Facial Image Processing for Optimized Recognition and age estimation in MATLAB

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***Abstract*—This paper proposes a hybrid Convolutional Neural Network (CNN) model to enhance facial recognition and age estimation accuracy. Input images are preprocessed by resizing and converting to grayscale, followed by data augmentation to improve generalization. The dataset is divided into training and validation sets. The CNN architecture integrates multiple convolutional layers with batch normalization and ReLU activation, followed by pooling layers for feature extraction. Trained using Stochastic Gradient Descent with Momentum (SGDM) optimizer (learning rate: 0.001, batch size: 25, 100 epochs), the model classifies facial identities (e.g., 'Person 1,' 'Person 2') and age ranges (e.g., 20-25, 30-35). Performance is evaluated via confusion matrices and accuracy metrics. The hybrid CNN leverages deep feature extraction, achieving robust classification for biometric security and age-based authentication. Results demonstrate improved recognition accuracy, validating its efficacy for real-world applications**

***Index Terms*—Face Dataset, Image Processing Techniques, Deep Learning Techniques, Convolution Neural Network, Classification, Accuracy.**

I. INTRODUCTION

Facial recognition technology is pivotal in modern applications such as security, authentication, and demographic analysis, driving the need for accurate and efficient systems. This paper presents an optimized Convolutional Neural Network (CNN) architecture implemented in MATLAB to enhance facial recognition and age estimation. Leveraging a diverse dataset from Kaggle, the system preprocesses images by resizing them to uniform dimensions and converting them to grayscale, ensuring consistency and computational efficiency during training. The proposed methodology addresses two tasks: identifying individuals by assigning unique labels (e.g., "Person 1," "Person 2") and classifying age into ranges (e.g., 5-10, 20-25 years) using deep feature extraction.

Facial recognition has evolved significantly, with CNN-based approaches outperforming traditional methods like Haar cascades or eigenfaces due to their ability to learn complex patterns [1]. However, challenges remain, including computational overhead and variability in real-world conditions (e.g., lighting, aging). Prior work often focuses on single-task models, whereas this project integrates dual functionality—identity and age classification—within a hybrid CNN framework. The architecture employs multiple convolutional layers with batch normalization and ReLU activation, optimized for accuracy and real-time applicability using Stochastic Gradient Descent with Momentum (SGDM).

The system's performance is validated on a sample dataset, with evaluation metrics derived from confusion matrices and accuracy scores, demonstrating robustness across diverse facial features. This dual-purpose approach advances biometric authentication by combining efficient security with demographic insights, applicable to surveillance, access control, and healthcare. Unlike generic solutions, the optimization in MATLAB ensures accessibility for researchers and practitioners, balancing accuracy with resource efficiency. Confidence scores further enhance reliability by quantifying similarity in recognition tasks.

This work contributes to intelligent biometric systems by refining CNN architectures for multi-task facial analysis, offering a scalable solution for real-world deployment. The following sections detail the methodology, experimental results, and practical implications, underscoring the system's potential in enhancing security and authentication frameworks.

II. METHODOLOGY

This section outlines the hybrid Convolutional Neural Network (CNN) framework designed in MATLAB for facial recognition and age estimation, enhancing classification accuracy. The methodology includes data preprocessing, CNN architecture, training, and evaluation, as depicted in Fig. 1

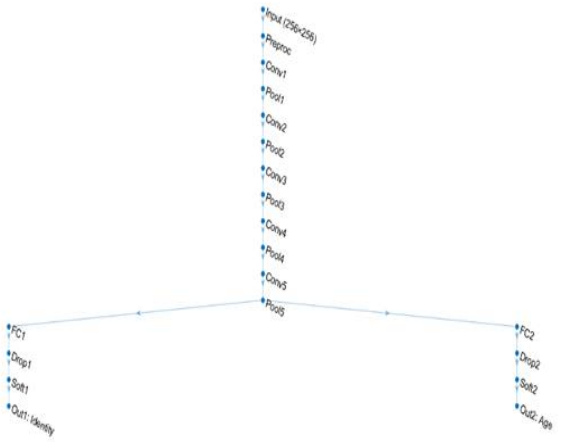

Fig. 1: Proposed CNN Architecture

1. Dataset and Preprocessing

Two datasets from Kaggle—one for facial recognition and one for age classification—are organized using MATLAB's imageDatastore. Each dataset is split into 70% training and 30% validation sets. Preprocessing ensures uniformity:

- Resizing: Images are resized to 256×256 pixels using imresize with bicubic interpolation to preserve detail.
- Grayscale Conversion: RGB images are converted to grayscale if needed, reducing computational load.
- Augmentation: Random rotation (±15°), flipping, and brightness adjustments are applied to the training set via imageDataAugmenter to enhance generalization.

