Do Alzheimer's Patients Appear Younger than Their Age? A Study with Automatic Facial Age Estimation

Abdullah Emir Zeylan
Student Member of IEEE
Utrecht University
Utrecht, The Netherlands
a.e.zeylan@students.uu.nl

Albert Ali Salah
Senior Member of IEEE
Utrecht University
Utrecht, The Netherlands
a.a.salah@uu.nl

Hamdi Dibeklioğlu
Member of IEEE
Bilkent University
Ankara, Turkey
dibekliogl u@cs.bilkent.edu.tr

Zeynep Tüfekçioğlu
Department of Neurology
Istanbul Faculty of Medicine
Istanbul University
Istanbul, Turkey

Başar Bilgiç
Department of Neurology
Istanbul Faculty of Medicine
Istanbul University
Istanbul, Turkey

Murat Emre
Department of Neurology
Istanbul Faculty of Medicine
Istanbul University
Istanbul, Turkey

***Abstract*—Facial age estimation from images is a challenging task, especially if the subjects are older, since idiosyncratic variations increase with age, and lifestyle factors have an impact on the appearance. In this paper, we test the hypothesis that the Alzheimer's patients appear younger than their real age. To do this objectively, and to be able to analyze the factors in case the hypothesis holds true, we use automatic age estimation methods for this task. We first propose training and normalization regimes to improve deep learning based facial age estimation. We fine-tune a pre-trained ImageNet model using first the APPA-REAL database and then the UTKFACE database. The experimental results show that the proposed approach predicts older faces more accurately compared to other studies, and improves the mean absolute error for the FG-NET database to 8.14 for the age group 60-69. We then run our approach on a special database collected from Alzheimer's patients and healthy controls, to test our main hypothesis. The database we collected for this purpose contains video recordings of 96 subjects with an age range between 64 and 87. Our findings show that automatic age estimation indeed underestimates the age of AD patients significantly more than the healthy subjects.**

***Index Terms*—Age estimation, age grouping, Face Super-Resolution, deep learning, CNN, Alzheimer's Disease.**

I. Introduction

Predicting the age of another person comes naturally to people. However, we are not always correct in our estimates. Age estimations are frequently measured with the mean absolute error (MAE) measure, and a recent study found that humans can estimate a person's age with a MAE of 7.2–7.4 years [20].

Actually, why do we choose a specific age? On which factors do we base our predictions? Wrinkles and white hair are obvious influences on the estimated age, but do glasses, beard, hair color, and facial expressions also have systematic influences? Age estimation is a difficult task for computers. In recent years, many computer vision approaches have been proposed on age estimation for different kinds of applications, such as forensics [1]. However, age estimation is an ill-posed problem, since during the aging of a human face, the facial appearance changes due to living conditions and medical status, plastic surgery, scars, and make-up [39].

Automatic facial age estimation from single images requires extracting a large amount of information, and good features from the facial image. Most approaches use static appearance features, derived from shape and texture. Only recently, dynamic features were also introduced, and it was argued that age changes the muscle tone in the face, and facial dynamics can provide additional cues about the real age of a person [9]. Fusing facial dynamics with static appearance features improved the age estimation significantly. It was shown that facial dynamics are affected by morphological changes such as muscle loss, fat tissue, and cartilage growth.

In this work, our hypothesis is that patients with Alzheimer's Disease (AD) appear younger than their age. This is a particularly challenging scenario for age estimation for several reasons. Most AD patients are older than a certain age, and because of the increased variance in living conditions, it is much more difficult to estimate the age of older people. In fact, all automatic age estimation approaches, as well as humans make more mistakes with elderly subjects on this task. A second problem is that there are no dedicated facial image and motion datasets for studying AD patients. Most research that links AD to face analysis focuses on impairments in face recognition in AD patients [22]. Our research questions requires us to study the patients' faces instead.

Patients with AD cannot express emotions well like healthy persons [3]. They struggle with expressing their emotions due to impairments of nerves. The patients will lose their their cognitive capacity and even their verbal communication ability. To the best of our knowledge, facial age for patients with AD have not been researched from an age estimation point of view.

