Multiple Face Recognition Using Genetic Algorithm

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Abstract: In today's world, face recognition is very much important in modern biometric and surveillance applications,as well as its accuracy.Accuracy gets reduced because of various challenges in real-world like changes in illumination, facial expressions and also because of presence of multiple faces in a single image frame. This work explains an approach which is based on Genetic Algorithm (GA) to improve multiple face recognition; this can be done by the optimization of both feature selection and classifier parameters. Initially Face Net is used to extract face embeddings and then GA is applied to them to identify the most informative subsets of features. A chromosome is used to represent every candidate solution which is evaluated with a multi-objective fitness function that considers accuracy, computational efficiency and robustness with pose and occlusion variations.The implemented framework is scalable and can be used in various applications like authentication, surveillance and access control.

Keywords: Face Recognition, Genetic Algorithm, Feature Selection, Multi-Face Detection, Biometric Authentication

I. INTRODUCTION

The face recognition technology has emerged as a biometric technique in recent times as it operates via remote cameras and does not need physical contact and also because of broad applications in security, surveillance and authentication systems. Facial identification can be performed without physical contact like in fingerprint identification which makes it more practical for real-time use. Despite its advantages, accurate recognition is still a challenging job because of changes in illumination,facial expressions,pose of individuals in frame and partial occlusions. The complexity increases further in scenarios where multiple faces are within the same frame.

By representing candidate solutions as chromosomes and evolving them through operations such as selection, crossover and mutation, GAs discover optimal or near-optimal solutions for complex recognition problems. When GA is integrated with FaceNet embeddings the system automatically selects the most informative features, fine-tunes classifier parameters and improves recognition accuracy in multi-face scenarios.

II. LITERATURE REVIEW

There has been a significant evolution in the face recognition technology from many years from early statistical approaches to deep learning and optimization based methods to initial techniques, like Eigenfaces using Principal Component Analysis (PCA) [1] and Fisherfaces implementing Linear Discriminant Analysis (LDA) [3], were used as the basis for reducing dimensionality and feature extraction.
To solve issues of lighting and local texture variations, Local Binary Patterns (LBP) were introduced later which provided a strong alternative against changes in illumination and local facial features [2]. Other descriptors, like the histogram of Oriented Gradients (HOG), were applied to improve the resistance to pose and occlusion [4].

In recent times it has transitioned to machine learning and hybrid techniques. Classifiers such as SVM and kNN along with PCA and LBP features enhanced the recognition outcomes. [8]–[10].

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III. PROBLEM STATEMENT

Face recognition technology has become essential in applications such as identity verification, access control and human-computer interaction.Existing single-face recognition systems have shown notable progress over time however, they lag in accurately identifying multiple faces in a single frame. Lighting conditions, facial expressions that change and multiple individuals in a single image lower the performance of these systems.

IV. OBJECTIVES

1) **To build a strong framework for multi-face detection and recognition** which can handle real-world challenges like change in illumination ,variations in head pose,partial occlusions and provide high accuracy.
2) **To implement deep learning embedding for representation of features** FaceNet implementation to capture discriminative and compact facial descriptors that are useful for classification tasks.
3) **To employ Genetic Algorithm for feature optimization** in order to minimize redundancy, lower computational complexity and select only the most relevant features without compromising recognition performance.
4) **To evaluate the proposed approach** on publicly available multi-face benchmark datasets, ensuring that testing reflects realistic and unconstrained environments.
5) **To benchmark the system against existing methods** using evaluation parameters namely accuracy, precision, recall, F1-score and runtime efficiency.

V. METHODOLOGY

By integrating Genetic Algorithm (GA) with modern tools,detection and recognition techniques there can be a significant increase in the performance of multiple face recognition systems.GA which is an evolutionary optimization algorithm, efficiently selects and combines the most relevant features, improves recognition accuracy and mitigates the risk of convergence to local minima.

