variables are the principal factors determining whether or not the heuristics are useful. The empirical return depends on the past performance and the heuristic frequency build indicates the level of confidence. These are both used to evaluate whether the heuristics are appropriate and applicable at the given operational state or not. Therefore, the firefly foraging approach can benefit from viable heuristics to the solutions. (Yang and He, 2013) Some of the initial problems of hyper heuristic firefly algorithm can be summarized as:

a. **Selection and generation of low-level heuristics:** One of the main problems of hyper heuristic firefly algorithm is the selection and generation of low-level heuristics which are good enough to increase the fitness of fireflies. This involves expertise in formulating heuristics and more importantly, choosing the most interesting ones while testing on the test problems, complexity and diversity.

b. **Combining exploration with exploitation:** A further difficulty consists of combining the exploration of the search space with the exploitation of the best solutions. Although the firefly has good exploration ability, it is easy to concentrate on flying to brighter solutions and it may be difficult to approach the best solution.

c. **Scalability:** As both the problem space and the dimensions grow in size, the cost of hyper heuristic firefly can be computationally costly. This may restrict the algorithm to be applicable on practical problems that have large datasets and complex number of inputs.

d. **Parameter sensitivity:** The capacity to control the performance of the algorithm through parameter values, like firefly moving strategy, attraction coefficient and mutation rates. The choice of the optimal values for these parameters is easier and harder

e. **Convergence rate:** The convergence rate of the proposed hyper heuristic firefly algorithm may be slow, especially when the problem size is large and the fitness landscape is rough. This may lead to an increase in the computation time or execution overhead of finding the optimal solution.

Zebra Optimization Algorithm

The Zebra Optimization Algorithm (ZOA) is a new kind of nature-inspired optimization algorithm, based on the zebra behavior in a herd. Although not fully developed, the ZOA represents a potential strength of the organ and several of its advantages. The following couple of advantages of the Zebra Optimization Algorithm (Trojovská et. al., 2022):

Robustness: the ZOA presents a strong robustness property in frontows classic and noisy objective functions optimization problems. It is capable to search in a complex search space and get rid of local optima, that is, it may be useful to solve practical optimization problems which are inevitably affected by noise and uncertainties.

1. **Population approach:** As most of bio-inspired optimization methods, ZOA iterates a population of solutions. This population-based strategy facilitates simultaneous searching and multiple exploration of the solution space. It also encourages exploration and exploitation at an appropriate ratio, which results in better convergence and higher quality of solutions.

2. **Adaptive strategy:** An adaptive strategy is implemented in the ZOA, where parameters and behaviors of the algorithm are dynamically adapted during optimization. This flexibility can enable the algorithm to react to changes in the search space or

problem features, which can improve the performance and convergence rate of the algorithm.

3. **Versatility:** ZOA can address a broad class of optimization problems on very diverse fields. No domain specific information, specific to the problem, is needed and no specific operators for the problem are used, making it simple to implement and use. This versatility makes the

4. **ZOA:** as a candidate for optimization problems from various domains of science and technology such as engineering, finance, and data science.

5. **Exploration:** Inspired by the zebra behaviour in a herding process, the ZOA includes exploration behavior to foster diversity and the global search. This facilitates in exploring the space of solutions, generating new emergent non-trivial and counter-intuitive solutions.

6. **Less parameter tuning:** ZOA usually needs less number of parameters to be tuned than other optimization strategies. This simplifies the tuning of parameters and lessens need of expertise user and so it is easy and user friendly.

One should mention that the Zebra Optimization Algorithm is still a young algorithm and more research and experiments are needed to conclude its capabilities against other optimization algorithms

