ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 3, Issue 2, February 2018

A Study on Physiological and Biological Feature Descriptors of Human Aging

[1] K. A. Patil
[1] Assistant Professor, MET's IOE, BKC, Nashik, India.

Abstract: **Human aging research now crosses all areas of physiology and biology. Human age prediction is applied in many real-world areas like forensic art, passport renewal, border security, finding a missing person or criminal, preventing vending machines from selling products, e.g., alcohol, tobacco, to under-aged individuals etc. Incredible changes found in human body during the craniofacial growth and behavioral pattern. This paper presents a study on various physiological and biological approaches used to predict human age. In this paper we discussed many interesting studies of these approaches and given a thorough analysis of problems in human age prediction.**

Keywords: Age Estimation, Face aging, Survey.

I. INTRODUCTION

Forensic Sciences is the recent area of applied research. Its value and importance as an assessment tool have risen exponentially as the needs for an informed opinion on the human age for the most judicial system. Human age is an important classifier in the most such systems, criminals and their victims, human trafficking, passport renewal, border security, finding a missing person, preventing vending machines from selling products, e.g., alcohol, tobacco, to under-aged individuals and many more human-computer interfaces [1-4]. We studied physiological and biological feature descriptors for human age prediction. In analyzing the aging system, it is necessary to predict the changes accurately in appearance resulting from the effects of aging. It must retain the identity of the person that is the viewer of an image must be able to see that it is the original person aged by a set amount. In this paper, we categorized age estimation features into two, physiological and biological. Physiological features include shape changes in overall appearance resulting from bone, cartilage, teeth, sagging, color changes resulting from aging and textural changes resulting from voice, gait, wrinkling, skin elasticity. Biological features include Deoxyribonucleic Acid (DNA), fingerprint, iris, face, palmprint, hand vein, palm vein, finger vein, periocular, ear, hand geometry, retina, sclera, Electrocardiograph (ECG), Electroencephalograph (EEG), whole blood and odor/scent. This study considers some of the above mentioned and more common circumstances that result in individuals.

II. PHYSIOLOGICAL FEATURE DESCRIPTORS

Teeth:

Forensic odontology which is direct or indirect application of age estimation [5]. Various tooth dimensions are measured to estimate the age with ±2 weeks by both methods. Best estimation can be done with vertical dimension of tooth i. e. the height of tooth. It is found that upper tooth dimensions called crown measurements such as Labio-lingual (LL), Masio-Distal (MD), and Tooth Height (TH) gives more accurate results by direct method. Indirect method can be a computerised tomography (CT) digital image [6].

This type of estimation mostly done in non-adult, infants and juvenile remains in forensic laboratory. In addition with dental development and eruption, bone fusion (ossification) or skeletal maturation and size features also considered for estimating the age.

Speech/voice:

Many physiological changes results from the childhood to adult growth of larynx and vocal folds [7-10]. Acoustic and prosodic features, specific combinations of plosives and vowels, these are relatable to the physical age of the speaker. In a speech signal, Voice Onset Time (VOT) is the period between the release of a plosive and the onset of vocal cord vibrations in the production of the following sound. Voice Offset Time (VOFT), on the other hand, is the period between the end of a voiced sound and the release of the following plosive. Factors affect the voice such as surrounding environment, jitter differences, Age, height, weight, physical and psychological health status of the speaker affect a variety of physical characteristics such as the size, tension and agility of the vocal cords, the length of the vocal tract, the power and resonance of the voice source, i.e. the lungs, the size and shape of the resonant cavities, muscle response in the vocal apparatus, and many other such factors. Due to this it is less possible to identify age from only voice of speaker.

Handwriting/Signature:

Most of the Handwriting based proposed system [11,12] used to predict the gender and handedness of human being. Features such as Directions, curvatures, tortuosities, chain codes, and edge-based directional features can predict the age ranges. Handwritten text images segmented into the number of cells. Gradient Local Binary Patterns (GLBP) and Gradient feature are computed and concatenated to constitute the image feature factor. With the help of SVM classifier age ranges can be predicted.

Language dependency is the most important factor which affects to age estimation. Other factors are gender, left handed or right handed; databases IAM dataset and KHATT corpus, QUWI dataset 14% handwritings were predicted age for seven different age groups [13, 14].

Gait:

Human gait means a person's manner of walking. Very few in literature [15-18] have worked on Gait based features to estimate the human age. Gait pattern significantly changes with the advancing age. It is observed that Gait speed decreases the increased human age. Stride based properties, reduced velocity, shorter step length and variable increased step timings are the characteristics considered for identifying the age. Walking surface is mattered in this type of approach [19, 20].

