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ORIGINAL ARTICLE

# Optimization of K-nearest neighbor using particle swarm optimization for face recognition

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**Abstract**

Face biometric has received more attention to recognize a person in a right way. However, the face recognition is considered to be hard due to size, ethnicity, illumination, pose, various expression, and age. In this work, a novel approach is proposed to recognize the human face based on K-nearest neighbor (KNN) with particle swarm optimization (PSO). Initially, the features are extracted using local binary pattern. The metaheuristic optimization algorithms such as genetic algorithm, PSO, and ant colony optimization are investigated for feature selection. The KNN classifier is optimized using the population-based metaheuristic algorithm PSO. Finally, the face recognition is performed using the proposed PSO–KNN algorithm. In this research, experiments have been conducted on real-time face images collected from 155 subjects each with ten orientations using Logitech Webcam and also on ORL face dataset. The experimental result of the proposed PSO–KNN is compared with other benchmark recognition techniques such as decision table, support vector machine, multilayer perceptron and conventional KNN, to conclude the efficacy of the proposed approach.

**Keywords** ACO · Face biometric · GA · KNN · LBP · PSO

## 1 Introduction

In an increasingly digital and more mobile world, it is quite difficult to protect the confidential data by means of conventional passwords and tokens. Furthermore, tokens can be lost or stolen and passwords can be guessed by the intruders. In recent years, the researchers have focused on biometric technology as they provide a higher level of security and are more sophisticated for the users [1, 2]. Biometric authentication refers to identifying persons availing their physiological and behavioral characteristics (or traits) such as fingerprint, face, iris, voice, gait, and much more [3]. In general, face recognition, as an integral component in security, is being exploited widely for personal authentication in military, forensic, and civilian applications because of its uniqueness, immutability, acceptance, easy integration, and low cost [4–6]. Currently, the research on face recognition focuses on texture-based matching. In such a situation, the most essential for texture analysis is to express the spatial behavior of intensity values exists in face image using its neighborhoods. Local binary pattern is one of the efficient and widely studied methods used to extract the most discriminating features from face images [7].

More recently, in the domain of computer vision, the feature selection is employed which is paramount to reduce the dimensionality of the feature space which increases the accuracy of recognition. In the digital era, evolutionary algorithms such as genetic algorithm, particle swarm optimization, and ant colony optimization are extensively used to eliminate redundant and irreverent facial features [8]. In this work, the evolutionary algorithms are studied to select the optimum features from the face image. Typically, K-nearest neighborhood has been used successfully in statistical estimation and pattern recognition for a long time [9]. Moreover, KNN is very simple and computationally effective algorithm for face recognition. However, it suffers from the initialization of the parameter K. Among the population-based optimization algorithms, PSO is

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extensively utilized to optimize parameters in pattern recognition tools as they do not suffer from local minima problem. Hence, in this work, PSO has been explored to fix the K value optimally in KNN algorithm. Therefore, the proposed PSO–KNN with optimal features from meta-heuristic algorithms can recognize the individuals accurately.

### 1.1 Motivation

In the current scenario, face recognition has received a lot of attention in the domain of pattern recognition and also in the market. During the past decades, a huge number of face recognition algorithms are explored. However, these algorithms could no longer handle the challenges in real-time applications due to the restrictions of many occasions. Recently, population-based metaheuristic algorithms have been actively used in optimization including face recognition.

### 1.2 Contribution

Biometric face authentication plays a significant role in our interactions in society and with computers. In this research work, a novel method is proposed to automatically authenticate a right person from the face image. It includes the following tasks: feature extraction, feature selection, and recognition. Initially, the most discriminate LBP features are extracted from the face image. The evolutionary optimization algorithms such as GA, PSO, and ACO are explored to reduce the dimensionality of the feature space. Then, the parameter K in KNN algorithm is optimized with the exploit of PSO method. Finally, the biometric face recognition is performed with the proposed PSO–KNN algorithm.

### 1.3 Paper organization

The paper is organized as follows. Section 2 discusses the related work. In Sect. 3, a set of LBP features are extracted from the face image. The dimensionality of the feature space is reduced in Sect. 4 using GA, PSO, and ACO. Face images are recognized using the proposed PSO–KNN in Sect. 5. Section 6 provides experimental results of the proposed method on face images. Finally, this paper concludes with some perspectives in Sect. 7.

