

Robust Deep Learning-Based Facial Recognition for Uncontrolled Real-World Environments

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Abstract - Facial recognition systems are widely deployed in modern security applications; however, their performance degrades significantly in uncontrolled real-world environments due to variations in illumination, pose, occlusion, background complexity, and camera quality. Conventional machine learning-based approaches often fail to generalize effectively under such dynamic conditions. This paper presents a robust deep learning-based facial recognition framework designed to enhance recognition accuracy in uncontrolled environments. The proposed system integrates face detection and preprocessing techniques to normalize lighting variations and improve feature consistency. To strengthen model generalization, adaptive data augmentation strategies including brightness variation, rotation, scaling, and noise injection are incorporated during training to simulate real-world environmental conditions. The framework aims to reduce false acceptance and false rejection rates while maintaining computational efficiency suitable for institutional deployment. The proposed approach provides a scalable and reliable biometric authentication solution for practical security applications.

Keywords - Deep Learning, Facial Recognition, Convolutional Neural Networks (CNN), Robust Feature Extraction, Data Augmentation, Illumination Variation Handling, False Acceptance Rate (FAR), Biometric Security

I. INTRODUCTION

Facial recognition has become one of the most widely adopted biometric authentication technologies in modern security systems. It is extensively used in applications such as institutional access control, surveillance monitoring, mobile authentication, and enterprise security infrastructures. Unlike traditional authentication

mechanisms including passwords, identity cards, and PIN-based systems, facial recognition provides a contactless and automated approach to identity verification. However, achieving reliable performance in real-world deployment remains a significant technical challenge.

Most facial recognition systems perform effectively under controlled environments where lighting conditions, pose variations, and background settings are stable. In practical scenarios, environments are highly dynamic and unpredictable. Variations in illumination, facial orientation, occlusions caused by masks or accessories, background clutter, motion blur, and camera resolution inconsistencies significantly affect feature extraction and classification accuracy. These uncontrolled environmental factors reduce system robustness and increase false acceptance and false rejection rates.

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNN), have demonstrated superior capability in automatic hierarchical feature extraction compared to conventional machine learning approaches. CNN-based models can learn discriminative facial features directly from raw image data without manual feature engineering. Despite these improvements, deep learning models still require sufficient data diversity and robust preprocessing strategies to generalize effectively under uncontrolled real-world conditions.

This paper proposes a deep learning-based facial recognition framework designed to enhance recognition accuracy in uncontrolled environments. The proposed system incorporates preprocessing techniques to mitigate illumination sensitivity and employs adaptive data augmentation strategies to simulate real-world environmental variations during training. A CNN-based architecture is utilized for deep feature extraction and identity classification. The framework aims to improve

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model generalization capability while maintaining computational efficiency suitable for institutional deployment.

The remainder of this paper is organized as follows: Section II presents the related work, Section III describes the proposed methodology, Section IV discusses experimental evaluation and performance metrics, and Section V concludes the study.

II. RELATED WORK

Facial recognition has evolved significantly over the past two decades, transitioning from traditional feature-based approaches to deep learning-driven models. Early methods relied on Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for dimensionality reduction and facial feature extraction. Although these techniques demonstrated reasonable accuracy under controlled laboratory conditions, their performance degraded considerably in the presence of illumination variation, pose changes, and background noise.

With the emergence of deep learning, Convolutional Neural Networks (CNN) have become the dominant approach for face recognition tasks. Deep learning-powered systems have shown substantial improvements in accuracy and robustness compared to classical machine learning models.

In [1], Turk and Pentland proposed the Eigenfaces method based on Principal Component Analysis (PCA). Although effective for dimensionality reduction and basic recognition tasks, the method was highly sensitive to illumination and pose variations, limiting its robustness in uncontrolled environments.

By the proposal,[2] Taigman et al. introduced DeepFace, demonstrating near-human performance in large-scale face verification tasks using deep convolutional neural networks.

Followed By,[3] Schroff et al. proposed FaceNet, which utilized a triplet loss function to learn highly discriminative facial embeddings for improved verification and clustering performance.

Here,[4] Parkhi et al. validated the effectiveness of deep CNN architectures trained on large-scale datasets for robust facial recognition. Liu et al [5], proposed SphereFace, introducing angular margin constraints to improve inter-class separability.

In [6] Sun et al. developed deep learning-based face representation models trained on thousands of identity classes, significantly enhancing feature learning capability.