In this paper we analyze the apparent age of AD patients and healthy subjects. Our aim is to investigate the possibility that patients with AD seem younger than healthy subjects. This hypothesis is born out of many years of our clinical interaction with AD patients. If true, this could be a possible cue for early detection of AD, or a good reason to deepen the investigation to see which factors are behind it.

To investigate the hypothesis, we use state-of-the-art facial age estimation techniques. This removes potential biases in human assessors, but of course, adds some other biases due to usage of algorithms. Our first contribution is to propose training and normalization regimes to improve deep learning based facial age estimation. Our second contribution is a database collected from elderly subjects, including both AD patients and healthy controls. Our results on this database indeed shows that our automatic algorithm significantly underestimates AD patients' ages, thus, they appear younger (than their healthy counterparts) to the algorithm.

The next section introduces the literature in age estimation. In Section III the proposed method of the age estimation is described. This approach includes face alignment, age estimation using convolutional neural network (CNN) and a curve-fitting based estimation of age from a range of predictions, obtained from the outer classification layer of the CNN. Section IV-A describes the databases used in this study, and their training settings. Section V reports comparative age estimation results between AD patients and healthy subjects. Sections VI and VII provide a discussion of our findings and some conclusions, respectively.

II. Related work

Automatic age estimation from facial images has been studied for around 20 years. The traditional problems plaguing face analysis, namely illumination, pose, resolution, and facial expression variations, also made apparent age analysis difficult. Subsequently, the results of automatic computer estimation are not great compared to humans, unless the imaging conditions are good, in which case computer algorithms trained with large sets are typically better than humans [20].

To create biologically inspired models, several papers discussed the aging process of a human face [2], [14], [35]. These papers investigated how humans perceive aging and how aging impacts the facial age estimation performance.

Facial age estimation starts with a detection algorithm to find faces in an image, followed by facial registration to make most of local feature information. A recent face detection framework was proposed by Zhang et al. [44]. A multi-task cascaded convolutional neural network (CNN) is developed for joint face detection and alignment. This approach outperformed several recent alternatives. Face detection was tackled in different stages: a fast proposal network that generates candidate bounding boxes, a refinement network, and an output network. The framework was evaluated on three different datasets (easy, medium and hard, respectively). Qin et al. used a similar joint training cascaded CNN for face detection [34]. This method achieved better accuracy compared to the proposed approach of Zhang et al. [44]. Recently, Yang et al. proposed a new face detection model through the Deep Facial Part Responses framework [43]. Generic object proposal approaches are used to detect faces with the model. Those approaches are often used to provide high-quality and category-independent bounding boxes. Ranjan et al. proposed a deep learning classification algorithm for face detection, facial landmark localization, as well as age estimation [36]. They used two different classification architectures using the AlexNet model and HyperFace-ResNet. Landmark localization is based on a 21 point markup and only bounding box regions with Intersection over Union (IOU) is considered where the overlap is greater than 0.35 with the ground truth for learning the task. Two landmark localization have been proposed for obtaining better performance: Iterative Region Proposals and Landmarks-based Non-Maximum Suppression. Wu et al. tweaked an existing vanilla convolutional neural network with fine-tuning and alignment-sensitive data augmentation to obtain more accurate landmark detection from images [42].

Most of the age estimation methods contain two steps after face detection, namely feature extraction and classification. Image-based age estimation approaches view the face image as a texture pattern. Several papers compared various feature extraction techniques [2], [7], [30], [38]. Features like local binary patterns (LBP) [17], local ternary patterns (LTP) [40], local phase quantization (LPQ) [31], and bio-inspired features (BIF) [19] are used for age estimation. Mandal et al. use optics based features, which can perform similar to face component based features [29]. Pontes et al. proposed a flexible hierarchical approach for facial age estimation based on multiple features, including both global and local features [32].