## 2 Related work

Face recognition is a fundamental and important problem in the field of computer vision and pattern recognition, which has been widely studied over the past few decades. Gao and Lee [10] have developed a method for recognizing the human by face images with scale-invariant feature transform (SIFT) and obtained an accuracy of 95%. Agarwal and Bhanot [11] have presented a radial basis function neural network (RBFNN) with firefly algorithm for human face recognition. The experiments conducted on ORL, Yale, AR, and LFW face databases expound the efficacy of the developed method. An accuracy of ORL-97.75%, Yale-99.83%, AR-93.15%, and LFW-60.50% was obtained. Zhu and Xue [12] have introduced random subspace method for face recognition. The tensor subspace method was utilized to extract the most discriminate features from the face image. Gunther et al. [13] have discussed the face recognition in mobile and other challenging environments with still images and video sequences. Experiments are performed on several freely available challenging still image and video face databases such as MOBIO, BANCA face database, including one mobile database. Jadoon et al. [14] have developed an extended collaborative neighbor representation method which utilizes the intrapersonal variation from generic subjects. Lu et al. [15] enhanced the sparsity representation using rank decomposition for the robust recognition of face biometric. The experiments conducted on FERET, ORL, and AR database showed the efficacy of the developed method. Kamencay et al. [16] have presented an SPCA-KNN method for face recognition. The scale-invariant feature transform features are extracted and reduced the dimensionality using PCA. Finally, KNN was exploited to match the face. Zun-xiong et al. [9] have introduced a face recognition algorithm using KNN. The experiment conducted on AR database provided an error rate of 12.99%. Xu and Zhu [17] presented a fast representation-based face recognition method which accurately classified than the nearest neighbor method. Jabid et al. [18] developed a novel local directional pattern feature descriptor for human face matching. Experiments conducted on FERET database expound the efficiency of the LDP method. Nazir et al. [19] explored discrete cosine transform (DCT) to extract the vital facial features. The gender was categorized with the exploit of K-nearest neighbor classifier. Sun et al. [20] have extracted the local binary pattern features on the FERET face dataset with their developed boosting LBP. Table 1 shows the summary of the related work.

## 3 Feature extraction

Feature detection and its extraction are considered to be an indispensable task for biometric face recognition [21]. In particular, the features are quantifiable measures of an image which specifies some significant characteristics of the image. They contain information relative to color,

**Table 1** Summary of related work

| References | Dataset | Methods | Result |
|---|---|---|---|
| Gao and Lee [10] | FERET | SIFT | An accuracy of 95% across poses within 40 degree was achieved |
| Agarwal and Bhanot [11] | ORL, Yale, AR, and LFW | Firefly Radial Basis Network with | FRBFNN revealed an accuracy of ORL-97.75%, Yale-99.83%, AR-93.15%, and LFW-60.50% |
| Zhu and Xue [12] | (AR, Yale, and CMU PIE | Random Subspace Method | An accuracy of CMU-93.14%, Yale-89.33 was obtained |
| Gunther et al. [13] | MOBIO, BANCA database | LDA, Gabor Wavelet | An open-source toolbox was developed including modeling techniques, evaluation protocols, and metrics |
| Jadoon et al. [14] | AR Face Database | Extended Collaborative Neighbor Representation | Achieved an error rate of 10.31% for the developed method |
| Lu et al. [15] | FERET, ORL, and AR database | Rank Decomposition with Least Square Method | The experiments conducted revealed the effectiveness of the developed method for face recognition |
| Kamencay et al. [16] | ESSEX face | SIFT, PCA, and KNN | An accuracy of 96% was obtained |
| Liu et al. [9] | Lab2, AR database | KNN | An error rate of 12.99% was achieved on AR database |
| Xu and Zhu [17] | ORL and Yale databases | Modified Nearest Neighbor | An error rate of 3.80% was obtained from Yale dataset |
| Jabid et al. [18] | FERET | Local Directional Pattern | The experiments showed the efficacy of the presented LDP method |
| Nazir et al. [19] | SUMS | KNN | An accuracy of 99.3% was obtained |
| Sun et al. [20] | FERET | LBP-AdaBoost | The study showed that the constructed method yields better recognition on face |

shape, texture, or context of an image. Among these, the texture is the most powerful feature descriptor of a biometric image. The texture defines the repeated pattern of information or arrangement of the structure with regular intervals. In this research work, one of the powerful texture descriptor methods, the local binary pattern which has been widely used in various pattern recognition problems [22–24], is accustomed to extracting the most discriminating features from the biometric face images. The extracted local binary pattern features are invariant to illumination effects, pose, expression, and age of human.

