NORTHERN ILLINOIS UNIVERSITY

PROJECT REPORT: CSCI 680 Neural Networks for Computer Vision

TOPIC: AGE AND GENDER DETECTION

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Project Title: Gender and Age Detection

Description: In this Project, we will use Deep Learning to identify the gender and age range of a person from a single image of a face from the Adience dataset. Depending on the input image gender and age range will be given as an output. We reimplemented existing architecture to achieve better results compared with other published papers. Also, we have added the capability to output the age and gender for real live stream images using laptop webcam using OpenCV.

Statistics and info about Dataset:

Total number of photos: 26,580

Size: Nearly 1 GB

Number of age groups / labels: 8 (0-2, 4-6, 8-13, 15-20, 25-32, 38-43, 48-53, 60-)

Dataset Link: https://www.kaggle.com/ttungl/adience-benchmark-gender-and-age-classification/discussion

ABSTRACT: Gender prediction and Age estimation from face images has become useful in an extremely large number of applications. Since the advancements in social media, this topic has attracted various researchers and engineers. Even though there are many existing methods, the accuracy of these methods is still low on real world face images. Each person's face is different from another. Everyone has different facial features that are unique. Social interactions and communications become easier when we get to know the age and gender of the person we are communicating with. For example, different types of reference such as he, she, him, her, salutations such as Mr., Mrs., Miss based on gender and similarly referring to a person as sir/madam based on age will all be relevant when we know the age and gender of the person we are referring to. Adience dataset is used for the analysis where we have implemented a CNN to predict the age and gender from a given image.

CNN AND EARLIER APPROACHES: Convolutional Neural Networks (CNNs) based methods have been extensively used for the classification task due to their excellent performance in facial analysis. The feature extraction extracts feature corresponding to age and gender, while the classification classifies the face images to the correct age group and gender. Age and gender classification can be especially helpful in several real-world applications including security and video surveillance, electronic customer relationship management, biometrics, electronic vending machines, human-computer interaction, entertainment, cosmetology, and forensic art.

Earlier approach: 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. This were not that much effective hence we tried to come up with much better architecture and implement it in our project.

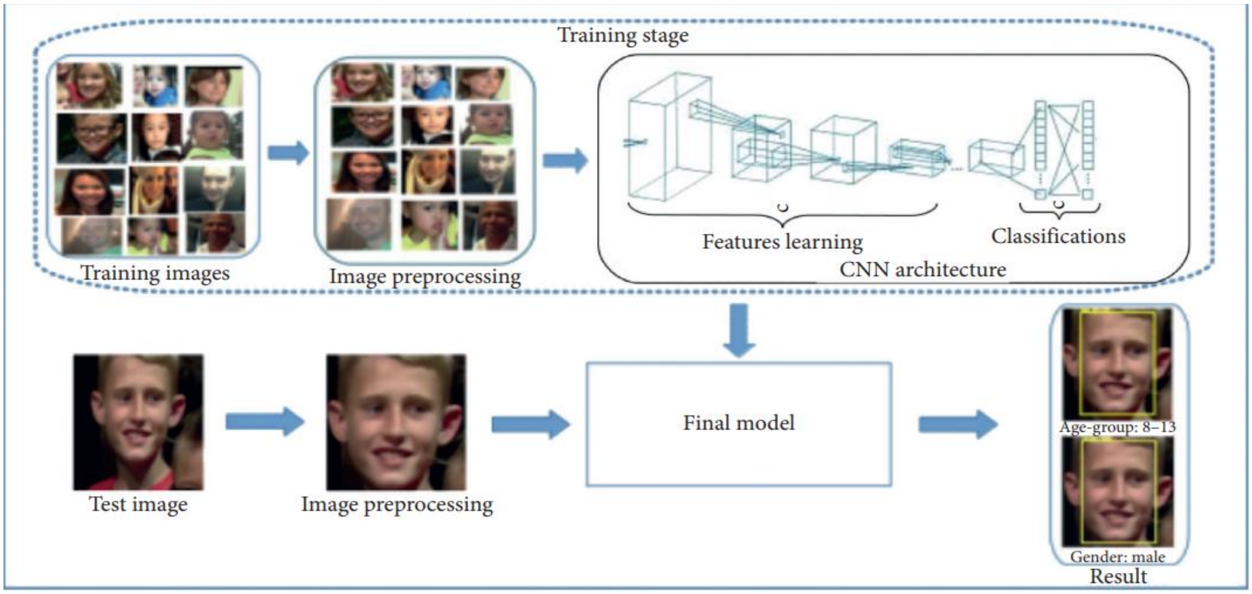
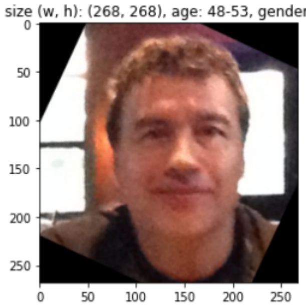


