ISSN 2350-1022

International Journal of Recent Research in Mathematics Computer Science and Information Technology
Vol. 10, Issue 2, pp: (53-62), Month: October 2023 – March 2024, Available at: www.paperpublications.org

Comparative Analysis of Selected Evolutionary Algorithms as Feature Selectors in Face Image Classification

Folasade M. Ismaila[1], Adeolu O. Afolabi[2], Oluwaseun O. Alo[3], W. Oladimeji Ismaila[4], Funmilayo A. Ajala[5]

[1]Department of Computer Science, Osun State Polytechnic, Iree, Nigeria

[2]Department of Cyber Security Science, Ladoke Akintola University of Technology, Nigeria

[3]Department of Information System Science, Ladoke Akintola University of Technology, Nigeria

[4.5]Department of Computer Science, Ladoke Akintola University of Technology, Nigeria

DOI: https://doi.org/10.5281/zenodo.10817398

Published Date: 14-March-2024

Abstract: **Feature selection aims to choose a small subset of the relevant features from the original ones by removing irrelevant, redundant, or noisy features. Nowadays, researchers employ evolutionary algorithms for feature selection in images classifications. However, the performances of these evolutionary algorithms varies in image processing, hence the best algorithm cannot be ascertain. Thus, this paper carried out a performance evaluation on some selected feature selector based evolutionary algorithms (Ant colony optimization, Gravitational Search algorithm, Particle Swarm Optimization and Firefly algorithm). 120 face images were collected and pre-processed to remove irrelevant features. The pre-processed images were subjected to each of the selected feature selectors to select salient features. Image matching was done with Back-propagation neural network. The results showed that GSA outperformed other techniques with 88.3%. while PSO gave 75.8%, ACO produced 76.7% and FA generated 80.8%.**

Keywords: **Feature selection, evolutionary algorithms, Ant colony optimization, Gravitational Search algorithm, Particle Swarm Optimization and Firefly algorithm.**

1. INTRODUCTION

In machine learning, *Feature Selection*, also known as variable selection, attribute selection or variable subset selection, is the process of selecting a subset of relevant features (variables, predictors) for use in model construction. as a dimensionality reduction technique, Feature selection usually leads to better learning performance, i.e., higher learning accuracy, lower computational cost, and better model interpretability. The central premise when using a feature selection technique is that the data contains some features that are either *redundant* or *irrelevant*, and can thus be removed without incurring much loss of information. [13,15]**.** The feature selection algorithm removes the irrelevant and redundant features from the original dataset to improve the classification accuracy. The feature selections also reduce the dimensionality of the dataset; increase the learning accuracy, improving result comprehensibility. The feature selection avoid over fitting of data. The feature selection method also includes the selection of subsets, evaluation of subset and evaluation of selected feature. [18].

Evolutionary computation refers to computer-based problem solving systems that use computational models of evolutionary processes, such as natural selection, survival of the fittest and reproduction, as the fundamental components of such computational systems.

Evolutionary algorithm is an umbrella term used to describe computer based problem solving systems which use computational models of evolutionary processes as key elements in their design and implementation. Several feature selection approaches are based on evolutionary algorithms (these are efficient heuristic search methods based on Darwinian evolution with powerful characteristics of robustness and flexibility to capture global solutions of complex optimization problems) [5,6,19]. The evolutionary algorithms include Genetic algorithm, Ant colony optimization, Firefly algorithm, Particle Swarm Optimization, Whale optimization algorithm, Gravitational Search algorithm, etc

Feature selection approaches are based on evolutionary algorithms (these are efficient heuristic search methods based on Darwinian evolution with powerful characteristics of robustness and flexibility to capture global solutions of complex optimization problems) [7, 20].

