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Evaluation of Performance in Optimization Algorithms for Face Recognition System

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ABSTRACT:

Face recognition systems play a crucial role in various security and authentication applications, where optimization algorithms significantly impact their performance. This study presents a comparative analysis of different optimization algorithms applied to feature selection, extraction, and classification in face recognition systems. We evaluate algorithms such as Particle Swarm Optimization (PSO), Fire Fly Optimization (FFO), Bee Colony Optimization (BCO), Bacterial Foraging Optimization (BFO), Ant Colony Optimization (ACO), Frog Leap Optimization (FLO), Bat Optimization (BO), Flower Optimization (FO) and Cuckoo Optimization (CO) methods in terms of accuracy, computational efficiency, error rate and robustness. Experiments are conducted using benchmark datasets to assess the impact of each algorithm on recognition rates, processing time, and scalability. The results highlight the strengths and weaknesses of each approach, demonstrating that heuristic and nature-inspired optimization techniques can enhance recognition accuracy while maintaining efficiency. The study provides insights into selecting the most suitable optimization technique for face recognition applications based on system requirements and computational constraints.

Keywords: Particle Swarm Optimization, Fire Fly Optimization, Bee Colony Optimization, Bacterial Foraging Optimization, Ant Colony Optimization, Frog Leap Optimization, Bat Optimization, Flower Optimization and Cuckoo Optimization

1. INTRODUCTION

Pattern recognition involved in the process of conversion of source data into machine readable form is termed as pre-processing of data. Pattern recognition domain consists of two types of frameworks: Statistical or fuzzy pattern recognition deals with noisy data and uncertainty whereas syntactic pattern or structural pattern recognition is based on formal language theory. In the statistical approach, patterns are viewed as features in n-dimensional space and the goal is to construct decision boundary to separate the patterns of different classes in feature space. In the syntactic pattern recognition, the patterns are represented as sentences of a language and the elementary sub patterns are termed as alphabet of a language and thus a complex pattern is composed of elementary sub patterns and grammatical rules which can be inferred from training data. The face recognition system discussed in this thesis falls under statistical pattern recognition.

2. FACE RECOGNITION SYSTEM

Face recognition governs a wide area in pattern recognition and computer vision for its numerous real time applications in the area of information security access, smart cards, law enforcement and surveillance systems. Face Recognition system consists of three main sections. The first section comprises face localization and extraction of features from the localized image. The second section is identification which requires searching, matching and comparing the extracted features with a database of known features. The third section is verification in which the compared features are verified so as to find whether the images are of same person thus making decisions easier.

3. OPTIMIZATION ALGORITHMS

Optimization algorithm serves as a tool in making decisions and examining physical systems. The goal is to find the best solution among all possible solutions. To achieve this, the objective function must be minimized or maximized subject to constraints. Optimizers can be designed for particular type of problems and it can use some structures such as ordered sets, least squares and quadratic objective functions to solve problems.

3.1 Particle Swarm Optimization

Particle Swarm Optimization is a stochastic optimization technique based on population holds some similarities with evolutionary computing. The algorithm can be applied in various fields such as function optimization, artificial neural networks and fuzzy systems [1]. It was inspired by the social behaviour of biological systems such as birds flocking or fish schooling to a food source. The searching ability was linked with optimization search for solutions. The procedure is as follows:

- Initialize all possible particles with its velocity throughout the search space in random manner.
- The algorithm updates each time step by reforming velocity and location of each particle by equations,

$$v_{id} = v_{id} + t\alpha_1(s_{id} - p_{id}) + t\alpha_2(s_{gd} - p_{id}) \quad (1.1)$$

$$p_{id} = p_{id} + v_{id} \quad (1.2)$$

where v_{id} is velocity of particle at dimension d, p_{id} is current particle, s_{id}, s_{gd} are best solutions before and after updating respectively, t is a constant, $\alpha_1$and α_2 are random numbers generated at every updating.

- The updating continues until the velocity reached v_{max} which is a threshold to limit the velocity of particle and s_{gd} is the best solution.