Because of great morphological differences between very young, adult, and very old subjects, age estimation is often tackled as a two-level estimation problem [8], [9]. In the first level, an age group is estimated for the subject. This can be treated as a discrete classification problem. In the second level, which is typically posed as a regression problem, the precise age is estimated within the age group. It is possible to permit overlaps between groups to deal with errors in the first estimation stage, and to eliminate boundary effects. In terms of classifiers, deep learning methods are recently new; in the past, many approaches were used, including Support Vector Machines [19], Nearest Neighbor classifiers [27], Multi Layer Perceptrons [26], and Support Vector Regression [18].

III. Proposed Method

Our proposed method will be used for estimating the age of both AD patients and healthy subjects. The main objective is to implement a CNN for age estimation to examine the performance of estimation on databases with faces above 50+

age. Naturally, the training is not restricted to elderly faces, but we are more interested in the performance on faces over 50.

We base our approach on the implementation of Deep EXpectation (DEX) of apparent age [37]. The proposed approach predicts the apparent age by first detecting the face on the image and then by applying a deep convolutional neural network with VGG-16 structure for the prediction. Instead of using VGG-16 architecture, we use a ResNet-50 architecture and fine-tune the pre-trained ImageNet model. In our approach, we treat age estimation as a classification problem, where we have 101 classes for ages from 0 to 100. While a regression approach is better for continuous age estimation, we will use a post-processing stage to accumulate results from the 100-dimensional classification output, and there perform the switch from discrete to continuous by using a softmax classifier. Each softmax output will be multiplied with their age class and then summed for the prediction. This will give us a number of predictions for each subject's age, given a neutral image selected automatically from the video as input. Then we fit a curve to the age distribution to obtain a single prediction as the maximum of the curve.

This section will discuss the implementation of the age estimation model. First, we will describe the pre-processing steps: face detection and alignment. Then age estimation with the CNN will be discussed.

A. Preprocessing

The images we used have different imaging conditions (e.g. pose, illumination and size). We apply face detection, alignment and cropping to obtain the face area, and discard the background. We use the Viola-Jones approach to detect faces from the images [41]. Since our database is frontal and clearly illuminated, a more elaborate detection approach is not needed. After detecting the face, a rectangular are is cropped from the image.

For face alignment, we used a facial landmark approach to align the face [24]. An annotated training set of images are used for training an ensemble of regression trees in this approach. As a result, the locations of 68 facial landmark are estimated from their pixel intensities. The dlib library[1] has a pre-trained facial landmark detector to detect these 68 landmark locations. Given the facial landmarks, the faces can be aligned such that the faces are rotated where the eyes lie horizontally at the same y-axis. As the images are aligned, the faces are cropped to a size of 224×224 pixels. A few images were missed by the face detectors due the image quality. As those images could decrease the performance for age estimation on elderly, we have removed them from the training set.

B. Convolutional Neural Networks

The apparent age is estimated with a convolutional neural network. We use the ResNet-50 architecture, which is a 50 layer Residual Network and includes a pre-trained ImageNet model [21]. In our proposed method, we fine-tune the pre-trained ImageNet model first with the APPA-REAL database [11], and then with the UTKFace database [45]. The implemented network uses input images with 224×224 pixels.

During fine-tuning, the layers of the pre-trained model are frozen and the last fully connected layer is removed from the model. Instead, several new layers are added to create a new classification or regression model. The features of the pre-trained model are thus transferred to the new model. The pre-trained ImageNet model contains an output layer of 1000 classes. We remove this output layer and replace it with 100 classes, to represent the age range from 0-100, and retrain with facial age data. We compute the softmax expected value on the output probabilities of those classes [37].

For testing, we automatically select a neutral frame from the video of the subject. The frames were extracted with an open source facial behavior analysis toolkit, namely OpenFace. This toolkit detects the locations of lip corners. The lip corners are used for calculating the temporal phases of facial expressions [9]. The Onset is the initial phase of facial expression, and it defines the duration from neutral to expressive state. The apex phase is the phase between the onset and the offset, which is a stable peak period of the facial expression. Likewise, the offset is the final phase from expressive to neutral state [23]. We automatically selected one neutral from the the onset phase.