Methodology

This dataset was obtained from publicly available sources (www.kaggle.com) including public datasets and individuals at LAUTECH. The dataset provides over 5000 hand written documents along with the corresponding images of real and forged signatures. And there are approximately 10 documents that are of handwritten texts for the same user id. In order to diversify the datasets retrieved from Kaggle repository, data augmentation was performed on the original images as described. Augmentation methods including rotation, vertical flip and horizontal flip will be used. For this research, images were divided into K train samples and test samples using the K-fold cross-validation algorithm, where k was defined as 10. In order to make the SSBR more suitable for accurate character recognition, the following pre-processing is performed for the characters: RGB to grayscale, binarization with threshold, image complementing and morphological opening. RGB to grayscale conversion: the intensity levels of the RGB picture are represented by "m-by-n-by-3 arrays of class unit 8, unit 16, single or double," often regarded as true colour image. Single or double array values are in the 0.1 range, while values for the 8 units lie in the 0-255 range. A digital picture in grayscale is one such that the only information about each pixel is its intensity. The black-and-white drawing is made of different shades of grey. It results in a monochrome image which keeps the brightness of the original picture. Thresholding: A process to turn the ( ) into a digital image (a picture in black and white). First, telegram damning-picture is damaged by aging, smearing, and smudging of text messages. Then, Thresholding is applied to convert the 2D form in which the input handwritten images are collected into a binary form. "0,1 array are treated as black and white array, reply" This binary image is obtained based on predetermined threshold.

Formulation of Enhanced Hyperheuristic Firefly Algorithm (HHZOFA)

Initialization: The firefly population is first initialized. This includes initialization of randomly distributed fireflies which each one of them is a candidate solution to the optimization problem.

1. **Fitness value:** After a population is randomly created, the various individuals are tested for fitness using the performance measure of the system. This mean the cost of each incumbent should be calculate and also number of candidates, in other word who will optimize the objective functions.

2. **Generation of low-level heuristics:** The next step is to produce a number of low-level heuristics to be applied to enhancing the quality of fireflies. For the hyper heuristic Zebra optimization firefly algorithm, Zebra optimization algorithm is used as a mechanism to create the low-level heuristic set. This algorithm belongs to the swarm intelligence algorithms and imitate the behavior of zebras in nature.

3. **Selection of low-level heuristics:** As soon as the low-level heuristics have all been generated, the next step is the selection of the most promising ones in terms of the overall improvement of the fitness of the fireflies. This process can be achieved by applying particular criteria, e.g., evaluation of the heuristics on benchmark problems, and their diversity and complexity.

4. **Low-level heuristic application:** The selected low-level heuristics were then used to respond to the fireflies to produce new solutions. This consists of adapting the fireflies' variables according to the chosen heuristics and assessing the fitness of solutions generated in this way.

5. **Movement of the fireflies:** The fitness of the new solution is taken and on the basis of it, the position of the fireflies is updated in the search space. This means that the fireflies are attracted towards better solutions depending on their fitness and attractiveness of neighboring fireflies.

6. **Termination:** The process of developing new fireflies and performing low any further level heuristics on them is continued until finally a solution that is satisfactory is found or a termination condition is satisfied. A constraint terminating criteria such as maximum number of iterations, target fitness, or a time limit can be set.

Development of HHZOFA based CNN for Handwritten System

Half of the convolution extracts high-level features of input patterns. It is mainly composed of four basic layers, namely, convolutional layer, activation layer, batch-normalization layer, and pooling layer. The convolution layer, where features are extracted from input patterns and it has a large number of filters with varying sizes. The activation layer is a nonlinear layer and it is a different activation function for preventing linearity in the system. The operation encourages activation function to focus on one subset of units and let others be ignored by optimizer, A commonly used activation function is ReLU, as it provides activation that is zero reigned which means there is no output in places where the input is negative, and it does not suffer the vanishing problems The third layer, batch normalization, is added to reduce training epoch and bring a performance gain in the network by rescaling every extracted feature vector y j of the convolutional layer. The final layer in the convolution half is pooling layer which reduces the dimension of feature vectors with down sampling. These expedite the high-level feature generation of the architecture, and reduce the computation time. The classification is the second part of the CNN architecture, where each pattern is classified according to the class in the input labels. The fully connected layer and drop out layer are the key components in the classifier half network. The activation layer locates in front of the full connection layer. in general, Sigmoidal and Softmax are two popular activation functions in fully connected layer for high efficiency of recognition. Softmax is being used as an activation function in multiple class classification problems and it express the decimal output range in terms of percentage for each class. The dense layer is usually involved after the fully connected layer. It's utilized to solve overfitting problem to the algorithm by removing the neurons and their tentative linking from the previous fully connected layer. An interactive Graphic User Interface (GUI) application was developed using handwritten and online sources of LAUTECH staff and students. The GUI was built in MATLAB 2020a environment by using image processing and computer vision and optimization toolboxes, and run on a computer with according to a specific system specification MATLAB 2020a software package.

