Age and Gender Recognition Using Convolutional Neural Network

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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 a pre-trained model that is a caffe model along with OpenCV. The proposed model can be used in surveillance purposes or in medical purposes.

I. Introduction (*Heading 1*)

Facial attribute recognition, including age, gender and emotion, has been a topic of interest among computer vision researchers for over a decade. One of the key reasons is the numerous applications of this challenging problem which range from security control, to person identification, to human-computer interaction. Due to the release of large labeled datasets, as well as the advances made in the design of convolutional neural networks, error rates have dropped significantly. In many cases, these systems are able to outperform humans . However, this still remains a difficult problem and existing commercial systems fall short when dealing with real world scenarios. In this work, we present an end-to-end system capable of estimating facial attributes including age, gender and emotion with low error rates. In order to support our claims, we tested our system on several benchmarks and achieved results better than the previous state-of-the-art. The contributions of this work are summarized below. We present an end-to-end pipeline, along with novel deep networks, that not only are computationally inexpensive, but also outperform competitive methods on several benchmarks. We present large datasets for age, emotion and gender recognition that are used to train state-of-the-art deep neural networks. We conducted a number of experiments on existing benchmarks and obtained leading results on all of them.

II. Literature Review

In this section we provide the age and gender classification literature and briefly describe a 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 International Journal of Advance Research, Ideas and Innovations in Technology © 2021, www.IJARIIT.com All Rights Reserved Page| 2269 different dimensions of facial features. These geometric features separate babies from adults successfully but are incapable of distinguishing between young adults and senior adults. 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 f],or 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.

III. PROPOSED METHODOLOGY

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

3.1 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 age and gender detection for our model. These are tensor flow files.

3.2 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].

3.2.2 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 the .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.

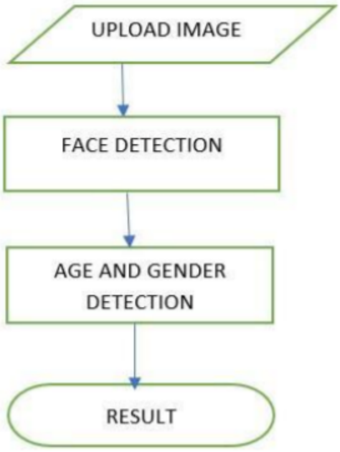


Figure 1: Flowchart of our proposed model

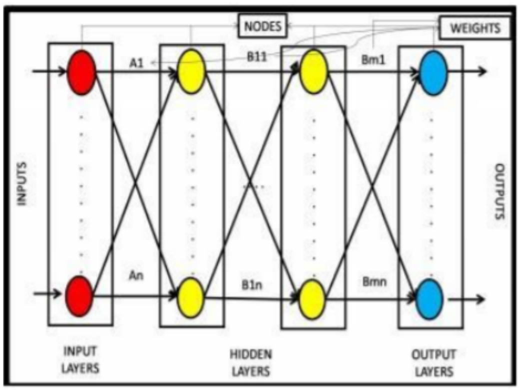


Figure 2: A Basic Neural Network

Artificial Neural Networks (ANN) which are 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 the same dimensions are used for the convolutions across rows and columns on the 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 neuron's connections or by zero padding[23,24].

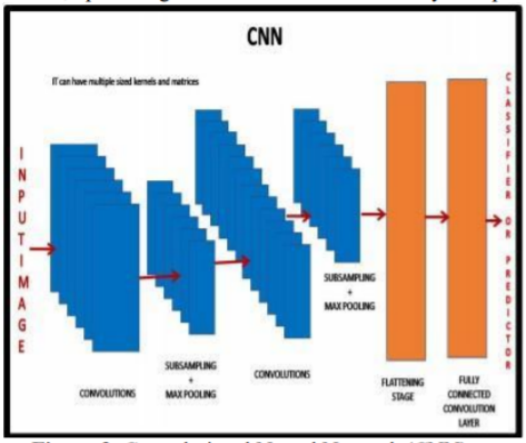
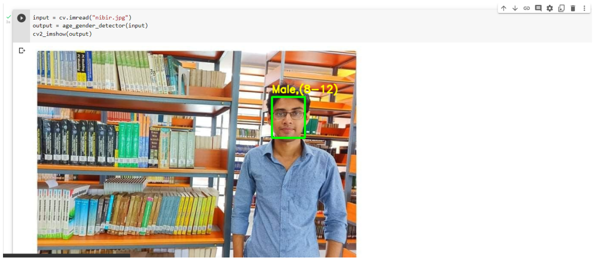


Figure 3: Convolutional Neural Network (CNN)

IV. Experimental Results

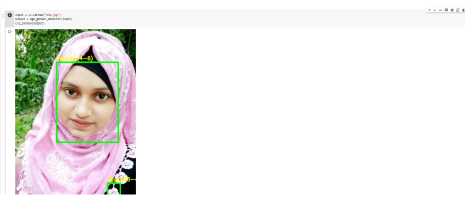
This section specifies the results obtained by conducting the experiment. We depict the testing results on various conditions.

4.1 Test case 1:



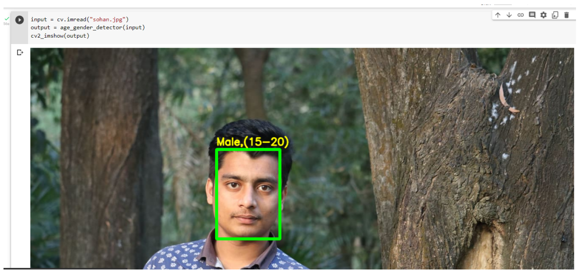
From the above figures when given a picture, the person's face is detected and the age,gender are shown. The person in the image is of the age group 4-6 who is a male. The output shows the age and gender. The output is shown with a green square box that shows the face of the child and above the box are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

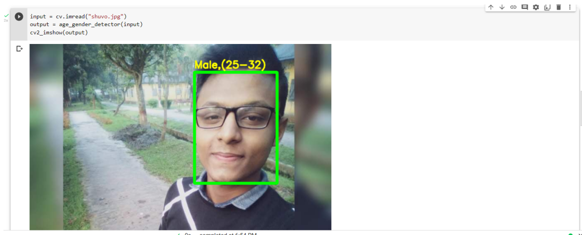
4.2 Test case 2:



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.

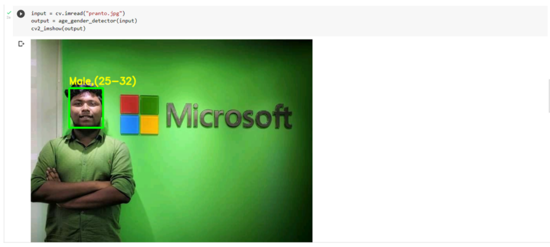
4.3 Test case 3:





In the above figure when given an image of an adult the face is detected and age,gender of the person are shown.The persons in this image are of the age group 15-20 and 25-32 who both are male. 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.

4.4 Test case 4:



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 25-32 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.

We got the accuracy 0.4%.

```
y_true: [0 1 2 1 0]
y_pred: [1 0 2 1 2]
accuracy: 0.4
```

V. 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 results with greater accuracy. We used protocol buffers and caffe 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 easier. 3) Enhancing this project to detect multiple individuals-this project can be enhanced such that 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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