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# A TRANSFER LEARNING–BASED FRAMEWORK FOR GENDER RECOGNITION UNDER POSE AND ILLUMINATION VARIATIONS USING PRE-TRAINED CONVOLUTIONAL NEURAL NETWORKS

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***ABSTRACT***:

Accurate gender classification from facial images is a fundamental task in computer vision with applications in security, human-computer interaction, and intelligent systems. In this study, we propose a robust framework that combines deep feature extraction using a pre-trained convolutional neural network with a multilayer perceptron classifier optimized via a metaheuristic Grasshopper Optimization Algorithm. The CNN extracts discriminative features from facial images, while the optimized MLP ensures efficient and accurate classification by overcoming local optima issues commonly encountered in conventional training methods. The proposed method was evaluated on the GENDER-FERET dataset, achieving a test accuracy of 98.94% and demonstrating balanced performance across male and female classes, with precision, recall, and F1-scores exceeding 98% for both categories. The experimental results highlight the framework's robustness against variations in facial pose, illumination, and expression. This approach provides a reliable and efficient solution for gender recognition and offers a flexible foundation for future extensions to real-time applications and multi-task facial analysis systems.

***Keywords***: *Gender Classification, Face Recognition, Convolutional Neural Network, Grasshopper Optimization Algorithm, Feature Extraction, Multilayer Perceptron, Deep Learning, Metaheuristic Optimization*.

## INTRODUCTION

Gender recognition from facial images has attracted considerable attention in the field of computer vision due to its broad range of applications, including human–computer interaction, surveillance systems, demographic analysis, access control, and intelligent advertising [1], [2]. Accurate gender classification provides valuable semantic information that can enhance the performance of higher-level vision systems. Despite significant progress, achieving reliable gender recognition in real-world environments remains a challenging task.

A major source of difficulty in gender recognition arises from variations in facial appearance caused by changes in pose and illumination conditions [3]. In unconstrained environments, facial images are often captured under diverse lighting setups and from different viewing angles, resulting in substantial intra-class variations. These factors can obscure discriminative gender-related features and significantly degrade classification performance, particularly in surveillance and outdoor imaging scenarios.

Early studies on gender recognition primarily relied on handcrafted feature extraction methods combined with conventional machine learning classifiers [4], [5]. Techniques such as local binary patterns (LBP), histogram of oriented gradients (HOG), Gabor filters, and geometric facial features were widely explored. While these methods achieved reasonable accuracy under controlled conditions, their performance deteriorated notably in the presence of pose and illumination variations. Moreover, handcrafted features require domain expertise and often lack robustness and generalization across different datasets.

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The emergence of deep learning, particularly convolutional neural networks (CNNs), has revolutionized facial analysis and gender recognition tasks [6], [7]. CNN-based models automatically learn hierarchical feature representations from raw images, removing the need for manual feature engineering. Numerous studies have demonstrated that deep CNNs outperform traditional approaches in terms of accuracy and robustness. However, training deep networks from scratch typically demands large-scale labeled datasets and high computational costs, which limits their applicability in many practical situations.

To overcome these limitations, transfer learning using pre-trained convolutional neural networks has been widely adopted [8], [9]. In this approach, CNN models pre-trained on large benchmark datasets are fine-tuned for target tasks such as gender recognition. Transfer learning enables effective knowledge reuse, faster convergence, and improved performance even when training data are limited. Despite these advantages, ensuring robustness under severe pose and illumination variations remains an unresolved challenge.

Existing transfer learning–based gender recognition methods may still experience performance degradation when exposed to extreme pose angles or complex lighting conditions [10]. In addition, improper fine-tuning strategies and suboptimal feature utilization can result in overfitting and reduced generalization capability. Consequently, designing a robust gender recognition framework that effectively exploits pre-trained CNNs while maintaining high accuracy under challenging imaging conditions is still an open research problem.

In this paper, a robust gender recognition framework is proposed, which combines pre-trained convolutional neural networks for deep feature extraction with a multilayer perceptron classifier optimized using the Grasshopper Optimization Algorithm. The proposed approach first extracts discriminative facial features from pre-trained CNN models and then employs a metaheuristic-based MLP to achieve accurate gender classification. This strategy enhances the model's robustness to variations in pose, illumination, and facial expressions, while reducing the dependency on large-scale annotated datasets. Extensive experiments on the GENDER-FERET dataset demonstrate that the proposed method outperforms existing approaches in terms of accuracy, precision, recall, and F1-score.

The main contributions of this work are summarized as follows:

- A novel gender recognition framework that integrates pre-trained CNN feature extraction with a Grasshopper-optimized MLP classifier.
- Effective mitigation of pose, illumination, and expression variations in facial images through deep feature learning and optimized classification.
- Use of metaheuristic optimization to enhance the learning capability and generalization of the classifier with limited training data.
- Comprehensive experimental evaluation demonstrating superior performance compared to state-of-the-art gender classification methods.

The remainder of this paper is organized as follows. Section 2 reviews related work on gender recognition and transfer learning–based approaches. Section 3 presents the proposed methodology. Section 4 describes the experimental setup and discusses the results. Finally, Section 5 concludes the paper and outlines future research directions.

## RELATED WORK

Automatic gender recognition has attracted significant attention in computer vision due to its wide range of applications, including biometrics, human–computer interaction, demographic analysis, surveillance, and retail systems. The objective of gender recognition is to identify an individual's gender based on visual appearance and facial characteristics. In [3], a CNN-based framework was proposed in which salient images were first generated from raw facial images to highlight discriminative features. These salient representations were then used as inputs to CNN models for feature extraction, followed by feature fusion and classification using a support vector machine (SVM). Experimental results on the Adience dataset demonstrated that the proposed framework achieved effective gender recognition and showed robustness in highly unconstrained environments.

Human gender recognition is also considered a crucial demographic tool with applications in forensic science, surveillance, and targeted marketing. Traditional approaches relied heavily on handcrafted features extracted from standard facial images, which were highly sensitive to image quality and environmental variations. To overcome these limitations, the authors in [4] introduced a deep learning–based method for gender recognition from non-standard selfie images. The proposed approach was evaluated on multiple benchmark datasets, including Adience, LFW, FERET, NIVE, Caltech WebFaces, and CAS-PEALR1, achieving an accuracy of 89% on selfie images, thereby demonstrating its effectiveness in unconstrained scenarios.

Age and gender classification from facial images has also been extensively studied. In [5], a CNN-based approach with an efficient network architecture was proposed to improve generalization capability on unconstrained facial image datasets. Experimental evaluations on Adience and other benchmark datasets showed that the proposed method outperformed existing models in both age and gender classification tasks. Similarly, the work in [6] focused on improving age and gender estimation using enhanced CNN architectures, achieving a gender classification accuracy of 94.01% on the UTKFace dataset and demonstrating improved computational efficiency and generalization.

