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PREDICTION OF AGE AND GENDER THROUGH IMAGE DATASET USING DEEP LEARNING

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Abstract-Gender is still a central aspect of personality, and in social life it is still an important factor.Gender and age projections for artificial intelligence can be used by many areas, such as the development of smart human-machine interfaces, fitness, cosmetics, e-commerce, etc. Age and gender prediction is a matter of continuous and active research for individuals from their facial images. A number of approaches to solving this issue have been suggested by the researchers, but the criteria and actual performance are still insufficient. This paper proposes a mathematical approach to recognition patterns in order to solve this problem.The Convolution Neural Network (ConvNet / CNN) and VGG16 learning algorithm is used as a Classification in the proposed solution. In this research, face images of individuals have been trained with convolution neural networks, and age and sex with a high rate of success have been predicted. More than 20,000 images contain age, gender and ethnicity annotations.

I. INTRODUCTION

Jupyter

Jupyter, previously known as IPython Notebook, is a web-based, interactive development environment. Originally developed for Python, it has expanded to support over 40 other programming languages including Julia and R.

Machine Learning

Will describe how to use some basic algorithms, and perform regression, classification, and clustering on some freely available medical datasets concerning breast cancer and diabetes, and will also take a look at a DNA microarray dataset.

SciKit-Learn

SciKit-Learn provides a standardized interface to many of the most commonly used machine learning algorithms, and is the most popular and frequently used library for machine learning for Python.

Clustering

Clustering algorithms focus on ordering data together into groups. SciKit-Learn have many clustering algorithms, but this section will demonstrate hierarchical clustering on a DNA expression microarray dataset using an algorithm from the SciPy library.

II. RELATED WORKS

[1].Anirudh Ghildiyal; Sachin Sharma;Ishita Verma; Urvi Marhatta-Age and Gender Predictions using Artificial Intelligence Algorithm

Gender is still a central aspect of personality, and in social life it is still an important factor. Gender and age projections for artificial intelligence can be used in many areas, such as the development of smart human-machine interfaces, fitness, cosmetics, e-commerce, etc. This paper proposes a mathematical approach to recognition patterns in order to solve this problem. ConvNet needs much less pre-processing than other classification algorithms. While the filters are hand-made in primitive methods, ConvNet can learn these filters / features with adequate training. In this research, face images of individuals have been trained with convolution neural networks, and age and sex with a high rate of success have been predicted.The images cover a wide range of poses, facial expression, lighting, occlusion, and resolution.

[2].Aryan Saxena; Prabhangad Singh; Shailendra Narayan Singh-Gender and Age detection using Deep Learning

Mankind has advanced technology to the extent that the 21st century is the crack of the dawn for unimaginable achievements. The aforementioned technology can be used for our benefit in identifying one's age and even their gender just based on their glimpse from a camera, image and even a video. This research paper will methodically chalk out the whole procedure, multiple methodologies and algorithms that can be used, which one is the most accurate and how it all comes together.Moreover, the map for the ways this technology can be used to our benefit and look at the huge spectrum where it can be implemented: ranging from security services, CCTV surveillance and policing to dating applications, matrimonial sites.

[3].Avishek Garain; Biswarup Ray; Pawan Kumar Singh; Ali Ahmadian-GRA_Net: A Deep Learning Model for Classification of Age and Gender From Facial Images

The problem of gender and age identification has been addressed by many researchers, however, the attention given to it compared to the other related problems of face recognition in particular is far less. The success achieved in this domain has not seen much improvement compared to the other face recognition problems. Any language in the world has a separate set of words and grammatical rules when addressing people of different ages. The decision associated with its usage, relies on our ability to demarcate these individual characteristics like gender and age from the facial appearances at one glance. Gender identification is a binary classification problem whereas prediction of age is a regression problem. We have decomposed this regression problem into a combination of classification and regression problems for achieving better accuracy.Obtained results have proven its effectiveness for both age and gender classification, thus making it a proper candidate for the same against any other state-of-the-art methods.

