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Age And Gender Detection Using Open CV

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ABSTRACT

This project presents a streamlined approach for multi-task learning in age and gender prediction from images, leveraging the capabilities of PyTorch and OpenCV. By integrating these technologies, the model offers a straightforward process for users to execute predictions by running the python script. Through this framework, users can efficiently harness the power of deep learning to simultaneously infer both age and gender from facial images, facilitating a wide range of applications across various domains such as demographic analysis, targeted marketing, and personalised user experiences. Age and gender detection is a crucial task in various fields such as demographic analysis, security systems, targeted advertising, and human-computer interaction.

This project explores the development of a system capable of predicting age and gender from facial images using Python and Convolutional Neural Networks (CNNs). CNNs have been widely recognized for their ability to extract meaningful features from images, making them suitable for this task. The model is evaluated using standard metrics such as accuracy and Mean Absolute Error (MAE) for age prediction. The results demonstrate the effectiveness of deep learning approaches in demographic classification, achieving notable accuracy in real-world applications.

This project serves as a foundation for further enhancements in precision, using more complex models or additional training data to improve predictions. The prediction will be in the form of categories where categories are a few age intervals like 0- 6,18-25, etc. The further goal of this project will be to predict the nearly exact age of the person .i.e , a single number rather than a range.Gender prediction – The prediction is a classifier based where categories are Male and Female.

INTRODUCTION

Human Classification is an age-old procedure and being done in various fields and technology such as biometrics, forensics sciences, Image processing, identification system, etc. With the development of Artificial Intelligence and techniques such as Neural Network and Deep Learning, it has become increasingly easier to classify human. These new technologies help identification, classification of individuals without the need of another professional or individual records. Also being immensely fast, these technologies can classify millions of individuals way faster than a professional.

Human Facial Image Processing provides many clues and cues applicable to industries such as security, entertainment, etc. Human face can provide immense amount of information like their emotional state, slightest agreement or disagreement, irony or anger, etc. This is the reason why faces have been long research topic in psychology. This data is very valuable as it help recognition, selection or identification of individual according to the requirement.

Age and Gender Detection can alone provide a lot of information to places such as recruitment team of organizations, Verification of ID cards, example: Voter ID cards which millions of individual uses to cast their vote at the time of election, etc. Human

Facial Image processing eases the task of finding ineligible or counterfeit individual.

In the modern age of artificial intelligence (AI) and machine learning (ML), significant advancements have been made in the area of computer vision, which involves enabling computers to perceive and interpret visual data in ways similar to human sight. One of the major applications of computer vision is age and gender prediction, an automated process that involves estimating an individual's demographic information based solely on their facial features. This task, while seemingly straightforward for humans, poses considerable challenges for machines due to variations in lighting, facial expressions, angles, and other external factors. The ability to automatically predict age and gender from images has become increasingly important for several industries, particularly in domains such as security, targeted advertising, retail, healthcare, and social media.

2-Literature Survey

Age and gender detection have been the subject of numerous studies and research projects in recent years. In this literature survey, we will discuss some of the key studies and approaches that have been used in age and gender detection, with a focus on those that use deep learning techniques. One of the earliest studies on age and gender detection was conducted by Geng et al. in 2007. In this study, the authors used a set of handcrafted features, such as facial texture, shape, and wrinkles, to predict age and gender. The results of the study showed. that these features could be used to predict age and gender with reasonable accuracy. However, the study was limited by the fact that the features were manually designed, and may not generalize well to new datasets. In recent years, deep learning techniques have been increasingly used in age and gender detection. One popular approach is to use Convolutional Neural Networks (CNNs), which are a type of deep learning model that is specifically designed for image classification tasks.

Another study that used CNNs for age and gender detection was conducted by Antipov et al. in 2017. In this study, the authors used a CNN architecture called the Age Gender DeepLearning (AGD) model to predict age and gender from facial images. The model was trained on a dataset of over 200,000 images and achieved an. accuracy of 96.4% for gender classification and an error of 4.15 years for age estimation. The results of the study showed that the AGD model was highly effective in predicting age and gender from facial images.

Another approach that has been used in age and gender detection is to use a combination of handcrafted features and deep learning techniques. One study that used this approach was conducted by Yan et al. in 2018. Golomb et al. employed the form shading (SFS) and multi layers perceptron (MLP) methods that Jing

Wu et al. provided for gender classification. During this time, Khan et al. used classifier reinforcement, namely adaboost, for gender prediction. Yamaguchi et al. revealed that distinctions between the features of an adult's face and a child's include the length of the face and the ratio of each side among research on age prediction.

