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Age and Gender Detection using Deep Learning Models

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Abstract— Computer vision is a field of computer science that works on enabling computers to see, identify and process data in the same way that human vision does, and then provide appropriate output. It is like imparting human intelligence and instincts to a computer. It includes methods for acquiring, processing, analyzing and understanding Videos or Images. The main goal is not only to see, but also process and provide useful results based on the observation.
Age and gender classification has become relevant to an increasing amount of applications, particularly since the rise of social platforms and social media. Nevertheless, performance of existing methods on real-world images is still significantly lacking, especially when compared to the tremendous leaps in performance recently reported for the related task of face recognition. This research report represents information regarding Age & Gender Detection of a person by using Deep Learning Models and Transfer Learning.

Keywords—Age & Gender Detection, Convolutional Neural Network, Deep Learning, Transfer Learning.

I. INTRODUCTION

Age and gender play fundamental roles in social interactions. Languages reserve different salutations and grammar rules for men or women, and very often different vocabularies are used when addressing elders compared to young people. Despite the basic roles these attributes play in our day-to-day lives, the ability to automatically estimate them accurately and reliably from face images is still far from meeting the needs of commercial applications. This is particularly perplexing when considering recent claims to super-human capabilities in the related task of face recognition [1]. While human capabilities to detect and identify multiple facets, such as age, gender, ethnicity and facial expressions, can be accomplished by a quick glance at a digital image, machines are required to be trained intensively in order to understand traits present in photographs. Facial recognition has been the main attraction of several products in these last couple of years and has recently returned to the mainstream media with the release of Apple's iPhone X. This phone offers facial detection technology as its primary unlocking/authentication security mechanism that surpasses the traditional fingerprint authentication. Hi-tech facial recognition is in active development around the world for a variety of applications. China has used facial recognition technology across multiple applications, e.g., Driver identification, pay with a smile, jaywalker identification, etc. In the USA, it has been used in churches to track worshipers, and in the UK, it has been used to stop shoplifters. A myriad of facial identification applications have already reached the marketplace; often surprising consumers by the capabilities and reach that they offer. The use cases for accurate age estimation are not only limited to child abuse investigation but are useful across a range of crimes[9]. Past approaches to estimating or classifying these attributes from face images have relied on differences in facial feature dimensions[2] or "tailored" face descriptors [3,4,5]. Most have employed classification schemes designed particularly for age or gender estimation tasks, including [6] and others. Few of these past methods were designed to handle the many challenges of unconstrained imaging conditions [4]. Moreover, the machine learning methods employed by these systems did not fully exploit the massive numbers of image examples and data available through the Internet in order to improve classification capabilities. In this paper we attempt to close the gap between automatic face recognition capabilities and those of age and gender estimation methods. Face recognition techniques described in the last few years have shown that tremendous progress can be made by the use of deep convolutional neural networks (CNN) using Transfer Learning. Dataset used are CelebA Dataset[7] and Adience Benchmark[8]Dataset for Gender and Age Detection respectively.

Rest of the paper is organized as follows, Section I contains introduction of Age and Gender detection, Section II contains Related Work done by different authors, Section III consists of flow of current system, Section IV gives information about different Methods and Methodologies used in this system, System V consists of Results obtained and Section VI concludes research work with future directions.

II. RELATED WORK

Before describing the proposed method we briefly review related methods for age and gender classification and provide a cursory overview of deep convolutional networks.

2.1. 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 fourth. Early methods for age estimation are based on calculating ratios between different measurements of facial features [12]. 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. 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 [14] or a manifold [15]. 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 [15, 16] ,FG-NET [17] and MORPH 18]). 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 [19]Gaussian Mixture Models (GMM) [20] were used to represent the distribution of facial patches. In [21] 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 were used in for representing face patch distributions. An alternative to the local image intensity patches are robust image descriptors: Gabor image descriptors [22] were used along with a Fuzzy-LDA classifier which considers a face image as belonging to more than one age class. In [20] a combination of Biologically-Inspired Features (BIF) and various manifold-learning methods were used for age estimation. Gabor and local binary patterns (LBP) features were used in [7] along with a hierarchical age classifier composed of Support Vector Machines (SVM) to classify the input image to an age-class followed by a support vector regression to estimate a precise age. Certain methods are used for distance learning and dimensionality reduction, respectively, with Active Appearance Models [8] as an image feature. All of these methods have proven effective on small and/or constrained benchmarks for age estimation.

