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Texture Analysis and Classification Based on Fuzzy Triangular Greylevel Pattern and Run- Length Features

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Texture Analysis and Classification Based on Fuzzy Triangular Greylevel Pattern and Run-Length Features

U Ravi Babu [α], Dr. V Vijaya Kumar [σ] & J Sasi Kiran [ρ]

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I. Introduction

Analysis of textures is a fundamental research topic in the area of computer vision and has many potential applications, for example, in industrial surface inspection, remote sensing, and biomedical image analysis. Classification refers to as assigning a physical object or incident into one of a set of predefined categories. Many texture classification problems usually require the computation of a large amount of texture features in order to characterize their associated patterns. This implies that texture classifiers frequently combine big sets of features without taking into account their relevance and redundancy. Thus, lowering the dimensionality of a feature set is necessary for preserving the most relevant features and it reduces the computational cost derived from unnecessary features [1, 2, 3, 34, 35].

Numerous algorithms of textural features extraction have been presented during the past decades [4, 5]. Textures are classified recently by various methods: preprocessed images [34], long linear patterns [35], edge direction movements [21], avoiding complex patterns [10], marble texture description [36], skeleton extraction of texture [7], long linear patterns using wavelets [8] wavelet transform [8, 9, 10]. and Gabor filters [11]. More recently, the local-binary-pattern (LBP) operator [12, 13, 14] is used for texture classification. LBP operator is a statistical texture descriptor of the characteristics of the local structure. LBP provides a unified description including both statistical and structural characteristics of a texture patch, so that it is more powerful for texture analysis. The concept of LBP is also extend in applications such as face recognition and age classification [15, 16, 17], industrial visual inspection [18, 19], segmentation of remote-sensing images [20], and classification of real outdoor images [21].

An efficient nonparametric methodology for texture analysis based on magnitude LBP (MLBP) [22, 23, 24, 25, 26] is recently proposed and it has been made into a powerful measure of image texture, in terms of accuracy and computational complexity in many empirical studies. To address the connectivity limitations of LBP and MLBP, we propose a matrix called Triangular Neighborhood Matrix (TNM), which generates 2×2 texton patterns. A fuzzy member ship is introduced on TNM to extract local texture information efficiently. The present paper derived run length matrix on the proposed scheme and evaluated runlength features for efficient, precise and accurate classification of textures.

The rest of the paper is organised as follows. Section 2 describes the proposed method. Section 3 describes the results and discussions and conclusions are given in section 4.

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II. Methodology

Derivation of TNM (Triangular Neighborhood Matrix)

The present paper derived FTGP to overcome the disadvantages of LBP and other local binary approaches. Runlength features are evaluated on FGTP for a precise classification in 5 steps.

Step 1: Formation of Local Grey level Matrix (LGM):

A neighborhood of 3×3 pixels is denoted by a set containing nine elements: P= {P1, P1 ...P9}, here P5 represents the intensity value of the central pixel and remaining value are the intensity of neighboring pixels as shown in Fig. 1(a). The Local Grey level Matrix (LGM) values of the neighboring pixels (LGMPi) are obtained by evaluating the absolute difference between the neighboring pixel and the gray value of the central pixel, as described by the Equation (1) as shown in Fig. 1.

P_1	P_2	P_3
P_4	P_5	P_6
P_7	P_8	P_9

(a)

$LGMP_1$	$LGMP_2$	$LGMP_3$
$LGMP_4$	$LGMP_5$	$LGMP_6$
$LGMP_7$	$LGMP_8$	$LGMP_9$

(b)

Fig. 1 : (a) A neighborhood of 3×3 (b) obtained LGM

$$\mathrm{LGMP_i} = \mathrm{abs}(\mathrm{P_i} - \mathrm{P_5}) \quad \text{for } \mathrm{i} = 1,2,\ldots 9 \tag{1}$$

Where $LGMP_i$ is the obtained grey value of the pixel P_i of the LGM. The equation 1 demonstrates that always $LGMP_5$ value (central pixel value) will be always zero.