The $LBP_{P,R}$ operator of a face image $I$ is defined as

$$LBP_{P,R} = \sum_{P=0}^{P-1} s(I_p - I_c)2^P \tag{1}$$

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{2}$$

where $s(x)$ is the thresholding function, $I_c$ indicated the intensity value of the central pixel, $I_p$ is the value of its neighbors, $P$ is the number of neighbors considered, and $R$ indicates the radius of the neighborhood. Let $M \times N$ be the size of a face image. After computing the LBP pattern of each pixel $(i, j)$, the whole face image is represented by building a histogram as

$$H(z) = \sum_{i=1}^{M} \sum_{j=1}^{N} f(LBP_{P,R}(i,j), z), z \in [0, Z] \tag{3}$$

$$f(x,y) = \begin{cases} 1, & x = y \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where $Z$ represents the maximal value of LBP exists in the face image.

## 4 Feature selection

More recently, the researchers are focused on selecting the optimal features with the advent of many population-based optimization algorithms [25]. A robust face recognition model could be built by identifying the most significant features of the face image. In this research work, meta-heuristic algorithms such as GA, PSO, and ACO are implemented for selecting the best features.

### 4.1 Genetic algorithm

In general, the Genetic algorithm is an evolutionary optimization algorithm which operates on a population of individuals to find an optimal solution [26, 27]. It could operate on large, noisy, and discontinuous data. Initially, a population of candidate solutions is created randomly. The selected LBP features are given as an input to the KNN classifier, and the fitness function (accuracy) is computed. The overview of genetic algorithm used to select best LBP features is given in Algorithm 1.

**Algorithm 1:** Genetic Algorithm for feature selection of face

Input: Original Feature Set; Output: Reduced Feature Set
Step 1: Generate a population of individuals randomly
Step 2: Evaluate the population using KNN classifier model
Step 3: While stopping condition is not met do
Step 4: The best individuals are selected for reproduction
Step 5: The selected individuals are breaded by crossover and mutation operation
Step 6: The fitness (accuracy) of new individuals are evaluated
Step 7: The worst individual is replaced with the individual having less accuracy
Step 8: Return the best feature subset

### 4.2 PSO

PSO is a population-based metaheuristic optimization algorithm proposed by Kennedy and Eberhart in 1995 [28]. In PSO, each particle's position represents a candidate solution (feature vector) to the feature selection problem. The overview of PSO used to select the best LBP features is given in Algorithm 2.

**Algorithm 2:** PSO for feature selection of face

Input: Original Feature Set; Output: Reduced Feature Set
Step 1: Initialize the particles randomly
Step 2: Evaluate the particles using KNN classifier model
Step 3: While stopping condition is not met do
Step 4: Compute gBest and pBest based on the fitness value (accuracy) from KNN
Step 5: The velocity is calculated for each particle, and the position is updated
Step 6: Return the best feature subset

### 4.3 ACO

Ant colony optimization is introduced by Dorigo et al. [29] which is inspired by the foraging behavior of ants. After finding a food source, the ant lays some pheromone in the path which indirectly says some useful information about the identified food source [30]. The overview of ACO used to select best LBP features is given in Algorithm 3. The probabilistic decision made by the ants is given by (5),

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{l}\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}, & \text{If } i \text{ and } j \text{ are admissable bodes} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where $P_{ij}^{k}(t)$ represents the transition probability from feature $i$ to feature $j$ for the $k$th ant at time step $t$; $\tau_{ij}$ indicates the quantity of pheromone trail on the path $(i, j)$; and $\eta_{ij}$ is the heuristic visibility of path $(i, j)$. The pheromone content of path $(i, j)$ at a time instance $t + 1$ is given by (6),

$$\tau_{ij}(\text{new}) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) + \Delta\tau_{ij}^{g}(t) \tag{6}$$

**Algorithm 3:** ACO for feature selection of face

Input: Original Feature Set; Output: Reduced Feature Set
Step 1: Initialize the pheromone randomly
Step 2: Evaluate the path using KNN classifier model
Step 3: While stopping condition is not met do
Step 4: Using the feature subset of the best k ants update the pheromone trails
Step 5: Return the best feature subset

## 5 Face recognition using PSO–KNN

The proposed face recognition using K-nearest neighbor with the optimization of PSO is discussed in this section.