Typically, a feature selection method consists of four basic steps [12], namely, subset generation, subset evaluation, stopping criterion, and result validation. In the first step,a candidate feature subset will be chosen based on a given search strategy, which is sent,in the second step, to be evaluated according to certain evaluation criterion. The subsetthat best fits the evaluation criterion will be chosen from all the candidates that have beenevaluated after the stopping criterion are met. In the final step, the chosen subset will bevalidated using domain knowledge or a validation set. Over the years, researchers have developed and used many evolutionary algorithms to select salient features in biometric traits because of high dimensionality produced by the feature extraction techniques. For instance, [21, 23] employed particle swarm optimization; [8] used Ant Colony Optimization Algorithm; [22], Correlation based method [11], Ant Bee Colony [6,7], [22] employed gravitational search algorithm, etc. However, the effectiveness and efficiency of each of those algorithms have been evaluated on the same of different dataset. This make it difficult to select the best algorithm among them. Hence, comparison between feature selection algorithms can only be done using a single dataset since each underlying algorithm will behave differently for different data. Thus this paper intends to evaluate and compare the performance of selected feature selection techniques on the same dataset.

Related Works

[14] presented the development of a face recognition system using a hybrid Genetic - Principal Component Analysis. The principal component analysis uses the eigenfaces in features extraction after image pre-processing (i.e. grayscale conversion and matrix to vector conversion) and the genetic algorithm helps in removing irrelevant features in the eigenface space. This ensures that only relevant features were used in the biometric verification. Euclidean distance was used as the similarity measure and various thresholds were set at different cropped image dimension to determine if a test image is “known” or “unknown”to a trained image database. The performance metrics used include the average recognition accuracy, average recognition time and total training time. These were measured by varying cropped image dimension between 30*30 and 80*80. The experiment was carried out on a database of 320 black faces and the result showed that the GPCA-based system has better recognition accuracy with 9.1665% cumulative increment in recognition accuracy over PCA-based system, better recognition time with a cumulative time gain of 0.085401 seconds over the PCA-based system. However, PCA-based system took less time to train image database than GPCA-based system.

[24] employed uniform local binary pattern to extract features from the face images and to reduce the dimensionality of the feature vector, the firefly algorithm -great deluge algorithm was employed. The developed technique was experimented on Japanese female facial expression database produced 96.7%. But the experiment was done on female faces with no identical samples. [22] proposed a new facial emotion recognition method based on gravitational search algorithm (GSA), from eyes and mouth features for colored images. Detection is implemented by part-based appearance manners (happy, neutral, sad, angry, fear and disgust) and these attributes are used in the recognition phase. In this phase, facial attributes and their mapping to emotion space are encoded using GSA-based optimization. Applying the method on FACES facial expression database using Euclidean distance for classification indicates 72.23 % accuracy.

[17] presented three metaheuristic strategies to solve the feature selection problem, specifically, GRASP, Tabu Search and the Memetic Algorithm. These three strategies are compared with a Genetic Algorithm and with other typical feature selection methods, such as Sequential Forward Floating Selection (SFFS) and Sequential Backward Floating Selection

ISSN 2350-1022

International Journal of Recent Research in Mathematics Computer Science and Information Technology
Vol. 10, Issue 2, pp: (53-62), Month: October 2023 – March 2024, Available at: www.paperpublications.org

(SBFS). The results show that, in general, GRASP and Tabu Search obtain significantly better results than the other methods. [16] presented a novel performance metric for feature selection algorithms that is unbiased and can be used for comparative analysis across feature selection problems. The baseline fitness improvement (BFI) measure quantifies the potential value gained by applying feature selection. Twenty nine of these University of California, Irvine repository classification datasets were used in this study. The feature selection Adaptive Multi-Swarm Optimisation, Random Feature Selection, Pearson Correlation Coefficient Ranker, Genetic Algorithm for Feature Selection, Pearson Correlation Coefficient Ranker, Information Gain Ranker, Generalised Sequential Forward Selection. Empirical results are presented to show that there is performance complementarity for a suite of feature selection algorithms on a variety of real world datasets. The performance complementarity forfeature selection algorithms in this study shows that choosing the **best** feature selectionalgorithm remains problem dependant.

