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Age Classification Based On Integrated Approach

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Abstract—The present paper presents a new age classification method by 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. The present paper derived four distinct patterns called Left Diagonal (LD), Right diagonal (RD), vertical centre (VC) and horizontal centre (HC) LBP's. For all the LBP's the central pixel value of the 3 x 3 neighbourhood is significant. That is the reason in the present research LBP values are evaluated by comparing all 9 pixels of the 3 x 3 neighbourhood with the average value of the neighbourhood. The four distinct LBP's are grouped into two distinct LBP's. Based on these two distinct LBP's GLCM is computed and features are evaluated to classify the human age into four age groups i.e: Child (0-15), Young adult (16-30), Middle aged adult (31-50) and senior adult (>50). The co-occurrence features extracted from the 4-DLBP provides complete texture information about an image which is useful for classification. The proposed 4-DLBP reduces the size of the LBP from 6561 to 79 in the case of original texture spectrum and 2020 to 79 in the case of Fuzzy Texture approach.

Index Terms—Age classification, Combined feature, Distinct-LBP, Fuzzy Texture, GLCM, Patterns.

I. Introduction

AGE-CENTERED COMPUTING (ACC) has long been an extensively interesting topic in both Human–Computer Interaction (HCI) and cognitive studies. The human traits displayed by facial attributes, such as personal identity, facial expression, gender, age, ethnic origin, and pose. Recently Human age classification has become an active research topic in computer vision because of its widespread potential real world applications such as electronic customer relationship management (ECRM) [1], security control and surveillance monitoring [2, 3, 4], biometrics [5], and entertainment. There are two fundamental problems in designing the techniques i.e face image analysis and face image synthesis. In both cases Age of face has also been considered as an important semantic or contextual cue in social networks [5] [6]. And age, is an information source for ACC, conveys significant nonverbal information for the communication and interaction between humans or between human and machine. Theoretically, Human Aging can be categorized into many phases as age between 1 to 10, 11 to 20, 21 to 50, 51 to 60 and above 60.Computationally, an age estimation system usually consists of two modules: image representation and age estimation. Age image representations include the anthropometric model [7, 8], wrinkle model [10], active appearance model (AAM) [9], AGing pattErn Subspace (AGES) [11, 12], age manifold learned from raw images [13, 14], local binary pattern features [15], and parts [7] or patch-based appearance model [16, 17]. Given a representation, age estimation can be viewed as a multi-class classification problem [18, 19, 20] or a regression problem [12, 22, 21, 13] or a hybrid of the two [24]. This age estimation method includes single age estimation, age group estimation and hierarchical estimation.

The present paper is organized as follows. The section 2 describes methodology, section 3 and section 4 describes results and discussion and conclusions respectively

II. Methodology

The present paper derived age classification based on the features derived from Grey Level Co-occurrence Matrix (GLCM) on 4-DLBP's. Most of the statistical methods [25, 26] suffer from the generalization problem due to the unpredictable distribution of the face images in real environment, which might be far different from that of the training face images. The structural method like LBP suffers from illumination effect. To avoid these problems, the present research combined structural and statistical methods based on 4-DLBP using GLCM features. The proposed method consists of nine steps described below.

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

Step 2 : Convert the RGB image into Grey scale Image by using HSV colour model.

Step 3 : Convert each 3×3 window of facial image into LBP based on the following equation.

$$BM = \begin{Bmatrix} 0 \ if \ X_{i,j} < V_0 \\ 1 \ if \ X_{i,j} \geq V_0 \end{Bmatrix} \ for \ i,j = 1,2,3 \quad (1)$$

Where V_0 is the mean of the 3×3 sub matrix.

Step 4: Convert each 3×3 LBP-window of facial image into four distinct patterns based – LBP's, named as Left Diagonal (LD-LBP), Right diagonal (RD-LBP), vertical centre (VC-LBP) and horizontal centre (HC-LBP), which are shown in Fig.1. All the four LBP's contains three pixels only.For all the LBP's the central pixel value of the 3 x 3 neighbourhood is significant. That is the reason in the present research LBP values are evaluated by comparing all 9 pixels of the 3 x 3 neighbourhood with the average value of the neighbourhood.