A single image will produce a 100-dimensional classification output. These predictions can be combined with a simple averaging, or the strongest activation can be selected, but this assumes a Gaussian distribution, which is not always the case. We have observed many cases where the distribution of the outputs is skewed, or has a heavy tail. Subsequently, we use curve-fitting to model the distribution, and select the maximum of the curve as the prediction. This approach improves on selecting the average.

C. Evaluation

The common performance measures for age estimation are the Mean Absolute Error (MAE). The MAE is the average of absolute error between the real age and the estimated age.

$$MAE = \frac{1}{n} \sum_{n=1}^{n} \|x_i - x\|$$

IV. Experimental Settings

In this section we present the experimental settings of our study. More specifically, employed databases and technical settings will be described.

A. Databases

The **APPA-REAL** database, provided by ChaLearn LAP, consists of 7,591 images that are identified with real and apparent age labels [11]. The images are divided into 166 train, 66 validation and 178 test images for 60+ ages. The database includes cropped and rotated face images with a 40% margin obtained from the face detection. This database also includes

[1] http://dlib.net/

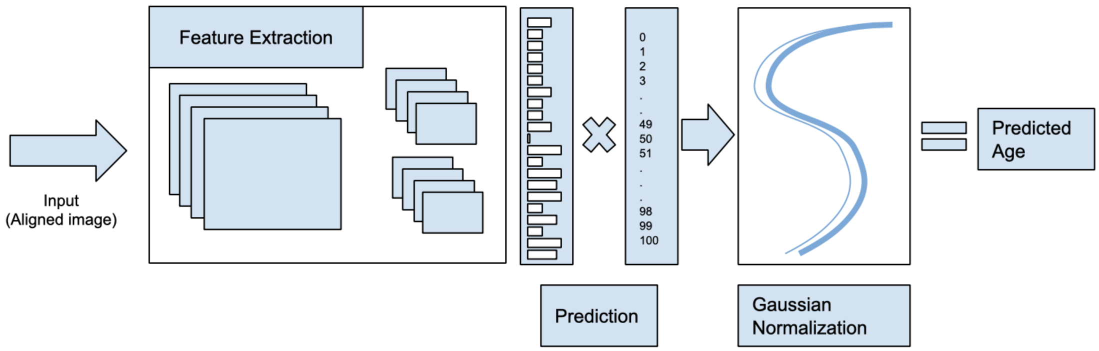

Fig. 1. Architecture of the proposed age estimation model.

some non-face and inappropriately cropped images that need to be cleaned. In our experiments, it is used for fine-tuning the ImageNet model.

The **UTKFace** database contains facial images of people with an age range of 0-116 years [45]. It has more than 20.000 images with annotations of age, gender, and ethnicity. It also provides aligned and cropped faces. This database contains 2,749 images for ages above 60+. The database is used for fine-tuning the APPA-REAL CNN model in the experiments.

The **FG-NET** database contains 1,002 images from age range 0-69 [13]. Since, this database is small, we only use it for evaluating the age group 60-69 for estimating older ages.

The **CAPA Alzheimer's Disease** database is collected at Istanbul University, Istanbul Faculty of Medicine in Istanbul, Turkey, for this study. It includes 94 videos from AD patients and healthy subjects. Each video has a different length and contains variations due to pose, illumination, and scale. The database is composed of RGB videos and is recorded in 1920×1080 pixels at a rate of 25 bits per second. The videos are from mini-mental state examinations conducted with different subjects by experts, and ethical approvals are obtained from Istanbul University. The CAPA Alzheimer's Disease database is used for testing our main hypothesis.

B. Settings

The training of the ResNet-50 is implemented using the Keras framework with Tensorflow backend [16]. The model is trained with the ADAM optimizer with a learning rate $\alpha = 0.001$ and a batch size of 64 [25]. The model is fine-tuned on the APPA-REAL dataset for 100 epochs. The UTKFace fine-tuned model is trained for a further 35 epochs, shorter as we applied the early stopping callback [33]. An L2 regularization with $\lambda = 0.0005$ weight on the loss function is applied for the UTKFace fine-tuned model. We also applied a dropout (0.3) for both models. We fine-tuned both models with two losses: the cross-entropy loss and the Euclidean loss. Freezing the weights of a pre-trained model prevents the update of a specific weight during back propagation. We freezed the first 26 layers. The datasets are each split into two folds, as 90% training set and 10% validation set, respectively. As we want to predict the age of Alzheimer's and healthy subjects, we have tested the model on the CAPA Alzheimer's Disease dataset, which was not used during training and parameter selection.

