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Facial Age Estimation Models for Deep Learning

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ABSTRACT:

Automated age estimation from face images is the process of assigning either an exact age or a specific age range to a facial image. In this paper a comparative study of the current techniquessuitable for this task is performed, with an emphasis on lightweight models suitable forimplementation. We investigate both the suitable modern deep learning architectures for featureextraction and the variants of framing the problem itself as either classification, regression or soft label classification. The models are evaluated on Audience dataset for age group classification and FG-NET dataset for exact age estimation. To gather in-depth insights into automated age estimation and in contrast to existing studies, we additionally compare the performance of both classification and regression on the same dataset. We propose a novel lossfunction that combines regression and classification approaches and show that it outperforms other considered approaches. At the same time, with a lightweight backbone, such architecture is suitable for implementation.

I. INTRODUCTION

Automated age estimation (AAE) from face images can be defined as the process of assigning either anexact age or a specific age range to a facial image. AAE has a wide scope of applications in human- computer interaction, security systems, biometric systems, advertising industry etc. Therefore, age estimation has become a topic of interest for both industry and academic community. In spite of a largebody of work dealing with facial age estimation, it is still a challenging problem, as the aging process significantly differs from one person to another. This is caused by internal factors such as genes, changesin the shape and the size of the face, but also by external factors like lifestyle and living conditions of an individual. It has been shown that in some cases it is very difficult to accurately infer the age of a person visually even for a human. While automated age estimation methods that approach or even surpass human performance have been The associate editor coordinating the review of this manuscript and approving it for publication was Yongming Li . Proposed, there is still significant room for improvements, especially in unconstrained conditions. Several examples that have proven difficult to correctly classify in this study are shown in Fig. 1, along with the closest model predictions and ground-truth labels. A typical pipeline of a state-of-the-art age estimation system consists of three steps: (i) pre-processing, including face detection and normalization, (ii) feature extraction, and (iii) applying the ageestimation algorithm (Fig. 2). Regarding feature extraction, AAE systems can be divided into two groups: (i) systems that use hand-crafted features and (ii) systems based on deep learning. The systemsthat use hand-crafted features work reasonably well on images taken in constrained conditions (i.e. single face, frontally aligned, simple background etc.) [1], [5]. However, with recent development of in-the-wild datasets, hand-crafted methods have increasingly been surpassed by deep learning models for feature extraction. Deep learning models, especially convolutional neural networks (CNNs), have proven themselves to be more robust to noise, variations in appearance, pose and lighting present in unconstrained datasets [6]. The problem of automated age estimation can be broadly framed either as aclassification problem or as a regression problem [1], [7]. When framing age estimation as a classification problem, the classifier predicts an age group, e.g. ‘‘35 to 39 years old’’. Classification with soft labels is another possibility, in which class assignments are not binary. When framing age estimation as a regression problem, the goal is to predict the exact age as a number.

II. LITERATURE REVIEW

V. Carletti, A. Greco, G. Percannella, and M. Vento Face analysis includes a variety of specific problems as face detection, person identification, gender and ethnicity recognition, just to name the most common ones; in the last two decades, significant research efforts have been devoted to the challenging task of age estimation from faces, as witnessed by the high number of published papers. The explosion of the deep learning paradigm, that is determining a spectacular increasing of the performance, is in the public eye;consequently, the number of approaches based on deep learning is impressively growing and this also happened for age estimation. The exciting results obtained have been recently surveyed on almost all the specific face analysis problems; the only exception stands for age estimation, whose last survey datesback to 2010 and does not include any deep learning based approach to the problem. This paper providesan analysis of the deep methods proposed in the last six years; these are analyzed from different points of view: the network architecture together with the learning procedure, the used datasets, data preprocessing and augmentation, and the exploitation of additional data coming from gender, race and face expression. The review is completed by discussing the results obtained on public datasets, so as theimpact of different aspects on system performance, together with still open issues.

O. Agbo-Ajala and S. Viriri explained that Age estimation using face images is an exciting and challenging task. The traits from the face images are used to determine age, gender, ethnic background, and emotion of people. Among this set of traits, age estimation can be valuable in several potential real-time applications. The traditional hand-crafted methods relied-on for age estimation, cannot correctly estimate the age. The availability ofhuge datasets for training and an increase in computational power has made deep learning with convolutional neural network a better method for age estimation; convolutional neural network will learn discriminative feature descriptors directly from image pixels. Several convolutional neural net work approaches have been proposed by many of the researchers, and these have made a significant impact on the results and performances of age estimation systems. In this paper, we present a thoroughstudy of the state-of-the-art deep learning techniques which estimate age from human faces. We discussthe popular convolutional neural network architectures used for age estimation, present a critical analysisof the performance of some deep learning models on popular facial aging datasets, and study the standardevaluation metrics used for performance evaluations. Finally, we try to analyze the main aspects that can increase the performance of the age estimation system in future.