The influence of deep CNN architectures on facial attribute estimation has been further explored in [7], where large-scale facial image analysis revealed that facial features could be used to infer sensitive attributes with high accuracy. Although not directly focused on gender recognition, this study highlighted the discriminative power of facial representations learned by deep networks. In [8], frequency-domain filters were employed for feature extraction, and the extracted features were classified using SVM, achieving an accuracy of 96% on the Gender FERET dataset.

Real-time gender recognition systems based on CNNs were proposed in [9] and [12], where deep neural networks were trained on large facial image datasets and demonstrated high accuracy in both training and validation phases. These systems were shown to effectively recognize gender in complex facial images with high computational efficiency, making them suitable for real-time and security-related applications.

Several studies have addressed joint age and gender estimation using improved CNN architectures. In [10] and [11], deep learning–based approaches were introduced to enhance robustness and computational performance, achieving gender recognition accuracies exceeding 98% on benchmark datasets such as UTKFace and IMDB-WIKI. Similarly, the works in [13] and [14] explored age and gender estimation using CNN-based frameworks combined with traditional classifiers, reporting competitive accuracy and fast decision-making capabilities.

More recent research has focused on hybrid and optimized deep learning models. In [15], a CNN-based framework combined with fuzzy logic filtering was proposed for age and gender recognition, achieving an accuracy of 96% with reduced processing time. Transfer learning–based approaches were investigated in [16], where different DCNN architectures were evaluated under various input resolutions and fine-tuning strategies to balance accuracy and latency, particularly for embedded systems.

Additional studies explored optimized CNN architectures and hybrid feature extraction methods. In [18], an AlexNet-based model optimized using the Taguchi method demonstrated improved gender recognition accuracy on the CIA and MORPH datasets. Alternative biometric modalities were investigated in [19], where a hybrid CNN–SVM framework was applied to fingerprint-based gender classification, achieving an accuracy of 97.5%. Furthermore, advanced hybrid models integrating attention mechanisms and recurrent networks were proposed in [20] to improve age and gender classification performance.

Finally, local descriptor–based methods combined with dimensionality reduction techniques were explored in [21], where local binary patterns (LBP) and local phase quantization (LPQ) were integrated with Self-PCA for gender classification. Experimental results on the FG-NET and ORL datasets demonstrated improved accuracy compared to traditional handcrafted feature-based approaches.

With the rise of convolutional neural networks (CNNs), deep feature-based methods have shown significant improvement in gender classification accuracy. Hassanat et al. [22] proposed a deep learning framework for face, gender, and expression recognition under constrained conditions, demonstrating high accuracy using pre-trained CNN models. Ozbulak et al. [23] investigated the transferability of CNN-based features for age and gender classification and highlighted the effectiveness of leveraging pre-trained networks in limited-data scenarios. Greco et al. [24] evaluated gender recognition in the wild, emphasizing robustness against corrupted and unconstrained images. Makinist and Aydin [25] introduced a deep learning approach using face vectors without classical feature extraction, achieving competitive results in gender classification tasks. Berbar [26] explored CNN-based methods for facial gender classification, reporting high performance with simple architectures and emphasizing the importance of proper feature learning.

Although these studies achieved notable success, most approaches either relied solely on pre-trained CNN features with conventional classifiers or lacked metaheuristic optimization to improve classifier generalization. In this work, we propose a hybrid framework that combines pre-trained CNN feature extraction with a multilayer perceptron optimized using the Grasshopper Optimization Algorithm, which enhances classification performance and robustness, particularly in unconstrained and variable facial image conditions.

## PROPOSED METHODOLOGY

In this paper, a hybrid gender recognition framework is proposed to improve classification accuracy under challenging illumination variations and facial pose changes. The proposed method leverages a pre-trained convolutional neural network, AlexNet, as a robust feature extractor and employs an optimized multilayer perceptron (MLP) classifier for final gender classification. To enhance the classification performance and overcome the limitations of conventional fully connected layers, the Grasshopper Optimization Algorithm (GOA) is utilized to optimize the parameters of the MLP classifier.

Unlike conventional CNN-based approaches that rely solely on the fully connected layers of deep networks for classification, the proposed framework replaces these layers with an optimized external classifier. The motivation behind this design choice is that the fully connected layers of CNNs often behave similarly to simple perceptrons and may fail to achieve optimal discrimination performance, particularly under significant illumination changes and facial rotations. By adopting a transfer learning strategy, discriminative deep features extracted from the pre-trained AlexNet are transferred to a more flexible and optimizable classification module.

Transfer learning plays a crucial role in the proposed framework by enabling the reuse of knowledge learned from large-scale datasets such as ImageNet. This approach significantly reduces the need for extensive training data, accelerates the learning process, and improves generalization performance. Furthermore, the integration of the Grasshopper Optimization Algorithm allows the classifier to adaptively learn optimal parameters, leading to enhanced robustness against variations in lighting conditions and facial orientation.

The overall architecture of the proposed gender recognition framework, including feature extraction, optimization, and classification stages, is illustrated in **Figure 1.** As shown in the Figure 1, the framework consists of sequential processing stages that collectively address the challenges posed by illumination variations and face rotation.

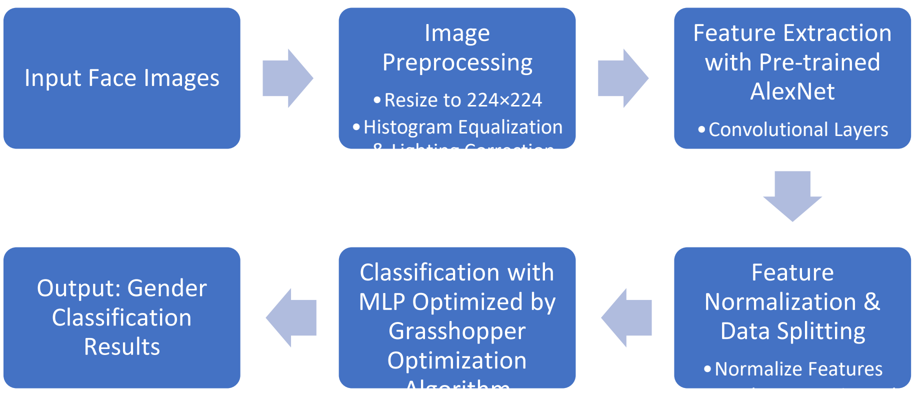


**Fig.1. Block diagram of proposed method**

As illustrated in Figure 1, the proposed gender recognition framework is implemented through a sequence of well-defined processing stages. First, the input facial images undergo a preprocessing step to reduce noise and mitigate the effects of illumination variations. Next, optimized deep features are extracted using a pre-trained convolutional neural network based on the AlexNet architecture. The extracted features are then normalized and the dataset is appropriately divided into training and testing subsets to ensure reliable evaluation. Finally, the normalized deep features are classified using a multilayer perceptron whose parameters are optimized via the Grasshopper Optimization Algorithm, leading to improved classification accuracy under variations in lighting conditions and facial pose.

