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DISCERNING FACIAL AGE FROM DIGITAL IMAGE THROUGH COMPONENTIAL TEXTURE MANIFOLD ALGORITHM

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Abstract—Face renders the hints which delineate the details of the person. The major expressions and features are used in plethora of applications such as decision making, digital accessing, applications, secured logins, passport renewal, investigation with regard of missing person, finding details of a person with image and so on. Face detection, age estimation, facial actions, gesture recognition are all bestowed in digital applications. In spite of various researches continued there is an urge to evolve a well sophisticated system to automate this process with least flaw. This research is focused on the system which can discern the age with aid of the input image of the person with better accuracy with the inclusion of images of both male and female belonging to various age groups. Componential texture manifold algorithm is used to identify the facial age value of the person from the received face image. The enhancement is obtained with versatile database encompassing images of various age groups, intra and inters age group images, twin images, celebrity images, images with and devoid makeup effects. Own database FG-NET and CACD were used. The testing was done on 1000images and the results have shown 89.5% accuracy.

Keywords—facial image; gesture; texture; database; FG NET; componential

I. INTRODUCTION

Digital analysis of face and recognizing a person from the extracted features are currently used in many human computer applications. To obtain fiducial features from the image of a face, the recognition of eye point is very vital. The algorithm of Viola-Jones is used for this purpose. The extraction of the facial features is achieved using Segmented Feature Texture Analysis method. From the given input image, the portion of face is received. The face is retrieved from input image. The process of normalization is done on the cropped face. In normalizing, the image, the histogram equalization is done to obtain the image in the normalized form. The illumination effects, noise effects are rectified and edge details are retained in the image. This will suit in proper face cropping. The image which is considered as input is normalized by the equalization technique. Histogram normalization is used. The image obtained from this step is a HIS image. The image is then checked for alignment of the face in the image. The alignment and orientation have a vital role in improving the accuracy of the algorithm. Features are received from the image and the extracted values are stored in database. By way of matching the features values from the database, the bifurcation of age is achieved. 1000 images were collected during the training phase of the project. The input image was preprocessed to obtain the face. If the cropped face was found to

have all the features, it was not considered to be a face and error message was generated. If the cropped face is found to have all the features, the image proceeded for further processing and the feature details were then obtained. Segmentation was done to achieve the information of fractals from the face. For checking of the image whether to be a face or not was done by matching the fractals obtained with the respective patterns. The extracted values were compared with the details stored in the database. The feature values were already stored in the database after extraction of them. After performing recognition of the pattern the respective age class was identified. The Segmented Fractal Texture Analysis algorithm was used for feature extraction. The received features are stored for prediction by labelling them in storage data. The details were further categorized according to the geometric and photometric measures. The input image was also subjected to analysis. The resultant values were compared with the training data values using the deep neural network for classification. Hence a final estimated age group was obtained as the output.

II. RELATED PAPERS

The recent era enhances the utilization of digital data in many applications in varying aspects. The researches have used the idea of recognizing a face from the input image as well as analyze the expressions, age and gender from the input face. With the identification and processing of facial features, many applications provide digital access as well as render advanced digital features. The facial details are utilized in the field of forensics, police vigilance, missing person, age estimation, gender identification, face recognition, surgery and treatments. The identification of facial features from the input face is very tedious. The estimation of age of a person from a given input image is challenging due to the transpiring of facial feature from the input image. The visage renders the actual detailing of the age, gender and expressions but it becomes tedious in obtaining these fiducial values from the input image. The challenges encompasses the quality factor of image, algorithm to capture face from the input image as well as extracting features from the input image inspite of pose, locality and illumination. The proposed algorithm enables to overcome these hurdles through way of an efficient approach which can provide a better solution through a confined age group.

III. PROPOSED METHOD

The proposed method as depicted in Figure.1 expresses the step by step process followed to identify the age of a person from the input image. The proposed algorithm recognizes a face from the input image using the haar features. The algorithm of Viola-Jones is used for this purpose. The extraction of the facial features is achieved using Segmented Feature Texture Analysis method. From the input image, the retrieving of face is done. The retrived face from image is normalized. Using histogram normalization, the normalized form of image is obtained. The illumination effects, noise effects are rectified and edge details are retained in the image. This will suit in proper face cropping. The image which is considered as input is normalized by the equalization technique. Histogram normalization is used. The image obtained from this step is a HIS image. The image is then checked for alignment of the face in the image. The alignment and orientation have a vital

role in improving the accuracy of the algorithm. Features are obtained from the normalized image and the values of the features are stored in database.

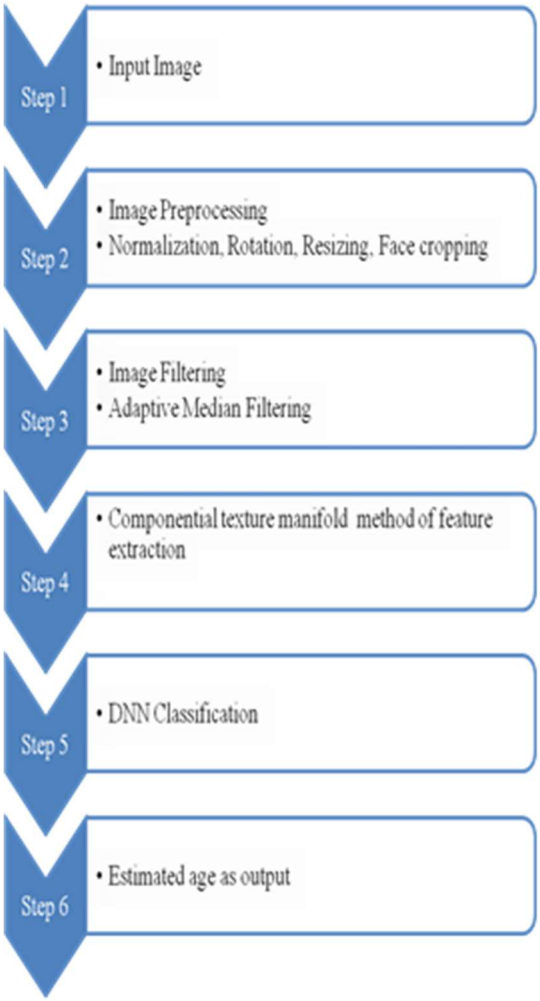


Fig. 1. Proposed steps

1000 images were collected during the training phase of the project. The input image was preprocessed to obtain the face. If the cropped face was found to have all the features, it was not considered to be a face and error message was generated. If the cropped face is found to have all the features, the image proceeded for further processing and the feature details were then obtained. Segmentation was done to achieve the information of fractals from the face. For checking of the image whether to be a face or not was done by matching the fractals obtained with the respective patterns. The extracted values were compared with the details labeled in the storage data. The feature values were already stored in the database after extraction of them. After performing recognition of the pattern the respective age class was identified. The Segmented Fractal Texture Analysis algorithm was used for feature extraction. The extracted features were then stored in the database. The details were further categorized according to the geometric and photometric measures. The input image was also subjected to analysis. The resultant values were compared

with the training data values using the deep neural network for classification. Hence a final estimated age group was obtained as the output.

