

Motif Patterns Based Age Group Classification on LDP

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ABSTRACT: Facial expression recognition is a research issue. An Age classification is one of a facial expression recognition system and it is based on facial representation from human face images. In this paper we are using classification system for gray-scale facial images. The present paper proposes procedure for extracting the local texture features on a facial image. In this paper, the Motif Patterns are used for extracting the texture features which are identified on a Local Directional Pattern (LDP) values. The present paper uses seven (7) different motif patterns and the patterns starting from the top left corner pixel and scan is should be related to the incremental order. Based on the patterns count the facial image is classified into one of the five categories. i.e. Child (0 to 10years), Young (11 to 25 years), Adult (26-40), senior (41 to 60 years), and Senior Adult Age (>60 years). It shows high rate of classification when compare with the other existing methods.

KEYWORDS: Motif Pattern, Local Directional Pattern, Age group Classification, Facial Image, Human Face.

I. INTRODUCTION

Facial recognition and classification of human faces are used in various fields in Human Computer Interaction, Machine Learning, Computer vision, Artificial Intelligence, Forensic Sciences etc. It is mostly used in security systems such as medical imaging work in medical applications. Biometrics, fingerprints and eye iris recognition system[1]. Facial expressions finds the problems on the representation and categorization of age group classification. There are many challenges in the estimation of the human based on the facial image of the human. The important point for age classification is that the feature of the human face changes with respect to the time.

Jabid et al. [2] presented an appearance-based texture descriptor, local directional pattern (LDP), to represent classification. A LDP feature is obtained by computing the edge response values in all eight directions at each pixel position of LBP and generating a code from the relative strength magnitude. The LDP features are computed from the edge response values which encode the local texture of facial appearance. Higashi et al. [3] presented a hybrid method which combines Gabor filters and LDP for age and gender classification. The facial features extracted by their method are robust to noise and illumination variations.

The main changes observed on the faces are identify distinctive features on the face, such as the contour of the eyes, nose, hair, chin and , formation of wrinkles in the fore-head. The first real human age estimation theory was proposed in [4], [5]. Wen-bing hong, zcheng ping lee and chun wen-chen at al[6], consider four age bunches for arrangement, which includes children, adolescent grown-up, moderately grown up and old grownups. Age of the person by using face of the person [7, 8, 9, 10, 11], but it is only recently that efforts have been made to address problems like age estimation, age transformation, etc.

Geng et al. [12] presented the AGES (Aging Pattern Subspace) method for age estimation. The basic idea is to model the aging pattern, which is defined as a sequence of images sorted in time order, by constructing a representative subspace. Age of the person being tested is determined by the projection in the subspace that can best reconstruct the face image [13]. More recently, Yuille Hallinan, and Cohen [14][15] used deformable templates to detect features of faces, in particular, eyes and lips. External energy functions of valley, peak, edge, and image intensity are defined. In past few decades so many approaches are available for estimation of age of the person by using face of the person proposed by B. Pittenger(1975), B.Pittenger(1979), Mark(1983), Mark(1980), Burt(1995), but it is only recently that

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efforts have been made to address problems like age estimation, age transformation, etc. from a computational point of view [Kwow(1995), Y Wu (1995), Lanitis(2004),Lantisis(2002),Ramanathan(2006),Solmoon(2006),Suo(2007), Geng(2007), Ramanathan(2006) and Radial Basis Function (RBF) [Yadzi(2012)], Back Propagation Network [Mehdi(2009)-]. For improving the accuracy of the age estimation approaches, integrated approaches were introduced such as Active Appearance Model (AAM) and Support Vector Machine [Lu (2009), Liu(2012)]. Dr VVK (2014) proposed a method called Topological Texture Features (TTF) to classifies the human age into five categories i.e. 0 to 12years, 13 to 25 years, 26 to 45years, 46 to 60years, and above 60 years. The proposed method is applied on three databases such that FgNET, Google and Scanned Images and achieved 96.5%. Kumar (2014) proposed a method called ORLVPLCM of TN-LBP. This method is also applied in three databases such as FgNET, Morph Google.

In this proposed approach reduce the time consuming for classification system. The main of the proposed method is that for developing a system for classification system. If correct features are extracted then no standard classification algorithm is used for classifying the human age group of facial images. For this, the present paper propose a methodfor classification of age group with motif patterns on LDP. The proposed method is more robust and less computational cost method for age group estimation.