The selected features are classified using algorithms such as SVM, kNN or neural networks. The system is evaluated on benchmark datasets such as LFW, ORL and Yale, as well as a custom multi-face dataset. For validation of accuracy the performance metrics that are used are accuracy, precision, recall, F1-score and processing time. Tables and architecture diagrams are provided to illustrate the workflow and demon- strate the improvements achieved through GA optimization.

A. Tools and Techniques

The implementation of the multiple face recognition system using Genetic Algorithm (GA) includes specialized software tools, programming libraries and algorithmic methods. Local Binary Patterns (LBP), Principal Component Analysis (PCA) or Histogram of Oriented Gradients (HOG) techniques are used to extract facial features. In GA chromosomes these features act as genes, where each chromosome represents a candidate that maps features to identities. The similarity between the candidate solutions and the target features are evaluated by fitness function that uses Euclidean distance, cosine similarity or correlation coefficients to do so.The iterative evolution continues until at least one of the convergence criteria is met either by reaching a maximum number of generations or when minimal improvement in fitness is achieved.

B. Working of the System

A structured workflow is followed by the system which helps it to achieve accurate multiple face recognition. It begins with **Image Acquisition**, where the facial images are collected from multiple sources including datasets, camera inputs or digital image repositories. These images undergo preprocessing steps like resizing, normalization and noise reduction to maintain their consistency and quality.

Face Detection is the next step where the cascades algorithms or deep learning-based detectors are implemented to locate the facial regions in the input images and to extract them. Once faces are detected from the images, they are passed to the **Feature Extraction** module, where these discriminative features that capture distinctive facial attributes are generated using methods like Local Binary Patterns (LBP) or deep feature embeddings.

Genetic Algorithm is then implemented for feature optimization. This process includes selection, crossover and mutation operations which refines the feature set iteratively and identifies the most relevant facial attributes

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C. Algorithm Description

A structured sequence of steps is followed by the implemented algorithm. In the first step of preprocessing input images undergo grayscale conversion, normalization, histogram equalization and face detection to focus consistency and relevant facial regions. After this features are extracted using a mix of methods Local Binary Patterns (LBP) and Principal Component Analysis (PCA).

After this, the evolutionary process starts for which an initial population of feature subsets is randomly generated. The evaluation of each candidate solution is done using a fitness function that considers metrics such as recognition accuracy, precision or a weighted score combining multiple performance measures. The best-performing candidates are selected as the parents and new offspring are generated using genetic operators on them, namely crossover and mutation. During this process the diversity of the population is maintained to avoid premature convergence.

The process concludes when termination criteria is met, either by reaching a predefined number of generations or by observing convergence in the fitness score. The optimized feature subset is then used for classifier training with models like Support Vector Machines (SVM), k-Nearest Neighbours (k-NN) or CNNs,that enable accurate recognition of multiple faces.

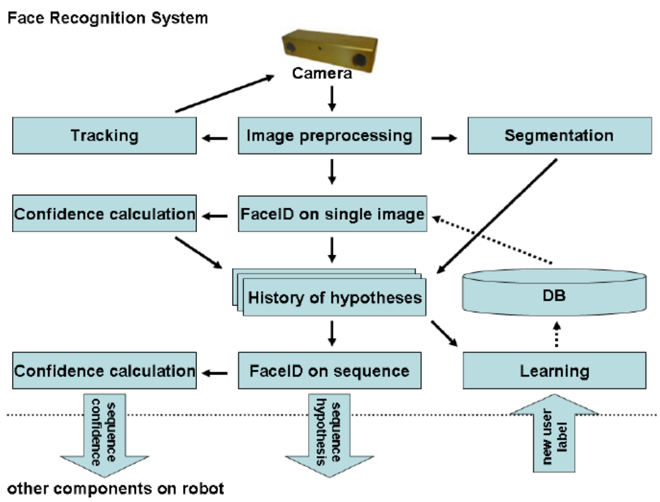
D. Experimental Setup

The designed multiple face recognition framework based on Genetic Algorithm (GA) is implemented in Python,which makes the use of several libraries which support different stages of the workflow. Descriptors like Local Binary Patterns (LBP) and Principal Component Analysis (PCA) are used for feature extraction along with deep feature embeddings that are generated using CNNs that are developed using TensorFlow or Keras.