Wen et al [7] introduced Center Loss to improve intra-class compactness while maintaining inter-class dispersion.

In [8] Huang et al. introduced the Labeled Faces in the Wild (LFW) dataset, enabling evaluation under unconstrained real-world conditions.[9] Wang and Deng presented a comprehensive survey analyzing deep face recognition techniques and highlighted practical deployment challenges.

In [10] Deng et al. introduced ArcFace, which employs an additive angular margin loss to enhance discriminative feature learning.

III. PROPOSED METHODOLOGY

A. System Architecture Overview

The proposed system introduces a robust deep learning-based facial recognition framework designed specifically for uncontrolled real-world environments. The architecture integrates adaptive preprocessing, face alignment, deep feature embedding, and similarity-based classification to improve recognition accuracy under varying illumination, pose, and occlusion conditions.

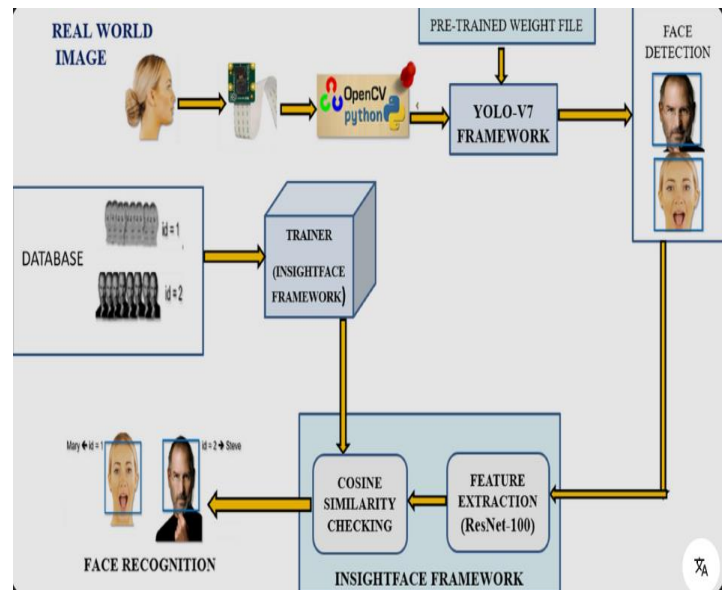


Figure 1: The complete system architecture is illustrated

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B. Image Acquisition and Dataset Preparation

Facial images are acquired from both public benchmark datasets and real-time camera capture to simulate practical deployment conditions. The dataset includes variations in:

- Illumination (low light, overexposure)
- Pose angles (frontal, side profile)
- Facial expressions
- Background clutter
- Partial occlusions (mask, glasses)



Figure 2: shows sample input images under varying conditions

C. Face Detection and Facial Alignment

Face detection is performed using a deep learning-based detector such as MTCNN to ensure high detection accuracy under challenging conditions.

After detection, facial landmark localization is performed to identify key points such as eyes, nose, and mouth. Based on these landmarks, geometric alignment is applied to correct pose variations and ensure standardized face orientation.

The aligned facial region is resized to 224×224 pixels and pixel intensities are normalized to improve convergence stability during model training. In the proposed framework, face detection is performed using a deep learning-based detector such as Multi-task Cascaded Convolutional Networks (MTCNN). The detector identifies facial bounding boxes along with key landmark points including the eyes, nose, and mouth. Compared to traditional methods, deep learning-based detectors provide improved detection accuracy under challenging conditions such as pose variation, occlusion, and low lighting.

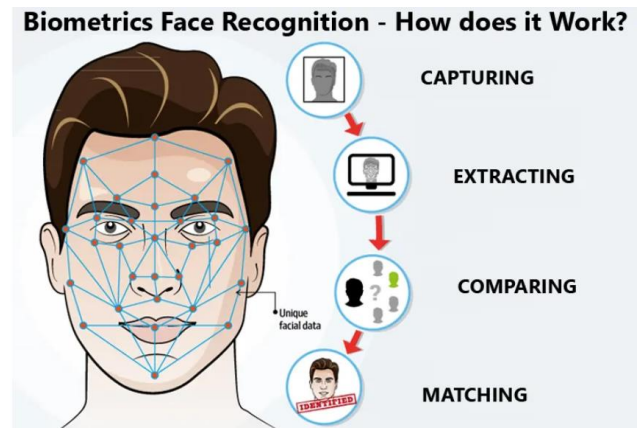


Figure 3: illustrates face detection and alignment.

