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Subject Review: Automatic Age Estimation System for Face Images

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ABSTRACT

Over the past few years, academics' interest was drawn to fascinating machine learning (ML) problem of the automatic age estimate from facial images. Models of age estimation are utilized in numerous human-computer interaction (HCI) applications, like content access control, targeted marketing, or soft-biometrics systems, to perform auxiliary functions such as the user filtering or identification. In the presented study, we provide a comprehensive review of recent studies on age estimation for face Images and aging. The preprocessing stage, the feature extraction (FE) stage, the techniques of classification stage, and the accuracy of research's findings were all compared.

Key Words: Classification, CNN Deep Learning, Face Images, Feature extraction (FE), Human-computer interaction (HCI).

1. INTRODUCTION

The past few years have seen a substantial increase in the amount of journal and conference papers published along with PhD and Masters theses defended in age estimation research. Age estimate is a method for automatically assigning a specific age or age range to a human face. This age may be estimated, perceived, actual, or appearance age. The amount of years one has lived since their birth, expressed as a numerical number, is their actual age. While estimated age is a subject's age as determined by a machine from facial visual appearance, appearance and perceived age are approximated depending on visual age information shown on the face. Even though there are variances because aging is stochastic among people, it is assumed that appearance age corresponds to actual age. Visual artifacts of appearance age are used to determine perceived age and estimated age. Age and age-group estimation have been the subject of comparatively few publications [1]. Age estimation and face detection are the two components of an automatic face image age estimation system. Locating faces in an image is the aim of face detection [2]. Facial age estimate is the process of teaching a model to provide a value that corresponds to an individual's age. This value might either be an age range (classification problem) or a precise age value (regression problem) [3]. Estimating human age from face images remains a difficult topic, despite the fact that automatic face detection of an image is a sophisticated method with many practical applications. The aging process is almost personal since it is portrayed differently not only between races, but even within the races. Additionally, outside variables including one's health, way of life, location, and weather conditions affect this process. As a result, the question of "how to find a robust representation featuring" is still up for debate [2]. The remaining portion of this study is structured as follows: Part 2 of this article will explore some of the Automatic Age Estimation System for Face Images proposals made during the past ten years. The comparison of the techniques presented in part 2 is done in part 3. In part four, conclusions are offered.

2. LITERATURE REVIEW

Ming-Feng Han, Jian-Hao Lai, Dong-Lin Li, Chin-Teng Lin, Jyh-Yeong Chang. [2] In this research, we provide an innovative and trustworthy framework for computer vision-based automatic age estimation. It uses orthogonal locality-preserving projections and Gabor wavelets to combine global face features. The suggested technique could also automatically extract real-time face aging features. This indicates that, in comparison to existing semiautomatic systems, the suggested system has greater application potential. Operators in age estimation may be able to design practical applications with the help of the results acquired from this unique approach. Anton Lebedev, Olga Stepanova, Vladimir Khryashchev, and others [4] We suggest a novel approach that consists of two stages: support vector machine (SVM) classification and adaptive feature extraction depending upon local binary patterns. We provide experimental findings from the MORPH, FG-NET, and our own data-base. Crowdsourcing is used to study how well people can estimate their age, allowing for a comparison of their abilities with those of machines.

Anil K. Jain, Charles Otto, and Hu Han, [5] offer a hierarchical method for calculating age automatically and analyze how aging affects various face features. According to experimental findings using the MORPH Album2, FG-NET, and PCSO data-bases, the eyes and nose provide more information on facial age assessment compared to other facial features. We also investigate the accuracy of human age estimations with the use of data gathered through crowdsourcing, and we demonstrate that our method's cumulative score (CS) within a 5-year mean absolute error (MAE) is superior to the human age estimation. Debaleena Datta, Rituparna Saha, and Ranjan Jana [6] presents a way for determining a person's real age by examining the wrinkled region of facial images. From a face image, wrinkle geographic areas are identified, and wrinkle features are retrieved. Each facial image is clustered with the use of fuzzy c-means clustering algorithm based on wrinkle features. Utilizing their clustering membership value and the average age of each cluster, estimated age is then determined. The outcomes are noteworthy and substantial. Shekhar Raheja, Didier Stricker, and Mohamed Selim [7] reviews research on frontal facial images-based real-time human age-group estimate. Our method is based on identifying telltale signs of aging, like the texture of the skin on the face. Uniform Local Binary Patterns (LBP) are used to characterize this information, and the K-Nearest Neighbor (KNN) classifier is used to estimate it. The FERET dataset is used to train the system in the current study. There are five main age groups represented in the training data. The age of the person is determined using facial images that were recorded in real-time utilizing the Microsoft Kinect RGB data. In the live testing, an accuracy of 81% was attained. Only facial regions impacted by the aging process are employed in the face description in the suggested method. Additionally, using uniform LBP is assessed in facial description and age estimation. The majority of facial texture data is depicted by the uniform LBP, according to the results. The result was a considerable reduction in the length of the feature vector, which sped up the entire process and made it more suitable for real-time applications. Chu-Song Chen, Bo-Yao Lin, Huei-Fang Yang, Kuang-Yu Chang, [8] suggest a general, deep ranking mechanism for AAE in this research. Our network first uses a scattering network (ScatNet) to extract features from a facial image, after that uses principle component analysis (PCA) to minimize the feature dimension, and then uses category-wise rankers to estimate the age. The following features of our method lend it robustness: (1) The scattering features are translation- and small-deformation-invariant; (2) The rank labels encoded in the network take advantage of the ordering relation among labels; and (3) The category-wise rankers carry out age estimation within the same group. On the massive MORPH dataset as well as the expression datasets Lifespan and FACES, our network performs better than other existing solutions.