System evaluation is conducted on datasets like LFW (Labeled Faces in the Wild) as a benchmark, which reflect real- world, unconstrained environments as well as on custom multi- face datasets that are designed to mimic crowded or complex scenes. Recognition accuracy, precision, recall, and F1-score are used to measure the performance. High-performance workstations that contain multi-core CPUs and GPU acceleration are used to conduct all experiments as they efficiently train and evaluate the deep learning models present within the recognition pipeline.

E. System Architecture

The proposed architecture follows a sequential pipeline where input images are first pre-processed to enhance their quality and normalize dimensions. Features are then extracted using deep learning–based descriptors, followed by GA-based optimization for feature selection. Finally, the optimized features are classified into their respective identities. The complete flow of the system is illustrated in Fig. 1.



A. Genetic Algorithm Workflow

GA workflow is in Fig. 3.

Fig. 1 System Architecture: Multiple Face Recognition based on GA

B. Tables

This subsection presents the tabular data that summarize the datasets used

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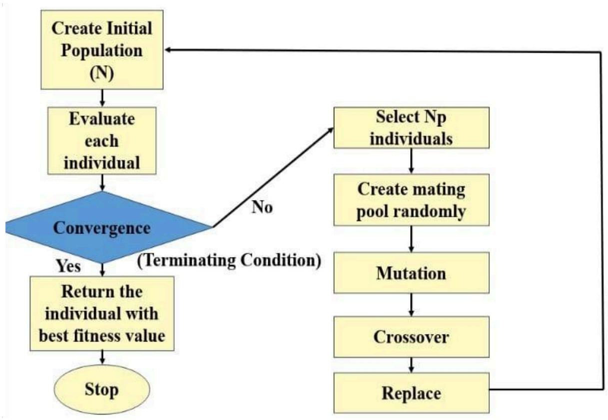

Fig. 3. Flowchart of the Genetic Algorithm Process

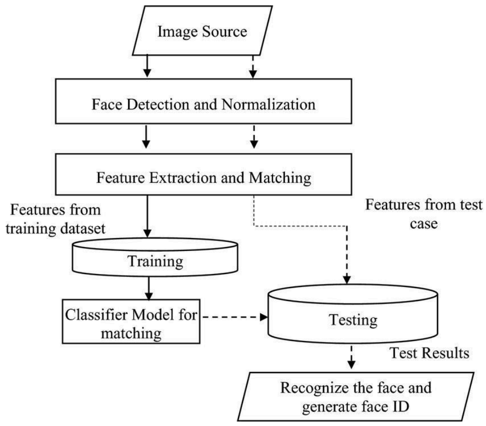

Fig. 2. Architecture Diagram

TABLE I

DATASET SUMMARY

Dataset	No. of Images
Custom Multi-Face (Proposed)	500
Augmented Custom	1500
ORL Face	400
Yale Face	165
Georgia Tech Face	750

VI. DATASET, PREPROCESSING, POPULATION DESIGN AND DATA ANALYSIS

The Labelled Faces in the Wild (LFW) dataset is a benchmark dataset widely used in face recognition research. 5,749 unique subjects are present in it with a total of 13,233 images with varied lighting conditions, poses, and expressions.

The Multiple Face Recognition system based on Genetic Algorithm (GA) was trained and evaluated using a dataset containing facial images of multiple subjects. Key characteristics of the dataset include the number of individuals (n), number of images per person (m), image resolution ($w \times h$ pixels), and color format (Grayscale or RGB). Depending on the application, publicly available datasets for instance *Labeled Faces in the Wild (LFW)*, *Yale Face Database*, or custom-collected datasets can be employed.