Step 2: Generation of Triangular Neighborhood Matrix (TNM) from LGM of step 1:

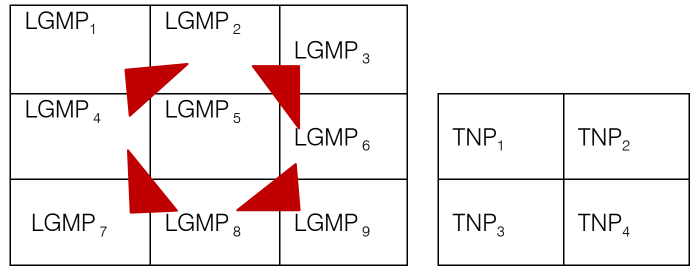
The 2 x 2 TNM is generated from LGM by taking the average value of the Triangular Neighbor Pixels (TNP) of the 3 x 3 LGM as shown in figure 3 and as given in equation 2,3, 4 and 5 . The triangular neighbors are considered because the central pixel of LGM is always zero. That is one need not necessary to consider this.

$$TNP_1 = \frac{(\mathrm{LGMP_1} + \mathrm{LGMP_1} + \mathrm{LGMP_1})}{3} \tag{2}$$

$$TNP_2 = \frac{(\mathrm{LGMP}\ \ {}_2 + \mathrm{LGMP_3} + \mathrm{LGMP_6})}{3} \tag{3}$$

$$TNP_3 = \frac{(\mathrm{LGMP_4} + \mathrm{LGMP_7} + \mathrm{LGMP_8})}{3} \tag{4}$$

$$TNP_4 = \frac{(\mathrm{LGMP_6} + \mathrm{LGMP_8} + \mathrm{LGMP_9})}{3} \tag{5}$$



(a) (b)

Figure 3 : Generation process of a 2 × 2 TNM from LGM (a) LGM matrix (b) TNM

Step 3: Conversion of TNM in to FTGP (Fuzzy Triangular Grey level Pattern):

Fuzzy logic has certain major advantages over traditional Boolean logic when it comes to real world applications such as texture representation of real images. LBP patterns are formed and counted from 0's and 1's. However, the dangerous situation of LBP is that even if the difference is minimum let us say 1 or maximum i.e. 255, it converts it into 1. That is LBP treats even the difference of 1 and 255 as homogeneous. This clearly indicates the patterns of LBP will never gives totally useful and significant information. The above property misuses the power of LBP method. To address this in the proposed method fuzzy member ship is introduced. The aim of fuzzy approach in forming FTGP is to extract local texture information from TNM pixels for representing the texture information accurately. To deal accurately with the regions of natural images even in the presence of noise and the different processes of caption and digitization FTGP is introduced on TNM. For example, even if the human eye perceives two neighboring pixels as equal, they rarely have exactly the same intensity values. The fuzzy patterns are chosen in the present paper because, recently, fuzzy based methods have been used in texture analysis and in image segmentation [28, 29]. The FTGP consists of fuzzy patterns with 5 values {0, 1, 2, 3 and 4} instead of two patterns of LBP. Though the present paper considers five possible fuzzy grey level values, but at any time only a maximum of four fuzzy patterns will appear because the FTGP is a 2 x 2 matrix. In LBP binary patterns are evaluated by comparing the neighboring pixels with central pixel. The FTGP are derived by comparing the each pixel of the 2 x 2 TNM with the average pixel values of the TNM. The FTGP representation is shown in Fig. 4. The following Eqn. (6) is used to determine the elements, $FTGP_i$ of the TNM.

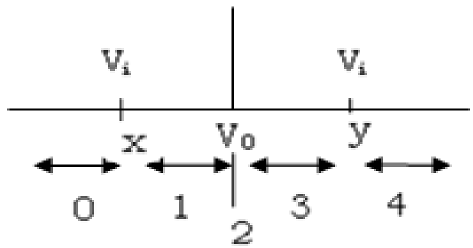


Fig. 4 : Fuzzy triangular grey level texture number representation

$$FTGP_i = \begin{cases} 0 & \text{if} \quad TNP_i < V_0 \quad \text{and} \quad V_i < x \\ 1 & \text{if} \quad TNP_i < V_0 \quad \text{and} \quad V_i \geq V_x \\ 2 & \text{if} \quad TNP_i = V_0 \\ 3 & \text{if} \quad TNP_i > V_0 \quad \text{and} \quad V_i > y \\ 4 & \text{if} \quad TNP_i > V_0 \quad \text{and} \quad V_i \leq y \end{cases} \quad \text{for } i = 1,2,3,4 \tag{6}$$

Where x, y are the user-specified values.

$$where\ V_0 = \frac{\left(\sum_{i=1}^{4} TNP_i\right)}{4} \tag{7}$$

For example, the process of evaluating FTGP from a sub TNM image of 2 x 2 is shown in Fig. 5. In this example x and y are chosen as $v_0/2$ and $3v_0/2$ respectively.