Facial image:

Among all approaches [21-36] face images are easily available evidences for the age estimation. Social networking websites, criminal database images provides many related images. For children, main appearance change is the shape change caused by craniofacial growth, For adults facial aging due to skin wrinkles and anthropometry/shape and texture, color, ethnicity are considered. Craniofacial growth helps in identifying young adults whereas loss in facial muscle elasticity, wrinkles on forehead, near cheek bones and next to eyes identify old age person. Problem arises with the face alignment; sideway face, blurred face, motion face and rotation of the image, illumination variations, pose variations, facial expressions etc. Other obstacles are change in hairstyle changes the face appearance, beard, and goggles/glasses. Simple method to tackle this problem is age synthesis i. e. generating the faces like in age progression. Sometimes it may not work due to limited training sample size data. MORPH Database, FGNET, FERNET database are most commonly used databases in recent studies. These databases directly consider age ranges/groups for age estimation.

III. BIOLOGICAL FEATURE DESCRIPTORS

MRI:

In Magnetic Resonance Imaging (MRI), human brain, the image can be segmented into gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) regions [37, 38]. Number of streamlines calculated as a proxy of connection strength between two regions using Diffusion Tensor Imaging (DTI). Structural connectivity networks based on DTI a weighted sum of the structural connectivity matrix for each subject as a raw score, where the weight of each connection was predefined as a correlation coefficient between edge weights and age over all subjects in the training group. Then, the raw score is converted to a predicted age with either linear or non-linear regression. It is useful for early detection of Alzheimer’s disease.

Whole blood:

Blood is one of the most often encountered and valuable traces found at a crime scene. Raman spectroscopy [39] was successful in species identification and blood ageing under laboratory conditions. The proposed spectral processing model [40,41] assumes a homogeneous blood stain with a constant thickness. These assumptions cause some deviations when compared to the reflectance spectrum measured in reality because of non homogeneity of thickness. Hemoglobin derivatives such as HbO2, MetHb and HC fraction measurements in blood stains considered as a function of time to estimate the age. Color of blood changes from red to dark brown factors that affects in whole blood age estimation. The accuracy of age estimates decreases with the age of the blood stain. Thus, to determine small differences in age, spectroscopic measurements should be performed as soon as possible after the crime. Environmental circumstances, humidity and temperature influence the speed of the chemical reactions within blood stains.

Skeletal Information:

Skeleton, hand-wrist bones, medial clavicle bones are used in such approaches to estimate the age. Tanner Whitehouse (TW) method is scoring method [42,43] developed in 1962 based on hand-wrist of an individual between 1 to 21 years of age. Maximum 20 individual bones are studied in hand-wrist and their different combinations of radius, ulna, and selected metarphal. This method cannot be applied for every individual because of verity of population like Japanese, Chinese, and German etc.

The study of medial clavicle [44-46] concentrates on radiographic data and Computed Tomography (CT) scans. In application of Schemeling method anterior and posterior radiographic imaging of medial clavicle is carried out at fusion stage. With the help of CT, it is concluded that medial clavicle is valid means of determining the minimum age in legal cases.

This type of approach mostly used in adults upto 40 Years age. It is very difficult in senior or older age adults age between 60-80 years by traditional method because of missing or decaying the bone information.

Fingerprint:
Morphological features such as ridges thickness, size or amount of pores, curvelet domain are the main area in fingerprint based estimation. Very less papers [47-49] are observed on fingerprint and study done for finding mostly the age groups of children, young and adults. Latent fingerprint features extracted are binary pixels, mean pixel, standard deviation. Problems faced in healing stages of wounds on fingers, luminescence behavior, degradation using chemical methods, chromatography, mass spectrometry and various surface types. Smooth, plain, non-porous and well reflecting surfaces like mirrors, glass, displays could give nearly accurate results.

Methodology Used:
Various classification and regression techniques [50-58] are used in both physiological and biological approaches. Multiple linear regressions (MLA), Principal component analysis (PCA), Klemera and Doubal's method (KDM) are commonly used methods.
Age estimation evaluation parameters; Mean Absolute Error (MAE), Cumulative Score (CS) and Accuracy is calculated after the training phase in mapping of testing feature vector.

