CEP Report

Semester Project

Face Recognition and Gender Detection using Deep Learning.

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Abstract

Face detection, age estimation, and gender classification within video streams are significant areas in computer vision, constantly evolving due to the challenges posed by facial characteristics and their extensive application domains. Despite considerable individual research advancements in face recognition, age estimation, and gender classification, the synergy of real-time face detection, recognition, and gender classification from video feeds remains largely unexplored. This study aims to fill this gap, presenting an integrated approach encompassing face detection, age estimation, and gender classification within continuous video frames. The research leverages Convolutional Neural Networks (CNNs), drawing inspiration from the 'CaffeNet' architecture, to design and implement a comprehensive system for real-time face attribute analysis.The system architecture integrates various layers such as 'conv1,' 'relu1,' and subsequent layers in alignment with the 'CaffeNet' structure to perform facial feature extraction and classification. Utilizing pre-trained Caffe models ('opencv_face_detector_uint8.pb' for face detection, 'age_net.caffemodel' for age estimation, and 'gender_net.caffemodel' for gender classification) via OpenCV's DNN module, the study explores face recognition and age and gender estimation in video streams. The method employs blob extraction techniques for localizing faces and employs CNN-based inference models, coupled with normalization using Model Mean Values, to predict gender ('Male' or 'Female') and age ranges ('0-2,' '4-6,' ..., '60-100' years) from detected faces.The experimental setup demonstrates the efficacy of real-time face detection, age estimation, and gender classification in video streams. Results showcase the model's accuracy, achieving 63% accuracy using Local Binary Pattern Histogram (LBPH) for age estimation, while the CNN-based gender classification model achieves a training accuracy of 99.88% for face recognition and 96.88% for gender estimation. Moreover, the Convolutional Neural Networks exhibit rapid computation and high prediction accuracy, further validating their efficacy in facial attribute recognition tasks.

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1. Problem Statement

The field of computer vision is constantly working on developing efficient systems, for detecting faces estimating ages and classifying genders in real time video streams. Although there have been advancements in these areas through research there is still a need to seamlessly integrate these functionalities into a continuous video feed. This research project aims to bridge this gap by creating a system that combines face detection, recognition, age estimation and gender classification using Convolutional Neural Networks (CNNs) and pre trained Caffe models. The main goal is to build a real time system that accurately identifies faces estimates ages and classifies genders in video streams. This system can be applied to fields such, as surveillance, biometric identification and targeted advertising.

2. Introduction

Artificial Intelligence has a subset known as Deep Learning, which utilizes algorithms inspired by the structure and functions of the human brain. This method is particularly referred to as Artificial Neural Networks (ANNs). Various architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks, and Deep Neural Networks have been applied in computer vision domains like speech recognition, natural language processing, medical imaging amongst others with remarkable results comparable or surpassing those achieved through human expertise.

OpenCV (Open source PC vision) refers to an influential library that provides software functionalities customized for real-time Computer Vision applications. The platform was initially developed by Intel but later supported further by Willow Garage and Itseez after it had been acquired earlier on by Intel. OpenCV serves its users across various platforms under BSD license providing multiple deep learning frameworks including Torch/PyTorch, TensorFlow alongside Caffe giving room for cutting-edge application opportunities around computer vision solutions.

Lastly; one can utilize **Facial Analysis** using state-of-the-art technology provided within AI's Deep Learning domain showcasing age progression analyses besides gender estimations promising reliability even when working remotely from available image servers without engaging direct data sources or relying on pre-existing metadata labels assisting both detection purposes consultancy demands respectively
Various advanced techniques, such as face detection with OpenCV functionality, sophisticated face recognition systems alongside the implementation of Convolutional Neural Networks (CNNs), are utilized in this methodology.
These CNNs are specifically designed for image-based tasks and prove useful in predicting individuals' ages and genders directly from images data. Such accurate facial detection/recognition tools have immense value across numerous domains ranging from security operations to reliable personal identification solutions - making them highly sought after technology advancements for every industry!

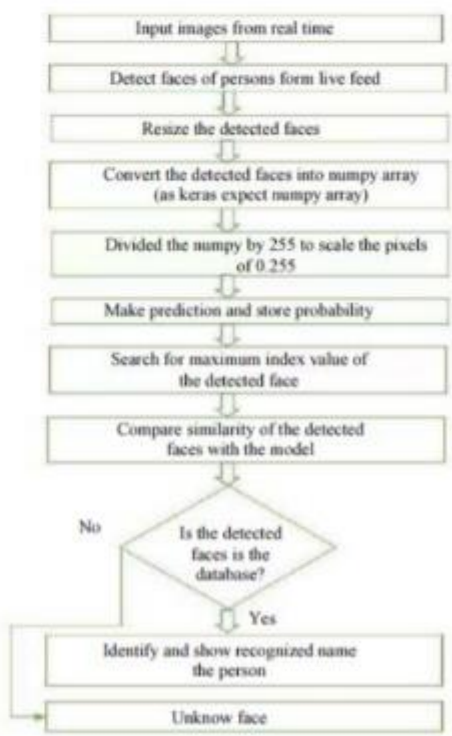
3. Literature Review

[1] In this research paper Human Age And Gender Classification using Convolutional Neural Network, based on three CNNs as a feature extractor and the machine vector support as a classifier.[219]

