Pattern based Dimensionality Reduction Model for Age Classification

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ABSTRACT
The two most popular statistical methods used to measure the textural information of images are the Grey Level Co-occurrence Matrix (GLCM) and Texture Units (TU) approaches. The novelty of the present paper is, it combines TU and GLCM features by deriving a new model called "Pattern based Second order Compressed Binary (PSCB) image" to classify human age in to four groups. The proposed PSCB model reduces the given 5 x 5 grey level image into a 2 x 2 binary image, while preserving the significant features of the texture. The proposed method intelligently compressed a 5x5 window into a 2x2 window and derived TU on them. Thus the derived TU also represents a TU of a 5x5 window. The TU of the proposed PSCB model ranges from 0 to 15, thus it overcomes the previous disadvantages in evaluating TU's.

Keywords
GLCM features; Texture Unit; Pattern; compressed model;

1. INTRODUCTION
Aging has a significant impact on the appearance of a face [16]. Consequently, face identification or verification can be significantly affected by variations in appearance due to age [17]. Currently, the research related on age estimation using face images is more important than ever, because it has many applications, such as an internet access control, underage cigarette-vending machine use, age-based retrieval of face images, age prediction systems for finding lost children and face recognition robust to age progression. In addition, the estimated age of consumers who look at billboards is used in age specific target advertising as consumer preferences differ greatly by age. To maintain identification/verification performance in the presence of age variation, some researchers have attempted to address this issue classifying the subjects age [18][19]. Unfortunately, age classification itself is very challenging due to the anatomical changes in the cranio-facial region, the bony portion of the head and the overlying soft-tissue caused by the aging progress [20].

Kwon and Lobo (1999) used facial feature detection and wrinkle detection to classify age to the three age groups: babies, young adults and seniors. Ueki et al. (2006) presented a classifier based on two phases using LDA (Linear Discriminant Analysis) and 2D-LDA to classify age. The benefit of their classifier is that it is robust under various lighting conditions. Ueki et al. (2006) experimented by using age ranges of 5 years, 10 years, and 15 years. The respective classification rates for each range were 46.3%, 67.8%, and 78.1%. The studies by Lanitis (2002) and by Lanitis et al. (2004) achieved roughly a 5-year mean error in the experiments where they used face images of people aged between 0 and 35 years. In the recent past many such classification strategies have been developed [21], [22].
The difficulty in automatic age estimation is mainly due to the specialty of aging effects on the face compared with other facial variations. The unique characteristics of aging variation mainly include: 1. The aging progress is uncontrollable. 2. Personalized aging patterns. 3. The aging patterns are temporal data.

When given a feature, feature classification steps are needed for age estimation. The feature classification can be divided into three approaches: the age group classification [23,24,25,26], the single- level age estimation [27,28,29,30,31] and the hierarchical age estimation [27,32,33]. Age group classification is an approach that roughly predicts an age group, whereas single-level and hierarchical age estimations are focused on detailed age prediction. The single-level age estimation is to find the age label in the total data set. On the other hand, the hierarchical age estimation is a coarse-to-fine method used to find the age label in a pre-classified group's small data set. As facial aging is perceived differently in different age groups, age estimation in a specific age group provides a more accurate result. Moreover age estimation on a smaller age group simplifies the computational load.

2. PROPOSED METHOD FOR AGE GROUP CLASSIFICATION OF FACIAL IMAGES BASED ON GLCM FEATURES ON TU of PSCB MODEL
The proposed TU-PSCB model consists of seven steps. The block diagram of the proposed method is shown in Fig.1.

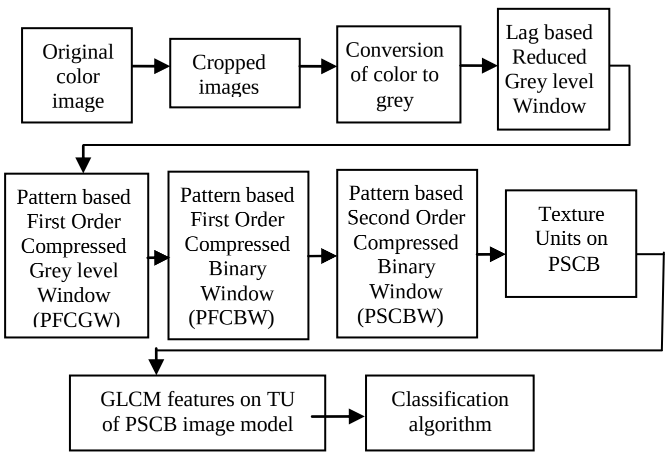

Fig. 1: Block diagram of the proposed PSCB image model.

