Gender and Age Detection with OpenCV

K. Neelima Santoshi, Sonia Peddinti, Krishna Saranya Korada, Ashika Patchigoolla, Karthik Varma Hanumanthu

Department of Computer Science Engineering, GITAM Deemed to be University, Visakhapatnam, India-530045

Abstract : The project on "Gender and Age Detection with OpenCV" represents a compelling venture within the domains of Data Science and Computer Vision. It explores the application of Convolutional Neural Networks (CNNs) to accurately discern both gender and approximate age from individual facial images. Recognizing the complexities inherent in real-world scenarios, such as variations in makeup, lighting conditions, and unique facial expressions, the project underscores the importance of practical and technical insights, making it a valuable asset to any data science portfolio. Moreover, given the recent surge in interest surrounding age and gender detection, this project holds significant potential for application across diverse fields. The project on "Gender and Age Detection with OpenCV" represents a compelling venture within the domains of Data Science and Computer Vision. It explores the application of Convolutional Neural Networks (CNNs) to accurately discern both gender and approximate age from individual facial images. Recognizing the complexities inherent in real-world scenarios, such as variations in makeup, lighting conditions, and unique facial expressions, the project underscores the importance of practical and technical insights, making it a valuable asset to any data science portfolio. Moreover, given the recent surge in interest surrounding age and gender detection, this project holds significant potential for application across diverse fields.

Keywords: Convolutional Neural Networks (CNNs), deep learning, OpenCV, gender detection, age prediction.

I. INTRODUCTION

Gender and age are significant factors in societal interactions, influencing various aspects of everyday life. With advancements in science and technology, the prevalence of smart devices has grown, capturing widespread attention. Consequently, there has been a surge in studies focusing on gender and age prediction, leading to the development of numerous applications employing specialized methods. These applications often rely on initial photographs to extract valuable information regarding human interactions. Techniques such as image transformation, feature extraction, and classification are commonly employed for gender identification and age estimation, with their usage tailored to suit the objectives of each study. Various approaches are utilized to process facial representations, and calculations are performed based on the outcomes of these analyses. Among these approaches, segmentation stands out as a fundamental and widely utilized method, involving the division of facial features into distinct parts or objects to address specific challenges. Deep learning methods have emerged as a powerful tool for tasks such as categorization, feature extraction, and object recognition, thereby enhancing the accuracy of gender and age prediction. Unlike earlier machine intelligence algorithms, which lacked the ability to handle large volumes of data available on the internet, modern deep learning methods leverage vast datasets to improve categorization capabilities significantly. This paper utilizes deep learning techniques to reliably predict gender and age from a single facial image capture. The classification of individuals into 'male' or 'female' categories is based on grammatical rules pertaining to sex or animateness. Age classification is also employed to estimate an individual's age based on experimental data. The significance of facial features, particularly the eyes, cannot be overstated, as they provide valuable cues for facial recognition and emotional expression. Human facial image processing offers insights into various domains, including healthcare, security, and entertainment, by deciphering emotions and sentiments conveyed through facial expressions. The study of faces has become integral to medical research, highlighting their importance in understanding human behavior and physiology. Gender detection holds potential applications in various fields, including identity verification for official documents like ID cards and voter registration cards, which are crucial for electoral processes worldwide. The ability to identify anomalies or deceptive practices through facial analysis further underscores the utility of gender detection technology in diverse contexts.

II.LITERATURE SURVEY

Title: Gender Recognition from Facial Images: A Survey (2011)

Publisher: P. J. Phillips et al.

This survey provides an overview of prevalent methods for gender recognition using facial images, encompassing traditional techniques and machine learning approaches.

Title: Age Estimation and Gender Classification: Two Birds, One Stone (2009)

Publisher: R. Rothe et al.

This paper introduces a combined framework for age estimation and gender classification, highlighting the correlation between these two tasks.

Title: Age and Gender Classification Using Convolutional Neural Networks (2017)

Publisher: Gil Levi and Tal Hassner

This study explores age and gender classification through Convolutional Neural Networks (CNNs), incorporating grammatical rules related to gender classification. Additionally, it introduces the IMDB-WIKI dataset specifically designed for this domain.

Title: Face Recognition with Age and Gender Variations: A Review (2018)

Publisher: Muhammad Usama et al.

This review article examines advancements and challenges in face recognition systems that consider variations in age and gender, offering insights into recent developments in this area.

