Age and Gender Detection Using Python and opencv

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Abstract: **The project aim is used to predict the age and gender of the person who was coming in front of the camera. An growing number of applications, especially after the increase in social networks and social media, are being concerned with automatic age classification. It is used to estimate a person's age and gender from a facial image using deep learning techniques. The system should be capable of working in real-time applications for security, marketing, and human-computer interaction. The proposed system aims to improve accuracy compared to traditional methods. In this project, we leverage Deep Learning and Computer Vision techniques to develop an Age and Gender Detection system using OpenCV and Convolutional Neural Networks (CNN). The system analyzes facial images to predict gender (Male/Female) and categorize individuals into predefined age groups. By utilizing CNN for feature extraction and a pre-trained Caffe model for classification, we achieve improved accuracy in age and gender prediction. The system is capable of real-time detection and has applications in security, marketing, human-computer interaction, and surveillance. The implementation focuses on efficient facial feature extraction, reducing computational complexity while maintaining high classification accuracy. The primary programming language used for this project is Python, due to its extensive support for machine learning and deep learning libraries. OpenCV is utilized for image processing and face detection, allowing efficient real-time detection of facial features. For classification, a Convolutional Neural Network (CNN) is implemented, enabling the model to accurately predict age and gender. Additionally, Haar Cascade Classifiers are employed for face detection, leveraging pre-trained models to identify human faces in images and video streams. This combination of technologies ensures high accuracy and performance in the detection process. In this project, we have successfully implemented an Age and Gender Detection system using Deep Learning and OpenCV. By utilizing Convolutional Neural Networks (CNN) and a pre-trained Caffe model, the system effectively identifies gender and estimates age from facial images. The model demonstrates reliable accuracy in classification while operating in real-time, making it suitable for applications such as security surveillance, marketing, and human-computer interaction.**

Keywords--- Face detection, OpenCV, Haar Cascade, Video surveillance, Security purpose, etc.

INTRODUCTION

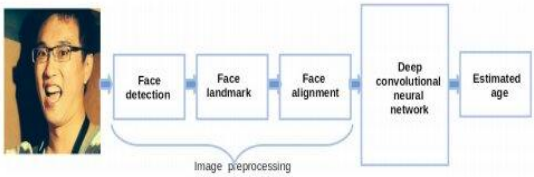
Artificial Intelligence (AI)is a computing technique which imitates human brain for the actions that are performed. These actions can be performed by the AI algorithms with the assistance of Machine Learning (ML) and Deep Learning (DL) algorithms. In order to be able to make decisions/predictions human-like, the model is required to be trained and then verified to decide the outputs. Testing is done to validate over what it has learnt at the training and verify the functionality. Based on input data, the neural network can use the algorithms of machine learning to improve accuracy. Machine learning algorithms like Regression, Classification for Supervised Learning and Clustering for unsupervised learning etc. can be used which help to improve the model's efficiency and accuracy as a supporting algorithm for the output prediction to the main model being developed. The output prediction depends on the present inputs for those algorithms. Deep Learning improves the overall performance and the efficiency of the model which has to detect characteristics of the person like age and gender by developing a neural network. The model being developed can be used for surveillance purposes. Deep learning's neural networks forms the basis for the entire model and then entire decision making process is done by the neurons of the neural network. The main objective of the paper is to determine the parameters like the age, gender of the person by using the model being developed. It is makes it easier for the sake of the video analytics, for medical purposes for the surveillance purposes and it can be achieved by the use of the computer vision.

MOTIVATION

In this section we provide the age and gender classification literature and briefly describe about few early methods which are most related to our proposed method, focusing on age and gender detection. Many early methods in age and gender detection were handcrafted, focusing on manually engineering the facial features from the face. To mention a few, in 1999, Kwon and Lobo developed the very first method for age estimation focusing on geometric features of the face that determine the ratios among different dimensions of facial features. These geometric features separate babies from adult successfully but are incapable of distinguishing between young adult and senior adult. Hence, in 2004, Lanitis et al. proposed an Active Appearance Model (AAM) based method that included both the geometric and texture features, for the estimation task. This method is not suitable for the unconstrained imaging conditions attributed to real-world face images which have different degrees of variations in illumination, expression, poses, and so forth. From 2007, most of the approaches also employed manually designed features for the estimation task: Gabor, Spatially Flexible Patches (SFP), Local Binary Patterns (LBP), and Biologically Inspired Features (BIF). In recent years, classification and regression methods are employed to classify the age and gender of facial images using those features. Classification methods in used Support Vector Machine (SVM) based methods for age and gender classification. Linear regression, Support Vector Regression (SVR), Canonical Correlation Analysis (CCA), and Partial Least Squares (PLS)are the common regression methods for age and gender predictions. Dileep and Danti also proposed an approach that used feed-forward propagation neural networks and 3-sigma control limits approach to classify people's age into children, middle-aged adults, and old aged adults. However they all were incompetent when given large datasets therefore, cannot be relied on to achieve respectable performance in practical application.