V. Experiments

This section presents the results of facial age estimation. Firstly, we compare our results with other age estimation studies that used the FG-NET Database. Then we describe the apparent age estimation errors between the Alzheimer's Disease patients and healthy subjects.

A. FG-NET

The aim of the proposed method is to improve the age estimation performance for elderly. Most classification methods in the literature use the FG-NET database for classifying age into age groups. To illustrate the performance of our approach in a comparable way, we report here results with FG-NET as well. In Table I, we compare our results with several previous studies that used FG-NET database for classifying age. As shown in the table, we perform better than most of the age estimation methods on ages above 60+. We achieve MAE of 8.14 for ages above 60+, but clearly, FG-NET is not adequate for this task, as there are only 8 samples with ages over 60. The fine-tuning on elderly requires a two-level classification approach, where different classifiers are used for the younger and older subjects. Subsequently, we do not report additional results on the younger subjects.

B. Age estimation results between healthy subjects and AD patients

1) Effect of Alzheimer's Disease: The MAEs and mean errors (ME) for Alzheimer's Disease patients and healthy subjects are given in Table II. The database has 50 AD patients and 44 healthy subjects. As shown in the table, the MAEs of AD patients are higher compared to healthy subjects. Automatic algorithms almost always underestimate the age of elderly subjects, and our approach is no exception to this general trend (as shown by negative ME results). The results show that on the average, AD patients are estimated to be 5.22 years younger than healthy subjects in the same age range. Using t-test, the difference is found to be statistically

TABLE I
COMPARISON OF AGE ESTIMATION METHODS ON THE 60+ SAMPLES OF THE FG-NET DATABASE

Method	# of 60-69 Samples	MAE
IIS-LLD (Single) [15]	8 images	32.13
IIS-LLD (Triangle) [15]	8 images	26.25
Enhanced BIF [12]	8 images	26.25
IIS-LLD (Gaussian) [15]	8 images	24.00
C-lsLPP [5])	8 images	23.37
C-lsMFA [5]	8 images	22.25
PCA + LPP + SS [6]	8 images	17.33
OURS	8 images	8.14
SR-AAM [28]	Not mentioned	5.32
AAM [10]	3 images	4.62
LBP [10]	3 images	**4.53**

significant ($p = 0.0071$). The effect of the gender on the Alzheimer's Disease has been assessed to understand that the AD patients seems younger.

TABLE II
COMPARISON FOR THE AGE ESTIMATION ON THE CAPA ALZHEIMER'S DISEASE DATABASE

Groups	# of samples	MAE	ME
AD Patients	50	10.9	-9.7
Healthy subjects	44	8.16	-4.48

2) Effect of gender: The effect of the gender on the results has been assessed. The MAEs and MEs for male and female subjects are given in Table III. MAEs for female and male estimates differ slightly. The automatic method estimates the age of males younger than that of females both for AD patients (3.23 years younger) and healthy subjects (5.38 years younger). However, these differences are not significant ($p \geq 0.05$). Also notice that the dataset is not large enough to derive any conclusions from these results. It is interesting to note that the difference of average error between healthy and AD male subjects is quite large (3.67). If this is a systematic bias that would manifest itself in larger sample sizes, it may suggest that age indicator is more reliable for diagnostic purposes in males, compared to females.

TABLE III
COMPARISON OF THE GENDERS FOR THE AGE ESTIMATION ON THE CAPA ALZHEIMER'S DISEASE DATABASE

Groups	Gender	# of samples	MAE	ME
AD Patients	Male	27	11.63	-11.19
	Female	23	10.04	-7.96
Healthy subjects	Male	24	7.96	-6.80
	Female	20	8.40	-1.42

VI. Discussion

To understand what the factors may be behind the younger appearance presented by AD patients, we investigate the facial regions and their contributions to the age estimation task. This, of course, is a computer-based analysis, and it may be the case that humans pay attention to different cues, including possibly facial dynamics.

