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Age and Gender Detection using OpenCV

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ABSTRACT

In this fast-emerging world Artificial Intelligence plays a very vital role in every field of science . Everything is being automated from operating a remote to driving a car using Artificial Intelligence. We show a glimpse of such automated experience with this project. In this project we show how easy it is to detect faces and identify gender along with gender with the help of CNN(Convolutional Neural Networks) and OpenCV. Using these fields of Artificial Intelligence, we can reduce the use of hardware components and complexities in this project. Along with CNN and OpenCV we use Adience dataset so that the output is achieved with accurate values in training and validation. For the output to be determined even with multiple parameters we use pre-trained model that is caffee model along with OpenCV. The proposed model can be used in surveillance purposes or in medical purposes.

Keywords: *Deep Learning, CNN, OpenCV, Protocol buffer, Audience dataset, Caffe model*

1. 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[1,2]. 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[3,4]. 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.

2. BACKGROUND AND RELATED WORK

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[5] 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. [6] 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[7], Spatially Flexible Patches (SFP)[8], Local Binary Patterns (LBP)[9,10], and Biologically Inspired Features (BIF)[11]. In recent years, classification and regression methods are employed to classify the age and gender of facial images using those features. Classification methods in [12,13-15] used Support Vector Machine (SVM) based methods for age and gender classification. Linear regression[16,17], Support Vector Regression (SVR)[18], Canonical Correlation Analysis (CCA)[19], and Partial Least Squares (PLS)[20] are the common regression methods for age and gender predictions. Dileep and Danti [21] 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.

3. PROPOSED MODEL

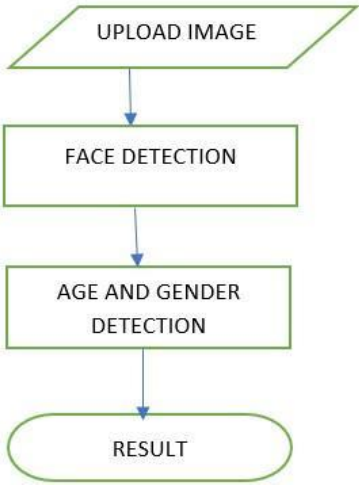


Figure 1: Flowchart of our proposed model

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[3,4].

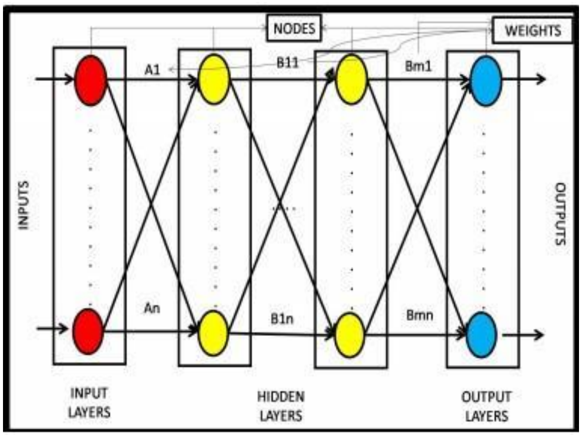


Figure 2: A Basic Neural Network

Artificial Neural Network (ANN) which is used to process the images are known as the Convolution Neural Networks (CNN). The 3 convolutional layers in convolutional neural network are:

- Convolutional layer: 96 nodes, kernel size 7
- Convolutional layer: 256 nodes, kernel size 5
- Convolutional layer: 384 nodes, kernel size 3[22]

It has 2 fully connected layers, each with 512 nodes, and a final output layer of softmax type. It is used for the features to be extracted every time when the convolutions are done. From the input image, a particular region is selected and then convolutions are done upon the intensity values of the pixels when the image is segmented. The convolutions are done in a matrix, wherein matrices of same dimensions are used for the convolutions across rows and columns on same input dataset with some dimensions. As the convolutions are completed in the convolutional layer with some kernel size, the data is given to the max pool layers to reduce the dimensions of the matrix so as to be able to do the computations on the large set of values. The data is sub sampled initially and after the max pooling by the help of strides, optimizing the neurons connections or by zero padding[23,24].