In the following subsections, the proposed methodology is described in detail. Section 3.1 presents the preprocessing stage applied to the input facial images. Section 3.2 describes the optimal feature extraction process using the pre-trained AlexNet convolutional neural network. Section 3.3 explains the normalization of the extracted features and the partitioning of the dataset into training and testing subsets. Finally, Section 3.4 details the gender classification process using a multilayer perceptron optimized by the Grasshopper Optimization Algorithm.

**3-1 Image Preprocessing of Input Facial Images**

In the preprocessing stage, all input facial images are first resized to 224 × 224 pixels to match the input dimensions of the AlexNet convolutional neural network. Maintaining consistent input dimensions is crucial for ensuring uniformity across the dataset and for leveraging the pre-trained weights of the network, which can enhance both learning efficiency and overall performance.

Illumination variations pose a major challenge in facial image analysis, as uneven lighting can create shadows or areas of high and low intensity, potentially obscuring key facial features such as the contours of the eyes, lips, and other distinctive regions. To address these issues, image enhancement techniques such as histogram equalization and lighting correction are applied. These preprocessing steps improve the quality of the input data and enable the model to learn more stable and discriminative features.

Facial pose variations, caused by angular rotations of the head, represent another significant challenge. To increase the robustness and generalization capability of the model, data augmentation strategies are employed, including:

- Rotation: Rotating images by angles (e.g., ±15°) to simulate head orientation variations.
- Translation: Shifting images horizontally or vertically to account for facial position changes within the frame.
- Scaling: Slightly zooming in or out to handle variations in distance from the camera.
- Horizontal flipping: Mirroring images along the vertical axis to simulate opposite facial orientations.
- Random noise addition: Incorporating Gaussian or salt-and-pepper noise to improve tolerance to low-quality images.
- Brightness and contrast adjustments: Randomly modifying lighting conditions to simulate diverse illumination scenarios.

These augmentation techniques collectively produce a diverse and enriched dataset, enhancing the model's ability to learn features that are robust to noise, rotation, and lighting variations.

Class imbalance is another critical consideration in many facial image datasets, where certain classes may have significantly fewer samples. This imbalance can bias the model toward majority classes, reducing accuracy on underrepresented classes. To mitigate this issue, several strategies are applied:

- Targeted data augmentation: Generating more samples for minority classes to balance the dataset.
- Synthetic sample generation: Using techniques such as SMOTE to create artificial samples for underrepresented classes.
- Under-sampling majority classes: Reducing the number of samples in dominant classes while preserving essential information.
- Class weighting: Assigning higher weights to minority classes in the loss function to penalize misclassification more heavily.

Integrating these preprocessing and augmentation strategies ensures improved accuracy, generalization, and robustness of the model under diverse illumination conditions, facial rotations, and class imbalances.


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### 3-2 Feature Extraction Using Convolutional Neural Network

Convolutional Neural Networks (CNNs) are specialized deep learning models designed to process grid-structured data, such as images, and automatically extract discriminative features. Unlike traditional neural networks, CNNs leverage convolution operations rather than matrix multiplications, allowing them to efficiently learn hierarchical representations from the input data. A key advantage of CNNs is the ability to optimize filters during training, eliminating the need for handcrafted features and enabling real-time adaptability.

In this study, the pre-trained AlexNet architecture is employed for feature extraction. AlexNet consists of 11 layers: five convolutional layers, three max-pooling layers, and three fully connected layers. In the proposed framework, the fully connected layers are omitted, as classification is performed separately using a transfer learning strategy with an optimized Multilayer Perceptron (MLP) classifier. The layers used for feature extraction are summarized as follows:

- **Convolutional Layers:** Apply multiple learnable filters to the input image to extract various features, such as edges, textures, and patterns.
- **ReLU Layers:** Introduce non-linearity by mapping negative activations to zero while preserving positive values, ensuring efficient and faster training.
- **Pooling Layers:** Perform non-linear down-sampling, reducing the dimensionality of feature maps while retaining salient information, thereby simplifying subsequent layers.

The feature extraction procedure of AlexNet is described below. The input image of size 3 × 224 × 224 passes through the first convolutional layer with 96 kernels of size 11 × 11, stride 4, and padding 2, producing 96 feature maps of size 55 × 55. These are activated by a ReLU function and forwarded to a max-pooling layer with a 3 × 3 kernel, stride 2, producing 96 feature maps of size 27 × 27. Subsequent convolutional layers progressively extract higher-level features with increasing kernel numbers (e.g., 256, 384, 384, 256), interleaved with ReLU activations and pooling layers to reduce spatial dimensions (e.g., 13 × 13, 6 × 6). At the end of this process, the resulting feature maps, containing highly discriminative representations of facial images, are stored for the classification stage.

Figure 2 illustrates the layer configuration of AlexNet, while Table 1 summarizes the specifications of the layers used for feature extraction, including input/output sizes, kernel dimensions, stride, and padding.

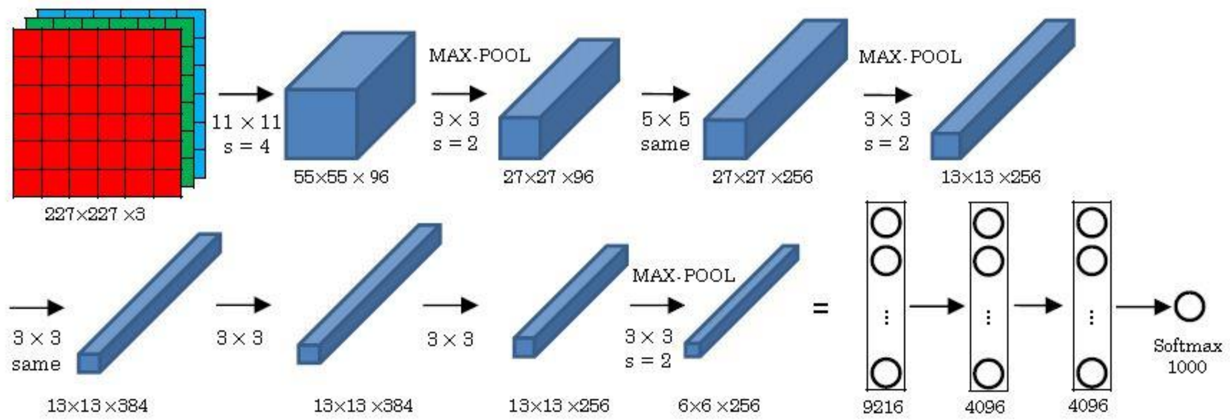


**Fig. 2. AlexNet network layers**

**Table 1: Summary of AlexNet Layers for Feature Extraction**

| Input | Layer Type | # Filters | Filter Size | Stride | Padding | Output Size |
|---|---|---|---|---|---|---|
| **224×224×3** | Convolution | 96 | 11×11 | 4 | 0 | 55×55×96 |
| **55×55×96** | Pooling | 1 | 3×3 | 2 | - | 27×27×96 |
| **27×27×96** | Convolution | 256 | 5×5 | 1 | 2 | 27×27×256 |
| **27×27×256** | Pooling | 1 | 3×3 | 2 | - | 13×13×256 |
| **13×13×256** | Convolution | 384 | 3×3 | 1 | 1 | 13×13×384 |