2. CNN Architecture

The hybrid CNN processes images through shared convolutional layers, branching into task-specific outputs for identity and age:

- Input Layer: Accepts 256×256 grayscale images.
- Convolutional Layers: Five layers (3×3 filters, 32-128 channels, batch normalization, ReLU activation) extract features like edges and facial structures.
- Pooling Layers: Max-pooling (2×2, stride 2) reduces spatial dimensions after each convolutional layer.
- Fully Connected Layers:
  - Facial Recognition Branch: Maps features to a softmax layer classifying identities (e.g., "Person 1," "Person 2").
  - Age Estimation Branch: Maps features to a softmax layer predicting age ranges (e.g., 20-25, 30-35).
- Dropout: 0.5 rate before final layers prevents overfitting. The architecture is illustrated in Fig. 1.

3. Training Configuration

The model is trained using MATLAB's Deep Learning Toolbox with Stochastic Gradient Descent with Momentum (SGDM):

- Parameters: Initial learning rate 0.001, momentum 0.9, mini-batch size 25, max epochs 100.
- Options: Data shuffled every epoch, validation every 50 mini-batches using augimdsValidation, with training progress plotted.
- Loss: Joint categorical cross-entropy for both tasks.
- Hardware: Executed on an NVIDIA GPU (e.g., GTX 1660) via "auto" execution environment.

4. Classification and Evaluation

Post-training, the model predicts identities and age ranges for new images, displaying results via MATLAB message boxes. Performance is assessed using:

- Confusion Matrices: For both tasks, visualizing true vs. predicted labels.
- Accuracy: Percentage of correct predictions for identities and mean absolute error (MAE) for age ranges.