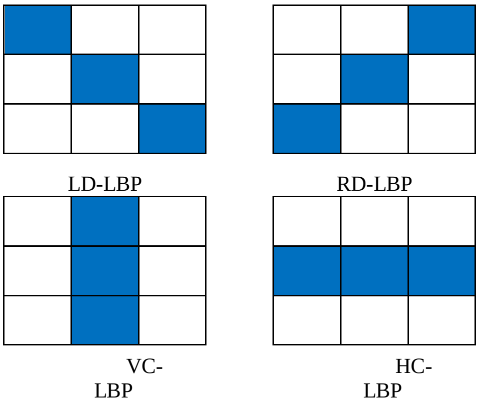

Fig 1: Four Different Patterns of LBP.

Step 5: Calculate the LBP unit values for LD-LBP, RD-LBP, VC-LBP and HC-LBP. Each of them will have LBP-value ranging from 0 to 7.

Step 6: Based on the step 5 the present paper divided the LBP units in to two categories i.e Diagonal and Horizontal Vertical (HV) as given in equation 2 and 3 respectively.

$$\text{Diagonal-LBP (DLBP)} = \text{LD-LBP} + \text{RD-LBP} \quad (2)$$

$$\text{HV-LBP (HVLBP)} = \text{VC-LBP} + \text{HC-LBP} \quad (3)$$

Step 7: Generate the co-occurrence matrix based on values generated in step 6. The proposed GLCM is constructed on the proposed Diagonal and HV-LBP (D-HV-LBP) by representing the DLBP values on X-axis and HVLBP values on Y-axis as shown in Fig.2(c). This GLCM is named as D-HV-LBP-GLCM. The D-HV-LBP-GLCM has the elements of relative frequencies in both DLBP and HVLBP as in Fig.2 (a) & (b). The values of DLBP and HVLBP ranges from 0 to 14. Thus the D-HV-LBP-GLCM will have a fixed size of 14 x 14.

DLBP	Fq1
0	
1	
2	
.	
.	
.	
14	

(a)

HVLBP	Fq2
0	
1	
2	
.	
.	
.	
14	

(b)

	0	1	2	.	.	.					14
0											
1											
2											
.											
.											
.											
14											

(c)

Fig 2: (a) & (b) Frequency occurrences of DLBP and HVLBP units (c) D-HV-LBP-GLCM matrix.

Step 8: From this D-HV-LBP-GLCM, a set of Haralick features i.e. energy, contrast, Homogeneity and correlation as given in equation 4, 5, 6 and 7 respectively.

$$\text{Energy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})^2 \quad (4)$$

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}\,(i-j)^2 \quad (5)$$

$$\text{Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (6)$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (7)$$

Where P_{ij} is the pixel value of the image at position (i, j), μ is mean and σ is standard deviation.

Step 9: By using K-nn Classifier on the proposed D-HV-LBP-GLCM features, the facial image is classified as one of the category (Child age (0-15), Young Age(16-30), Middle Age(31-50) and Senior Age(>50).

III. RESULTS AND DISCUSSIONS

The proposed scheme established a database from the 1002 face images collected from FG-NET database, 500 images from Google database and other 600 images collected from the scanned photographs. This leads a total of 2102 sample facial images. In the proposed D-HV-LBP-GLCM method the sample images are grouped into four age groups of Child age(0-15), Young Age(16-30), Middle Age(31-50) and Senior Age(>50). A few of them are shown in Fig.3. The Contrast, Correlation, Energy and Homogeneity features are extracted from D-HV-LBP-GLCM of different facial images and the results are stored in the feature database. Feature set leads to representation of the training images. The Contrast, Correlation, Energy and Homogeneity features derived from D-HV-LBP-GLCM of four age groups of facial images are shown in tables 1, 2, 3, and 4 respectively. To evaluate the proposed method, 30 different facial expressions are considered from FG-NET aging database, Google database and scanned images as a test data base. The present paper estimated distance between feature database and test database by using Euclidian distances. To classify the test images into appropriate age group the present paper utilized minimum distance K-nearest neighbour classifier. Successful classification results of test data bases for the proposed D-HV-LBP-GLCM method are shown in table 5.