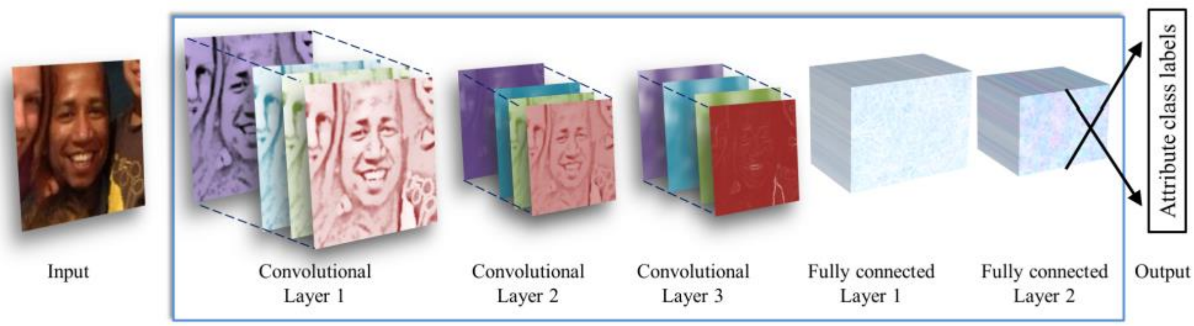
FIGURE 1: The pipeline of our framework for age group and gender.

ARCHITECTURE: We have used Adience face dataset to train and test the proposed project, which contains 26,580 photos totally, out of which 2,284 are unique faces. Each of those images has details of the person in that image (age and gender). It uses different classifiers for different genders. A face image of size 256 x 256 pixels is provided as the input to the algorithm, and it is cropped to 227 x 227 pixels, and is then fed into one of the classifiers. The age of the face is obtained in a range. There are 8 ranges for age in the dataset and hence the classifier gives a number from 0 to 7 representing the age range. The gender classifier gives either 0(indicating male or 1(indicating female). A chained gender-age network is developed that would first classify an image as male or female (gender classification), and then based on the gender classification, the image is fed into an age classifier trained only on men or only on women. First step is face detection, followed by facial landmark detection and alignment. As the proposed network is for a single face only, the most centered face is chosen if there are more than one detected face in the input image. The images are changed to 256 x 256 size and are cropped to 227 x 227 size before feeding to the network. PyTorch, OpenCV, TensorFlow with python language are used for implementing the code along with Graphical Processing unit (GPU) which has given great accuracy. The dataset images are unzipped into a folder, where data folds consisting of a text file with image path and age and gender labels are maintained. A dataset class is defined to perform read operation on the image and the text data File. Various Hyperparameters required while building a neural network model are defined accordingly. Batch size: The number of samples of data given to the network at one go while training. No of Epochs: The number of iterations on the original dataset required to fully train the model. Learning Rate: It decides the rate at which the weights in the model should be updated while Training. As it was taking lot of time for training, we purchased Google colab Pro for achieving faster results. We have uploaded the dataset which was divided into 5 folds onto GitHub so that we can access the dataset from the URL from any machine or google colab. The most important fields of the images were user_id, which was the folder name, original image which is the name of the image, age range and gender which was labelled. We have performed some data processing before building our model. We have mapped females with 0 and male with 1 and, we have mapped the age range like 0,1,2… respectively.

/content/DATASET/AdienceBenchmarkGenderAndAgeClassification/faces/10044155@N06/coarse_tilt_aligned_face.134.11343759245_695b4d73ff_o.jpg



As we can see we are able to display the picture with gender and the age range. Now we divided the data into test and training set (70/30) ratio. Also resizing of the image was done to 227 * 227. For our proposed model we have used 3 convolution layers each followed by activation function Relu, pooling layer and dropout layer. We have also used data augmentation. And, we have used 3 fully connected layers. For gender model we were able to achieve 87.27 % accuracy on test data and for age range model we were able to achieve 54.95% accuracy on test data. The accuracy for age estimation is very low in almost all approaches compared to gender prediction, reasons being that there are only 2 classes for gender and a greater number of classes for age, gender specific facial features are more distinctive than age specific features. Even with the pro version it was taking a lot of time as the image dataset was huge. On an average to run 30 epochs it took nearly 3 hours with the pro colab.



OPENCV: We have also used OpenCV to add extra functionality to our project. We also used pre trained caffe model for age and gender detection for testing purpose but have made our model discussed above from scratch. we load the images from the webcam, extract the face from the webcam image, pass it to the model for prediction, get the predictions, format, and extract meaningful data from it and display it on the screen.

