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

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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 (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) 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 Gravitational Search algorithm outperformed other techniques with accuracy of 88.3% while Particle Swarm Optimization gave 75.8%, Ant colony optimization produced 76.7% and Firefly algorithm generated 80.8%.

Keywords: Feature Selection, Evolutionary Algorithms, Ant Colony Optimization, Gravitational Search Algorithm, Particle Swarm Optimization and Firefly Algorithm

Introduction

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. [1], [2]. However, In machine learning. Feature

Selection is the process of selecting a subset of relevant attributes for use in model construction. 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. [3].

Typically, a feature selection method consists of four basic steps [4], 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 subset that best fits the evaluation criterion will be chosen from all the candidates that have been evaluated after the stopping criterion were met. In the final step, the chosen subset will be validated 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, [5], [6, 12] employed particle swarm optimization; [7] used Ant Colony Optimization Algorithm; [8;9] employed Memetic Algorithm, Bat Algorithm by [10]; [18, 19] employed gravitational search algorithm and genetic algorithm by [11]; artificial bee colony algorithm BY [13; 14] etc. However, the effectiveness and efficiency of each of those algorithms have been evaluated on the same or different dataset. This makes 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 human face image dataset.

Related Works

Several works have been done on image processing using evolutionary algorithms as highlighted below. The authors in [15] developed 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 and the genetic algorithm helps in removing irrelevant features in the eigenface space. Euclidean distance was used as the similarity measure at various thresholds on different cropped image dimensions. The experiment was carried out on a database of 320 black faces and the results showed that the GPCA-based system has better recognition accuracy and recognition time with 9.1665% and 0.085401 seconds cumulative increment in recognition accuracy and recognition time over the PCA-based system.

[8] authors proposed a new facial emotion recognition method based on gravitational search algorithm, 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. [16] presented a new approach for the recognition of facial images, using Intensified Firefly Algorithm and extreme machine classifier. This approach employed multi linear sparse principal component analysis method for features extraction and Extreme Learning Machine for image matching. The proposed technique three popular databases and the experimental results revealed excellent recognition accuracy 99.7%.

[17] employed an evolutionary approach, Firefly Algorithm, for feature selection to develop a Firefly Algorithm Radial Basis Function Neural Network (FRBFNN) based face recognition system. The author used four online different face databases with total images of 948 of varying poses (neutral face, open/closed eye, smiling/not smiling, variations in illumination, smile, anger, scream. Occlusions). The proposed FRBFNN technique used Firefly Algorithm to obtain natural sub-clusters of training face images formed around acquired faces. Also, Firefly inspired algorithm was employed for designing hidden layer of Radial Basis Function Neural Network (RBFNN). The results obtained by the developed FRBFNN technique gave average recognition accuracy of 90.25%. [9] 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 and Sequential Backward Floating Selection. The results show that, in general, GRASP and Tabu Search obtain significantly better results than the other methods.

[20] 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 measure quantifies the potential value gained by applying feature selection. Twenty nine of these University of California, Irvine repository classification datasets were used. 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 for feature selection algorithms in this study showed that choosing the best feature selection algorithm remains problem dependant.

Also, the authors in [21] presented a paper that investigated the influence of feature selection approach in the prediction of skin diseases using data mining techniques. Principal Component Analysis, Information Gain 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. 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%. [22] proposed work we evaluate the PIMA Indian Diabetes 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%.
Thus, it is obvious from above reviewed works that little work was done on comparing the performance of different evolutionary algorithms in terms of their effectiveness as feature selectors. Hence there is need to evaluate the performances of some selected evolutionary-based feature selector techniques.

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 and Firefly algorithm. The outputs of the feature selectors were subjected to classifier, which is back-propagation neural network. 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 2.



