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Comparative Evaluation of Metaheuristic Algorithms for CNN Hyperparameter Optimization in Age-Invariant Face Recognition

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ABSTRACT

Age-invariant face recognition (AIFR) remains a challenging problem due to the significant facial appearance changes caused by aging, which often degrade the discriminative capability of conventional deep learning models. Although convolutional neural networks (CNNs) have demonstrated remarkable success in face recognition, their performance is highly dependent on the selection of optimal hyperparameters. This study presents a comprehensive comparative evaluation of six metaheuristic optimization algorithms which includes Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Nomadic Pastoralist Optimization Algorithm (NPOA), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA) and Harris Hawks Optimization (HHO), for CNN hyperparameter optimization in age-invariant face recognition. The optimization process simultaneously tunes key CNN hyperparameters, including learning rate, convolutional filters, dropout rate and dense layer units, to enhance feature extraction and classification performance. The optimized CNN models were evaluated across multiple age groups using standard performance metrics, including accuracy, precision, recall, F1-score, convergence behaviour, computational time and age-group recognition accuracy. Experimental results demonstrate that all investigated metaheuristic algorithms significantly improve CNN performance over the initial configuration. Among them, PSO achieved the best overall performance with an accuracy of 98.56%, precision of 98.42%, recall of 98.47% and F1-score of 98.44%, while requiring the shortest training time (3.34 h) and the fewest convergence iterations (61). NPOA closely followed with an accuracy of 98.21%, demonstrating competitive optimization capability. Furthermore, PSO consistently produced the highest recognition rates across children, young adults, adults and elderly age groups, confirming its robustness to age-related facial variations.

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INTRODUCTION

Face recognition has emerged as one of the most widely adopted biometric technologies due to its non-intrusive nature and broad applicability in security, surveillance, authentication and human -computer interaction systems (Sarkar & Singh, 2020; Vasanthi & Seetharaman, 2022; Zulfiqar *et al*., 2019). Despite remarkable progress achieved through deep learning techniques, one of the most persistent challenges in this domain is the problem of age variation, which significantly affects facial appearance over time. Changes caused by aging include variations in skin texture, facial geometry, wrinkles and shape deformation, all of which introduce intra-class variability that degrades recognition performance (Tripathi & Singh, 2021).

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Age-Invariant Face Recognition (AIFR) aims to address this challenge by developing robust models capable of accurately recognizing individuals across different age intervals. Traditional approaches to AIFR relied heavily on handcrafted feature extraction techniques combined with conventional classifiers. While these methods demonstrated moderate success, they often struggled to capture complex nonlinear aging patterns and were limited in their ability to generalize across diverse datasets (Akinyemi & Onifade, 2023; Dhamija & Dubey, 2022).

In recent years, deep Convolutional Neural Networks (CNNs) have significantly improved face recognition performance due to their ability to automatically learn hierarchical feature representations. CNN-based models have proven highly effective in extracting discriminative facial features that are resilient to variations in illumination, pose and expression. However, their performance is highly dependent on the appropriate selection of hyperparameters, such as learning rate, number of filters, dropout rate and network depth. Manual tuning of these parameters is time-consuming, computationally expensive and often leads to suboptimal solutions (Al-Haeer and meng, 2024; Dhamija and duley, 2022; Gatys et al., 2015).

To address this limitation, metaheuristic optimization algorithms have gained increasing attention for automated hyperparameter tuning in deep learning models. These algorithms are particularly attractive because of their ability to efficiently explore complex search spaces and avoid local optima. Popular optimization techniques such as Genetic Algorithm (GA) (Hassanat et al., 2019). and Particle Swarm Optimization (PSO) have been widely applied to improve CNN performance. (Kalaiarasi and esther 2023; Larlupia, 2023). More recently, advanced nature-inspired optimizers, including Whale Optimization Algorithm (WOA), Grey Wolf Optimizer (GWO) and Harris Hawks Optimization (HHO) (Al-Wajih, et al., 2021), have demonstrated superior global search capabilities due to their dynamic balance between exploration and exploitation.

