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Gender Prediction Using Machine Learning

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***Abstract* - The objective of this project is to identify the gender of the individuals. This is a case of supervised learning where the algorithm is first trained on a set of female and male faces, and then used to classify new data. We have not taken genders other than male and female into account. A preliminary check has to be performed before running the application to make sure that the image is that of a human before classification begins. Python based gender recognition is an application in which machine learning is used for classification of images and python flask web framework is used for user interface. Application accepts input in two ways either through a web camera or through an input image. The input image is then passed to the machine learning model for the classification and the model outputs the resulting image annotated with gender of the person present in the image. Automatic face recognition aims to extract the meaningful pieces of information and put them together into a useful representation in order to perform a classification/identification task on them.**

***Index Terms* - Deep learning (DL), Machine Learning (ML), Convolutional neural networks, Classification.**

I.INTRODUCTION

A common job of machine learning algorithms is to recognize objects and being able to separate them into categories. This process is called classification, and it helps us segregate vast quantities of data into discrete values, i.e.: distinct, like 0/1, True/False, or a pre-defined output label class. Classification is defined as the process of recognition, understanding, and grouping of objects and ideas into preset categories a.k.a "sub-populations". With the help of these pre-categorized training datasets, classification in machine learning programs leverage a wide range of algorithms to classify future datasets into respective and relevant categories.

Gender is a key facial attribute, play a very foundational role in social interactions, making gender estimation from a face image an important task in intelligent applications. There are various applications which are based on gender such as Human-Computer Interaction, Marketing Intelligence, Visual Surveillance and Women Safety.

The Gender Recognition is essential and critical for many applications in the commercial domains such as applications of human-computer interaction and computer-aided physiological or psychological analysis, since it contains a wide range of information regarding the characteristics difference between male and female. Some have proposed various approaches for automatic gender classification using the features derived from human bodies and/or behaviours. Gender Prediction is a classification problem. The output layer in the gender prediction network is consists of 2 nodes indicating the two classes "Male" and "Female". Male and Female faces have different nodal points. Using these points, we can easily classify male and female faces.

Past researches have shown that the brain has specialized nerve cells that respond to specific local features of a scene, like lines, edges, angles, or movement. Our visual area combines these scattered pieces of data into useful patterns. The automatic/Natural face recognition technique focuses on extracting these important pieces of data and putting them together into a useful representation so as to perform a classification task on them. While we plan to identify gender from countenance, we are often interested in what features of the face are most vital in determining gender. Are localized features such as eyes, nose, and ears more important or overall features such as head shape, hairline, and face contour more important?

II. LITERATURE REVIEW

Machine learning involves computers discovering how they will perform tasks without being explicitly programmed to try and do so. For easy tasks assigned to computers, it's possible to program algorithms telling the machine the way to execute all steps required to unravel the matter at hand; on the

computer's part, no learning is required. For more advanced tasks, it is often challenging for a person to manually create the needed algorithms. In practice, it can end up to be simpler to assist the machine develop its own algorithm, instead of having human programmers specify every needed step. The discipline of machine learning employs various approaches to assist computers learn to accomplish tasks where no fully satisfactory algorithm is out there.
Gender classification is a two-class problem in which the given information is assigned as male or female. Gender classification is a relatively easy task for humans but a challenging task for machines. Human beings are often able to make accurate and fast decisions on gender through visual inspection.
For example, on the most basic characteristic, gender is a relatively invariant aspect of faces [1].
Humans can readily determine gender for most faces, and additional information from hairstyle, body shape, clothing, eyebrows, and posture will support the evidence gained from the visual image [2]. There are acoustical differences in the voices of male and female which have also been discussed by researchers [3] which can make a notable difference.
There are various neural and psychological studies which have shown the diversity that exhibits with different genders on the basis of facial expressions and head movement when they are simulated [4][5].
Research on gender classification using facial images. started at the beginning of the 1990s. In 1990, Golomb et al. [6] used a multi–layer neural network to classify gender based on human faces. They reported a gender classification error rate of 8.1% by using a Cottrell-style back-propagation image compression network. Since then, applications of gender classification were developed extensively in various domains, bringing the emergence of gender classification approaches, from which iris [7], hand shape [8] and eyebrows [9] were considered as features in the literature.
Gender information extraction can vary due to the factors like pose, illumination, age, expression, ethnicity [10]. Even during image capture process image quality can become an issue, factors like noise, low-resolution and dithering becomes a challenging issue [11]. The classification techniques are also affected by feature extraction and classification algorithms.