1. Existing Hhfa and the Developed Hhzofa

Hyper-Heuristic firefly algorithm (HHFA) and Hyper-Heuristic Zebra Optimization firefly algorithm (HHZOFA) are evolutionary variants of the traditional Firefly Algorithm (FA) designed for solution to optimization problem via heuristic and adaptive process. HHFA is largely based upon firefly inspired emergence with bright and attractive moves. HHFA advocates a modular manner for exploration, including a repertoire of heuristic operators that yield refinements of solutions randomly or repeatedly depending on performance. HHZOFA, on the other hand, enriches the FA model by introducing Zebra dynamics for improved exploitation, where positions are updated. One of the most important differences between the HHFA and HHZOFA is the mechanism used for electron extraction. Nevertheless (HHFA) has heuristic elimination operation that used for improving the solutions of firefly position and Zebra Based Exploitation introduced by HHZOFA which integrates social behavior and the adaptive dynamic parameter into the algorithm, so that it helps the algorithm to the balance between exploring and the exploiting at the beginning of iteration and close into the end of cycle and cannot trapping in the local minimum problem. HHFA lacks adaptive mechanisms and employs the diversity based on random or performance heuristic selection. With respect to convergence strategies, both methods iterate the solutions they find best, though HHZOFA includes more robustness through its adaptive escape energy and position refinement. The HHFA ends when the maximal number of the iterations (MaxIter) is achieved. HHZOFA not only interates a convergence criterion into the optimization process appended to biased with the fitness changes, also has its Zebra dynamic nature that provides more robust and reliable learning of the location of the global optimum. Therefore, it can be seen that HHZOFA is an advancement of HHFA with stronger adaptability and exploitation capabilities for high-dimensional and complex optimization problems.

Algorithm: Hyper-Heuristic Zebra Optimization Firefly Algorithm (HHZOFA)
INPUT: a. Optimization Parameters: Number of fireflies (N_f), maximum iterations (MaxIter), firefly parameters (α, β_0, γ). Zebra parameters (- escape energy, λ - position adjustment factor). Problem-specific search space bounds $(\theta_{\min}, \theta_{\max})$. Heuristic operators ($H = \{h_1, h_2, \ldots, h_m\}$) for hyperparameter tuning. b. Objective Function: $F(\theta)$, which evaluates the solution fitness. Step 1: Initialization (a) Firefly Initialization: Generate N_f fireflies, each representing a solution θ_i initialized randomly within the bounds: $\theta_i = \text{rand} \times (\theta_{\max} - \theta_{\min}) + \theta_{\min},\ i = 1, 2, \ldots, N_f$ (b) Fitness Evaluation: Compute the objective function $F(\theta_i)$ for each firefly. (c) Set Initial Best Solution: Identify the best solution θ^* as the one with the highest fitness. Step 2: Main Loop For $t = 1$ to MaxIter: Step 2.1: Firetly Movement (Exploration) (a) For each firefly i, move it towards a brighter (better) firefly $j(F'(\theta_j) > F'(\theta_i)$) using:

$$\theta_i^{(t+1)} = \theta_i^{(t)} + \beta_{ij}\left(\theta_j^{(t)} - \theta_i^{(t)}\right) + \alpha \cdot \text{ rand },$$

where:

- $\beta_{ij} = \beta_0 e^{-\gamma\left\|\theta_i^{(t)} - \theta_j^{(x)}\right\|^2}$ (attractiveness).
- α : Randomness factor.
- rand $\sim \mathcal{U}(-1,1)$: Uniformly distributed random number.
- α : Randomization parameter for stochastic exploration.
- β_0 : Base attractiveness of fireflies.
- γ : Light absorption coefficient, controlling the attractiveness decay with distance.
- ρ : Escape energy in the Zebra Optimization Algorithm, decreasing over iterations.
- λ : Position adjustment factor for exploitation in ZOA.
- θ^* : Best solution representing the optimal hyperparameters.