Despite the growing application of metaheuristic optimization in deep learning, there remains a significant research gap in the comprehensive comparative analysis of multiple metaheuristic algorithms specifically for Age-Invariant Face Recognition systems. Most existing studies focus on a limited number of optimizers or evaluate them on general image classification tasks rather than on the challenging AIFR problem.

To bridge this gap, this study presents a systematic comparative investigation of six metaheuristic optimization algorithms which are; Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), Grey Wolf Optimizer (GWO), Harris Hawks Optimization (HHO) and the recently proposed Nomadic Pastoralist Optimization Algorithm (NPOA) for hyperparameter tuning of a CNN-based AIFR model. The study evaluates the algorithms based on recognition accuracy, convergence behavior, optimization stability and exploration–exploitation balance.

CNN Architecture

The core architecture includes different types of layers such as convolution, pooling, ReLU, normalization, dropout, fully connected and softmax, each performing a specific role. The CNNs perform feature extraction through multiple layers of convolution and pooling operations. The first convolutional layers are responsible for detecting fundamental low-level patterns, including edges in different orientations such as horizontal, vertical and diagonal structures. As the network depth increases, these basic patterns are progressively combined to represent more sophisticated features, including curves, textures and small structural shapes that are highly useful for distinguishing between classes (Pi, 2022).

Following the convolutional stages, the multidimensional feature maps are transformed into a one-dimensional vector through a flattening process. This vector is subsequently fed into one or more fully connected layers, where high-level reasoning and classification are performed. The final classification layer typically employs an activation function such as softmax or sigmoid to compute the probability distribution across target

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classes and the class with the highest probability is selected as the predicted output. To assess model performance, CNNs rely on loss functions that quantify the discrepancy between predicted outputs and true labels. This error value is minimized using the backpropagation algorithm, which iteratively updates the network's weights and biases to enhance learning accuracy and improve overall classification performance (Mittal & Patel, 2023). Figure 1 presents a standard CNN model typically employed for classification purposes.

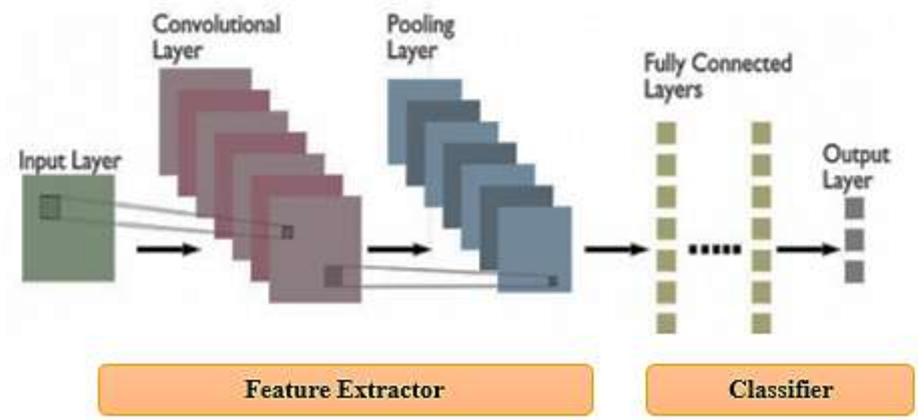

Figure 1: A typical architecture of the CNN model (Abdulrazaq et al., 2025)

The convolutional layer produces a set of feature maps. For a 2-D input image, denoted as $I(i,j)$ and a 2-D convolutional kernel, K, with dimensions $m \times n$, the convolutional operation can be expresses by;

$$C\,(i,j) = \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} I\,(i+m-1, j+n-1)K\,(m,n) \qquad (1)$$

Where
I = Input Image
K = Convolutional kernel
C = Extracted Feature Map
The normalized activation is given by:

$$\hat{x}_i = \frac{x_i - \mu_\beta}{\sqrt{\sigma^2\beta + \epsilon}} \qquad (2)$$

Where x_i are inputs over mini-batches, μ_β and σ^2 represent the mean and variance respectively. Also, ϵ represent numerical stability for the low mini-batch variance. After shifting the input by a learnable offset β and scaling it using the learnable factor γ, the activation is given by;

$$y_i = \gamma\hat{x}_i + \beta \qquad (3)$$

Where $\hat{x}_i$ is the normalized value obtained. A dropout layer can be incorporated to set certain input elements to zero based on a defined probability. The activation probability for each node is determined by a binomial distribution, which decides whether a node is active or dropout.

