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GENDER AND AGE PREDICTION USING WIDERESNET ARCHITECTURE

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Abstract - *Automatic Gender and age prediction has been evident in today's cyberspace, especially with the introduction of social platforms. This Gender and age prediction system is one of the most thriving applications in Face recognition and is in huge demand, which provides a better security and more convenience than conventional approaches like biometric authentication. Several methods were developed using principal component analysis(PCA), local binary patterns(LBP),support vector machine(SVM). But what lacks in these existing systems is its performance issues like inaccurate results due to poor lightening conditions, angle at which the image is captured etc. In this paper we will enhance these performance issues of the system by using WideResnet which is one of the popular convolutional Neural Network and frameworks such as Tensorflow and keras .This system can be implemented using cascade classifier. This proposed system evaluates on the basis of the IMDB dataset which contains nearly 5 lakh trained images.*

Key Words: **Face recognition, Convolutional Neural Networks, Wideresnet, keras, Tensorflow,**

1. INTRODUCTION

Automatic Gender and Age prediction play a quite interesting role in various social platforms. Applications for these systems include everything from suggesting who to tag in Facebook, polling systems, Automatic suggestions in e-commerce websites. The objective of this project is to classify the gender and age of an individual in real time.

A real time Gender and Age prediction is a challenging problem when compared to other tasks in computer vision. The fundamental explanation behind this disparity in trouble lies in the idea of information that is utilized to prepare the model. This requirement regarding selecting a dataset containing several thousands and millions of images tests our mettle. The reason for this is that in order to have labels for the images we need to collect the personal information of the subjects such as date of birth, time at which the image is taken, gender. In this paper we used IMDB wiki dataset containing 500k+ face images containing the above mentioned attributes. This paper proposes an gender and age prediction system using Wideresnet which is one of the convolutional Neural Network(CNN).

The input for this project is an image of human face which is trimmed and then fed into WideResnet architecture. The gender classifier restores a twofold outcome where 0 demonstrates male and 1 speaks to female. The age classifier restores a whole number speaking to the age scope of the person.

2. RELATED WORK

Early methods for gender and age estimation were based on local features for representing face images. Gaussian Mixture Models (GMM) were used to represent the facial patches. This model uses Fuzzy-LDAclassifier which considers a face image as belonging to more than one class. Later Local Binary Pattern(LBP) method is used for estimation of gender and age of a person. The recognition is performed using a nearest neighbour classifier in the computed feature space with Chi square as a dissimilarity measure. Gabor and local binary patterns (LBP) features were used in 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. Similarly other methods such as SVM classifiers were used especially for gender prediction. Later usage of SVM classifiers is ousted with the introduction of Adaboost . However it leads to overfitting issues .

Through this paper we would like to improve the overall performance of the existing systems with the concept of Neural Networks by using Wideresnet architecture**.**

3. METHODOLOGY

Convolutional Neural Networks(CNN or ConvNet):

In neural networks, Convolutional neural network (ConvNets or CNNs) is one of the main categories to do images recognition, images classifications. CNN image classifications takes an input image, process it and classify it under certain categories. Technically, deep learning CNN models to train and test, each input image will pass it through a series of convolution layers with filters (Kernals), Pooling, fully connected layers (FC) and apply Activation function to classify an object.

Figure 1- process of image classification

Convolutional Neural Networks are best in class models for Image Classification, Segmentation, Object Detection and numerous image processing tasks. To improve the accuracy of the CNN models , there are several architectures like VGGNet , Inception Net, Alex Net, ResNet etc. This paper describes how **Wideresnet architecture** builds Gender and Age prediction system.

3. 1 NETWORK ARCHITECTURE

The network is generally a two layered convolutional network containing parameters like kernel size, no of strides, padding length. Firstly, the image (RGB) captured from webcam is converted to Grayscale image. The **Cascade Classifier** identifies whether the captured image is a face or not. Later, the face is then cropped in order to capture the facial features for further prediction. This cropped face is then fed into model in order to evaluate results. The model is built using wideresnet architecture.

Our proposed architecture in developing the gender and age prediction is illustrated in figure 2.

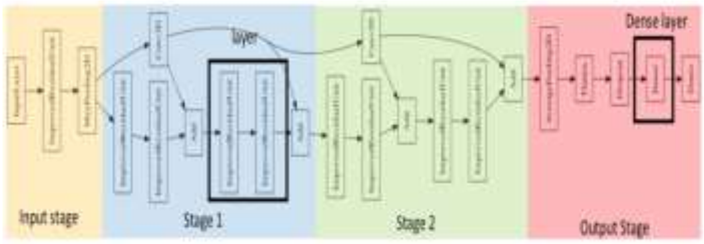

Figure 2- Wideresnet architecture

- The image(l*w*h) is applied as an input to the convolutional layer, followed by striding and padding operations. Then the output of the previous layer is passed to the next convolutional layer with same set of operations.
- The fully connected layers receives the output from second convolutional layer followed by RELU and dropout layer. we apply Batch Normalisation technique to maintain stability of neural networks and to improve the performance.