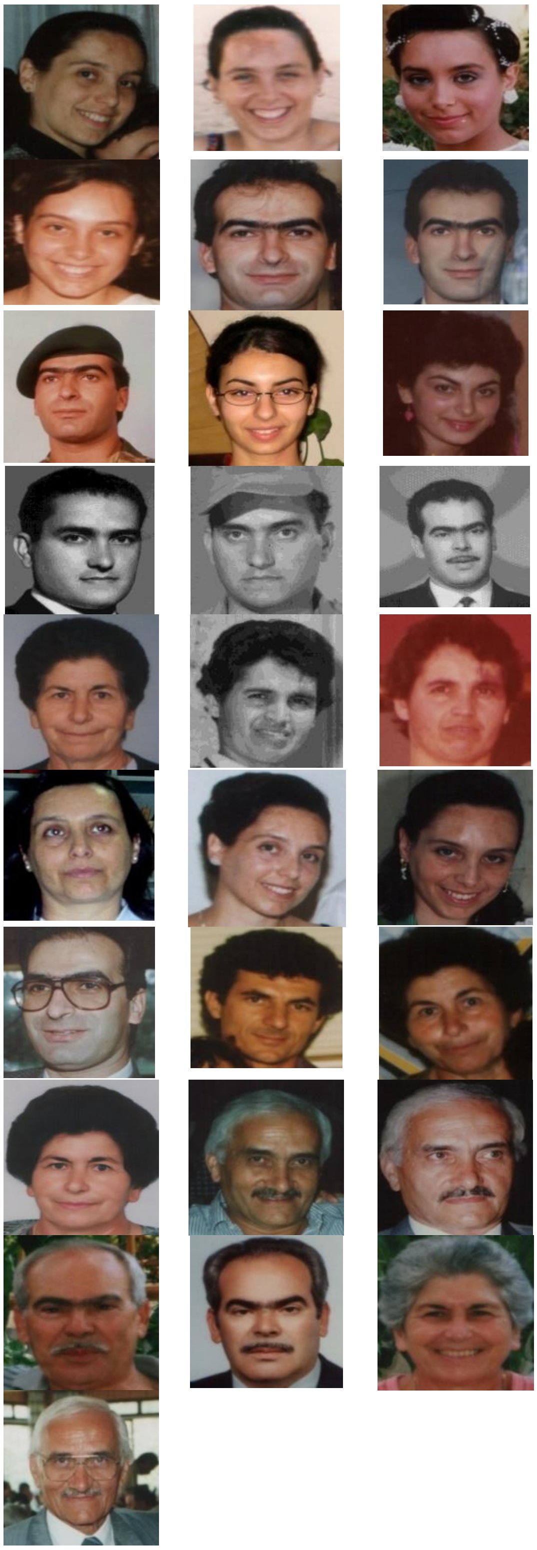

Fig.3: FG-NET aging database: 011A07, 011A05, 010A10, 010A09, 010A07b, 001A14, 019A07, 009A14, 009A13, 009A11, 008A16, 008A13, 010A05, 010A04, 010A01, 009A09, 009A05, 004A21, 002A29, 002A26, 002A23, 002A21, 001A29, 001A28, 001A22, 009A22a, 008A21, 004A28, 004A26, 006A36, 005A40, 011A40, 001A43b, 002A31, 001A33 007A37, 005A52, 005A49, 004A53, 004A51, 048A54 , 006A61, 005A61, 004A63.

Table 1: Feature set values of d-hv-lbp-glcm for child age images.