COMPARISON WITH EXISTING METHODS: Our network contains three convolutional layers, each followed by a rectified linear operation, pooling layer, and dropout. Also, three fully connected layers are used. The method introduced by Levi and Hassner uses small convolutional neural network to classify face image into 8 age classes and 2 gender classes. The network consists of only 3 convolutional layers and 2 fully connected layers. Authors argue that such a small network will reduce the risk of overfitting. As you can see the state of the art for age is 83.1 and gender is 96.2 provided by the paper mentioned in green. Our proposed solution achieved age accuracy of 54.95 and gender accuracy of 87.27. Our model performed better than most of the models as you can see below, and we tried to achieve the SOTA, but we couldn't do much progress. We tried different parameter tuning as well to achieve this. For SOTA the CNN architecture is a novel six-layer network, comprising four convolutional and two fully connected layers. It contains the convolutional layer, activation layer (rectified linear unit (ReLU)), batch normalization (instead of the conventional Local Response Normalization), max-pooling layer, and a dropout (all the convolutional layers have a fixed dropout of 25%). The classification stage, on the other hand, contains two fully connected layers, that handle the classification phase of the model. The first fully connected layer contains 512 neurons, followed by a ReLU, then batch normalization, and, finally, a dropout layer at a dropout ratio of 0.5.

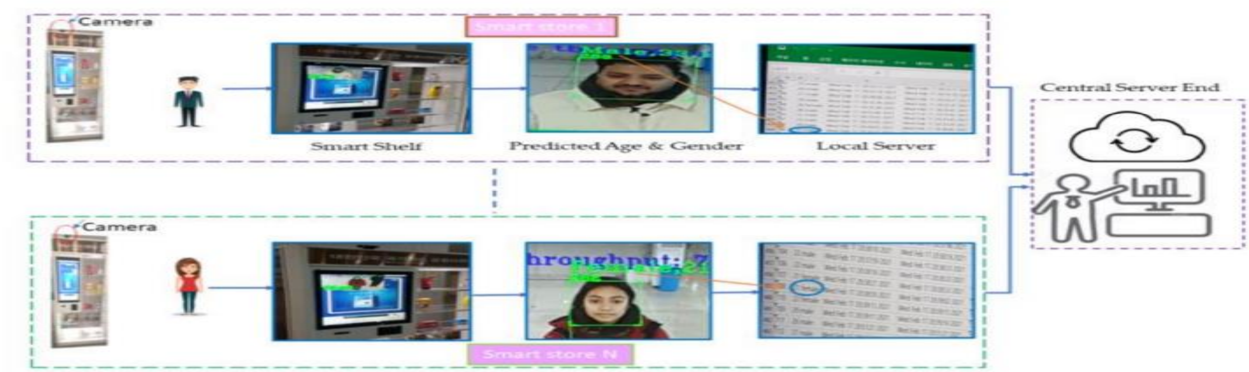
PAPER	AGE ACCURACY	GENDER ACCURACY
E. Eidinger, R. Enbar, and T. Hassner, "Age and gender estimation of unfiltered faces,	45.1	79.1
G. Levi and T. Hassncer, "Age and gender classification using convolutional neural networks,	50.7	86.8
M. Duan, K. Li, C. Yang, and K. Li, "A hybrid deep learning CNN–ELM for age and gender classification	52.3	88.2
W. Liu, L. Chen, and Y. Chen, "Age classification using convolutional neural networks with the multi-class focal loss,"	54	
Deeply Learned Classifiers for Age and Gender Predictions of Unfiltered Faces	83.1	96.2
T. Hassner, S. Harel, E. Paz, and R. Enbar. Effective face frontalization in unconstrained images.		79.3
Our Proposed solution	54.95	87.27

APPLICATIONS: Application where age and gender estimation can play a useful part include
(I) access control e.g., curbing the entry of an underaged person to sensible items from vending machines or to an event where only people of specific gender can join.
(ii) human–computer interaction (HCI) e.g., providing a different product advertisement or offer by looking at the gender and age of a person automatically.
(iii) law enforcement e.g., a criminal demographic estimation can help the law enforcement agency to find out the suspects more proficiently from previous records.
(iv) surveillance e.g., an automated system recognizing unattended minors to some unexpected places and times.
(v) electronic customer relationship management e.g., companies may use internet-based platforms to interact with customers to perceive their preferences and customize their store products. Similarly, for welcoming salutations, the content and manner are quite different based on age and gender.

(vi) To affluence the offline smart shopping and to update the future stock by analyzing the customer demographics (i.e., age and gender) due to the new shopping nature amid the Covid-19 pandemic situation.