Step 1: The original facial image is cropped based on the location of two eyes in the first step as shown in Fig. 2.

(a) (b)

Fig. 2: a) Original image b) cropped image

Step 2: In the step 2, if the original facial images are color images then those are converted into a grey level facial texture image by using color quantization of 7-bit binary code, as explained below. In order to extract grey level features from colour information, the proposed method utilized the RGB colour space which quantizes the colour space into 7-bins to obtain 128 grey levels. The index matrix of 128 colour image is denoted as C(x, y). The RGB quantization process is done by using 7-bit binary code of 128 colors as given in Eqn. (1.1) to (1.4).

$C(x,y)=16*I(R)+2*I(G)+I(B)$ where (1.1)

$I(R)= 0,\ 0\leq R\leq 16,\ I(R)= i,\ ((16*i)+1) \leq R \leq (16*(i+1))$
$i = [1, 2, \ldots,7]$ (1.2)

$I(G)= 0,\ 0\leq G\leq 16, I(G)= i,((16*i)+1)\leq G\leq(16*(i+1)$
$i=[1, 2,\ldots,6]$ (1.3)

$I(B)= 0,\ 0\leq B\leq 32, I(B)=i,((32*i)+1)\leq B\leq(32*(i+1)$
$i=[1, 2, 3]$ (1.4)

Therefore, each value of C(x, y) is a 7 bit binary code ranging from 0 to 127.

Step 3: Generation of Lag based Reduced Grey level Window (LRGW): Consider the 5×5 window of the image. Replace each pixel value by the absolute differences of that pixel value with central pixel value of the 5×5 window. If the absolute difference value is zero then corresponding pixel value is replaced with 2, if the absolute difference value is in between 1 to lag value then corresponding pixel value is replaced with 1 other wise pixel value is replaced with zero. Lag value is chosen as the average value of the central 3 x 3 window of the 5 x 5 window. Apply this on entire image by non overlapping manner. By this the pixel values of entire image will have values either 2 or 1 or 0. This forms the Lag based Reduced Grey level Window (LRGW).

Step4: Derivation of Pattern based First order Compressed Grey level Window (PFCGW): For reducing dimensionality for each 5×5 window, the proposed method adopted conditional pattern based approach. The 5 x 5 LRGW of the step 3 is shown in Fig. 3(a). The pixel values of 5 x 5 LRGW ranges from 0 to 2. The Fig. 3(b) represents the Pattern based First order Compressed Grey level window (PFCGW). The g1, g2, …, g9 pixel values of PFCGW represents the patterns of five horizontal, two diagonals, center vertical line and inner 3×3 window of LRGW, which are derived from the Eqn. (1.5) to (1.13).

v_1	v_2	v_3	v_4	v_5
v_6	v_7	v_8	v_9	v_{10}
v_{11}	v_{12}	v_{13}	v_{14}	v_{15}
v_{16}	v_{17}	v_{18}	v_{19}	v_{20}
v_{21}	v_{22}	v_{23}	v_{24}	v_{25}

(a)

g_1	g_2	g_3
g_4	g_5	g_6
g_7	g_8	g_9

(b)

b_1	b_2	b_3
b_4	b_5	b_6
b_7	b_8	b_9

(c)

Fig. 3: (a) Local 5×5 LRGW (b) generated 3×3 PFCGW (c) generated 3×3 PFCBW.

$g_1 = v_1 + v_2 + v_3 + v_4 + v_5$ (1.5)
$g_2 = v_6 + v_7 + v_8 + v_9 + v_{10}$ (1.6)
$g3 = v_{11} + v_{12} + v_{13} + v_{14} + v_{15}$ (1.7)
$g_4 = v_{16} + v_{17,} + v_{18} + v_{19} + v_{20}$ (1.8)
$g5 = v_7 + v_8 + v_9 + v_{12} + v_{13} + v_{14} + v_{17} + v_{18} + v_{19}$ (1.9)
$g_6 = v_{21} + v_{22} + v_{23} + v_{24} + v_{25}$ (1.10)
$g_7 = v1 + v_7 + v_{13} + v_{19} + v_{25}$ (1.11)
$g_8 = v_5 + v_9 + v_{13} + v_{17} + v_{21}$ (1.12)
$g_9 = v_3 + v_8 + v_{13} + v_{18} + v_{23}$ (1.13)