### 5.1 K-nearest neighborhood algorithm

The K-nearest neighborhood algorithm is the simplest and an instance-based learning algorithm. The advantage of the KNN is that it quickly finds the closest object from the large training set [31]. Moreover, it is a better-focused learning method. KNN algorithm is more suitable for recognizing persons based on their face images due to its less execution time and better accuracy than other commonly used methods which include decision table, MLP, and SVM. Generally, KNN exploits distance metric to find the closest person from the training set. The KNN algorithm for face recognition is given in Algorithm 4.

**Algorithm 4:** KNN for face recognition

Input: Query face image; Output: Matched Person

Step: 1 Each person in the dataset has assigned a class label, Class = {$P_1$, P2,…,$P_n$}

Step: 2 Initialize K value and the distance matrix (K = 2, 3, 5,…)

Step: 3 Find the K-closest neighbors for an input sample using the distance matrix.

Step: 4 Apply majority voting scheme to find the most common person

Step: 5 Assign the most common label of the person to the test sample

### 5.2 PSO–KNN

The PSO algorithm is motivated by the social behaviors of bird flocking and fish schooling. The underlying phenomenon of PSO is the communication and learning. In PSO, each particle's position represents a candidate solution to the optimization problem under consideration. At every iteration, each particle searches for the better position by changing its velocity.

**Algorithm 5:** Proposed PSO–KNN for face recognition

Input: Query face image; Output: Matched Person

Step: 1 Each person in the dataset has assigned a class label, Class = {$P_1$, P2,…,$P_n$}

Step: 2 Initialize the PSO parameters (swarm size, inertia weight (W), personal learning coefficient ($C_1$), and global learning coefficient ($C_2$))

Step: 3 Train the KNN algorithm with random K value and compute the accuracy which is the fitness function

Step: 4 Evaluate the position of each particle according to the fitness function

Step: 5 If a particle current position is better than its previous best position, update the position of the particle by

$\mathrm{P}_i^{t+1} = \mathrm{P}_i^t + \mathrm{V}_i^{t+1}$

Step: 6 Determine the best particle in the swarm according to the particles previous best position.

Step: 7 Update the velocity of the particles using

$\mathrm{V}_i^{t+1} = \mathrm{W}^t + \mathrm{C}_1\mathrm{R}_1^t\left(\mathrm{pBest}_i^t - \mathrm{p}_i^t\right) + \mathrm{C}_2\mathrm{R}_2^t\left(\mathrm{gBest}_i^t - \mathrm{p}_i^t\right)$

Step: 8 Move particles to their updated position

Step: 9 Go to step 3 until stopping conditions are satisfied or maximum iterations are reached

Step: 10 Train the KNN algorithm with optimized K value and find the K-closest neighbors for an input sample

Step: 11 Apply majority voting scheme to find the most common person

Step: 12 Assign the most common label of the person to the query sample

The position ($P$) and velocity ($V$) of each particle are updated using the following equations

$$P_i^{t+1} = P_i^t + V_i^{t+1} \tag{7}$$

$$V_i^{t+1} = W^t + C_1R_1^t\left(pBest_i^t - p_i^t\right) + C_2R_2^t\left(gBest_i^t - p_i^t\right) \tag{8}$$

In Eq. (8), $C_1R_1^t\left(pBest_i^t - p_i^t\right)$ is used for learning and $C_2R_2^t\left(gBest_i^t - p_i^t\right)$ is for global communication. The K-nearest neighborhood algorithm is the widely employed for face recognition. However, it suffers from the optimum initialization of K value. Hence, in this work, PSO is studied to optimize the initial K value of KNN. The proposed PSO–KNN algorithm is given in Algorithm 5.

## 6 Experimental result and discussion

The proposed PSO–KNN algorithm for face recognition has been implemented and discussed. The experiments have been conducted on the real-time face dataset and benchmark ORL face dataset. The features obtained from LBP are further reduced to better recognize the face images.

### 6.1 Dataset

Face dataset has been created from 155 subjects each with ten different postures of each individual using 2 Mega Pixel Logitech Web Camera as shown in Fig. 1.