S No	Image Name	Contrast	Correl-tion	Energy	Homo-Geneity
1	001A05	7.20958	0.68932	0.02766	0.49165
2	001A08	7.18185	0.70819	0.02699	0.50230
3	008A12	7.06797	0.68230	0.02975	0.49620
4	001A14	7.27466	0.67894	0.02677	0.49043
5	001A02	7.47466	0.81932	0.02779	0.48165
6	001A10	7.00958	0.83819	0.02732	0.51230
7	002A04	7.16797	0.81230	0.02837	0.48730
8	002A05	6.98185	0.80894	0.02632	0.48120
9	002A07	7.28185	0.80932	0.02666	0.47543
10	002A12	7.07466	0.82819	0.03025	0.50165
11	002A15	7.26797	0.80230	0.02716	0.48620
12	009A00	7.13185	0.79894	0.02599	0.46665
13	009A01	7.15958	0.67230	0.02749	0.48043
14	009A03	7.01797	0.66894	0.02729	0.50620
15	009A05	7.22466	0.66932	0.02649	0.47665
16	009A09	7.10958	0.68819	0.02816	0.47120
17	009A11	6.96797	0.66230	0.02782	0.49230
18	009A13	7.17466	0.65894	0.02829	0.50043
19	009A14	7.37466	0.69819	0.02737	0.47730
20	010A01	7.30958	0.67230	0.02727	0.46543
21	010A04	6.86797	0.70032	0.02887	0.49620
22	010A05	7.38185	0.71919	0.02875	0.47337
23	010A06	7.03185	0.69330	0.02682	0.47071
24	010A07a	7.05958	0.68994	0.02577	0.46806
25	010A07b	6.91797	0.69032	0.02925	0.46541
26	010A09	7.12466	0.70919	0.02679	0.46275
27	010A10	7.32466	0.68330	0.02787	0.48262
28	010A15	7.25958	0.67994	0.02627	0.46010
29	011A02	6.81797	0.67932	0.02681	0.45744
30	010A12	7.33185	0.69819	0.02556	0.45479

Table 2: Feature set values of d-hv-lbp-glcm for young age images.

Sno	Image Name	Contrast	Correlati on	Energy	Homo-geneity
1	001A16	7.3658	0.7331	0.0258	0.4970
2	001A19	7.5204	0.7218	0.0259	0.4937
3	001A29	7.5762	0.6780	0.0261	0.4966
4	002A16	7.5262	0.7082	0.0263	0.4970
5	001A18	7.2458	0.7196	0.0258	0.4950
6	001A22	7.4004	0.7055	0.0250	0.4947
7	001A28	7.4562	0.6530	0.0277	0.4919
8	002A18	7.2791	0.7446	0.0284	0.4929
9	002A20	7.4338	0.7305	0.0263	0.4970
10	002A21	7.4896	0.6780	0.0268	0.4970
11	002A23	7.3991	0.7071	0.0266	0.4967
12	002A26	7.5538	0.6930	0.0282	0.4960
13	002A29	7.6096	0.6405	0.0263	0.4964
14	004A19	7.3958	0.7696	0.0282	0.4967
15	004A21	7.5504	0.7555	0.0261	0.4959
16	004A26	7.6062	0.7030	0.0279	0.4949
17	004A28	7.5158	0.7446	0.0255	0.4959
18	004A30	7.6704	0.7305	0.0253	0.4944
19	005A18	7.7262	0.6780	0.0258	0.4990
20	005A24	7.1958	0.6696	0.0260	0.4972
21	005A30	7.3504	0.6555	0.0255	0.4979
22	006A24	7.4062	0.6030	0.0287	0.4939
23	006A28	7.2208	0.7445	0.0255	0.4959
24	007A18	7.3754	0.6930	0.0263	0.4957
25	007A22	7.4312	0.7336	0.0282	0.4980
26	007A23	7.3408	0.7335	0.0282	0.4975
27	007A26	7.4954	0.6710	0.0268	0.4939
28	008A17	7.5512	0.6786	0.0258	0.4977
29	008A29	7.3158	0.7448	0.0272	0.4969
30	008A30	7.4704	0.6330	0.0264	0.4987

Table 3: Feature set values of d-hv-lbp glcm for middle age images.