By observing the equations of g_1, g_2, g_3, g_4, g_6, g_7, g_8 and g_9 it is evident that that each of these pixel values can have a maximum value of 10. Further the equation for g5 clearly indicates that g5 can have a maximum value of 18. To convert them in to Pattern based First order Compressed Binary window (PFCBW) a condition is applied as given in Eqn. (1.14) and (1.15). By this the 3 x 3 "PFCGW" is converted in to binary window "PFCBW" as shown in Fig. 3(c).

if $g_i >= 5$ then $g_i = 1$ otherwise $g_i = 0$
for i=1,2,3,4,6,7,8,9 (1.14)
if $g_5 >= 9$ then $g_5 = 1$ otherwise $g_5 = 0$ (1.15)

Step 5: Generation of PSCBW of 2 x 2 from PFCBW of 3 x 3: The PFCBW of 3 x 3 generated in the previous step consist pixel values only either 0 or 1. This step reduces each of the 3 x 3 sub image of (PFCBW) into "Pattern based Second order Compressed Binary Window (PSCBW)" of 2x2 using the following conditional Eqn. as represented from (1.16) to (1.20) as shown in below Fig. 4.

b_1	b_2	b_3
b_4	b_5	b_6
b_7	b_8	b_9

q_1	q_2
q_3	q_4

$q_1 = b_1 + b_5 + b_7$ (1.16)
$q_2 = b_3 + b_5 + b_7$ (1.17)
$q_3 = b_2 + b_5 + b_8$ (1.18)
$q_4 = b_4 + b_5 + b_6$ (1.19)
Where if $q_i >= 2$ then $q_i = 1$
otherwise $q_i = 0$ for i = 1 to 4 (1.20)

By observing the equations of q_1, q_2, q_3 and q_4 it is evident that that each of these pixel values can have a maximum value of 4. Again to convert those in to Pattern based Second order Compressed Binary Window (PSCBW) of size 2 x 2, a condition is applied as given in equation (1.20). By this the 3 x 3 PFCBW is compressed in to second order binary window of size 2 X 2 without losing significant features. By applying steps 3, 4 and 5 on entire image on a 5x5 non-overlapped window basis, the entire texture image is converted into PSCB image model.

Step 6: Generation of TU on PSCB image model: The proposed method extracted local image information in the form of texture unit on each of the PSCBW. The proposed TU-PSCBW is different from usual texture unit represented in the literature, which is derived only on 3 x 3 windows. The proposed method intelligently compressed a 5x5 window into a 2x2 window and derived TU on them. Thus the derived TU also represents a TU of a 5x5 window. From each 2×2 PSCBW, TU value is calculated by using the Eqn. (1.21). This process is applied on entire image, then the image represents TU of PSCB image model.

$$\sum_{k=0}^{3} \text{Power}(2,k) * q_i \quad i = 1,2,3,4 \qquad (1.21)$$

TU of PSCBW consist the values ranging from o to 15 (totally 16) only. There is no unique way to label and order the texture units. To achieve unique way and rotational invariant property, the proposed TU on PSCBW considered the minimum value.

(a)

1	0
1	0

(b)

2^0	2^1
2^3	2^2

(c)

2^3	2^0
2^2	2^1

(d)

2^2	2^3
2^1	2^0

(e)

2^1	2^2
2^0	2^3

Fig. 5: Different ways of 2x2 neighborhoods.

The value of the TU changes by the representation of the weights. The TU can be calculated in 4 different ways for a 2 x 2 neighborhood is shown in Fig.5. That is for any 2 x 2 neighborhood one can generate four TU values. The TU value for the Fig. 5(a) in all four directions as represented in Fig. 5(b), 5(c),5(d) and 5(e) is given as 13, 14, 7 and 11 respectively.

The illustration process of generating the TU from original image of size 5 x 5 is shown in Fig. 6.