3.2 Firefly Algorithm

Firefly algorithm is a nature inspired Meta heuristic algorithm designed for optimization based on the flashing attributes of fireflies [2]. A firefly is characterized by its unique flashing pattern and is influenced by light attenuation on the distance and mutual attraction. The algorithm represents the special feature as all fireflies are unisex so that the attractiveness inversely proportional to distance but directly proportional to brightness and the light intensity is limited by light absorption coefficient, γ.

The position of i^{th} firefly which is attracted to j^{th} firefly after $(t+1)^{th}$ movement is given by,

$$x_i(t+1) = x_i(t) + \alpha\left(x_j(t) - x_i(t)\right) + \gamma \quad (1)$$

3.3 Artificial Bee Colony Optimization

Artificial Bee Colony (ABC) optimization is inspired by the intelligent behaviour of honey bees. Artificial bee colony algorithm meant for optimizing multivariable functions [3]. The algorithm contains colony size and maximum cycle number as parameters and the process includes the following steps:

- Compute the amount of nectar by directing employed and onlooker bees to the food source
- Find the scout bees
- Move them into available food sources

3.4 Bacterial Foraging Optimization

Bacterial Foraging Optimization Algorithm (BFOA) is inspired by the foraging behaviour of *Escherichia coli* and it has been recognized as global optimization algorithm. The algorithm can be used to solve optimization problems [4]. The algorithm can be used with soft computing techniques for higher efficiency [5]. The foraging decision taken by a bacterium depends on two factors, the chemo tactic movement to a food source and cell to cell communication by conveying signals.

In computation, the movement of the bacterium is given by,

$$\varphi_i(j+1,k,l) = \varphi_i(j,k,l) + C(i)\alpha(i) \quad (2)$$

where$\varphi_i(j,k,l)$ denotes i^{th} bacterium at j^{th} chemo tactic, k^{th} reproductive and l^{th} elimination and dispersal step, $C(i)$ is step size and $\alpha(i)$ is the random direction.

The function representing cell to cell attraction is given by,

$$J_{cc}(\varphi, P(j,k.l)) = \sum_{i=1}^{S} J_{cc}(\varphi, \varphi_i(j,k,l)) \quad (3)$$

3.5 Ant Colony Optimization

Ant Colony Optimization (ACO) algorithm is inspired by the foraging behaviour of a group of ants [6]. Later it can be extended to solve continuous optimization problems [7]. Pheromones and incremental solution are the main specifications in ant colony optimization. Apart from initialization step, the algorithm is composed of few steps. Develop ants solution under probability theory which is followed by a local search, then the pheromone detail is updated and the process is iterated until the termination criteria is convinced.

3.6 Frog Leap Optimization

Frog Leap Optimization algorithm is designed to solve global optimization problems [8]. The algorithm consists of feasible solutions described by a set of frogs which are subdivided as memeplexes and each memeplex performs a local search by modifying the information hold by an individual frog results in the evolution of memes. As memetic evolution proceeds, the information is passed among memeplexes in a shuffling process. Both local search and shuffling process pursues until the constraints are converged.

3.7 Bat Algorithm

Inspired by the echolocation behaviour of bats, bat algorithm was designed [9]. The formulation of bat algorithm has been generalized to three rules.

- Bats sense the distance and can able to perceive the difference between food and obstacle.
- Bats fly at a random velocityv_i, frequency F_{min} with varying wavelength and loudness in searching for prey.
- Depending on the location of the prey, they can adjust the wavelength or frequency automatically.

3.8 Flower Algorithm

Inspired by the characteristics of flower pollination, flower algorithm was developed to solve multi objective optimization problems [10]. The following rules are applied for implementing flower algorithm in computation.

- In global optimization process, pollinators such as birds, flies, bees and bats carry the pollen and move in a particular way.
- Self-pollination is used for local pollination
- Flower consistency is maintained by pollinators which is proportional to reproduction probability lead to the similarity of two flowers.
- Both local and global optimization can be controlled by a switch probability $p \epsilon [0,1]$

3.9 Cuckoo Search

A meta heuristic optimization algorithm called Cuckoo Search which is the inspiration of brood parasitism behavior of cuckoo species which involves laying eggs in the nest of other birds [11]. For implementing as an algorithm, each egg is represented as a solution and the search can be idealized into three rules.