Recurrent Neural Networks (RNN) [59] and Convolutional Neural Networks (CNN) [60-69] architectures are used in age estimation. RNN focuses on face aging pattern whereas CNN deals with our multiclass classification problems like demographic estimation such as age, gender, and ethnicity, face alignment via landmark detection, face rotation, and face verification, in face recognisation and age estimation. CNN has gained great success in the past few years.

IV. CONCLUSION:

In this paper, we studied many physiological and biological feature descriptors for human age estimation. These approaches have their own advantages and disadvantages and various applications. We discussed factors that affects to these approaches. Most of literature defines facial images are good and easily available source for age estimation. We studied that every approach is not suitable and doesn't provide accurate age estimation. Facial images using CNN attracts attention towards image recognisation and can give more accurate results regarding age estimation. For accurate results we can use various combinations of above discussed approaches.

REFERENCES:

[1] Zhenzhen Hu, Yonggang Wen, Jianfeng Wang, Meng Wang, Richang Hong, and Shuicheng Yan, "Facial Age Estimation with Age Difference", 2016 IEEE transactions on image processing, DOI 10.1109/TIP.2016.2633868.

[2] M. Fatih Aydogdu and Vakkas Celik and M. Fatih Demirci, "Comparison of Three Different CNN Architectures for Age Classification", 2017 IEEE computer society 11th International Conference on Semantic Computing, DOI 10.1109/ICSC.2017.61, pp. 372 – 377.

[3] Zhiqin Zhang, "Apparent Age Estimation with CNN", Atlantis Press, ICMMITA 2016, Advances in Computer Science Research, volume 7, pp. 152 – 157.

[4] V. Thomas, N.V. Chawla, K.W. Bowyer, and P.J. Flynn, "Learning to Predict Gender from Iris Images", In Proc. IEEE Int. Conf. Biometrics: Theory, Appl. Syst., pp. 1–5, 2007.

[5] Aka P. Sema, Yagan Murat, Canturk Nergis and Dagalp Rukiye, "Direct and Indirect Forensic Age Estimation Methods for Deciduous Teeth", 2015, Forensic Research, http://dx.doi.org/10.4172/2157-7145.1000273.

[6] Andreas Schmeling, Reinhard Dettmeyer, Ernst Rudolf, Volker Vieth, Gunther Geserick, "Forensic Age Estimation", Article published in Deutsches Ärzteblatt International, Dtsch Arztebl Int 2016; 113: pp. 44–50.

[7] Rita Singh , Joseph Keshet, Deniz Gencaga, Bhiksha Raj, "The Relationship Of Voice Onset Time And Voice Offset Time To Physical Age" 2016 IEEE, ICASSP 2016, 978-1-4799-9988-0/16, pp. 5390-5394.

[8] Charl van Heerden, Etienne Barnard, Marelie Davel, Christiaan van der Walt Ewald van Dyk, Michael Feld, Christian M. Uller, "Combining Regression And Classification Methods For Improving Automatic Speaker Age Recognition" 2010 IEEE ICASSP 2010,978-1-4244-4296-6/10, pp. 5174 -5177.

IFERP connecting engineers... developing research

ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)
Vol 3, Issue 2, February 2018

[9] N. Minematsu, M. Sekiguchi, and K. Hirose, "Automatic Estimation of One's Age with His/Her Speech Based upon Acoustic Modeling Techniques of Speakers", In Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., pp. I-137–I-140, 2002.

[10] C. Muller, F. Witting, and J.Baus, "Exploiting Speech for Recognizing Elderly Users to Respond to Their Special Needs", In Proc. Eur. Conf. Speech Communication and Technology, 2003.

[11] C.I. Tomai, D.M. Kshirsagar, and S.N. Srihari, "Group Discriminatory Power of Handwritten Characters", In: Electronic Imaging, pp. 116–123, International Society for Optics and Photonics, 2003.

[12] K. Bandi and S.N. Srihari, "Writer Demographic Classification Using Bagging and Boosting", In Proc. Int. Graphonomics Society Conference, pp. 133–137, 2005.

[13] Somaya Al Maadeed and Abdelaali Hassaine, Al Maadeed and Hassaine "Automatic prediction of age, gender, and nationality in offline handwriting", EURASIP Journal on Image and Video Processing, Springer.

[14] Nesrine Bouadjenek, Hassiba Nemmour and Youcef Chibani, "Age, Gender and Handedness Prediction from Handwriting using Gradient Features", IEEE 2015 13th International Conference on Document Analysis and Recognition (ICDAR), pp: 1116-1120.