S. no	Image Name	Contrast	Corre lation	Energy	Homo geneity
1	001A43a	7.6185	0.6472	0.0281	0.4970
2	002A31	7.5360	0.6681	0.0266	0.4951
3	002A38	7.5829	0.6728	0.0288	0.4927
4	003A35	7.6185	0.6693	0.0294	0.4981
5	003A47	7.4068	0.7221	0.0287	0.5023
6	003A49	7.5360	0.7611	0.0291	0.4996
7	001A43b	7.5310	0.7399	0.0276	0.5026
8	001A33	7.5829	0.6451	0.0283	0.4879
9	001A40	7.4068	0.7221	0.0257	0.4959
10	003A47	7.6185	0.6513	0.0272	0.4926
11	002A36	7.4568	0.6735	0.0292	0.4986
12	003A38	7.6185	0.6951	0.0278	0.5019
13	004A37	7.4068	0.7228	0.0313	0.4909
14	004A40	7.5329	0.6728	0.0293	0.5007
15	004A48	7.5360	0.7221	0.0271	0.4992
16	006A31	7.3568	0.7388	0.0267	0.4939
17	006A36	7.5360	0.6451	0.0277	0.5016
18	006A40	7.5360	0.6679	0.0303	0.4976
19	006A42	7.5860	0.6728	0.0282	0.4921
20	006A44	7.4068	0.6673	0.0282	0.5009
21	006A46	7.4318	0.7721	0.0272	0.4956
22	006A48	7.5829	0.6690	0.0277	0.4988
23	006A50	7.5829	0.7444	0.0267	0.4969
24	008A41	7.6079	0.6951	0.0262	0.4971
25	008A43	7.6685	0.7013	0.0286	0.5011
26	008A45	7.6435	0.6629	0.0301	0.4929
27	008A47	7.5685	0.6895	0.0268	0.4946
28	011A34	7.4860	0.6513	0.0302	0.4974
29	011A40	7.5610	0.6906	0.0282	0.4989
30	011A42	7.6329	0.6618	0.0252	0.5049

Table 4: Feature set values of d-hv-lbp-glcm for senior age images

S. no	Image Name	Contrast	Correlati on	Energy	Homo geneity
1	003A51	8.4213	0.6165	0.0262	0.4722
2	003A53	8.4213	0.6381	0.0278	0.4676
3	003A58	8.3158	0.6024	0.0255	0.4909
4	003A60	8.3658	0.6346	0.0271	0.4763
5	003A61	8.3543	0.6065	0.0267	0.4812
6	004A51	7.9646	0.6074	0.0233	0.4743
7	004A53	7.9212	0.5974	0.0261	0.4802
8	004A55	8.1146	0.6362	0.0271	0.4716
9	004A57	8.3713	0.6008	0.0268	0.4772
10	004A62	8.5488	0.6412	0.0269	0.4792
11	006A55	7.9146	0.6918	0.0228	0.4900
12	003A60	7.8212	0.6331	0.0261	0.4899
13	004A63	8.3213	0.6122	0.0250	0.4702
14	006A61	8.2658	0.6015	0.0272	0.4696
15	006A69	8.4488	0.5924	0.0261	0.4763
16	003A57	8.2043	0.6431	0.0268	0.4879
17	004A55	7.9212	0.6262	0.0254	0.4682
18	004A57	8.1543	0.6312	0.0238	0.4696
19	004A59	8.0146	0.7002	0.0257	0.4702
20	004A61	8.0212	0.6222	0.0260	0.4706
21	004A63	8.3658	0.6415	0.0256	0.4783
22	004A65	8.4988	0.7068	0.0277	0.4910
23	004A67	8.5213	0.6172	0.0264	0.4880
24	004A69	8.5488	0.6205	0.0266	0.4773
25	006A51	8.2543	0.7018	0.0236	0.4899
26	006A54	8.4658	0.6272	0.0279	0.4919
27	006A57	8.0146	0.6481	0.0234	0.4900
28	006A60	7.8712	0.6115	0.0259	0.4712
29	006A63	8.2543	0.6968	0.0282	0.4920
30	006A66	8.6488	0.6099	0.0266	0.4792

IV. Comparison of the Proposed Method with Other Existing Methods

The proposed D-HV-LBP-GLCM method is compared with other existing methods like Identification of facial parts and RBF Neural Network Classifier proposed by M. Yazdi et.al [15] and two geometric features and three wrinkle features from a facial image proposed by Wen-Bing Horng [16]. The classification rates are listed in table 6. The graphical representation of this is shown in Fig.4.

Table 5: Test vector feature set values of d-hv-lbp-glcm for different dataset images.