Gender classification. We quickly survey relevant methods. One of the early methods for gender classification that uses a trained neural network on a small set of near-frontal face images. In [23] the combined 3D structure of the head (obtained using a laser scanner) and image intensities were used for classifying gender. SVM classifiers were used, applied directly to image intensities. Rather than using SVM, [24] used AdaBoost for the same purpose, here again, applied to image intensities. Finally, viewpoint-invariant age and gender classification was presented by [24]. More recently, used the Webers Local texture Descriptor for gender recognition, demonstrating near perfect performance on the FERET or audience benchmark [8]. In intensity, shape and texture features were used with mutual information, again obtaining near-perfect results on the FERET or Adience benchmark. Most of the methods discussed above used the FERET or Adience benchmark benchmark [8] both to develop the proposed systems and to evaluate performances. FERET images were taken under highly controlled condition and are therefore much less challenging than in-the-wild face images. Moreover, the results obtained on this benchmark suggest that it is saturated and not challenging for modern methods. It is therefore difficult to estimate the actual relative benefit of these techniques. As a consequence, experimented on the popular Labeled Faces in the Wild (LFW) [25] benchmark, primarily used for face recognition. Their method is a combination of LBP features with an AdaBoost classifier. As with age estimation, here too, we focus on the Adience set which contains imagesmore challenging than those provided by LFW, reporting performance using a more robust system, designed to better exploit information from massive example training sets.

Age and Gender Classification Flavio et al[26] has in this paper used dataset from unrestricted environment such as surveillance footage, social media photos and live broadcasts is used. In this type of images and videos include no control over illumination, position, size, occlusion, and facial expressions. The main topics that have been covered are: (1) Face detection (2) Facial image quality (3) Head pose estimation (4) Face alignment (5) 3D face reconstruction (6) Gender and age estimation (7) Facial expressions and emotions and (8) Face recognition. And by using Two State CNN Model high accuracy is achieved.

Bartłomiej Hebda et al[27] applied Deep Convolutional Neural Network architecture for age and gender estimation is proposed. The input image size was defined as 32 × 32 pixels. Due to which 98.60% accuracy for gender and 85.34% for age in 10 years intervals on the FERET database and for a much more demanding Adience database 62% gender and 42% age accuracy is measured. These are results respectively 25% and 8% worse than for the large DCNN with input image size 227 × 227 pixels.

Vladimir Khryashchev et al[28] used MORTH dataset but authors have focused on real-life audience measurement video data. Gender recognition algorithm, proposed in this paper, is based on non-linear support vector machine (SVM) classifier with radial basis function (RBF) kernel. Detected fragments are pre-processed to align their luminance characteristics and to transform them to uniform scale. After that to extract information from image fragment and to move to a lower dimension feature space local binary patterns (LBP) whereas to calculate age Mean Absolute Error (MAE) and Cumulative Score (CS) are used.

Gil Levi et al[29] in this paper they have attempted to close the gap between automatic face recognition capabilities and those of age and gender estimation methods. Fuzzy- LDA (Linear Discriminant Analysis) classifier is used which considers a face image as belonging to more than one age class. In a combination of Biologically-Inspired Features (BIF) and various manifold-learning methods are used for age estimation. Whereas for Gender Estimation AdaBoost classifier is used.

Vladimir Khryashchev et al[30] proposed a system that allows to extract all the possible information about depicted people from the input video stream it consists of five consecutive stages: face detection, face tracking, gender recognition, age classification and statistics analysis. The crucial part of the system is gender classifier construction on the basis of machine learning methods. A novel algorithm consisting of two stages: adaptive feature extraction and support vector machine classification.

Lijia Lu et al[31] has developed a real-time robust gender classification system is presented in this paper. The system mainly consists of three principal modules: image pre-processing, face detector and gender classifier. They have achieved fairly good recognition accuracy and high processing speed.