IV. INTERPRETATION OF RESULTS/OUTPUTS

The Componential texture manifold analysis done on around 1000 facial images and the obtained results were plotted in a graphical representation. The 45 feature values with respect to the rate of transition of the values in each category highlighted the way the classification was carried out. The details of the features were extracted from all the input images. The extracted feature values were plotted in respect of three major criteria. The obtained results proved that the proportion of variation of value of feature remain the same in the images of similar age group. The images belonging to different age category are as depicted in Fig. 2 and Fig. 3

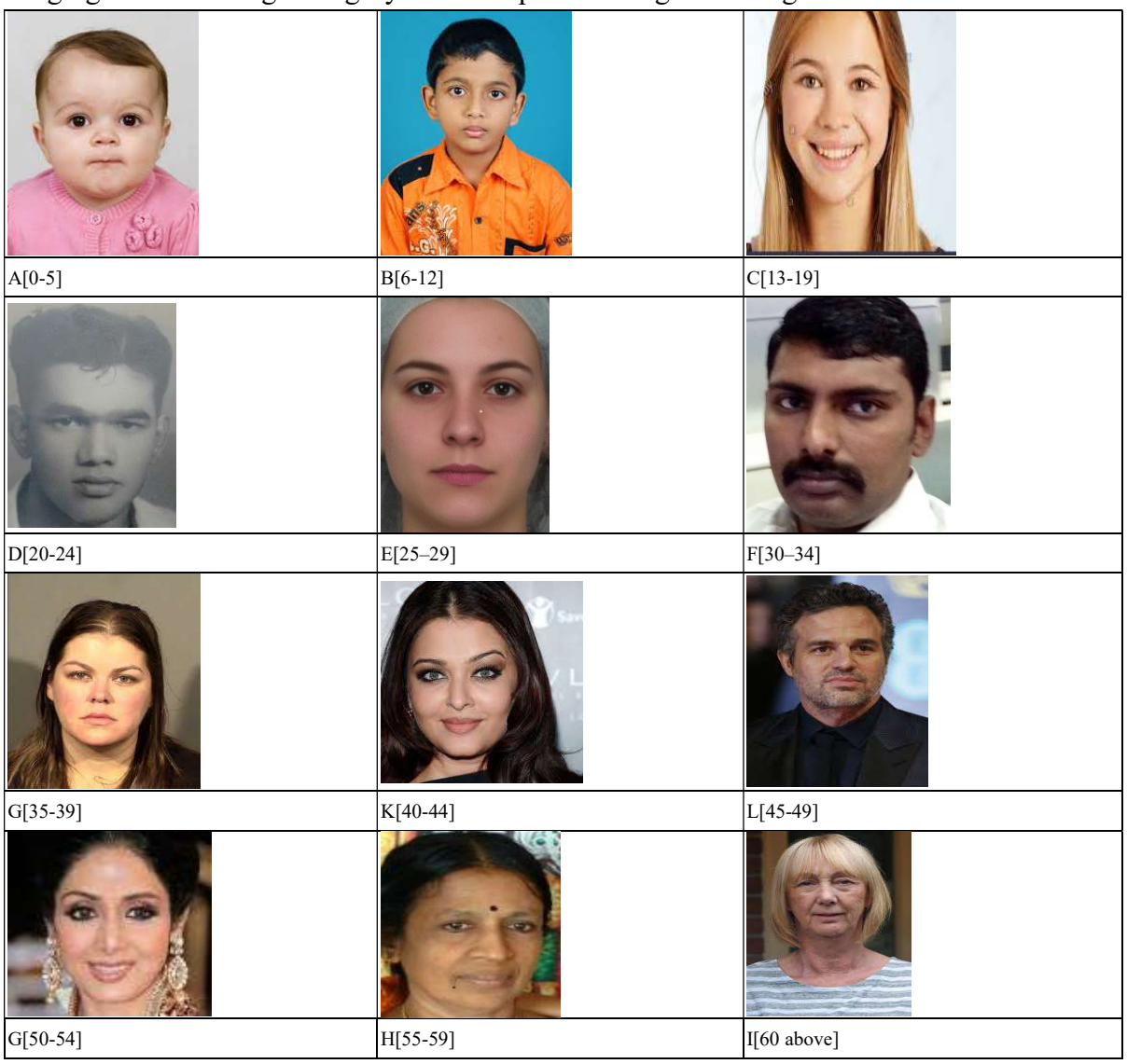


Fig. 2. Image set 1 cross age group

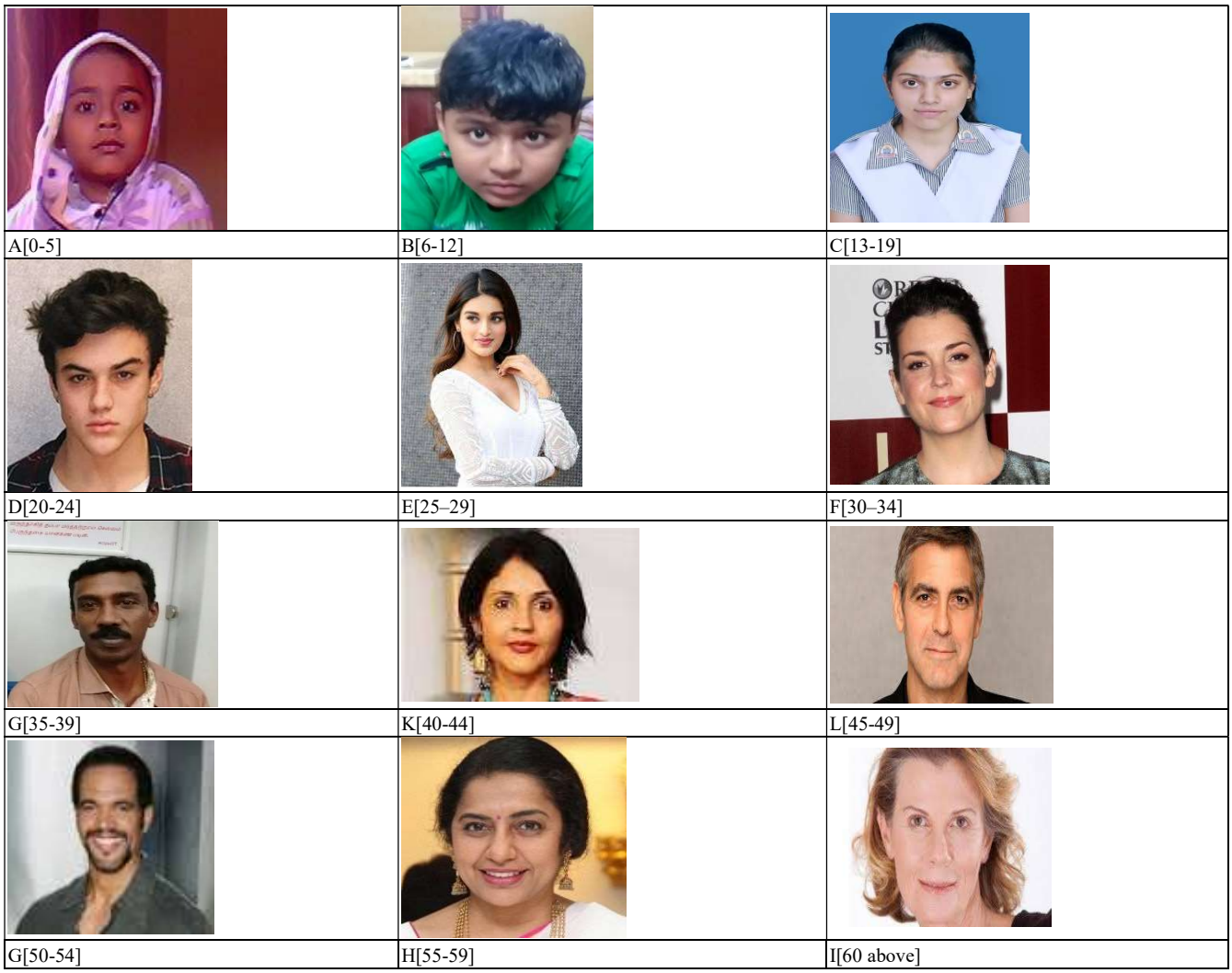


Fig. 3. Image set 2 cross age group

The two sets of images were selected in a manner so that the images were of different categories with respect to texture, gender, expression with or without makeup effects. This sorted selection of images was done to estimate the efficiency of algorithm to find the age with a higher accuracy rate in-spite of the images belonging to different categories. The images were selected without any constraints so that the selected images were within the range of each age group such as any age from 0-5 in the first age group. The subject age in image set 1 is of 1 year and image set 2 is of 4 years. This selection was done to estimate if the classified age was defined to a common age group. The obtained results expressed that both the images belonged to a common age group(0-5 years).