Ueki and Coll also described a method of identifying age groups by linear discriminating analysis. Burt and Perrett researched the age estimation based on the usage of average faces of adults between 25 and 60 years of age. Although the SVM has been tested for age classification several times. Kwon and Lobo defined a method for classifying input images into one of three age groups: child, young and old using texture information. However, almost all previous research has been based on craniofacial development method and analysis of skin wrinkles.

The study entails a thorough documentation of individual differences based on age, gender, identity, and other characteristics. In 2001, D. Kornack and P. Rakic proposed Adult Primate Neocortex. Age estimation using convolutional network was introduced by Chenjing Yan. The face-matching brain activation tests are carried out and tested outside of the scanner. In terms of facial processing, both older and younger persons showed the same results.

M. Young with proposed identical facial perspectives in both scenarios, performance is excellent. There is no single cause for the aging of the elderly. The accounting of such findings is the consequence of a mix of many elements. The findings, which are based on all credentials stored in certain environments, need to be monitored. In this research, Hang Qi et al. Made the claim that a number of methods have emerged for the detection of faces that can also determine a person's age. Here, an automated system that can determine the age and assist in differentiating between a child's and an adult's face has been suggested. The system is composed of three components. A. Kumar and F. Shaik's theory about age categorization, face alignment, and face detection are the three. The standard face detection and alignment techniques are used to build the face samples. Eran Eidinger, Roee Enbar, and Tal Hassner's theory helps with unfiltered face. The local face components that are visible in the photos are extracted using ICA. It has been demonstrated that this system is substantially faster and that the outcomes: effective.

Aditya K. Saxena, Shweta Sharma and Vijay K. Chaurasiya used curvalet domain. Therefore, this system may be used as a prototype in the future. The Conditional Probability Neural Network (CPNN), a distributed learning technique used for age prediction from facial expressions, was proposed by Chao Yin et al in the paper. Age estimation using a hierarchical classifier based on global and local facial features. The goal values and the conditional feature vectors are utilized as the input in a three-layer neural network-based model. This may aid in its learning of actual ages. The neural network's link between the facial image and the associated label distribution is how this system learns According to the earlier strategy, the connection should be applied in accordance with the maximum entropy model. CPNN has demonstrated that it outperforms all previously developed methodologies in terms of results. Results were easily obtained using this procedure, and there was computationally involved and the outcomes are very efficient and good in this case.

3-SOFTWARE AND HARDWARE REQUIREMENTS

In this chapter will be discussing about software requirements for Age and Gender Predictions using Python.

Libraries and Tools Overview

OpenCV (Open Source Computer Vision Library)

Overview: OpenCV is a widely used open-source computer vision and machine learning software library. It supports various programming languages such as C++, Python, and Java, making it versatile for a variety of applications.

Key Features:

- Image processing (filtering, edge detection, transformations)
- Object detection and tracking
- Face and gesture recognition
- Video analysis (motion analysis, background subtraction)

Hardware Requirements

The hardware requirements will depend on the complexity of the task, but for typical applications involving OpenCV and the DNN module, the following specifications are recommended.

Processor: Intel Core i5 or equivalent, with multiple cores (quad-core or higher preferred) for parallel processing.

RAM: Minimum of 8 GB (for basic tasks); 16 GB or higher recommended for more intensive tasks involving deep learning models.

Graphics Card (GPU): A dedicated GPU, such as NVIDIA with CUDA support, is recommended for faster processing, especially when using the DNN module for deep learning tasks.

Storage: SSD with at least 256 GB for fast read/write access during model training and deployment. Peripherals: Camera modules (if using for image processing), sensors, and network capabilities for real-time applications.

4-SYSTEM DESIGN AND METHODOLOGY

System design for age and gender detection using OpenCV involves planning and structuring the various components required to accurately detect and classify the age and gender of individuals from images or video streams. This includes designing the workflow for image capture, preprocessing, face detection, and classification using pre-trained deep learning models. The system integrates OpenCV's tools for image processing, such as face detection and feature extraction, with neural networks to categorize age and gender. The objective is to create a robust, real-time system that efficiently processes visual data and delivers accurate predictions.