LATEST ADVANCEMENTS: Deep Learning Based Real Age and Gender Estimation from Face Image towards Smart Store Customer Relationship Management

A smart store customer relationship management system to estimate the customer's age and gender for simplifying the shopping experience by facilitating personalized product recommendation and advertisement to promote the smart trading along with developing an inventory for future business promotion. The COVID-19 pandemic markedly changed the human shopping nature, necessitating a contactless shopping system to curb the spread of the contagious disease efficiently. Consequently, a customer opts for a store where it is possible to avoid physical contacts and shorten the shopping process with extended services such as personalized product recommendations. Automatic age and gender estimation of a customer in a smart store strongly benefit the consumer by providing personalized advertisement and product recommendation; similarly, it aids the smart store proprietor to promote sales and develop an inventory perpetually for the future retail.



A smart store can use artificial intelligence-based customer management systems to extract customer information in real-time and can provide the best product recommendations by analyzing the customer information for steering additional trades in real-time. A smart store can help the purchaser's preferences by knowing their age and gender. Deep learning-based smart store management systems can arrange their store by placing items alongside to promote cross-selling based on customers demographic choices. When a customer approaches the smart shelf, the camera attached with the shelf automatically captures the image of the customer and the installed age and gender estimation model will predict the demographics of the respective customer. During the interaction of the customer and automated system, the customer will get the personalized product recommendation, advertisement, and offer. In a smart store enterprise solution, several outlets are operating simultaneously under the same setup. Therefore, the customer data will be stored in a local server that exists on the outlet and to the central server from the different outlets through a communication network.

CHALLENGES: The classification failure could be because of the extremely challenging viewing conditions of the OIU-Adience images including low resolution, lighting conditions, and heavy makeup, hence hindering our image preprocessing algorithm in either correctly detecting or aligning the face for the classification process. A CNN for age and gender estimation Gathering a large, labeled image training set for age and gender estimation from social image repositories requires either access to personal information on the subjects appearing in the images (their birth date and gender), which is often private, or is tedious and time-consuming to manually label. Datasets for age and gender estimation from real-world social images are therefore relatively limited in size and presently no match in size with the much larger image classification datasets (e.g., the ImageNet dataset). Overfitting is a common problem when machine learning based methods are used on such small image collections. This problem is exacerbated when considering deep convolutional neural networks due to their huge numbers of model parameters. Care must therefore be taken to avoid overfitting under such circumstances.

RESULTS AND CONCLUSION: Performance metric is given in the form of accuracy which is the ratio of number of exact matches to the total number of samples tested. As age is difficult to predict compared to gender because of the large number of variations and classes. For gender we got an accuracy of 85% on the test data and on age we got 55 % on test data. The confusion matrix and the accuracy of test data for the gender model is given below:

The accuracy of test data is
87.27 %

The test confusion matrix is..

	m	f
m	87.06 %	12.94 %
f	10.23 %	89.77 %

The confusion matrix and the accuracy of test data for the Age model is given below:

The accuracy of test data is
54.95 %

The test confusion matrix is..

	0-2	4-6	8-13	15-20	25-32	38-43	48-53	60+
0-2	79.62 %	14.22 %	1.66 %	0.47 %	3.79 %	0.24 %	0.00 %	0.00 %
4-6	27.20 %	54.40 %	10.24 %	2.88 %	3.36 %	1.76 %	0.00 %	0.16 %
8-13	2.27 %	13.75 %	54.23 %	8.46 %	15.71 %	4.38 %	0.91 %	0.30 %
15-20	1.25 %	3.23 %	8.78 %	37.99 %	33.51 %	12.19 %	3.05 %	0.00 %
25-32	0.51 %	1.03 %	5.26 %	8.02 %	65.60 %	15.34 %	3.34 %	0.90 %
38-43	0.57 %	0.57 %	5.01 %	6.48 %	31.74 %	47.33 %	5.92 %	2.39 %
48-53	1.12 %	0.75 %	6.37 %	6.37 %	22.10 %	26.97 %	28.46 %	7.87 %
60+	1.51 %	1.13 %	2.26 %	4.15 %	14.72 %	20.00 %	18.49 %	37.74 %

As shown above we have achieved an accuracy of 87% on gender model and nearly 55% on age model. The state of the art for gender was 96.2 % and for age it was 83.1 % as discussed in Research Article: Deeply Learned Classifiers for Age and Gender Predictions of Unfiltered Faces. But we have outperformed many of the other papers and have achieved a better model. The comparison was discussed in the above section for various and our proposed models.
We have uploaded the google colab notebook online if anyone wants to take the project forward and more advancements.

CODE LINK: https://github.com/omer1997/NEURAL-NETWORK--GENDER-AGE-DETECTION

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