[4].Xuan Liu; Junbao Li; Cong Hu; Jeng-Shyang Pan-Deep convolutional neural networks-based age and gender classification with facial images

In this paper, we build an age and gender classification system including two networks to classify age and gender based on GoogLeNet with the help of Caffe deep learning framework. It outputs gender and age groups of the facial images captured from the camera. We use Adience dataset to train GoogLeNet. Asynchronous Stochastic Gradient Descent based on multi-GPUs is used to optimize the training process.For instance, it can apply to a targeted delivery in a bus stop or department store. The results indicate that the accuracy of the classification network can be improved by pre-training. In addition, the multi-GPUs training platform can improve the training speed during the recognition. Overall system reaches a speed of 8fps with a high accuracy to classify age and gender.

III. PROPOSED SYSTEM

The test accuracy goes to 82% for randomly picked 50 test images. The first column shows the actual age while the second column shows what our model predicted. Digit 1 here represents male while 2, female. In a few cases the prediction is wrong. This indicates that the network requires further training and maybe further fine tuning with technological advancement to have the accuracy as close to unity as possible. The other reason for a good test accuracy is that there was no overfitting, which is usually characterized by the loss starting to rise after falling for a few epochs. The recall rate is 100% in this case since there was cleaning done before images were used.

The trained Age model gave test results in Table.2. Age test accuracy is 7% for 100 test images. This can be accounted for because the training data of 1500 is too small as mentioned earlier. Ages from 0-9 years and 71-100 years are not properly covered by the training data, yet the range appears in the test data. The CNN imitates human neurons and thus brain, the same way it would be difficult for us humans to sport age difference between two individuals who are 25 and 26 years old or say 80 and 81 years old, this CNN finds this even more hard too, therefore may miss the exact figure of a person's These percentages are determined on precision thus the closeness to a given age is ignored. This makes the age prediction to even be much lower as predicting an age of 45 instead of actual 46 is considered inaccurate.

A lot of training using large datasets is to be done to improve on the model accuracy. This requires longer durations and high machine specifications to achieve high accuracy especially with age training.

IV. MODULE DESCRIPTION

We generally took the 12,500 people who are on the Kaggle website which included their images and information from their profiles. We do not consider the images which have a time label on it, and we also did not accept the images which are easily recognizable and authorized.We were able to assign the (real) biological age to each of these images using the algorithm and eventually we get a rectangular shape on a person's face indicating their age and gender. Of course, we cannot say with certainty the accuracy of the designated age information. Apart from incorrect information about time, we have images which are in turn snapped during filmography as well as in theaters.In summary, we received 600 face photos from Kaggle for the personalities.In total, there were 400 face photos with age information included.As some images also have other data people, but we don't consider why facial features must qualify at least a minimum threshold, if they meet the conditions, they are included. To make the network equally discriminating for all generations, we normalize the age distribution, i.e.we arbitrarily discard some of the images from the most frequent eras.

Data Collection:

So as to encourage the investigation old enough and sex acknowledgment, we give an informational collection and benchmark of face photographs. The information remembered for this assortment is planned to be as evident as conceivable to the difficulties of certifiable imaging conditions. Specifically, it endeavors to catch all the varieties in appearance, clamor, posture, lighting and that's only the tip of the iceberg, that can be anticipated from pictures taken without cautious planning or presenting.

Preparing and pre-processing the dataset:

Data is the foundation of any machine learning project.The second phase of project implementation is complex and involves data collection, selection, pre-processing and transformation.Each of these phases can be divided into several phases.It's time for a data analyst to step up and lead the way in implementing machine learning.The job of a data analyst is to find ways and sources to collect relevant and complete data, interpreting it and analyzing the results using statistical techniques.The type of data depends on what you want to predict.

Data Augmentation:

The purpose of preprocessing is to convert raw data into a form that fits machine learning.Clean and structured data allows a data scientist to get more accurate results from an applied machine learning model. The technique includes data formatting, cleaning, and sampling,anonymization,image preprocessing,read images,resizing images.

Data Splitting:

A dataset used for machine learning should be partitioned into three subsets - training, test, and validation sets.