System Design Objective

- OpenCV (Open Source Computer Vision Library) is used for processing images captured from various sources, such as camera feeds. OpenCV provides tools for image handling, feature extraction, and facial analysis.

The primary goal is to enhance the image quality and extract meaningful features for further classification.

Key Steps in Image Processing with OpenCV:

- Image Enhancement: Improve the input images to make them suitable for analysis. This may include resizing, noise reduction, and normalization using OpenCV functions such as cv2.resize() and cv2.GaussianBlur().
- Face Detection: OpenCV's pre-trained Haar Cascades or DNN (Deep Neural Network) models are used for detecting faces within the image (cv2.CascadeClassifier() or cv2.dnn.readNetFromCaffe()).
- Face Cropping: After detecting the face, the image is cropped to focus on the facial region, which helps in improving the accuracy of age and gender detection.

Existing System

The existing systems for age and gender detection generally rely on computer vision techniques and deep learning models. These systems are designed to analyze images or video frames to predict an individual's age group and gender based on facial features. Below are some key aspects of the existing systems:

1. Techniques and Tools

1. OpenCV: An open-source computer vision library widely used for facial detection and image processing. It helps in pre-processing images, detecting faces, and cropping face regions from larger images.
2. Deep Learning Models: Most systems use deep learning models, particularly Convolutional Neural Networks (CNNs), which are excellent for image classification tasks. Pre-trained models such as:

Proposed System

For the proposed system of Age and Gender Detection using OpenCV, a structured approach by combining OpenCV for image processing and a deep learning model for age and gender classification can be used. The steps involved in the design are:

1. Deep Learning-Based Age, Gender, and Region Detection System: Utilize convolutional neural networks (CNNs) for feature extraction from facial images. Train separate models for age estimation, gender classification, and region detection. Implement data augmentation techniques to enhance model robustness. Integrate the models into a unified system for simultaneous detection of age, gender, and region from facial images.

2. Transfer Learning-Based Approach: The pre trained deep learning models such as VGG, ResNet, or MobileNet for feature extraction. Finetune the pre-trained models on a dataset containing annotated facial images for age, gender, and region. Employ techniques like transfer learning to adapt the learned representations to the specific detection tasks. Develop an efficient inference pipeline for real-time detection of age, gender, and region from input images or video streams.

Flow Chart

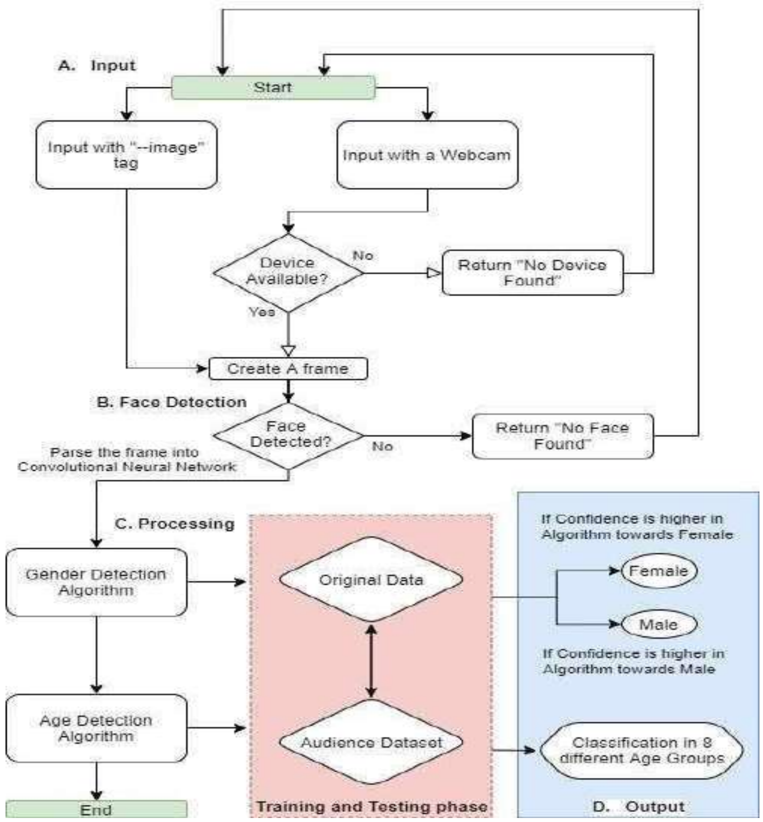


Figure 3.1: Flow chart of Age and Gender Prediction

Methodology

1. Deep Learning with Convolutional Neural Networks (CNNs):

Utilize deep learning techniques, particularly CNNs, to develop models for age, gender, and region detection from images. Train CNN models on labelled datasets containing images with corresponding age, gender, and region labels. CNNs can automatically learn hierarchical features from raw image data, making them effective for complex tasks like age, gender, and region detection.