The reason is that the face shape of this age group remained in a round shape and the facial features were confined to a minimum distance. The eye region alone remained more prominent as compared to the other features. This shows similarity in the plots which are represented in graphical format as in Figure 4 and Figure 5 for the images A in image set 1 and image set 2. The representations showed that they belong to a common age group 0-5 which was based on the values as shown in Tables 1 and 2.

TABLE I. FEATURE VALUES AS OBTAINED FROM IMAGE A IN IMAGE SET 1

0-5 Age Group Data set 1				
Texture	**Color & Gradient**	**Key point**	**Orientation**	**Shape**
0.886111	49.78317	75	91	1.011897
0.890516	60.24679	75	96.46848	1.119327
0.987631	69.26324	187	114.9552	1.126731
0.998151	73.52673	209	118.6101	1.427121
1.314999	95.04367	232.1648	151.9838	1.547185
1.318125		309	156.1121	
1.403202		330	178.6986	
1.435126		701	180.1979	
1.463685		701	214.3733	
1.473845		1010	217.0933	
		1094		
		1154		
		1285		
		1322		
		1809		

TABLE II. FEATURE VALUES AS OBTAINED FROM IMAGE A IN IMAGE SET 2

0-5 Age Group Dataset 2				
Texture	**Color & Gradient**	**Key point**	**Orientation**	**Shape**
0.967215	48.66116	121	127.2179	1.310646
0.984337	77.54032	124	144.6397	1.426841
1.082349	82.056	206.8556	149.3274	1.431331
1.118277	99.73991	223	164.2077	1.465199
1.18484	120.3681	250	165.6961	1.476371
1.263712		390	181.3157	
1.368393		690	182.122	
1.373319		848	194.5601	
1.393233		901	195.4695	
1.436103		959	568	
		1116		
		1122		
		1149		
		1286		
		1401		