The sample face images acquired from the subjects are depicted in Fig. 2. Each image size ranges from 144 to 150 kb. The proposed method is also validated on the standard ORL face dataset which contains 400 face images as shown in Fig. 3 [32].


**Fig. 1** Biometric face sensor

**Fig. 2** Sample face images collected from the subjects

**Fig. 3** Sample face images from ORL dataset

## 6.2 Experimental results

The efficacy of the proposed PSO–KNN algorithm has been compared with the standard benchmark classifiers such as decision table, SVM, MLP, and KNN. Generally, the algorithms receive the reduced feature set obtained from population-based optimization techniques such as

GA, PSO, and ACO. The parameters of GA, PSO and ACO algorithms are reported in Tables 2, 3, and 4, respectively.

The list of features selected using GA, PSO, and ACO methods are listed in Table 5. The relative distance measures such as Euclidean, Cosine, Cityblock, Correlation, and Mahalanobis are given in Table 6. Generally, the Euclidean distance between two vectors is always greater than or equal to zero. The Cosine and Correlation distance range from + 1 to − 1. The Cityblock distance is also referred as Manhattan distance in which the distance is always greater than or equal to zero. The Mahalanobis distance is a measure of the distance between a point $X$ and a distribution $D$. The performance analysis of accuracy and error rate of KNN algorithm with various distance measures is given in Tables 7 and 8, respectively. The comparative analysis of accuracy and error rate of the proposed PSO–KNN with decision table, SVM, MLP, and KNN are shown in Tables 9 and 10, respectively.

The quantitative results of the KNN algorithm with different similarity measures such as Euclidean, Cosine, Cityblock, Correlation, and Mahalanobis have been compared and given in Table 7. It is observed that the highest and lowest recognition rates are 92.38, and 81.03%, respectively, with KNN algorithm. Among the similarity measures, Cosine similarity outperforms the others. Moreover, with Cosine similarity, the highest and lowest accuracies are 92.38, and 84.19%, respectively. The accuracies of decision table, SVM, MLP, KNN, and PSO–KNN with actual feature set are 87.07, 84.71, 87.60, 88.71, and 92.38%, respectively. The graphical representation of KNN algorithm with different similarity measures is given in Figs. 4 and 5.

The decision table reveals an accuracy of 90.64% for GA, 91.61% for PSO, and 91.29% for ACO, respectively. The highest accuracy obtained with decision table is 91.61% for PSO. The SVM provides accuracies of 89.67% for GA, 90.96% for PSO, and 89.80% for ACO, respectively. The highest accuracy obtained with SVM is 90.96% for PSO. The MLP exhibits accuracies of 90.32% for GA, 92.45% for PSO, and 92.84% for ACO, respectively. The highest accuracy obtained with SVM is 92.45% for PSO. The KNN reveals the highest accuracy of 94.20% for PSO.

**Table 2** GA parameter

| Parameter | Value |
|---|---|
| Population size | 10 |
| No. of generation | 10 |
| Probability of crossover | 0.9 |
| Probability of mutation | 0.2 |

**Table 3** PSO parameters

| Parameter | Value |
|---|---|
| Swarm size | 20 |
| Inertia weight | 0.72 |
| Personal learning coefficient | 1.4 |
| Global learning coefficient | 1.4 |

**Table 4** ACO parameters

| Parameter | Value |
|---|---|
| No. of ants | 10 |
| Pheromone exponential weight | 1 |
| Heuristic exponential weight | 1 |
| Evaporation rate | 0.08 |

Similarly, the error rates of decision table, SVM, MLP, KNN, and PSO–KNN with PSO feature selection method are 8.39, 9.04, 7.55, 5.8, and 2.59%, respectively.

From Tables 9, 10, and from Figs. 6 and 7, it is clearly understood that the proposed KNN–PSO gives a better result than decision table, SVM, MLP, and KNN. It is observed that the highest and lowest recognition rates are 97.41 and 92.38% with the KNN–PSO algorithm. The PSO with 26 features provides the accuracy of 97.41%, and for ACO with 30 features provides the accuracy of 96.45%. GA algorithm selects 34 features which provide the accuracy of 95.48%. Among these three algorithms, PSO provides higher accuracy with 97.41% which is 0.96% higher than ACO and 1.93% higher than GA with PSO–KNN.