(a)

95	96	97	98	97
95	96	97	98	97
195	96	97	97	197
195	95	96	97	97
94	195	86	97	196

(b)

1	1	2	1	2
1	1	2	1	2
0	1	2	1	0
0	1	1	2	2
1	0	1	2	0

(c)

1	1	0
1	0	1
1	1	1

(d)

1	0
1	1

(e)

7

Fig.6: (a) Original 5 x 5 grey level window (b) a 5 x 5 LRGW
(c) a 3 x 3 PFCBW (d) 2×2 PSCBW (e) TU-PSCBW value.

Step 7: Generation of GLCM features on the derived TU of PSCB image model (PSCBI-TU): Grey Level Co-occurrence Matrix (GLCM) introduced by Haralick [3] attempt to describe texture by statistically sampling how certain grey levels occur in relation to other grey levels. One of the major inconveniences of Co-occurrence Matrix (CM) is the large range of its possible values (256 grey values) at the same time that these values are not correlated. It also requires more computation time. In general, the size of GLCM depends on grey level range of values of the image. To reduce grey values range in image and also to reduce overall dimension of the image, the present paper derived TU on PSCB image model. The PSCB image model reduces the overall dimensionality in to [2M/5 x 2N/5], (Where image size is (M X N)). Further the TU of PSCB image model reduces the overall grey level range from 0 to 15. Therefore the proposed TU-PSCB image is more suitable to evaluate GLCM features.

A set of GLCM features i.e; contrast, homogeneity, and correlation are extracted on the TU of PSCB facial images. They are represented from Eqn. (1.22) to (1.24). The proposed TU of PSCB image model combines the merits of both statistical and structural information of images and thus represents complete information of the facial image.

$$\text{contrast} = \sum_{i,j=0}^{N-1} -\ln (P_{ij})^2 \qquad (1.22)$$

$$\text{Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \qquad (1.23)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \qquad (1.24)$$

Where P_{ij} is the pixel value in position (i,j) of the PSCBW-TU image, N is the number of grey levels in the image, $\mu = \sum_{i,j=0}^{N-1} iP_{ij}$ mean of the image and $\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij} (i-\mu)^2$ variance of the image.

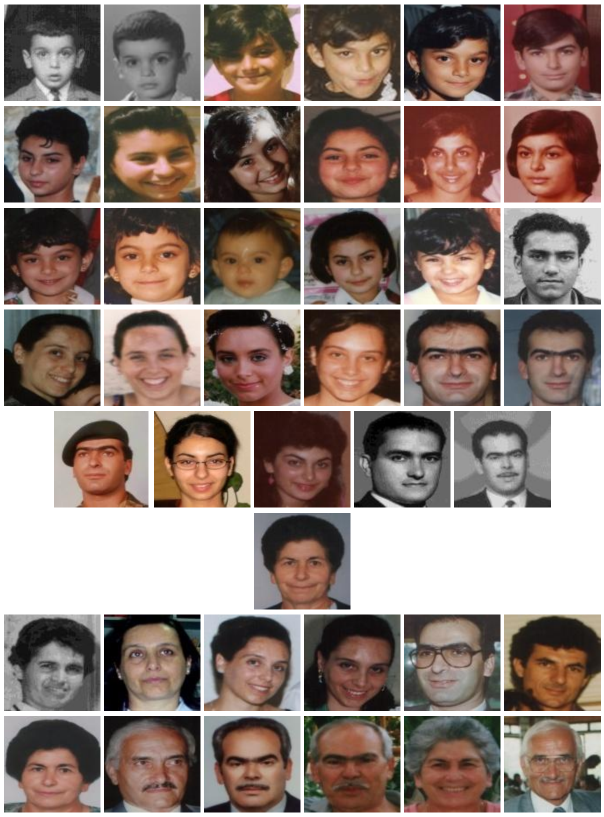

Fig. 7: FGNET aging database: 011A07, 011A05, 010A10, 010A09, 010A07b, 001A14, 019A07, 009A14, 009A13, 009A11, 008A16, 008A13, 010A05, 010A04, 010A01, 009A09, 009A05, 004A21, 002A29, 002A26, 002A23, 002A21, 001A29, 001A28, 001A22, 009A22a, 008A21, 004A28, 004A26, 006A36, 005A40, 011A40, 001A43b, 002A31, 001A33 007A37, 005A52, 005A49, 004A53, 004A51, 048A54 , 006A61, 005A61, 004A63.