Model Training:

It's time to train the model with this limited number of images. fast.ai offers many architectures to use, which makes it very easy to use transfer learning.We can build a convolutional neural network (CNN) model using pre-trained models that work for most applications/datasets.We will use the ResNet architecture, as it is fast and accurate for many datasets and problems.The 18 in the resnet18 represents the number of layers in the neural network.We also pass the metric to measure the quality of the model predictions using the data loader validation set.We use error_rate which tells us how often the model makes incorrect predictions.

Classification:

A classifier is a function that takes features as input and generates a class label prediction. Based on the learning function and underlying assumptions, different types of classifiers can be developed. Neuroimaging studies have applied various classifiers for mental illness prediction. The dimensionality issue associated with the relatively large number of features and the small number of samples should be accounted for while applying such classification algorithms.

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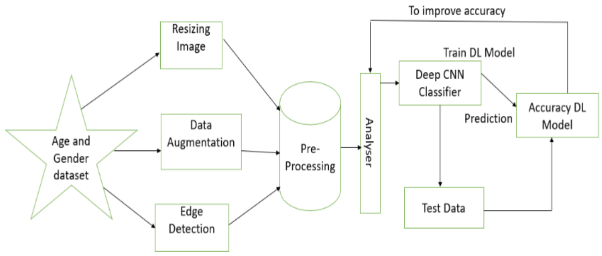
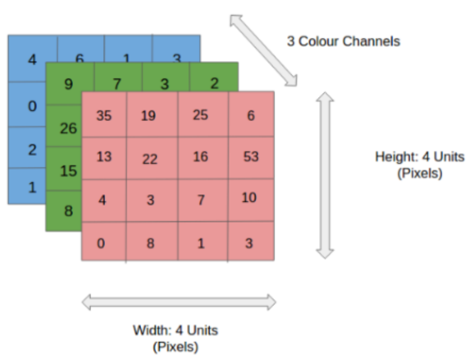
ARCHITECTURE DIAGRAM:

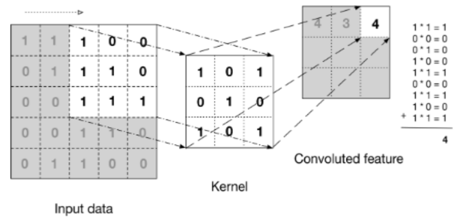


V. TABLES:

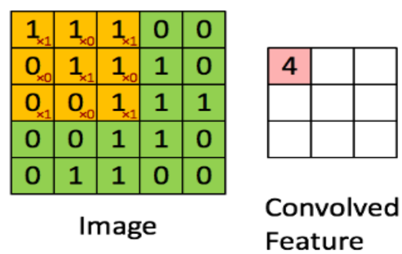
Before we go to the working of CNN's let's cover the basics such as what is an image and how is it represented.An RGB image is nothing more than a matrix of pixel values with three planes while a grayscale image is the same but has a single plane.Look at this image to learn more.



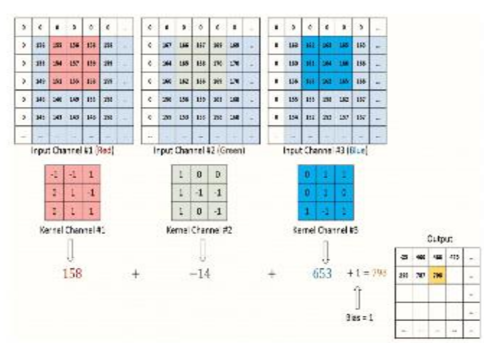
For simplicity, let's continue with the grayscale images as we try to understand how CNNs work.



The image above shows what a convolution is.We take a filter/kernel (3×3 matrix) and apply it to the input image to get the convoluted function.This conveyed functionality is taken to the next level.



In the case of RGB color, the channel takes a look at this animation to understand its working.