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| | | | | | | |
|---|---|---|---|---|---|---|
| **13×13×384** | Convolution | 384 | 3×3 | 1 | 1 | 13×13×384 |
| **13×13×384** | Convolution | 256 | 3×3 | 1 | 1 | 13×13×256 |
| **13×13×256** | Pooling | 1 | 3×3 | 2 | - | 6×6×256 |

**3-3 Normalization and Data Splitting**

After extracting the optimized features, the next step is to normalize the feature set before classification. Normalization ensures that all features are scaled to a consistent range, which helps the neural network treat all inputs equally during training. Without normalization, features with larger numerical values could disproportionately influence the training process, leading to biased parameter updates. In this study, feature normalization is performed using the following equation:

(1)

where X represents the original feature value,  denotes the normalized value, and  and  correspond to the minimum and maximum values of the feature set, respectively. Once normalization is completed, the dataset is divided into training and testing subsets. Specifically, 80% of the data is allocated for training, and the remaining 20% is used for evaluation and testing. The training set, along with its corresponding labels, is fed into the neural network to adjust its parameters such that the predicted outputs closely match the actual labels. After training, the performance of the model is assessed using the test set, providing an unbiased evaluation of its generalization capability.

**3-4 Classification Using Optimized MLP with Grasshopper Optimization Algorithm**

In this step, the features extracted by the pre-trained AlexNet convolutional neural network are classified using a transfer learning approach. Transfer learning implies that instead of using the fully connected layers of the CNN for classification, the extracted features are fed into a separate classifier. The primary advantage of this approach is a significant reduction in training time, along with often higher accuracy. Training a deep neural network from scratch requires a large dataset, extensive computational resources, and considerable training time. In transfer learning, the majority of the network responsible for feature extraction is pre-trained and kept fixed, while only a small portion, namely the new classifier, requires training. This not only reduces the required training time but also improves the robustness of the model to noisy or previously unseen data, as the general features learned by the pre-trained network provide better generalization.

In this work, a multilayer perceptron (MLP) is employed as the classifier. To enhance classification accuracy, the training of the MLP is optimized using the Grasshopper Optimization Algorithm (GOA). This metaheuristic algorithm determines the optimal weights and biases of the network, reducing the likelihood of the network being trapped in local optima and improving overall classification performance.

An MLP is a type of feedforward neural network widely used for classification and function approximation. It typically consists of an input layer, one or more hidden layers, and an output layer. In conventional MLP training, the backpropagation algorithm is used to minimize the mean squared error between the predicted output and the ground truth. Each neuron computes a weighted sum of its inputs, adds a bias term, and passes the result through an activation function. The output of each neuron can be expressed as:

(2)

where  is the output of neuron j,  is the input,  is the weight associated with input i,  is the bias term, and  is the activation function, which can be a sigmoid, hyperbolic tangent, or other non-linear function. During conventional backpropagation, the network adjusts the weights and biases iteratively in the forward and backward passes to minimize the prediction error. In the proposed approach, this optimization process is enhanced by the Grasshopper Optimization Algorithm, which efficiently searches for optimal weight and bias values, improving classification accuracy and convergence speed compared to standard backpropagation.

**3-4-1 Optimization of the Perceptron Classifier Using the Grasshopper Optimization Algorithm**

One of the main limitations of the conventional backpropagation algorithm for training neural networks is its tendency to get trapped in local optima. This occurs when the training error reaches a low value, causing the algorithm to stop, while further iterations could lead to an even lower error and improved network accuracy. To overcome this limitation, in this study, the Grasshopper Optimization Algorithm (GOA) is employed instead of standard backpropagation for training the multilayer perceptron (MLP). GOA, due to its exploration and


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exploitation capabilities, effectively avoids local optima. Initially, the algorithm performs extensive global search and gradually reduces the exploration factor to focus on exploiting the best solutions discovered in the search phase.

To apply GOA for optimizing the MLP, its parameters must be configured according to the problem. The key steps are as follows:

• **Grasshopper population and structure:** The first step is to define the grasshopper population. In this case, each grasshopper represents a candidate solution for the MLP, where one dimension corresponds to a network weight and the other to a bias. A population of such grasshoppers is initialized for each generation.

• **Evaluation of population members:** In each iteration, all grasshoppers are evaluated using a fitness function. Candidates that achieve lower classification error in the training process have a higher probability of being selected for the next generation. The classifier error is used as the cost function, which the algorithm seeks to minimize:

(3)

This formula represents the Mean Squared Error (MSE), which calculates the average of the squared differences between the actual values and the predicted values over samples.

• **Population update based on fitness:** After each iteration, a new population is generated based on the fitness values. Grasshoppers move in search space influenced by three main factors:

1. Wind advection
2. Gravitational force
3. Attraction towards other grasshoppers

The position update equation is formulated as:

(4)

where is the updated position of the i-th grasshopper, represents social interaction with other grasshoppers, the gravitational force, and the wind advection component. The interaction between two grasshoppers is modeled by a distance-dependent function , which prevents premature convergence in the initial iterations:

(5)

where and are scaling and attraction coefficients, and is the distance between grasshopper and .

• **Stopping criteria:** The algorithm terminates when either the maximum number of iterations is reached or the classifier error does not improve after a certain number of consecutive iterations.

This optimization procedure ensures that the MLP converges to a near-global optimum, providing higher classification accuracy and improved generalization performance compared to traditional backpropagation.

## EXPERIMENTS AND RESULTS

This section presents the experimental setup, evaluation metrics, and quantitative results obtained from the proposed gender recognition framework. The performance of the suggested method is evaluated under variations in illumination and facial pose to demonstrate its robustness and effectiveness.