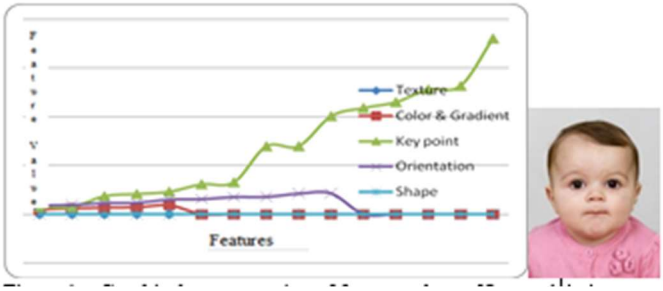


Figure 4 Graphical representation of feature values of Image A in image set 1

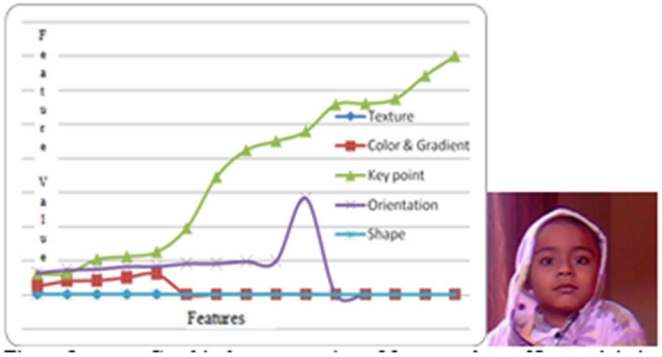


Figure 5 Graphical representation of feature values of Image A in image set 2

In the second age group(6-12 Years), the face was visualized with proper definition of the outline of the face. The face gets off from the puffy fat and the evenness of the texture was found in this age group. The extracted feature values of the images B in first image set and the second image set are represented in the Tables 3 and 4. Figures 6 and 7 depicts the values of features which were exracted. The proper definition of the facial features such as the mouth, nose, eye are represented by the ups and downs in the rate of intensity change due to the detection of edges of the facial parts. This is represented by the M like representation of the key point values. The shape values and the texture values are found to be having likely features in this age group.

TABLEIII. FEATURE VALUES AS OBTAINED FROM IMAGE B IN IMAGE SET 1

Age Group 6-12 Data set 1				
Texture	**Color &Gradient**	**Key point**	**Orientation**	**Shape**
1.251317	31.52166	577	75.09146	1.388946
1.260133	47.61075	577	102.4161	1.364516
1.342743	19.36364	831	129.4852	1.374433
1.384489	38.04783	947	155.021	1.435179
1.387254	65.06106	944	172.3354	1.437297
1.373404		904	492	
1.315012		826	93.06316	
1.203388		198.1504	124.0409	
1.305871		440	151.1269	
1.420506		690	171.9226	
		868		
		855		
		1125		
		1127		
		1008		

TABLE IV FEATURE VALUES AS OBTAINED FROM IMAGE B IN IMAGE SET 2

6-12 Age group Data set 2				
Texture	**Color & Gradient**	**Key point**	**Orientation**	**Shape**
1.175368	39.88235	391	78.80662	1.344693
1.256444	56.34099	566	102.1167	1.427734
1.334673	36.8738	786	122.8	1.418978

1.378152	53.83629	891	143.6099	1.38528
1.294441	77.58414	785	162.511	1.360529
1.251068		605	276	
1.202722		501	100.176	
1.234285		184.8587	121.574	
1.333426		523	144.5809	
1.335321		788	166.5524	
		1135		
		1074		
		932		
		797		
		715		

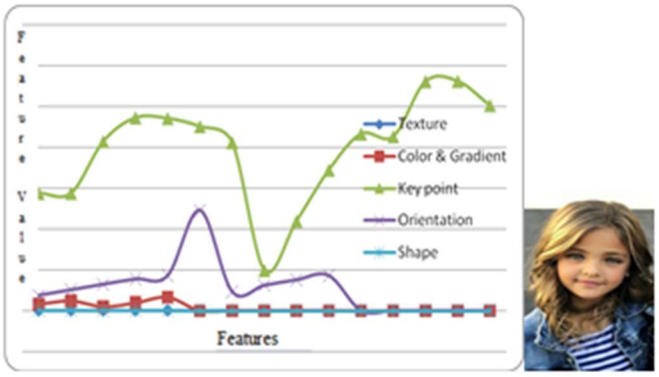


Figure 6 Graphical representation of feature values of Image B in image set 1

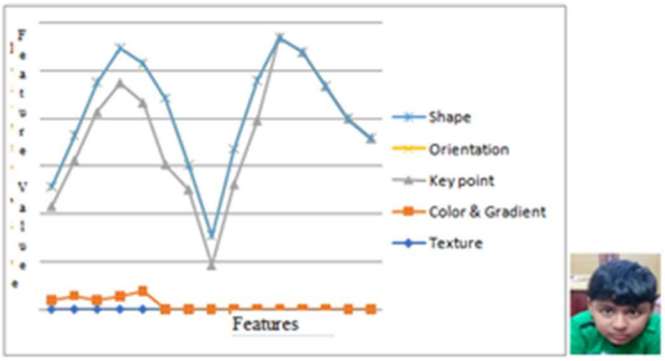


Figure 7 Graphical representation of feature values of Image B in image set 2

In the third age group(13-19 years), the face starts to appear matured. This results with fact that the facial features are well defined. The extra fat from overall face gets well toned. The cranio facial growth makes the bones properly defined. Hence the muscles are fixed well to the bone making the exact definition of the facial features. This was observed from the feature values as represented in the

Tables 5 and 6. The image C in dataset 1 and 2 were analyzed to retrieve the feature values. The graphical representation of the feature values as in Figures 8 and 9 show similar representations of the feature values. The two peak values of the shape features around the value of 1600-1800 extracted from the forehead and eye region and 1000-1200 from the mouth, chin and cheek region

were obtained as common average values for both the images. Similarly the key point value in the range of 1000-1200 and in the range of 600 were the max values with respect to the 15 key point values. The rate of change of the values remained common in both the figures for estimating the age group in the range 13-19 years which is the teen age group. In this teen age category, the texture showed changes in the forehead region and the facial parts such as the lip, eye, nose which became flatter due to uneven distribution of tone become evenly distributed. The change in the muscles portion is reflected in the change of texture on a child face. The outline of the face gets transformed into a continuous outline rather being uneven as in the previous age groups from 0-5 and 6-12 years of age. In the teen age group, the puffy fat of the face gets completely changed and the cheek bones make the change more visible.

