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AGE CLASSIFICATION BASED ON FEATURES EXTRACTED FROM THIRD ORDER NEIGHBORHOOD LOCAL BINARY PATTERN

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Abstract

The present paper extended the work carried out by Kumar et. al. [10] on Third order Neighbourhood LBP (TN-LBP) and derived an approach that estimates pattern trends on the outer cell of TN-LBP. The present paper observed and noted that the TN-LBP forms two types of V-patterns on the outer cell of TN-LBP i.e. Outer Right V Patterns (ORVP) and Outer Left V Patterns (OLVP). The ORLP and OLVP of TN-LBP consist of 5 pixels each. The present paper derived Grey Level Co-occurrence Matrix (GLCM) features based on LBP values of ORVP and OLVP. This GLCM is named as ORLVP-GLCM (Outer cell Right and Left V-Patterns of GLCM) and on this four features are evaluated to classify human into child (0 to 12 years), young (13 to 30 years), middle aged (31 to 50 years) and senior adult (above 60 years). The proposed method is experimented on FGNET, GOOGLE and Scanned facial images and the results are compared with the existing methods. The results demonstrate the efficiency of the proposed method over the existing methods.

Keywords:

GLCM, LBP-Code, Outer Layer, Size of GLCM

1. INTRODUCTION

Age estimation is an important task in facial image classification. Age estimation can be defined as determination of a person's age or age group. In recent years age estimation of human, based on facial images is an interesting and a challenging topic for research.

A human face, as a visual cue conveys lot of nonverbal information to facilitate human-to-human communication in the real-world. Now there is an every necessity to develop modern intelligent systems with the capability to accurately recognize and interpret human faces in real time. Facial attributes such as identity, age, gender, expression, and ethnic origin, play a crucial role in real facial image analysis applications including multimedia communication, human computer interaction (HCI) etc. In such applications, various attributes can be estimated from a captured face image to infer the further system reactions. If the user's age can be estimated by a computer, an age specific human computer interaction (ASHCI) system can be developed for secure network / system access control. The ASHCI system can be used in areas like restricting young kids from viewing the porn/adult web pages, refusing the sale of alcohol/cigarettes to underage people through automatic vending machines [1, 2].

Image based age estimation methods can be categorized into three categories [3]. They are anthropometric model [4, 5], aging pattern subspace [1], and age regression [2, 6, 7, 8, 9]. In creating the anthropometric model, the cranio-facial development theory and facial skin wrinkle analysis are used to. In this model, the changes of face shape and texture patterns related to growth are measured to categorize a face into several age groups and these are suitable for coarse age estimation or modelling ages just for young people [5]. However, they are not designed for continuous or refined age classification [4]. The AGing pattErn Subspace (AGES) method [1] models a sequence of individual aging face images by learning a subspace representation and this is suitable to handle incomplete data such as missing ages in the training sequence. In regression methods, Active Appearance Models (AAMs) [13] extracts facial features that incorporate the shape and appearance information together.

Several methods have been introduced to classify the human facial images into 2, 3 or more age groups [14, 15][18]. In the present paper estimation of age is done based on two-dimensional images of human faces and derives Grey Level Co-occurrence Matrix (GLCM) features based on LBP values of ORVP and OLVP. The proposed system can be explained using the following block diagram shown in Fig.1.

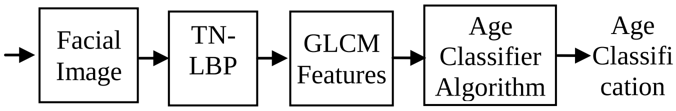


Fig.1. Block diagram for age classification system

The present paper is organized as follows. The section 2 describes different orders of neighbourhood and LBP. The section 3 and 4 describes the proposed method and results and discussions respectively. Conclusions of the proposed method are given in section 5.