Table 1

Title of Paper	**Dataset Used**	**Method Used**	**Results Achieved**
Face Analysis in the Wild [26]	AFLW	Convolutional Neural Network	High Accuracy
A compact deep convolutional neural network architecture for video based age and gender estimation[27]	FERET and Adience Benchmark Databases	Deep Convolutional Neural Network	FERET-98.60% for Gender and 86.40% for Age Adience Benchmarck-62.00% for Gender and 42.00% Age
Gender and age recognition for video analytics solution[28]	MORTH	Non-linear Support Vector machine (SVM) classifier with Radial Basis Function (RBF) kernel	92%
Age and Gender Classification using Convolutional Neural Networks[29]	Imagenet Dataset	Deep Convolutional Neural Network, AdaBoost, Fuzzy-LDA	86.80%
Gender Classification for Real-Time Audience Analysis System[30]	FERET	Convolutional Neural Network, SVM classifier, Adaptive feature extraction	90%
Automatic Gender Detection for Unconstrained Video Sequences based on Collaborative Representation[31]	AR Database and Self-built face database	Eigenface features, HAAR features, AdaBoost Trained Classifier	AR Database-95% & Self-Built Database-90%
Age Group and Gender Estimation in the Wild with Deep RoR Architecture[32]	IMDB-WIKI	Convolutional Neural Network, Pre Trained VGG Model	85.50%
Gender Classification from Unconstrained Video Sequences[33]	FERET	Markov Model, Bayesian Framework, SVM Classifier.	90.00%
Heterogeneous Face Attribute Estimation: A Deep Multi-Task Learning Approach[34]	CelebA and LFWA	CNN for deep multi-task learning (DMTL) network	CelebA-81.00% and LFWA-86.00%
Evaluating Automated Facial Age Estimation Techniques for Digital Forensics[9]	FERET, IMDB and WIKI	Transfer Learning	In this Paper they have given Mean Absolute Error (MAE) per service:- AWS-9.286 Azure-7.614

Ke Zhang et al[32] has proposed a new Residual networks of Residual networks (RoR) architecture for high resolution facial images age and gender classification in the wild is proposed. Two modest mechanisms, pre-training by gender and training with weighted loss layer, are used to improve the performance of age estimation. Pre-training on ImageNet is used to alleviate overfitting. Further fine tuning on IMDB and WIKI is for the purpose of learning the features of face images. This work explores the application of RoR on large scale and high resolution image classifications in the future.

Meltem Demirkus et al[33] has used Markov model is used to represent temporal dependencies, and classification involves determining the maximum a posteriori class at a given time. Showing the robustness of the proposed system, the Bayesian framework is first trained on a database collected under controlled conditions, and then applied to the previously unseen faces obtained from an unconstrained video database.

Hu Han et al[34] used a Deep Multi-Task Learning (DMTL) approach to jointly estimate multiple heterogeneous attributes from a single face image. Parameters such as Moustache, Goatee, narrow eyes, pointy nose, rosy cheeks, heavy makeup, wearing earrings, wearing hat, are considered. A CNN with three convolutional layers and two FC layers are proposed.

Felix Anda et al[9] it this Paper authors have given Mean Absolute Error (MAE) per service:- AWS-9.286 Azure-7.614 DEX8.079 and they have used Transfer learning to get estimated age of person. Moreover, a dataset generator is used to generate dataset from FERET, WIKI and IMDB datasets. They have further used cloud-based biometric services is that are obtained by classifiers developed by experienced companies in the space, such as Amazon, Microsoft, and IBM.

III. FLOW OF SYSTEM

Figure 1: Flow of System

The flow of proposed system is as above, dataset used is Adience Benchmark (Age Detection) and CelebA (Gender Detection).Using datasets CNN model is retrained for Age & Gender detection from Image.

IV. METHODS & METHODOLGIES

Different tools and methodologies used to implement them used in proposed system are briefed below.

Deep Learning is also known as deep structured learning or hierarchical learning. Deep Learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. Deep learning models are vaguely inspired by information processing and communication patterns in biological nervous systems. Deep learning is a class of machine learning algorithms that uses a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. Each successive layer uses the output from the previous layer as input. Learning is done across multiple levels of representations that correspond to different levels of abstraction, the levels form a hierarchy of concepts [30].

CNN(Convolutional Neural Network) is a feed forward Neural Network which can be used for Image Classification. It only considers current input.
CNN has 4 layers namely: Convolution layer, ReLU layer, Pooling and Fully Connected Layer. Every layer has its own functionality and performs feature extractions and finds out hidden patterns.

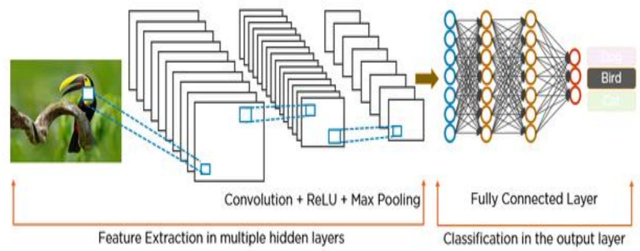

Figure 2: Flow of Convolutional Neural Network [31]

Flow of CNN
1. Input Image 2. Convolution 3. ReLU 4. Pooling
The Convolution layer is the core building block of a Convolutional Network that does most of the computational heavy lifting [31]. It consist of ConvNets which are used to match pieces of image and then apply filter.
ReLU is an activation function just like Sigmoid. It converts all negative values to Zero.

Pooling is shrinking the image. There are three types of Pooling: Maximum, Minimum and Average pooling.