Sno	Image Name	Contrast	Correla-tion	Energy	Homo geneity	Group	Result
1	gogle_im_01	7.6068	0.7334	0.0333	0.5109	Middle	Success
2	gogle_im_02	7.1457	0.7356	0.0267	0.4735	Child	Success
3	gogle_im_03	7.5497	0.7290	0.0264	0.4955	Young	Success
4	gogle_im_04	7.1462	0.7211	0.0264	0.4786	Child	Success
5	gogle_im_05	6.6068	0.6334	0.0223	0.4511	Middle	Fail
6	gogle_im_06	8.0669	0.6293	0.0244	0.4691	Senior	Success
7	gogle_im_07	7.5694	0.6674	0.0285	0.4946	Middle	Success
8	gogle_im_08	8.0377	0.6287	0.0246	0.4689	Senior	Success
9	gogle_im_09	7.5610	0.7238	0.0267	0.4954	Young	Success
10	gogle_im_10	7.5384	0.7342	0.0261	0.4956	Young	Success
11	076A14	7.1283	0.7557	0.0263	0.4749	Child	Success
12	077A00	7.1213	0.6691	0.0269	0.4914	Child	Success
13	082A20	7.4731	0.7625	0.0271	0.4963	Young	Success
14	082A25	7.5118	0.7590	0.0266	0.4961	Young	Success
15	067A33	7.5569	0.6662	0.0290	0.4960	Middle	Success
16	067A39	7.5610	0.6704	0.0293	0.4948	Middle	Success
17	048A52	6.5527	0.5520	0.0287	0.4971	Middle	Fail
18	048A54	8.2935	0.6068	0.0261	0.4699	Senior	Success
19	067A48	7.5548	0.6641	0.0289	0.4965	Middle	Success
20	048A65	7.0605	0.6912	0.0271	0.4953	Child	Success
21	sca.img-001	7.1248	0.7124	0.0266	0.4832	Child	Success
22	sca.img-002	7.4924	0.7608	0.0269	0.4962	Young	Success
23	sca.img-003	8.2797	0.6042	0.0266	0.4698	Senior	Success
24	sca.img-004	7.7123	0.6911	0.0257	0.4978	Young	Success
25	sca.img-005	6.2960	0.7141	0.0276	0.4835	Senior	Fail
26	sca.img-006	8.2866	0.6055	0.0263	0.4699	Senior	Success
27	sca.img-007	7.5073	0.7206	0.0275	0.4972	Middle	Success
28	sca.img-008	7.5451	0.6948	0.0276	0.4980	Middle	Success
29	sca.img-009	7.6983	0.7042	0.0255	0.4967	Young	Success
30	sca.img-010	7.1031	0.7134	0.0269	0.4844	Child	Success

Table 6: Classification rate of the proposed d-hv-lbp-glcm method with other existing methods

Image Dataset	Identification of facial parts and RBF Neural Network	Geometric and wrinkle features	Prposed D-HV-LBP-GLCM Method
G-NET	89.67	90.52	93.23
Google	85.3	81.58	92.5
Scanned	88.72	85.42	91.5
Average	87.9	85.84	92.41

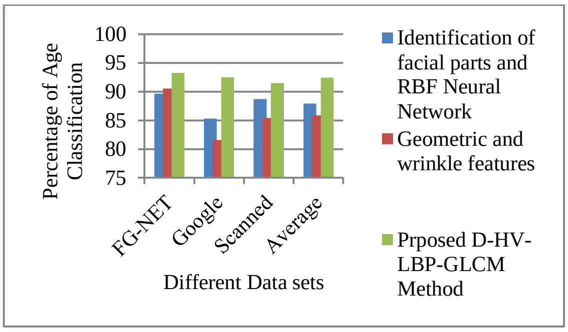

Fig 4: Classification chart of proposed method and other existing methods.

V. Conclusion

The proposed DL-LBP-GLCM reduced the computational time complexity because of the reduced size of the DL-LBP from 6561 to 14 as in the case of original LBP and 2020 to 14 as in the case of Fuzzy LBP. This new method combines the merits of both GLCM and DL-LBP for the effective age classification purpose.

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