2. DIFFERENT ORDERS OF NEIGHBORHOOD AND LOCAL BINARY PATTERNS (LBP)

Most of the image analysis problems are related to the neighborhood properties i.e. edge detection, segmentation, dilation, closing, opening, LBP, Texture Unit (TU), etc. Each pixel in a neighborhood or image is considered as a random variable, x_r, which can assume values x_r € $\{0, 1\ldots G1\}$, where G is the number of grey levels of the image. The probability P (x_r = x_r| r), where r is the neighbor set for the element x_r. The Fig.2 illustrates different orders of neighborhood for a central pixel. Most of the research involved in image processing is mostly revolved around second order neighborhood only. This is because all the 8- neighboring pixels are well connected with central pixel and the methods based on second order neighborhood have given extraordinary results in various issues.

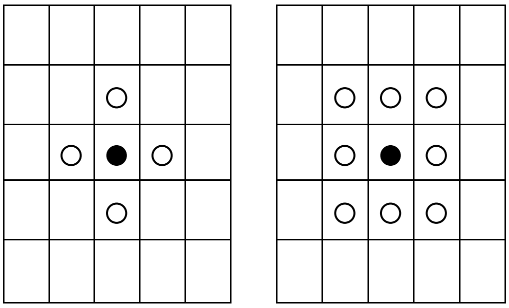


Fig.2(a) Fig.2(b)

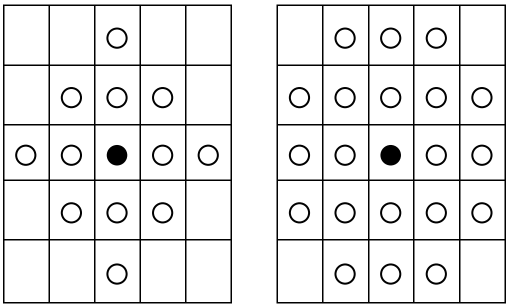


Fig.2(c) Fig.2(d)

Fig.2. Neighborhood for a central pixel: (a). First Order, (b). Second Order, (c). Third Order, (d). Fourth Order

A very high discriminative power for texture classification initially was achieved by Local Binary Pattern (LBP), which was first introduced by Ojala et al. [92-itam] on second order neighbourhood. LBP shows monotonic grey level changes a due to its invariance. It is a grey-scale invariant texture measure computed from the analysis of a 3 × 3 local neighbourhood (second order neighbourhood) over a central pixel. The LBP is based on a binary code describing the local texture pattern. This code is built by thresholding a local neighborhood by the grey value of its centre. LBP is a simple yet efficient operator to describe local image pattern, and it has achieved impressive classification results on representative texture databases [93-itam]. LBP has also been adapted to many other applications.

Considering the difficulties and complexities involved in the Third order Neighborhood (TN), the present paper derived a new, simple and efficient LBP model called as Third order Neighbourhood - LBP (TN-LBP) for image analysis and classification.

3. DERIVATION OF ORLVP-GLCM OF TN-LBP

The proposed method evaluated GLCM features on Outer Left V Patterns (OLVP) and Outer Right V Patterns (ORVP) of TN-LBP. The proposed method consists of 9 steps as described below.

Step 1: Take facial image as Input Image (Img).

Step 2: Convert the RGB image into grey scale Image by using HSV color model.

Step 3: Crop the grey scale image to size 128 × 128.

Step 4: The present research evaluated TN-LBP on each 5 × 5 sub image. The TN contains only 13 pixels of 25 pixels of 5 × 5 neighbourhoods as shown in Fig.3. The TN-LBP grey level sub image is converted into binary sub image by comparing the each pixel of TN grey level sub image with the mean value of TN grey sub image. The following Eq.(1) is used for grey level to binary conversion.

		P1		
	P2	P3	P4	
P5	P6	P7	P8	P9
	P10	P11	P12	
		P13		

Fig.3. Third Order Neighborhood for a central pixel

$$TN - P_i = \begin{Bmatrix} 0 & if\ P_i < V_0 \\ 1 & if\ P_i \geq V_0 \end{Bmatrix} for\ i = 1,2,..13 \qquad (1)$$

where, V_0 is the mean of the TN-LBP.