Title: Large-scale, long-term, and continuous performance evaluation of age and gender estimation algorithms (2018)

Publisher: Gil Levi and Tal Hassner.

The authors present a comprehensive evaluation of age and gender estimation algorithms using a standardized dataset, assessing their performance over extended periods and under diverse conditions.

III.PROPOSED METHODOLOGY

3.1 COMPUTER VISION:

Computer vision, a domain within artificial intelligence (AI) and computer science, empowers computers to comprehend and interpret visual data. It encompasses the development of algorithms and methodologies enabling machines to extract meaningful insights from images and videos, akin to human vision. OpenCV harnesses facial detection capabilities to identify human faces in video frames by analyzing pixel data with precision. Upon detection, essential facial features like eyes, nose, and mouth are extracted, crucial for accurate age and gender estimation. Image preprocessing techniques such as normalization and resizing are employed to standardize input data, optimizing subsequent predictions. These preprocessed facial regions are then fed into deep learning-based models, predominantly Convolutional Neural Networks (CNNs), trained to predict age and gender based on learned patterns. Finally, the predicted age and gender labels are overlaid onto the video frames, showcasing the practical application of computer vision for real-time interpretation and annotation of visual data.

3.2   **Deep Learning:** To enable software to detect objects, it must be trained with a large volume of categorized object images. Both gender and age classification models are deep neural networks trained on extensive datasets. These networks have been trained to extract discriminative features from faces, facilitating accurate prediction of gender and age. Deep learning empowers models to discern complex patterns and relationships in data, leading to more precise predictions compared to traditional methods. By integrating fundamental elements such as shape, edges, and corners, images can be trained within the network to recognize items such as characters, faces, etc.
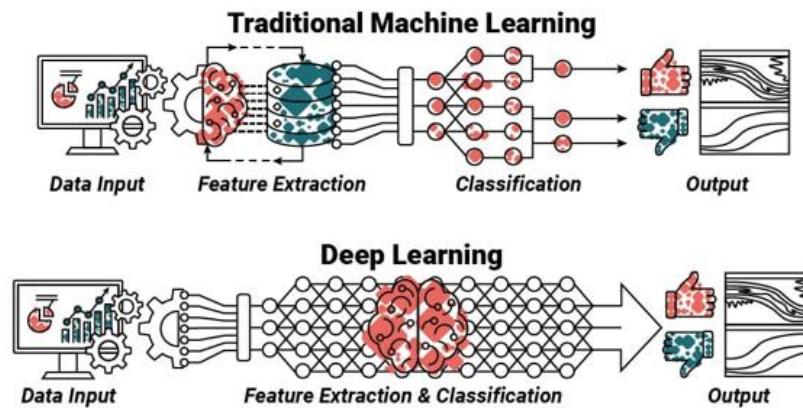
Fig 3.2: Information about traditional Machine learning vs Deep Learning

3.3   **Convolutional Neural Networks:** Convolutional Neural Networks (CNNs) excel in image recognition tasks compared to other models. They comprise multiple layers, including convolutional layers that extract features from input images. In this context, face images are fed through layers of pre-trained CNNs, extracting relevant features for gender and age prediction. These extracted features are then utilized for making predictions, facilitating accurate estimation of gender and age. CNNs possess translation invariance, recognizing patterns irrespective of their position in the image, achieved through pooling layers and shared weights. This parameter sharing minimizes overfitting risks and enables learning of robust features, making CNNs resilient to variations in object position and orientation.
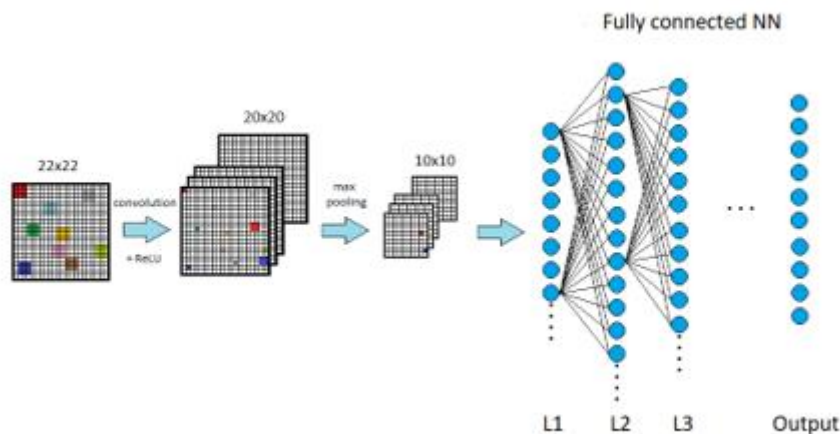

Fig 3.3: Information about implementation of CNNs

3.4   **Face Detection:** Face detection utilizes a pre-trained model provided by OpenCV, employing a Single Shot Multibox Detector (SSD) framework to detect faces in input frames. Each frame is passed through the face detection model, extracting bounding boxes around detected faces with a confidence threshold of 0.7.

