Available online at www.elixirpublishers.com (Elixir International Journal)

Computer Engineering

Elixir Comp. Engg. 118 (2018) 50814-50819

ISSN: 2229-712X

Age & Gender Classification Using Histogram of Oriented Gradients and Back Propagation Neural Network

Shiva Verma and Krupa N. Jariwala

Department of Computer Engineering, Sardar Vallabhbhai National Institute of Technology Surat, India.

ARTICLE INFO

Article history:

Received: 08 April 2018;

Received in revised form:

12 May 2018;

Accepted: 23 May 2018;

Keywords

Facial Aging,

Age Estimation,

Aging Database,

Age Progression.

ABSTRACT

The human face has been serving as an identity since the beginning of mankind but it has more to offer than a recognition key of an individual. Facial features helps define the gender, expression, reactions and age of that individual. The objective of this paper is to take in consideration the ability of facial features to determine the age of an individual. This is done by taking in regard certain geometrical factors like distinguishable landmarks, the different valleys and peaks that contribute for facial features termed as nodal points. Each human face has approximately 80 nodal points i.e. just 80 pixels out of thousands of them are to be segregated for further use. Some of these are distance between the eyes, jaw line length, eye sockets depth, nose width, cheekbones shape, wrinkle topography etc. Taking into account the surface and age data we propose Histogram of Gradient algorithm along with Back Propagation Neural Network for the age and gender classification. The proposed algorithm do the classification in three different age group(child, adult and old) in addition to this we approach for gender classification in the age group child, adult and old with the same technique. The acquired results for the age classification gives an accuracy of around 92%. For the gender classification it works well for the old age group.

I. INTRODUCTION

Facial analysis can be considered as one of the most researched zone of computer vision among the various other zone. The Face of a human provide lot of information such as identity, gender, age, race and among all the characteristics age is an special attribute[1]. Aging is a process which depend on many internal and external factors like weather, living condition, race, and health of the individual and it is uncontrollable and irreversible. As computer vision engineers and researchers have been trying to understand the human face from very early days, hence it is a novel job to study and quote the work done in this field. Primarily one basic point to be kept in mind is that we consider 'Facial Feature Analysis' under consideration as per the objective of this paper rather than focusing on 'Facial Recognition'. Distribution of Geometrical Points play an important role for which particular models are defined like Point Distribution Model, Active shape model etc. Point distribution models rely on landmark points. A landmark is a point focusing on a given area for every shape instance existing in the population. We applied Histogram of Oriented Gradient (HOG) algorithm on a Back Propagation Neural Net thus training it for the purpose of age and gender classification. The acquired result are huge when observed and the reason for this success is mentioned in the below section of the paper. There are various application on human age classification in real world e.g. surveillance and security [2], HCI (human-computer interaction) based on age, Biometrics [3], Parental control over system etc.

II. LITERATURE SURVEY

Age classification was first researched by Kwon and Lobo [4]. In their research they have used gray scale images and classified these images into three different age group, senior adults, babies, young adults. For doing this the use of anthropometric model for the face is done and hence calculated the primary features of the facial images using six ratios and classified babies from the senior adults and young adult age group. The wrinkle index analysis is used to differentiate young adult group from senior adults. They have achieved an accuracy of 68% for the classification of the first group and because they have used a small database, it was difficult for the evaluation of the system performance. Another approach for age estimation is proposed by Geng et al [6] and is termed as Aging Pattern subspace (AGES). Geng used the sequential facial images of the individual distributed over time to create the model. For the encoding of face images of the subject around 200 AAMs features are used. They have used FG-NET Database in their research and calculated a Mean Absolute Error of 6.77. The problem found is that facial wrinkles for senior peoples are not well represented by AAM. Lanitis et al [5] has given a method for estimation of age by giving a function *age=f (b)* known as Aging Function. The variation on a face due to age can easily be represented by this function. For the above function age represent subject real age, f represent aging function and feature vector is represented by b which can be calculated with the help of AAM and it has 50 raw model attributes [2]. A database of 500 facial images was used to carry out the experiment and contains 60 subject images these subjects are mainly in the range of 1 to 35 years in age. An accuracy of around 71% is found in the recognition of the age. Hayashi et al [7] came out with another approach in the age estimation technique.

