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Real time user access control on Social Network using Deep Learning

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Abstract— **In the past few years, there has been a huge growth in the use of Social Networking Platform. Real-time age estimation has been essential in the field of human computer interaction and computer vision. Accuracy of age estimation of the face image is really challenging. In this project, we build a model which restrict user to login the social networking sites. We used Deep Learning for face recognition. After recognizing the face it will classify as per the age group. If certain age group has permission then that person will get access. We used CNN with LSTM for having more accurate prediction of biological age of the person. We used MTCNN for face detection and feature extraction.**

Keywords- CNN, LSTM, MTCNN, Real time user access, deep learning.

I. INTRODUCTION

Automatic face detection in image/video has attracted strong interests in recent years. Age estimation is an available technique for many applications, which are depends on accurate age information, such as medical diagnosis (premature facial aging due to various causes), age-based human-computer interaction system, advanced video surveillance, demographic information collection, soft biometrics, etc. There is a research to combining eigenface for feature extraction and naive Bayes for predict class of images dataset. The result of eigenface feature extraction to predict the face. [74]. and the Local Binary Pattern Histogram (LBPH) algorithm is a simple solution on face recognition problem, which can recognize both front face and side face. However, the recognition rate of LBPH algorithm under the conditions of illumination diversification, expression variation and attitude deflection is decreased. To solve this problem, a modified LBPH algorithm based on pixel neighborhood gray median (MLBPH) is proposed. The gray value of the pixel is replaced by the median value of its neighborhood sampling value, and then the feature value is extracted by the sub blocks and the statistical histogram is established to form the MLBPH feature dictionary, which is used to recognize the human face identity compared with test image. [73]. Also Particle Swarm Optimization algorithm for Human Face Recognition is applied to coefficients extracted by two feature extraction techniques: the discrete cosine transform (DCT) and the discrete wavelet transform (DWT). The proposed PSO-based feature selection algorithm is utilized to search the feature space for the optimal feature subset where features are carefully selected according to a well-defined discrimination criterion. Evolution is driven by a fitness function defined in terms of maximizing the class separation (scatter index). The classifier performance and the length of selected feature vector are considered for performance evaluation using the ORL face database. [72].

Face Recognition techniques in last few years have shown that tremendous progress can be made by use of deep learning [e.g. (65, 66, 69, 70)]. Automatic age and gender classification has become relevant to an increasing amount of applications, particularly since the rise of social platforms and social media. A simple convolutional net architecture that can be used even when the amount of learning data is limited. It evaluate method on the recent Audience benchmark for age and gender estimation and show it to

Dramatically outperform current state-of-the-art methods. CNN can be used to provide improved age and gender classification results, even considering the much smaller size of contemporary unconstrained image sets labeled for age and gender. The simplicity of this model implies that more elaborate systems using more training data may well be capable of substantially improving results beyond those reported. [75]. There have been a research proposed, hand-designed features behave unsatisfactorily on benchmarks of unconstrained images. Later research approached age estimation from face images in convolutional neural network (CNN) manner, automatically extracting feature representations for input images [3]. There are two reasons why automatic age estimation is regarded as a very challenging task. First, discriminative feature extraction for age estimation is easily affected by large variations in facial gestures, lighting, makeup, background, noise, etc. [4]. Second, the similarity and subtle differences in face images with adjacent ages are hardly handled. Therefore, distinguishing age with only global features of face may not achieve better results, while searching for age-sensitive regions (wrinkles, hair, liver spots, etc.) can provide more distinctive features for age estimation. Inspired by fine-grained image categories and attention conceptions [5], a wide array of fine-grained classification methods exist [6] [7] [8] [9] and are still deployed with additional supervisory information which increases computational complexity. Currently, none of the several public large age datasets mark certain image parts, which severely limits the development of fine-grained age estimation. Therefore, there is an urgent demand on how to automatically obtain position information of age-sensitive regions.

In this paper we use convolutional neural network to recognize the face. After recognizing the face it will classify as per the age group. If certain age group has permission then that

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person will get access. This module give real time access to specific user if criteria is fulfilled. This will fulfill our requirement to restrict the person whose age is not matched as per the criteria. Our main goal is to restrict the user whose age is less than 18 that person should not get access to social sites.

II. RELATED WORK

Before describing the proposed method we briefly review the overview of deep convolutional networks. 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. Detail study of algorithm LBPH found in [73] where a modified LBPH algorithm based on pixel neighborhood gray median (MLBPH) is proposed. The gray value of the pixel is replaced by the median value of its neighborhood sampling value, and then the feature value is extracted by the sub blocks and the statistical histogram is established to form the MLBPH feature dictionary, which is used to recognize the human face identity compared with test image. The Study of eigenface algorithm found in [74] for face detection and recognition. Facial features can be identified using Support vector machine (SVM) algorithm found in [66, 67, and 68]. Particle swarm optimization (PSO) algorithm is applied to coefficients extracted by two feature extraction techniques: the discrete cosine transform (DCT) and the discrete wavelet transform (DWT) found in [72].