Figure 2: Sample of face subjects

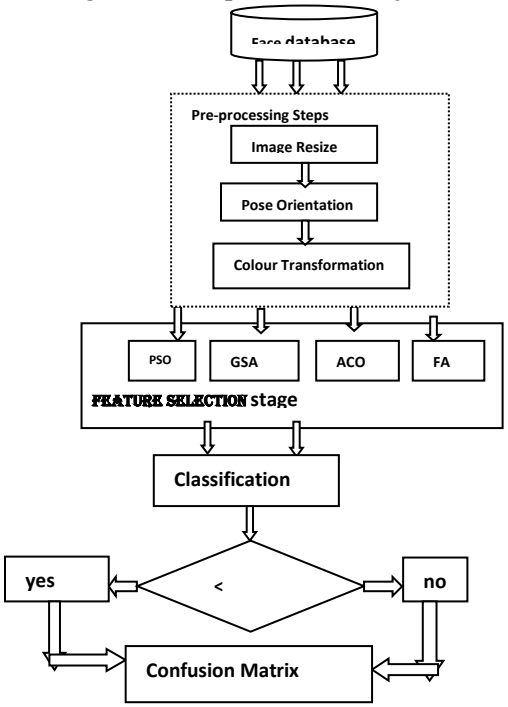


Figure 1: Flow diagram of the Image Classification System

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 3a) involves resizing the face images into moderate sizes. The colour adjustment involve enhancing the face images (as shown in figure 3b) 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.



(a) (b) (c)

Figure 3: Sample of preprocessing outputs (a) Image resize (b) pose orientation (c) Colour transformation

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.

Ant Colony Optimization

Ant colony optimization method is purely inspired from the foraging behaviours of ants colonies. Ants are social insects that prefer community survival and sustain. They communicate with each other using sound, touch and pheromone (organic chemical compounds secreted by the ants that trigger a social response in members of same species). Ants use the soil surface to leave pheromone trails since ants live on the ground so that others may be followed (smelled) by other ants. ACO has a positive feedback mechanism and is effective in dealing with distributed problems. But ACO takes longer time to search and it is easy to fall into local minimum. (for more information see [23]).

Figure 4: ***ACO Pseudocode***

Step1: Randomly initialize Swarm population of N particles X_i (i=1, 2, …, n)
Step2: Select hyperparameter values w, c_1 and c_2
Step 3: For Iter in range(max_iter): # loop max_iter times
For i in range(N): # for each particle:
a. Compute new velocity of ith particle
*swarm[i].velocity = w*swarm[i].velocity +*
*r1*c1*(swarm[i].bestPos - swarm[i].position) +*
*r2*c2*(best_pos_swarm - swarm[i].position)*
b. Compute new position of ith particle using its new velocity
swarm[i].position += swarm[i].velocity
c. If position is not in range [minx, maxx] then clip it

if swarm[i].position < minx:
swarm[i].position = minx
elif swarm[i].position > maxx:
swarm[i].position = maxx
d. Update new best of this particle and new best of Swarm
if swaInsensitive to scaling of design variables.rm[i].fitness < swarm[i].bestFitness:
swarm[i].bestFitness = swarm[i].fitness
swarm[i].bestPos = swarm[i].position
if swarm[i].fitness < best_fitness_swarm
best_fitness_swarm = swarm[i].fitness
best_pos_swarm = swarm[i].position
End-for
End -for
Step 4: Return best particle of Swarm

Particle swarm optimization

Particle swarm optimization (PSO) is a powerful meta-heuristic optimization technique, and inspired by swarm behavior observed in nature such as fish and bird schooling which was developed by [12]. 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 insensitive to scaling, free of derivative, has a few parameters and very efficient global search algorithm. However, PSO is of weak local search ability (for more information see [24;29]).