Step 2.2: Zebra-Based Exploitation

For every firefly i :

(a) Update position based on Zebra Exploitation:

$$\theta_i^{(t+1)} = \theta_i^{(t)} + \lambda \cdot \left(\theta^* - \theta_i^{(t)}\right) + \rho \cdot \text{ rand}.$$

where:

- λ : Position adjustment factor, controls the intensity of movement towards θ^*.
- ρ : Escape energy, adds perturbations to avoid local minima.

(b) Integrate Zebra's social behavior:

Update ρ dynamically:

$$\rho = \rho_0 \cdot \exp(-t / \text{ MaxIter })$$

where ρ_0 is the initial escape energy?

Step 2.3: Heuristic Application

(a) Apply a randomly selected heuristic operator h_k from H to the fireflies:

$$\theta_i^{(t+1)} \leftarrow h_k\left(\theta_i^{(t+1)}\right)$$

(b) Ensure updated solutions remain within bounds:

$$\theta_i^{(t+1)} = \max\left(\min\left(\theta_i^{(t+1)}, \theta_{\max}\right), \theta_{\min}\right)$$

Step 2.4: Fitness Evaluation and Update

(a) Evaluate $F'\left(\theta_i^{(t+1)}\right)$.

(b) Update the best solution θ^* :

$$\theta^* = \arg\max_{\theta_i} F'(\theta_i), \forall i = 1, \dots, N_f$$

Step 3: Convergence Check

If $t =$ MaxIter or no significant improvement in $F'(\theta^*)$, terminate.

OUTPUT: Return the best solution θ^* and its fitness value $F'(\theta^*)$.

Result and Discussion

Table1: Performance of HHFA-CNN technique

Model	Class	Thres hold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	time(sec)
HHFA-CNN	ALL	0.24	2864	96	104	2856	3.513514	96.486486	96.75676	96.495957	96.621622	166.478938
HHFA-CNN	ALL	0.36	2863	97	101	2859	3.412162	96.587838	96.72297	96.592443	96.655405	171.737974
HHFA-CNN	ALL	0.5	2862	98	98	2862	3.310811	96.689189	96.68919	96.689189	96.689189	182.355653
HHFA-CNN	ALL	0.8	2861	99	96	2864	3.243243	96.756757	96.65541	96.753466	96.706081	183.29289

Table 2: Performance of HHZOFA-CNN technique

Model	Class	Thres hold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	time(sec)
HHZOFA-CNN	ALL	0.24	2920	40	48	2912	1.621622	98.378378	98.64865	98.382749	98.513514	127.105403

HHZOFA-CNN	ALL	0.36	2919	41	45	2915	1.52027	98.47973	98.61486	98.481781	98.547297	125.090701
HHZOFA-CNN	ALL	0.5	2918	42	42	2918	1.418919	98.581081	98.58108	98.581081	98.581081	125.184891
HHZOFA-CNN	ALL	0.8	2917	43	40	2920	1.351351	98.648649	98.5473	98.647278	98.597973	124.906653

The result of the HHFA-CNN and HHZOFA-CNN at different thresholds was presented in Tables 1 and 2. The hyper-parameter employed in the investigation was no of filter, filter size, number of layers and batch size. Recognition rates of 99.36, and 99.59 were obtained for HHFA and HHZOFA, respectively, by using the two hyper parameters. Table show that four thresholds were detected and the actions of two algorithms were AZ demonstrated. There is a better accuracy and better performance of HHZOFA-CNN over HHFA-CNN.