3. RESULTS AND DISCUSSIONS

The proposed GLCM feature on TU of PSCB image model is experimented with a database of the 1002 face images collected from FG-NET database, 500 face images collected from Google database and other 600 images collected from the scanned photographs. This leads a total of 2102 sample facial images. Sample images are shown in Fig.7. In the proposed method the sample images are grouped into four age groups of 0 to 15, 16 to 30, 31 to 60, and above 60. The GLCM features are extracted on TU of PSCB facial images of different age groups and the results are stored in the feature database. Feature set leads to representation of the training images. The GLCM features on TU of PSCB image model for four age groups of facial images are shown in Tables 1, 2, 3, and 4 respectively. Based on this information the proposed method derives an algorithm called "age classification based on TU of PSCB model" to efficiently classify the facial images into four groups which is represented in algorithm 1.

Table 1: GLCM feature set values on the derived TU of PSCB facial images with age group from 0 to15 years.

S.No	Image Name	Contrast	Correlation	Homogeneity
1	001A02	45.9345313	0.3633283	0.692991371
2	001A05	46.4697197	0.41410471	0.683276235
3	001A08	48.7631203	0.27325552	0.681913713
4	001A10	46.9281193	0.3500283	0.669533747
5	001A14	46.7345313	0.33716873	0.670538852
6	002A03	47.2345276	0.32657822	0.66689456
7	002A04	46.4453113	0.29325552	0.67564327
8	002A05	47.8712528	0.40610471	0.665437864
9	007A01	48.1073522	0.36753456	0.6908765
10	002A07	46.6343513	0.33716873	0.619821713
11	002A12	47.2348731	0.42134567	0.689533747
12	002A15	49.1109823	0.41410471	0.670288672
13	008A06	48.8087656	0.33716873	0.701546378
14	008A12	46.9341354	0.29098765	0.690895642
15	008A13	47.5643872	0.27325552	0.675298624

Table 2: GLCM feature set values on the derived TU of PSCB facial images with age group from 16 to 31 years.

S.No	Image Name	Contrast	Correlation	Homogeneity
16	001A16	48.3467123	0.28674357	0.614537654
17	001A18	49.2087653	0.2789345	0.63765438
18	001A19	49.109659	0.2995802	0.64650099
19	001A22	48.0728629	0.30173542	0.62490603
20	001A28	48.8278028	0.3146596	0.645582946
21	001A29	47.8896544	0.31235644	0.64975435
22	002A20	48.9876534	0.2987569	0.63215674
23	002A21	46.7798753	0.31316548	0.64856352
24	002A23	49.5075635	0.32657432	0.612865935
25	002A26	47.8974325	0.29858456	0.606546322
26	002A29	48.8889765	0.31087574	0.599856487
27	009A18	47.0876789	0.28087378	0.62452678
28	009A22b	47.3423577	0.31278462	0.598793422
29	011A30	49.0067543	0.28956345	0.64327468
30	011A20	48.0334217	0.31278735	0.59452783

Table 3: GLCM feature set values on the derived TU of PSCB facial images with age group from 31 to 60 years.

S.No	Image Name	Contrast	Correlation	Homogeneity
31	001A33	55.7686567	0.24786431	0.59462119
32	001A40	57.0984567	0.29456425	0.613709382
33	001A43a	56.6678546	0.26745198	0.623144237
34	001A43b	59.0672561	0.25648423	0.614934593
35	013A34	63.3367549	0.32316548	0.589734271
36	013A41	59.0007658	0.31657432	0.599562119
37	013A44	57.8723649	0.28858456	0.603709382
38	014A40	58.5643873	0.32095774	0.633144237
39	014A42	56.7785463	0.31298623	0.612493459
40	001A43a	60.7647059	0.23055462	0.569734271
41	004A53	57.0497657	0.25031893	0.609709382
42	003A60	54.284227	0.25402058	0.633144237
43	004A51	58.5272254	0.23141568	0.640934593
44	002A31	62.0067673	0.23102486	0.597873427
45	007A37	63.768543	0.2451297	0.652493459
46	006A36	64.5673252	0.26756823	0.659734271
47	003A38	60.7076754	0.30768562	0.600009382
48	003A35	63.9098675	0.2987456	0.633144237
49	002A38	64.0897655	0.28956433	0.631343476

Table 4: GLCM feature set values on the derived TU of PSCB facial images with age above 60 years.