Age and gender classification using Deep Convolutional Neural Network (CNN) found in [69, 70, and 71]. But in Depth using Audience dataset we found in [75] and [65]. We show our proposed method to outperform the results they report on the more challenging Audience dataset, calculate the accurate age. We are not interested in gender in this paper. We only focus on age, as user will get access on age.

Age estimation has historically been one of the most challenging problems within the field of facial analysis. Age estimation used to extract facial features manually in the past, but now CNN methods [27] are preferred due to achievements in training CNN directly on age datasets. Face age datasets are divided into biological age datasets and apparent age datasets, and diverse age datasets can apply different age estimation methods. Much research has been devoted to age estimation from a face image under the more familiar biological age estimation. Adience, MORPH Album 2 and FG-NET are prevalent benchmarks for biological age estimation; their image labels are marked by the age group or actual age; thus the predicted output is the biological age of a person

A. Apparent Age Estimation

Age estimation is very challenging but using Convolutional neural network we can achieve it. Still researchers are not confined to the study of biological age estimation. Xu et al. [39] proposed a deep label distribution method with distribution based loss functions and used the Coc-DPM algorithm [40] and face point detector [41] for face search. Zhu et al. [42] used the Microsoft Project Oxford API [44] and Face ++ API [43] to preprocess LAP dataset, and then got GoogleNet pretrained on several other datasets. Kuang et al. [45] studied the age-related discriminative performance over multiple age datasets of MORPH, FG-NET, Adience, FACES [46], and mixed with random forest and quadratic regression as well as local adjustment methods. Lin et al. [47] fused real-word value-based regression models and Gaussian label distribution based classification models, which were pretrained on CASIA WebFace [48], CACD(computer aided conceptual design) [49], WebFaceAge [50] and MORPH datasets, and were finetuned on the ChaLearn LAP dataset. Deep EXpectation (DEX) formulation [52] was proposed for apparent age estimation and won the LAP 2015 challenge. Agustsson et al. [53] proposed a nonlinear regression network called Anchored Regression Network (ARN), which achieved the state-of-theart results on 15LAP validation set. The 2016 ChaLearn LAP Apparent Age Estimation (AAE) competition [61] had been completed and expanded the dataset scale based on the 15 LAP dataset. Face age estimation made a development of the convolution neural network. Apparent age estimation was originally inspired by the 2015 ChaLearn Looking at People (LAP) competition [51], where the apparent age dataset was released. A method called logistic boosting regression (Logit Boost) [38] was proposed, which realized the network optimization progressively. Gurpinar et al. [54] proposed a two-level system for estimating the apparent age of facial images, where the samples were classified into eight age groups. Duan et al. [55] proposed a CNN2ELM method, where apparent age was estimated by the Race-Net + Age-Net + Gender-Net + ELM Classifier + ELM Regression (RAGN). Malli et al. [56] divided the LAP dataset into age groups and age-shifted groups and used these groups to train the VGG-16 model. Uricar et al. [57] extracted the deep features and formulated a SO-SVM multi-class classifier on top of it. Huo et al. [58] proposed a novel method called deep age distribution learning (DADL) to use the deep CNN model to predict the age distribution. Dehghan et al. [59] introduced a large dataset of 4 million face recognition images to pretrain their model, and then predicted apparent age on the age dataset. Antipov et al. [60] employed different age encoding strategies for training general and children networks, including 11 "general" models and 3 "children" models, which achieved the state-of-the-art results using on 16 LAP dataset. In conclusion, whether biological age estimation or apparent age estimation, one of the pivotal issues in age estimation is how to learn the distinctive features of face age.

B. Biological Age Estimation Specifications

Aging pattern Subspace (AGES) [28] was constructed to model the aging pattern, which was implemented for automatic age estimation. Chang et al. [29] proposed OHRank for estimating human age via facial images. Wang et al. [30] proposed a new framework for age feature extraction based on a manifold learning algorithm and the deep learned aging pattern (DLA), which greatly improved the age estimation performance. Chen et al. [31] proposed a cumulative attribute concept based on support vector regression (SVR) for learning a regression model, and it gained a notable advantage based on its accuracy for age estimation. Guo et al. [33] proposed a KCCA method, which could derive an extremely low dimensionality in estimating age, but the amount of kernel calculation was tremendous. All of these methods had the same scope of applicability. Some research on CNN showed that CNN models [12] [17] [19] [15] and [16] [13] [18] [14] could learn compact and discriminative feature, so an increasing number of researchers have started to use CNN for age estimation. Levi et al. [20] applied DCNN for the first time to age classification on an unconstrained Adience benchmark. Yi et al. [34] proposed a multi-scale convolution neural network based on the traditional face analysis method. Hou et al. [21] proposed a VGG-16 model with smooth adaptive activation function (SAAF) to predict age group on the Adience benchmark. Then they used the exact squared Earth Movers Distance (EMD2) [22] as the loss function for CNN training and obtained better age estimation results. Rothe et al. [35] combined the VGG-16 network pretrained on ImageNet dataset, using the principal component analysis (PCA) method to obtain a lower mean absolute error (MAE) value on MORPH Album 2. Then, they transformed the age regression into an age classification problem through the Deep EXpectation (DEX) method [23] and achieved better results. Recently, Hou et al. [25] used the R-SAAFc2+IMDB-WIKI method to obtain best results on a FG-NET dataset. Zhang et al. [27] proposed an age-and-gender estimation method combining a multi-level residual network (RoR) with two modest mechanisms, which they actively presented to achieve state-of-the-art results on the Adience benchmark. Gao et al. [37] proposed a deep label distribution learning (DLDL) method, which effectively utilized the label ambiguity in both feature learning and classifier learning; thus, the best MAE value on the MORPH dataset was achieved.