TABLE V 45 FEATURE VALUES AS OBTAINED FROM IMAGE C IN IMAGE SET 1

13-19 Age Group Data set 1				
Texture	**Color & Gradient**	**Key point**	**Orientation**	**Shape**
1.081818	55.85534	281	103.5177	1.367549
1.118771	74.8494	332	131.8086	1.271546
1.268971	28.46893	588	158.5519	1.298724
1.341799	53.66379	794	176.9363	1.428592
1.441096	86.4874	877	193.2553	1.452234
1.416055		1160	816	
1.367198		1038	117.4019	
0.981542		208.1066	151.0892	
1.148731		177	173.1426	
1.499727		348	194.6116	
		591		
		622		
		1065		
		1212		
		1501		

TABLE 6 45 FEATURE VALUES AS OBTAINED FROM IMAGE C IN IMAGE SET 2

13-19 Age Group data Set 2				
Texture	**Color & Gradient**	**Key point**	**Orientation**	**Shape**
1.141155	52.83799	358	100.9753	1.37234
1.218383	69.12653	490	125.9142	1.242962

1.27753	29.85057	608	144.4209	1.288073
1.338847	49.9858	793	162.5479	1.374786
1.390665	80.02213	898	176.5703	1.449352
1.398289		991	591	
1.276691		1010	107.5886	
1.146647		191.7597	134.0379	
1.231141		348	158.1591	
1.474254		493	176.9216	
		497		
		581		
		898		
		1238		
		1340		

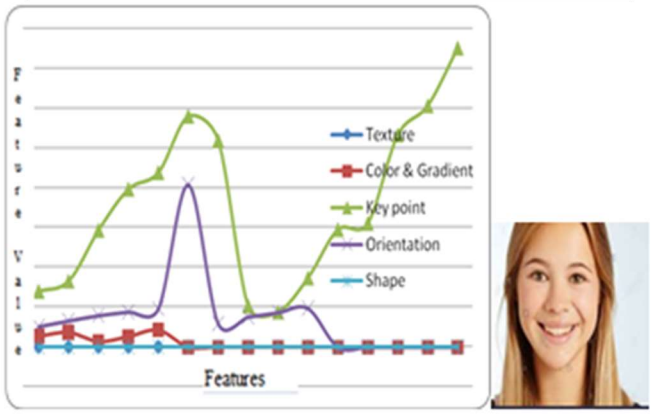


Figure 8 Graphical representation of feature values of Image C in image set 1

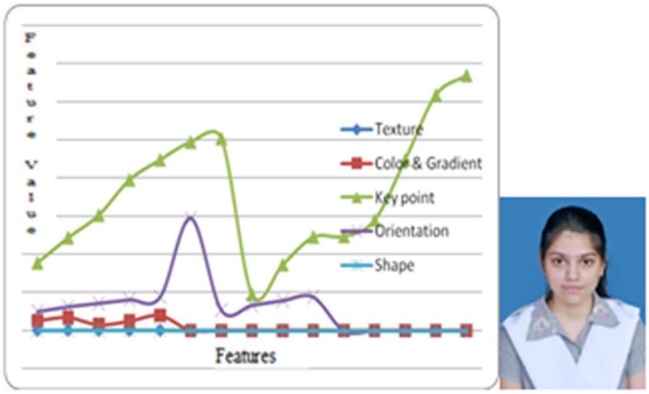


Figure 9 Graphical representation of feature values of Image C in image set 2

In the fourth age group, the face becomes properly matured. The enlargement of the face in equal proportion of muscles and tissues is observed in this age group. The Tables 7 and 8 show the feature values obtained from the images D from image set 1 and 2. The graphical visualization of

the feature value which were received is shown in the Figures 10 and 11. The observation from the graphical representation is that the orientation and the shape values remains almost the same in this age group. The key points as retrieved from both the images had differences in the fiducial points. The orientation also had differences but the average rate in the change of intensity values of the images provide the results of classification to be in the same age group.

The above representation which depicts the feature values obtained from two different images of the similar category age infers that the rate of change of the value of each feature with regard to shape, texture, orientation, key points, color and gradient remained the same. The classification was achieved by the estimators on considering the matching of the value with the actual values which were stored in the dataset. The percentage of relevance in each class group was identified. With the classified percentage value, the weightage was allocated. The class group which had the highest weightage was estimated as the age group of the input face image. The age group classification was obtained from the classification and the regression tree. This was a predictive modeling which mapped the input to the respective output through function approximation.

The classification was obtained by predicting a discrete class label for the input. The approximation task was done by the mapping function and the relevance of the input was considered and the output was defined according to the input. The classification was possible in one or more classes and the weightage was given as per the highly related value. The class label which had the highest weightage as compared to the classified classes was considered and the prediction was made accordingly. The classification had the internal nodes which were the attributes and the outcome of the test were the branches. Each leaf was the class label.

Every node was evaluated by setting up a threshold outcome. The process was repeated on each derivative in a recursive manner. The matching was calculated at every level of the deep network by the following equations. The entropy and the gini are the measures used to estimate the relevance at each given impurity of the node. The node which had several classes as related classes was found to be impure and the node which had a single node as relevant seemed to be the pure class. The entropy and the gini were calculated by Equations (1) and (2) respectively.

$$Entropy = \sum_{i=1}^{n} -p(C_i) log_2(p(C_i)) \quad (1)$$

$$Gini = 1 - \sum_{i=1}^{n} p^2 (C_i) \quad (2)$$

Where p(Ci) is the probability or the percentage of each class C. The estimation of the age was done at a better level by comparing the results with the reference papers.

The reference papers considered the estimation of the age by using different methodologies as given in Table7. As per the reference papers a less number of the factors were considered and the age groups classified were also less. The accuracy of ratio in the number of age groups classified was also observed to be less. In the proposed method, the factors considered for classification were increased thereby increasing the count of age class in considering age. The table shows the obtained accuracy from a minimum of 50% to a maximum of 84%. In the proposed method, the accuracy is increased to 89% by making a progress in the accuracy level.