Figure 5: PSO pseudocode

Input: m: the swarm size; c1 , c2 : positive acceleration constants. w: inertia weight.
MaxGen: maximum generation.
MaxFit: _tness threshold.
Output: Global best position
1: Initialize a population of particles with random positions and velocities features dimensions pbesti=0, Gbest=0, Iter=0.
2: while Iter < MaxGen or gbest < MaxFit do
3: for i = 1 to number of particles m do
4: Fitness (i)=Evaluate(i)
5: if Fitness(i) > Fitness (pbesti) then
6: Fitness (pbesti)= Fitness(i)
7: Update pid = xid
8: end if
9: if Fitness(i) > Gbest then
10: Gbest=Fitness(i)

11: Update gbest = i
12: end if
13: for each dimension d do
14: Update the velocity vector.
15: Update the particle position.
16: end for
17: end for
18: Iter= Iter+1
19: end while
20: Return the Global best position.

Gravitational Search Algorithm

Gravitational Search Algorithm (GSA) is an optimization algorithm based on Newton's universal gravitational law. The GSA, inspired by universal gravitational and motion laws, has an efficient computing. 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. For more information see [24; 25]. Gravitational search algorithm pseudocode is presented in figure 6.

Figure 6: Pseudocode: Standard GSA [24; 25]

```
k = randint (1..D)
for each dimension d do
   if rand(0, 1) < CR or d = k do
      trial.x[d] = target.x[d] + rand(0,1) × (best.x[d] – worst.x[d])
   else
      calculate velocity with equation (5)
      update position with equation (6)
   end if
   check boundary of trial.x[d]
end for
compute fitness value trial.fitness of the temp agent
if trial.fitness is better than target.fitness then
   update position of target with position of trial agent
   target.fitness ← trial.fitness
end for
```

Firefly Algorithm

FA is one of the well-known stochastic algorithms for optimization proposed by Yang. This algorithm works 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 (for further information see [26; 27]). However, Firefly possesses multi-modal characteristics and can handle multi-modal problems efficiently with fast convergence rate. It is helpful in global problem solver as well as local search heuristic.

Figure 7: Pseudo code of the Firefly [1].

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_1), 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

Image Classification Phase

The image classification was done by Back-propagation neural network. The back propagation algorithm is implemented using following steps.

F*igure 8:* **Pseudocode of Back-propagation algorithm** [28]

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

2. Feed input vector X_1,X_2....Xn through Network and computing weighting sum coming into node and then apply the sigmoid function

$$S_h = (W_{ih})^T X \quad \text{..... (1)}$$

Where W_{ih} is weights between input nodes and hidden nodes,
S_h is weighting sum coming into hidden node.

$$Y_h = \frac{1}{1+e^{-S_h}} \quad \text{... (2)}$$

Where Y_h is probability of each hidden node for each pixel

$$S_j = (W_{hj})^T Y_h \quad \text{..... (3)}$$

Where W_{hj} is weights between hidden nodes and output nodes,
Sj is weighting sum coming into output node

$$Y_j = \frac{1}{1+e^{-S_j}} \quad \text{.... (4)}$$

3. Calculate error term for each output unit

$$\delta_j = Y_j(1-Y_j)(d_j - Y_j) \quad \text{..... (5)}$$

4. Mean square error(MSE) of output node

$$e = \frac{\sum_{i=1}^{j}(d_j - Y_j)^2}{2} \quad \ldots. \ (6)$$

5. Calculate error term of each of hidden nodes

$$\delta_h = (W_{hj} - \delta_h)Y_h(1 - Y_h) \quad \ldots. (7)$$

6. Adjust weights to minimize mean square error

$$W_{ih} = W_{ih} + \alpha X \delta_h + \beta(W_{ih} - W_{ih1}) \quad \ldots. (8)$$

$$W_{hj} = W_{hj} + \alpha Y_h \delta_j + \beta(W_{hj} - W_{hj1}) \quad \ldots. (9)$$

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. Recognition accuracy is the ratio of correctly recognized faces to the total acquired faces. Specificity states the probability that a detected face does not match another face image of a different face. Recall expresses the probability that a detected face is compatible with other facial images of the same face [30,31].