Tele:

E-mail address: shiva.verma9@gmail.com

They extracted the skin regions from the facial images. To enhance the wrinkles on the face they applied histogram equalization and further the Face wrinkles are extracted using Hough Transform. They classified age groups for the facial images having a 10 year interval. Their method performance was around 27 % and also they haven't consider variation of the age until 15. Local Binary pattern (LBP) is used by the Dehshibi and Bastanfard [8] has gone through a different approach for age classification. To classify babies from the other age groups they have used 7 ratios as distances between primary facial features. After this canny edge detector is used on predefined area to locate wrinkle and as an output found three wrinkle densities. The face images were classified further based on these computed wrinkle densities.

Gunay and Nabiyev [9] in their research for age estimation has done the age classification of individual using LBP as face descriptor for the facial images. The face is divided into m regions and spatial histogram were produced for each region using the Local Binary Pattern. A global descriptor of the facial image is built by adding all the regional histogram of the face. They have achieved an accuracy of around 80% for their proposed method. Choi et al [10] talk about local, global and hierarchical features in the case of feature extraction. Sobel filter system is used in extracting nearby components like wrinkles, skin, hairs and other geometrical components. Among various worldwide component AAM technique and Gabor wavelet transform methods are used. In the latter model Gabor channel is used to remove wrinkles whereas LBP system is used for skin identification. Global face elements were taken into consideration and were operated upon by Gabor wavelets and orthogonal locality preserving projections by C.T. Lin et al [11]. Gabor wavelet transformation gives a boost to the SVM classifier being used. Hu Han et al [12] examined the face pre-preparing, facial part restriction, feature extraction and hierarchical age estimation. SVM-BDT (Binary Decision Tree) was used to achieve age group classification .A different SVM age repressor is prepared to predict the final age. Geng et al [13] uses another technique for age estimation by using Adaptive label distribution. The result which comes out as the system is efficient and algorithm perform better. Ankit Rajinder and Dontaraju [14] in their research has calculated geometrical and wrinkle feature of a facial image. They have used these feature to estimate the age of a person. They have achieved an accuracy of around 62% in their research work.

Lee, Seung Ho et al. in [15], classified the age based on local age group modeling, which is erected by clustering trained faces. This method also helped in dealing with large variations of facial appearance. Whole training images of an age group were decomposed into a different set of face clusters that avoided the degradation of classification due to some disagreeable faces. They used LBP histogram features were extracted from them and then classify the age group based on hierarchical clustering and the achieved estimation rate about 60%. Yang, Xi, et al. in [16], modeled the problem of age estimation based on the framework of Multiple Instance Learning (MIL) and proposed an algorithm called Witness based Multiple Instance Regression (WMIR). The main idea behind multiple instance regression algorithms (WMIR) is to find the both positive instances and the negative instances and use both these instances to train the classifier.

Over here the HOG (Histogram of Oriented Gradient) is used in a different approach for the algorithm of age estimation and gender classification. The given approach with the help of Back propagation Neural Network tends to classify an input image in to one out of three different age group and also try to classify an image as male or female. The proposed method contain three different step and these are 1) Preprocessing 2) Hog feature Extraction 3) Classification of age and gender.

The paper in the upcoming section is structured in the below given form the section 3 shows various stages in the proposed methodology as we go to section 4 the experimental results are discussed and further in section 5 the conclusion is given

III. THE PROPOSED METHOD

As we have already mentioned in section II that our method contain three different steps which are 1) Preprocessing 2) Hog feature Extraction 3) Classification of age

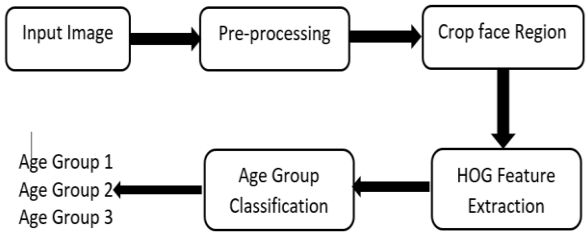

Fig 1. Block Diagram of the proposed method for Age group Classification.