TABLE 7 EXISTING FINDINGS AS PER LITERATURE SURVEY

Paper	Factors	Methodology	Accuracy	MAE
Age estimation from images: challenging problem for audience measurement systems-Vladimir khryaschev, Alexander Ganin,Olgastephanova, Anton Labedev, Yaroslavl state university	Genetic , lifestyle expression and environment	i) adaptive feature extraction(LBP) ii) support vector machine classification Database:FG-NET,MORPH	84%	<7
Estimating the age of human face in image processing using mat lab- Aditi Sengupta,PiyasmondelIJECS, 2015	Texture	Preprocessing,thresholding,segmentation,edgedetection,medianfiltering,canny edge detection(optimal edge detection)	80%	NA
A hierarchical framework for facial age estimation- YuyUliang ,Xianmai Wang, LiZhang, Zhiliang wang, 2014	appearance features, (fore head, eye corner, face cheek, 68 facial land marks), Wrinkle feature(wrinkle density), shape ratio feature	ULBP (Uniform local binary pattern), Wrinkle density (WD), LOPO testing strategy	85%	4.97
Age-Invariant Face Recognition Unsang Park, Member, IEEE, Yiying Tong, Member, IEEE, and Anil K. Jain, Fellow, IEEE, 2010	Shape,texture	PCA,AAM Database:FG-NET,MORPH,BROWN	50-60%	NA
Face Verification Across Age Progression, Chellappa, Ramanathan, 2006	Texture	Bayesian classification,PCA	50-70%	8.5

The Mean Absolute Error is calculated from the Sum of the Absolute Error(SAE). The equation used to calculate the SAE is given by Equation (3)

$$SAE = \sum_{i=1}^{n} |x_i - x_t| \quad (3)$$

Where the range of I value is from 1 to n and t is the true value. To avoid a negative value output, the mod operation is used. When multiple sets of images are considered, the process is repeated with the summation of all the absolute errors. The Mean Absolute Error (MAE) is computed from the sum of the SAE divided by the number of sets considered. This is given by the Equation (4),

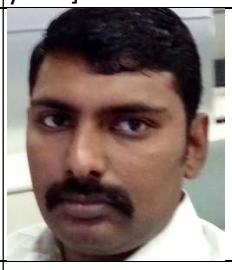
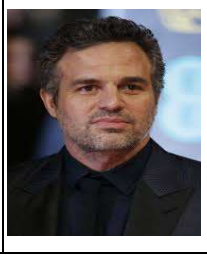
$$MAE = (\sum_{i=1}^{n} |x_i - x_t| \, /n \quad (4)$$

where I value ranges from 1 to n and t is the test value. To obtain an accurate value, the rounding off the result is done.

The MAE of the input images was measured from the system and the estimation was tested for the accuracy rate. The MAE was obtained as 6.732 after comparing the results rate with the results obtained from the estimation of the images. The obtained results are shown in Table.26. The obtained results and the count of images considered for training and number of images analyzed for testing were consolidated. The obtained result expressed the testing rate and improvement in accuracy of using 1000 images in training. From the testing set of images image set, eighty eight percent of images were classified with high perfection. The analysis provided the rate of accuracy of 89.5%. The results were interpreted in the form of a confusion matrix. The confusion matrix was easy for observation as the results are displayed in the form of yes or no. The yes is when there is correct match in the classification and no when there is a wrong matching found in classification. The process of estimating age with inclusion of local features has provided the age with almost approximation. The degree of angle obtained from the coordinate position of eye point and mouth portion is used for the process of estimating the age of the person. The result obtained from proposed model has rendered better result on comparison with the consideration of angle value alone. The comparison is as shown in Table. 26.

The Figure 29 shows the accuracy level obtained by comparing 1000 images in the training set. The accuracy was obtained as 92.7%. On comparing 500 images in the testing proved 87.2% accuracy as depicted in Figure 30. On the whole of 1500 images, the estimation rate was achieved with an accuracy of 89.5%. This overall accuracy rate is shown through the Figure 29. which explains the accuracy rate overall as well as individually for testing and training images. The Table 26, discusses the results of images where accurate results were obtained. In the first age group retrieved through output O1, the age of the baby image was of 1 year old and the classified output obtained was in the same age group. In the second age group, the child face belonged to the age 9 and the classified age group was obtained as output O2. In the third age group, the image of person belonging to 15 years was classified in the age group O3 as an exact match. In the image of person belonging to age 23 the classification was in the age group O4. In the image having the persons age to be 26 was classified to the output O5. In the image of person of age 33, the classified age was O6. The person belonging to age 37 was classified to age group O7.

TABLE 8 ACCURATE RESULTS OBTAINED IN ESTIMATION OF AGE

		
Actual age:1	Actual age:9	Actual age:15
Estimated age group O1[0-5 years]	Estimated age group O2[6-12 years]	Estimated age group O3[13-19 years]
		
Actual age:23	Actual age:26	Actual age:33
Estimated age group O4[20-24 years]	Estimated age group O5[25–29 years]	Estimated age group O6[30–34 years]
		

Actual age:37	Actual age:42	Actual age:46
Estimated age group O7[35-39 years]	Estimated age group O8[40-44 years]	Estimated age group O9[45-49 years]
		
Actual age:53	Actual age:58	Actual age:66
Estimated age group O10[50-54 years]	Estimated age group O11[55-59 years]	Estimated age group O12[60 above years]

The person belonging to age group 42 was classified to the age group O8. The person belonging to age 46 was classified in the age group of O9. The person belonging to age group 53 was classified to the age group O10. The person belonging to age 58 was classified to age group O11. The person belonging to age 66 was classified to age group O12. All the images which had the clear visibility of the facial features were classified in the proper age groups.

From the obtained results with the image set, the accuracy was measured for the images as shown in Figure 10. The accuracy rate was measured with the number of perfect matches obtained. On considering the number of images in each category, the ratio of images that were found to match with the actual age of the person were identified. From the observed results it was found that maximum rate of matching was obtained in the age group 60 and above. In this age the shape and the texture details were clearly visible and so the classification was found to be more accurate. The next maximal matching of the age was found in the age group 55 to 59 years and 0 to 5 years. In both these age categories the shape was well defined and less violation of the fiducial values was observed which provided a better accuracy in these age groups. The next better accuracy rate was found in the age category of twenty to 24 years and fortyfive to 49 years. The next better accuracy was observed in the age groups 6 to 12 years and 35 to 44 years. The rate of accuracy in these age groups was better due to the fiducial values and the shape features. The better accuracy rate was achieved in the age group fifty to 54 years of age. The improved rate of accuracy is achieved in the age group thirty to 34 years. In this age, the beginning of signs of aging occurs and the delay in aging was observed only in a few persons. Due to this reason there was only 88 percent accuracy available in this age group. The less percentage of accuracy was found in the age group of teen age and twenty five to 29 age group. The early matured looking faces in the teen age group is one reason and the early signs of aging seen in twenty five to 29 age group is another reason for this variation. The age estimation accuracy matrix in Table 9 explains the details. The Figure 11 and Figure 12 explain the accuracy of the images in the training category and the testing category. The overall accuracy rate is depicted in the Figure 13.