[10] described the various methods and steps for feature selection, including filters, wrappers and embedded methods, andcompares the resulting feature sets with regard to the achievable goodness of the quality models that were created usings even different supervised machine learning algorithms for regression. [9] proposed work we evaluate the PIMA Indian Diabtes data set of UCI repository using machine learning algorithm like Random Forest along with feature selection methods such as forward selection and backward elimination based on entropy evaluation method using percentage split as test option. The experiment was conducted using R studio platform and we achieved classification accuracy of 84.1%. From results we can say that Random Forest predicts diabetes better than other techniques with less number of attributes so that one can avoid least important test for identifying diabetes. [8] presented a paper that investigated the influence of feature selection approach in the prediction of skin diseases using data mining techniques. Principal Component Analysis (PCA), Information Gain (GA) and Chi-square were the feature selection algorithms used to reduce features of skin diseases dataset. The classification was done using Random Forest, C4.5 Decision Trees and Functional Tree (FT). Experimental results of the developed predictive model on skin diseases have revealed that the feature selection algorithms did not necessarily improve the accuracy and sensitivity of these algorithms and in situation where they brought an improvement; it was just a little about 1 percent. But PCA-FT produced highest accuracy of 96.99%.

Thus, it is obvious from above reviewed works that little work was done on applying evolutionary algorithms as feature selectors. And the applied evolutionary algorithms were not adequately compared in terms of their effectiveness as feature selectors. Hence there is need to evaluate the performances of some selected evolutionary-based feature selector techniques.

2. MATERIALS AND METHOD

This work investigates the performances of five selected evolutionary-based feature selectors in a well defined dataset of face images. The feature selection techniques are Particle Swarm Optimization, Ant Colony Optimization, Gravitational Search algorithm, Firefly algorithm and Genetic algorithm. The outputs of the feature selectors were subjected to classifier, which is back-propagation neuralnetwork. The performance metrics used are recognition accuracy, Specificity, Recall and Precision. The model architecture is shown in figure 1.

Description of Datasets

The data set used contained 120 acquired facial images. The face images comprises of normal face, angry face, distanced-face and laughing faces. The subject faces variants are of 30 each. The samples of the acquired face images are shown in figure 1.

Images Pre-processing

The acquired face images underwent pre-procession stages viz: cropping of image, colour adjustment and image normalisation. The cropping of face images (as shown in figure 2a) involves resizing the face images into moderate sizes. The colour adjustment involve enhancing the face images (as shown in figure 2b) to make them more visible for better processing. And normalisation of face images entails transforming the face image into consistent input form that can be easily trained.

ISSN 2350-1022

International Journal of Recent Research in Mathematics Computer Science and Information Technology
Vol. 10, Issue 2, pp: (53-62), Month: October 2023 – March 2024, Available at: www.paperpublications.org

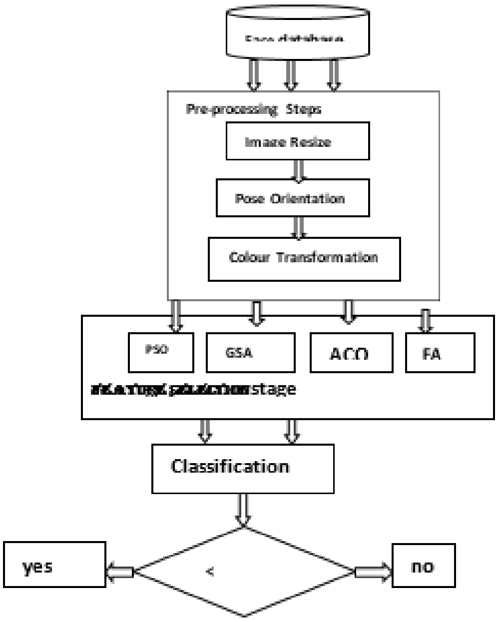

Fig 1

Feature selection

This stage involves dimensionality reduction of the pre-processed acquired face images by removing redundant and irrelevant features. There are four selected feature selection techniques employed for comparative analysis.