III. METHODOLOGY

A. *Convolutional Neural Network*

Convolution Neural Networks are neural networks that share their parameters. In deep learning, a **convolutional neural network (CNN/ConvNet)** is a class of deep neural networks, most commonly applied to analyze visual imagery. Now when we think of a neural network we think about matrix multiplications but that is not the case with ConvNet. It uses a special technique called Convolution. Now in mathematics **convolution** is a mathematical operation on two functions that produces a third function that expresses how the shape of one is modified by the other..

B. *Libraries Used*

- **Tensorflow:** Tensorflow is a free and open source software library for machine learning and artificial intelligence. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks.
- **OpenCV:** OpenCV is a library of programming functions mainly aimed at real-time computer vision. Mainly developed by Intel.
- **Numpy:** NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.
- **Pandas:** Pandas is a software library written for the Python programming language for data manipulation and analysis. In particular, it offers data structures and operations for manipulating numerical tables and time series.
- **keras-utils:** Keras provides numpy utility library, which provides functions to perform actions on numpy arrays.
- **PIL:** Python Imaging Library is a free and open-source additional library for the Python programming language that adds support for opening, manipulating, and saving many different image file formats.
- **Skimage:** skimage, is an open source Python package designed for image preprocessing. a collection of algorithms for image processing and computer vision.
- **Math:** This module provides access to the mathematical functions defined by the C standard.

IV. PROPOSED METHOD

We made a tool which scan users face. We used CNN with LSTM for having more accurate prediction of biological age of the person. We used MTCNN Architecture and customized image dataset of 10,000 images for more fined grained prediction of the person which returns age, gender and race. Iterative training process for refining the model. Extracting the features from the image which will specifically target age, gender, race prediction. If User's age is below 18 years it will not allow user to login into any social sites. It will redirect to Home page. If User's age is above 18 years it will allow user to access all social sites.

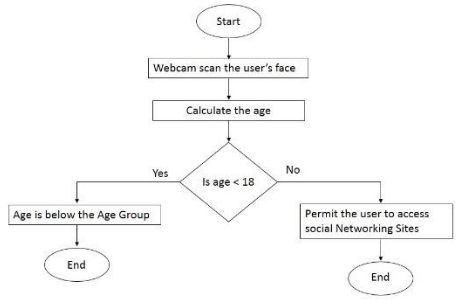

Figure 1. Flow chart of proposed method

The input images are first resized to a fixed-size of 198 x 198 before entering the network. Basic layers conv run with different activation functions used for different models. For Age – we used "Linear", For Gender we used "Sigmoid" and For Race we used "softmax". There were some max pulling and drop out due to variety of data and adding more hidden layer to the network.

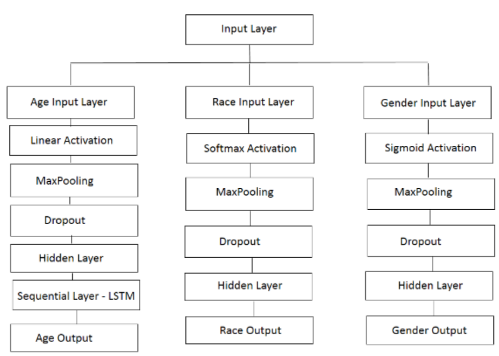

Figure 2. Pictorial representation of process.

V. Experiment and Analysis

We tried to train on bare minimum architecture and results without using pre-trained models. We analyze the effects of different training strategies, network structures and network depths to develop the best strategies, and then achieve the new state-of-the-art performance on different age datasets.

VI. Future Work

We have made web based tool to recognize the age of person and give access to social sites according to the age criteria. In future, Android mobile company can add this feature to restrict the user to access the social sites as per the criteria.

VII. Conclusion

This paper proposes CNN and LSTM multi model architecture for the task of facial biological age, gender and race. After recognizing the face it will classify as per the age group. If certain age group has permission then that person will get access.

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