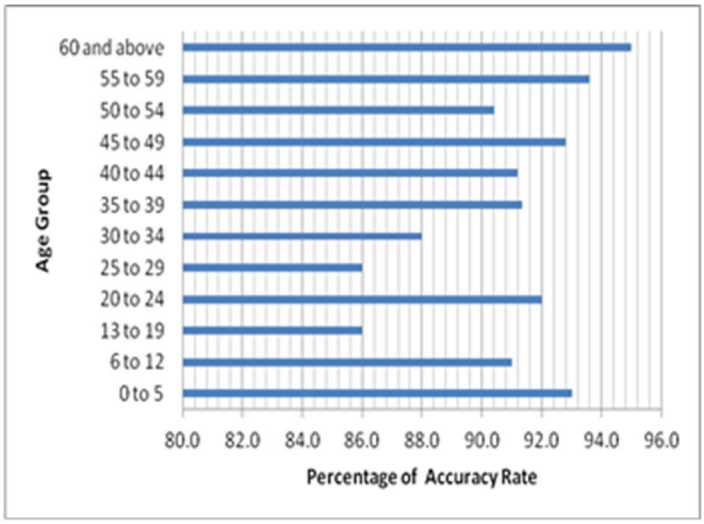


Figure 10. Accuracy Rate and age Group Considered

TABLE 9 AGE ESTIMATION ACCURACY MATRIX

Image set	Number of Images	Confusion matrix		Accuracy
		Correct	*Wrong*	
Training Set	1000	925	75	92.5%
Testing Set	500	436	64	87.2%
Total	1500	1361	139	89.5%

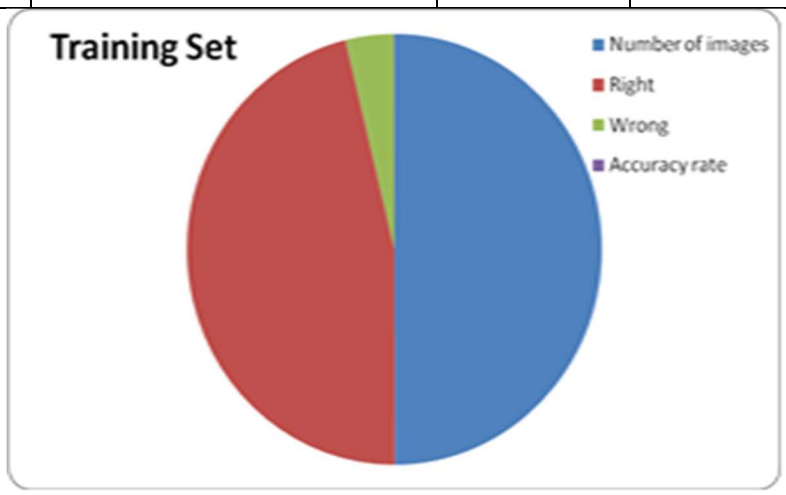


Figure 11 Accuracy achieved with training set images

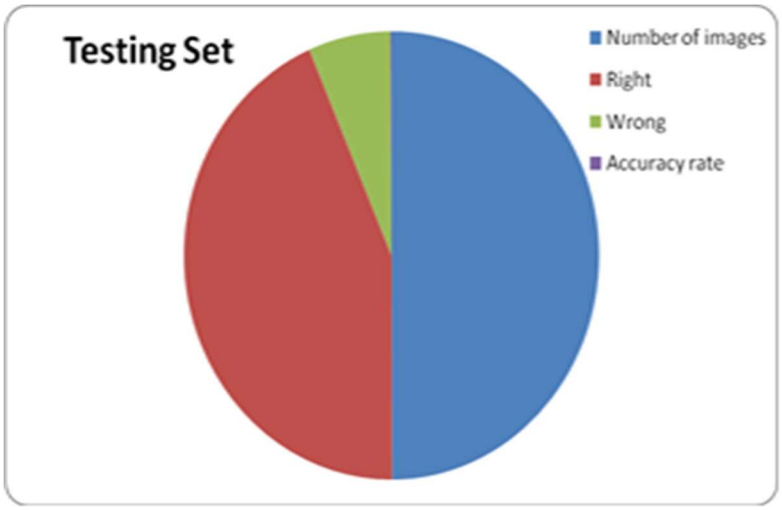


Figure 12 Accuracy achieved with Testing set images

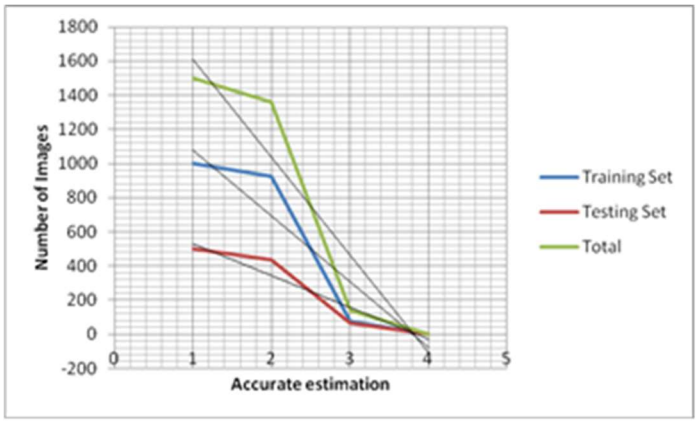


Figure 13 Overall accuracy rate

The classification results depicted in the initial three rows provides nearly uniform values. Whereas the values in the bottom rows have variation in values. The age was classified with improved accuracy. The number of age groups was enlarged and more features were included for classification. This made the proposed method trustworthy. The performance of the system was calculated with respect to the results obtained from the training phase. The conjugate scale back propagation methodology regulated the values of gradient level in the order of decreasing value. In each cycle of operation, the size of the step was revised. The conjugate gradient direction was utilized to identify the step size. With the result in finding the direction the size of step value was calculated. The training of network was done with the derivatives of the values, input value and the function used for transfer. By aid of approximation of quadratic values, the neighborhood error was reduced. Using the mechanism of scaling factor and the way of reducing the critical points, the reduction in error was achieved. The values obtained from training set is represented in Figure 14. The number of passes over the training set were given by the epochs. The epochs were plotted as shown in Figure 15. The ROC curve which had the receiver operator characteristics showed the true and false identity of the age of the input image. The region of coverage under the curve showed

maximum coverage of the positive results. Hence the system proved to have good hit rate ratio in the field of classification. The confusion matrix which was the grid of all labels of the classifier showed the performance of the classifier. It evaluated whether the system was capable of classifying the images in an accurate manner. The epoch and the classification of the age showed that the failed values were less in the estimation process. The prediction of the wrong classifier or the labels which provided invalid classification could be learnt from the confusion matrix.