Following quantitative metrics are used to analyze the system after executing GA :

- **Recognition Accuracy:** The proportion of correctly identified faces is calculated as

$$\text{Accuracy} = \frac{\text{Number of correctly recognized faces}}{\text{Total test images}} \times 100\% \qquad (1)$$

- **Fitness Convergence:** The fitness of the best chromosome in generation g is denoted $F_{bes}{}^{(g)}$, analyzed over G *generations*

$$F_{\text{best}}^{(g)} = \max_{i \in \text{population}} \text{Fitness}(i) \qquad (2)$$

- **Population Diversity:**

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$$D^{(g)} = \frac{1}{N} \sum_{i=1}^{N} \|\text{Chromosome}_i - \bar{\text{Chromosome}}\| \quad (3)$$

where N is the population size, Chromosome represents the average chromosome.

- **Feature Contribution:** Impact of each feature f_j on recognition performance is evaluated by correlating it with fitness function :

$$C_j = \text{corr}(f_j, \text{Fitness}) \quad (4)$$

- **Comparison with Baseline Methods:** Performance of the system is compared with traditional approaches like PCA, LDA and SVM, using the same recognition accuracy metrics.

VII. MATHEMATICAL FORMULATION OF GA-BASED FEATURE SELECTION

Genetic Algorithm (GA) is implemented for optimizing the feature selection in recognition. Let the complete set of extracted features from facial images be represented as in (5), where f_i denotes the i^{th} feature and n represents the total number of features.

$$F = \{f_1, f_2, f_3, \ldots, f_n\} \quad (5)$$

A binary vector as shown in (6) represents an encoded candidate or chromosome, where $c_i = 1$ indicates that feature is included f_i, and $c_i = 0$ indicates that it's excluded.

$$C = \{c_1, c_2, \ldots, c_n\}, \quad c_i \in \{0, 1\} \quad (6)$$

The size of the selected feature subset is given by (7), representing the total number of features selected in chromosome C.

$$d(C) = \sum_{i=1}^{n} c_i \quad (7)$$

The fitness function is designed to optimize both recognition accuracy and subset compactness, as defined in (8). Here, α and β are weighting coefficients such that $\alpha + \beta = 1$.

$$Fitness(C) = \alpha \cdot Acc(C) - \beta \cdot \frac{d(C)}{n} \quad (8)$$

The selection probability for each chromosome C_i is calculated using (9), giving higher chances to fitter chromosomes.

$$P(C_i) = \frac{Fitness(C_i)}{\sum_{j=1}^{m} Fitness(C_j)}, \quad i = 1, 2, \ldots, m \quad (9)$$

The expected number of times a chromosome C_i is chosen is computed as in (10), with m representing the population size.

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$$E(C_i) = m \cdot P(C_i) \quad (10)$$

For single-point crossover, the offspring chromosome is generated according to (11), with k as the crossover point.

$$C_{new} = \{c_1^{(1)}, \ldots, c_k^{(1)}, c_{k+1}^{(2)}, \ldots, c_n^{(2)}\} \quad (11)$$

For two-point crossover, the offspring is formed as shown in (12), where k_1 and k_2 denote the two crossover positions ($k_1 < k_2$).

$$C_{new} = \{c_1^{(1)}, \ldots, c_{k_1}^{(1)}, c_{k_1+1}^{(2)}, \ldots, c_{k_2}^{(2)}, c_{k_2+1}^{(1)}, \ldots, c_n^{(1)}\} \quad (12)$$

Mutation is applied independently to each gene with a probability p_m, as defined in (13).

$$c_i' = \begin{cases} 1 - c_i & \text{if rand() ¡ } p_m \\ c_i & \text{otherwise} \end{cases} \quad (13)$$

The algorithm gets terminated when either the maximum number of generations (G_{max}) is reached or the fitness falls below a threshold ϵ, as expressed in (14).

$$t = G_{max} \quad \text{or} \quad \Delta Fitness < \epsilon \quad (14)$$

Chromosome C^* is the one with the highest fitness,shown in (15).