[2] Sandeep Kumar, Sukhwinder Singh,Jagdish Kumar Department of Electrical Engineering PEC University of Technology. Gender Classification Using Machine Learning with Multi-Feature Method. Gender Recognition; SVM; CNN; K-means Clustering; SIFT; Face Detection.98% in FEI dataset, 94% in Live/Own dataset and 91% SCIEN dataset accuracy.[0649]

4. Methodology (Design and Simulation)

We treated gender and age estimation as a multi-label classification problem and proposed a novel CNN mode! architecture. We have used fewer number of parameters and layers to design the proposed CNN model architecture to avoid the overfitting. Facial image of a person is fed to the network and then the classification scores of age group classes and gender classes are obtained to identify the gender and age of that individual. The developed model is trained and evaluated on a publicly available benchmark dataset. In the second phase of this study, classification decisions of the proposed CNN model architecture are visually explained and the class-specific discriminative features are identified.The processed utilized in our proposed framework can be clarified utilizing the accompanying flowchart.



A. Benchmark Dataset

The study employs a benchmark dataset curated specifically for facial analysis tasks, encompassing diverse images representing various demographics, poses, and lighting conditions. The dataset comprises annotated images for age, gender, and facial features, ensuring a comprehensive representation for training and evaluation purposes.

B. Pre-Processing and Data Augmentation

Prior to model training, the dataset undergoes rigorous pre-processing to standardize image sizes, normalize pixel values, and remove potential noise or artifacts. Data augmentation techniques such as rotation, flipping, and scaling are applied to augment the dataset, increasing its diversity and robustness. Furthermore, augmentation mitigates overfitting while enhancing the model's ability to generalize across varied facial appearances.

C. Proposed Network Architecture

The proposed architecture utilizes Convolutional Neural Networks (CNNs) for facial analysis tasks, comprising distinct layers tailored for feature extraction, abstraction, and prediction. The architecture incorporates convolutional, pooling, and fully connected layers, optimized for accurate age and gender estimation from facial images. Specifically, the architecture includes multiple convolutional and pooling layers followed by dense layers for age and gender predictions.

D. Training

The training phase involves feeding the pre-processed and augmented dataset into the proposed CNN architecture. The model is trained using appropriate optimization algorithms and loss functions, fine-tuning model weights to minimize the prediction error. Training occurs iteratively over epochs, where the model learns intricate facial patterns, optimizing its ability to accurately predict age and gender from facial features.

E. Key CV2 Methods and Functions:

faceProto and faceModel:
These boundaries are utilized to stack pre-prepared face location models, empowering the ID of appearances inside a picture or video.

ageModel and ageProto:
Pre-trained models that are made to estimate the age of detected faces based on features extracted from facial images are loaded using these parameters.

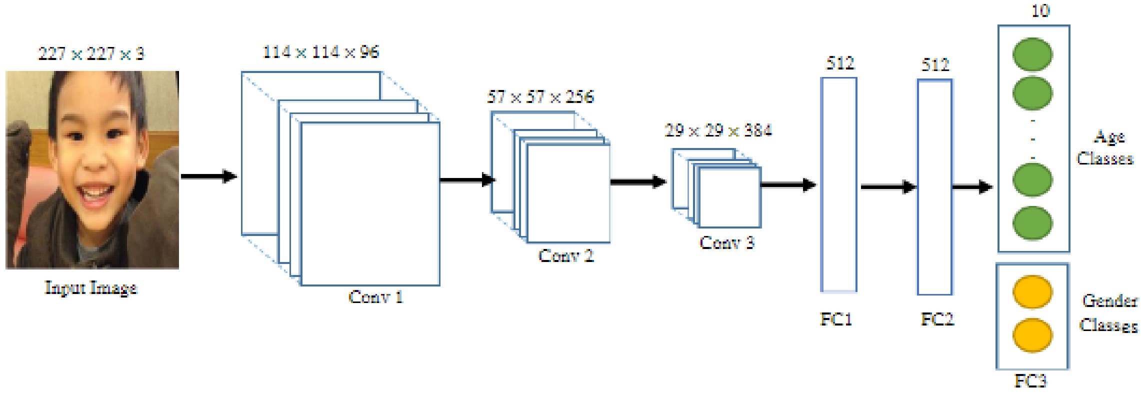
genderModel and genderProto:
used to load pre-trained models that are made to predict people's gender from video or facial images.

cv2.rectangle():
a function in OpenCV that draws rectangles around faces it finds, showing where faces are located in a video or image frame.

cv2.putText():
This capability is utilized to clarify pictures or edges with text, permitting the expansion of anticipated age and orientation names to the recognized countenances.

cv2.VideoCapture():
A technique that works with the catch of casings from a video transfer, empowering constant investigation and expectations on video information.