Step 5: The present research observed that TN-LBP divides the LBP in to two types of cells i.e. outer and inner cells. The present research derived a relation between outer V-patterns based on LBP code. Both Outer Left V Pattern (OLVP) and Outer Right V Pattern (ORVP) of TN-LBP consist of 5 pixels. OLVP of TN-LBP and ORVP of TN-LBP are shown in the Fig.4(a) and Fig.4(b) respectively with shaded regions. The Pixels P1, P2, P5, P10, and P13 form OLVP of TN-LBP and the pixels P1, P4, P9, P12 and P13 forms ORVP of TN-LBP.

Step 6: LBP code is evaluated on the OLVP and ORVP of TN-LBP. To achieve rotational invariance the minimum code is taken. The LBP code ranges from 0 to 31.

Step 7: Formation of ORLVP-GLCM from TN-LBP. The proposed ORLVP-GLCM is obtained by representing the LBP code values of ORVP on X-axis and LBP code values of OLVP on Y-axis as shown in Fig.5(c). This ORLVP-GLCM has the elements of relative frequencies of LBP codes of both ORVP and OLVP as in Fig.5(a) and Fig.5(b). The ORLVP-GLCM will have a fixed size of 31 × 31, since the values of ORVP and OLVP of TN-LBP code range from 0 to 31. This new method combines the merits of both GLCM and TN-LBP of the texture analysis and gives complete texture information about an image. The size of GLCM depends on gray level range of the image. The ORLVP-GLCM irrespective of gray level range of the image has a fixed size of 31 × 31. The proposed ORLVP-GLCM reduced the computational time complexity, because of the reduced size of the ORLVP-GLCM.

		P1		
	P2	P3	P4	
P5	P6	P7	P8	P9
	P10	P11	P12	
		P13		

Fig.4(a)

		P1		
	P2	P3	P4	
P5	P6	P7	P8	P9
	P10	P11	P12	
		P13		

Fig.4(b)

Fig.4. Considered V patterns of outer cell of TN-LBP: (a). Outer Left V Pattern (OLVP), (b). Outer Right V Pattern (ORVP)

Step 8: Extract the Haralick features energy, contrast, homogeneity and correlation features [16][17] on ORLVP-GLCM of TN-LBP as given in Eq.(2), Eq.(3), Eq.(4) and Eq.(5) respectively. The above ORLVP-GLCM features are evaluated for 0°, 45°, 90°, and 135° and their sum is noted in the Tables.1 to 4. This achieves further rotational invariance.

$$Energy = \sum_{i,j=0}^{N-1} -\ln\left(P_{ij}\right)^2 \tag{2}$$

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}\left(i-j\right)^2 \tag{3}$$

$$Homogenity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+\left(i-j\right)^2} \tag{4}$$

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij}\,\frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{5}$$

ORVP TN-LBP	**Fq_1**
0	
1	
2	
.	
.	
31	

Fig.5(a)

OLVP TN-LBP	**Fq_2**
0	
1	
2	
.	
.	
31	

Fig.5(b)

	0	**1**	**2**	**.**	**.**	**.**					**31**
0											
1											
2											
.											
.											
.											
31											

Fig.5(c)

Fig.5.(a) & (b). Frequency occurrences of ORVP and OLVP LBP codes, (c). Formation of ORLVP-GLCM