A. Ant colony optimization

In order to solve an optimization problem, a number of artificial ants are used to iterativelyconstruct solutions. In each iteration, an ant would deposit a certain amount of pheromoneproportional to the quality of the solution. At each step, every ant computes a set of feasibleexpansions to its current partial solution and selects one of these depending on two factors:local heuristics and prior knowledge. It is worth mentioning that Ant colony optimization(ACO) makes probabilistic decision in terms of the artificial pheromone trails and the localheuristic information. This allows ACO to explore larger number of solutions than greedyheuristics. Another characteristic of the ACO algorithm is the pheromone trail evaporation,which is a process that leads to decreasing the pheromone trail intensity over time (Parpinelliet al. 2002), Ani (2005).

B. Particle swarm optimization

Particle swarm optimization (PSO) is a population-based stochastic optimization technique, and was developed by [3]. PSO simulates the social behavior of organisms, such as bird flocking and fish schooling, to describe an automatically evolving system. In PSO, each single candidate solution is “an individual bird of the flock”, that is, a particle in the search space. Each particle makes use of its individual memory and knowledge gained by the swarm as a whole to find the best solution.

PSO is an evolutionary computation technique, in which each potential solution is seen as a particle with a certain velocity flying through the problem space. PSO requires only primitive and simple mathematical operators, and is computationally inexpensive in terms of both memory and runtime. [3].

C. Gravitational Search Algorithm

Gravitational Search Algorithm (GSA) is an optimization algorithm based on Newton's universal gravitational law which proposed by [1,2]. The GSA, inspired by universal gravitational and motion laws, has an efficient computing capability. In GSA, the performance of each solution is shown by the mass of the solution. Each mass gravitates the other masses in the search space with universal gravitational force. Thus, there is interactions between the masses. This gravitation allows all masses to move towards the heaviest mass. Therefore, the masses move together in the direction of gravitational forces. Gravitational search algorithm flowchart is show in Figure 1.

ISSN 2350-1022

International Journal of Recent Research in Mathematics Computer Science and Information Technology
Vol. 10, Issue 2, pp: (53-62), Month: October 2023 – March 2024, Available at: www.paperpublications.org

Algorithm 2.1: Traditional GSA

BEGIN

Create *p* particles and make randomized initialization of their *n* dimension positions X

Initialize iteration number i = 1,

REPEAT:

FOR *i* = 1 to *p*

Calculate fitness *fit(i)*

END FOR

Calculate global best fitness: best(t) $\min_{i\epsilon(1,2,\ldots p)}$

Calculate global worst fitness: worst(t) $\max_{i\epsilon(1,2,\ldots p)}$

FOR i = 1 to P

Calculate mass: $m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} m_i(t) = \frac{m_i(t)}{\sum_{i=1}^{p} m_i(t)}$

Calculate gravitational constant: $\mathrm{G(t)} = \mathrm{G(t_0)x}\, (\frac{t_0}{t})^{\beta}$, $\beta < 1$, $t_0 = 1$

FOR j = 1 to p, j ≠ 1

Calculate distance between two particles: $R_{ij} == \left\| X_i(t),\ X_j(t) \right\|$

Calculate force between two particles:

FOR *d* = *1 to n*

$$F_{ij}^d(t) = G(t) \frac{M_i(t)\ x\ M_j(t)}{R_{ij}(t) + \in} (x_i^d - x^i(t))$$

END FOR

END FOR

FOR *d* = *1 to n*

Calculate total force on *ith* particle: $F_i^d(t) = \sum_{j=1, i=1}^{p} Rand_i F_{ij}^d(t)$

Calculate acceleration: $a_i^d(f) = \frac{F_i^d(t)}{M_i(t)}$

Calculate velocity: $v^d i\ (t + 1) = \gamma j\ v^i(t) + a^i(t)$

Calculate position: $x^d i\ (t + 1) = x^i(t) + v^i(t + 1)$

END FOR

END FOR

UNTIL termination criterion is satisfied

END

[1]