2. Feature Extraction and Classification:

Extract relevant features from images using techniques such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), or facial landmark detection. Use machine learning classifiers, such as Support Vector Machines (SVMs) or Random Forests, to classify extracted features into age groups, gender categories, or geographic regions. This approach relies on handcrafted features and traditional machine learning algorithms for classification.

3. Facial Landmark Detection and Regression:

Employ facial landmark detection algorithms, such as the Shape Predictor model from DLib, to localize key facial landmarks (e.g., eyes, nose, and mouth). Utilize these landmarks to compute geometric or appearance-based features that are indicative of age, gender, and region. Train regression models, such as linear regression or decision trees, to predict age or infer gender and region based on the extracted features.

5-RESULTS

Table 2 and Table 3 presents our results for gender and age classification respectively. Table 4 further provides a confusion matrix for our multi-class age classification results. For age classification, we measure and compare both the accuracy when the algorithm gives the exact age-group classification and when the algorithm is off by one adjacent age-group (i.e., the subject belongs to the group immediately older or immediately younger than the predicted group). This follows others who have done so in the past, and reflects the uncertainty inherent to the task – facial features often change very little between oldest faces in one age class and the youngest faces of the subsequent class. Table 2 also provides a comparison with which used the same gender classification pipeline of applied to more effective alignment of the faces; faces in their tests were synthetically modified to appear facing forward.

Table 1. The AdienceFaces benchmark.

	0-2	4-6	8-13	15-20	25-32	38-43	48-53	60-	Total
Male	745	928	934	734	2308	1294	392	442	8192
Female	682	1234	1360	919	2589	1056	433	427	9411
Both	1427	2162	2294	1653	4897	2350	825	869	19487

Breakdown of the AdienceFaces benchmark into the different Age and Gender Evidently, the proposed method outperforms the reported state-of-the-art on both tasks with considerable gaps. Also evident is the contribution of the over-sampling approach, which provides an additional performance boost over the original network. These show that many of the mistakes made by our system are due to extremely challenging viewing conditions of some of the Adience benchmark images. Most notable are mistakes caused by blur or low resolution and occlusions (particularly from heavy makeup). Gender estimation mistakes also frequently occur for images of babies or very young children where obvious gender attributes are not yet visible.

Table 2. Gender estimation results on the Adience

benchmark.

Method	Accuracy
Best from [10]	77.8 ± 1.3
Best from [23]	79.3 ± 0.0
Proposed using single crop	85.9 ± 1.4
Proposed using over-sample	**85.9 ± 1.4**

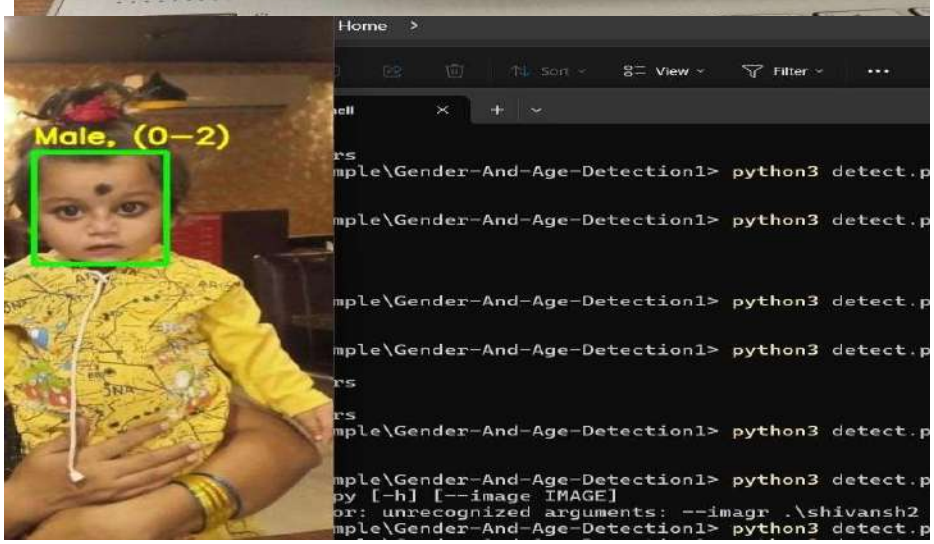
Listed are the mean accuracy ± standard error over all age categories. Best results are marked in bold.