Figure 2 shows a representative face with a heatmap depicting the relative importance of facial areas for our automatic age estimation model. This figure is obtained by systematically blurring patches on the faces and observing the differences in estimated ages, a larger difference indicating a more important area. By investigating such depictions, we see that the age estimation mostly relies on eye corners, top of the mouth, and the cheeks. In this particular instance, and in many others, the vertical wrinkles on the cheeks on either side of the mouth are the most important marks of age, and blurring them decreases the apparent age of the subject.

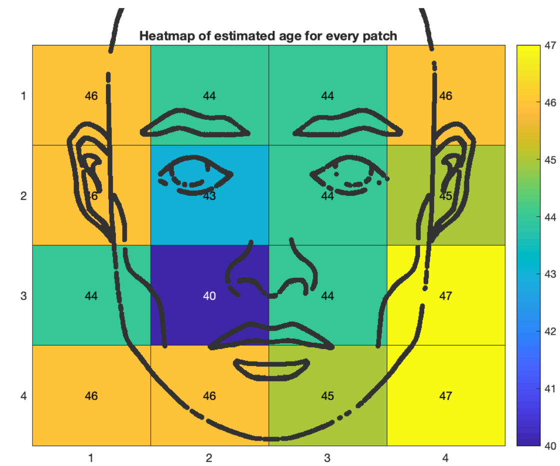

Fig. 2. Important regions of the face for age estimation. To protect confidential information, we cannot show patient images. The grid illustrates (roughly) the effect of blurring each facial area, on a single example. The colors and values indicate the estimated age.

AD initially effects the limbic areas of the brain, highly associated with memory functions and emotions. These areas have connections with the nucleus of facial nerve which innervates facial mimic muscles. Facial mimics related with the expression of emotions are important for healthy people to estimate the age of the others. AD patients were found to have altered facial mimic activity during emotional states [4]. This may be the reason of relatively younger appearance of the AD patients. We note that our subjects are early stage patients with no depression.

VII. Conclusions

The experiment with estimating age of AD patients and healthy subjects show that the proposed age estimation approach indeed estimates AD patients to be younger than their real age, and in particular, this effect is stronger in male subjects. This finding is a small step towards supporting our hypothesis, and encourages us to investigate this issue further.

Our age estimation pipeline uses a standard CNN architecture, but seeks to improve performance on elderly subjects by fine-tuning the network with two databases. One of our contributions is a new video database, called CAPA Alzheimer's Disease Database, with 94 subjects. We will extend our investigation with this resource by contrasting facial dynamics between AD and healthy subjects.

References

[1] A Midori Albert, Karl Ricanek Jr, and Eric Patterson. A review of the literature on the aging adult skull and face: Implications for forensic science research and applications. *Forensic science international*, 172(1):1–9, 2007.

[2] Raphael Angulu, Jules R Tapamo, and Aderemi O Adewumi. Age estimation via face images: a survey. *EURASIP Journal on Image and Video Processing*, 2018(1):42, 2018.

[3] Benoit Bediou, Ilham Ryff, Bernadette Mercier, Maud Milliery, Marie-Anne Henaff, Thierry D'Amato, Marc Bonnefoy, Alain Vighetto, and Pierre Krolak-Salmon. Impaired social cognition in mild alzheimer disease. *Journal of geriatric psychiatry and neurology*, 22(2):130–140, 2009.

[4] Keith W Burton and Alfred W Kaszniak. Emotional experience and facial expression in alzheimer's disease. *Aging, Neuropsychology, and Cognition*, 13(3-4):636–651, 2006.

[5] Wei-Lun Chao, Jun-Zuo Liu, and Jian-Jiun Ding. Facial age estimation based on label-sensitive learning and age-oriented regression. *Pattern Recognition*, 46(3):628–641, 2013.