ISSN 2350-1022

International Journal of Recent Research in Mathematics Computer Science and Information Technology
Vol. 10, Issue 2, pp: (53-62), Month: October 2023 – March 2024, Available at: www.paperpublications.org

D. Firefly Algorithm

FA is one of the well-known stochastic algorithms for optimization proposed by Yang. This algorithm is based on the flashing behavior of fireflies, most of the fireflies have a brightness as luminance. This luminance is used to attract the opposition and prey. Every firefly can send luminance signals to another firefly. FA is generally dependent on brightness and attractiveness [19]. These are well-known rules of FA.

a. All fireflies are unisex means all can attract other fireflies regardless of their sex.

b. Attractiveness between two fireflies is directly proportional to the Intensity of light or luminance hence brighter means more attractive. Fireflies having low light intensity will move toward the brighter ones.

c. Brightness of fireflies is achieved through the cost function or fitness function which is used for searching purposes.

Algorithm 2.2: Pseudo code of the Firefly Algorithm.

Objective Function f(X), X= (x_1, x_2, ……x_n)

Generate the initial population of n fireflies, x_1, i = 1, 2,…, n

Light intensity l_i at x_1 is determined by f (x_1)

Define the light absorption coefficient γ

while (t <MaxGeneration)

for i = 1:n, all n fireflies

for j = 1:n, all n fireflies (inner loop)

if ($I_i < J_I$), Move firefly *i* towards j;

end if

Vary attractiveness with distance *I* via exp[- γr^2]

end for *j*

end for *i*

Rank the fireflies and find the current global best solution g*

end while

Post-process the results

[19]

Image Classification

The image classification was done by Back-propagation neural network. The algorithm of BNN is given below.

The back propagation algorithm is implemented using following steps.

1. Initialize weights to small random values W_{ih} ,W_{hj}.

2. Feed input vector X_1,X_2....through Network and computing weighting sum

coming into node and then apply the sigmoid function

$$S_h = (W_{ih})^T X \quad (11)$$

Where W_{ih} is weights between input nodes and hidden nodes,

S_h is weighting sum coming into hidden node.

ISSN 2350-1022
International Journal of Recent Research in Mathematics Computer Science and Information Technology
Vol. 10, Issue 2, pp: (53-62), Month: October 2023 – March 2024, Available at: www.paperpublications.org

$$Y_h = \frac{1}{1+e^{-S_h}} \quad (12)$$

Where Y_h is probability of each hidden node for each pixel

$$S_j = (W_{hj})^T Y_h \quad (13)$$

Where W_{hj} is weights between hidden nodes and output nodes,

Sj is weighting sum coming into output node

$$Y_j = \frac{1}{1+e^{-S_j}} \quad (14)$$

3. Calculate error term for each output unit

$$\delta_j = Y_j(1-Y_j)(d_j - Y_j) \quad (15)$$

4. Mean square error(MSE) of output node

$$e = \frac{\sum_{i=1}^{j}(d_j - Y_j)^2}{2} \quad (16)$$

5. Calculate error term of each of hidden nodes

$$\delta_h = (W_{hj} - \delta_h)Y_h(1-Y_h) \quad (17)$$

6. Adjust weights to minimize mean square error

$$W_{ih} = W_{ih} + \alpha X \delta_h + \beta(W_{ih} - W_{ih1}) \quad (18)$$

$$W_{hj} = W_{hj} + \alpha Y_h \delta_j + \beta(W_{hj} - W_{hj1}) \quad (19)$$

Repeated all the steps except 1 till MSE is within reasonable limits.

7. After training neural network using Training pixels, find Y_h and Y_j for each pixel using weights W_{hj}, W_{ih} which is obtain from training of neural network.

8. Pixel goes in Y_j class if Y_j have maximum probability for this pixel. According to this all pixels of image are classified.

Performance Metrics

The performance metrics employed are Recall, Specificity, Precision and Recognition Accuracy.