III. METHODOLOGY

Gender contains a wide range of information regarding to the characteristics difference between male and female. Successful gender recognition is essential and critical for many applications of human-computer interactions and computer aided physiological or psychological analysis. The main objective of this project is to identify and classify humans into two genders, that is “male” and “female”. Male and Female faces have different nodal points. Using these points, we can easily classify male and female faces.
The model uses some python tools and machine learning techniques for the prediction of gender. Python is used for face detection and machine learning techniques like CNN is used for gender recognition. For prediction of gender artificial neural network is used, namely – Convolutional neural network, Rectified linear unit layers and Pooling layers. Output is the prediction given by the mentioned network. For accuracy improvement we are using the Rectified Linear Unit (ReLU) and Pooling method in Convolutional Neural Network (CNN) for achieving better performance through activation functions. Also, in our system users can input images both via image and web camera hence interaction is easy as compared to existing systems. Since we are using ReLU and Pooling with CNN, output of the model is supposed to be more accurate and besides better accuracy this model also provides a convenient option of web camera input that makes this model more reliable and user friendly.

A. Convolutional Neural Network (CNN)

A convolutional neural network is a deep learning algorithm which can take in an input image, assign importance(weights) to various objects in the image and be able to differentiate one from the other. The preprocessing required in a convolutional neural network is much lesser as compared to other classification algorithms. While in primitive method filters are hand engineered, with enough training, CNN has the ability to learn these filters over time. The Convolutional layer is the first layer in the network that takes an image as an input. The transformed matrix of pixel values. Reading of the image starts from the top left corner of the matrix, then a filter is selected. Filter is a smaller matrix which is also called core or neuron. Then the filter moves along the input image, the filter multiplies its value with the pixel value. All these multiplications are summed up and one number is obtained at the end. This process is followed for rest blocks of the matrix and results in a matrix which is smaller than the input matrix. Convolutional Neural Networks are a kind of Deep Learning Algorithm that take the image as an input and learns the varied features of the image through filters. this enables them to find out the important objects present within the image, allowing them to discern one image from the opposite. For instance, the convolutional network will learn the precise features of cats that differentiate it from the dogs in order that once we provide input of cats and dogs, it can easily differentiate between the 2. One important feature of the Convolutional Neural Network that sets it aside from other Machine Learning algorithms is its ability to pre-process the info by itself. Thus, you'll not spend tons of resources in data pre-processing. During the start, the filters may require manual engineering but with progress in training, they're ready to adapt to the learned features and develop filters of their own. Therefore, CNN is continuously evolving with growth within the data.

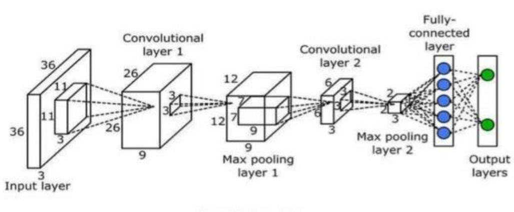

Figure 1: Representation of Multi layered CNN

B. Rectified Linear Unit (ReLU)

The rectified linear activation function is a function that outputs the same value as input if the input value is greater than or equal to 0 and output 0 if the input value is less than 0. It has been used as a default activation function for many neural networks because it is easier to use. The models which use this function can be trained easily and also gives better performance. A node or unit that implements this activation function is mentioned as a rectified linear activation unit or ReLU for brief. Often, the network that uses the rectifier function for the hidden layers is mentioned as a rectified network. The non-linear layer is added after each convolution operation. it's an activation function, which brings nonlinear property. Without this property, a network wouldn't be sufficiently intense and cannot be ready to model the response variable (as a category label). In our model, ReLU is the main component which is used to improve the accuracy of the model and it also makes it easier for the training of the model.