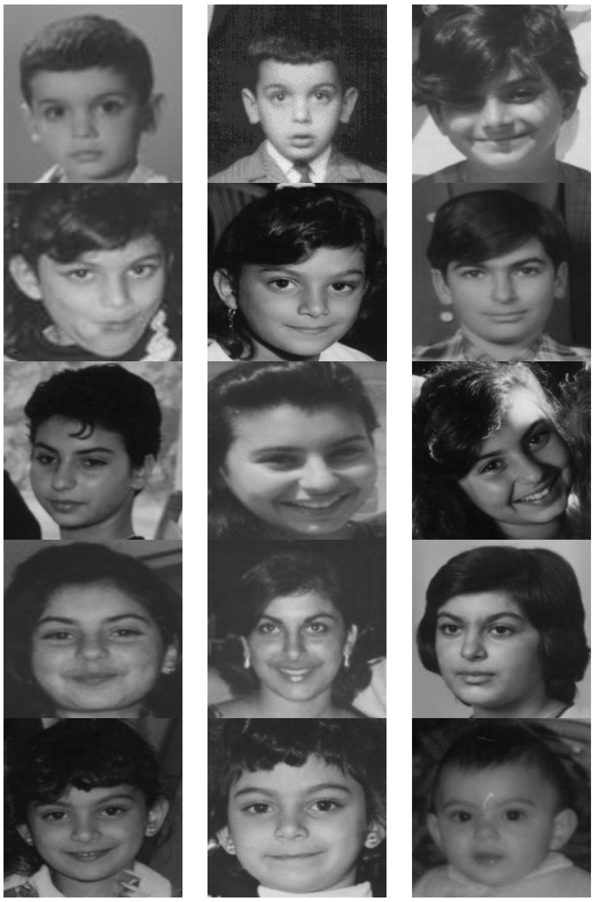
Step 9: Based on four feature values of the proposed ORLVP-GLCM, facial image is classified as one of the four categories (child (0-12), young (13-30), middle aged (31-50) and senior adult (51 -70)).

4. RESULTS AND DISCUSSIONS

In implementing the proposed scheme, a database is established by collecting 1002 facial images from FG-NET database, 500 images from Google database and other 600 images collected from the scanned photographs, which resulted in a total of 2102 sample facial images. A few of them are shown in Fig.6. In the proposed age classification method the sample images are grouped into four age groups of child (0-12), young (13-30), middle aged (31-50) and senior adult (51 -70). The statistical features are extracted from the proposed ORLVP-GLCM of TN-LBP for different equal size facial images and the results are stored in the feature database. Feature set leads to representation of the training set. The statistical features of four age groups of facial images are shown in Tables.1, 2, 3 and 4 respectively.

Based on the derived features, on ORLVP-GLCM of TN-LBP, an algorithm 1 is derived by the present research to classify the facial image into one of the categories i.e. child (0-12), young (13-30), middle aged (31-50) and senior adult (51 -70).

To evaluate the efficacy of the proposed method various facial images are considered and ORLVP-GLCM features of TN-LBP are evaluated on them. Based on the proposed age classification algorithm the age classification rate of the test images is established and noted in Table.5. The time complexity of this implementation is $O(n^2)$.