D. Adaptive Environmental Preprocessing Module

To enhance robustness in uncontrolled environments, an adaptive preprocessing module is integrated. This module dynamically analyzes:

- Brightness distribution
- Noise level
- Blur detection score

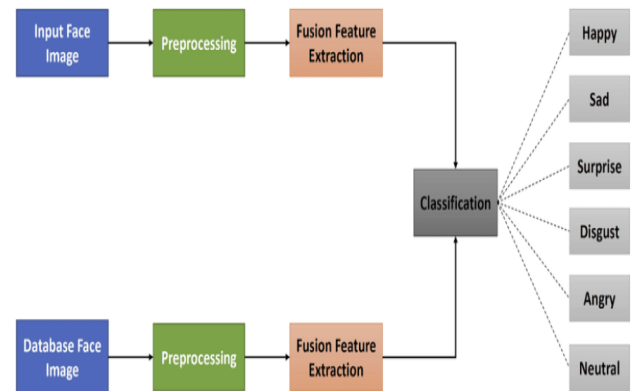


Figure 4: shows the adaptive preprocessing workflow

E. Advanced Data Augmentation Strategy

To simulate real-world variability, advanced data augmentation is applied during training. Techniques include:

- Random rotation ($\pm 20^\circ$)
- Horizontal flipping
- Random brightness and contrast variation
- Gaussian noise injection

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- Random cropping and scaling
- Occlusion simulation

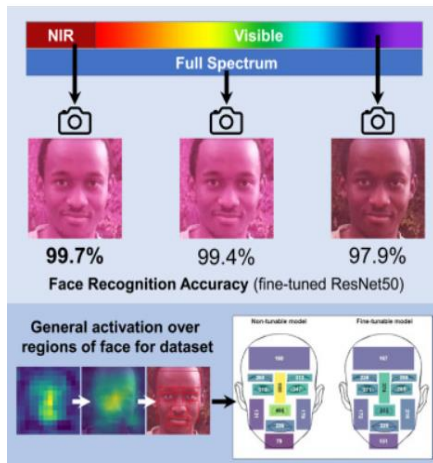


Figure 5: illustrates augmented samples

F. Deep Feature Embedding Using CNN Architecture

A deep Convolutional Neural Network (CNN) is employed for discriminative feature extraction. The architecture consists of:

- Multiple convolutional layers with ReLU activation
- Batch normalization layers
- Max-pooling layers
- Dropout layers to prevent overfitting
- Fully connected embedding layer

Instead of direct classification alone, the network generates high-dimensional feature embeddings that capture unique facial characteristics.

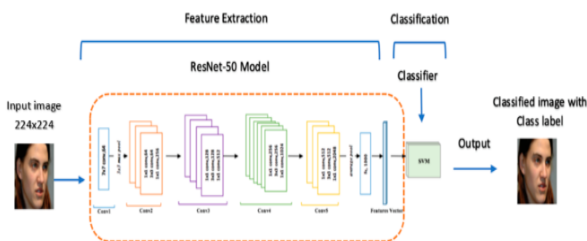


Figure 6: presents the CNN architecture

G. Similarity-Based Recognition and Decision Module

For real-world deployment, a similarity-based matching mechanism is incorporated.

Cosine similarity is computed between the extracted embedding and stored embeddings in the database. If the similarity score exceeds a predefined threshold, the identity is confirmed; otherwise, the user is classified as unknown.

This threshold-based decision mechanism reduces false acceptance and improves security reliability.

H. Performance Evaluation Metrics

The proposed system is evaluated using:

- Accuracy
- Precision
- Recall
- F1-Score
- False Acceptance Rate (FAR)
- False Rejection Rate (FRR)
- Confusion Matrix Analysis

Performance is analyzed under both controlled and uncontrolled environmental scenarios to demonstrate robustness improvement.