[15] Jungseock Joo, Francis F. Steen, and Song-Chun Zhu "Automated Facial Trait Judgment and Election Outcome Prediction: Social Dimensions of Face", IEEE Xplore, 2015.

[16] J.W. Davis, "Visual Categorization of Children and Adult Walking Styles", In Audio-and Video-Based Biometric Person Authentication, pp. 295–300, 2001.

[17] Y. Makihara, H. Mannami, and Y. Yagi, "Gait Analysis of Gender and Age Using a Large-Scale Multi-View Gait Database", In Proc. Asian Conf. Comput. Vis., pp. 440–451, 2010.

[18] J. Man and B. Bhanu, "Individual Recognition Using Gait Energy Image", IEEE Trans. Pattern Anal. Mach.

Intell., vol. 28, no. 2, pp. 316C-322, 2006.

[19] J. Lu and Y.P. Yan, "Gait-Based Human Age Estimation", IEEE Trans. Inf. Forensics Security, vol. 5, no. 4, pp. 761–770, 2010.

[20] R.K. Begg, M. Palaniswami, and B. Owen, "Support Vector Machines for Automated Gait Classification", IEEE Trans. Biomed. Eng., vol. 52, no. 5, pp. 828–838, 2005.

[21] Yunlian Sun, Man Zhang, Zhenan Sun, and Tieniu Tan, "Demographic Analysis from Biometric Data: Achievements, Challenges, and New Frontiers", 2017, IEEE Transactions on Pattern Analysis and Machine Intelligence, DOI 10.1109/TPAMI2017. 2669035.

[22] Nitesh Kumar, Vivek Jaglan, Akshat Agrawal, "A Review of various Face Prediction Models using Image Processing", 2016 IJCA (0975 – 8887), Volume 142 – No.3, pp. 18-22.

[23] Jinli Suo , Song-Chun Zhu , Shiguang Shan and Xilin Chen , "A Compositional and Dynamic Model for Face Aging", Aging Journal Of Latex Class Files, January, 2009.

[24] Poonam Yadav, "Face Prediction Model for an Automatic Age Invariant Face Recognition System", 2015, arXiv 1506.0604v1.

[25] Hsuan T. Chang and Hsiao W. Peng, "Facial Image Prediction Using Exemplar-based Algorithm and Nonnegative Matrix Factorization", IEEE Xplore, 2012.

[26] Qi Yin, Xiaoou Tang, Jian Sun, "An Associate- Predict Model for Face Recognition",

[27] Kathryn Bonnen and Brendan Klare and Anil K. Jain, "Component-Based Representation in Automated Face Recognition," IEEE Transactions on Information Forensics and Security-Volume 8, pp 239-253, 2013.

[28] B. Schuller, S. Steidl, A. Batliner, F. Burkhardt, L. Devillers, C.A. Muller, and S. Narayanan, The INTERSPEECH 2010 Paralinguistic Challenge, In Proc. INTERSPEECH, pp. 2795–2798, 2010.

[29] Y.H. Kwon and N.D.V. Lobo, "Age Classification from Facial Images", In Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., pp. 762–767, 1994.

[30] A. Lanitis, C.J. Taylor, and T.F. Cootes, "Toward Automatic Simulation of Aging Effects on Face Images", IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 4, pp. 442–455, 2002.

[31] S.K. Zhou, B. Georgescu, X.S. Zhou, and D. Comaniciu, "Image Based Regression Using Boosting Method", In Proc. IEEE Int. Conf. Computer Vision, pp. 541–548, 2005.

[32] L. Wiskott, J.M. Felous, N. Kruger, and C. von der Malsburg, "Face Recognition and Gender Determination", pp. 92–97, 1995.

[33] R. Brunelli and T. Poggio, "HyberBF Networks for Gender Classification", In Proc. DARPA Image Understanding Workshop, pp. 311–314, 1992.

[34] H. Han, C. Otto, X. Liu, and A. Jain, "Demographic Estimation from Face Images: Human vs. Machine Performance", IEEE Trans. Pattern Anal. Mach. Intell., vol. 37, no. 6, pp. 1148–1161, 2015.

[35] S. Escalera, J. Gonz alez, X. Baro, P. Pardo, J. Fabian, M. Oliu, H.J. Escalante, I. Huerta, and I. Guyon, "ChaLearn Looking at People 2015, New Competitions: Age Estimation and Cultural Event Recognition", In Proc. IEEE Int. Joint Conf. Neural Netw., pp. 1–8, 2015.