The proposed face recognition model is also validated on the standard ORL face dataset and the attained results are given in Tables 11 and 12. The graphical representation of proposed PSO–KNN with existing benchmark algorithms on ORL dataset is given in Figs. 8 and 9. Among the metaheuristic population-based feature selection methods, PSO generates best feature subset for face recognition. In summary, features from PSO with the proposed PSO–KNN reveal more accuracy than decision table, SVM, MLP, and KNN.

In addition, the proposed method reveals better recognition rate and yet effective than ORB-based bag-of-interest points using RANSAC (ORB$^2$-IPR) proposed by Vinay et al. [33] and a case-based reasoning (CBR) human face recognition system under partial occlusion conditions [34]. The experimental results expound that the PSO–KNN provides more accuracy compared with uncorrelated discriminant SPP (UDSPP) algorithm [35].

**Table 5** Selected features using evolutionary algorithms

| Method | Selected features |
|---|---|
| GA | $f_{25}, f_{52}, f_{28}, f_{41}, f_{42}, f_{50}, f_{51}, f_{21}, f_{33}, f_{43}, f_{29}, f_{32}, f_{47}, f_{18}, f_{40}, f_{30}, f_{16}, f_{9}, f_{22}, f_{5}, f_{7}, f_{55}, f_{46}, f_{39}, f_{17}, f_{23}, f_{58}, f_{13}, f_{4}, f_{15}, f_{19}, f_{20}, f_{21}, f_{24}$ |
| PSO | $f_{11}, f_{13}, f_{15}, f_{16}, f_{18}, f_{20}, f_{21}, f_{22}, f_{26}, f_{27}, f_{29}, f_{30}, f_{31}, f_{32}, f_{33}, f_{35}, f_{36}, f_{37}, f_{38}, f_{39}, f_{41}, f_{43}, f_{45}\ f_{2}, f_{8}, f_{52}$ |
| ACO | $f_{23}, f_{31}, f_{57}, f_{44}, f_{47}, f_{21}, f_{25}, f_{22}, f_{55}, f_{43}, f_{17}, f_{56}, f_{35}, f_{13}, f_{7}, f_{52}, f_{2}, f_{15}, f_{29}, f_{49}, f_{40}, f_{26}, f_{4}, f_{38}\ f_{4}, f_{45}, f_{19}, f_{2}, f_{39}, f_{9}$ |

**Table 6** Relative distance measures

| Measure | Formula |
|---|---|
| Euclidean | $\sqrt{\sum_{i=1}^{n} (X_i - Y_i)^2}$ |
| Cosine | $\frac{\sum_{i=1}^{n} X_i Y_i}{\sqrt{\sum_{i=1}^{n} X_i^2}\sqrt{\sum_{i=1}^{n} Y_i^2}}$ |
| Cityblock | $\sum_{i=1}^{n} \lvert X_i - Y_i \rvert$ |
| Correlation | $\frac{COV(X,Y)}{STD(X)STD(Y)}$ |
| Mahalanobis | $\sqrt{(X_i - Y_i)^T S^{-1} (X_i - Y_i)}$ |

**Table 7** Performance analysis of accuracy of KNN algorithm with various distance measures

| | Euclidean | Cosine | Cityblock | Correlation | Mahalanobis |
|---|---|---|---|---|---|
| $K = 2$ | 89.03 | 92.38 | 90.65 | 90.06 | 89.03 |
| $K = 3$ | 86.83 | 88.71 | 89.03 | 87.94 | 86.84 |
| $K = 4$ | 87.1 | 89.03 | 86.65 | 86.71 | 85.03 |
| $K = 5$ | 83.94 | 86.39 | 85.48 | 85.74 | 83.94 |
| $K = 7$ | 81.03 | 84.19 | 83.10 | 82.65 | 81.06 |

**Table 8** Performance analysis of error rate of KNN with various distance measures

| | Euclidean | Cosine | Cityblock | Correlation | Mahalanobis |
|---|---|---|---|---|---|
| $K = 2$ | 10.97 | 07.62 | 09.35 | 09.94 | 10.97 |
| $K = 3$ | 13.17 | 11.29 | 10.97 | 12.06 | 13.16 |
| $K = 4$ | 12.90 | 10.97 | 13.35 | 13.29 | 14.97 |
| $K = 5$ | 16.06 | 13.61 | 14.52 | 14.26 | 16.06 |
| $K = 7$ | 18.97 | 15.81 | 16.90 | 17.35 | 18.94 |