3. DISCUSSION OF RESULTS

The simulation of the four selected feature selection techniques were done in MATLAB7 version 2021. Experiments were performed with the faces data trained and tested using cross validation method. The cross validation took 2 folds in 50% of data for training and 50% for testing and vice versa. The simulation was run with four different thresholds between 0.0 and 1.0 (0.22, 0.35, 0.50 and 0.76) to produce highest number of face matching. The results of the simulations for the four techniques is shown in figure Table 1 at threshold of 0.76 which produced highest results among the chosen thresholds.

As stated in Table 1, at the threshold value of 0.76, PSO produced 20.0%, 28.3%, 71.7%, 80.0%, 80.0%, 78.2% and 75.8% for FMR, FNMR, Recall, SPEC, PREC and ACC respectively; ACO generated 21.7%, 25.0%, 75.0%, 78.3%, 77.6% and 76.7% for FMR, FNMR, Recall, SPEC, PREC, and ACC respectively; FA gave 21.7%, 16.7%, 83.3%, 78.3%, 79.4% and 80.8% for FMR, FNMR, Recall, SPEC, PREC, and ACC respectively and GSA produced 15.0%, 8.3%, 91.7%, 85.0%, 85.9% and 88.3% for FMR, FNMR, Recall, SPEC, PREC, and ACC respectively. The ROC graphs of Specificity vs thresholds, Recall vs thresholds, and Accuracy vs thresholds are shown in figure 6, 7 and 8 respectively.

ISSN 2350-1022

International Journal of Recent Research in Mathematics Computer Science and Information Technology
Vol. 10, Issue 2, pp: (53-62), Month: October 2023 – March 2024, Available at: www.paperpublications.org

Table 1: Results of Gabor-BPNN system

Technique	Recall %	SPEC %	PREC %	ACC %
PSO	71.7	80.0	78.2	75.8
ACO	75.0	78.3	77.6	76.7
FA	83.3	78.3	79.4	80.8
GSA	91.7	85.0	85.9	88.3

The results produced by GSA in terms of:

(i) Recall: The results revealed that GSAhas highest Recall than others, that is, GSA has the ability to identify the presence of faces in the database than others.

(ii) Specificity: The results showed that GSA has highest Specificity than others which implies that GSA has the ability to identify the absence of faces in the database than other techniques.

(iii) Precision: The results showed that GSAis more precise than other techniques which implies that the GSA has better positive predictive capability than PSO, ACO and FA.

(iv) Recognition Accuracy: The results revealed that GSA is more accurate than PSO, ACO and FA, that is, GSA has the ability to identify the presence and absence of faces in the database than other techniques.