4. Training and testing:

Initialisation: The weights in all layers are intialised with pre trained models and labels available from IMDM data set. The test data is compared with the pretrained models and haar cascade frontal faces prepared from dataset.

- Target values for training are represented as sparse, binary vectors corresponding to the ground truth classes. For each training image, the target, label vector is in the length of the number of classes (two for gender, eight for the 101 age classes of the age classification task). The class 0 indicates male and class 1 indicates female.

5. IMDB dataset :

Since the publicly available face image datasets are regularly of small to medium size, rarely surpassing tens of thousands of images, and frequently without age information we decided to gather a large dataset of celebrities. For this purpose, we took the rundown of the most popular 100,000 actors as listed on the IMDb website and collected their profiles date of birth, name, gender and all images related to that person. when the photo was taken). Assuming that the images with single faces are likely to show the actor and that the timestamp and date of birth are correct, we were able to assign to each such image the biological (real) age. In total we obtained 460,723 faces from IMDB dataset.

	dob	photo_taken	full_path	gender	name	face_location	face_score	second_face_sco
0	723671	2009	[17/10000217_1981-05-05_2009.jpg]	1.0	[Sam Jauhojarvi]	[[111.29109473290997, 111.29109473290997, 252...	4.300962	Na
1	703186	1964	[48/10000548_1925-04-04_1964.jpg]	1.0	[Dettmar Cramer]	[[252.48330229530742, 126.68165114765371, 354...	2.645639	1.9492
2	711677	2008	[12/100012_1948-07-03_2008.jpg]	1.0	[Marc Okrand]	[[113.52, 169.83999999999997, 366.08, 422.4]]	4.329329	Na
3	705061	1961	[65/10001965_1930-05-23_1961.jpg]	1.0	[Aleksandar Matanović]	[[1, 1, 634, 440]]	-inf	Na
4	720044	2012	[16/10002116_1971-05-31_2012.jpg]	0.0	[Diana Damrau]	[[171.61031405173117, 75.57451239763239, 269.7...	3.408442	Na

6. Technical details:

Activation functions used in wideresnet architecture include:

Rectified Linear Unit :

The Rectified Linear Unit is the most commonly used activation function in deep learning models. The function returns 0 if it receives any negative input, but for any positive value it restores that value back. So it can be written as f(x)=max(0,x)

The Purpose of ReLu

Traditionally, some prevalent non-linear activation functions, like sigmoid(or logistic) and hyperbolic tangent, are utilised in neural networks to get activation values corresponding to each neuron. As of late, the ReLu function has been used rather to calculate the activation values in traditional neural network or deep neural network paradigms. The reasons of replacing sigmoid and hyperbolic tangent with ReLu consist of:

1. **Computation saving** - the ReLu function is able to accelerate the training speed of deep neural networks compared to traditional activation functions since the derivative of ReLu is 1 for a positive input. Due to a constant, deep neural networks do not need to take additional time for computing error during training phase.

Softmax:

At the top of the proposed architecture lies a softmax layer, which computes the loss term that is enhanced during training and furthermore the class probabilities during a classification. While some loss layers like multiclass SVM loss treat the output of the final fully connected layer as the class scores, softmax (also known as multinomial logistic regression) treats these scores as the unnormalized log probabilities of the classes. That is, if we have z_i is the score assigned to class i after the final fully connected layer, then the softmax function is

$$F_j(z) = e^{z_j} \;/\; \sum_k e^{z_k}$$

Because we want to maximize the log likelihood of the correct class, the term we want to minimize is the negative log likelihood.

$$L_i = -\log(\, e^{f_{y_i}} \;/\; \sum e^{f_j})$$

Because the softmax function takes real-valued scores being output from f and normalizes them by their exponentiated sum, it guarantees that the sum of all softmax scores is 1, thereby allowing it to be interpreted as a true class probability.

7. RESULTS:

The model displays the face of a person captured through webcam along with gender and age of the person.

The algorithm runs continuously as long as the webcam is active. The following are the pixel values of the face that are being read by the webcam.

8. CONCLUSION:

In spite of the fact that numerous past techniques are developed regarding Gender and age prediction, they do not yield accurate outcomes. This is due to certain specifications like light conditions, alignment of face near webcam etc. Also those previous methods can only detect few faces. Our proposed System rectifies all those above problems and produces accurate results. Our system can identify nearly around seven faces at a time. This improvement in performance is due to WideResnet architecture. The features like dropout, weight decay reduced the training time required for the network. Lastly, the simplicity of our model infers that more intricate systems using more training data may well be capable of substantially improving results beyond those reported here.

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