Table 3 Threshold 0.24

Model	Class	Thres hold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	time(sec)
HHFA-CNN	ALL	0.24	2864	96	104	2856	3.513514	96.486486	96.75676	96.495957	96.621622	166.478938
HHZOFA-CNN	ALL	0.24	2920	40	48	2912	1.621622	98.378378	98.64865	98.382749	98.513514	127.105403

Table 4: Threshold 0.36

Model	Class	Thres hold	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	time(sec)
HHFA-CNN	ALL	0.36	2863	97	101	2859	3.412162	96.587838	96.72297	96.592443	96.655405	171.737974
HHZOFA-CNN	ALL	0.36	2919	41	45	2915	1.52027	98.47973	98.61486	98.481781	98.547297	125.090701

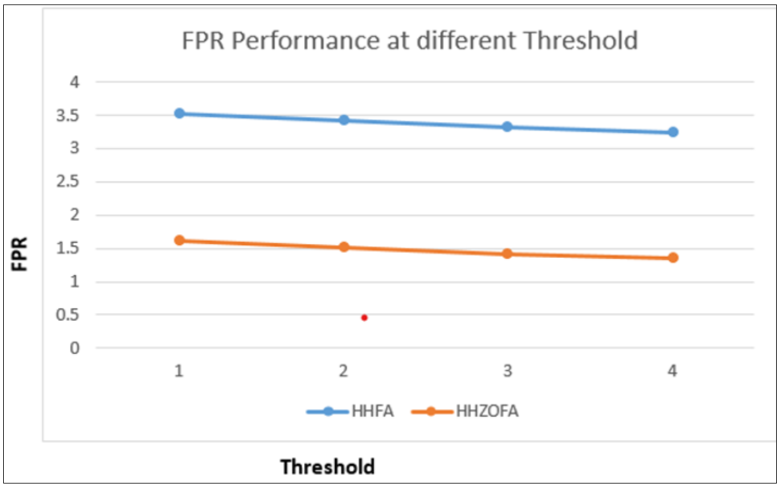
Table 5: Threshold 0.5

MODEL	CLASS	THRES HOLD	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	TIME(SEC)
HHFA-CNN	ALL	0.5	2862	98	98	2862	3.310811	96.689189	96.68919	96.689189	96.689189	182.355653
HHZOFA-CNN	ALL	0.5	2918	42	42	2918	1.418919	98.581081	98.58108	98.581081	98.581081	125.184891

Table 6: Threshold 0.8

MODEL	CLASS	THRES HOLD	TP	FN	FP	TN	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	TIME(SEC)
HHFA-CNN	ALL	0.8	2861	99	96	2864	3.243243	96.756757	96.65541	96.753466	96.706081	183.29289
HHZOFA-CNN	ALL	0.8	2917	43	40	2920	1.351351	98.648649	98.5473	98.647278	98.597973	124.906653

Tables 3,4,5,6. Showed the comparison of the two algorithms at different threshold, each of them reflected an improvements of the enhanced algorithm HHZOFA over the HHFA. At the threshold of 0.24, the true positive (TP) and the true negative (TN) values were 2864, 2856 respectively for HHFA, while 2920, 2912 were the TP and TN values recorded for HHZOFA. High values for TP and TN showed a reliable model, this also showed that the HHZOFA had an improvement over the HHFA which means the model was able to differentiate between the forged and the original handwritten documents. The FPR at 0.24 threshold were 3.5 and 1.6 for both HHFA and HHZOFA respectively, it reflected low value, by implication the FPR showed the extent to which the model was able to misclassify the forged and the original data set, a lower value of HHZOFA showed that the HHZOFA performed better than the HHFA. The accuracy values for HHFA was 96.62% while the value of accuracy for HHZOFA was 98.51%. High accuracy value implies that the model is reliable and that the model is making a large value of correct predictions. From the table, the time usage for HHFA was 166 seconds, while the time for HHZOFA was 127 seconds, which makes the use of HHZOFA model an added advantage over HHFA. This can be observed all through for tables 4,5 and 6



