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AGE AND GENDER CLASSIFICATION USING CNN

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Abstract: A gender and age classification is the visible manifestation of the affective state, cognitive activity, intention, personality and psychopathology of a person and plays a communicative role in interpersonal relations. Automatic recognition of gender and age can be an important component of natural human-machine interfaces; it may also be used in behavioral science and in clinical practice. An automatic gender and age classification system needs to perform detection and location of faces in a cluttered scene, facial feature extraction, and gender and age classification. Gender and age classification system is implemented using Convolution Neural Network (CNN). This project focuses on coupling the architectures for age and gender classification to take advantage of gender-specific age characteristics inherent to images / live camera. This stemmed from the observation that gender classification is an inherently easier task than age classification, due to both fewer numbers of potential classes and more prominent intra-gender facial variations. By training different age classifiers for each gender, an improvement in age classification is observed.

I.INTRODUCTION

Recently, the usage of images over the internet has grown at an exponential rate. This afresh wealth of data has now enabled us to tackle computer vision problems that were previously complex to solve. There exist accurate and efficient face detection and recognition frameworksthat leverage convolution neural networks. Its applications range from suggesting “who to tag “to pedestrian detection. The next major step is to extract the characteristics of the subjects in such images. Following the successful example laid down by face detection and recognition systems, similar gains can be obtained with simple network architecture for age and gender classification, designed by considering the limited availability of accurately labeled datasets. Data scarcity is mainly because of the nature of the data that is required. The reason behind this is in order to have age and gender labels for images, access to the personal information like: date of birth, gender of the subjects is needed, which is a rare and private piece of information. Thus, we must take this into consideration and alter the network architectures and algorithmic approaches to cope with these limitations. These reasons are the primary motivations behind choosing to implement a relatively shallow architecture for age and gender classification using convolution. We test our network on the Audience benchmark - collection of unfiltered face images. The data included in this collection is intended to be as true as possible to the challenges of real-world imaging conditions. Although results by provide a remarkable baseline for deep-learning-based age and gender classification approaches, they leave room for improvement for more elaborate system designs, which are presented in this paper. Proposed System: We have developed a convolution neural network based model for classifying gender and age through live video frame in real time. We use transfer learning on the fully connected layers of an existing convolution neural network which

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was pre-trained for human gender and age classification. Finally, a live video stream connected to a face detector system give feeding of images to the neural network. The results facilitate the easiness of implementing convolution neural networks in real time to detect gender and age. The results demonstrate the feasibility of implementing neural networks in real time to detect human emotion.

II. LITREATURE SURVEY

Age and Gender Classification Age classification. The problem of automatically extracting age related attributes from facial images has received increasing attention in recent years and many methods have been put forth. A detailed survey of such methods can be found in [11] and, more recently, in [21]. We note that despite our focus here on age group classification rather than precise age estimation (i.e., age regression), the survey below includes methods designed for either task. Early methods for age estimation are based on calculating ratios between different measurements of facial features [29]. Once facial features (e.g. eyes, nose, mouth, chin, etc.) are localized and their sizes and distances measured, ratios between them are calculated and used for classifying the face into different age categories according to hand-crafted rules. More recently, [41] uses a similar approach to model age progression in subjects under 18 years old. As those methods require accurate localization of facial features, a challenging problem by itself, they are unsuitable for in-the-wild images which one may expect to find on social platforms. On a different line of work are methods that represent the aging process as a subspace [16] or a manifold [19]. A drawback of those methods is that they require input images to be near-frontal and well-aligned. These methods therefore present experimental results only on constrained data-sets of near-frontal images (e.g UIUC-IFP-Y [12, 19] ,FG-NET [30] and MORPH [43]). Again, as a consequence, such methods are ill-suited for unconstrained images. Different from those described above are methods that use local features for representing face images. In [55]Gaussian Mixture Models (GMM) [13] were used to represent the distribution of facial patches. In [54] GMM were used again for representing the distribution of local facial measurements, but robust descriptors were used instead of pixel patches. Finally, instead of GMM, Hidden-MarkovModel, super-vectors [40] were used in [56] for representing faces patch distributions. An alternative to the local image intensity patches are robust image descriptors: Gabor image descriptors [32] were used in [15] along with a Fuzzy-LDA classifier which considers a face image as belonging to more than one age class.

III. IMPLEMENTATION

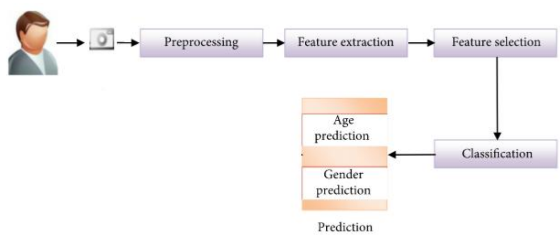

Fig-3: SYSTEM ARCHITECTURE

MODULES DESCRIPTION

1. Camera input stream

First of all, we need to feed the input stream of our webcam to our python script. Connecting to a webcam and displaying the live image feed is using opencv.

2. **Face detection with Haar cascades**

This is a part most of us at least have heard of. OpenCV provide direct methods to import Haar-cascades and use them to detect faces.

3. **Gender Recognition with CNN**

Gender recognition the CNN models trained by them in this module. We are going to use the OpenCV's Cnn package In the Cnn package, OpenCV has provided a class called

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Net which can be used to populate a neural network. These packages support importing neural network models from well known deep learning frameworks like caffe, tensorflow and torch.

4. **Age Recognition with CNN**

This is almost similar to the gender detection in this CNN consists of 8 values for 8 age classes (“0–2”, “4–6”, “8–13”, “15–20”, “25–32”, “38–43”, “48–53” and “60-”)

IV.RESULTS

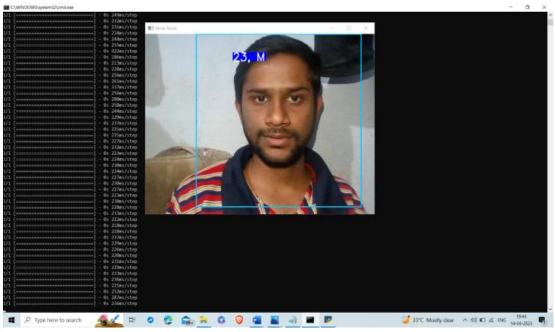

Fig-:4 Output Results

CONCLUSION

Age and Gender Classification is never ending prolonged research as it has no perfect ending with the accuracy. We have tried a perfect solution to detect Eventhough,it is not 100% accurate, but it makes the most out of any other existing models. Our model can be used in various applications like humanoid robots, military, etc.

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