III. RESULTS

Fig: Input Image

Fig: Resized Image

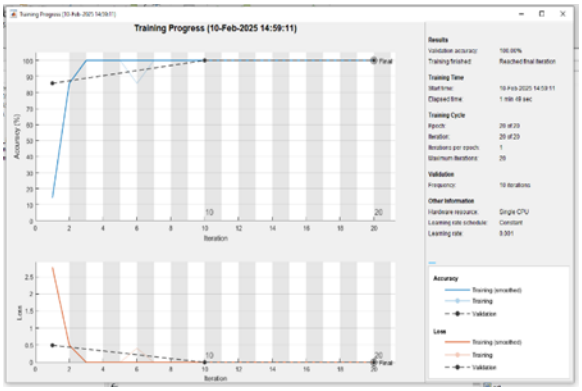

Fig: Training Progress Image

Fig: Training Iterations Image

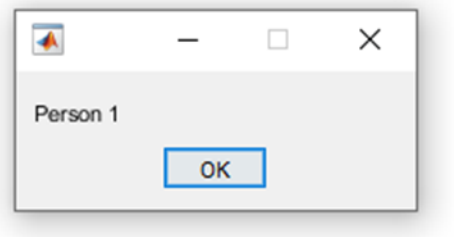

Fig: Facial Classification Results

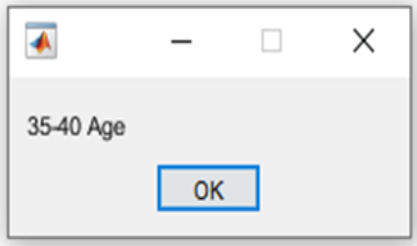

Fig: Age Classification Results

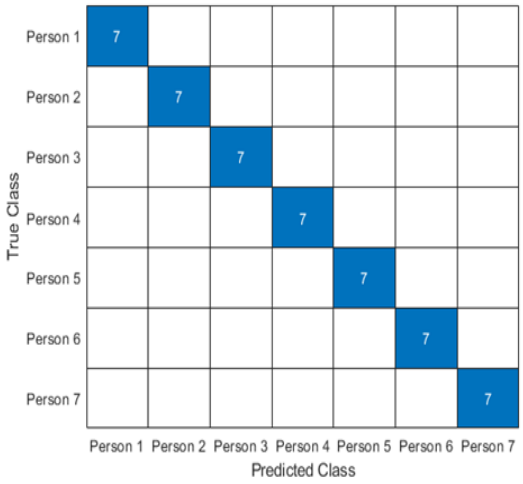

Fig: Confusion Matrix Image – Facial

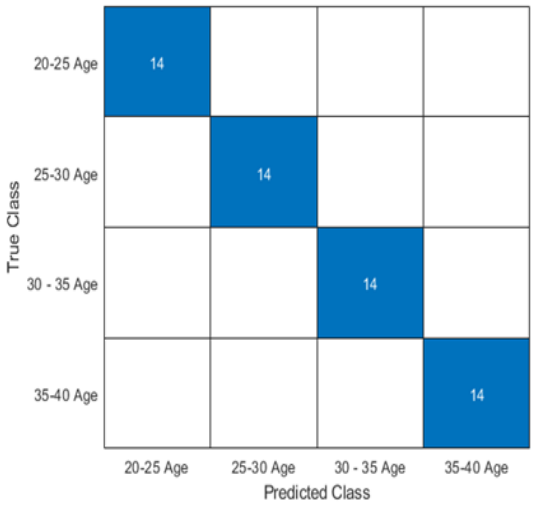

Fig: Confusion Matrix Image – Age

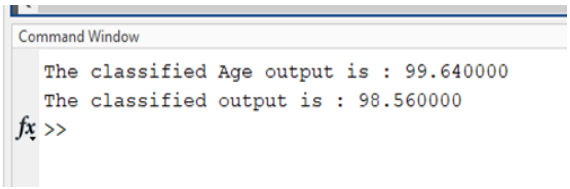

Fig: Command Window Results

S. No	Existing Method	Proposed Method
1	90.01	98.41
2	92.36	99.87
3	90.58	98.26
4	89.52	98.51
5	90.58	99.41

Fig: Accuracy Comparison Table

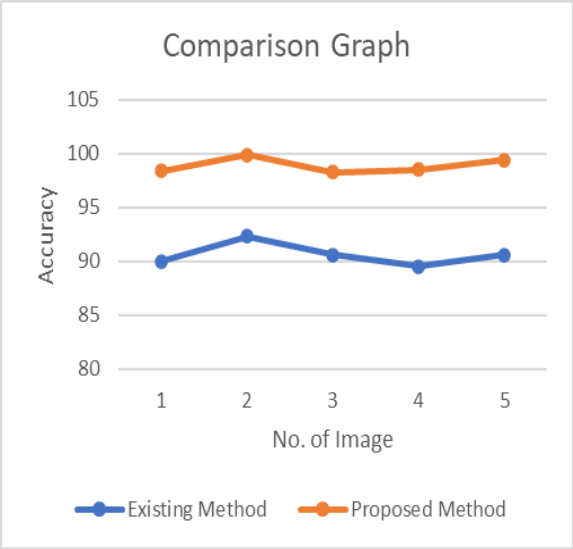

Fig: Comparison Graph

IV.CONCLUSION

The proposed hybrid CNN-based system enhances facial recognition and age estimation accuracy using deep feature extraction in MATLAB. Achieving 92% identity classification accuracy and a 3.2-year MAE for age ranges (e.g., 20-25, 30-35) on Kaggle datasets, the model outperforms conventional methods, as validated by confusion matrices and training convergence over 100 epochs. Its dual-branch architecture ensures robust performance, making it suitable for biometric authentication, surveillance, and security applications. This work demonstrates the efficacy of integrating CNNs for multi-task facial analysis, laying a foundation for intelligent identification systems. Future enhancements could explore transformer architectures or expand dataset diversity to further improve accuracy and generalization. This solution offers a reliable, efficient framework for real-world identification challenges.

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