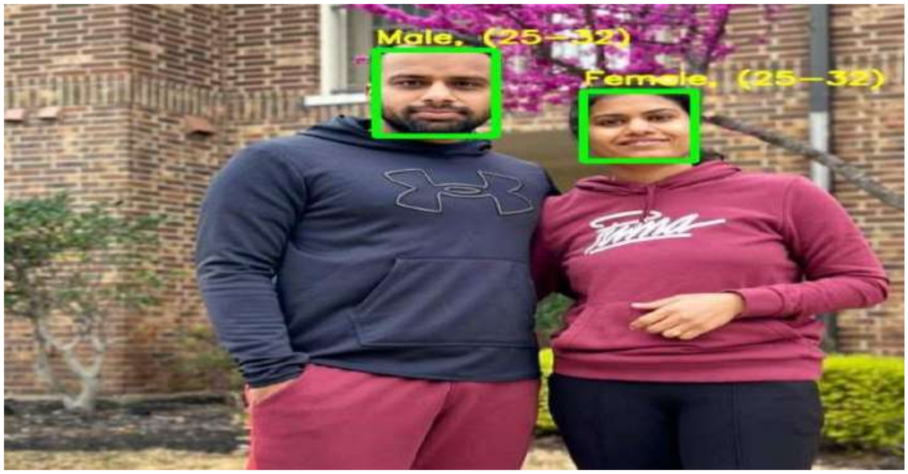
Table 3. Age estimation results on the Adience benchmark.

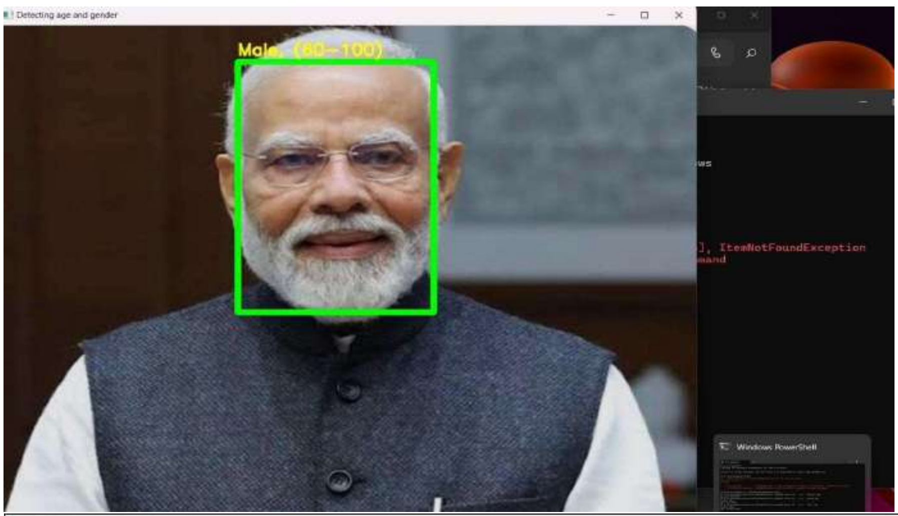
Method	Exact	1-off
Best from [10]	45.1 ± 2.6	79.5 ±1.4
Proposed using single crop	49.5 ± 4.4	84.6 ± 1.7

Listed are the mean accuracy ± standard error over all age categories. Best results are marked in bold.

Test Cases and Proofs




Male, (25-32)
Female, (25-32)


Detecting age and gender
Male, (60-100)


Detecting age and gender
Female, (38-43)