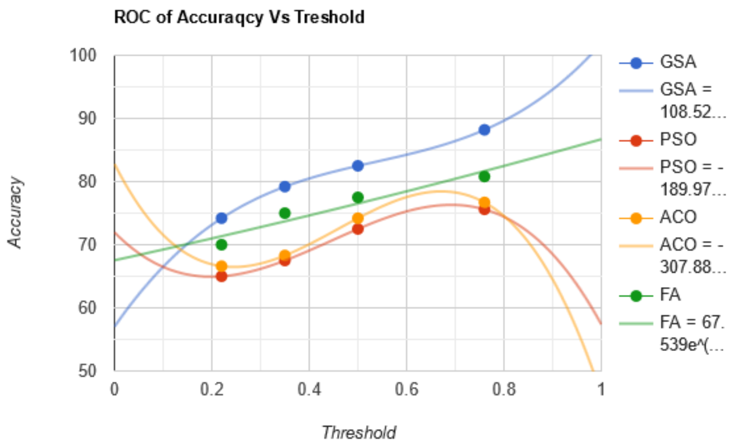

Figure 5: ROC graph of Accuracy vs Thresholds

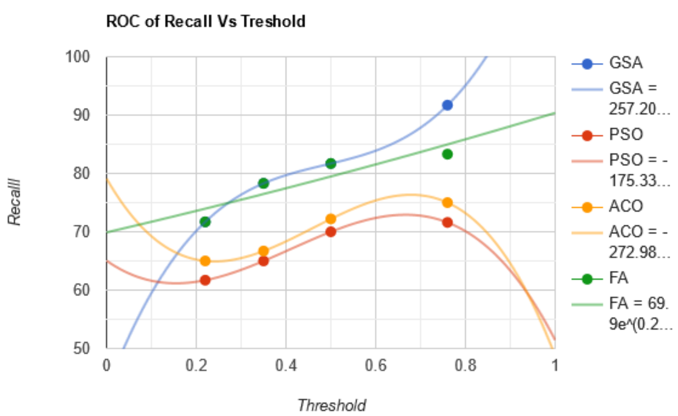

Figure 7: ROC graph of Recall vs Thresholds

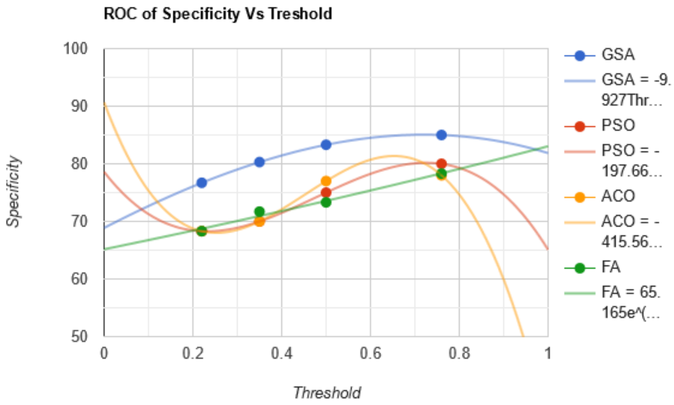

Figure 6: ROC graph of Specificity vs Thresholds

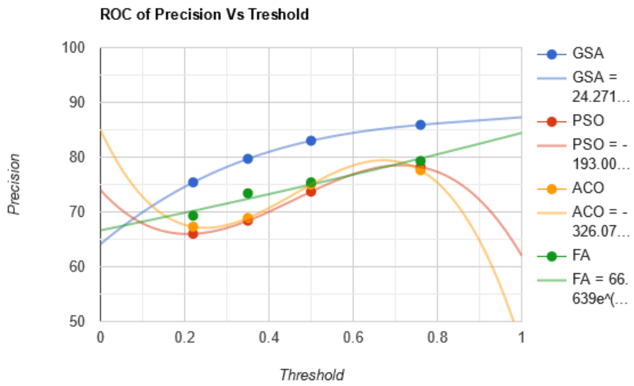

Figure 8: ROC graph of Accuracy vs Thresholds

Acknowledgement

I appreciate TETFUND for her financial support toward the successful completion of this research..

4. CONCLUSION

This paper provided a platform for comparing the performance of some selected feature selector techniques viz; PSO, GSA, FA and ACO. One hundred and twenty face images were acquired and pre-processed. The selected feature selector techniques were used to selected salient features from the pre-processed images. The face images were then classified by Back-propagation neural network. The results showed that GSA highest accuracy value compared to other techniques.However, this research can be

REFERENCES

[1] E. Rashedi,, H. Nezamabadi-Pour, & Saryazdi, S. (2009). GSA: a gravitational search algorithm. information sciences, 179(13), 2232-2248.

[2] E. Rashedi, H. Nezamabadi-Pour, & Saryazdi, S. (2010). BGSA: binary gravitational search algorithm. Natural Computing, 9(3), 727-745.

[3] J. Kennedy, R. C. Eberhart (1995) Particle swarm optimization. In: Proceedings of the 1995 IEEE international conference on neural networkds, vol 4. Perth, Australia, pp 1942–1948

[4] X. Wang, J. Yang, X. Teng, W. Xia, R. Jensen (2007) Feature selection based on rough sets and particle swarm optimization. Pattern Recognit Lett 28:459–471

[5] M. Bonabeau, Dorigo, and G. Theraulaz, (1999). Swarm intelligence: from natural to artificial systems (No. 1). Oxford university press.