The present paper is organized as follows. The proposed methodology is described in section 2, section 3 deals with results and discussions and comparing with other existing methods are discussed in section 4. The conclusions of the present approach are given in section 5

II. PROPOSED METHOD

The proposed method of Age group classification can be represented by the block diagram in figure 1. The Age group classification system mainly consists of 5 steps. In the first step, considers the facial image and crop the facial gray level image. In the second step, convert the RGB facial image into Gray level image using Weighted RGB conversion method. Generate the Local Directional Pattern (LDP) matrix from gray level image in the third step. In fourth step, Identify the seven categories of motif patterns in LDP matrix. Based on the frequency occurrence of motif patterns derive a classification algorithm for classifying the facial image into one of the five categories i.e. Child (0 to 10 years), Young (11 to 25 years), Young Adult (26-40), senior (41to 60 years) and Senior adult Age (>60 years) is discussed in step 5.

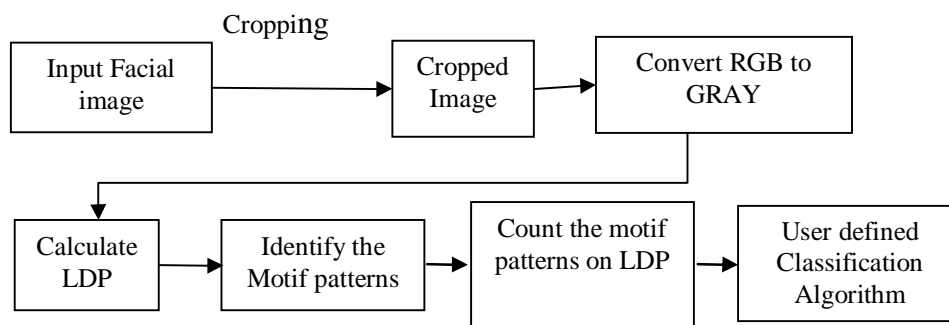


Figure 1: Block Diagram of Age Group Classification system

2.1 Cropping the facial image:

Generally, the input facial image consists like hair, neck and other unwanted information. To remove the unwanted information from the facial image cropping is applied. For correction classification motif patterns are identified on facial skin area only. The proposed method cropping is identifying the facial skin edges. It is based on the skin area of the human face. So to remove unwanted area from the facial image cropping is necessary for effective results. Then convert the cropped facial image into grayscale image. The input image and resultant cropped image is shown in figure 2.

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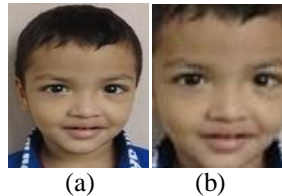


Figure 2: Image Cropping of facial image. a) Original image b) cropped image

2.2 Convert RGB to Gray level image:

To extract the shape features from the facial image, first need to convert the input RGB color image into gray level image. The proposed method utilizes the Weighted RGB conversion method. Generally, the RGB image is composed by 3 dominated colors i.e. Red (R), Green (G) and Blue (B). In Weighted RGB conversion process, different weights are assigned to each color component and these three components are utilized for converting the color image into grey level image the conversion process is represented by using the equation (1). The resultant image is shown in figure 3.

$$G(x, y) = 0.3 * R(x, y) + 0.59 * G(x, y) + 0.11 * B(x, y) \quad (1)$$

Where G is gray value at location (x,y) and R G B are the color component values and x,y are the pixel positions.



Figure 3: resultant grey level image

2.3 Generating LDP matrix of gray level facial image:

The LDP is mainly based on Local Binary pattern (LBP). The LDP approach is suitable for age group classification. It is consider as the edge response values in all different directions instead of surrounding neighboring pixel intensities like LBP. In the presence the edge responses are more illumination changes and noise in various schemes of facial image. The LDP generates eight-bit binary code and it is assigned to each 3x3 sub window of an input image. These patterns are calculated by their relative edge response value of each pixel. Figure. 4 shows an original image and the corresponding image with illumination changes. After that illumination s change, 5th LBP bit changed from 1 to 0, The LBP pattern changed from uniform to a non-uniform code. These are more stable than gray value.