Backpropagation algorithm is used to find a local minimum of the error function as the network must recognize whether a new input vector is similar to learned patterns or not and further produce a similar output The gradient of the error function is computed and used to correct the initial weights.

Gradient Descent is used to adjust weight to minimise error and reach optimal output.

Transfer Learning[34] is a machine learning method where a model developed for a task is reused for second task. It is a popular approach in deep learning where pre-trained models are used as the starting point on computer vision and natural language processing tasks given the vast compute and time resources required to develop neural network models on these problems and from the huge jumps in skill that they provide on related problems [34]. It is an optimization that allows rapid progress or improved performance when modelling the second task. Transfer learning has two approaches: Develop Model Approach and Pre-trained Model Approach. Popular Model for Transfer Learning with Image Data: Oxford VGG Model, Google Inception Model and Microsoft ResNet Model.

Python Libraries used are:
NumPy is the fundamental package for scientific computing in Python.
Scikit-image is an open source image processing library for Python.
Caffe is a deep learning framework developed by the Berkeley Vision and Learning Center (BVLC). It is written

in C++, Python and Matlab bindings. And is used to train CNN model.
Algorithmia is a library developed in Python for exploring concepts of Deep Learning.

Google Inception Model[32] Google has released a model called Google Inception V3 with Tensorflow which is a pre-trained CNN Inception Model trained by 20Lakh images of over a thousand different classes. The Inception network is an important milestone in the development of CNN classifiers. CNNs are just stacked convolution layers deeper and deeper, hoping to get better performance whereas Inception model uses a lot of tricks to push performance both in terms of speed and accuracy. Its constant evolution lead to the creation of several versions of the network. Every layer performs its own function such as Edge Detection, Shape Detection and ReTraining layers according to Transfer Learning requirement.

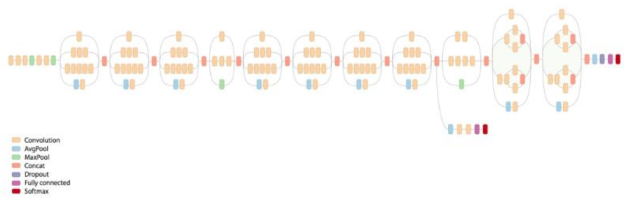

Figure 3: Architecture of V3 Model [32]

Tensorflow is an open source library for numerical computation, specializing in machine learning applications

V. Results

Tensorflow version 1.9 along with Python version 3.6 as scripting language is used to implement Google Inception Model and Caffe Zoo Model. Datasets used for Gender Detection is CelebA Image Dataset whereas dataset used for Age Detection is Adience Benchmark Dataset, both are public dataset respectively. CelebA Dataset consists of over 20K images of celebrities of Hollywood and Bollywood. Adience Benchmark Dataset consists of 26,580 photographs with different Age Groups. Testing Datasets consists of 1000 image.
Result Matrix obtained is as follows:

Gender Detection
Using Caffe Zoo Model

N = 1000	Predicted FEMALE	Predicted MALE
Actual FEMALE (540)	480	60
Actual MALE (460)	80	380

Accuracy obtained is 86%
Using Google Inception V3 Model

N = 1000	Predicted FEMALE	Predicted MALE
Actual FEMALE (540)	504	36
Actual MALE (460)	50	410

Accuracy obtained is 90%

Age Detection
Using Google Inception V3 Model

N=1000	Predicted YOUNG	Predicted MIDDLE	Predicted OLD
Actual YOUNG (330)	303	27	0
Actual MIDDLE (330)	40	255	45
Actual OLD (340)	05	65	265

Accuracy obtained is 82.30%

VI. CONCLUSION

Until now, Gender Detection from Image is done by using GOOGLE INCEPTION Model and Caffe Zoo Model. CelebA Dataset is used and accuracy obtained by Inception V3 and Caffe Zoo Model is 90% and 86% respectively. Also Gender Detection from group image is done by using Algorithmia Library of Python that uses Caffe Zoo Model. Similarly Age Detection from Image is done by using Google Inception Model. Dataset used is Adhience Benchmark and accuracy obtained is 82.30%. Gender Detection from Group Image is also done by using Caffe Zoo Model. In future the aim is to develop a modern efficient machine learning algorithm which can attain good results in different environments and to apply this algorithm to videos and generate a system which will recommend Advertisements. Such a system can be used to develop Smart Boards for digital advertisements by displaying ads on the basis of majority target audience in crowd which can be used for showcasing advertisements in Malls, Movie Theatres, Amusement Parks, Educational Institutes, at Events and various other public places.

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