PROPOSED MODEL

In our proposed model we use CNN and Opencv for facial recognition. This proposed model can detect faces, divide into Male/Female based facial features, divide an image with face of a person into one of 8 age ranges. Convolutional neural networks (CNN): There are various neural networks available which can be used as per the requirement or inputs being given. They have 3 main layers are input layer, hidden layer(s) and the output layer. Each layer has large number of neurons where each is associated with a certain value of weights. The values of the weights are updated at the time of forward and backward propagations, along with the help of an activation function at every layer/neuron in order to activate them. Updating the weights, governs the overall accuracy of the neural network model, as the cost/loss function is reduced to a minimum value, at a certain point in the gradient descent



Convolutional Neural Network (CNN):

In your project, Convolutional Neural Networks (CNNs) play a central role in accurately detecting and classifying the age and gender of a person from a facial image. The CNN is a deep learning model that is designed to automatically extract important features from images, such as the shape of the eyes, nose, lips, skin texture, and overall facial structure. Once the face is detected using OpenCV (through Haar Cascade classifiers), the cropped facial image is passed into the CNN model. This model then analyzes the features and makes two predictions: one for gender (Male or Female) and another for age group (e.g., 0–2, 4–6, 8–13, etc.). Unlike traditional machine learning methods that require manual feature extraction, CNNs automatically learn these patterns from large datasets, making them highly effective and accurate even under real-world conditions such as different lighting, head positions, or facial expressions. In short, CNN is the core component that allows your system to intelligently and efficiently recognize age and gender just by looking at a person's face.

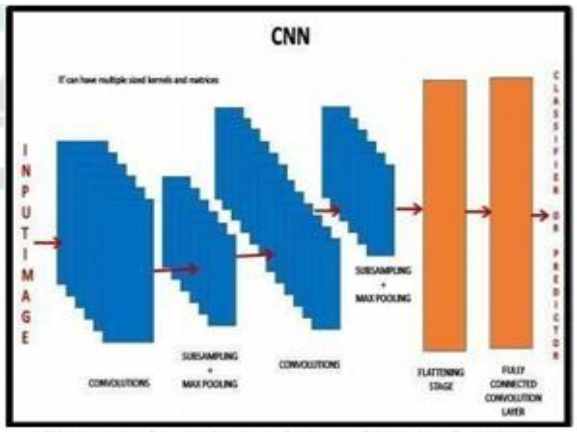


Figure 3: Convolutional Neural Network (CNN)

OIU-Adience is a collection of face images from real-life and unconstrained environments. It gives all the features that are anticipated from an image that is collected from various real -world scenarios etc are facial images that were uploaded to Flickr website from smart phone without any filtering. Adience images, therefore, display a high-level of variations in noise, pose, saturation, brightness and appearance, among others. , entire collection of OIU Adience dataset is about 26,580 face images of 2,284 subjects and with an age group label of eight comprising 0 2, 4–6, 8–13, 15–20, 25–32, 38–43, 48–53, and 60+

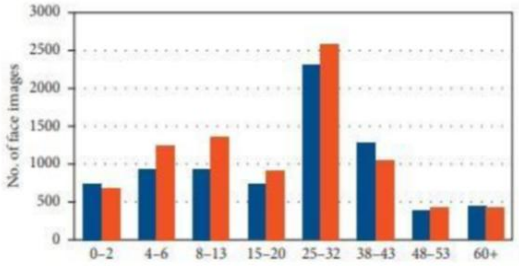


Figure 4: Age-groups for male and female (in years)

Face Detection:

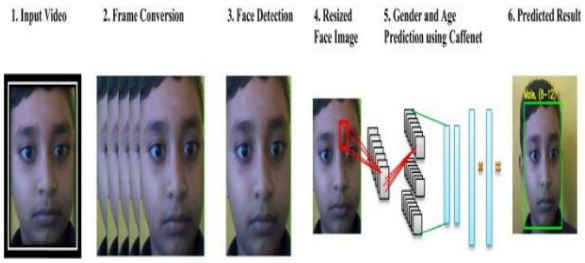
In your project, face detection is the first and most essential step that enables the system to identify and locate human faces in an image or video stream. This is achieved using OpenCV's Haar Cascade Classifier, which is a machine learning-based approach where a cascade function is trained from a large number of positive and negative images. The face detection algorithm scans the entire image and looks for patterns that match the structure of a human face, such as the eyes, nose, and mouth arrangement. Once a face is detected, it is cropped from the image and sent to the CNN model for further analysis like age and gender classification. Accurate face detection is crucial because it ensures that the CNN receives the correct facial region, which directly impacts the overall performance and accuracy of the system. The use of Haar cascades allows for real-time and efficient face detection, making the entire process fast and reliable for practical applications.