Furkan G. Urpnar, Albert Ali Salah, Hamdi Dibeklio, Heysem Kaya [9] suggested a 2-level system for the estimation of the apparent age from the facial images. This technique divides samples to overlapping age groups initially. Local regressors are utilized to estimate the apparent age within every group, and outputs are after that combined to get the final estimate. We employ a face detector depending on a deformable parts model and features from a trained deep CNN. For the classification, kernel extreme learning machines have been employed. This system has been tested by using ChaLearn Looking at People 2016 - Apparent Age Estimation challenge data-set, and the sequestered test set results show a typical score of 0.3740. Seyed Muhammad Hossein Mousavi [10], in this study, age estimation is accomplished by summing the entropy edges of depth images and the RGB image edges' gray values. Additionally, a new approach to face extraction and detection from depth images is described. It is based on ellipse fitting, the standard deviation filter, and a few pre- and post-processing methods. This technique's quickness and capacity to handle a single image aspect are advantages. This method does not require the learning or classification procedure. The suggested approach is 10 to 20 times faster but less precise. System is tested against benchmark RGB-D face databases, and results were adequate and encouraging when compared to those of other age estimation techniques. This approach can be used in real-time applications because of its fast speed. It should be noted that this study is the first to estimate age using RGB-D images. We examined the effectiveness of the algorithms of wrinkle detection on the entire face with Remah Mutasim Elbashir and Moi Hoon Yap [11] and offered an enhancement approach to boost the effectiveness. More specifically, they have utilized 25 images from Sudanese data-set and 45 from the Face Recognition Technology dataset (FERET). The researcher personally labeled the chosen images for ground truth annotations. In comparison to state-of-the-art approaches, the trials indicated that the approach with enhancement was more effective at detecting face wrinkles. The average Jaccard similarity indices for the methods of enhancement, including Hybrid Hessian Filter and Gabor Filter, when assessed on FERET, were 56.17%, 31.69%, and 15.87%, respectively.

Dr. K S. Kumar, V. Hemasree [12] age estimation from a human facial image is a highly challenging technique because age is impacted by a variety of elements like gender, living style, workplace, mental state of the individual, and others. The LBP histogram is created to estimate age, and wrinkles are estimated with the use of Gabor filter to produce Gabor feature vectors depending on wrinkle levels. With the suggested Fusion Extreme Learning Classifier, testing and training are conducted. The suggested fusion classifiers integrate Gabor feature vectors and LBP histograms, and they estimate age depending on the

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outcomes of the classification and manual voting. Higher accuracy levels with simple computation are achieved during testing using the FG-Net database. O.A. Mohammed, M.S.H. Al Tamimi, and F.K. Al Jibory [13] the objective of this work was to provide an approach to estimate human ages from the frontal view of the face in a way that is as accurate as feasible and consider the majority of the difficulties encountered by current approaches to age estimation. Utilizing the data set (IMDB-WIKI) that forms the basis for the face estimation system in this area. We were able to accomplish our goal by employing the CNN deep learning approach, which produced results with an accuracy of 0.960 %, as well as preparatory processing tasks to build and train the data for collecting cases.

This study that has been conducted by Dr. K. Jagan Mohan, S. Sivachandiran, and Dr. G. Mohammed Nazer [14] offers a method for automatically determining gender and age depending on deep convolutional neural networks utilizing facial images. The gender and age of the people represented by the facial images are to be ascertained using the suggested ADCNN-AGC model. Face recognition and age/gender classification are two steps that the ADCNN AGC model takes to achieve this. In order to identify faces in the input images, the MTCNN model is primarily used. Additionally, the One-Dimensional Convolutional Neural Network (1DCNN) is used for classification after the Efficient Net model is used to extract feature vectors correctly. Benchmark datasets have been used to assess the ADCNN-AGC model's performance validation, and results have been seen in many different ways. The experimental results showed that the ADCNN-AGC model outperformed more contemporary state-of-the-art methods. Elijah Olusayo Omidiora, Victor Chukwudi Osamor, and Oluwasegun Oladipo, [15] by combining a genetic algorithm with a back propagation (BP)-trained ANN and employing the local binary pattern feature extraction technique (LBGANN) with a focus on black faces, this study created a novel age estimate system. The system was trained using a face database that contained a large percentage of black faces, and the outcome was compared to that of a typical ANN system (LBANN). The outcomes demonstrated that, in terms of the proper classification rate, the developed system LBGANN outperformed LBANN. Qaswaa Khaled Abood, Farah khiled AL-Jibory, [16] it takes a comprehensive study procedure to determine a person's gender and age. Since DL has become so popular, the study of face systems has undergone a radical transformation. Today, estimation accuracy is a critical metric for assessing algorithms and their ability to accurately predict absolute ages. The approach was evaluated using the UTKFace dataset, which forms the basis of the face estimation system. The basis for this function is provided by the forehead, nose, lips, cheeks, and eyes. Over the course of its system results, AlexNet maintains an accuracy record of 98%.