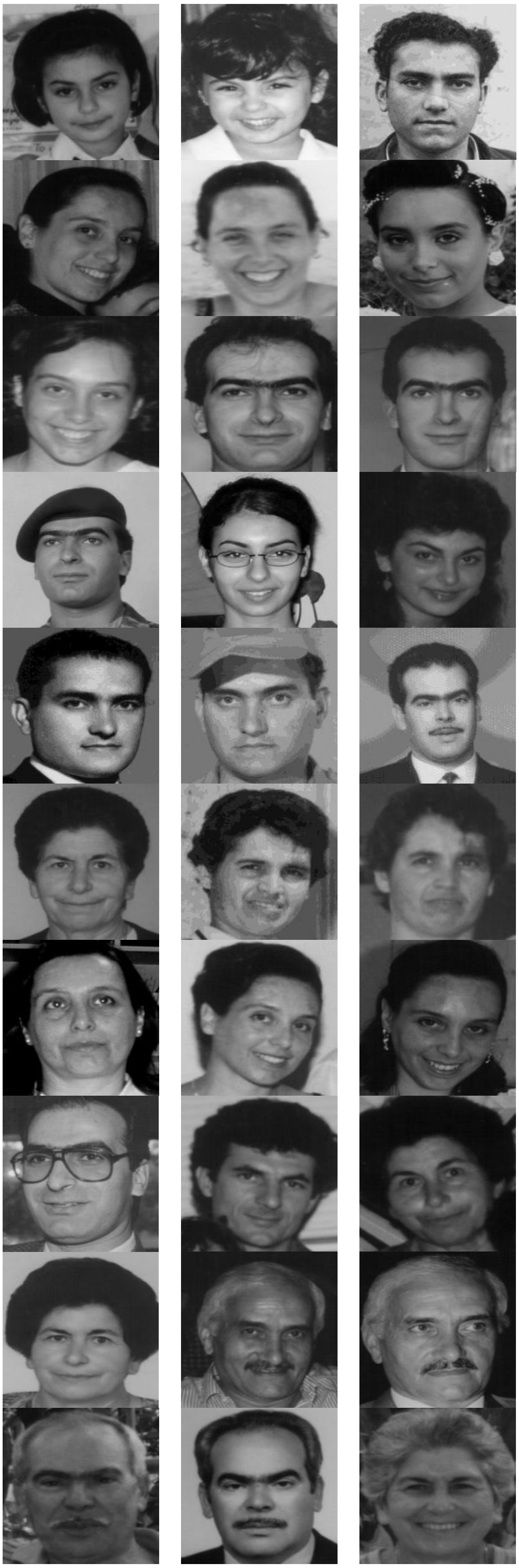


Fig.6. FGNET aging database: 011A07, 011A05, 010A10, 010A09, 010A07b, 001A14, 019A07, 009A14, 009A13, 009A11, 008A16, 008A13, 010A05, 010A04, 010A01, 009A09, 009A05, 004A21, 002A29, 002A26, 002A23, 002A21, 001A29, 001A28, 001A22, 009A22a, 008A21, 004A28, 004A26, 006A36, 005A40, 011A40, 001A43b, 002A31, 001A33 007A37, 005A52, 005A49, 004A53, 004A51, 048A54 , 006A61, 005A61, 004A63

Table.1. Feature set values for child age group extracted from ORLVP-GLCM of TN-LBP

SI. No	**Image Name**	**Contrast**	**Correlation**	**Energy**	**Homogeneity**
1	001A02	39.6755	0.6231	0.0382	0.3929
2	001A05	46.6864	0.5260	0.0380	0.3917
3	001A08	39.7073	0.7557	0.0382	0.3929
4	001A10	43.7227	0.6920	0.0380	0.3922
5	002A03	34.6404	0.6985	0.0384	0.3938
6	002A04	43.6908	0.5675	0.0381	0.3922
7	002A07	46.7183	0.6443	0.0379	0.3917
8	008A06	35.6601	0.6881	0.0384	0.3936
9	009A00	35.6920	0.8301	0.0384	0.3936
10	010A01	38.6876	0.7661	0.0382	0.3931
11	010A09	35.6601	0.6881	0.0384	0.3936
12	024A05	39.6755	0.6231	0.0382	0.3929
13	024A10	43.6908	0.5675	0.0381	0.3922
14	025A00	35.6601	0.6881	0.0384	0.3936
15	025A03	38.6557	0.6318	0.0383	0.3931
16	025A07	38.6557	0.6341	0.0383	0.3931
17	002A12	45.6985	0.6507	0.0380	0.3918
18	009A11	35.6601	0.6881	0.0384	0.3936
19	025A12	42.7029	0.6992	0.0381	0.3924
20	026A11	46.7183	0.6443	0.0379	0.3917

Table.2. Feature set values for young age group extracted from ORLVP-GLCM of TN-LBP