3.5   **Gender Prediction:** A pre-trained gender classification CNN model is loaded using OpenCV's DNN module. The detected face is pre-processed as a blob and input to the gender CNN model. The model predicts the gender of the face, interpreted from the model's output.

3.6   **Age Prediction:** Similarly, an age classification CNN model is loaded, and the preprocessed face blob is input to the age CNN model. The model predicts the age group of the face, which is interpreted from the model's output.

3.7 Pre-trained Models: Pre-trained models are CNNs trained on large datasets for specific tasks. Leveraging these pre-trained models avoids training from scratch, and they can be fine-tuned for specific applications**.**

3.8 Real-time Video Processing: Real-time video processing involves capturing video frames from a source (e.g., webcam) using cv2.VideoCapture, processing frames in a loop until interrupted by user input. Processed frames with age and gender labels are displayed using cv2.imshow. Resources are released and windows closed gracefully upon loop termination. This entails analyzing each frame to perform tasks such as object or face detection, typically at a high frame rate. Enhancements include padding around detected faces for better extraction and applying normalization and resizing for improved model performance. Overall, it combines face detection with deep learning-based age and gender estimation for real-time analysis, showcasing OpenCV's capabilities in building computer vision applications.

IV. ACCURACY TESTING:

To ensure the accuracy of the age and gender detection system, various approaches can be employed:

▪ Diverse Dataset Selection: Choose a dataset with labeled age and gender information spanning different demographics and facial expressions.

▪ Evaluation Metrics: Assess the model's performance using metrics such as accuracy, precision, recall, and F1-score.

▪ Cross-Validation: Validate the model's consistency by dividing the dataset into subsets and testing across different portions.

▪ Confusion Matrix Analysis: Visualize the model's predictions across different age and gender categories to identify areas of improvement.

▪ Hyperparameter Optimization: Fine-tune model settings like learning rate and architecture to enhance performance.

▪ Data Augmentation: Increase dataset diversity by applying transformations like rotation and scaling to improve the model's robustness.

▪ Baseline Comparison: Evaluate the deep learning model against traditional methods to understand its effectiveness.