3. ANALYSIS OF COMPARED SCHEMES

In table1 depicts comparative explanation between previously mentioned systems.

Table1.1: Comparative explanation of various schemes of cancer disease

Ref.	preprocessing	Extraction of the Features	Classification Methods	Accurateness and efficiency	Year
[2]	the image is scaled to 64 by 64 pixels and a face detector created with the use of the AdaBoost method is then applied.	Gabor wavelets transform and orthogonal locality preserving projections	SVM	Operators age estimation can now design practical applications with the help of the results.	2012
[4]	color space transformation, scaling and histogram equalization procedure.	local binary patterns	SVM	Human perception ability in the estimation of age has been examined with the use of crowd sourcing that allows the comparison of the abilities of the humans and machines	2012
[5]	Nonreflective similarity transformation is used to convert all color face images to grayscale and normalize every face image based on two eyes, then resized and interpupillary distanced to match.	BIF features from individual facial components.	hierarchical age estimation	our method's cumulative score (CS) within a 5-year MAE outperforms human-provided age estimates.	2013
[6]	The face image is cropped into a rectangle shape, and many facial features, including the	Extraction of local and global features is made from face images.	Using feature 7(wrinkle features),faces are classified with the use	The obtained results are Remarkable and significant.	2014

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	eye pair, mouth, nose, and chin, are recognized. Forehead and wrinkle area on the face image are detected depending on the face's geometric structure.	Edge detection is widely used	of fuzzy C-Means clustering algorithm for getting membership value for every cluster.		
[7]	Haar-cascades are used to find the face, and the distance between the eyes is used to crop the face, after that smoothed with a little Gaussian blur before being resized to a previously determined size of 150x150.	the local binary pattern operator is applied to selected facial regions.	K-NN Classifier	In the live testing, an accuracy of 81% was attained.	2015
[8]	------	a wavelet scattering network (ScatNet) that extracts face representations and dimensionality reduction component by PCA	FCLs	On the massive MORPH dataset as well as the expression datasets Lifespan and FACES, our network performs better.	2015
[9]	DPM based face detector	deep network pretrained	Kernel ELM	our system uses a fairly coarse alignment mechanism, but we think that using a landmark detection system to get a finer alignment can increase the estimation accuracy even further.	2016
[10]	Viola and Jones algorithm	standard deviation filter and ellipse fitting	-------	The suggested approach is between 10 to 20 times faster, yet with low accuracy	2018
[11]	DL method for detecting the face, a face template or mask has been utilized with 10 pre-defined wrinkle areas with fixed coordinates for the mouth and eyes	Jerman et al.'s method, It utilized 2^{nd} -order intensity derivative or Hessian for all of the image points, besides Gaussian scale-space of an image.	-------	The average Jaccard similarity indices for the enhancement methods—Hybrid Hessian Filter and Gabor Filter—were 56.17%, 31.69%, and 15.87%, respectively, when assessed on FERET.	2020
[12]	-------------	For the estimation of age, LBP (Local Binary Pattern) histogram is generated and the wrinkle estimation is carried out with the use of Gabor filter resulting with Gabor feature vectors based on the levels of the wrinkles.	Fusion Extreme Learning Machine Classifier	Higher accuracy levels with simple computation are achieved during testing using the FG-Net database.	2021
[13]	Resizing image	Region of Interest (ROI)	CNN deep learning method	Results produced by CNN deep learning have an accuracy of 0.960%.	2022
[14]	Face Detection with the use of MTCNN Model	Efficient Net model has been applied for properly extracting feature vectors	1D-CNN for classifying gender and age	The experimental results showed that the ADCNN-AGC model outperformed more contemporary state-of-	2022

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				the-art methods.	
[15]	grayscale format, viola jones algorithm, Histogram equalization	local binary pattern feature extraction technique (LBGANN)	combination of a GA and a BP-trained ANN	According to the findings, the created LBGANN outperforms LBANN in terms of the rate of correct classifications.	2022
[16]	--------	Region of Interest (ROI) and Image resizing	CNN (AlexNet) model for determining the gender and age of an individual depending on a face image.	Over the course of its system results, AlexNet maintains an accuracy record of 98%.	2023

4. CONCLUSION

In order to establish the primary characteristics of Age Estimation System performance and to achieve results, this study presents a survey of several approaches utilized for Automatic Age Estimation System for Face Images for the period (2012–2023). On the basis of preprocessing, FE, classification approaches, and the accuracy of research's findings, comparisons were made. Facial age estimation is a popular topic of study, but it can be a challenging undertaking for a number of reasons, like a lack of training data or a model which can account for all the diverse ageing patterns.

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