28	39
61	9

(a)

1	2
4	0

(b)

Fig. 5 : The process of evaluating FTGP from TNM (a) TNM (b) FTGP

Step 4: Generation of Run Length Matrices on Fuzzy Texture Grey level Pattern (RLM- FTGP)

The membership values of FTGP neighboring pixels are useful for characterization of textures. To address this difficulty the present approach derived Run length matrix (RLM) on the FTGP of the image.

Definition of the Run-Length Matrices: Galloway proposed the use of a run-length matrix for texture feature extraction [12]. For a given texture image, a run-length matrix P(i; j) is defined as the number of runs with fuzzy value i and run length j. Various texture features can then be derived from this run-length matrix.

For a given image, the proposed method defines a RLM (i,j) on FTGP as number of runs starting from location (i,j) of the FTGP image. The proposed method derived five different RLM- FTGP. The RLM-$FTGP_0$, RLM- $FTGP_1$, RLM- $FTGP_2$ RLM- $FTGP_3$ and RLM- $FTGP_4$ contain the run length values for zero, one, two, three and four.

Step 5: Extraction of Texture Features on RLM – FTGP:

Many researchers used three sets of texture features from RLM for texture classification. The first set of RLM Features (RF) is *Traditional Run-Length Features.* The five original features of run-length statistics derived by Galloway [27] are *Short Run Emphasis (SRE)*, *Long Run Emphasis (LRE)*, *Gray-Level Non uniformity (GLN)*, *Run Length Non uniformity (RLN)*, and *Run Percentage (RP)* are described by the Equation (8) to Equation (12). Chu *et al.* [30] proposed another set of two new features, such as *Low Gray-Level Run Emphasis (LGRE)*, and *High Gray-Level Run Emphasis (HGRE)* are described in Equation (13) to Equation (14). In a recent study, Dasarathy and Holder [31] described another set of four feature extraction functions following the idea of joint statistical measure of gray level and run length, as follows: *Short Run Low Gray-Level Emphasis (SRLGE)*, *Short Run High Gray-Level Emphasis (SRHGE)*, *Long Run Low Gray-Level Emphasis (LRLGE), and Long Run High Gray-Level Emphasis (LRHGE)* are described in Equation (15) to Equation (18).

The novelty of the present study is it evaluated the first five RFs as described in equations from 8 to 12 for efficient classification purpose on FTGP. For a comparative analysis the present paper also evaluated all the features for classification purpose.

$$SRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{P(i,j)}{j^2} \tag{8}$$

$$LRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j) * j^2 \tag{9}$$

$$GLN = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{P(i,j)}{j^2} \tag{10}$$

$$GLN = \frac{1}{n_r}\sum_{i=1}^{M}\left(\sum_{j=1}^{N}P(i,j)\right)^2 \tag{11}$$

$$RP = \frac{n_r}{n_p} \tag{12}$$

In the above equations, n_r is the total number of runs and n_p is the number of pixels in the image.

$$LGRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{P(i,j)}{i^2} \tag{13}$$

$$HGRE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j) * i^2 \tag{14}$$

$$SRLGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{P(i,j)}{i^2 * j^2} \tag{15}$$

$$SRHGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{P(i,j) * i^2}{j^2} \tag{16}$$

$$LRLGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{P(i,j) * j^2}{i^2} \tag{17}$$

$$LRHGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j) * i^2 * j^2 \tag{18}$$

III. Results and Discussions

Experiments are carried out to demonstrate the effectiveness of the proposed FTGP – with RF for stone texture classification. The present paper carried out the experiments on two Datasets. The Dataset-1 consists of various brick, granite, and marble and mosaic stone textures with resolution of 256×256 collected from Brodatz textures, Vistex, Mayang database and also from natural resources from digital camera. Some of them in Dataset-1 are shown in the Fig. 6. The Dataset-2 consists of various brick, granite, and marble and mosaic stone textures with resolution of 256×256 collected from Outtex, Paulbourke color textures database, and also from natural resources from digital camera. Some of them in Dataset-2 are shown in the Fig. 7. Dataset-1 and Dataset-2 contains 80 and 96 original color texture images respectively. For classification the proposed method initially divide the texture images into non-overlapping windows of size 32×32 and the resulting windows are then divided into two disjoint sets, one for training and one for testing. The distance classifier Euclidean distance (d) is used for classification in the present paper. The classifier computes the distance between the features for each sample and that of the texture classes and assigns the unknown sample to the texture class with the shortest distance. The classification results for each of the two Data sets are shown in Table I, Table II.