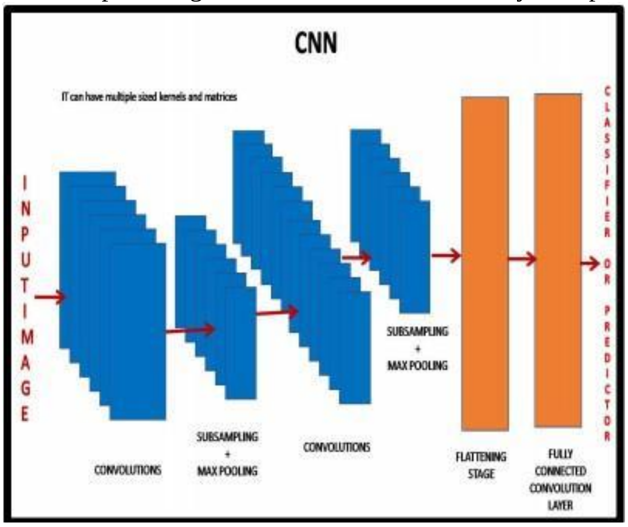


Figure 3: Convolutional Neural Network (CNN)

4. EXPERIMENTAL SETUP

In this section, we describe all the elements used in the experiment to explore our proposed model approach in age and gender detection. This includes the dataset description and implementation of the proposed model.

4.1 Dataset

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+ [25].

Table 1: Training Details with OIU-Adience

Classifier	Optimizer	No. of epochs	Initial learning rate	Momentum term	L2 weight decay
Age group	Adam	150	0.0001	—	0.0005
Gender	SGD	140	0.01	0.9	0.0005

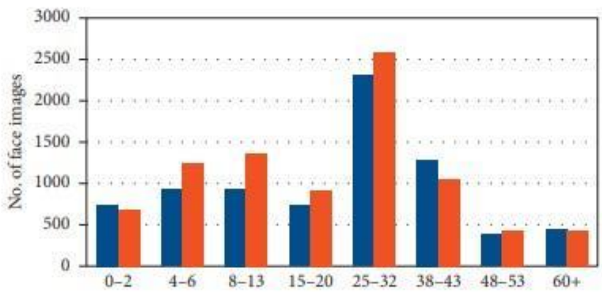


Figure 4: Age-groups for male and female (in years)

4.2 OpenCV

OpenCV (Open Source Computer Vision Library) is a library of programming functions used for image processing. It is available for free of cost at Berke;y Software Distribution License. This library has 2500 algorithms which can be used to identify objects,recognize human faces, etc. OpenCV was started at Intel in the year 1999 by Gary Bradsky. It has interfaces for Python,Java and C++. OpenCV-Python is the python API for OpenCV. OpenCV-Python is not only fast but is also easy to code and deploy [26]. This makes it a great choice to perform computationally intensive programs. Packages for standard desktop environments (Windows, macOS, almost any GNU/Linux distribution)

- run(pip install opencv-python)if you need only main modules.
- run(pip install opencv-contrib-python)this gives other modules including main modules.

Figure 5: OpenCV logo

4.3 Face detection

For facial recognition a protocol buffer file can be used which has all the trained weights of the model. The protobuf files with .pb extension hold data in binary format whereas the files with .pbtxt hold data in text format. These can be used to run the trained model. These protobuf files also involve in age and gender detection for our model. These are tensor flow files.

4.4 Gender and Age detection

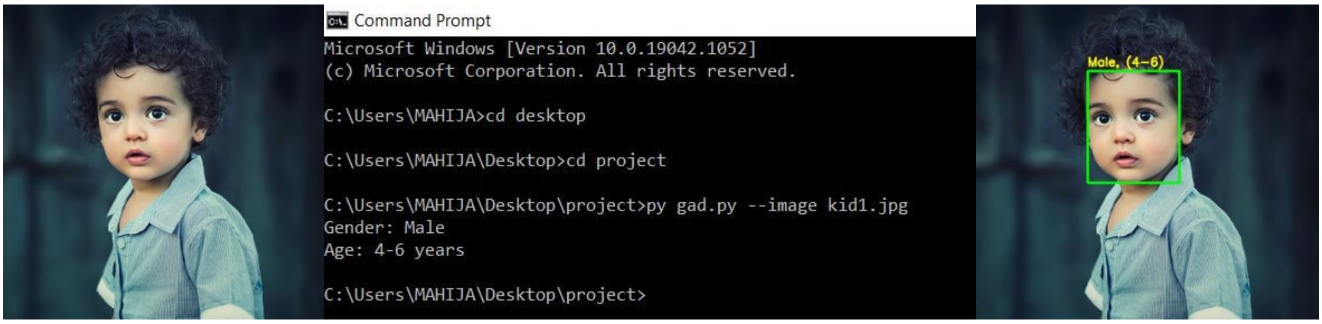
4.4.1 CAFFE Model: CAFFE (Convolutional Architecture for Fast Feature Embedding) is a deep learning framework, originally developed at University of California, Berkeley. It is open source, under a BSD license. It is written in C++, with a Python interface. Caffe supports types of deep learning concepts related in the fields of image classification and image segmentation. It supports CNN and fully connected neural network designs.Caffe supports kernel libraries such as NVIDIA, CNN and Intel MKL.In this project caffe model helps us define the internal states of the parameters of the layers[27].