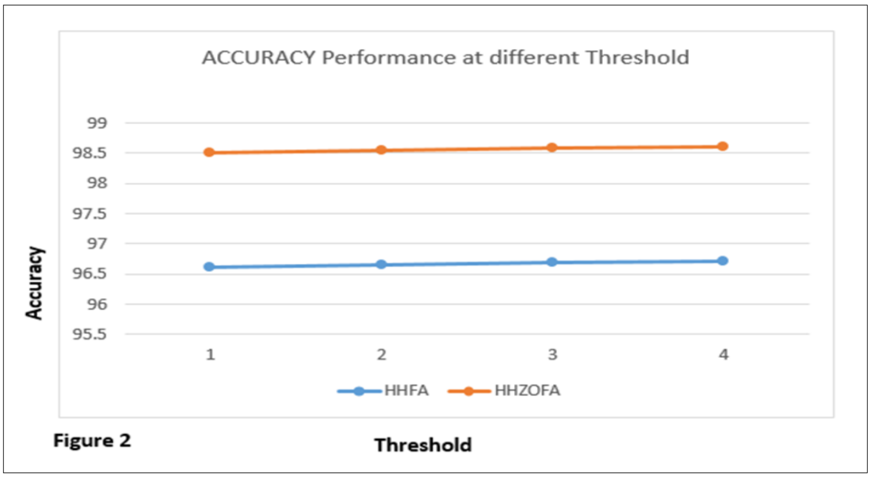


Fig 1. Summary of the t test result for HHZOFA and HHFA

Figures 1, 2 and 3 showed the plots of the FPR, accuracy and time. It reflected an improvement of HHZOFA over the HHFA, figure 1 showed a lower value of HHZOFA over HHFA at different thresholds, while figure 2 showed an improved accuracy of HHZOFA over HHFA algorithm, the HHZOFA recorded an accuracy between98% and above, the HHFA recorded 96%. Figure 3 showed an improved time of HHZOFA, HHZOFA spent less time of execution than the HHFA.

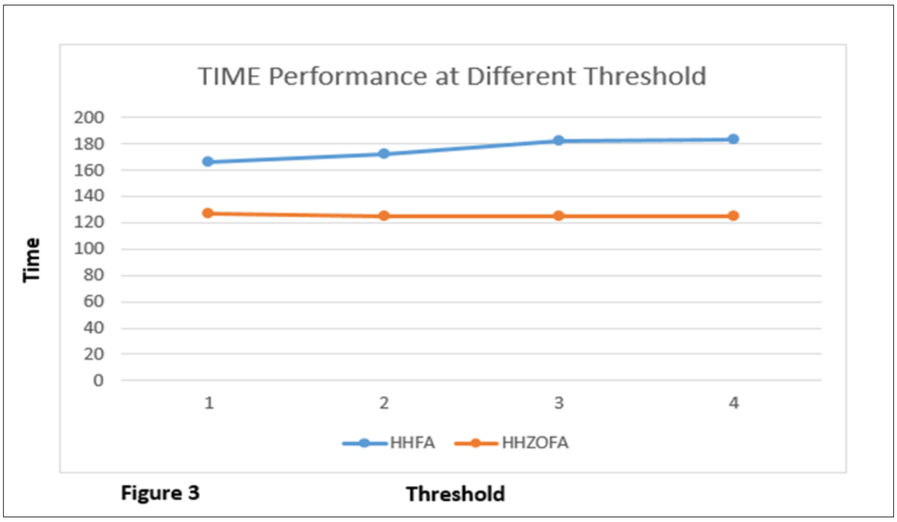


Table 7: Summary of t-test Result for HHZOFA-CNN and HHFA-CNN

Parameter	T	Degree of Freedom (df)	p-value	Comment
FPR	-271.791	3	0.000	Significant
Sensitivity	2678.418	3	0.000	Significant
Precision	1237.825	3	0.000	Significant
Accuracy	446.901	3	0.000	Significant
Computation Time	-11.146	3	0.002	Significant

An hypoyhesis was postulated to showed whether there is no significant difference between HHFA and HHZOFA and an alternative hypothesis is to showed that there is a significant difference between HHFA and HHZOFA.Based on the table above the p value is zero ($p<0.5$) the null hypothesis of no difference between HHFA and HHZOFA was rejected to accept the alternative hypothesis of a significant difference between them. Thus, we can say that the HHFA was obviously different from HHZOFA. This means HHZOFA did better (mode with high accuracy) than the HHFA.

Conclusion

HHZOFA performs better than the HHFA. It is a modified version of HHFA. It can be used to detect falsified and genuine handwritings. This method can be also applied to other classification problems.

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