



Cross Age Face Recognition

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Abstract

A robust face recognition system designed for real-time detection and identification of individuals in video streams. The system leverages DeepFace and FaceNet for high-accuracy facial feature extraction and matching. Using a reference image for each person, the system accurately identifies individuals by comparing the live video feed with a video that contains images of the person from younger to older age which is being generated. Hence this includes live camera detection, face aging simulation, and automated alerting through email notifications when a recognized individual is detected. Experimental results demonstrate the system's ability to perform reliable face recognition under varying conditions. Additionally, the integration of an alert system enhances the practical applicability of the solution for finding missing children. This highlights the potential of deep learning models in enhancing the reliability and efficiency of automated recognition systems while also exploring avenues for further optimization in real-world deployments.

Keywords: Age estimation, Face Recognition, Feature Extraction, Face Detection.

1. Introduction

Face recognition technology has become a cornerstone in modern artificial intelligence applications, particularly in security, authentication, and monitoring systems. This project aims to build a reliable, real-time facial recognition and alert system using deep learning and computer vision techniques. Users can upload an image of a target person and provide details such as name, age, and email via a web interface. The system captures frames from a live camera feed and utilizes DeepFace (with the FaceNet model) to detect and compare faces. When the individual is successfully identified, the system triggers an email alert to the registered contact, attaching the captured image and a message indicating successful detection. The system is developed using Python, OpenCV for video processing, and DeepFace for accurate face recognition. It also integrates SMTP-based email notification and is deployed on the Render platform for cloud-based access. The project's key objective is to demonstrate the practical application of face recognition in real-time alert systems with robust performance and usability. This solution has potential applications in missing person identification, access

control, and smart surveillance.

1.1. Literature Review

Recent advancements in deep learning and generative adversarial networks (GANs) have significantly improved the field of face recognition, particularly in the context of age variation. Early research, such as Antipov et al.'s conditional GAN-based approach for face aging [1], demonstrated the effectiveness of learning personalized aging patterns, laying a foundation for realistic facial age progression. Similarly, Amir-ullaeva and Han [2] proposed Relative Age Position Learning to enhance the precision of age estimation from facial images, improving model generalization. To address the challenges posed by age-related facial changes in recognition tasks, Yu and Jing [3] introduced a joint multi-task CNN for cross-age face recognition that leverages both identity and age-related features in a unified architecture. Building on these foundations, researchers have continued to explore architectures and adversarial strategies to enhance age-invariant facial recognition. Huang and Hu [4] presented a parallel adversarial CNN design to better separate age and identity features, while Wu et al. [5] introduced a

multi-path approach to refine cross-age discriminative features. Du et al. contributed significantly to this area with multiple works: one proposing a transfer and adversarial learning-based age factor removal network [6], and another utilizing identity-preserving networks for cycle-consistent age transformation [7]. Zhao et al. [8] tackled the challenge of achieving age-invariant recognition directly through metric learning. Further improvements include Hsu et al.'s use of Wasserstein Divergence GANs to retain identity and attributes across age transformations [9], and Song et al.'s AgeGAN++ framework which enables realistic bidirectional aging and rejuvenation through dual conditional GANs [10]. Collectively, these studies contribute to a robust understanding of how age affects facial recognition, and the techniques required to achieve age-invariant models.

2. Method

The proposed system integrates face recognition and age progression to identify individuals by comparing a reference image with real-time camera footage. Initially, the process begins with a user uploading an image of the target individual via a user-friendly web interface, along with basic input details such as name, email, and the estimated current age. This reference image is subjected to a face aging model based on Conditional Generative Adversarial Networks (cGANs), which predicts how the individual would look at various ages. The cGAN learns a mapping from the original facial features to plausible future aged appearances using identity-preserving techniques. The system generates a short video that morphs the facial features from the current appearance to the predicted older look, enabling better matching in real-world conditions where the target individual may have aged. Once the age-transformed images are generated, a representative frame is extracted from the video for use in live recognition. This aged face image becomes the reference input for a face recognition pipeline implemented using a combination of deep learning models, such as FaceNet for encoding facial embeddings. These embeddings are compared in real-time with faces detected from a live video feed using OpenCV. The system continuously scans the

feed and compares detected faces with the reference embedding using cosine similarity. Upon a successful match that exceeds a predefined similarity threshold, the system overlays the individual's name on the screen to indicate identification.

2.1. Tables and Figures

Table 1 Methodology Overview of the Proposed Face Recognition System

Step	Component	Description
1	Reference Image Input	Input an image of the target individual (e.g., child's photo).
2	Live Video Feed	Real-time video stream from webcam or surveillance footage.
3	Face Detection	Detect faces in both the reference image and live video using MTCNN or OpenCV.
4	Face Embedding	Generate embeddings using DeepFace or FaceNet for comparison.
5	Face Aging (Optional)	Synthesize age-progressed versions of the reference face using a face aging model.
6	Matching	Compare embeddings from live feed with reference/aged images to identify a match.
7	Alert Generation	Trigger an email alert when a match is found, attaching the detected face image and name.