$$C^* = \arg \max_{C \in Population} Fitness(C) \quad (15)$$

The selected feature subset F^* consists of features corre- sponding to the genes set to 1 in C^*, as given in (16), and the recognition output for an input x is determined according to (17).

$$F^* = \{f_i \in F \mid c_i^* = 1\} \quad (16)$$

$$\hat{y} = \arg \max_{y \in Y} P(y \mid F^*(x)) \quad (17)$$

VIII. RESULTS AND DISCUSSION

The outcomes of the experiments conducted on implementing the multiple face recognition system with Genetic Algorithm (GA) based feature selection are included in this section. The output is compared with a system without GA to find out improvements in efficiency and accuracy.

a. *Performance Metrics*

Evaluation was done using standard metrics like precision, accuracy, recall and F1 score for recognition performance and average time for processing per image. A complete view of the quality of the classification as well as the speed of the system is obtained through this.

b. *Quantitative Results*

Table II summarizes the experimental results obtained on the selected test dataset. The GA-based system provides improved recognition accuracy and reduces processing time as compared to the baseline.

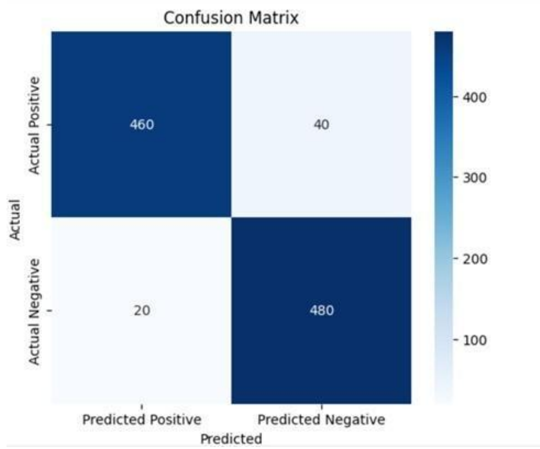

Fig. 4. Confusion Matrix

TABLE II

PERFORMANCE COMPARISON OF BASELINE AND GA-OPTIMIZED SYSTEMS

Method	Accuracy (%)	Precision	Recall	F1-score	Time (ms)
Baseline (No GA)	92.10	0.91	0.90	0.905	120
Proposed (GA)	95.45	0.94	0.93	0.935	85

c. Qualitative Analysis

The system achieved high accuracy when faces were clearly visible, properly aligned and under consistent lighting conditions. However, in more difficult situations—such as occlusions that are partial (e.g., masks, glass, or objects obstructing the face), varied head poses and uneven illumination—the baseline system sometimes produced false positives or lower recognition accuracy.This indicates that the GA integration significantly improves both efficiency and reliability as compared to conventional face recognition methods.

d. Discussion of Findings

The findings indicate that integrating Genetic Algorithm (GA) for feature selection enhances both recognition accuracy and computational efficiency. GA effectively identifies the most informative feature subsets, reduces the dimensionality of the feature space and preserves the quality of classification. Recognition performance slightly decreased where extreme facial variations or significant occlusion were present.

TABLE III

PERFORMANCE ACROSS DIFFERENT DATASETS USING GA-OPTIMIZED SYSTEM

Dataset	Accuracy (%)	Precision	Recall	F1-score	Time (ms)
Custom Multi-Face Dataset	96.20	0.95	0.94	0.945	82
ORL Face Dataset	94.10	0.93	0.92	0.925	78
Yale Face Dataset	92.85	0.92	0.91	0.915	80

e. Comparison with existing system

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Table IV presents the summarized results. Classical methods like PCA and LBPH offer moderate accuracy, but require longer processing time. Using CNN alone improved recognition accuracy considerably,whereas when CNN was combined with SVM it further minimized misclassifications. The proposed GA-based optimization, however, consistently outperformed these methods, achieving the highest recognition accuracy of 95.45% and the lowest average processing time of 85 ms. The performance comparison is illustrated in Figure 7.