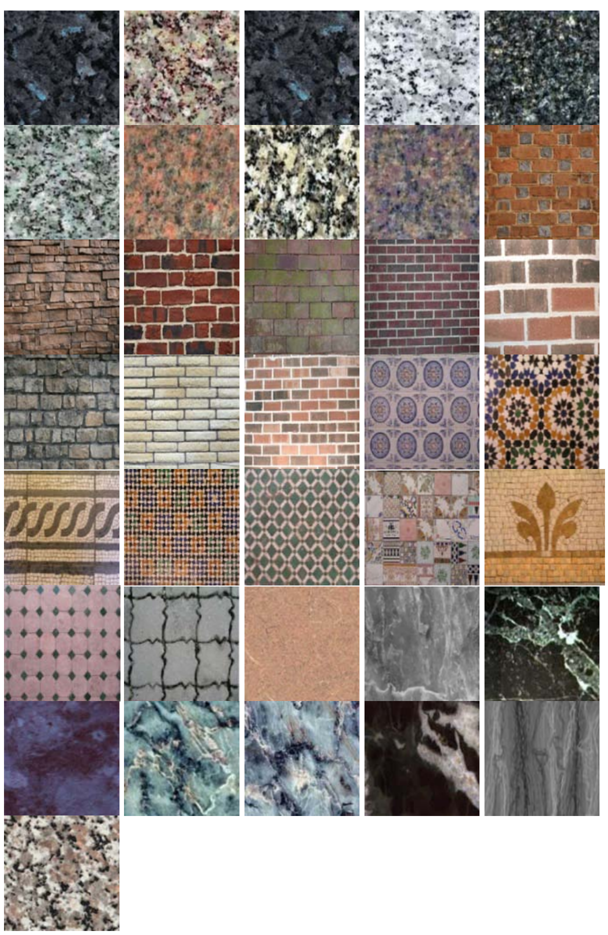


Fig. 6 : Input texture group of 9 samples of Granite, Brick, Mosaic, and Marble in Dataset-1

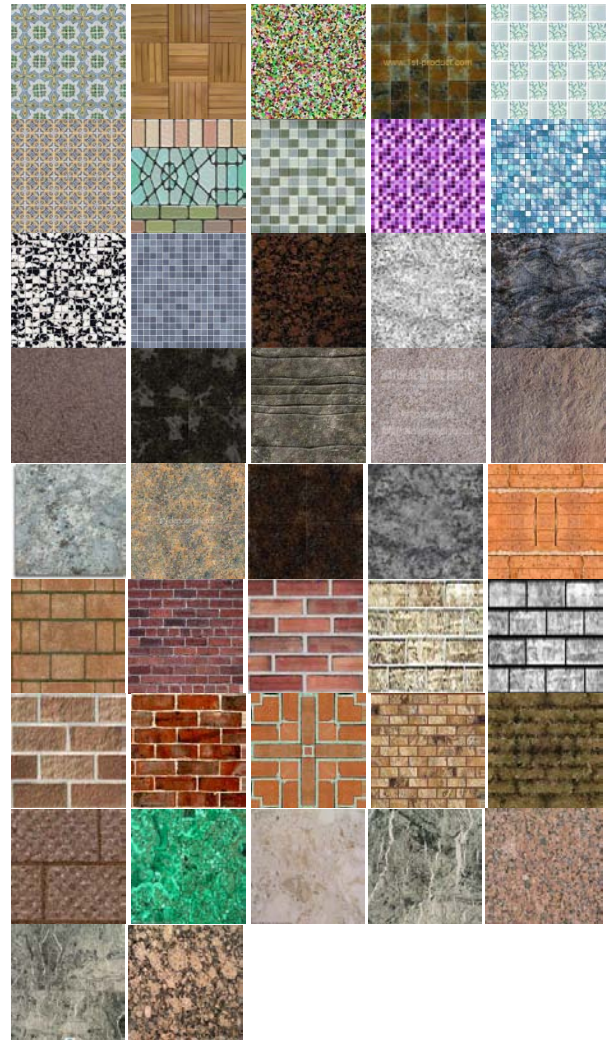


Fig. 7 : Input texture group of 12 samples of Mosaic, Granite, Brick, and Marble with size of 256×256 in Dataset-2

Table Ia : Results of texture classification by proposed RF on FTGP of mosaic and brick textures in Dataset-1