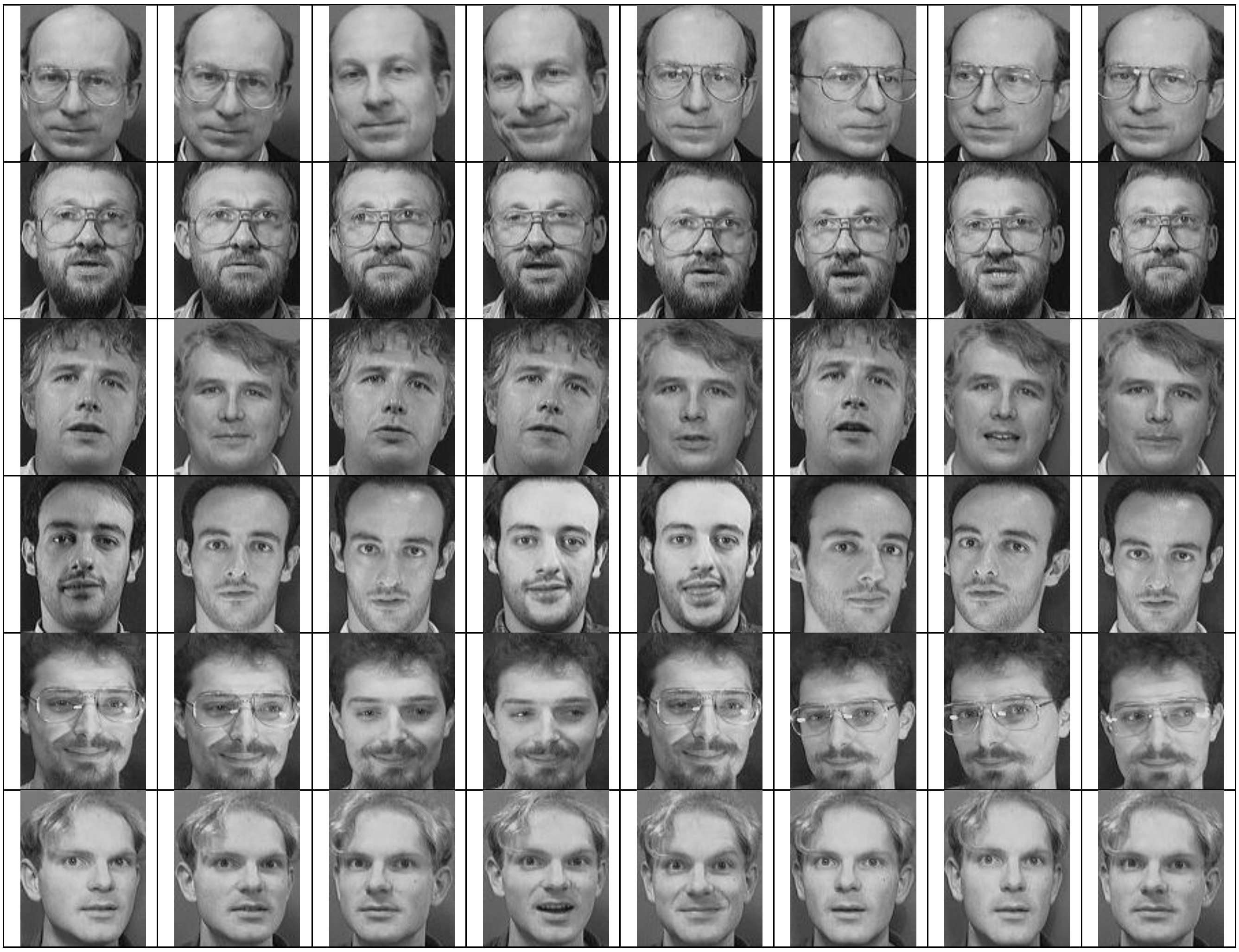
- Each bird lays an egg at a time and leaves it in host bird's nest which is randomly chosen.
- Best eggs (solutions) with its nest can be carried over to the next generations.
- As host nests are fixed, the host bird can either throw the egg or leave the nest so as to build a new nest in a new location.

4. RESULTS AND DISCUSSION

Experiments are verified using ORL and JAFFE data sets and the simple description of the data sets and performance comparison graphs are given below:

ORL: The database contains images of 40 individuals and each subject had its own 10 variations of pose, time, expression and illumination conditions. An example is shown in Figure 1.