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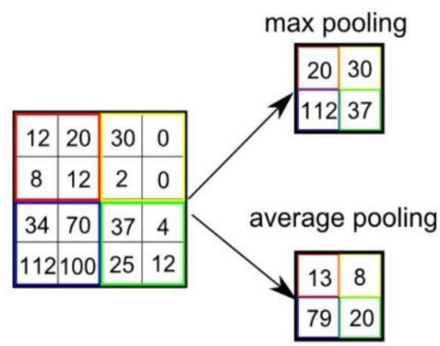
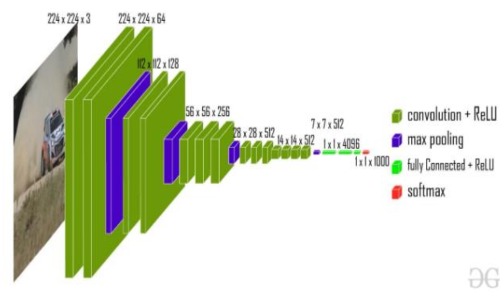
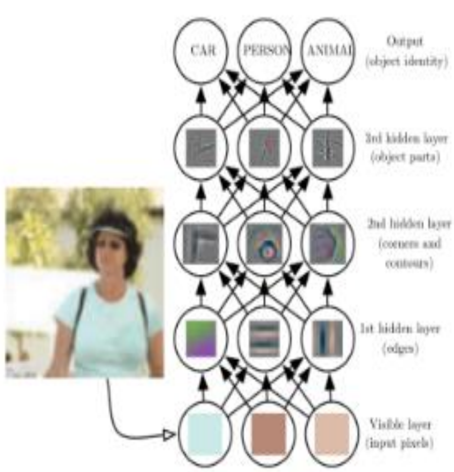
The first layer usually extracts basic features such as horizontal or diagonal edges.This output is passed to the next level which detects more complex features such as combined corners or edges.As we progress through the network, it can identify even more complex features like objects, faces, etc.Based on the activation map of the final convolution level, the classification level produces a confidence sat scores (values between 0 and 1) which specify the probability that the image belongs to a "class".For example, if you have a ConvNet network that detects cats, dogs, and horses, the file output final layer is the possibility that the input image contains any of those animals.

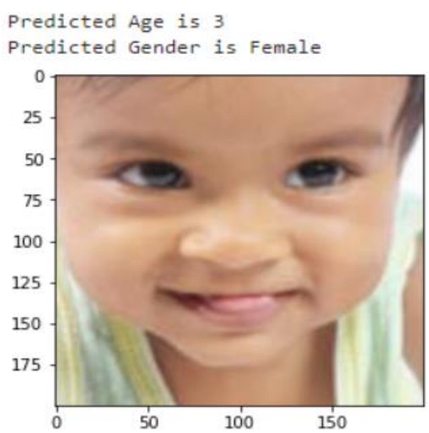






This model achieves 92. 7% top-5 test accuracy on ImageNet dataset which contains 14 million images belonging to 1000 classes.The ImageNet dataset contains images of fixed size of 224*224 and have RGB channels.Therefore, we have a tensor of (224, 224, 3) as an input. This model processes the input image and outputs a vector of 1000 values.This vector represents the classification probability for the corresponding class. Suppose we have a model that predicts that image belongs to class 0 with probability .1, class 1 with probability 0.05, class 2 with probability 0.05, class 3 with probability 0.03, class 780 with probability 0.72, class 999 with probability 0.05 and all other classes with 0.

VI. SNAPSHOT OF RESULT:



VII. CONCLUSION:

Although many earlier methods addressed the topic of the problem as grouping of images, in this paper we set a benchmark for the task based on our own observations and conclusions and show that chaining age predictions with gender predictions can improve overall precision. We deliver results with an architecture of open neural networks in such a way that we avoid all kinds of mismatches of data. Compared with any of the latest network designs, our network is "shallow," thereby the amount of its parameters and the possibility to overfit. By unnaturally attaching cropped variants of the photos into our training set, we have broadened our data model. From our results we can draw two important conclusions. First, CNN can be used to deliver better results in age and gender classification, even analyzing the much smaller size of contemporaneous unconstrained sample images that are marked. Secondly, with the help of our model, other people who are doing the same project or may do in the future which needs more training data sets can further improve the system.

VIII. FUTURE WORK:

We recently came across Quividi, an AI software application that is used to detect the age and gender of users who pass by based on online face analyses and automatically starts playing advertisements based on the targeted audience.

Another example would be AgeBot, an Android app that determines your age from your photos using facial recognition. It can guess your age and gender along with that and can also find multiple faces in a picture and estimate the age for each face.

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