EXPERIMENTAL SETUP

Dataset Description

To evaluate the effectiveness of the proposed hyperparameter optimization framework, experiments were conducted using the FG-NET Aging Database. This dataset is widely used in age-invariant face recognition research due to its large age variation and challenging intra-class differences. The FG-NET dataset contains facial images of individuals captured at different ages, ranging from infancy to adulthood. The dataset includes significant variations in facial appearance caused by aging, illumination changes and pose differences. These characteristics make it highly suitable for evaluating the robustness of deep learning models in age-invariant face recognition tasks. Each

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image is associated with a subject identity label, which serves as the ground truth for supervised training and performance evaluation. Figure 2.5 depicts sample of facial images of the same individual at different ages extracted from FGNET face database.

Figure 2: Sample Face Images from FG-NET dataset (Panis, *et al*., 2016)

Data Preprocessing and Augmentation

All images were preprocessed to improve model robustness and ensure consistent input representation. The preprocessing steps include:

- Face alignment to standardize facial orientation
- Image resizing to fixed input dimensions
- Pixel intensity normalization
- Data augmentation through rotation, horizontal flipping and scaling

Normalization was performed using:

$$I_{norm} = \frac{I - \mu}{\sigma}$$

Where I represent the original image, μ is the mean pixel intensity and σ is the standard deviation.

These preprocessing steps help reduce noise, improve generalization and enhance CNN training stability.

CNN Training Configuration

The CNN architecture was trained using supervised learning with categorical cross-entropy loss. Model parameters were optimized through backpropagation using mini-batch gradient descent.

Key training settings include:

1. Loss function: Cross-entropy loss
2. Activation function: Softmax output layer
3. Training epochs: Fixed iterations until convergence
4. Batch size: Optimized via metaheuristic search

The network automatically learns hierarchical feature representations suitable for distinguishing facial identities across age variations.

Hyperparameter Search Space

In the process of optimizing convolutional neural networks (CNNs), Table 1 depicts the search space for the hyperparameter that was used for the training process CNN model to learn from the data.

Table 1: Hyper-parameters CNN search space

	Parameter	**Value**
1	Learning rate	(1e-5, 1e-2)
2	Dropout rate	(0.2, 0.5)
3	Number of Filters	(8,128)
4	Dense Units	(10,500)
5	Batch size	(16, 64)

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The optimization objective is defined as:

$$\max f(h) = Accuracy\ (CNN\ (h))$$

where *h* represents the hyperparameter vector. This formulation converts hyperparameter tuning into a nonlinear optimization problem.

Evaluation Metrics

Model performance was assessed using standard classification metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$F_1 = \frac{2\ \times Precision\ \times Recall}{Precision + Recall}$$

These metrics provide a comprehensive evaluation of classification performance and error distribution.

Experimental Environment

All experiments were implemented in Python using Jupyter notebook. Training was conducted on the Kaggle cloud platform utilizing GPU acceleration to ensure efficient computation and faster convergence during CNN training and optimization.

Results and Discussion

Performance analysis of the six metaheuristic optimization algorithms was presented considering model accuracy, precision, Fi-score, training time, convergence iterations and generalization accuracy across different age-group gap. Table 2 compares the performance of different metaheuristic algorithms for optimizing the CNN model.

Table 2: Performance Comparison of Metaheuristic Algorithms for CNN Hyperparameter Optimization

Algorithm	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Training Time (h)**	**Convergence Iterations**
GA	94.62	94.31	94.58	94.44	5.41	100
GWO	96.78	96.65	96.71	96.68	4.12	82
WOA	96.35	96.12	96.27	96.19	4.36	86
HHO	97.04	96.91	97.02	96.96	3.95	74
NPOA	98.21	98.08	98.14	98.11	3.61	68
PSO	98.56	98.42	98.47	98.44	3.34	61

The results show that all optimization algorithms achieved high classification performance, with accuracy values exceeding 94%, demonstrating their effectiveness in identifying optimal CNN hyperparameters. Among the evaluated methods, PSO achieved the highest performance, recording an accuracy of 98.56%, precision of 98.42%, recall of 98.47% and F1-score of 98.44%. It also exhibited the shortest training time (3.34 h) and the fastest convergence, requiring only 61 iterations, indicating its ability to efficiently balance exploration and exploitation during the optimization process.