SI. No	**Image Name**	**Contrast**	**Correlation**	**Energy**	**Homogeneity**
1	001A22	39.6755	0.6231	0.0282	0.3929
2	001A28	51.7215	0.4772	0.0258	0.3908
3	001A29	51.7215	0.4772	0.0228	0.3908
4	003A23	47.6294	0.8600	0.0267	0.3951
5	003A25	47.6908	0.5675	0.0261	0.3922
6	012A21	55.6601	0.6881	0.0264	0.3936
7	012A23	58.7324	0.4118	0.0255	0.3895
8	012A24	51.7215	0.4772	0.0258	0.3908
9	012A26	52.6710	0.5751	0.0261	0.3924

10	012A27	49.7227	0.6920	0.0260	0.3922
11	012A30	59.7522	0.4960	0.0224	0.3893
12	024A23	47.7062	0.5194	0.0259	0.3915
13	024A25	68.8027	0.4274	0.0251	0.3877
14	027A22	52.7413	0.5688	0.0257	0.3906
15	027A25	79.8290	0.3515	0.0246	0.3857
16	027A30	55.6601	0.6881	0.0264	0.3936
17	047A23	56.7566	0.5278	0.0255	0.3899
18	047A27	46.6864	0.5260	0.0260	0.3917
19	048A30	59.7841	0.5061	0.0254	0.3893
20	001A14	48.6557	0.6318	0.0263	0.3931

Table.3. Feature set values of middle age group extracted from ORLVP-GLCM of TN-LBP

SI. No	Image Name	Contrast	Correlation	Energy	Homogeneity
1	001A33	54.7490	0.5507	0.0376	0.4262
2	001A40	54.7171	0.4460	0.0377	0.4266
3	002A31	58.7324	0.4118	0.0375	0.4250
4	003A35	50.7336	0.5947	0.0378	0.4277
5	003A38	49.6755	0.6231	0.0382	0.4325
6	012A32	49.6908	0.5675	0.0381	0.4309
7	013A34	63.7676	0.3760	0.0373	0.4230
8	018A33	48.6755	0.6231	0.0382	0.4325
9	018A34	50.7336	0.5947	0.0378	0.4277
10	019A37	51.7215	0.4772	0.0378	0.4277
11	020A36	61.7280	0.3854	0.0374	0.4238
12	021A35	66.7950	0.4437	0.0371	0.4215
13	021A39	47.3691	0.5675	0.0381	0.4309
14	025A34	62.7797	0.4759	0.0373	0.4230
15	025A39	62.7797	0.4759	0.0373	0.4230
16	039A35	60.7401	0.3950	0.0374	0.4242
17	047A33	52.7094	0.4631	0.0377	0.4273
18	001A43	74.8257	0.3854	0.0368	0.4184
19	003A47	54.7171	0.4460	0.0377	0.4266
20	003A49	66.2533	0.4375	0.0372	0.4217

Table.4. Feature set values of senior age group extracted from ORLVP-GLCM of TN-LBP

SI. No	Image Name	Contrast	Correlation	Energy	Homogeneity
1	003A51	47.6908	0.5675	0.0381	0.5322
2	003A57	47.7062	0.5194	0.0379	0.5315
3	003A58	48.7259	0.6159	0.0379	0.5313
4	003A59	58.7643	0.5114	0.0375	0.5295
5	003A60	58.7643	0.5114	0.0375	0.5295
6	004A53	58.7643	0.5114	0.0375	0.5295
7	006A54	47.6710	0.5769	0.0381	0.5324
8	006A55	55.7369	0.4398	0.0376	0.5300
9	006A56	54.7490	0.5507	0.0376	0.5302
10	039A52	47.7380	0.6367	0.0379	0.5315
11	047A55	47.0291	0.7008	0.0381	0.5324
12	004A62	65.7752	0.4476	0.0372	0.5083
13	004A63	48.6876	0.7640	0.0382	0.5331
14	006A61	54.7490	0.5507	0.0376	0.5302
15	006A67	56.7248	0.4272	0.0376	0.5299
16	006A69	61.7599	0.4802	0.0373	0.5290
17	045A64	56.7248	0.4272	0.0376	0.5299
18	045A65	61.7599	0.4802	0.0373	0.5090
19	045A66	57.7445	0.5160	0.0375	0.5297
20	069A52	60.7720	0.4916	0.0374	0.5291