S.No	Image Name	Contrast	Correlation	Homogeneity
50	006A69	56.4833941	0.19715349	0.609899042
51	003A62	58.3499219	0.22749949	0.592662009
52	003A61	60.9599167	0.21450343	0.538748375
53	004A53	57.8763249	0.20765466	0.599734271
54	004A62	55.6786567	0.2278658	0.623144237
55	004A63	57.2989567	0.20781567	0.622493459
56	005A61	64.5667752	0.19875742	0.614934593
57	006A61	60.7276754	0.2067146	0.603709382
58	006A67	63.764583	0.18571258	0.641343476
59	004A64	64.5236752	0.1975562	0.609562119
60	004A61	58.5222754	0.16762925	0.613144237

Algorithm 1: Age group classification algorithm based TU of PSCB image model.

```
Begin
If ((Contrast < 50) and (Homogeneity > 0.65))
        Print ("age is in between 0 to 15"); // Childhood
Else If ((Contrast < 50) and (Homogeneity < 0.65))
        Print ("age is in between 16 to 30"); // young age
Else If ((Contrast > 50) and (Correlation >= 0.23))
        Print ("age is in between 31 to 60"); // middle age
Else If ((Contrast > 50) and (Correlation < 0.23))
        Print ("age is above 60"); // old age
End
```

To evaluate the accuracy and significance of the present method, probe or test images are taken. On probe image, GLCM features are evaluated on TU of PSCB model of facial image. As an experimental case 40 face samples, randomly collected from FG-NET, Google database and some Scanned images are considered. The features extracted on the facial images with their successful classification results using present scheme is given in Table 5. The classification percentage of three datasets is shown in Table 6 and classification graph of three datasets are shown in Fig. 8.

Table 5: Age classification table with GLCM feature of test data on the proposed PSCBW-TU model.

S. No	Image Name	Contrast	Correlation	Homogeneity	Classified age group
1	001A08	46.5311	0.29553561	0.67564327	0-15
2	002A18	47.8897	0.31235644	0.64975435	16-30
3	003A20	48.8977	0.2957869	0.6327644	16-30
4	005A24	47.9646	0.33215644	0.649457135	16-30
5	063A05	49.8923	0.40715664	0.674823881	0-15
6	064A16	47.9997	0.35321644	0.64579435	16-30
7	064A59	56.7855	0.26345314	0.623763	31-60
8	065A03	49.8226	0.41665362	0.672384881	0-15
9	067A18	47.9654	0.31675325	0.645435	16-30
10	022A28	48.6534	0.29231876	0.635612574	16-30
11	023A29	47.4332	0.36542836	0.62316735	16-30
12	024A30	48.3425	0.29324569	0.63215674	16-30
13	025A48	56.7855	0.261976	0.623134763	31-60
14	027A30	56.6662	0.26564276	0.6144237	31-60
15	017A62	63.8302	0.1864355	0.634216756	>60
16	018A34	59.0008	0.31632	0.59900772	31-60
17	020A36	57.2786	0.29990846	0.590709382	31-60
18	025A59	58.5644	0.32095774	0.633144237	31-60
19	Sci-1	48.7677	0.2723561	0.681914493	0-15
20	Sci-2	57.4654	0.30000908	0.600040938	31-60
21	Sci-3	47.5644	0.31453288	0.649967535	16-30
22	Sci-4	57.7666	0.25423498	0.627334763	31-60
23	Sci-5	56.6233	0.26745198	0.623144237	31-60
24	Sci-6	47.3745	0.30345644	0.644328675	16-30
25	Sci-7	48.5342	0.30987569	0.635327854	16-30
26	Sci-8	47.1238	0.30564336	0.634253674	16-30
27	20-2	48.3421	0.29651239	0.643215674	16-30
28	25-1	60.0008	0.32557432	0.599562231	31-60
29	25-2	58.9077	0.28856	0.600739382	31-60
30	25-3	58.5644	0.325774	0.613344237	31-60
31	40-6	49.0008	0.30054743	0.599562119	31-60
32	40-1	57.8724	0.28858456	0.673109382	31-60
33	40-2	58.5644	0.32095774	0.633144237	31-60
34	40-3	57.7779	0.26124233	0.689453733	31-60
35	40-4	56.5462	0.2671976	0.687653488	31-60
36	40-5	64.7646	0.18571258	0.641343476	>60
37	35-1	56.8545	0.251976	0.623143348	31-60
38	50-1	56.2318	0.267476	0.637334763	31-60
39	50-2	63.5643	0.2413375	0.631221343	>60
40	50-3	64.8302	0.18125758	0.674563426	>60

Table 6: % age group classification on three datasets by the proposed PSCB image model.