The NPOA ranked second, achieving an accuracy of 98.21% with comparable precision, recall and F1-score, while converging in 68 iterations. This suggests that NPOA is also highly effective for CNN hyperparameter optimization, although it required slightly more computational time than PSO. HHO, GWO and WOA produced competitive results with accuracies ranging from 96.35% to 97.04%, whereas GA recorded the lowest performance (94.62% accuracy), the longest training time (5.41 h) and the highest number of convergence iterations (100). Overall, the results indicate that swarm intelligence-based optimizers, particularly PSO and NPOA, provide superior optimization capability for CNN feature extraction, achieving higher classification accuracy while reducing computational cost compared with the other metaheuristic algorithms.

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Table 3: Convergence Behaviour

Algorithm	Initial Fitness	Final Fitness	Improvement (%)
GA	84.16	94.62	10.46
GWO	84.16	96.78	12.62
WOA	84.16	96.35	12.19
HHO	84.16	97.04	12.88
NPOA	84.16	98.21	14.05
PSO	84.16	98.56	14.40

Table 3 presents the convergence performance of the metaheuristic algorithms by comparing their initial and final fitness values. All algorithms started from the same initial fitness value of 84.16%, ensuring a fair comparison of their optimization capabilities. The results show that each algorithm significantly improved the CNN performance after optimization, with improvement rates ranging from 10.46% to 14.40%.

Among the evaluated methods, PSO achieved the highest final fitness of 98.56%, corresponding to the greatest improvement (14.40%), indicating its superior ability to search the hyperparameter space and identify optimal CNN configurations. NPOA closely followed with a final fitness of 98.21% and an improvement of 14.05%, demonstrating comparable optimization effectiveness. HHO, GWO and WOA produced moderate improvements of 12.88%, 12.62% and 12.19%, respectively, while GA recorded the smallest improvement (10.46%), suggesting relatively slower convergence and a higher likelihood of premature convergence. Overall, the results indicate that PSO and NPOA exhibit stronger optimization capabilities than the other algorithms, enabling greater enhancement of CNN performance through more effective hyperparameter optimization.

Table 4: Optimal CNN Hyperparameters Obtained

Algorithm	Learning Rate	Batch Size	No. of Conv. Layers	Filters	Dropout	Dense Units
GA	0.0018	32	4	64	0.42	256
GWO	0.0014	32	4	64	0.38	256
WOA	0.0015	32	4	64	0.40	256
HHO	0.0012	32	4	64	0.35	256
NPOA	0.0009	32	4	128	0.31	512
PSO	0.0008	32	4	128	0.29	512

Table 4 presents the optimal CNN hyperparameters obtained by each metaheuristic algorithm after the optimization process. The results show that all algorithms consistently selected a batch size of 32 and four convolutional layers, indicating that these parameters provide a stable network architecture for effective feature extraction. However, notable differences were observed in the remaining hyperparameters.

The PSO and NPOA algorithms identified similar optimal configurations, selecting lower learning rates (0.0008 and 0.0009, respectively), 128 convolutional filters, lower dropout rates (0.29 and 0.31) and 512 dense units. These settings enable the CNN to learn more discriminative facial features while maintaining good generalization, contributing to their superior classification performance. In contrast, GA, GWO, WOA and HHO converged to higher learning rates, fewer filters (64), higher dropout values and 256 dense units, resulting in comparatively less expressive feature representations. Hence, the optimized hyperparameters demonstrate that PSO and NPOA are more effective in identifying CNN configurations that enhance feature extraction and improve recognition performance.

