Age Detection and Face Matching – Technical Report

1. Introduction

This report documents the design, implementation, and evaluation of an age-aware face detection and identity matching system. The objective of the project is to predict the age of an individual from a facial image and determine whether two facial images belong to the same person, even in the presence of significant age variation.

The system is implemented using a **two-stage** deep learning pipeline. In the first stage, age prediction is performed using **convolutional neural networks**. In the second stage, face identity matching is achieved using **ArcFace** embeddings.

The work is implemented in a modular and production-oriented manner, supporting multiple inference interfaces including a **Command Line Interface (CLI)**, a **RESTful API using FastAPI**, a **Flask-based Web UI**, and **Docker Compose** for containerized deployment.

The repository can be found at: https://github.com/walid404/Age-Detection-and-Face-Matching

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2. Background and Motivation

Age-invariant face recognition remains a challenging problem in computer vision. Facial appearance changes non-linearly over time due to aging effects such as variations in skin texture, facial geometry, and soft tissue distribution. These changes significantly complicate identity verification across large age gaps.

The motivation behind this project is to build a practical and deployable system that combines age estimation with face identity matching. By integrating both tasks into a single pipeline, the system enables age-aware identity verification suitable for real-world applications.

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3. Dataset and Preprocessing

The FG-NET Aging Dataset was selected for this project due to its explicit modeling of age progression across identities. The dataset contains facial images of individuals captured at different ages, making it well-suited for studying age-related facial variation.

Preprocessing steps include resizing images to a fixed input resolution, normalizing pixel values to the range [0,1], and applying data augmentation techniques such as random horizontal flipping, rotation, and color jitter during training. An identity-aware dataset splitting strategy is used to ensure that images belonging to the same individual do not appear in multiple data subsets, preventing identity leakage.

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4. System Architecture

The system architecture is organized into modular components, including dataset loaders, model networks, training controllers, and inference interfaces. This separation of concerns improves maintainability and extensibility.

The architecture also supports containerized deployment using Docker and Docker Compose, enabling reproducible execution across different environments and simplifying deployment of the API and Web UI services.

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5. Model Implementation

The age prediction task is formulated as a regression problem. Several convolutional neural network architectures were evaluated, including ResNet18, ResNet34, ResNet50, EfficientNet, AlexNet, and MobileNet.

Although MobileNet was not the absolute best-performing model in terms of raw accuracy, it was selected as the final model due to its strong trade-off between performance and efficiency. MobileNet achieves performance very close to the best model while using approximately one-fifth of the number of parameters. This results in significantly faster inference speed and reduced computational cost, making it more suitable for real-world and resource-constrained deployment scenarios.

For face identity matching, ArcFace is used to extract highly discriminative facial embeddings. Cosine similarity is applied to compare embeddings, and a configurable threshold is used to determine whether two images belong to the same identity.

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6. Training and Evaluation

Age prediction models are trained using Mean Squared Error (MSE) loss with early stopping to prevent overfitting. Evaluation metrics for age prediction include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the R2 score.

Face matching performance is evaluated using accuracy, precision, recall, and F1-score. Threshold optimization is performed to select an appropriate similarity threshold for identity verification.

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7. Deployment and Inference Interfaces

The system supports multiple inference interfaces. A CLI is provided for batch and script-based inference, a FastAPI-based REST service enables programmatic access, and a Flask-based Web UI allows interactive usage.

Docker and Docker Compose are used to deploy the FastAPI backend and Flask UI in a consistent and reproducible manner.

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8. Conclusions

This project successfully demonstrates an end-to-end age-aware face matching system that combines age prediction and identity verification into a unified pipeline. The use of ArcFace embeddings enables robust face matching across age variations.

MobileNet was selected as the final age prediction model due to its near-optimal performance with significantly fewer parameters, resulting in faster inference and improved deployment efficiency. This balance between accuracy and computational efficiency makes the proposed system well-suited for practical, real-world applications.