A. S. Al-Shannaq and L. A. Elrefaei discussed that Recently, a vast attention has grown in the field of computer vision and especially in facerecognition, detection and facial landmarks localization. Many significant features can be directly derived from human face such as age, gender and race. Estimating the age can be defined as the automatic process of classifying the facial image into the exact age or to a specific age range. Practically,age estimation from face is still a challenging problem due to the affecting from many internal factors such as gender and race and external factors such as environments and lifestyle. Huge efforts have beenaddressed to reach an accepted and satisfied accuracy of age estimation task. In this review paper we aretrying to: analyze the main aspects that can increase the performance of the age estimation system, present the hand-crafted based models and deep learning-based models and show how the evaluations are being conducted, discuss the proposed algorithms and models in age estimation, show the main limitations and challenges facing the age estimation process. Also, different aging databases that containage annotations are discussed. At the end, few guidelines and the future prospective related to age estimation are investigated.

K. ELKarazle, V. Raman, and P. Then Automatic age estimation from facial images is an exciting machine learning topic that hasattracted researchers' attention over the past several years. Numerous human–computer interaction applications, such as targeted marketing, content access control, or soft-biometrics systems, employage estimation models to carry out secondary tasks such as user filtering or identification. Despitethe vast array of applications that could benefit from automatic age estimation, building an automaticage estimation system comes with issues such as data disparity, the unique ageing pattern of eachindividualand facial photo quality. This paper provides a survey on the standard methods ofbuilding automatic ageestimation models, the benchmark datasets for building these models, andsome of the latest proposed pieces of literature that introduce new age estimation methods. Finally, we present and discuss the standard evaluation metrics used to assess age estimation models. In addition to the survey, we discuss the identified gaps in the reviewed literature and present recommendations for future research.

Parneet Recently, the estimation of facial age has attracted much attention. This letter extends andimproves a recently developed method (Guehairiaetal., 2020) for fusing multiple deep facial features forage estimation. This method was based on deep random forests. We propose a new pipeline that integrates tensor-based subspace learning before applying DRFs. Deep face features of a training set arerepresented as a 3D tensor. Multi-linear Whitened Principal Component (MWPCA) and Tensor Exponential Discriminant (TEDA) are used to extract the most discriminative information. The tensor subspace features are then fed into DRFs to predict age. Experiments conducted on five public face databases show that our method can compete with many state-of-the-art methods.

III. METHODOLOGY

The scope involves leveraging deep learning techniques to develop robust and accurate facial age estimation models capable of predicting ages from facial images, accounting for diverse factors and ensuring practical deployment in various domains where age estimation is crucial.

Facial age estimation models in deep learning pursue several objectives to create accurate and reliable systems for predicting ages from facial images. These models aim to accurately gauge age, consideringfacial features indicative of aging, such as wrinkles and texture, while ensuring robustness across variousdemographics, including different ethnicities and genders. A key goal is to develop models that generalize well, effectively estimating ages for new faces not seen during training. Addressing challenges like variations in lighting, expressions, and accessories is vital to ensure the models'reliability in real-world scenarios.

EXISTING SYSTEM:

We perform a comparative study of the current techniques suitable for the automated age estimation task, with an emphasis on running age estimation on embedded devices. Moreover, the intended application is adapting multimedia content to the age of a viewer, which does not require high age estimation accuracy. We investigate both the suitable modern deep learning architectures for feature extraction and the variants of framing the problem itself as classification, regression or soft label classification. To gather in-depth insights into automated age estimation and in contrast to existing studies, we additionally compare the performance of both classification and regression on the same dataset.

EXISTINGSYSTEM DISADVANTAGES:

- VGG-16 might struggle with tasks where highlighting specific areas of an image is critical foraccurate analysis
- VGG-16 can be a bit slow because it has many layers and needs a lot of computer power.
- It was taught and might not understand new things as well.

PROPOSED SYSTEM

Deep learning techniques excel in various domains such as image and speech recognition, natural language processing, recommendation systems, and autonomous vehicles, among others. The success of deep learning stems from its ability to learn intricate patterns and representations directly from raw data, leading to remarkable performance in tasks that involve understanding and interpreting complex information.

PROPOSED SYSTEM ADVANTAGES:

- Deep learning can understand really complicated stuff in data, like recognizing objects images or understanding speech, better than other methods.
- It works well with lots and lots of data
- It learns important things from the data itself.