[36] Y.H. Kwon and N.D.V. Lobo, "Age Classification from Facial Images", In Proc. IEEE Int. Conf. Computer Vision Pattern Recognition, pp. 762–767, 1994.

[37] G. Guo, G. Mu, Y. Fu, and T.S. Huang, "Human Age Estimation Using Bio-Inspired Features", In Proc. IEEE Int. Conf. Computer Vision Pattern Recognition, pp. 112–119, 2009.

[38] Tzu-Wei Huang, Hwann-Tzong Chen, Ryuichi Fujimoto, Koichi Ito, Kai Wu, Kazunori Sato Yasuyuki Taki,Hiroshi Fukuda and Takafumi Aoki, "Age Estimation From Brain MRI Images Using Deep Learning", , IEEE 2017, pp: 849-852.

[39] Gerda J. Edelman, Martin Roos, Annabel Bolck, Maurice C. Aalders, "Practical Implementation of Blood Stain Age Estimation Using Spectroscopy", IEEE Journal of Selected Topics in Quantum Electronics 2016.

[40] Ferdi Sarac, Huseyin Seker , Ahmed Bouridane, "Exploration of Unsupervised Feature Selection Methods to PredictvChronological Age of Individuals by Utilising CpG dinucleotics from Whole Blood", IEEE 2017, pp. 3652-3655.

[41] Huimin Sun, Yongfang Dong, Pingli Zhang, aoyong Meng, Wei Wen, Nan Li, Zhiyou Guo, "Accurate Age Estimation of Bloodstains Based on Visible Reflectance Spectroscopy and Chemometrics Methods", IEEE Phonetics Journal, Volume 9, Number 1, February 2017.

[42] Ijaz Khan, Muhammad Mahadi Abdul Jamil,Tengku Nadzlin Tengku Ibrahim , Faridah Mohd Nor, "Automated Human Age Estimation at Death via Bone Microstructures", 2016 6th IEEE International Conference on Control System, Computing and Engineering, 25-27 November 2016, Penang, Malaysia,pp: 580-583.

[43] Marjan Mansourvar , Maizatul Akmar Ismail, "Automatic Method for Bone Age Assessment Based on Combined Method", IEEE conference paper,2014.

[44] Derek T. Anderson and James M. Keller, Melissa Anderson and Daniel J. Wescott, "Linguistic Description of Adult Skeletal Age-at-Death Estimations from Fuzzy Integral Acquired Fuzzy Sets", 2011 IEEE International Conference on Fuzzy Systems June 27-30, 2011, Taipei, Taiwan.

[45] Darko Stern, Martin Urschler, "From Individual Hand Bone Age Estimates To Fully Automated Age Estimation Via Learning-Based Information Fusion", IEEE, 2016, PP. 150-154.

[46] Cheol E. Han , Luis R. Peraza, John-Paul Taylor, Marcus Kaiser "Predicting Age across Human Lifespan Based on Structural Connectivity from Diffusion Tensor", IEEE conference paper, 2014.

[47] Ronny Merkel, Jana Dittmann and Claus Vielhauer, "Resource-Efficient Latent Fingerprint Age Estimation for Adhoc Crime Scene Forensics: Quality Assessment of Flat Bed Scans and Statistical Features" IEEE 2016.

[48] Aditya K. Saxena, Shweta Sharma and Vijay K. Chaurasiya, "Neural Network based Human Age-group Estimation in Curvelet Domain", Elsevier, ScienceDirect, Eleventh International Multi-Conference on Information Processing-2015 (IMCIP-2015), pp. 781-789.

[49] Ronny Merkel, Jana Dittmann, and Claus Vielhauer, "A First Public Research Collection of High Resolution Latent Fingerprint Time Series for Short- and Long-Term Print Age Estimation", IEEE Transactions on Information Forensics and Security, VOL. 12, NO. 10, October 2017, pp:2276-2291.

[50] T.S. Lee, "Image Representation Using 2D Gabor wavelets", IEEE Trans. Pattern Anal. Mach. Intell., vol. 18, no. 10, pp. 959C-971, 1996.

[51] M. Ngan and P. Grother, "Face Recognition Vendor Test (FRVT) Performance of Automated Age Estimation Algorithms", NIST Interagency Report, 7995, 2014.

[52] Y. Deng, P. Luo, C.C. Loy, and X. Tang, "Learning to Recognize Pedestrian Attribute", In: ArXiv Preprint ArXiv:1501.00901, 2015.