Gender and Age detection:

Age and gender detection is the core functionality of your project, where the system analyzes a detected face and predicts the person's age group and gender using deep learning techniques. After the face is detected and cropped from the image using OpenCV, it is passed into a pre-trained Convolutional Neural Network (CNN) model. This model has been trained on large datasets containing thousands of facial images labeled with age and gender. The CNN processes the facial features—such as skin texture, facial structure, and other visual cues—and classifies the gender as either Male or Female, and the age into one of several predefined groups (e.g., 0–2, 4–6, 8–13, etc.). The use of CNNs allows the system to automatically learn and identify key patterns in the face without manual feature extraction, making the predictions more accurate and reliable. This functionality is especially useful in real-world applications like surveillance, targeted advertising, and access control systems where knowing a person's age and gender can enhance personalization and security.

Result Display Module:

The Result Display Module is responsible for presenting the final output of the system by showing the predicted age and gender of the detected person directly on the screen. Once the CNN model processes the cropped facial image and generates the predictions, this module takes the results and overlays them on the live video feed or image frame. This is implemented using OpenCV's putText() function, which allows the system to draw text on the frame at a specific position near the detected face. The displayed information typically includes the age group and gender (e.g., "Male, 25-32"), making the system interactive and user-friendly. This module plays an important role in making the output easily understandable and visually accessible to the user in real time.



LITERATURE SURVEY

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METHODOLOGY/ WORKING

1. Data Acquisition Module

This module is responsible for initiating and handling the video stream. It uses OpenCV to connect to the system's webcam and continuously captures frames for real-time processing. The function cv2.VideoCapture(0) initializes the webcam, and a loop is used to read frames continuously. This forms the foundation for all subsequent modules.

Key Responsibilities:

- Initialize webcam.
- Capture video frames in real-time.
- Provide continuous input for face detection.

2. Face Detection Module

The face detection module identifies human faces from the captured frames. It uses OpenCV's Deep Neural Network (DNN) module and pre-trained face detection models (.pb and .pbtxt files). The image is converted into a blob, which is then fed into the neural network. Detected faces are highlighted using rectangles.

Key Responsibilities:

- Load and use deep learning-based face detection model.
- Convert image to blob format.
- Predict bounding boxes around faces.
- Draw visual boxes for each detected face.

3. Preprocessing Module

Once faces are detected, this module processes the detected facial regions before they are fed into the age and gender models. It extracts each face, applies padding to avoid cutting off facial features, and converts it into a blob format suitable for model input.

Key Responsibilities:

- Extract facial region from the full image.
- Apply padding to ensure complete facial capture.
- Convert face image to blob format (227x227 pixels).
- Normalize data using mean values required by the model.

4. Model Loading Module

This module loads the pre-trained deep learning models for face detection, age prediction, and gender prediction. The models are based on the Caffe deep learning framework. The function cv2.dnn.readNet() is used to load .caffemodel and .prototxt files.

Key Responsibilities:

- Load face detection model.
- Load age prediction model.
- Load gender prediction model.
- Ensure compatibility with OpenCV's DNN module.

5. Age and Gender Prediction Module

This module performs the actual classification. The face blob is passed through the gender and age models. The prediction scores from the models are processed to determine the most likely age group and gender.

Key Responsibilities:

- Use blob input to perform prediction.
- Determine the gender (Male/Female).
- Determine the age group (e.g., 0-2, 25-32, 60-100).
- Map numerical outputs to human-readable labels.

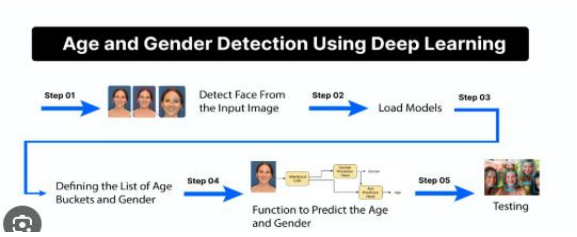
6. Result Display Module

After obtaining the prediction results, this module overlays the information on the video frame. OpenCV's putText() and rectangle() functions are used to display the predicted age and gender above the person's face in the video feed.

Key Responsibilities:

- Overlay age and gender text on the frame.
- Draw colored boxes for clear visibility.
- Maintain real-time performance with smooth display.

SYSTEM ARCHITECHTURE



CONCLUSION

In this project, we have successfully implemented an Age and Gender Detection system using Deep Learning and OpenCV. By utilizing Convolutional Neural Networks (CNN) and a pre-trained Caffe model, the system effectively identifies gender and estimates age from facial images. The model demonstrates reliable accuracy in classification while operating in real-time, making it suitable for applications such as security surveillance, marketing, and human-computer interaction.

Although the system performs well, challenges such as variations in lighting, facial expressions, and image quality can affect accuracy. Future enhancements could involve training with larger, more diverse datasets and integrating advanced deep learning techniques for improved prediction. Overall, this project highlights the potential of AI-driven facial analysis in various real-world applications.

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