**Table 9** Comparative analysis of accuracy of proposed PSO–KNN with existing benchmark algorithms

| | Decision table | SVM | MLP | KNN | PSO–KNN |
|---|---|---|---|---|---|
| Actual features | 87.07 | 84.71 | 87.60 | 88.71 | 92.38 |
| GA | 90.64 | 89.67 | 90.32 | 93.23 | 95.48 |
| PSO | 91.61 | 90.96 | 92.45 | 94.20 | 97.41 |
| ACO | 91.29 | 89.80 | 92.84 | 93.94 | 96.45 |

**Table 10** Comparative analysis of error rate of proposed PSO–KNN with existing benchmark algorithms

| | Decision table | SVM | MLP | KNN | PSO–KNN |
|---|---|---|---|---|---|
| Actual features | 12.93 | 15.29 | 12.4 | 11.29 | 7.62 |
| GA | 9.36 | 10.33 | 9.68 | 6.77 | 4.52 |
| PSO | 8.39 | 9.04 | 7.55 | 5.8 | 2.59 |
| ACO | 8.71 | 10.2 | 7.16 | 6.06 | 3.55 |

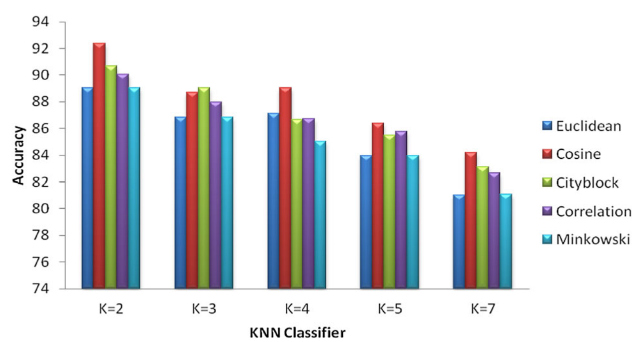


**Fig. 4** Performance analysis of accuracy of KNN algorithm

## 7 Conclusion and future enhancement

Face recognition is considered to be the most reliable method of biometric recognition. In this article, PSO–KNN is introduced for the first time for face recognition. Initially, a set of rich discriminatory information existing in the face image is extracted by utilizing LBP method. Typically, the biometric face has several irrelevant and redundant features, so the recognition of the face image is extremely difficult. In this research work, the dimensionality of the feature set is further reduced with the exploit of population-based algorithms such as GA, PSO, and ACO. The parameter 'K' in KNN algorithm is optimized using PSO method. Finally, the face recognition is done with the