4.4.2 Protocol Buffer Files: Protocol Buffers (Protobuf) is a free and open source cross-platform library. They are used for data serialization. These are tensorflow files which are used to describe the network configuration. The protobuf files are written in xml which has .pbtxt extension. Whereas the files with .pb extension contain data in binary format which is hard to read. Google developed Protocol Buffers for internal use and provided a code generator for multiple languages under an open source license.These Protocol Buffers were designed with an aim for simplicity and better performance. Also were aimed to be faster than XML. However these are used at Google to store and interchange various kinds of data. Also used for many inter-machine communication.

5. EXPERIMENTAL RESULTS

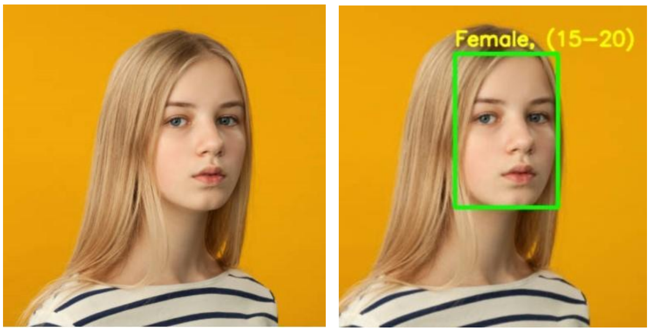
This section specifies the results obtained by conducting the experiment. We depict the testing results on various conditions.

5.1 Test case 1: Picture of a child



From the above figures when given a picture, the child's face is detected and the age,gender are shown. The child in the image is of the age group 4-6 who is a male. The output satisfies the age and gender. The output is shown with a green square box that shows the face of the child and above the box are the gender and age.

5.2 Test case 2: Picture of a teen



In the above figure when given an image of a teen the face is detected and age, gender the person are given. The person in this image is of the age group 15-20 who is a female. The output satisfies the age and gender. The output is shown with a green square box that shows the face of the teen and above the box are the gender and age.

5.3 Test case 3: Picture of an adult

In the above figure when given an image of an adult the face is detected and age,gender of the person are shown.The person in this image is of the age group 38-43 who is a female. The output satisfies the age and gender. The output is shown with a green square box that shows the face of the woman and above the box are the gender and age.

5.4 Test case 4: Picture of an old person

Just like the other cases in this case also the face is detected and gender along with age of the person in the image are depicted.The person in this image is of the age group 60-100 who is a male. The output satisfies the age and gender. The output is shown with a green square box that shows the face of the person and above the box are the gender and age.

5.5 Test case 5: Picture with no person

When given a picture with no human being in it. "No face detected" is given as output.

6. CONCLUSION

The age and gender detection using OpenCV will be very beneficial in authorization purposes,medical purposes or surveillance purposes. The CNN and OpenCV combined can give great results. The OIU-Adience dataset used in the project gives result with greater accuracy. We used protocol buffer and caffee model files. This project shows how OpenCV can be used for face detection without any other complicated process.

6.1 The future scope of work

This project can be enhanced in few ways such that this project can be used to its fullest:
1) Application- The project can be developed into a web application or a mobile application such that it is easily accessible.
2)In public places- using sensors this can be used in public places like restaurants, ATM places, shops such then when a theft happens the scope of finding the person could be much more easy.
3) Enhancing this project to detect multiple individuals-this project can be enhanced such it can estimate age and gender even for a group of individuals in the image. This model does detect the face of individuals in a group but cannot give the accurate age and gender estimation.

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