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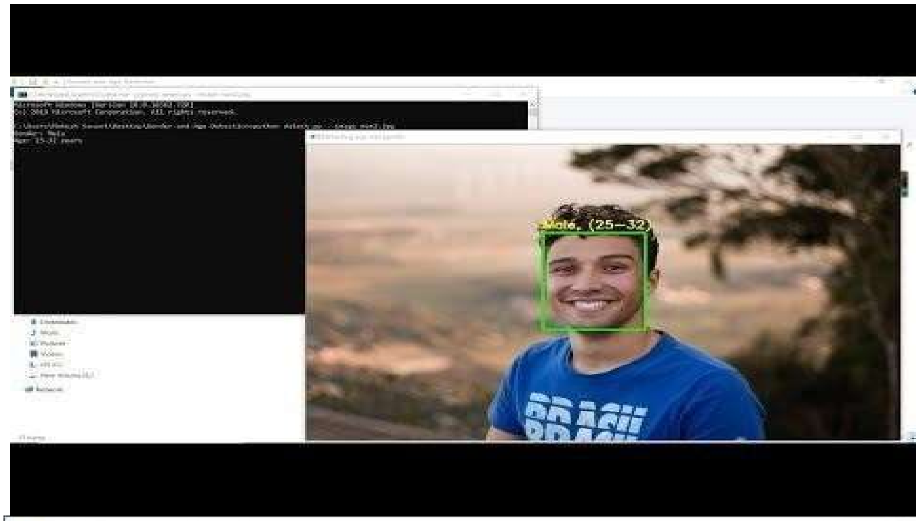

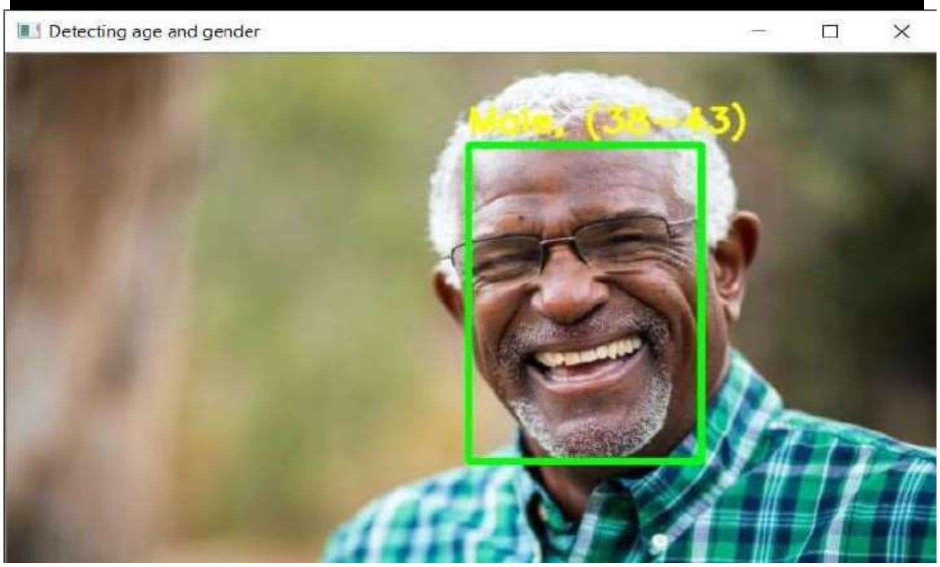

6 ADVANTAGES & DISADVANTAGES

Advantages:

1. **Open-source Libraries**: Python has a vast ecosystem of open-source libraries such as TensorFlow, Keras, OpenCV, and dlib, which simplify building and deploying age and gender prediction models.
2. **High-Level Abstractions**: Python's high-level programming nature allows developers to focus on implementing machine learning algorithms with fewer lines of code, making it easy to prototype and test ideas.
3. **Platform Independence**: Python is cross-platform, meaning age and gender prediction models can be developed and deployed on different operating systems such as Windows, Linux, and macOS.

Disadvantages

1 **Privacy Concerns**: Collecting and processing facial images can raise significant privacy issues

2. **Bias and Fairness**: Models can inherit biases from the training data, leading to unfair predictions across different demographic groups.

3. **Data Dependency**: The accuracy of predictions heavily depends on the quality and diversity of the training data.

7-CONCLUSION

In conclusion, age and gender prediction using Python and CNN-based deep learning models offers a promising approach for automatic demographic classification from facial images. Despite the advancements in technology, several challenges remain, including dataset biases, variations in facial features, and environmental factors such as lighting and pose. Moreover, ethical concerns around privacy and inclusivity must be addressed to ensure fair and responsible use of these systems. While current models provide reasonable accuracy, further improvements can be achieved by leveraging diverse datasets, optimizing model architectures, and adopting methods to enhance generalization across different populations. As research continues, these systems have the potential to become more reliable and applicable in a range of real-world applications.

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