[6] D. Karaboga, and B. Akay, (2009). A comparative study of artificial bee colony algorithm. *Applied mathematics and computation*, *214*(1), 108-132.

[7] D. Karaboga, and B. Basturk, (2008). On the performance of artificial bee colony (ABC) algorithm. *Applied soft computing*, *8*(1), 687-697.

[8] O. C. Abikoye, R. G. Komolafe1 and T. O. Aro (2019). Performance Evaluation of Feature Selection Algorithms On Skin Disease Prediction, FUW Trends in Science & Technology Journal, 4(2), 337 – 342.

[9] S. Raghavendra, K. J. Santosh (2020). Performance evaluation of random forest with feature selection methods in prediction of diabetes. International Journal of Electrical and Computer Engineering (IJECE), 10(1), 353~359.

[10] A. S. Struchtrup, Dimitri Kvaktun and Reinhard Schiffers (2019). Comparison of Feature Selection Methods for Machine Learning based Injection Molding Quality Prediction, *Proceedings of PPS2019 Europe-Africa Regional Conference of the Polymer Processing Society* AIP Conf. Proc. 2289, 020052-1–020052-5;.

[11] Chaudhary, S. Kolhe, Rajkamal (2013). Performance Evaluation of feature selection methods for Mobile devices, *Journal of Engineering Research and Applications, 3(6), 587-594*

[12] H. Liu and L. Yu. (2005). Toward integrating feature selection algorithms for classification andclustering. IEEE Transactions on Knowledge and Data Engineering, 17(4):491.

[13] Guyon and A. Elisseeff, André (2003). *"An Introduction to Variable and Feature Selection". JMLR*.

[14] O. Omidiora, O. Oladipo,C. A. Oyeleye, W. O. Ismaila (2013): A Study of Genetic–Principal Component Analysis in the Feature Extraction and Recognition of Face Images. Journal of Computer Science and Engirg, 19(1), 1-6.

[15] F. M Ismaila. (2022). Hybridized Local Binay Pattern-Levyflight Firefly Algorithm based Human face Recognition Access Control System, PhD Thesis, Unpublished, Ladoke Akintola University of Technology, Nigeria

[16] W. Mostert, K. M. Malan, Engelbrecht A.P., (2021). A Feature Selection Algorithm Performance Metric for Comparative Analysis. Algorithms, 14, 100.

[17] Yusta (2009) Different metaheuristic strategies to solve the feature selection problem. Pattern Recognit Lett 30:525–534

[18] S. Vanaja and K. Rameshkumar (2015). Performance Analysis of Classification Algorithm on Medical Disgnosis. A Survey. Journal on Computer Science, 11(1), 30-52.

[19] X. S. Yang, (2008).Nature-inspired metaheuristic algorithms. Luniver Press.

[20] L. Dora, Agrawal, S., Panda, R. and Abraham,A. (2017b). An Evolutionary Single Gabor kernel-based filter Approach to FaceRecognition. Engineering Applications of Artificial Intelligence, 62, 286–301.

[21] M. Arunkumar and S. Valarmathy (2013). Palmprint and Face Based Multimodal Recognition Using PSO Dependent Feature Level Fusion, *Journal of Theoretical and Applied Information Technology*, 57(3), 337-346.

[22] S. F. Fatemeh, S. Mansour and Ali F. (2013). Facial Emotion Recognition Using Gravitational Search Algorithm for Colored Images, AISP 2013, CCIS 427, 32–40.

[23] O. M Aly., Gouda I. Salama, A. Tarek Mahmoud, Hoda M. Onsi (2013). An Adaptive Multimodal Biometrics System using PSO, *International Journal of Advanced Computer Science and Applications*, **4**(7), 158-165.

[24] Elmadhoun and Nordin (2018) Facial Expression Recognition using Uniform Local Binary Pattern with improved Firefly Feature Selection. ARO-The Scientific Journal of Koya University.6(1)..