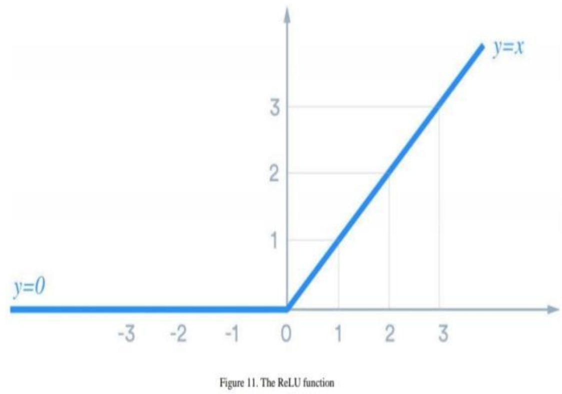

Figure 2: Representation of ReLU function

C. Pooling

Pooling is a layer which is added after non-linearity (ReLU) has been applied to the feature maps which are output by a convolutional layer. The ordering of layers are as follows.

1) Input Layer
2) Convolutional layer
3) No-linearity Layer (ReLU)
4) Pooling

The pooling layer follows the nonlinear layer. It manipulates the width and height of the image and performs a down-sampling operation on them. As a result the image volume is reduced. this suggests that if some features (as for instance boundaries) have already been identified within the previous convolution operation, than an in depth image is not any longer needed for further processing, and it's compressed to less detailed pictures.

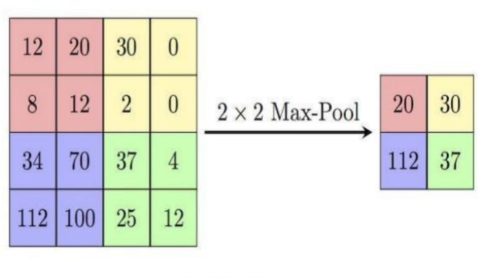

Figure 3: Matrix showing pooling process

D.Fully Connected Layer

After completion of the above-mentioned procedure, the last step is to connect the totally connected layer. This layer takes the output from the convolutional network. Placing a totally connected layer to the top of the network leads to an N-dimensional vector, where N is the number of classes from which the model selects the specified class. CNN's have similar performance to the standard fully connected Neural Networks. These convolutional networks have weights that will learn from the input and biases. Every neuron connected within the network receives input and performs a scalar product thereon. This proceeds during a non-linear fashion. there's a singular differentiable score function at the top. This function consists of scores that we obtain from the varied layers of the neural network. Finally, a loss function at the top to gauge the performance of the model. The convolutional neural network is different from the quality Neural Network within the sense that there's a particular assumption of input as a picture. This assumption helps the architecture to the definition in a more practical manner. for instance, unlike the linear arrangement of neurons during a simple neural network. These neurons have an overall structure of three dimensions – Length, Width, and Height. As an example, images within the CIFAR 10 dataset will contain images of dimensions 32x32x3 and therefore the final output will have a singular vector of the pictures of dimensions 1x1x10.

E. OpenCV

OpenCV stands for open-source computer vision and it is used in computer vision real-time processing. In our system, OpenCV is used for capturing face in an image. After capturing face, the face is converted into a set of numerals which is used for further processing. OpenCV is an open-source (http://opensource.org) computer vision library available from http://SourceForge.net/projects/opencvlibrary. The e-library is written in C and C++ and runs under Linux, Windows, and Mac OS X. There are active development platforms like Python, Ruby, Matlab, and other languages. OpenCV was designed for computational efficiency and with a robust specialize in real-time applications. OpenCV is written in optimized C and may cash in of multicore processors. If you like further automatic optimization on Intel architectures, you'll buy Intel’s Integrated Performance Primitives (IPP) libraries [IPP], which consist of low-level optimized routines in many various algorithmic areas. OpenCV automatically uses the acceptable IPP library at runtime if that library is installed.