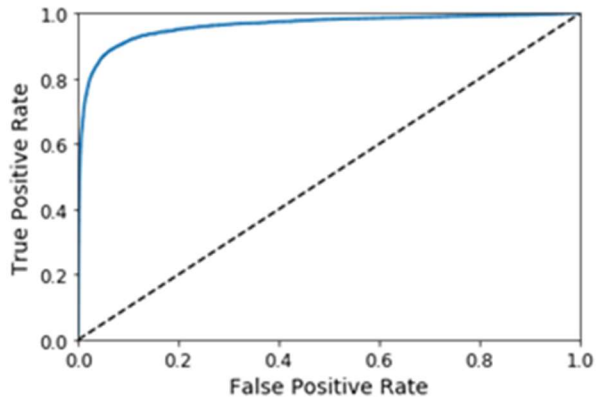


Figure 14 ROC of the classifier

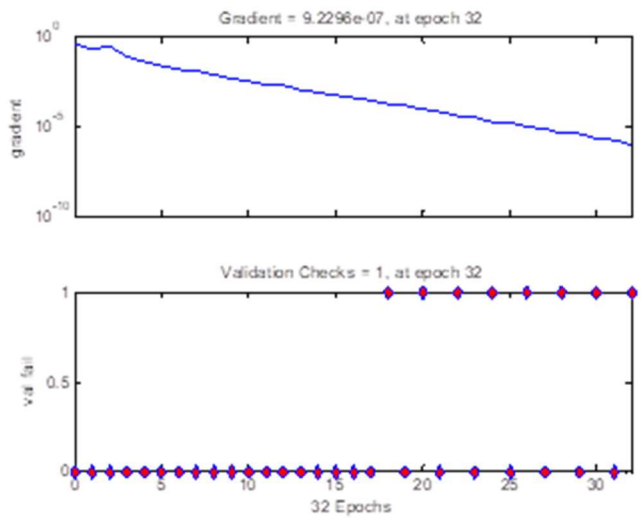


Figure 15 Training of the system

The performance of the system was checked using cross entropy and confusion matrices. Minimal confusion was found in the way of categorizing age. The obtained results and their analysis provided the inference that the images were classified by angular classification method to speed up the process of estimation. The delay in the evaluation of matching of values with all the class labels was reduced by finding the highly related angular set values to be compared. In cases, where the matching was found to be least, the analysis of the values of the nearby class groups was done to evaluate the system. The matching of the angular features when failed provided less matching in the class groups from 1 to 12. In these cases, the matching label with high relativity of match was obtained from the nearby class groups. Hence the ultimate value which was extracted from

the classifier was probably the accurate age of the input image. The mismatch was possible in case of the images where there was less focus of the whole face of the person. If the face does not compose the full features such as the eyes, nose, mouth, cheeks and forehead region of the facial parts, the extraction of features cannot provide the detailing of the face. The cropping of face from the input image did not provide the successful information. In case of spectacles, the eye details were not available and the estimation could not provide an accurate result. In case of images with multiple faces, manual segregation of the required input was done. But when the image availed was with all the facial features, the estimation could be done in a more accurate manner. This was possible because the algorithm retrieved the face from the image and resizing along with rotation made the image exactly suitable for the analysis purpose.

V. DATABASE USED

The dataset used in this research is own dataset and CACD. In the own dataset, images of 200 person with various pose and in different age were collected. The Cross Age Celebrity Dataset(CACD) consisted of 163,446 images of person who are celebrities. The images were obtained through way of search engines. The key used for searching was the year and name of the celebrity person. The age could be availed by calculating the photo taken year and the year of birth of celebrity. The downloaded dataset had two MATLAB structures one of the celebrity data and the other of the celebrity image data. The celebrity data had 2000 celebrity images. The name, identity, birth, rank of the celebrity and the identity of the celebrity was available in the LFW dataset and were all provided. The celebrity image data contained the information of the face images such as the age, identity, year, name and feature details. In the research work by Nguyen (2014), the Local Binary Pattern was used for identifying the features and matching the pattern stored in the training set. Similarly the pattern matching was also searched which aided in the estimation of age in the presence of cosmetic effects. The own database was used to obtain images of several regions due to unavailability of image of a person in different age, illumination and pose. These information were available from the own image dataset. In the CACD dataset, the available celebrity images were tested with the algorithm for makeup effects too. The dataset had images with varying pose, with or without makeup effects. These databases play a wide role in any algorithm by enhancing the accuracy of the algorithm with the proper choice of the data so that the data has a scope in providing valid inference from the obtained result.

VI. CONCLUSION

Face recognition is a smart technology of biometric with improved potential in development. It has versatile application in the a plethora of domains such as social security, banking, public welfare, crime and investigation, medical treatments. The proposed method provided improved accuracy in age estimation. This improvement is with rendering age estimation in twelve different age groups. The progress in the training set obtained promising results. The estimation of age was done on images of the intra age person and inter age person. On comparison of the retrieved results, higher accuracy achieved in estimating the age of the person. The testing

was done on images under varying conditions of brightness. The results obtained have inferred the improvement in accuracy. The challenges obtained in experimenting results by considering either of the feature value such as texture or shape. The regulation is done by integrating both the parameters. The neural network feed forward methodology has provided the better results in grouping the age of the person under different category of age slot. Using the process of normalization, the removal of eminent values in predicting the age has been controlled so that the major age challenging factor has been resolved. The scaled conjugate gradient method has provided better results in estimation of age category and softmax method has rendered the classification in approximate age category. The inclusion of fractal codes in eight different aspects has enhanced the accuracy level. The major drawbacks such as brightness, pose, size have been resolved. The width of age group has been narrowed down with increasing age classes.

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