26	35	85
10	50	53
48	32	63

(a)

LBP = 00111000
LDP = 00010011

(b)

26	35	85
10	50	49
48	32	5

(c)

LBP=00101000
LDP=00010011

(d)

Figure.4. Calculating the LDP and LBP values in two different situations (a) Original Image (b) LBP LDP values of original image (c) Image with Noise (d) the corresponding LBP and LDP values.

The LDP approach is more suitable for age group classification system why because most of the facial images have illumination changes. Even though, illumination changes occurs in facial images correct age group is estimation is required, for effective and efficient age group classification system LDP approach is most suitable.

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2.4 Identifying the Motif patterns:

The present paper identifies seven categories of Motif patterns on LDP facial image. The present define six types of motifs patterns for facial image analysis. The motif patterns are defined over a 2x2 sub window, each depicting a distinct sequence of pixels starting from the top left corner as shown in figure 5 for age group classification. The six motifs are defined over a 2x2 grid, each depicting a distinct sequence of pixels starting from the top left corner as shown in figure 5. In figure 5, the six motifs are denoted as Z, N, U, C, Gamma and Alpha respectively. Each grid is scanned from top-left and those pixels formed a motif pattern. Reverse direction of motifs are also considered. So, a total of 12 patterns are considered for facial image analysis. The first top-left six motifs of a 2x2 grid are shown in figure 5.

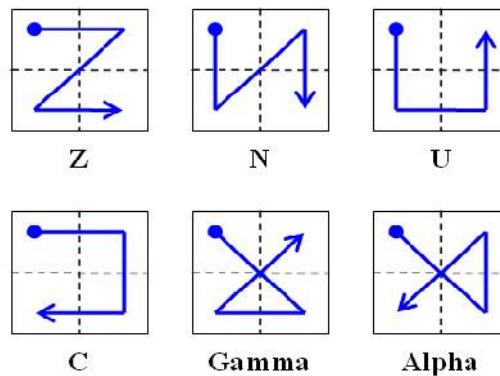
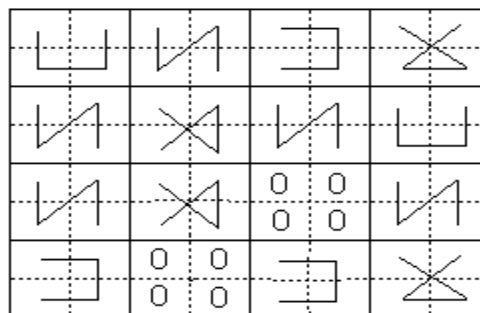


Figure 5: Six motifs patterns over a 2x2 grid

Once the motifs patterns are selected, the original image is divided into 2x2 grids. Each of the 2x2 grids contains four pixel values i.e., P_1, P_2, P_3 and P_4 . If the four pixel values of a 2x2 grid are distinct apply a suitable motif as in Figure 5 otherwise 2x2 grid will be zero. The working mechanism of motif detection for the proposed method is illustrated in Figure 6.

202	53	149	54	255	254	253	124
78	55	84	52	57	190	186	250
129	68	35	128	160	38	36	255
183	29	140	68	54	31	144	182
176	52	47	43	47	53	145	156
145	38	61	45	47	62	140	176
150	186	188	188	220	211	87	167
99	196	189	174	155	159	151	106

(a)



(b)

Figure 6: illustration of the motif pattern detection a) 8x8 LDP facial image b) motifs pattern matrix

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Once the motifs are identified, the present paper evaluates the frequency occurrences of all 6 different patterns as shown in Figure 6 with different orientations. To have a precise and accurate age group classification, the present study considered sum of the frequencies of occurrences of all six different motif patterns on each 2x2 block.

III. RESULTS AND DISCUSSIONS

To test the proposed method, among numerous available face databases around the globe four of them are considered which incorporates huge set of images. The MORPH Database is made out of 17,000 images of about 4,000 people, between 15-68 age of males and females. The second considered database is FG-NET (Face and Gesture Recognition Research Network) ageing database. FG-NET database is made out of 1002 images of more than 80 people, from the ages of 0 - 69 years and 500 images of 50 people from Google database. 600 images gathered from the scanned photos in the age range from 0 to 80. This leads a sum of 19102 example facial images. In the proposed system the test images age group estimate into five age groups of Child (0 to 10 years), Young (11 to 25 years), Adult (26-40), Senior (41 to 60 years) and Senior adult Age (>60 years). Some of the images from different data bases are shown in Figure 7. The frequency occurrence of the motif pattern in each category is listed out in tables 1, 2, 3, 4 and 5. The values in the tables are frequency occurrences of motif structural patterns of facial image whose size is 300x300. The classification graph of the proposed method is shown in figure 8. Based on values in tables, an algorithm 1 is designed by the present research to classify the facial image into one of the category of Child (0 to 10 years), Young (11 to 25 years), Adult (26-40), Senior (41 to 60 years) and Senior Adult Age (>60 years) irrespective of the size.