Algorithm 1:

```
Age group classification based on features generated
by ORLVP-GLCM of TN-LBP
BEGIN
  if (Contrast >=47.0) & (Homogeneity > 0.5)
        print ("Facial image is senior adult (51-70)")
   else
     if (Contrast >=47.0) & (Homogeneity < 0.5) and
                               (Homogeneity > 0.4)
        print("Facial image is middle aged (31-50)")
      else
        if (Contrast >= 47.0) & (Energy >=0.02) &
                                   (Energy<=0.03)
        print("Facial image is young (13-30)")
        else
          if (Contrast < 47.0)
        print ("Facial image is child (0-12)")
END
```

5. COMPARISON OF THE PROPOSED ORLVP-GLCM OF TN-LBP METHOD WITH OTHER EXISTING METHODS

The proposed method of age classification is compared with the existing methods [11, 12]. The method proposed by M. Yazdi et.al [11] classified human age using RBF Neural Network Classifier. The age classification method proposed by Wen-Bing Horng [12] is based on two geometric features and three wrinkle features of facial image. The percentage of classification of proposed method and other existing methods are listed in Table.5. The graphical representation of the percentage mean classification rate for the proposed method and other existing methods are shown in Fig.7.

Table.5. Classification rate of the proposed ORLVP-GLCM of TN-LBP method with other existing methods

Image Dataset	Existing age classification method [11]	Existing age classification method [12]	Proposed ORLVP-GLCM of TN-LBP Method
FG-NET	89.67	90.52	90.83
Google	85.3	81.58	86.45
Scanned	88.72	85.42	87.23
Average	87.9	85.84	88.17

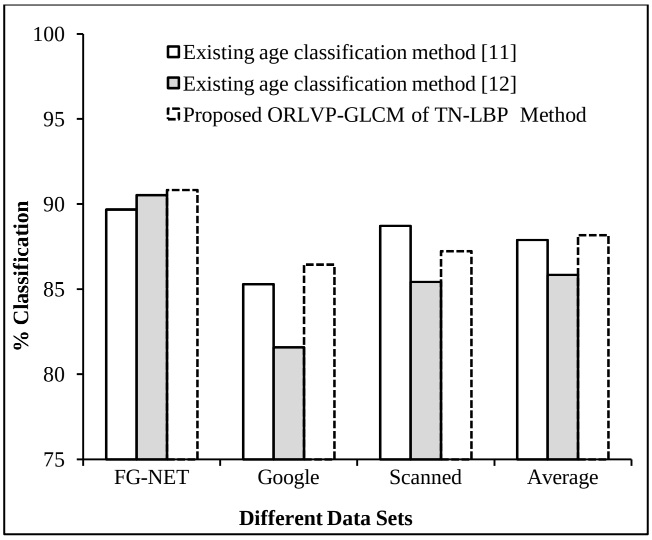


Fig.7. Classification chart of proposed outer ORLVP-GLCM of TN-LBP method and other existing methods

6. CONCLUSION

Evaluating features on TN-LBP is a crucial and difficult task because it consists of 13 pixels. The proposed method identified the formation of two cells on a TN-LBP called outer and inner cells. Further the proposed method evaluated the left and right V-pattern trends on outer cell of LBP. These two patterns consist of 5-pixels only. These two patterns V-patterns have two common pixels. The proposed ORLVP-GLCM of TN-LBP has given a new direction to the feature researchers, in evaluating features on TN-LBP by dividing it into two different patterns. The proposed ORLVP-GLCM of TN-LBP has reduced the overall complexity by reducing the size of the GLCM in to 31 × 31. This is achieved by dividing the TN-LBP in to dual LBP. Further the proposed work achieved a good classification results by computing only four features. The proposed method achieved a good classification rate on average when compared to the existing methods.

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