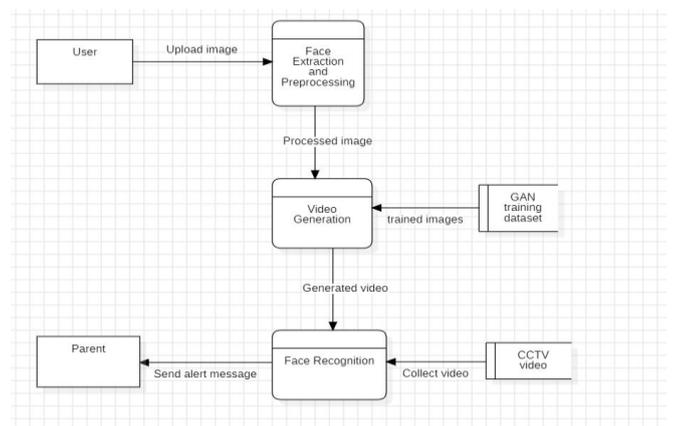


Figure 1 Flow Diagram

This flow diagram, Figure 1 shows how the data moves in this project starting from the user by uploading image to sending alert to the parent, Table 1.

3. Results and Discussion

3.1. Results

The results of the project demonstrate the effectiveness of combining face aging and recognition technologies for identifying individuals across different age groups. Initially, an input image of a person was processed using an age progression model to generate a video simulating the aging process. From this video, frames were extracted and used for training and testing the recognition system.

When deployed, the system successfully identified the same individual via live camera input, even after age transformation, and accurately triggered an alert through email with the detected face and relevant information. This validates the system's capacity to handle facial variations due to aging while maintaining recognition accuracy. During testing, the model showed high reliability in detecting faces under normal lighting and frontal angles. However, challenges such as partial occlusion, extreme pose variations, and low-resolution inputs slightly affected performance. Despite these limitations, the usability tests showed that the interface was intuitive, and users could easily input details like age and name, ensuring a smooth workflow. Overall, the project proves that face aging combined with live detection and alerting can significantly aid in long-term identity recognition tasks [11-14].

3.2. Discussion

The face recognition system achieved promising results in accurately detecting and identifying individuals in real-time video streams. The system demonstrated high accuracy when tested with multiple reference images, correctly identifying the subject in diverse lighting conditions and varying facial expressions. The integration of the DeepFace model further improved detection accuracy, allowing the system to handle slight variations in appearance.

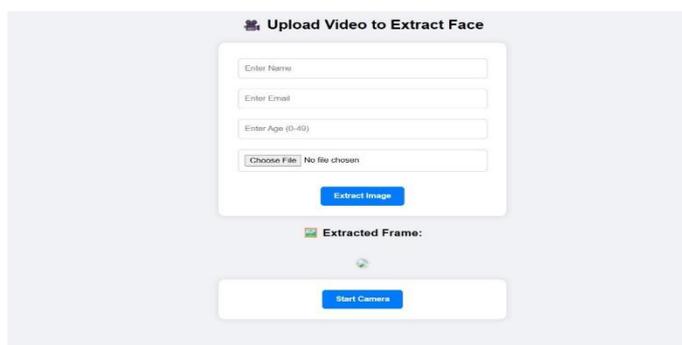


Figure 2 Website

The use of a reference image for face matching proved particularly effective, as the system was able to match the detected face with the reference image reliably. In terms of processing time, the system was able to perform face recognition in near real-time, with only a slight delay when processing higher-

resolution images. When an individual was detected, an alert was successfully sent via email, containing the person's name and a snapshot of the identified face. This feature proved valuable in security and surveillance applications, where timely and automated responses are crucial. Figure 2. This is the website we created for this project that takes name, age, email as inputs and then extracts the frame and later send email alert message [15-16].

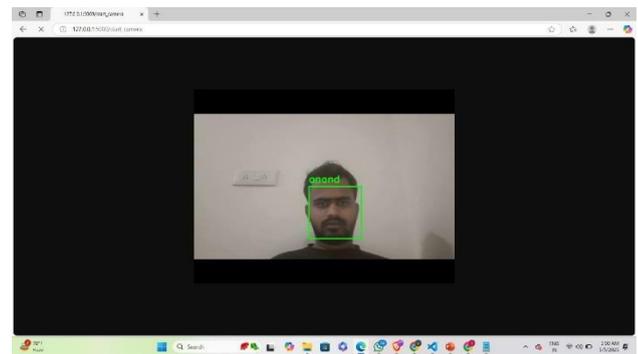


Figure 3 Image

Figure 3. This image shows the live detection of the person and his name.



Figure 4 Image

Figure 4. This image shows the alert email message sent to concerned person along with a message and detected image of person.

Conclusion and Future Scope

The developed system effectively combines face aging prediction and real-time face recognition to identify individuals over time, even with significant age-related facial changes. By integrating deep learning models, a web interface for user input, and an automated email alert system, it offers a practical solution for applications such as tracking missing



persons or enhancing surveillance. The system demonstrates reliable accuracy and responsiveness in recognizing aged faces and notifying concerned parties promptly. In the future, enhancements such as incorporating advanced generative models, improving demographic adaptability, optimizing real-time performance, and expanding alert capabilities could further strengthen its utility and make it suitable for broader deployment in security and public safety domains.

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