Sno	Texture Name	Classification Rate	Texture Name	Classification Rate
1	concrete_bricks_170756	94.22	Brick.0001	95.06
2	concrete_bricks_170757	94.58	Brick.0002	91.49
3	concrete_bricks_170776	89.64	Brick.0003	97.28
4	crazy_paving_5091370	95.2	Brick.0004	95.9
5	crazy_paving_5091376	96.56	Brick.0005	93.39
6	crazy_tiles_130356	93.54	Brick.0006	96.65
7	crazy_tiles_5091369	95.88	Brick.0007	94.51
8	dirty_floor_tiles_footprints_2564	93.17	Brick.0008	93.25
9	dirty_tiles_200137	93.99	Brick.0009	93.37
10	floor_tiles_030849	96.55	Brick.0010	95.96
11	grubby_tiles_2565	94.68	Brick.0011	92.46
12	kitchen_tiles_4270064	95.48	Brick.0012	94.52
13	moroccan_tiles_030826	96.35	Brick.0013	93.62
14	moroccan_tiles_030857	95.77	Brick.0014	91.48
15	mosaic_tiles_8071010	96.16	Brick.0015	93.61
16	mosaic_tiles_leaf_pattern_201005060	94.97	Brick.0016	92.01
17	mosaic_tiles_roman_pattern_201005034	90.91	Brick.0017	94.58
18	motif_tiles_6110065	95.34	Brick.0018	92.47
19	ornate_tiles_030845	96.44	Brick.0019	96.13
20	repeating_tiles_130359	90.84	Brick.0020	95.37

Table Ib : Results of texture classification by proposed RF on FTGP of granite and marble textures in Dataset-1

Sno	Texture Name	Classification Rate	Texture Name	Classification Rate
1	blue_granite	95.9	apollo	94.09
2	blue_pearl	96.32	canyon_blue	91.81
3	blue_topaz	93.26	cotto	95.53
4	brick_erosion	90.69	curry_stratos	94.02
5	canyon_black	91.48	flinders_blue	95.98
6	dapple_green	96.61	flinders_green	94.54
7	ebony_oxide	97.58	forest_boa	93.71
8	giallo_granite	96.46	forest_stone	94.82
9	gosford_stone	92.26	goldmarble1	92.03
10	greenstone	92.11	green_granite	93.14
11	interlude_haze	97.12	grey_stone	93.15
12	kalahari	91.43	greymarble1	94.02
13	mesa_twilight	92.98	greymarble3	94.69
14	mesa_verte	94.35	marble001	94
15	monza	94.46	marble018	93.39
16	pietro_nero	91.61	marble034	95.17
17	russet_granite	96.19	marble033	94.51
18	granite10	94.07	marble012	94.53
19	granite13	94.94	marble014	94.43
20	granite20	92.89	marble020	89.93

Table 2a : Results of texture classification by proposed RF on FTGP of mosaic & brick textures in Dataset-2

Sno	Texture Name	Classification Rate	Texture Name	Classification Rate
1	images_024	89.81	alternating_brick_3121141	95.18
2	images_027	93.9	alternating_brick_3121142	93.27
3	images_028	94.07	brick_1241070	96.13
4	images_044	95.99	brick_3141206	92.81
5	images_057	93.92	brick_3141207	97.09
6	images_065	92.65	brick_4161585	92.64
7	images_080	89.74	brick_and_wood_wall_3141270	95.81
8	images_101	93.48	brick_blotchy_litchen_2562	96.1
9	images_132	92.32	brick_closeup_5013216	93.51
10	images_133	94.09	brick_detail_6080096	95.03
11	images_144	92.21	brick_flooring_1010262	94.19
12	images_153	88.51	brick_lichen_closeup_2561	87.44
13	images_158	93.56	brick_P3012913	96.4
14	images_178	90.73	brick_removed_plant_2560	97.76
15	images_197	92.07	brick_square_pattern_9261479	93.39
16	images_239	93.3	brick_texture_221691	92.69
17	images_240	89.29	brick_texture_4161572	97.47
18	images_271	88.46	brick_texture_9181117	93.45
19	images_285	97.02	brick_wall_3141250	94.26
20	images_287	91.47	brick_wall_3141267	93.73
21	images_289	91.39	brick_wall_7070215	93.72
22	images_290	92.31	brick_wall_7070225	93.88
23	images_296	95.81	brick_wall_7070226	95.39
24	images_326	88.51	brick_wall_7070227	95.2