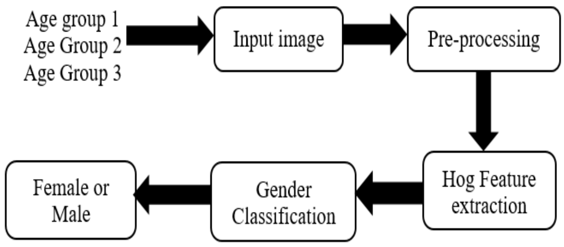

Fig 2. Block Diagram of the proposed method for Gender Classification.

(*1) Pre-processing*

The database which we have used in our proposed method is provided by the Open University of Israel [17] which contained unfiltered face images of individuals. It contains images of age group from 0 to more than 60 year of age also this database is freely available and can be easily used for facial feature analysis. Fig 3 shows some images which are used in the proposed method.

Fig 3. Some Images from the database.

The color images are first converted into the grayscale images as step 1 for the extraction of only face region from the images. The face region from an image is cropped with the help of standard viola jones procedure. To avoid the complication of face detection and localization method in an image we have used viola jones in our work. Also the problem of illumination, color of skin and shading problem is handled using viola jones.

As the age of an individual increases according to the time there are various permanent textural features can be seen on the face of the individual such as fine wrinkles and dullness of the skin which causes more deep [18] wrinkles. These textural features can easily be seen over the forehead region, near the corners of the eye, over the cheek bones, below the eyes region. Our main consideration is on these HOG features only.

(2) HOG Feature Extraction

After the extraction of face region from the preprocessed image HOG algorithm is applied on the cropped image for the HOG features. The gradient orientation of an image gives a description which can be said as HOG description. This technique is used to get the Histogram of Oriented Gradients (HOG) in the local region of the particular image. Histogram of Oriented Gradients can be considered as similar to edge orientation histogram, the shape of the context and the histogram of the scale invariant features. But in HOG the cell play an important role as the histograms are made based on these cells having high in density and to get high in accuracy, and for this overlapping block normalization method is applied.

Dalal and Triggs [19] were the first to introduce HOG in 2005. This algorithm was used to detect the pedestrian in an image, but they didn't stop here they carried out their test on certain other problems like detection of object in static images, detection of human being in video and films. The main working idea behind the HOG is this it this that the way it distribute the local intensity gradients is unique and this is used to characterize the local appearance and the object shape in an image or video. To implement HOG the image is divided into small regions which are called as cells, and also a one dimensional histogram of gradient orientations is added to every particular cell as shown in fig 4. The bin over here represent the similar gradient orientation by adding all the gradient magnitude. The Histogram of Oriented Gradients description is represented by the collection of these histograms. A large spatial region is used for calculating the intensity which is termed as Block, the result came is utilized for the normalization of the histogram of the cell in each particular block

The Normalization of the block is done to correct the contrast variation in local regions to get the better lightning invariance, shadowing etc [19].

A) Gradient Computation

In step 1 of HOG feature extraction the gradient values are computed. The most common method is to apply the 1-D centered, point discrete derivative mask in one or both of the horizontal and vertical directions to calculate gradient value as shown Fig 4. This task can be done by using the below filter kernel for filtering the image:

$$g_x = [-1,0,1] \quad (1)$$

$$g_y = [-1,0,1]^T \quad (2)$$

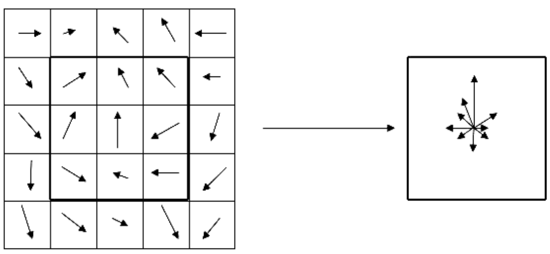

Fig 4. Merging all the 1 D gradient orientations [19].