Figure7: Sample facial images of various age groups

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Table 1: frequency occurrences of Motif patterns of Child group (0 to 10 years) images

sno	Image Name	1	2	3	4	5	6	Total
1	001A02	256	1025	843	2017	1752	3548	9441
2	001A05	234	1125	861	2083	1852	3648	9803
3	001A08	235	1268	593	3025	1864	2658	9643
4	001A10	568	1024	831	2036	1956	3622	10037
5	002A03	652	1035	877	2586	1645	3596	10391
6	002A04	845	968	886	2546	2035	3523	10803
7	002A07	853	1248	864	3281	2055	3041	11342
8	008A06	951	1428	879	2684	2334	3037	11313
9	009A00	1245	1125	884	2710	2016	2323	10303
10	010A01	1356	1175	822	2468	1995	2342	10158
11	gi008	1358	1123	882	2568	1955	3256	11142
12	gi003	1793	1259	731	2485	1513	3005	10786
13	gi002	1856	1248	675	2648	1512	3110	11049
14	gi009	1945	1256	659	2659	1507	3001	11027
15	gi007	2358	1313	943	2031	1258	3557	11460
16	gi005	2485	1237	634	2485	1500	3064	11405
17	si001	2546	1423	958	2195	1238	2985	11345
18	si003	2566	1235	602	2784	169	3129	10485
19	si005	3125	1399	853	2015	2*951	3596	10988
20	si009	3256	1225	920	2013	2468	265	10147

Table 2: frequency occurrences of Motif patterns of Young group (11-25 years) images

sno	Image Name	1	2	3	4	5	6	Total
1	009A13	2654	1410	853	2061	2230	3023	12231
2	001A14	3426	1338	458	2397	1785	3485	12889
3	002A15	2865	1351	685	3025	1762	2956	12644
4	001A16	2534	1414	687	2654	2016	3015	12320
5	001A18	3125	1326	695	2486	1856	3281	12769
6	011A17	1569	1225	753	2315	2685	3936	12483
7	003A25	2354	1123	755	3011	1358	3852	12453
8	012A21	2678	1063	766	3015	1648	3685	12855
9	012A23	1768	1165	845	2558	2974	3026	12336
10	gi016	1785	1166	850	2995	2200	3254	12250
11	gi020	2012	2536	850	2015	1503	3654	12570
12	gi013	2646	1298	861	2573	1684	3669	12731
13	gi018	1689	1135	870	2454	2756	3582	12486
14	gi020	3125	1229	911	2110	2185	3025	12585
15	gi022	1684	1133	930	2334	3015	3259	12355
16	gi025	1964	1288	942	2008	2935	3568	12705
17	gi021	2158	1199	950	2001	2954	3152	12414
18	gi012	1352	1446	953	3202	2556	3125	12634
19	si015	2569	1345	972	2563	1349	3611	12409
20	si017	2567	987	995	2546	2015	3125	12235

Table 3: frequency occurrences of Motif patterns of Adult age group (26-45 years) images

sno	Image Name	1	2	3	4	5	6	Total
1	012A32	2964	1364	956	3015	1648	2963	12910
2	013A34	3495	1069	733	2648	1684	3658	13287
3	018A34	2354	1124	844	3021	1954	3954	13251
4	019A37	3025	1266	965	2006	2648	3512	13422
5	020A36	2764	1276	842	3152	1598	3448	13080
6	021A39	4145	1279	861	2354	1523	3006	13168
7	025A34	3025	1325	795	2856	1954	3578	13533
8	001A43a	3645	1327	895	2684	1762	3258	13571
9	005A45	3785	1339	689	2793	1685	3659	13950
10	006A42	3325	1345	659	3105	1954	2569	12957
11	gi026	3642	1364	817	2584	1648	3644	13699
12	gi028	4516	1368	926	2145	1259	3622	13836
13	gi040	3415	1369	934	2485	1257	3699	13159