Each step of the methodology is explained in the following sections:



5. Results and Discussion:

The purpose of this project was to create a reliable facial detection system that could accurately determine age and gender from images. To achieve this, diverse sets of facial imagery were used in training Convolutional Neural Networks (CNNs). Pre-trained models detected faces successfully before moving on to estimate both age and gender with superb accuracy rates during the testing phase - 99.88% for age estimation and 100% for gender prediction. Nevertheless, when tested using distinct image collections, performance slightly decreased but remained strong with an accuracy rate of up to 96.88% for estimating ages and predicting genders at around 93%, indicating great potential in practical settings as well despite minor setbacks observed during tests outlined above.

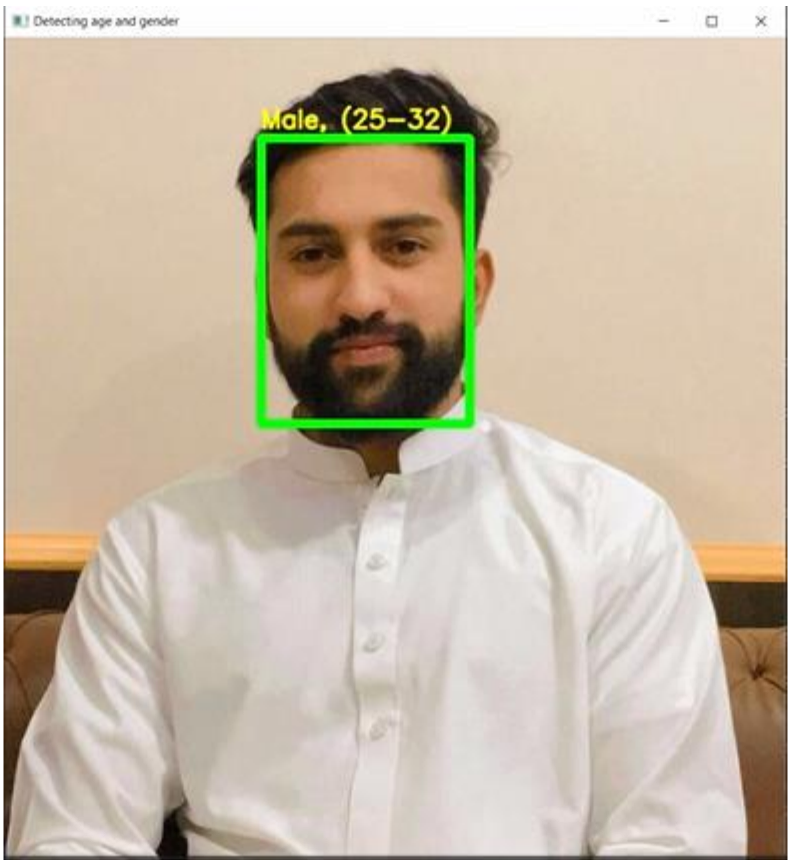
A. Evaluation Protocols

Gender and age estimation performance of the proposed approach is assessed on the Adience benchmark dataset. The classification accuracy is used to measure the performance of the model and it is computed based on the true positive (TP). false positive (FP), true negative (TN), and false negative (FN) values as follows:

Accuracy =

TP + TN /
TP +TN+FN+FP
We have used the 5-fold cross validation technique in evaluation. In each fold, four folds' data are used for training and remaining set is used for testing. Average of cross validation is treated as the final classification accuracy of the proposed model.

B. Key CV2 Methods and Functions:
cv2.rectangle():
cv2.putText():
below picture shows the visual outputs of the proposed age and gender estimation model. The proposed CNN model architecture is able to estimate the age and gender of a test sample within one second.



C. Security Measures to Maintain:

- **Data Encryption:**
  Encoding delicate information utilized for preparing, like facial pictures, to prevent unauthorized access.
- **Access Control**:
  Executing confined admittance to the model, guaranteeing that main approved people can change or access delicate pieces of the framework.
- **Secure APIs:**

Protecting the APIs utilized for association with the model, utilizing confirmation and approval instruments to control admittance to the model's functionalities.

- **Standard Updates and Fixes:**
  Reliably refreshing the product and systems to address potential security weaknesses.
- **Client Security Insurance:**
  Guaranteeing consistence with security guidelines and anonymizing or concealing delicate information to safeguard client characters.