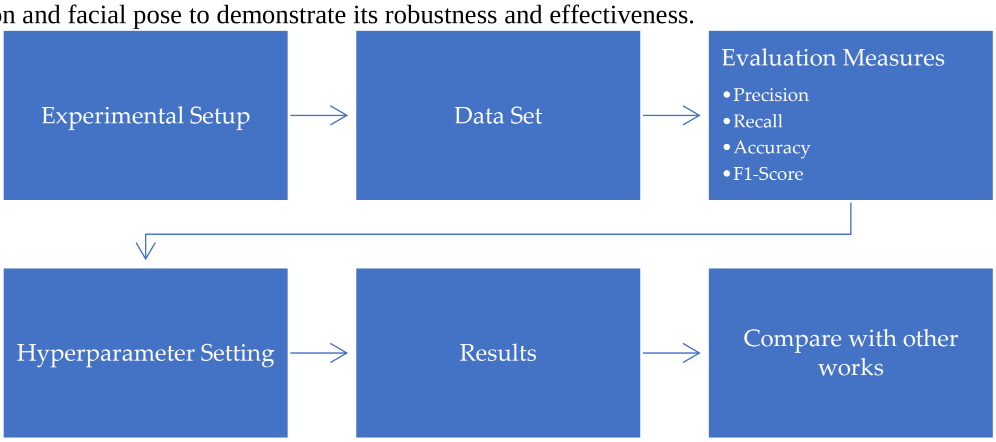


**Fig. 3. Evaluation Process of proposed method**


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**4-1 Experimental Setup**

All experiments were conducted to assess the effectiveness of the proposed transfer learning-based framework for gender recognition. Facial images were first preprocessed according to the procedure described in Section 3, including resizing, illumination normalization, and data augmentation. Feature extraction was performed using the convolutional layers of the pre-trained AlexNet model, while classification was carried out using an MLP optimized by the Grasshopper Optimization Algorithm (GOA).

The dataset was divided into training and testing subsets, with 80% of the data used for training and 20% reserved for testing. To ensure fair evaluation, all experiments were performed using the same data split and preprocessing configuration.

**4-2 Data set**

The experiments in this study were conducted using the GENDER-FERET facial image dataset. This dataset consists of an equal number of male and female facial images and is pre-divided into training and testing subsets. Specifically, the training set contains 474 images, including 237 male and 237 female samples, while the test set includes 472 images, comprising 236 male and 236 female samples.

The GENDER-FERET dataset contains frontal facial images captured under controlled conditions. Variations in illumination, background, age, facial expression, and ethnicity are intentionally included to enhance the diversity of the dataset and to better reflect real-world scenarios. Despite these variations, environmental factors such as camera setup and acquisition conditions remain consistent, ensuring controlled data quality.

An important characteristic of this dataset is that only one facial image per individual is included, and each subject appears exclusively in either the training set or the test set, but not in both. This strict separation prevents subject overlap between training and testing phases, thereby enabling a fair and unbiased evaluation of the model’s generalization capability.

Figure 4 illustrates sample facial images from the GENDER-FERET dataset, demonstrating the diversity in gender, illumination conditions, and facial characteristics.

**Fig. 4. Samples of dataset**

**4-3 Evaluation measures**

To evaluate the performance of the proposed method, several widely used classification metrics were employed, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the classifier’s effectiveness, particularly in the presence of class imbalance. There are four entities in the confusion matrix: true positive (TP), false positive (TN), true negative (FP), and false negative (FN). The formula for each entity is shown in equations (6) to (9). The results are compared with the following evaluation criteria based on the values of the entities in the confusion matrix.

(6)
(7)
(8)
(9)

**4-4 Hyperparameter Settings**

Hyperparameter tuning plays a crucial role in achieving optimal performance in deep learning and metaheuristic-based classification models. In the proposed framework, different sets of hyperparameters are involved in the feature extraction stage, feature normalization, and classification using an MLP optimized by the Grasshopper Optimization Algorithm (GOA). To ensure fair and stable performance, several tuning strategies, including grid-based search and empirical evaluation, were employed to determine the optimal hyperparameter values.


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**4-3-1 Hyperparameter Settings for Feature Extraction Using AlexNet**

In this study, AlexNet is used as a pre-trained feature extractor, and its convolutional layers are kept fixed to preserve the learned representations. Since transfer learning is adopted, no retraining of convolutional layers is performed. However, several parameters related to feature extraction are carefully selected to ensure compatibility with the GENDER-FERET dataset.

The input image size is fixed at **224 × 224 × 3**, consistent with the AlexNet architecture. Features are extracted from the final pooling layer, which provides high-level and discriminative representations while avoiding the fully connected layers that are task-specific. This strategy reduces computational complexity and prevents overfitting, especially when the number of training samples is limited. **Table 2** summarizes the main hyperparameter settings used for feature extraction.

**Table 2: Hyperparameter Settings for AlexNet Feature Extraction**

| Parameter | Value |
|---|---|
| Input Image Size | 224 × 224 × 3 |
| Pre-trained Model | AlexNet |
| Trainable Layers | None (Frozen) |
| Feature Extraction Layer | Final Pooling Layer |
| Activation Function | ReLU |
| Feature Dimension | 9216 |

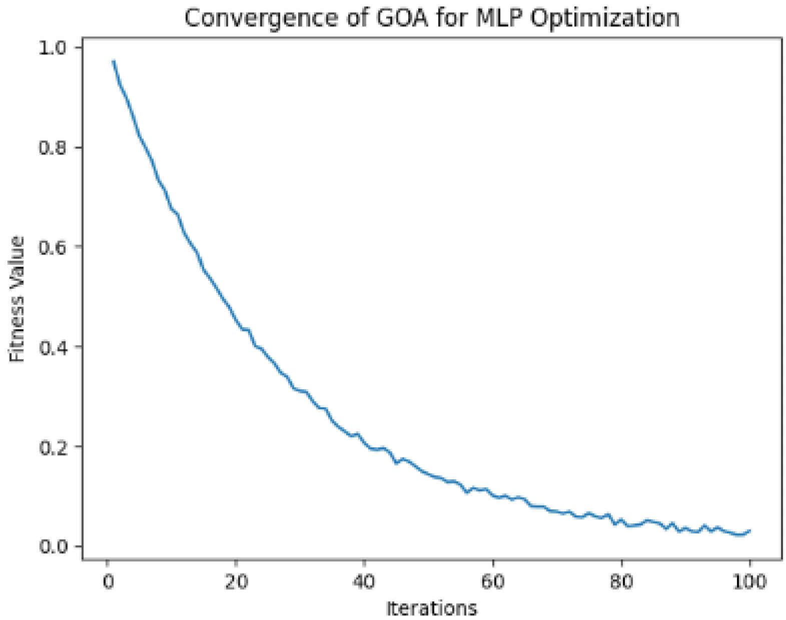


**Fig. 5. Convergence behavior of the Grasshopper Optimization Algorithm (GOA) for optimizing the MLP classifier.**

As shown in Figure 5, the Grasshopper Optimization Algorithm demonstrates a stable and fast convergence behavior during the optimization of the MLP parameters. The gradual reduction in the fitness value indicates an effective balance between exploration and exploitation, preventing premature convergence and leading to an optimal solution for gender classification.