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14	gi042	2531	1419	951	3064	2001	3025	12991
15	gi045	2486	1429	854	3025	2256	3026	13076
16	si039	2546	1455	830	2017	2541	3592	12981
17	si045	4265	1456	826	1945	2066	3047	13605
18	si038	2463	1556	815	3256	2653	3015	13758
19	si041	3265	1664	953	2586	2648	2351	13467
20	si035	1458	1664	862	3256	2856	3048	13144

Table 4: frequency occurrences of Motif patterns of Senior Aged group (41-60 years) images

sno	Image Name	1	2	3	4	5	6	Total
1	003A51	1462	1148	958	2448	2246	3269	11531
2	003A57	2558	1068	988	2358	1684	3485	12141
3	003A58	1683	1122	853	2115	3152	3258	12183
4	003A59	1753	1143	953	2331	2118	3251	11549
5	003A60	1853	1146	952	2665	2225	3258	12099
6	004A53	1623	1147	959	2699	2336	3269	12033
7	006A54	1532	1149	957	2688	2235	3267	11828
8	006A55	1957	1155	960	2488	2119	3268	11947
9	039A50	1359	1164	752	2148	2843	3658	11924
10	003A47	1523	1188	920	2166	3019	3257	12073
11	003A49	2301	1212	613	2758	1955	3025	11864
12	004A48	2485	1227	756	2874	1358	3120	11820
13	gi046	2640	1235	612	2685	1950	3059	12181
14	gi048	3201	1245	648	2358	1503	3067	12022
15	gi050	2456	1248	587	2651	1248	3648	11838
16	gi052	2564	1268	843	2658	1592	3011	11936
17	gi055	2354	1362	934	2345	1348	3622	11965
18	gi041	2654	1425	786	2185	2105	2987	12142
19	gi052	1856	1442	954	2133	2116	3256	11757
20	gi055	1963	1554	823	2015	2175	3025	11555

Table 5: frequency occurrences of Motif patterns of Senior Citizen group (> 60 years) images

sno	Image Name	1	2	3	4	5	6	Total
1	006A69	3654	1428	856	2658	2556	3029	14181
2	003A61	8456	953	776	2348	2035	3223	17791
3	004A53	956	997	825	2365	19320	3521	27984
4	004A62	6542	1027	833	2486	1559	3658	16105
5	004A63	3025	1228	922	2330	3215	3659	14379
6	005A61	5684	1259	529	3025	1966	3945	16408
7	006A61	3365	1320	820	2658	18426	3592	30181
8	006A67	3125	1335	768	2541	2648	3952	14369
9	004A64	3265	1345	860	2456	23485	3542	34953
10	004A61	5834	1356	928	2541	1358	3633	15650
11	gi066	6542	1359	729	2365	1340	3600	15935
12	gi068	2261	1365	862	2015	13485	3559	23547
13	gi065	2364	1376	758	20395	1956	2983	29832
14	gi062	2764	1384	685	3024	2854	3998	14709
15	gi065	4321	1423	831	2985	2044	3045	14649
16	si070	1526	1445	834	29442	2035	3025	38307
17	si068	4325	1478	826	2993	2034	3056	14712
18	si071	4225	1489	842	2994	2095	3059	14704
19	si269	231	3253	862	2018	16037	3553	25954
20	si066	3125	12426	875	2953	2665	3031	25075