[6] Cuixian Chen, Yaw Chang, Karl Ricanek, and Yishi Wang. Face age estimation using model selection. In *Proc. IEEE CVPR Workshops*, pages 93–99. IEEE, 2010.

[7] Twisha Dhimar and Kinjal Mistree. Feature extraction for facial age estimation: A survey. In *Wireless Communications, Signal Processing and Networking (WiSPNET), International Conference on*, pages 2243–2248. IEEE, 2016.

[8] Hamdi Dibeklioğlu, Fares Alnajar, Albert Ali Salah, and Theo Gevers. Combining facial dynamics with appearance for age estimation. *IEEE Transactions on Image Processing*, 24(6):1928–1943, 2015.

[9] Hamdi Dibeklioğlu, Theo Gevers, Albert Ali Salah, and Roberto Valenti. A smile can reveal your age: Enabling facial dynamics in age estimation. In *Proc. 20th ACM Int. Conf. on Multimedia*, pages 209–218. ACM, 2012.

[10] Chi Nhan Duong, Kha Gia Quach, Khoa Luu, Hoai Bac Le, and K Ricanek. Fine tuning age estimation with global and local facial features. In *IEEE International Conference on Acoustics, Speech and Signal Processing, Prague, Czech Republic*, pages 2032–2035, 2011.

[11] S Escalera X Baro I Guyon R Rothe. E Agustsson, R Timofte. Apparent and real age estimation in still images with deep residual regressors on appa-real database. In *12th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition*. IEEE, 2017.

[12] Mohamed Y El Dib and Motaz El-Saban. Human age estimation using enhanced bio-inspired features (ebif). In *2010 IEEE International Conference on Image Processing*, pages 1589–1592. IEEE, 2010.

[13] Yanwei Fu, Timothy M. Hospedales, Tao Xiang, Yuan Yao, and Shaogang Gong. Interestingness prediction by robust learning to rank. In *Proc. ECCV*, 2014.

[14] Yun Fu, Guodong Guo, and Thomas S Huang. Age synthesis and estimation via faces: A survey. *IEEE transactions on pattern analysis and machine intelligence*, 32(11):1955–1976, 2010.

[15] Xin Geng, Chao Yin, and Zhi-Hua Zhou. Facial age estimation by learning from label distributions. *IEEE transactions on pattern analysis and machine intelligence*, 35(10):2401–2412, 2013.

[16] Antonio Gulli and Sujit Pal. *Deep Learning with Keras*. Packt Publishing Ltd, 2017.

[17] Asuman Gunay and Vasif V Nabiyev. Automatic age classification with lbp. In *Computer and Information Sciences, 2008. ISCIS'08. 23rd International Symposium on*, pages 1–4. IEEE, 2008.

[18] Guodong Guo, Yun Fu, Thomas S Huang, and Charles R Dyer. Locally adjusted robust regression for human age estimation. In *Applications of Computer Vision, 2008. WACV 2008. IEEE Workshop on*, pages 1–6. IEEE, 2008.

[19] Guodong Guo, Guowang Mu, Yun Fu, and Thomas S Huang. Human age estimation using bio-inspired features. In *Proc. IEEE CVPR*, pages 112–119. IEEE, 2009.

[20] Hu Han, Charles Otto, Xiaoming Liu, and Anil K Jain. Demographic estimation from face images: Human vs. machine performance. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, (6):1148–1161, 2015.

[21] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proc. IEEE CVPR*, pages 770–778, 2016.

[22] John R Hodges, David P Salmon, and Nelson Butters. Recognition and naming of famous faces in alzheimer's disease: A cognitive analysis. *Neuropsychologia*, 31(8):775–788, 1993.

[23] Bihan Jiang, Michel F Valstar, Brais Martinez, and Maja Pantic. A dynamic appearance descriptor approach to facial actions temporal modeling. *IEEE Trans. Cybernetics*, 44(2):161–174, 2014.

[24] Vahid Kazemi and Josephine Sullivan. One millisecond face alignment with an ensemble of regression trees. In *Proc. IEEE CVPR*, pages 1867–1874, 2014.