Hence for vertical as well as horizontal direction gradients can be calculated as:

$$G_x(x, y) = I(x, y) * g_x \quad (3)$$

$$G_y(x, y) = I(x, y) * g_y \quad (4)$$

Where (*) = Convolution Operator and I is the intensity in the image at (x,y) point,

The gradient orientation & magnitude at (x,y) of an image is defined as:

$$|\nabla I| = \sqrt{(G^2_x + G^2_y)} \quad (5)$$

$$\angle \nabla I = \tan^{-1}(G_y / G_x) \quad (6)$$

There are some other much complex masks which are sobel operator or diagonal masks which are explored by Dalal and Triggs but these masks does not perform well in human detection problem.

B) Orientation Binning

In phase 2 of HOG feature extraction, the construction of cell histogram is done. An evenly extended distribution from 0 to 180^0 or 0 to 360^0 of the histogram channel is made also a particular shape of the cell is used which is radial or rectangular but it depend on the signed and unsigned gradient definition. For the voting contribution the gradient magnitude of a pixel can give a vote or some other function of gradient magnitude like, gradient magnitude square root or gradient magnitude square can give the vote.

C) Block Normalization

The gradient magnitude are normalized locally for the account of contrast and illumination change. This is done by making blocks which contain group of cell into larger spatial region. These blocks are generally overlapped which means that one block can have more than one cells which is already considered in some other block as shown in Fig 5 [19]. There are two types of block (1) Rectangular block (R-HOG blocks Fig 6), (2) circular block (C-HOG blocks Fig 7).

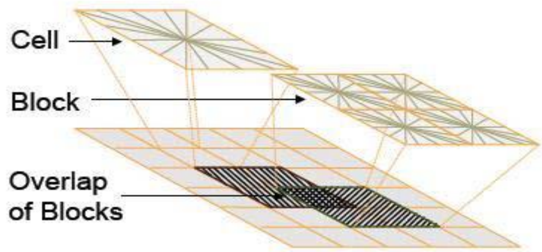

Fig 5. Creation of block by overlapping cells [19].

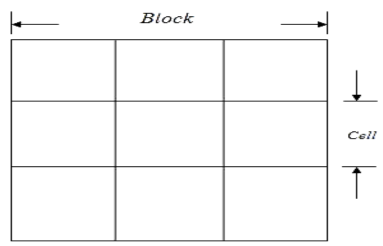

Fig 6. R-HOG[19].

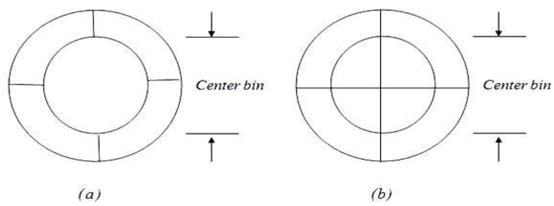

Fig 7. C-HOG [19].

For block normalization there are four different methods which are explored by Dalal and Triggs [19]. Let v = normalized vector which contain all the histogram in a particular block. Let $\|v_1\|$ be its 1-norm, $\|v_2\|$ be its 2-norm. The normalization factor can be calculated by the below given equations also let **e** = some small constant (this e doesn't affect the result).

$$L_{2\text{-}norm}\text{: } f = \frac{v}{\sqrt{(\|v\|_2^2 + e^2)}} \tag{6}$$

$$L_{1\text{-}norm}\text{: } f = \frac{v}{\|v\|_1 + e} \tag{7}$$

$$L_{1\text{-}sqrt}\text{: } f = \frac{\sqrt{v}}{\sqrt{(\|v\|_1 + e)}} \tag{8}$$

After the extraction of the HOG feature from the facial images these features are then stored in the form of Feature Vector for the further step in the proposed method which are training and testing of the classifier.

Fig 8. Sample output of HOG Feature extraction.