JAFFE: The Japanese Female Facial Expression database contains images of 10 distinct persons, under same illumination and different face expressions. An example is given in Figure 2.



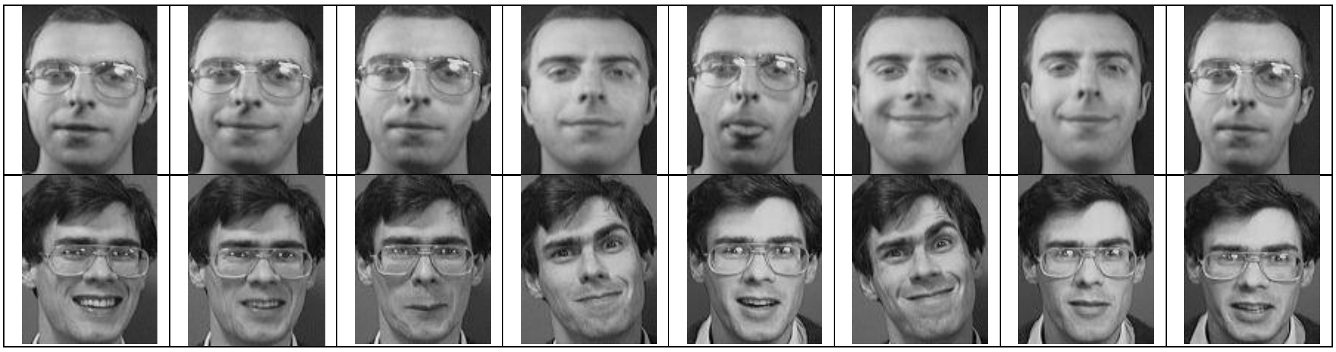


Figure 1 Sample images from ORL database and each dataset had its own variations of pose, time, expression and illumination conditions