IV. IMPLEMENTATION

Dataset Preparation

Start by selecting a suitable dataset and performing necessary preprocessing steps.

Datasets:

IMDB-WIKI: Contains images with corresponding age labels.

MORPH: Contains images annotated with age.

FG-NET: Smaller but with well-annotated age labels.

Preprocessing:

Face Detection: Use a pre-trained face detector (e.g., MTCNN, OpenCV Haar Cascades) to detect and crop faces from images.

Facial Alignment: Align faces to a canonical view using facial landmarks (e.g., Dlib or MTCNN).

Data Augmentation: Apply augmentations like random cropping, rotation, scaling, and color jittering to make the model robust.

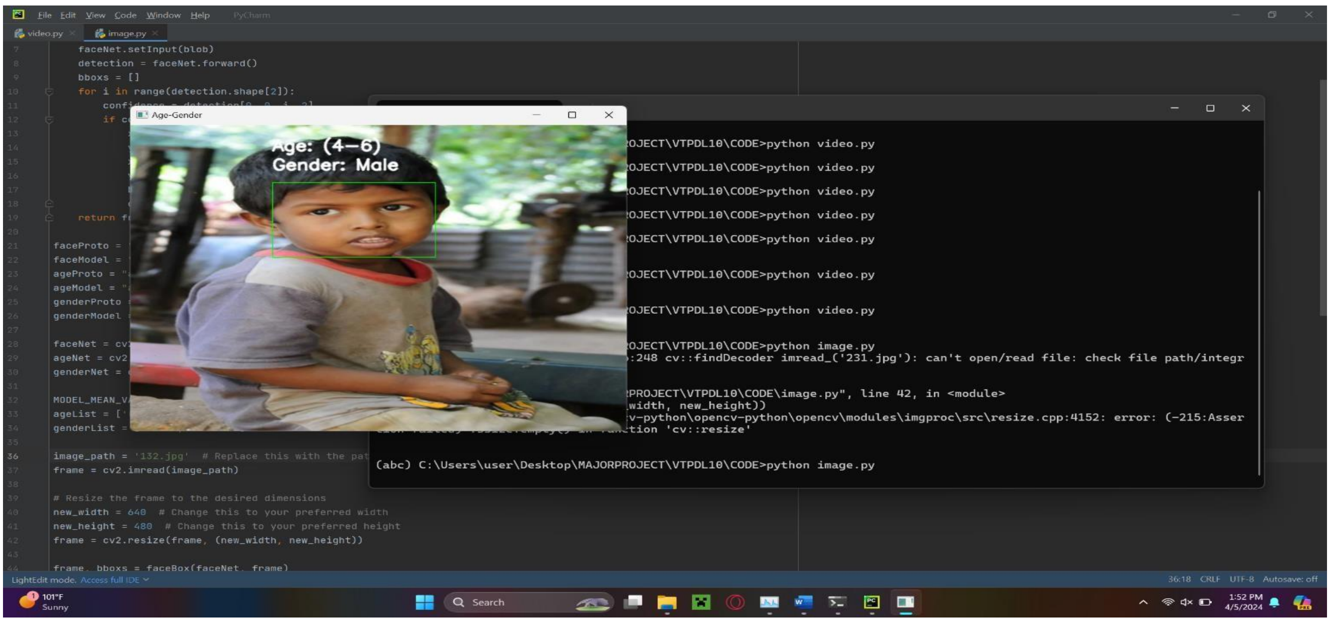
Model Selection

Choose a suitable model architecture. Popular choices include VGG, ResNet, and EfficientNet. For this example, we'll use ResNet-50 with transfer learning.

V. EXPERIMENTAL RESULTS

This project is implements like application using python and the Server process is maintained usingthe SOCKET & SERVERSOCKET and the Design part is played by Cascading Style Sheet.

SNAPSHOTS



VI. CONCLUSION

We considered several approaches to age estimation problem. All evaluated architectures used standard convolutional backbones for feature extraction, while the output head was configured according to the defined task. In all experiments we pretrained the backbone on a large face image dataset. The first approach was based on classification into predefined age groups and it was evaluated on Adience dataset. The experiment showed that models using backbones of very different capacity obtained similarresults, thereby supporting the application of a lighter model appropriate for embedded implementation.The hybrid approach performed the best, obtaining the state-of-the-art result on FG-NET dataset. A finalexperiment was designed to compare different approaches on a common task and dataset. To that end we adapted the exact age dataset FG-NET for age group estimation task.

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