(3.A) Classification of the age

In this phase of the method a Back Propagation Neural Network Classifier is constructed which is used for the purpose of classifying the facial images into one out of child adult or old. The age range for these groups are given below:
Age Group 1: 0-16 years old (child)
Age Group2: 17-45 years old (adult)
Age Group3: >45 years old (old)

We have use database provided by the Open University of Israel. We have made a dataset of around 150 images in which all the Age group contains 50 images each means every age group has 50 images in their dataset folder. The images in these group are put based on the human perception of estimating the age of an individual. So we already taken out the hog features of these image images in the previous step and store these feature of 150 image in the form of feature vector. Now this feature vector is passed to the BPNN for the training testing and validation purpose. Finally the training and testing is done based on this feature vector. Training and testing of the classifier is based in the ratio of 70 and 30 so the hog feature of around 70 % images is taken for Training purpose from each age group and the remaining hog feature of around 30 % images are taken for testing purpose from each age group. The images which are selected from each age group for the training and testing purpose are taken on the random basis by the BPNN.

(3.B) Gender Classification

In this phase also a BPNN is constructed which is used for the classification of the gender from the facial images into Male and female.

The step 1 and 2 of the proposed method are same for this classification. For gender classification there exist three group which are given as below
Age Group 1: 5-16 years old (Child Male or Female)
Age Group 2: 17-45 years old (Adult Male or Female)
Age Group 3: >45 years old (Old Male or Female)

We have use the same database for this purpose so in this case we have made a dataset of around 300 images in which all the age group contains 100 images each means 50 image of female and 50 images of male are there in each age group. The images in these folder are based on human perception for the classification of the gender. The preprocessing and Hog feature extraction of these images can be done using step 1 and 2 of the proposed method and the HOG features are stored in the feature vector. For the classification of these images in male and female the same process is applied on BPNN as applied in *3.A.* The training and testing is done in the same way as done before and in the same ratio as discussed before.

IV. EXPERIMENTAL RESULTS

IV.A For Age Classification

After the training and testing of the BPNN we have shown the complete recognition rate in the form of confusion matrix to show the complete evaluation of the implemented method. For the Age group 1 the recognition rate is found around 96.0%. The recognition rate for Age group 2 is found around 88.9 % and the recognition rate for Age group 3 is found around 91.1%. Hence the overall age group recognition comes around 92.0% for all the age Group. The above given values are based on the plot of confusion matrix as shown in Fig 9 by the BPNN. As we have reached around 92% accuracy in our system hence it can be said that our proposed method is good in performance. In the confusion matrix 1 is depicting AG1, 2 is depicting AG2 and 3 is depicting AG3.

Table 1. Summarization of the confusion matrix for Age Classification method.

Age Group	Recognition Rate	Overall recognition Rate
1	96.0%	92.0%
2	88.9%	
3	91.1%	

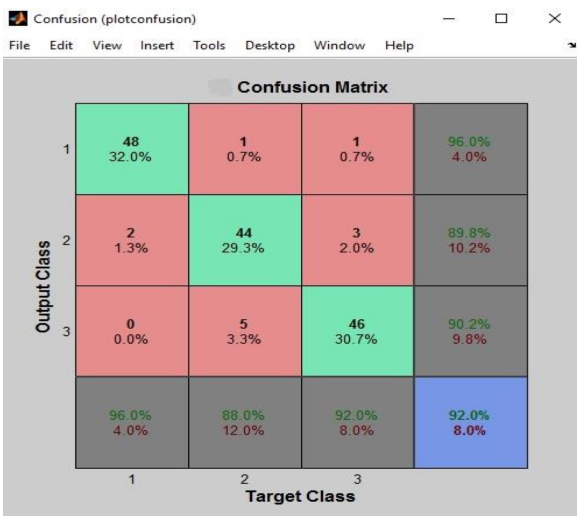

Fig 9. Confusion matrix showing accuracy of the Age Classification system.

We would also like to say that in process of age group estimation, there is some percentage of intrinsic ambiguity of assigning ages to the age group. This ambiguity is due to those ages which are close to the above mentioned age group boundaries.

For said let us take an e.g. of label 10 then the age group for this particular label is Age group 1 and its quiet an easy task but for a label of 16 it is not clear to assign this age to age group 1or age group 2. So those age label which are found close to the boundary of the age group are vague images.