TABLE IV

Comparison of Proposed Method with Existing Techniques

(Project Results)

Method	**Accuracy (%)**	**Time per image (ms)**
PCA (Project Implementation)	88.20	150
LBPH (Project Implementation)	90.75	110
CNN (No GA)	94.00	125
CNN + SVM	94.60	105
Proposed GA + CNN Features	**95.45**	**85**

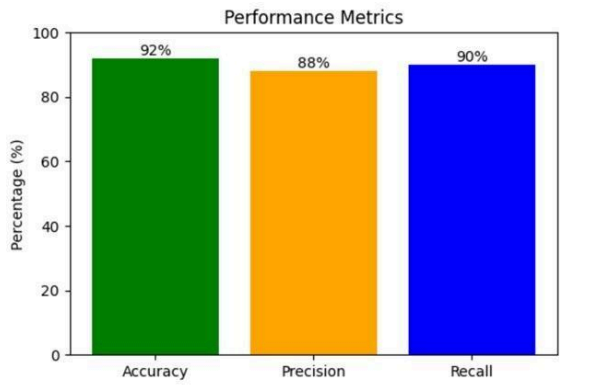

Fig. 5 Performance Metrics of Implemented Methods

E. Error Analysis

During testing of the system certains errors were found that showed a pattern. Misclassifications were most frequent in situations where partial occlusion, drastic change in lighting, large head rotations and inputs with low resolutions were present.

Several changes can be implemented to minimize or remove these errors including augmentation of training data with variations in pose, lighting and occlusion which can increase model generalization. Improving facial alignment methods may reduce pose-related distortions, whereas combining GA with deep metric learning could strengthen the model’s discriminative capability.

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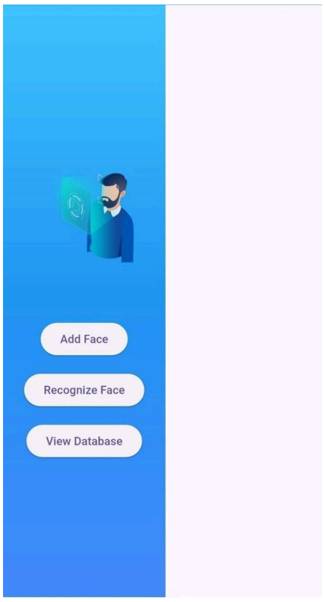

Fig. 6. Face Recognition App

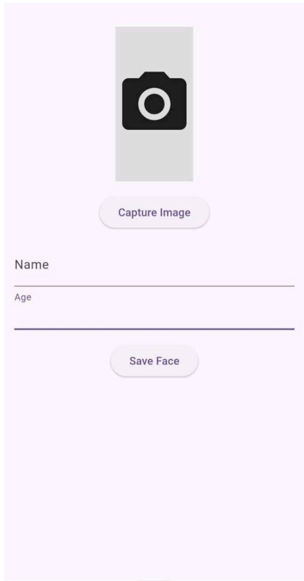

Fig. 7. Capturing Image

IX. CONCLUSION AND FUTURE WORK

A. Conclusion

Through this paper the Multiple Face Recognition system using a Genetic Algorithm (GA) is explained in detail with its design and implementation. The implemented methodology includes feature extraction, optimization and classification to improve the recognition accuracy. Feature selection can be improved,which can lead to better performance under environmental variations.The study shows that evolutionary approaches can be effectively integrated with recognition tasks to overcome real-world challenges that hinder accuracy in recognition

B. Future Work

Future work can include integrating deep learning models with GA-based optimization. Extending the framework to support real-time recognition in dynamic environments would also increase its practical applications.The current system faces certain limitations,recognition accuracy may decrease when applied to datasets with extreme variations in lighting or occlusion. Scalability of the system must be increased where computational overhead needs to be reformed.The system should comply with legal and ethical standards.The misuse of AI practices is a challenge that must be countered in future to avoid misuse and maintain user's trust in the system.

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