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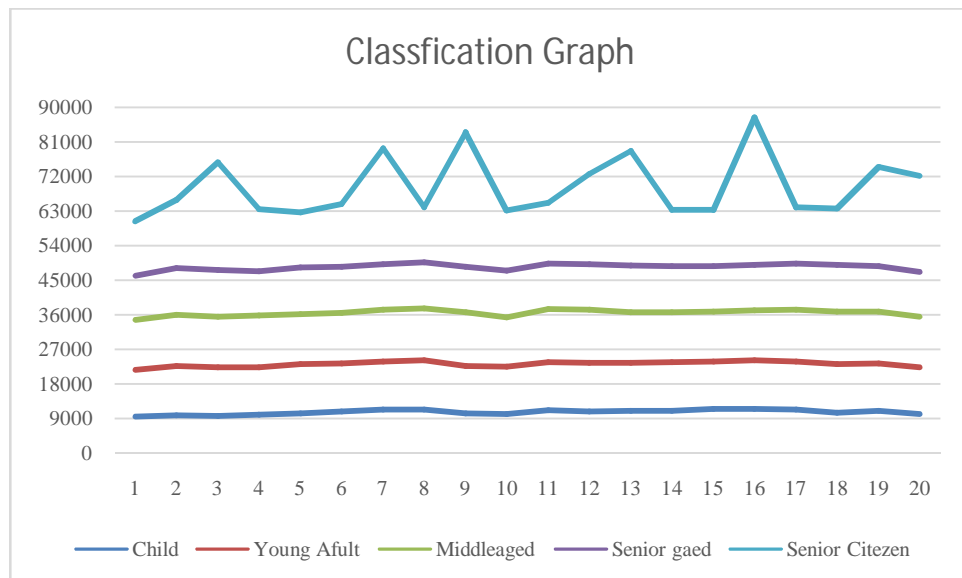


Figure 8: classification graph of the proposed method

Algorithm 1: Estimation of age group of a person using facial image with dimensions 300×300 based on occurrence of structural motif patterns.

Let FOM is the frequency occurrence of structural motif patterns

START

if FOM is lea than 11500 then

print“ Test image age group is Child age (0 to 10 years)”

else if FOM>11500 and FOM< 12200 then

print“ Test image age group is Senior age (46 to 60 years) “

else if FOM>= 12200 and FOM<12900 then

print“ Test image age group is Young age (11to 25 years) “

else if FOM> = 12900 and FOM<14000 then

print“ Test image age group is Middle aged group(26 to 45 years) “

else if FOM> = 14000 and FOM<39000 then

print“ Test image age group is Senior Adult age (>60 years) “

otherwise

print “ unknown Age group”

END

The frequency occurrences of motif patterns are dependent on the dimension of the facial image. To address this problem the present paper also derived another classification algorithm which is a ratio dependent with the original dimension of the images considered *i.e.*, 300×300 with the dimension of the test image R×C. If the value of the test image falls within the range of minimum to maximum occurrences of structural motif pattern of a particular group then test image age is estimated at that age group. The basic classification algorithm for estimating the age group of a person using the facial image based on occurrences of motif patterns is given in Algorithm 2. The algorithm2 is worked independent of the facial image dimension.

Algorithm 2: Estimation of age group of a person independent of the facial image dimension based on occurrence of structural motif patterns.

Let FOM is the frequency occurrence of structural motif patterns

START

if FOM is lea than $((R \times C) / 90000) * 11500$ then

print“ Test image age group is Child age (0 to 10 years)”

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else if FOM> ((RxC)/90000)*11500 and FOM< ((RxC)/90000)*12200 then
    print " Test image age group is Senior age (46 to 60 years) "
else if FOM>= ((RxC)/90000)*12200 and FOM<((RxC)/90000)*12900 then
    print " Test image age group is Young age (11 to 25 years) "
else if FOM>= ((RxC)/90000)*12900 and FOM<((RxC)/90000)*14000 then
    print " Test image age group is Middle aged group(26 to 45 years) "
else if FOM>= ((RxC)/90000)*14000 and FOM<((RxC)/90000)*39000 then
    print " Test image age group is Senior Adult age (>60 years) "
otherwise
    print " unknown Age group"
    