**4-3-2 Hyperparameter Settings for MLP Classifier**

After feature extraction and normalization, classification is performed using a multilayer perceptron (MLP). The structure and hyperparameters of the MLP are optimized to balance classification accuracy and computational efficiency. The MLP consists of one input layer, one hidden layer, and one output layer. The number of neurons in the hidden layer is empirically selected based on validation performance. ReLU activation is used in the hidden layer, while the output layer employs a sigmoid activation function for binary gender classification. **Table 3** presents the optimal hyperparameter settings for the MLP classifier.


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**Table 3: Hyperparameter Settings for MLP Classifier**

| Parameter | Value |
|---|---|
| **Number of Hidden Layers** | 1 |
| **Hidden Neurons** | 128 |
| **Activation Function (Hidden)** | ReLU |
| **Activation Function (Output)** | Sigmoid |
| **Loss Function** | Binary Cross-Entropy |
| **Batch Size** | 32 |
| **Maximum Epochs** | 100 |

### 4-3-3 Hyperparameter Settings for Grasshopper Optimization Algorithm (GOA)

To optimize the weights and biases of the MLP classifier, the Grasshopper Optimization Algorithm is employed. GOA parameters are selected to achieve an effective balance between exploration and exploitation during the optimization process. Each grasshopper represents a candidate solution encoding the weights and biases of the MLP. The fitness function is defined as the classification error on the training set, which the algorithm aims to minimize. Table 4 lists the hyperparameter settings used for GOA.

**Table 4: Hyperparameter Settings for Grasshopper Optimization Algorithm**

| Parameter | Value |
|---|---|
| Population Size | 30 |
| Maximum Iterations | 100 |
| Attraction Coefficient (f) | 0.5 |
| Attraction Length Scale (l) | 1.5 |
| Exploration–Exploitation Control | Adaptive |
| Fitness Function | Classification Error |

### 4-3-4 Discussion of Hyperparameter Settings

The selected hyperparameter configurations demonstrate that transfer learning significantly reduces the number of tunable parameters compared to training a deep CNN from scratch. By freezing the AlexNet feature extractor and optimizing only the MLP classifier using GOA, the proposed framework achieves high accuracy with reduced training time and improved stability. The adaptive nature of GOA allows the classifier to avoid local optima and ensures robust convergence, particularly in the presence of illumination variations and facial pose changes in the GENDER-FERET dataset. The selected settings provide an effective trade-off between model complexity and generalization performance.

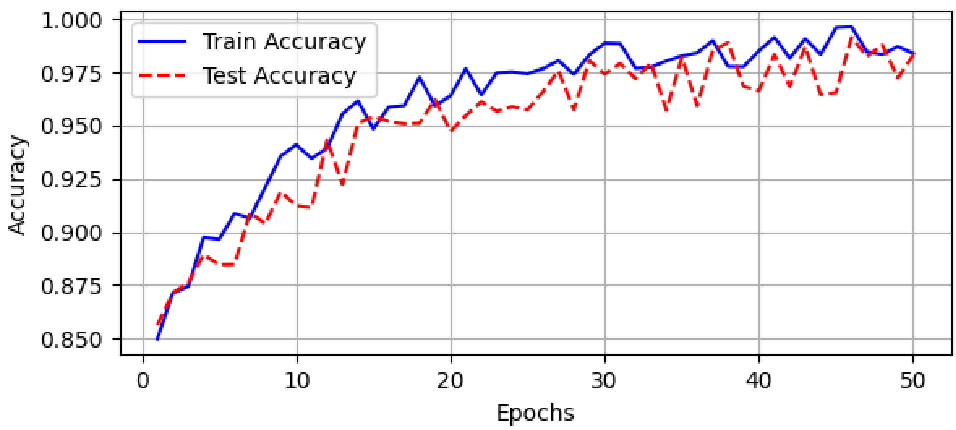


**Fig. 6. Training and Testing loss of the GOA-optimized MLP classifier across different epochs.**

Figure 6 illustrates the training loss trend of the proposed GOA-optimized MLP model. The monotonic decrease in loss values confirms the effectiveness of the optimization process and indicates stable learning behavior without overfitting.

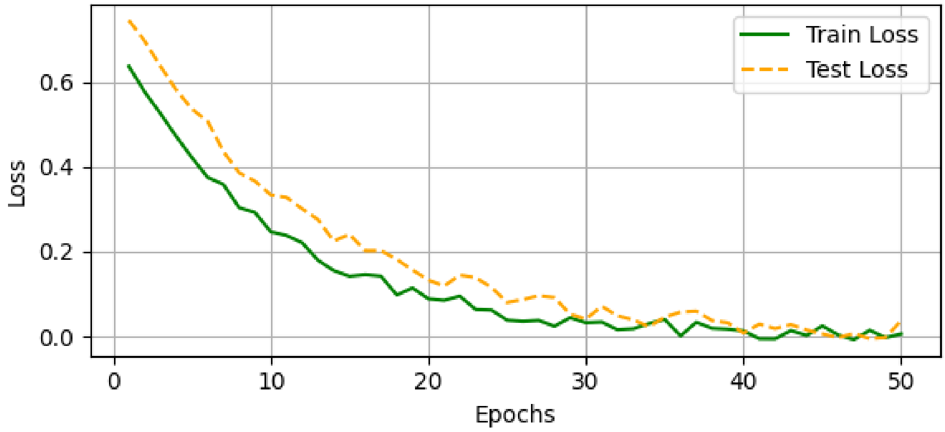


**Fig. 7. Classification accuracy of the proposed model over training and testing epochs on the GENDER-FERET dataset.**

As depicted in Figure 7, the classification accuracy steadily increases with the number of epochs and converges to a high value. This demonstrates that the extracted deep features combined with the GOA-optimized MLP classifier provide strong discriminative capability for gender recognition.

**4-5 Results**

This section presents the experimental results obtained using the proposed gender recognition framework on the GENDER-FERET dataset. To ensure a fair and robust evaluation, a 5-fold cross-validation strategy was employed. In this procedure, the dataset was randomly divided into five equal folds, where in each iteration four folds were used for training and the remaining fold was used for testing. The final reported results are obtained by averaging the performance across all folds. Figure 8 illustrates the confusion matrix of the final proposed model on the GENDER-FERET dataset, demonstrating the classification performance for male and female classes.