[25] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

[26] Sarah N Kohail. Using artificial neural network for human age estimation based on facial images. In *Innovations in Information Technology (IIT), 2012 International Conference on*, pages 215–219. IEEE, 2012.

[27] Andreas Lanitis, Chrisina Draganova, and Chris Christodoulou. Comparing different classifiers for automatic age estimation. *IEEE Transactions on Systems, Man, and Cybernetics, Part B*, 34(1):621–628, 2004.

[28] Khoa Luu, Tien Dai Bui, Ching Y Suen, and Karl Ricanek. Spectral regression based age determination. In *Proc. IEEE CVPR Workshops*, pages 103–107. IEEE, 2010.

[29] Bappaditya Mandal and Nizar Ouarti. Spontaneous vs. posed smiles-can we tell the difference? *arXiv preprint arXiv:1605.07026*, 2016.

[30] Seyyid Ahmed Medjahed. A comparative study of feature extraction methods in images classification. *International Journal of Image, Graphics and Signal Processing*, 7(3):16, 2015.

[31] Ville Ojansivu and Janne Heikkilä. Blur insensitive texture classification using local phase quantization. In *International conference on image and signal processing*, pages 236–243. Springer, 2008.

[32] Jhony K Pontes, Alceu S Britto Jr, Clinton Fookes, and Alessandro L Koerich. A flexible hierarchical approach for facial age estimation based on multiple features. *Pattern Recognition*, 54:34–51, 2016.

[33] Lutz Prechelt. Early stopping-but when? In *Neural Networks: Tricks of the trade*, pages 55–69. Springer, 1998.

[34] Hongwei Qin, Junjie Yan, Xiu Li, and Xiaolin Hu. Joint training of cascaded cnn for face detection. In *Proc. IEEE CVPR*, pages 3456–3465, 2016.

[35] Narayanan Ramanathan, Rama Chellappa, Soma Biswas, et al. Age progression in human faces: A survey. *Journal of Visual Languages and Computing*, 15:3349–3361, 2009.

[36] Rajeev Ranjan, Vishal M Patel, and Rama Chellappa. Hyperface: A deep multi-task learning framework for face detection, landmark localization, pose estimation, and gender recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2017.

[37] Rasmus Rothe, Radu Timofte, and Luc Van Gool. Deep expectation of real and apparent age from a single image without facial landmarks. *International Journal of Computer Vision*, 126(2-4):144–157, 2018.

[38] M Merlin Steffi and J John Raybin Jose. Comparative analysis of facial recognition involving feature extraction techniques. 2018.

[39] Kestutis Sveikata, Irena Balciuniene, and Janina Tutkuviene. Factors influencing face aging. literature review. *Stomatologija*, 13(4):113–6, 2011.

[40] Sibt ul Hussain and Bill Triggs. Visual recognition using local quantized patterns. In *Proc. ECCV*, pages 716–729. Springer, 2012.

[41] Paul Viola and Michael Jones. Rapid object detection using a boosted cascade of simple features. In *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*, volume 1, pages I–I. IEEE, 2001.

[42] Yue Wu, Tal Hassner, KangGeon Kim, Gerard Medioni, and Prem Natarajan. Facial landmark detection with tweaked convolutional neural networks. *IEEE transactions on pattern analysis and machine intelligence*, 2017.

[43] Shuo Yang, Ping Luo, Chen Change Loy, and Xiaoou Tang. Faceness-net: Face detection through deep facial part responses. *IEEE transactions on pattern analysis and machine intelligence*, 40(8):1845–1859, 2018.

[44] Kaipeng Zhang, Zhanpeng Zhang, Zhifeng Li, and Yu Qiao. Joint face detection and alignment using multitask cascaded convolutional networks. *IEEE Signal Processing Letters*, 23(10):1499–1503, 2016.

[45] Zhifei Zhang, Yang Song, and Hairong Qi. Age progression/regression by conditional adversarial autoencoder. In *Proc. IEEE CVPR*, pages 5810–5818, 2017.