$$\text{Accuracy} = \frac{\text{TrueNegative} + \text{Truepositive}}{\text{TruePositive} + \text{TrueNegative} + \text{Falsepositive} + \text{FalseNegative}} \ldots.. (10)$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative+False Positive}} \ldots.. (11)$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \ldots \ldots (12)$$

$$\text{Precision} = \frac{\text{Tue Positive}}{\text{True Positive} + \text{ False Positive}} \ldots \ldots (13)$$

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 71.7%, 80.0%, 80.0%, 78.2% and 75.8% for Recall, SPEC, PREC and ACC respectively; ACO generated 75.0%, 78.3%, 77.6% and 76.7% for Recall, SPEC, PREC, and ACC respectively; FA gave 83.3%, 78.3%, 79.4% and 80.8% for Recall, SPEC, PREC, and ACC respectively and GSA produced 91.7%, 85.0%, 85.9% and 88.3% for Recall, SPEC, PREC, and ACC respectively. The ROC

graphs of Specificity vs thresholds, Recall vs thresholds, and Accuracy vs thresholds are shown in figure 9, 10, 11 and 12 respectively.

Table1: 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 revealed that GSA has highest Recall than others, that is, GSA has the ability to identify the presence of faces in the database than others.

(ii) Specificity 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 showed that GSA is more precise than other techniques which implies that the GSA has better positive predictive capability than PSO, ACO and FA..

(iv) Recognition Accuracy 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.

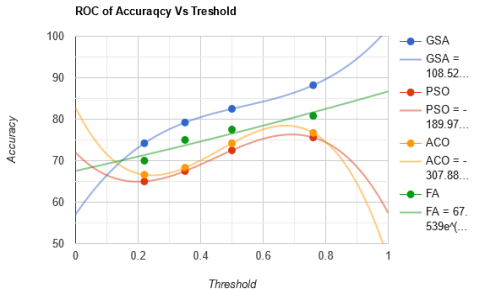


Figure 9: ROC graph of Accuracy vs Thresholds

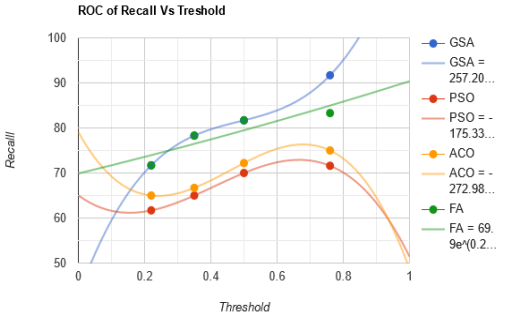


Figure 10: ROC graph of Recall vs Thresholds

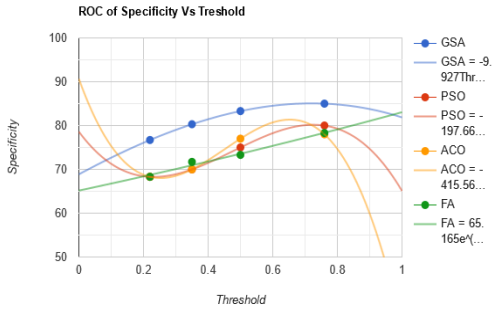


Figure 11: ROC graph of Specificity vs Thresholds

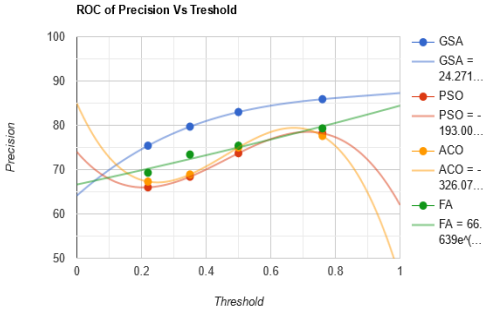


Figure 12: ROC graph of Precision vs Thresholds

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 extended to involve other evolutionary algorithms like Lion optimization, Aquila Optimization, Genetic Algorithm, Bee Colony Optimisation, etc.

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