[53] A. Lanitis, C. Draganova, and C. Christodoulou, "Comparing Different Classifiers for Automatic Age Estimation", IEEE Trans. Syst., Man, Cybern. B,Cybern., vol. 34, no. 1, pp. 621–628, 2004

[54] H. Meinedo and I. Trancoso, "Age and Gender Classification Using Fusion of Acoustic and Prosodic Features", In Proc. INTERSPEECH, pp. 2818–2821, 2010.

[55] Yun Fu, Guodong Guo, Thomas S. Huang, "Age Synthesis and Estimation via Faces: ASurvey", Member, IEEE Transactions on Pattern Analysis and Machine Intelligence, VOL. 32, NO. 11, November 2010, pp: 1955-1976.

[56] Choon-Ching Ng, Yi-Tseng Cheng, Gee-Sern Hsu, Moi Hoon Yap, "Multi-layer Age Regression for Face Age Estimation", 2017 Fifteenth IAPR International Conference on Machine Vision Applications (MVA) Nagoya University, Nagoya, Japan, May 8-12, 2017, pp: 294-297.

[57] Aswathy Unnikrishnan ,Ajesh F, Dr. Jubilant J Kizhakkethottam , "Texture-based estimation of age and gender from wild conditions", Elsevier Procedia Technology 2016 , pp. 1349 – 1357.

[58] Zhouzhou He, Xi Li, Zhongfei Zhang, Yaqing Zhang, Jun Xiao, and Xue Zhou , "Structure-Aware Slow Feature Analysis for Age Estimation", IEEE Signal Processing Letters, Vol. 23, No. 12, December 2016, pp. 1702-1706.

[59] Wei Wang, Zhen Cui, Yan Yan, Jiashi Feng, Shuicheng Yan, Xiangbo Shu, and Nicu Sebe, "Recurrent Face Aging", 2016 IEEE Conference on Computer Vision and Pattern Recognition, pp:2378-2386.

[60] Twisha Dhimar , Ms. Kinjal Mistree ,"Feature extraction for Facial Age Estimation: A Survey", IEEE WiSPNET 2016,pp: 2243-2248.

[61] Dileep M R and Ajit Danti, "Multiple Hierarchical Decision on Neural Network to predict Human Age and Gender", IEEE 2016.

[62] Vojtech Franc and Jan Cech , "Learning CNNs for face recognition from weakly annotated images", 2017 IEEE 12th International Conference on Automatic Face & Gesture Recognition, pp. 933- 940.

[63] Ke Zhang, Ce Gao, Liru Guo, Miao Sun, Ixingfang Yuan, Tony X. Han, Zhenbing Zhao, And Baogang Li, "Age Group and Gender Estimation in the Wild With Deep RoR Architecture", IEEE Access, Special Section On Recent Advantages Of Computer Vision Based on Chinese Conference on Computer Vision (CCCV) 2017.

[64] Nisha Srinivas, Harleen Atwal, Derek C. Rose, Gayathri Mahalingam, Karl Ricanek and David S. Bolme, "Age, Gender, and Fine-Grained Ethnicity Prediction using Convolutional Neural Networks for the East Asian Face Dataset", 2017 IEEE 12th International Conference on Automatic Face & Gesture Recognition, pp. 953-960.

[65] Songhe Feng, Congyan Lang, Jiashi Feng, Tao Wang and Jiebo Luo, "Human Facial Age Estimation by Cost-Sensitive Label Ranking and Trace Norm Regularization", IEEE Transactions on Multimedia, 2016.

[66] Shaoxin Li, Meina Kan, Jie Zhang, Shuzhe Wu, Wenxian Liu, Shiguang Shan, "AgeNet: Deeply Learned Regressor and Classifier for Robust Apparent Age Estimation", 2018, IEEE xplore, pp. 16-24.

[67] Hlaing Htake Khaung Tin Subjective, "Age Prediction of Face Images Using PCA", 2012, International Journal of Information and Electronics Engineering, Vol. 2, No. 3, May 2012.

[68] Z. Yang and H. Ai, "Demographic Classification with Local Binary Patterns", In Proc. IAPR Int. Conf. Biometrics, pp. 464–473, 2007.

[69] T. Bocklet, A. Maier, J.G. Bauer, F. Burkhardt, and E. Noth, "Age and Gender Recognition for Telephone Applications Based on GMM Supervectors and Support Vector Machines", In Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., pp. 1605–1608, 2008.