IV.B For Gender Classification

After we have completed the process of training and testing of the BPNN and now we are ready for the gender classification. The accuracy of the system is shown through with the help of confusion matrix. For the Age group 1 the overall gender recognition rate is found around 88%, for Age group 2 is found around 91% and the gender recognition rate for Age group 3 is found around 93%. These values are based on the plot of confusion matrix shown in the Fig 10, 11, and 12 respectively. In each of the confusion matrix below 1 is depicting female and 2 is depicting male for each age group.

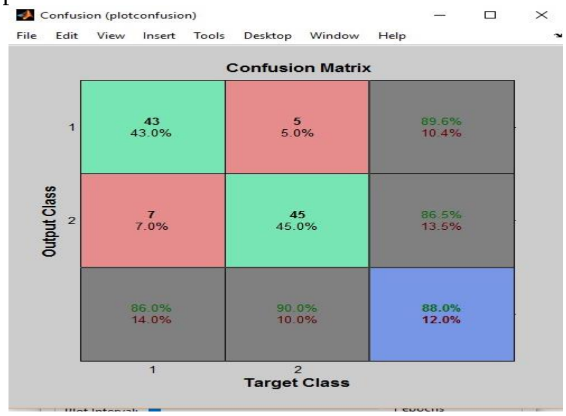

Fig 10. Confusion matrix showing accuracy of the gender classification for AG1.

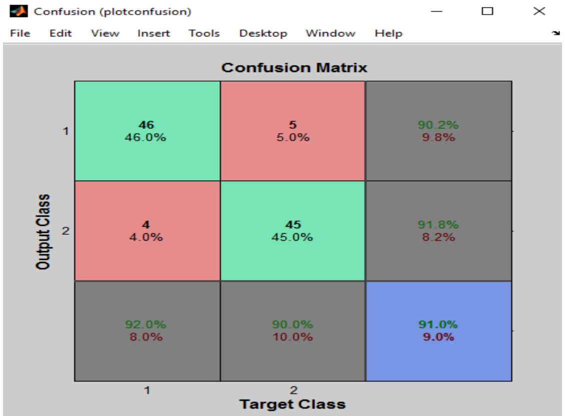

Fig 11. Confusion matrix showing accuracy of the gender classification for AG2.

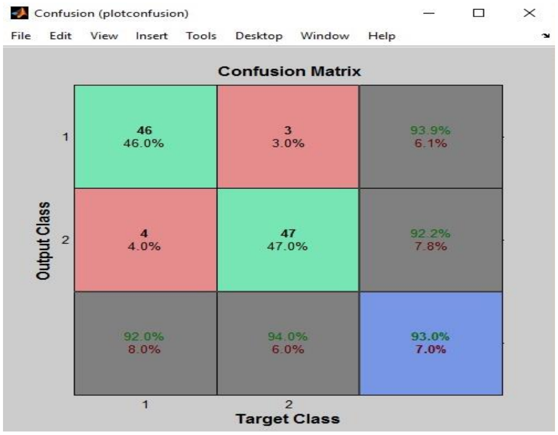

Fig 12. Confusion matrix showing accuracy of the gender classification for AG3.

Table 2. Summarization of the confusion matrix for gender classification.

Age Group	Recognition Rate
1	88.0%
2	91.0%
3	93.0%

We have shown the comparison of other method proposed by different author for age group classification with our proposed method in Table 3.

Table 3. Comparison of the different method with proposed method.

Author	Overall Accuracy
Lee, Seung Ho[15]	60.0%
Soni, A.K [14]	76.0%
Gunay and Nabiyev[9]	80.0%
Dehshibi and Bastanfard[8]	86.0%
Proposed Method	92.0%

CONCLUSION

This paper talks about an algorithm for age-group and gender classification which is proposed by us and we have used Histogram of Oriented Gradients for extraction of the facial feature and then we have used BPNN for the age & gender classification. The Experimental result which can be seen from confusion matrix demonstrate that the performance of the proposed method is very good for age and gender classification. In future we will try to do Age and Gender estimation in video based input and also we will go for future face prediction.