```

END

After developing the algorithm to find out the efficiency of the proposed method some facial images are considered as test images and identify structural patterns count using the proposed method. Based on the proposed age classification algorithm1, the age group of the test images is found. It is also checked whether they are correctly classified. The classification results of the proposed method are listed out in table 6. The overall efficiency of the proposed method is 96.18.

Table 5: percentage of Classification of age group classification system

Age group	Classification Rate Databases			
	Morph	Fg-Net	Google	Scanned
Child (0 to 12 Years)	96.64	95.43	96.65	96.62
Young Adult (13-25 years)	95.06	95.14	96.3	97.06
Middle aged(26 to 40 Years)	96.62	96.67	96.62	96.37
Senior Aged (41-60 years)	97.27	96.43	96.04	96.48
senior citizen (>60 years)	94.56	95.38	95.88	96.45

IV. COMPARISON WITH OTHER EXISTING METHODS

From the table 6 observe that the efficiency of the proposed method is good. To evaluate the efficiency of the proposed method is compared with other age classification techniques [13,15]. The method proposed by Pullela SVVSR Kumar et.al [2] classifies facial images into four age groups based on integrating the features derived from Grey Level Co-occurrence Matrix (GLCM) with a new structural approach derived from four distinct LBP's (4-DLBP) on a 3 x 3 image. In SICFRG model mainly contains 3 steps. In the first step reduce the size of the image to 25%. In second step fuzzy rules are applied on the reduced matrix and in the last step generate co-occurrence matrix and extract the features. Dr. V. Vijaya Kumar et.al proposed another method to classify the human age group into five categories based on Topological Texture Features (TTF) of the facial skin. The classification percentage of proposed method and other existing methods are listed in table 7. The graphical representation of the percentage mean classification rate for the proposed method and other existing methods are shown in figure 9.

Table 7: Classification rate results of the proposed method with other existing methods

Group Name	D-HV-LBP-GLCM Method [2]	RBF Neural Network Approach	SICFRG model[4]	TTF Model[5]	Proposed Method
Child	93.23%	89.67%	96.40%	97.50%	98.23%
Young age	92.50%	85.30%	96.50%	95.00%	98.07%
Young Adult	91.50%	88.72%	95.50%	97.50%	98.15%
Adult	92.41%	87.90%	95.09%	95.00%	97.69%
Senior Adult	93.50%	90.15%	98.78%	97.50%	97.95%

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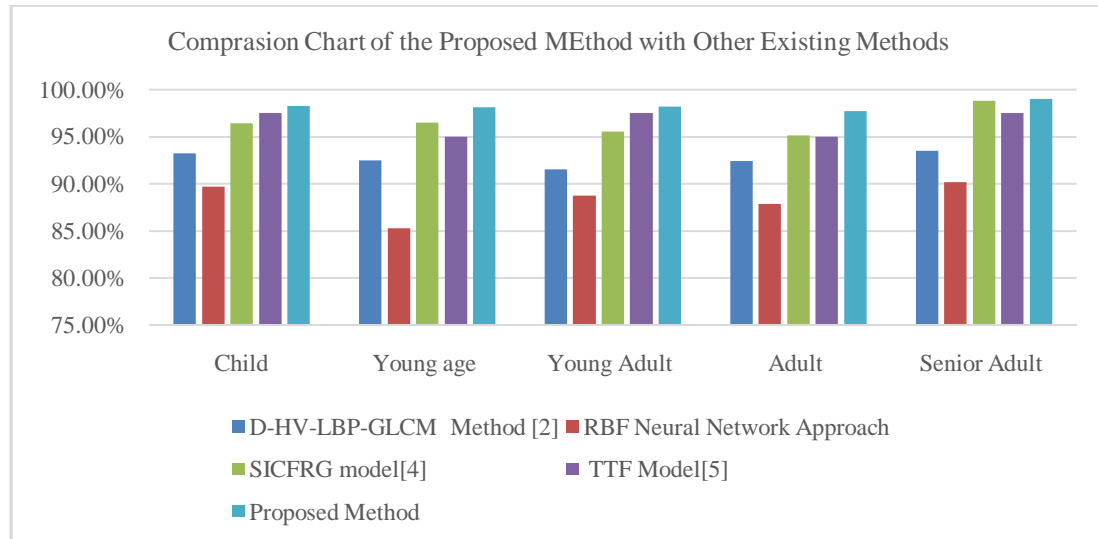


Figure 9: Classification chart of proposed method and other existing methods

V. CONCLUSION

The proposed method uses the advantages of the edge concept to identify the wrinkle on the face. The proposed method identifies the Motif Patterns are extracted on a Local Directional Pattern (LDP) The proposed method drastically reduced the computational time because of simply identifies the four distinct patterns on each 3×3 window. The proposed method utilizes the advantages of the edge concept to get more accurate results and reduce the amount of data to be processed that causes reducing the computational cost. The innovate of the proposed method is that no standard classification algorithm is used to classify the facial image into one five categories with high classification rate. The efficiency of the proposed method is highly compared to all other methods and no method has correctly classified the human age into five categories. The proposed method exhibits high average rate of classification when compared to the existing methods.

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