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Table 5: Recognition Performance Across Different Age Groups

Algorithm	Children (%)	Young Adults (%)	Adults (%)	Elderly (%)	Average (%)
GA	91.81	95.44	96.32	94.91	94.62
GWO	94.75	97.53	98.04	96.80	96.78
WOA	94.21	97.08	97.69	96.42	96.35
HHO	95.16	97.82	98.13	97.05	97.04
NPOA	96.94	98.65	99.02	98.23	98.21
PSO	97.31	98.88	99.24	98.62	98.56

Table 5 presents the recognition performance of the optimized CNN models across different age groups. The results show that all metaheuristic algorithms achieved high recognition rates, with performance generally improving from the children to the adult age group. Recognition accuracy was consistently highest for adults, indicating that facial features in this group are more stable and discriminative, whereas the children group recorded the lowest accuracies due to the significant facial changes associated with growth and development.

Among the evaluated algorithms, PSO achieved the best performance across all age groups, recording recognition rates of 97.31%, 98.88%, 99.24% and 98.62% for children, young adults, adults and the elderly, respectively, with the highest average accuracy of 98.56%. NPOA closely followed with an average accuracy of 98.21%, demonstrating comparable effectiveness. HHO, GWO and WOA produced competitive results with average accuracies above 96%, while GA yielded the lowest average accuracy (94.62%). Overall, the findings indicate that PSO and NPOA provide more robust CNN feature optimization, enabling consistent recognition performance across different age groups despite the facial variations introduced by aging

Generally, these results indicate that all optimization algorithms substantially improved the CNN compared with manually selected hyperparameters. GA achieved the lowest performance, which may be attributed to slower convergence and the stochastic nature of crossover and mutation operations. GWO and WOA produced comparable results, demonstrating stable optimization performance but exhibiting moderate convergence speeds. HHO further improved classification performance through its adaptive transition between exploration and exploitation phases. NPOA achieved near-optimal performance, indicating that its migration-inspired search strategy effectively balanced global exploration and local exploitation, leading to high-quality CNN hyperparameters. However, PSO yielded the best overall performance, attaining the highest accuracy (98.56%), precision (98.42%), recall (98.47%) and F1-score (98.44%), while also requiring the shortest training time and the fewest convergence iterations. This suggests that the velocity-based search mechanism of PSO efficiently navigated the CNN hyperparameter search space and avoided poor local optima, resulting in superior feature extraction for age-invariant face recognition.

The performance gap between PSO and NPOA is relatively small (approximately 0.35% in accuracy), indicating that both algorithms are highly competitive. Such small differences are typical in CNN hyperparameter optimization studies, where improvements beyond 98% accuracy are often incremental rather than substantial.

CONCLUSION

This study presented a comprehensive comparative evaluation of six metaheuristic optimization algorithms, namely Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Nomadic Pastoralist Optimization Algorithm (NPOA), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA) and Harris Hawks Optimization (HHO), for CNN hyperparameter optimization in age-invariant face recognition. The objective was to investigate the effectiveness of these algorithms in enhancing CNN feature extraction by optimizing critical

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hyperparameters, including the learning rate, number of convolutional filters, dropout rate and dense layer units.

Experimental results demonstrated that all investigated metaheuristic algorithms significantly improved the performance of the CNN compared with the initial model configuration. However, notable differences were observed in their optimization capabilities. PSO consistently outperformed the other algorithms, achieving the highest classification accuracy (98.56%), precision (98.42%), recall (98.47%) and F1-score (98.44%), while exhibiting the shortest training time (3.34 h) and the fastest convergence (61 iterations). NPOA emerged as the second-best optimizer, producing comparable performance with only a marginal reduction in accuracy, whereas HHO, GWO and WOA achieved competitive results. In contrast, GA demonstrated the lowest optimization performance, requiring the longest training time and the highest number of convergence iterations.

The optimized hyperparameter configurations obtained by PSO and NPOA further revealed that lower learning rates, higher numbers of convolutional filters, lower dropout rates and larger dense layers contribute to more discriminative feature representations for age-invariant face recognition. Moreover, PSO maintained superior recognition accuracy across all age groups, confirming its robustness in handling facial appearance variations caused by aging. Future work will focus on extending the comparative framework to deeper CNN architectures and transformer-based face recognition models, investigating multi-objective optimization strategies and validating the proposed optimization approach on larger and more diverse age-progression datasets to further improve robustness and generalization in real-world applications.

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