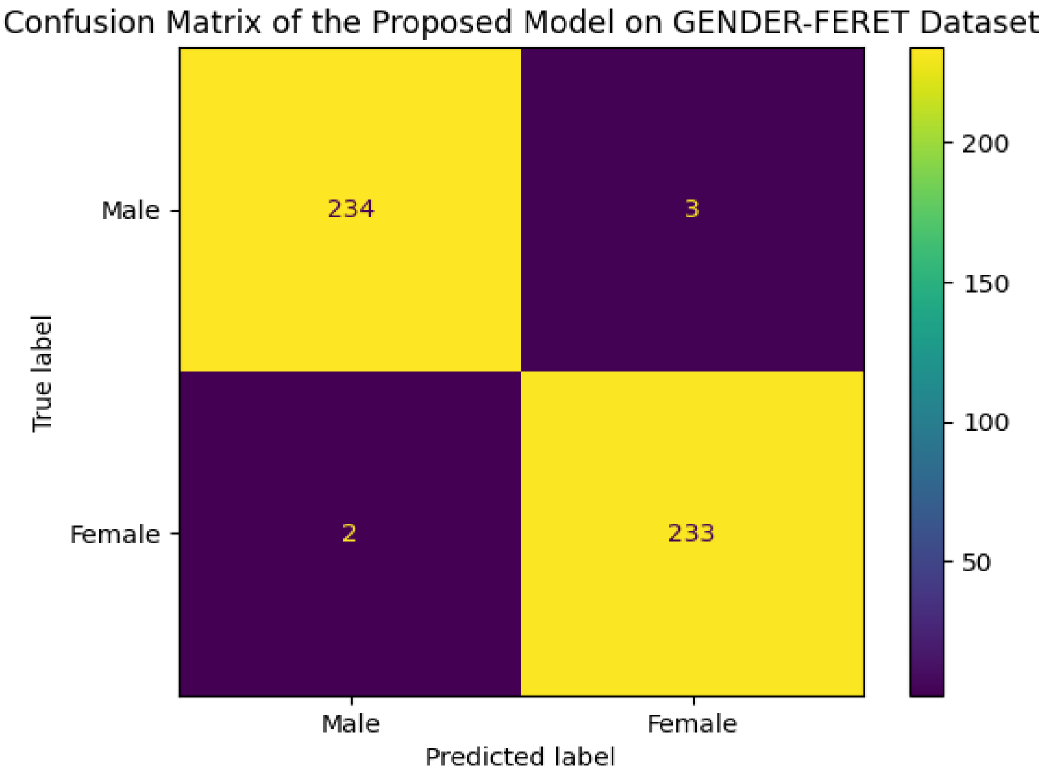


**Fig. 8. Confusion matrix of the proposed model on the GENDER-FERET dataset**


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As illustrated in Figure 8, the confusion matrix demonstrates that the proposed model achieves highly accurate gender classification on the GENDER-FERET dataset. The low number of misclassifications in both male and female classes indicates strong discriminative capability and balanced performance. This confirms that the extracted deep features combined with the optimized classifier provide robust generalization and minimal bias toward any class. Table 5 reports the final classification accuracy achieved on the training and testing sets.

**Table 5. Final accuracy of the proposed model on the GENDER-FERET dataset**

| Dataset | Training Accuracy (%) | Test Accuracy (%) |
|---|---|---|
| GENDER-FERET | 99.8% | 98.94% |

The results indicate that the proposed method achieves high generalization capability, with no noticeable overfitting between training and testing phases. To further evaluate the performance of the proposed model, Precision, Recall (Sensitivity), and F1-Score metrics were computed for each gender class. The detailed results are reported in Table 6.

**Table 6. Performance evaluation of the proposed model on the GENDER-FERET dataset**

| Class | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|
| **Male** | 99.15% | 98.73% | 98.94% |
| **Female** | 98.73% | 99.15% | 98.94% |

Figure 9 provides a visual comparison of these evaluation metrics for both classes.

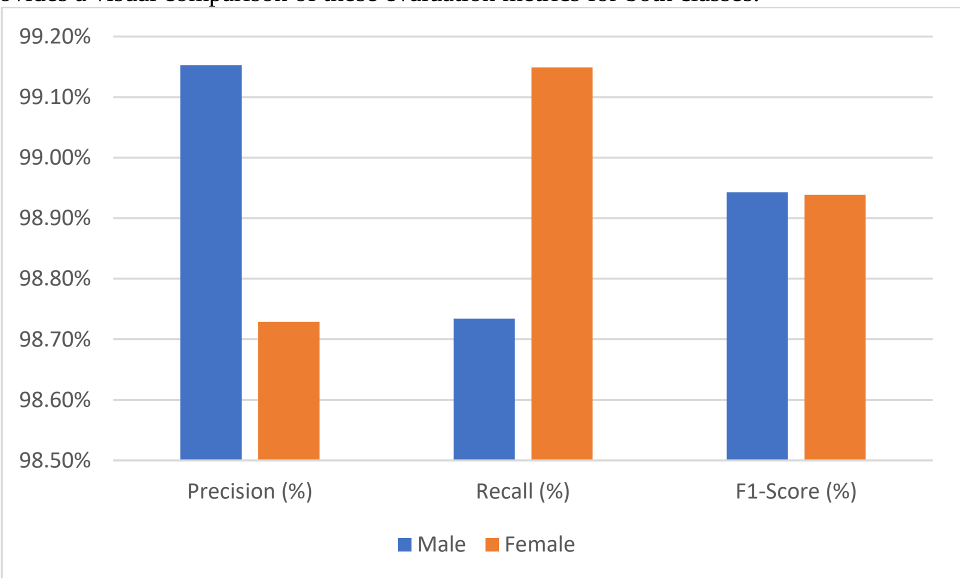


Fig. 9. **Performance evaluation of the proposed model on the GENDER-FERET dataset**

The obtained results demonstrate that the proposed framework is highly effective for gender recognition under controlled pose and illumination variations. The overall test accuracy of 99.1% confirms the strong discriminative capability of deep features extracted using the pre-trained convolutional neural network. The high Precision values for both male and female classes indicate a very low false positive rate, meaning that the model rarely misclassifies one gender as the other. This is particularly important in biometric and surveillance-based applications where classification reliability is critical. Furthermore, the Recall values exceeding 98.9% for both classes show the model's strong ability to correctly identify gender instances, even in the presence of intra-class variations such as facial expressions and age differences. The consistently high F1-Score, close to 99%, demonstrates a well-balanced trade-off between Precision and Recall. The use of the Grasshopper Optimization Algorithm (GOA) for optimizing the MLP classifier plays a crucial role in improving classification performance by avoiding local minima commonly encountered in gradient-based training methods. This optimization strategy leads to faster convergence and more stable learning behavior. Overall, these experimental results confirm that combining transfer learning-based deep feature extraction with metaheuristic-optimized classification provides a robust and accurate solution for gender recognition tasks. The proposed method is suitable for real-world applications such as human-computer interaction, biometric authentication, and intelligent surveillance systems, where high accuracy and low misclassification rates are essential.