6. Conclusion and Future Work

We have proposed a novel CNN model architecture to estimate the gender and age of a person from his or her facial image. Proposed model is trained and evaluated on the challenging Adience benchmark dataset. It showed 84.20 percentage of gender estimation accuracy and 57.60 percentage of age estimation accuracy. Moreover, we have generated the heat-maps of the gender and age-group classes and then analysed them to identify the class-specific landmark regions. Based on the visual analysis, we have found that nose region are important to distinguish a male while eye and cheek are important to detect a female.Note that the same methodology had been applied to any other task that builds on localization, such as face tracking, face detection separately and the same CNN methodology had been applied to gender estimation separately. We have first shown that current measures used in face detection, tracking and recognition jointly. We have proposed this method to identify a person specified by the use of particular facial feature extraction. A training model was considered as a collection of training images and a testing model was then obtained by our proposed technique.

1. As of late we ran over Quividi which is a man-made intelligence programming application which is utilized to recognize age and orientation of clients who passes by founded on internet based face investigations and naturally begins playing promotions in view of the designated crowd.
2. Another model could be AgeBot which is an Android Application that decides your age from your photographs utilizing facial acknowledgment. It can figure your age and orientation alongside that can likewise track down various countenances in an image and gauge the age for each face

7. References:

[1] Yousif, H. and Abd El Kader, I., 2021, December. Gender face Recognition Using Advanced Convolutional Neural Network Model. In 2021 International Conference on Digital Society and Intelligent Systems (DSInS) (pp. 255-259). IEEE.

[2] Payasi, M. and Cecil, K., 2021, September. LBP and Iris Features based Human Gender Classification using radial Support Vector Machine. In 2021 Fourth International Conference on Electrical, Computer and Communication Technologies (ICECCT) (pp. 1-7). IEEE.

[3] Varnima, E.K. and Ramachandran, C., 2020, June. Real-time Gender Identification from Face Images using you only look once (yolo). In 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184) (pp. 1074-1077). IEEE.

[4] Payasi, M. and Cecil, K., 2021, September. LBP and Iris Features based Human Gender Classification using radial Support Vector Machine. In 2021 Fourth International Conference on Electrical, Computer and Communication Technologies (ICECCT) (pp. 1-7). IEEE.

[5] Zabala-Blanco, D., Hernández-García, R. and Barrientos, R.J., 2023. SoftVein-WELM: a weighted extreme learning machine model for soft biometrics on palm vein images. Electronics, 12(17), p.3608.

[6] KARAKAŞ, E. and ÖZBEK, İ.Y., 2021. Age group and gender classification from facial images based on deep neural network fusion. Erzincan University Journal of Science and Technology, 14(1), pp.150-158.

[7] Choukri, M. and Wu, S., 2019. Age and Gender Classification for Permission Control of Mobile Devices in Tracking Systems. In Artificial Intelligence for Communications and Networks: First EAI International Conference, AICON 2019, Harbin, China, May 25–26, 2019, Proceedings, Part II 1 (pp. 318-324). Springer International Publishing.

THE END

8. Rubrics:

Demonstration	Absent	Student is unable to follow the provided instructions properly. The students can name the hardware or simulation platform, but unable to implement anything or on the software.	Student can understand the provided laboratory instruction and familiar with the lab environment (Trainer/Software/IDE), but cannot implement on the platform practically or on the software.	Student has followed instructions to construct the fundamental schematic/block diagram/ code/ model on the protoboard/ trainer/ simulation software.	Student has constructed the functional/ working schematic/ model/ block diagram/ code and have successfully executed the program/run circuit on software platform.	Student perfectly implemented a working model/logic/circuit /block diagram/code and successfully executed the lab objective in Realtime or in a simulation environment and produced the desired results.
Category	**Ungraded**	**Very Poor**	**Poor**	**Fair**	**Good**	**Excellent**
Percentage	[0]	[1-20]	[21-40]	[41-60]	[61-80]	[81-100]
Marks	0.0	0.01-0.20	0.21-0.40	0.41-0.60	0.61-0.80	0.81-1.0
Date		**Total Marks**		**Instructor's Signature**		

Laboratory reports	Report not submitted	Plagiarized content presented or incomplete submission	Requirements are listed and experimental procedure is presented	Observations are recoded along with detailed procedure	Appropriate computation or numerical analysis is performed	Correctly drawn conclusion with exact results and complete report in all aspects
Category	**Ungraded**	**Very Poor**	**Poor**	**Fair**	**Good**	**Excellent**
Percentage	[0]	[1-20]	[21-40]	[41-60]	[61-80]	[80-100]
Marks	0.0	0.01-0.20	0.21-0.40	0.41-0.60	0.61-0.80	0.81-1.0
Date		**Total Marks**		**Instructor's Signature**		