▪ Real-world Scenario Testing: Deploy the model in practical settings to assess its performance under various conditions such as different lighting and camera angles**.**
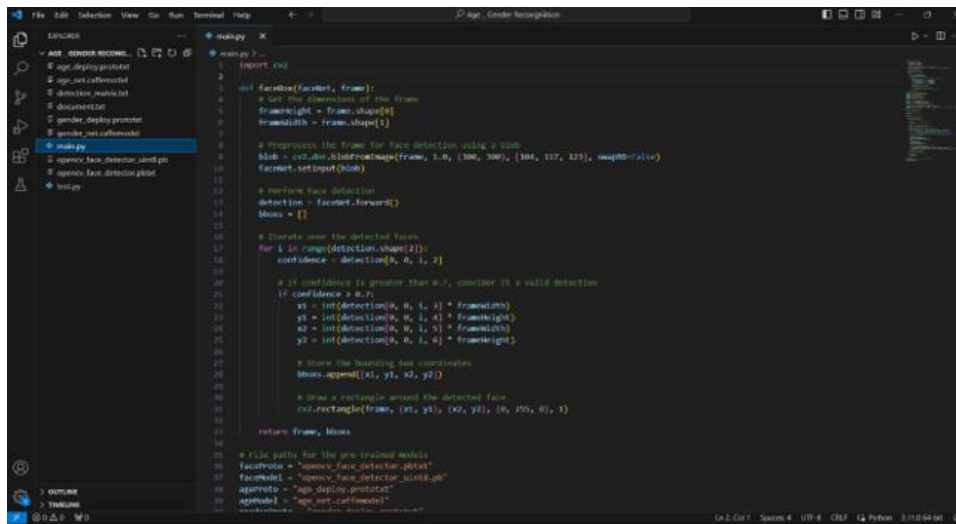
V. ALGORITHM FOR AGE AND GENDER DETECTION:
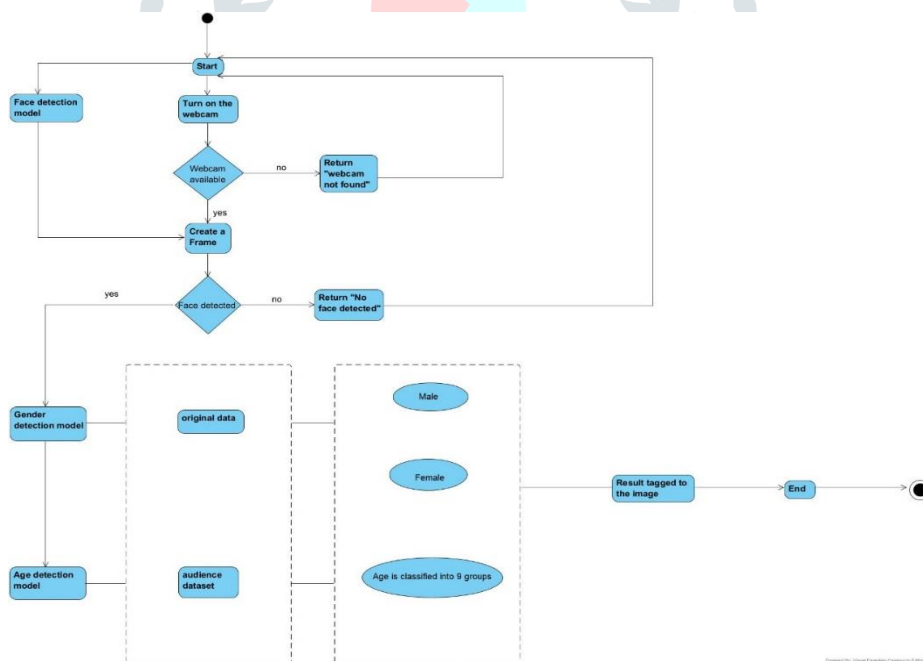
VI. IMPLEMENTATION:

● Library Import: Begin by importing necessary libraries, particularly cv2 (OpenCV), for image processing and computer vision tasks.

● Model Loading: Load pre-trained models for face detection, age prediction, and gender prediction using OpenCV's DNN module. Define constants and lists for age and gender prediction, including model mean values, age categories, and gender labels.

● Video Capture Initialization: Initialize video capture from a camera using OpenCV's Video Capture function. Define a padding value to extract faces with additional space around them.

• Face Detection: Utilize the faceBox function to perform face detection on the current frame using the loaded face detection model. Extract bounding boxes for detected faces.

• Preprocessing: For each detected face, extract the face region with padding to ensure the entire face is captured. Preprocess the extracted face region by creating a blob, a pre-processed image representation suitable for age and gender prediction models.

• Prediction: Pass the pre-processed face blob to the gender and age prediction models separately. Retrieve the predicted gender and age categories based on the highest probability scores from the model outputs. Associate the predicted gender and age with the corresponding bounding box.

• Live Video Processing: Execute the Python code in a development environment (e.g., Visual Studio) to capture live video through the device camera. The camera will display a rectangular box capturing the face and predict the gender and age, tagged to the box, throughout the video.

• Result Display: The result, indicating whether the person is male or female and their approximate age, is displayed within the rectangular box throughout the video. Upon completion, exit the application by clicking the stop button, turning off the camera and stopping live video capture.