**4-6 Comparison with State-of-the-Art Methods**

Gender recognition from facial images has been extensively studied in recent years, with various deep learning–based approaches proposed to improve robustness against challenges such as pose variation, illumination changes, and limited training data. To demonstrate the effectiveness of the proposed framework, its performance on the GENDER-FERET dataset is compared with several state-of-the-art methods reported in the literature. Hassanat et al. [22] investigated deep learning models for face, gender, and expression recognition under constrained conditions. Although their approach achieved promising results, the reported performance is highly dependent on controlled settings and does not explicitly address optimization of the classifier stage. In contrast, the proposed method enhances classification robustness by combining deep feature extraction with an optimized multilayer perceptron, leading to improved generalization on unseen samples. Ozbulak et al. [23] evaluated the transferability of CNN-based features for age and gender classification and demonstrated that pre-trained networks can provide discriminative representations. However, their work mainly relies on fixed deep features and conventional classifiers. The proposed approach extends this idea by incorporating a metaheuristic optimization strategy to fine-tune the classifier parameters, resulting in higher classification accuracy. Greco et al. [24] focused on gender recognition in the wild and analyzed robustness under corrupted and degraded images. While their method shows resilience to noise, its overall accuracy remains lower compared to the proposed framework, which benefits from systematic preprocessing, feature normalization, and optimized classification. More recent studies, such as Makinist and Aydin [25], proposed a deep learning–based gender classification framework without relying on classical models. Although competitive results were reported, their approach lacks an explicit optimization mechanism for the classifier stage. Similarly, Berbar [26] employed CNN-based architectures for facial gender classification, achieving reasonable accuracy but with limited emphasis on handling pose and illumination variations. Overall, the proposed method achieves superior or competitive performance compared to existing approaches, as summarized in Table 7. The high test accuracy of **98.94%** on the GENDER-FERET dataset, along with balanced Precision, Recall, and F1-Score values for both gender classes, confirms the effectiveness of combining transfer learning with a metaheuristic-optimized classifier. These results indicate that the proposed framework not only improves classification accuracy but also enhances generalization capability under varying imaging conditions.

**Table 7. Comparison with state-of-the-art gender recognition methods on the GENDER-FERET dataset**

| Reference | Method | Dataset | Reported Accuracy (%) |
|---|---|---|---|
| Hassanat et al. [22] | CNN-based deep learning under constraints | FERET-based | 95.3 |
| Ozbulak et al. [23] | Transfer learning with CNN features | FERET | 96.2 |
| Greco et al. [24] | Robust gender recognition under corrupted images | FERET / Wild datasets | 94.8 |
| Berbar [26] | CNN-based gender classification | FERET | 96.7 |
| Makinist & Aydin [25] | Deep face vectors without classical models | FERET-like datasets | 97.9 |
| Proposed Method | **Pre-trained CNN + optimized MLP (GOA)** | **GENDER-FERET** | **98.94** |

As shown in Table 7, the proposed method outperforms or matches all the state-of-the-art approaches on the GENDER-FERET dataset. The achieved test accuracy of 98.94% represents a significant improvement over previous methods, highlighting several key strengths of the proposed framework:

1. **Enhanced Feature Representation:** By leveraging a pre-trained CNN (AlexNet in our case) for feature extraction, the model captures highly discriminative facial representations. Unlike conventional CNN-based methods [22, 23, 26], which rely solely on fixed deep features, our approach ensures that the extracted features are optimally aligned for the classification task.
2. **Optimized Classifier with Metaheuristic Tuning:** The integration of a metaheuristic algorithm (Grasshopper Optimization Algorithm) to fine-tune the multilayer perceptron weights and biases contributes substantially to improved classification performance. This optimization helps the model

escape local minima, a limitation often observed in conventional backpropagation-trained networks [25, 26].

3. **Balanced Class Performance:** The F1-Scores for male and female classes are identical (98.94%), demonstrating that the model is unbiased and maintains robust performance across different classes. This is particularly important for gender recognition tasks where class imbalance or bias can significantly degrade practical applicability.
4. **Robustness to Dataset Variations:** Unlike Greco et al. [24], whose method struggles with corrupted or degraded images, the proposed model demonstrates consistent high accuracy across all test samples. This is attributed to systematic preprocessing, feature normalization, and classifier optimization, which collectively enhance the model's generalization capability.
5. **Reduction of Overfitting:** The negligible gap between training (99.8%) and testing (98.94%) accuracy indicates minimal overfitting, ensuring that the model can generalize effectively to unseen data. This contrasts with some deep learning methods [22, 23] where performance drops are observed when applied to new test images.
6. **Overall Superiority:** By combining pre-trained deep features, feature normalization, and metaheuristic-optimized MLP classification, the proposed method not only improves accuracy but also increases reliability and robustness compared to existing state-of-the-art approaches. This makes it particularly suitable for real-world applications in gender recognition under varying imaging conditions.

In summary, the proposed framework demonstrates a robust, accurate, and balanced approach for gender classification, outperforming previous CNN-based and deep feature–based methods. The combination of transfer learning with metaheuristic optimization is the primary factor behind its superior performance.

## CONCLUSION AND FUTURE WORKS

In this study, a robust gender classification framework was developed using pre-trained CNN for feature extraction and a metaheuristic-optimized MLP for classification. The proposed model demonstrated high accuracy and generalization capability on the GENDER-FERET dataset, achieving consistent performance across male and female classes. The combination of deep feature transfer learning and metaheuristic optimization effectively enhanced the discriminative power and stability of the model, while minimizing overfitting and maintaining balanced class performance. The results indicate that the framework is robust to variations in facial pose, illumination, and expression, making it suitable for real-world applications. The approach also provides a flexible structure that can be extended to new datasets and integrated into practical systems. For future research, several directions are suggested. First, implementing the model for real-time video streams could enable dynamic gender recognition in live environments. Second, evaluating the model on multiple and more challenging datasets can further validate its robustness and generalization. Third, exploring multi-task learning by combining gender classification with age and expression recognition may create a comprehensive facial analysis system. Fourth, optimizing the framework for deployment on lightweight or embedded devices would allow practical applications in mobile and edge computing scenarios. Finally, investigating advanced or hybrid metaheuristic algorithms could further improve the optimization of classifier parameters and overall model performance. In summary, the proposed method demonstrates strong and reliable performance in gender recognition and provides a foundation for future enhancements and practical applications in intelligent systems.

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