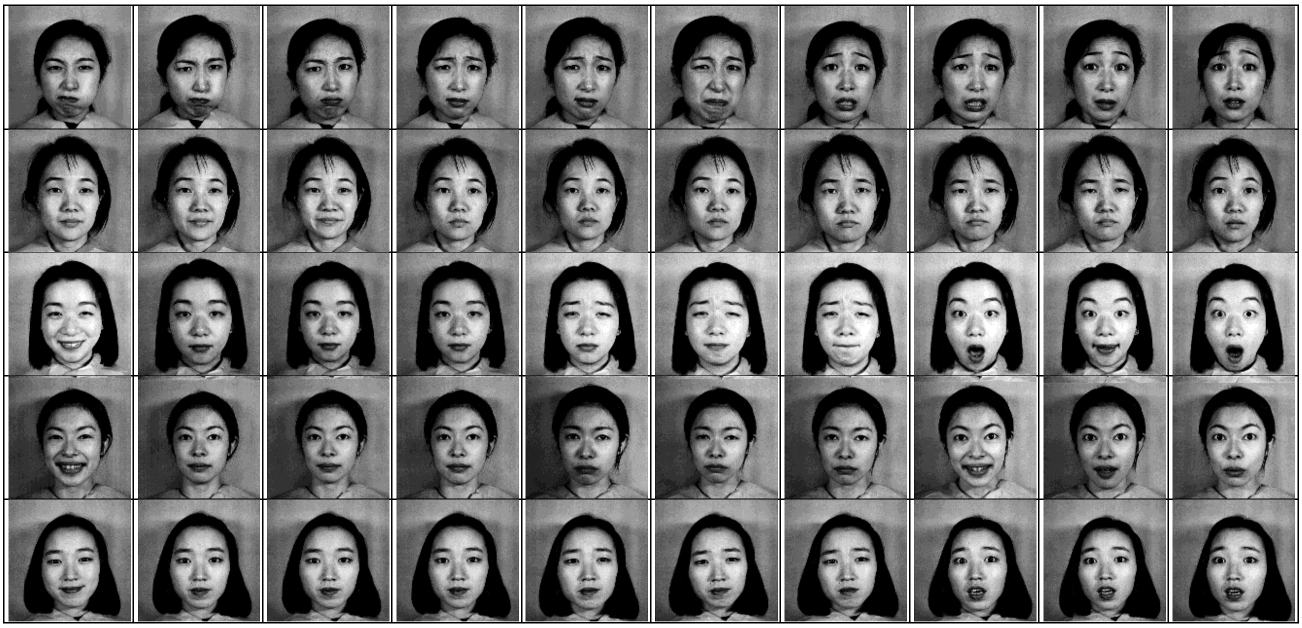
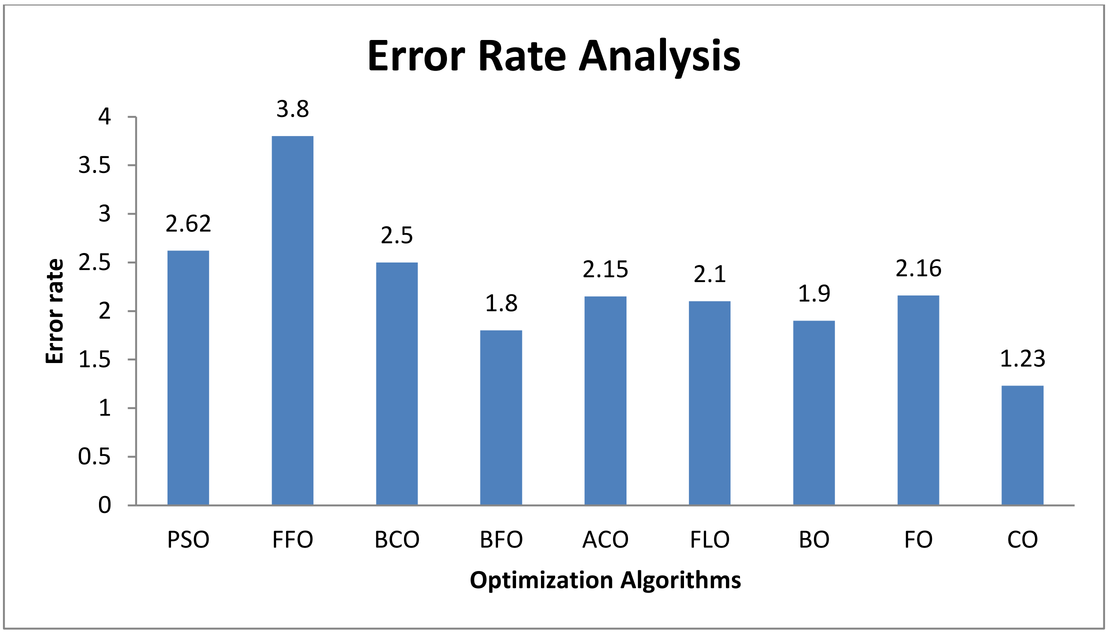


Figure 2 Sample images of JAFFE database under same illumination and different face expressions

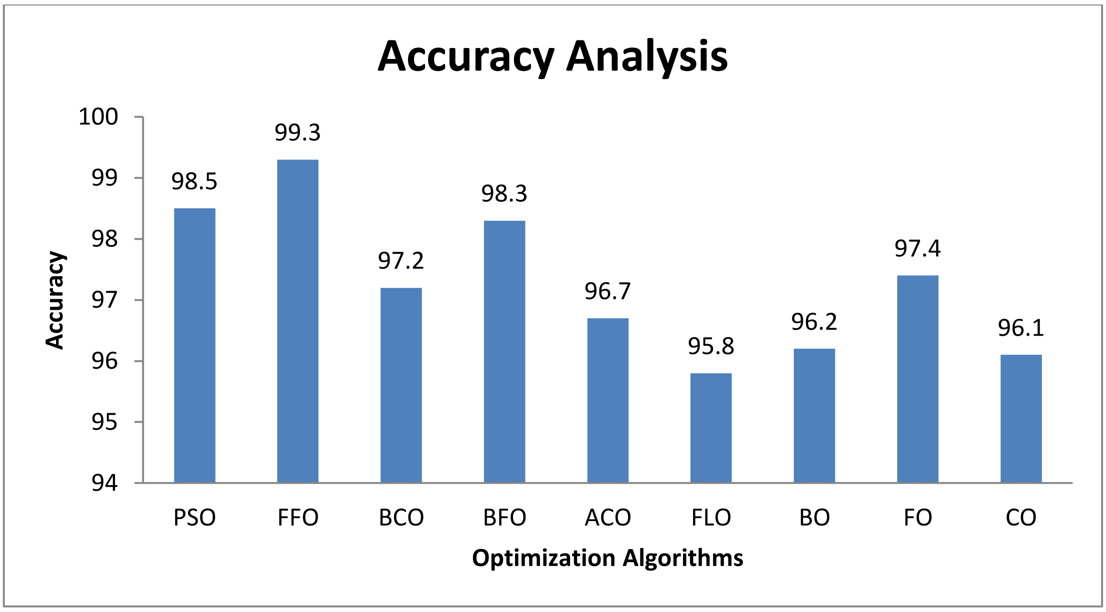
4.1 Error Rate Analysis:

When examining error rate with the above datasets, the number of training images may vary from 50 to 250 images. From the figure 3, it is observed that bacterial foraging optimization attains low error rate.



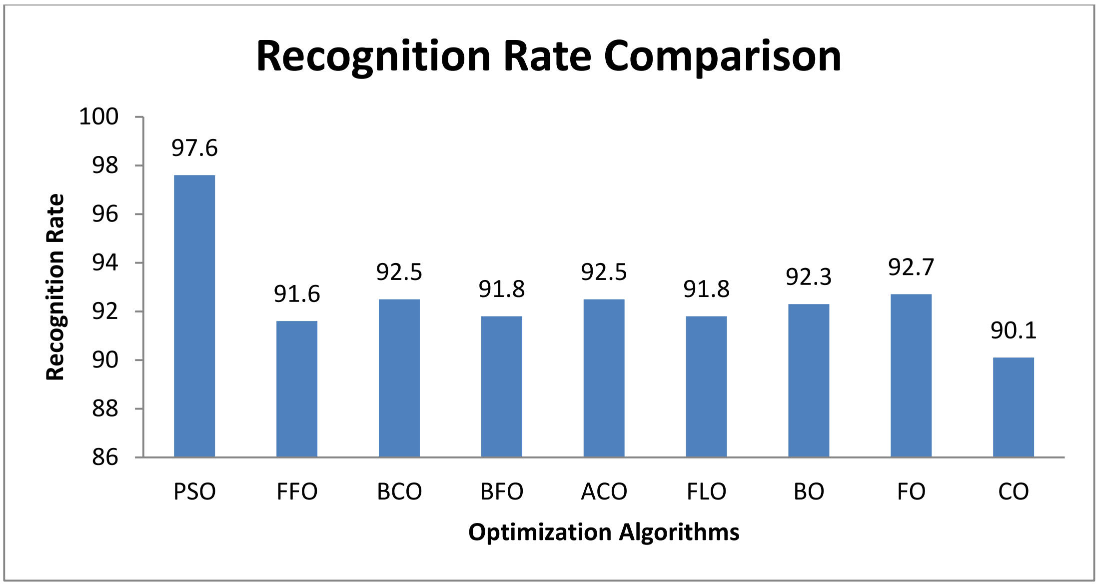
4.2 Accuracy Analysis:

When examining accuracy rate with the above datasets, the number of training images may vary from 50 to 250 images. From the figure 4, it is observed that fire fly optimization attains higher accuracy rate.



4.3 Recognition Rate Analysis:

When examining recognition rate with the above datasets, the number of training images may vary from 50 to 250 images. From the figure 5, it is observed that particle swarm optimization attains higher recognition rate.



5. CONCLUSION

In conclusion, the performance comparison of optimization algorithms in face recognition systems highlights the significant impact of algorithm selection on accuracy, efficiency, and computational cost. Through empirical evaluation, it is evident that different optimization techniques exhibit varying levels of effectiveness depending on factors like dataset complexity, feature extraction methods, and model architecture. In this research, some algorithms excel in achieving lower error rate, higher recognition rate and accuracy, making them suitable for real-time applications. Ultimately, selecting the optimal algorithm requires a balance between precision and efficiency, tailored to the specific needs of the face recognition system. Further research can explore hybrid optimization approaches to enhance overall performance and adaptability.

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