Fig 6.1: Contains code in visual studio

In figure 6.2 we can see the following execution, the camera will pop up to capture faces for real-time gender and age detection using OpenCV.
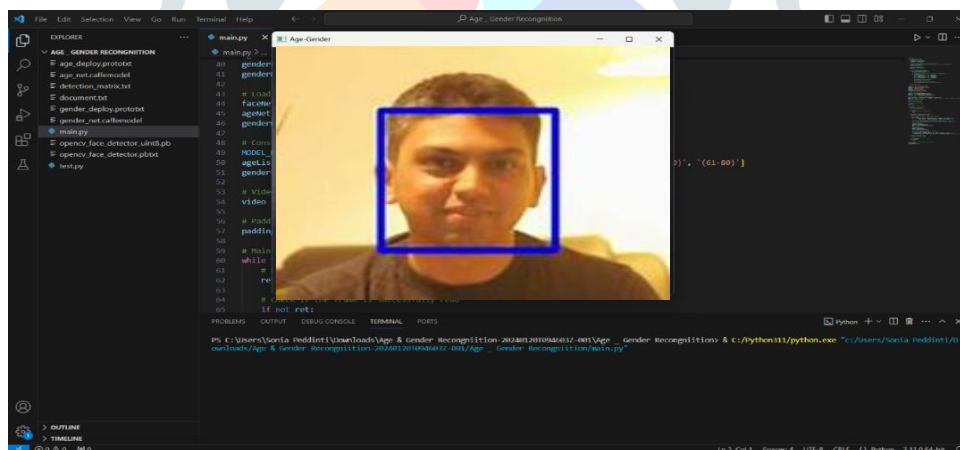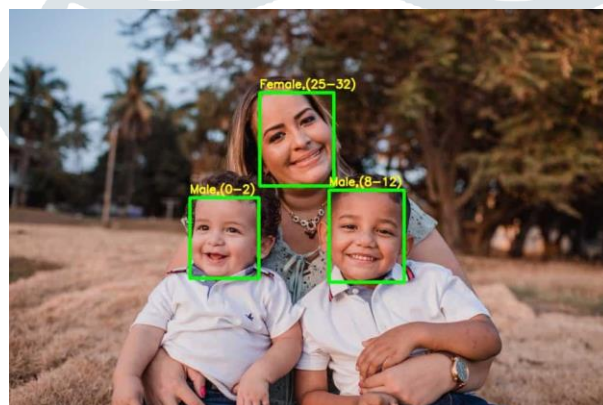

Fig 6.2: Camera detecting user face

DATASET:

Fig 6.3: Training dataset

OUTPUT:

Fig 6.4: Result showing age and gender

VII.TOOLS AND LIBRARIES:

- Python (programming language).
- Visual Studio Code (for Python code).
- OpenCV (for image and video processing).
- Deep learning frameworks like TensorFlow (for CNN implementation).
- Model is pre-trained and inserted in the code.
- Caffe models which are commonly used for various computer vision tasks due to their efficiency and effectiveness.

VIII.CHALLENGES:

- Face Detection Accuracy: Achieving consistent accuracy in face detection can be challenging due to variations in lighting conditions, occlusions, and facial orientations within video frames. Ensuring robust face detection across diverse real-world scenarios is crucial.
- Robustness to Variability: Faces exhibit significant variability in terms of pose, expression, and appearance, posing challenges for models to accurately predict age and gender. Designing models that are robust to these variations is essential.
- Generalization to Diverse Demographics: Age and gender prediction models may perform differently across diverse demographic groups due to variations in facial features. Ensuring the system generalizes well across different populations is critical for fairness and effectiveness.
- Real-Time Performance: Processing video streams in real-time requires efficient algorithms and optimization techniques to maintain accuracy while processing frames quickly.
- Privacy and Ethical Considerations: Analyzing individuals' age and gender raises privacy and ethical concerns. Ensuring the system respects individuals' privacy and operates ethically is paramount, especially when dealing with sensitive information.

IX. Applications:

- Marketing: Retailers can use this system to analyze customer demographics by deploying cameras at store entrances or checkout counters.
- Education: Educational institutions can automate attendance tracking during classes or events by installing cameras in classrooms or lecture halls.
- Smart Home Devices: Smart home devices can personalize user experiences using facial recognition and age-gender estimation, such as suggesting TV shows based on detected viewer demographics.
- Healthcare: Age and gender detection technology can facilitate patient monitoring, personalized care, and demographic analysis in healthcare settings.
- Forensics: Investigators can accurately identify suspects and victims using surveillance footage or forensic images, speeding up case resolutions and creating precise victim profiles for missing persons.

X. CONCLUSION:

In conclusion, the age and gender detection project presented here demonstrates the effective integration of computer vision techniques, primarily using the OpenCV library and deep learning models. Through face detection and facial feature extraction, the system accurately identifies faces in video streams and extracts relevant information for age and gender estimation. Preprocessing steps like normalization enhance data quality, leading to more reliable predictions. Leveraging pre-trained deep learning models enables real-time analysis and annotation of video frames. This project showcases the practical application of computer vision in facial analysis tasks, with potential implications in various fields. It underscores the importance of robust preprocessing, model selection, and integration for successful computer vision solutions. Overall, this project highlights the power of combining computer vision techniques with deep learning for accurate and efficient age and gender detection in real-world scenarios.

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