Image Dataset	FG-NET database	Google database	Scanned images
Childhood (0-15)	100.00%	92.50%	90.00%
Young adults (16-31)	97.50%	95.00%	93.00%
Middle Adults (31-60)	100.00%	92.50%	92.50%
0ld Adults (> 60)	97.50%	95.00%	93.00%

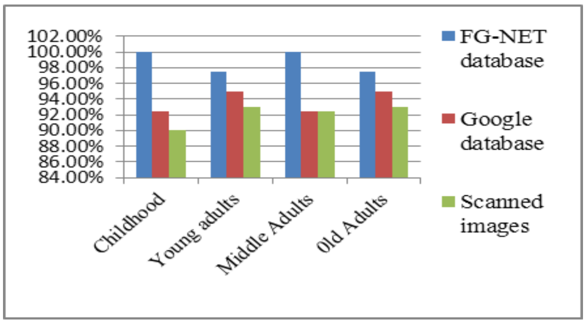

Fig. 8: % age classification graph of three datasets based on algorithm 1.

4. COMPARISON WITH OTHER EXISTING METHODS

The proposed method is compared with geometric feature based age classification system [1] and image-based age-group classification method [2] methods. The percentage of classification rates of the proposed method and other existing methods [1, 2] are listed in Table 7. The Table 7 clearly indicates that the proposed method yields better classification rate when compared with existing methods.

Fig. 9 shows the comparison chart of the proposed method with the other existing methods of Table 7.

Table 7: % mean classification rates of the proposed PSCB image model and other existing methods.

Image Dataset	Geometric feature based age classification system	Image-based age-group classification method	Proposed PSCB image model
Childhood	76.00%	90.15%	95.00%
Young adults	76.50%	89.50%	92.50%
Middle Adults	76.00%	88.50%	95.00%
0ld Adults	75.50%	90.15%	92.50%

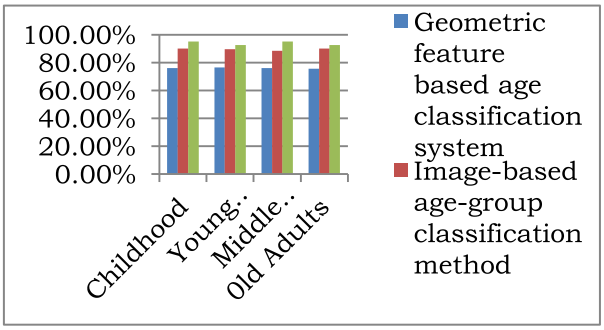

Fig. 9: Comparison graph of proposed method with other existing methods.

5. SUMMARY

This paper presented a novel approach for age group classification, including childhood (0-15), young adults (16-30), middle adult (31-60) and the old adults (above 60) based on GLCM features on the derived Texture units of the PSCB image model. The novelty of the proposed PSCB image model is, it reduced the overall dimensionality in to [2M/5 x 2N/5], (Where image size is (M X N)). The proposed TU-PSCBW is different from usual texture unit represented in the literature, which is derived only on 3 x 3 windows. The proposed method intelligently compressed a 5x5 window into a 2x2 window and derived TU on them. Thus the derived TU also represents a TU of a 5x5 window. There is no unique way to label and order the texture units. To achieve unique way and rotational invariant property, the proposed TU on PSCBW considered the minimum value. In the previous approaches, the TU ranges from 0 to 3561 [4], 0 to 2020 [5, 6, 7, 8], 0 to 255 [10, 11, 12, 13, 14, 15] and 0 to 79 [9]. To overcome this, the proposed model of TU of PSCB image reduced the overall TU's from 0 to 15. Therefore the proposed TU-PSCB image is more suitable to evaluate GLCM features than the previous approaches. For a precise, significant and accurate classification, the present study evaluated only three GLCM features on the derived TU of PSCB facial images. The present method is also tested for three FG-NET, Google aging database and Scanned images. The performance of the present system is more effective for the FG-NET aging database when compare with Google Images and scanned images. The average recognition rate is 93.33%.

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