One of OpenCV’s goals is to supply a simple-to-use computer vision infrastructure that helps people build fairly sophisticated computer vision applications quickly. The OpenCV library contains more than 500 functions that span many areas in vision, including factory product inspection, medical imaging, security, interface, camera calibration, stereo vision, and robotics. Because computer vision and machine learning often go hand-in-hand, OpenCV also contains a general-purpose Machine Learning Library (MLL). This sub library is concentrated on statistical pattern recognition and clustering. The MLL is highly useful for the visual tasks that are at the core of OpenCV’s mission, but it's general enough to be used for any machine learning problem.

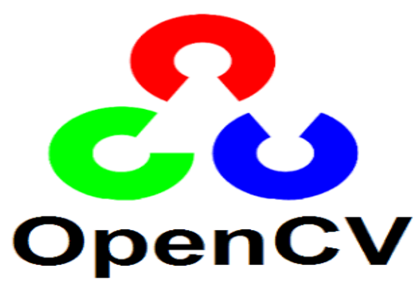

Figure 4: Representation of OpenCV

IV. CONCLUSION

Traditional methods based on hand-engineered features that provided state-of-the-art accuracy only a few years ago have been replaced by deep learning methods based on CNNs. Indeed, face recognition systems based on CNN's have become the standard due to the significant accuracy improvement achieved over other types of methods. Moreover, it is straightforward to scale-up these systems to achieve even higher accuracy by increasing the size of the training sets and/or the capacity of the networks. However, collecting large amounts of labelled face images is expensive, and very deep CNN architectures are slow to train and deploy. There have been numerous aspects affecting the general working capability of computer-based estimation of age, i.e. Database, collection of various face photos utilized for the training purposes, preprocessing as well as face alignment, an approach for extracting the characteristics and age mastering approach. Here, we have supplied an extensive survey of age prediction and the proposed approach will attempt to triumph over the present demanding situations of various methods.

REFERENCES

[1] Vicki Bruce and Andy Young. In the eye of the beholder: the science of face perception. Oxford University Press, 1998.

[2] Vicki Bruce, A Mike Burton, Elias Hanna, Pat Healey, Oli Mason, Anne Coombes, Rick Fright and Alf Linney. Sex discrimination: how do we tell the difference between male and female faces? Perception, 1993.

[3] Elvira Mendoza, Nieves Valencia, Juana Munoz, and Humberto Trujillo. Differences in voice quality of men and women. Journal of Voice, 10(1):59-66, 1996.

[4] Harold Hill and Alan Johnston. Categorizing sex and identity from the biological motion of the faces. Current Biology, 11(11):880-885, 2001.

[5] Alice J O'Toole, Dana A Roark and Herve Abdi. Recognizing moving faces: A psychological and neural synthesis. Trends in cognitive sciences, 6(6):261-266, 2002.

[6] Beatrice A Golomb, David T Lawrence and Terrence J Sejnowski. Sexnet: A neural network identifies sex from human faces. In NIPS, pages 572-579, 1990.

[7] Vince Thomas, Nitesh V Chawla, Kevin W Boywer and Patrick J Flynn. Learning to predict gender from iris images. In Biometrics: Theory, Applications, and Systems, 2007. BTAS 2007. First IEEE International Conference on, pages 1-5, 2007.

[8] Gholamreza Amayeh, George Bebis, and Mircea Nicolescu. Gender classification from hand shape. In Computer Vision and pattern Recognition Workshops, 2008. CVPRW'08. IEEE Computer Society Conference on, pages 1-7. IEEE, 2008.

[9] Yujie Dong and Damon L Woodard. Eyebrow shape-based features for biometric recognition and gender classification: A feasibility study.In Biometrics (IJCB), 201 International Joint Conference on, page 1-8. IEEE, 2011.

[10] Muthumari Paluchamy, D Suganya, and S Ellammal. Human gait-based gender classification uing various transformation techniques, IJRCCT, 2(11):1315-1321, 2013.

[11] Choon Boon ng, Yong Haur Tay, and Bok Min Goi. Vision-based human gender recognition: a survey.arXiv preprint arXiv:1204.1611, 2012.