Table 2b : Results of texture classification by proposed RF on FTGP of marble & granite textures in Dataset-2

Sno	Texture Name	Classification Rate	Texture Name	Classification Rate
1	images_002	93.54	blotched_marble_2052007	97.21
2	images_006	95.75	bricklike_marble_2052068	93.94
3	images_009	96.29	coarse_marble_9261512	94.7
4	images_011	94.86	dotted_marble_2052053	92.68
5	images_020	97.23	dotty_marble_92398723	95.8
6	images_065	96.7	faded_marble_9160023	96.21
7	images_024	97.26	fine_textured_marble_9181141	97.12
8	images_030	96.05	fossils_A220534	96.63
9	images_032	95.04	marble_cracks_circles_4168	93.17
10	images_033	94.56	marble_fossils_4167	91.76
11	images_038	98.13	marble_texture_9181134	96.46
12	images_040	93.97	marble_texture_B231063	93.07
13	images_041	93.02	marble_with_fossils_4165	92.82
14	images_047	93.96	marble_with_fossils_4166	93.31
15	images_050	95.24	marblelike_stone_9261514	94.39
16	images_051	92.83	patterned_stone_C050573	93.12
17	images_052	96.92	rose_coloured_marble_9181131	96.27
18	images_053	95.3	rounded_markings_marble_2397234	91.46
19	images_058	93.28	rounded_pattern_marble_2052013	95.98
20	images_062	93.59	roundy_marble_297234	96.19
21	images_065	95.27	shiny_reflective_marblelike_stone_9261513	92.03
22	images_067	94.07	specked_marble_9261515	94.71
23	images_068	94.07	specked_marble_C050546	93.23
24	images_071	97.65	spotty_marble_4142267	95.51

a) Comparison of the Proposed RLMF on FGTP with other existing Methods

Table 3 shows the classification rate for various group of textures by the proposed FTGP-RF with other existing methods like compound local binary pattern (CLBP) of Faisal Ahmed et.al [32] and run-length features for image classification by Yung-Kuan Chan et.al [33]. From Table 3, it is clearly evident that, the proposed FTGP-RF exhibits a high classification rate than the existing methods. The graphical representation of the percentage mean classification rate for the proposed RLM-FTGP and other existing methods are shown in Fig.8.

Table 3 : Classification rates of the proposed FTGP-RF with other existing methods

Image Dataset	Compound Local Binary Pattern (CLBP)	Run-length Features	Proposed Method (FTGP-RF)
Brodatz	90.29	93.79	96.31
VisTex	91.53	93.56	95.85
Mayang	92.34	94.43	97.32
Outtex,	91.59	93.63	96.96
CUReT	91.76	93.46	97.54
Paulbourke	90.98	94.56	96.77
Average	91.41	93.91	96.79

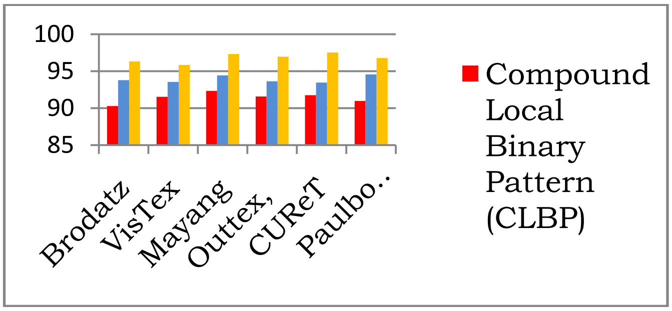


Fig. 8 : Classification chart of proposed FTGP-RF with other existing methods

IV. Conclusion

The proposed FTGP scheme reduces the overall dimension of the image while preserving the significant attributes, primitives, and properties of the local texture. The proposed RLM-FTGP overcomes the disadvantages of the previous Run length matrices for texture classification. LGM is an efficient tool that overcomes the traditional neighborhood problems. By directly using the entire run-length matrix for feature extraction, much of the texture information is preserved. The novelty of the proposed scheme is, it is proved that one need not necessary to evaluate all the RF on the FTGP for classification purpose. For a precise, significant and accurate classification, the present paper evaluated only 5 RLMF on FTGP, which reduced overall complexity. Comparisons of this new approach with the compound local binary pattern (CLBP) by Faisal Ahmed et.al [32] and run-length features for image classification by Yung-Kuan Chan et.al [33] demonstrated the supremacy of the proposed FTGP method.

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