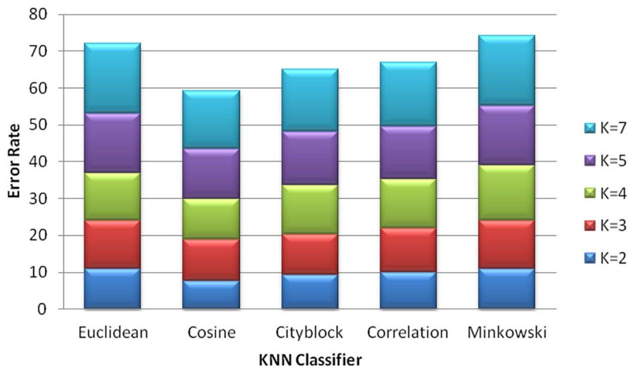


**Fig. 5** Performance analysis of error rate of KNN algorithm

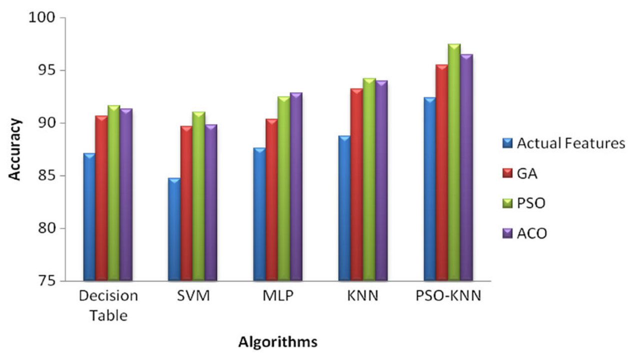


**Fig. 6** Performance analysis of accuracy of various algorithms

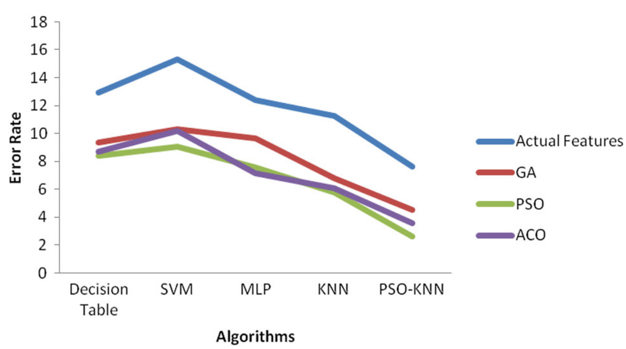


**Fig. 7** Performance analysis of error rate of various classifiers

**Table 11** Comparative analysis of accuracy of proposed PSO–KNN with existing benchmark algorithms on ORL dataset

| | Decision table | SVM | MLP | KNN | PSO–KNN |
|---|---|---|---|---|---|
| Actual features | 89.50 | 91.25 | 89.30 | 92.75 | 94.50 |
| GA | 90.25 | 92.50 | 91.50 | 94.25 | 96.25 |
| PSO | 93.25 | 95.0 | 93.75 | 95.43 | 98.75 |
| ACO | 91.25 | 92.87 | 92.25 | 94.50 | 97.50 |

**Table 12** Comparative analysis of error rate of proposed PSO–KNN with existing benchmark algorithms on ORL dataset

| | Decision table | SVM | MLP | KNN | PSO–KNN |
|---|---|---|---|---|---|
| Actual features | 10.5 | 8.75 | 10.7 | 7.25 | 5.5 |
| GA | 9.75 | 7.5 | 8.5 | 5.75 | 3.75 |
| PSO | 6.75 | 5.0 | 6.25 | 4.57 | 1.25 |
| ACO | 8.75 | 7.13 | 7.75 | 5.5 | 2.5 |

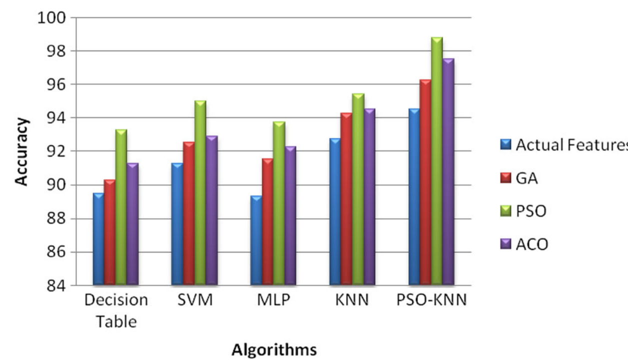


**Fig. 8** Performance analysis of accuracy of various classifiers on ORL dataset

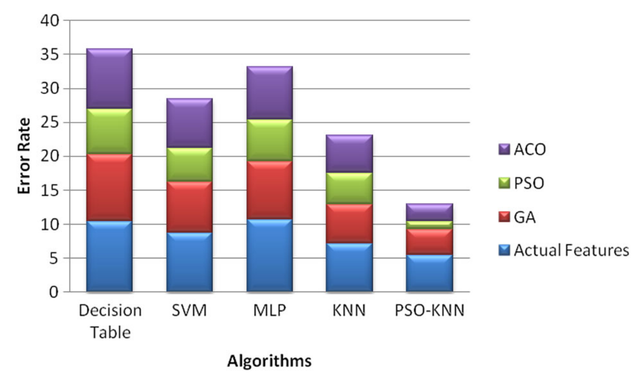


**Fig. 9** Performance analysis of error rate of various classifiers on ORL dataset

proposed PSO–KNN algorithm. The experimental results expound that the proposed PSO–KNN reveals better results than existing methods for recognition such as decision table, SVM, MLP, and KNN. Additionally, the PSO gives better accuracy with the smaller number of features than GA and ACO. Hence, the proposed method is effectual in recognizing other biometric modalities and simpler than CBR, ORB$^2$-IPR, and UDSPP method of face recognition. In future, variants of KNN will be incorporated with other optimization algorithms to recognize face image.

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## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflicts of interest.

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