REFERENCES

[1] Zebrowitz, L., 2018. *Reading faces: Window to the soul?*. Routledge.

[2] Fu, Y., Guo, G. and Huang, T.S., 2010. Age synthesis and estimation via faces: A survey. *IEEE transactions on pattern analysis and machine intelligence*, *32*(11), pp.1955-1976.

[3] Gao, Feng, and Haizhou Ai. "Face age classification on consumer images with gabor feature and fuzzy lda method." In *International Conference on Biometrics*, pp. 132-141. Springer, Berlin, Heidelberg, 2009.

[4] Y. Kwon and N. Lobo, “Age Classification from Facial Images,” Computer Vision and Image Understanding, vol. 74, no. 1, pp.1-21, 1999.

[5] Lanitis, A., 2002. On the significance of different facial parts for automatic age estimation. In *Digital Signal Processing, 2002. DSP 2002. 2002 14th International Conference on* (Vol. 2, pp. 1027-1030). IEEE.

[6] Geng, Xin, et al. "Learning from facial aging patterns for automatic age estimation." *Proceedings of the 14th ACM international conference on Multimedia*. ACM, 2006.

[7] Hayashi, J.I., Yasumoto, M., Ito, H., Niwa, Y. and Koshimizu, H., 2002, August. Age and gender estimation from facial image processing. In *SICE 2002. Proceedings of the 41st SICE Annual Conference* (Vol. 1, pp. 13-18). IEEE.

[8] Dehshibi, M.M. and Bastanfard, A., 2010. A new algorithm for age recognition from facial images. *Signal Processing*, *90*(8), pp.2431-2444.

[9] A. Gunay and V. Nabiyev, “Automatic Age Classification with LBP,” Proc. Int’l Symp. Computer and Information Sciences, 2008

[10] Choi, S.E., Lee, Y.J., Lee, S.J., Park, K.R. and Kim, J., 2011. Age estimation using a hierarchical classifier based on global and local facial features. *Pattern Recognition*, *44*(6), pp.1262-1281.

[11] Lin, C.T., Li, D.L., Lai, J.H., Han, M.F. and Chang, J.Y., 2012.Automatic age estimation system for face

images. *International Journal of Advanced Robotic Systems*, *9*(5), p.216.

[12] Han, H., Otto, C. and Jain, A.K., 2013, June. Age estimation from face images: Human vs. machine performance. In *Biometrics (ICB), 2013 International Conference on* (pp. 1-8). IEEE.

[13] Geng, X., Wang, Q., & Xia, Y. (2014, August). Facial age estimation by adaptive label distribution learning. In *Pattern Recognition (ICPR), 2014 22nd International Conference on* (pp. 4465-4470). IEEE.

[14] Soni, A.K., Kumar, R. and Kishore, D.K., 2015, October. Estimation of age groups based on facial features. In *Applied and Theoretical Computing and Communication Technology (iCATccT), 2015 International Conference on* (pp. 681-687). IEEE.

[15] Lee, Seung Ho, and Yong Man Ro. "Local age group modeling in unconstrained face images for facial age classification." *Image Processing (ICIP), 2014 IEEE International Conference on*. IEEE, 2014.

[16] Yang, Xi, et al. "Facial age estimation from web photos using multiple-instance learning." *Multimedia and Expo (ICME), 2014 IEEE International Conference on*. IEEE, 2014.

[17] http://www.openu.ac.il/home/hassner/Adience/data.html

[18] Ramanathan, N., Chellappa, R. and Biswas, S., 2009. Computational methods for modeling facial aging: A survey. *Journal of Visual Languages & Computing*, *20*(3), pp.131-144.

[19] Dalal, N. and Triggs, B., 2005, June. Histograms of oriented gradients for human detection. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on* (Vol. 1, pp. 886-893). IEEE.

[20] Verma, S. and Jariwala, K.N., 2018, February. Comparison and analysis of age classification techniques. In ARSSS International conference 4th February, 2018, Pune India