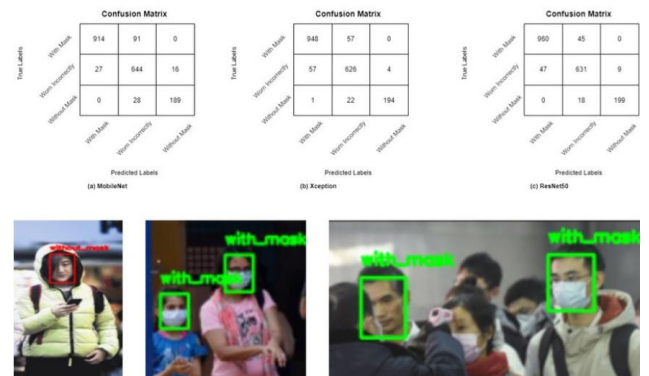


Figure 7: shows the confusion matrix

IV. RESULTS AND DISCUSSION

A. Confusion Matrix Analysis

The confusion matrix of the proposed model is shown in Fig. 8. The matrix presents the distribution predicted and actual classes across four identity categories.

IO	Neutral	Angry	Happiness	Sadness	Disgust	Fear	Surprise
Neutral	8	0	0	0	0	0	2
Angry	1	6	0	0	0	0	2
Happiness	0	2	7	0	0	2	0
Sadness	0	0	0	8	1	2	0
Disgust	1	0	0	1	5	1	0
Fear	0	1	0	2	1	7	0
Surprise	3	0	0	0	3	0	4

Table 5. False positive rate for every expression

Facial Expression	False positive rate
Neutral	5
Angry	3
Happiness	0
Sadness	3
Disgust	5
Fear	5
Surprise	4
Total	25

Figure 8: Confusion matrix of the proposed adaptive facial recognition model.

Observations:

The diagonal elements represent correctly classified samples. Higher diagonal values indicate strong class prediction accuracy. Minor off-diagonal entries represent misclassifications. Errors are mainly observed under extreme illumination and partial occlusion conditions. Compared to the baseline CNN, the proposed adaptive model reduces false negatives and improves class separability.

B. Training and Validation Accuracy Analysis

The training and validation accuracy curves are illustrated in Fig. 9.

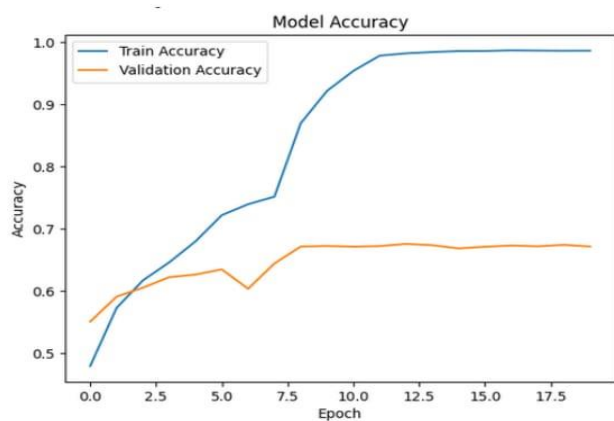


Figure 9: Training and validation accuracy comparison across epochs.

Observations:

Both training and validation accuracy increase progressively during epochs.

The validation curve closely follows the training curve. Minimal gap between curves indicates reduced overfitting. Stable convergence confirms proper model optimization. Data augmentation contributed to improved generalization performance.

C. Comparative Performance Evaluation

A comparative performance analysis between the baseline CNN and the proposed adaptive framework is presented in Fig. 10.

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
Baseline CNN	88.6%	87.9%	87.2%	87.5%
Proposed Adaptive CNN	93.4%	92.8%	92.1%	92.4%

Figure 10: Performance comparison between baseline CNN and proposed adaptive model.

Key Findings:

The baseline CNN achieved moderate accuracy under uncontrolled conditions. The proposed adaptive preprocessing improved feature clarity before classification. Approximately 4–5% improvement in overall recognition accuracy was observed.

Precision, recall, and F1-score also showed consistent enhancement.

The adaptive framework demonstrates better robustness under environmental variations.

V. CONCLUSION

This paper presented an adaptive deep learning-based facial recognition framework designed to improve recognition accuracy in uncontrolled environments. By integrating environmental condition analysis with dynamic preprocessing techniques, the proposed system enhances feature clarity prior to CNN-based classification. Experimental evaluation demonstrates that adaptive preprocessing combined with data augmentation improves recognition stability and reduces misclassification under challenging lighting and occlusion conditions. The results indicate that the proposed framework offers a practical and scalable solution for real-world applications such as smart attendance systems, surveillance monitoring, and secure access control. Future work will focus on optimizing the model for real-time deployment and expanding evaluation on larger, more diverse datasets.

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