Classification of Natural Textures using Rule Based Rank Matrix

K.S.R.K.Sarma, M.Ussenaiah

Abstract*: This paper derives a new frame work for the classification of natural textures based on gradient rank vectors derived on a 2 X 2 grid. This paper identified the ambiguity in deriving ranks when two or more positions of the grid possess the same value. To attend this ambiguity and without increasing the total number of rank vectors on d positions this paper derived a rule based rank vector frame work. This paper replaced the 2 X 2 grid with the column position of the Rule based Rank Word Matrix (RRWM). The range of column positions will be d! for d positions. This paper then divides RRW texture image, into a 3 X 3 grid and derives cross and diagonal rule based rank words. From this, the present paper derived Rule based Rank Word-Cross and Diagonal Texture Matrix (RRW-CDTM) and derives GLCM features for effective texture classification. The experimental results on various texture databases revels the classification accuracy of the proposed method. The proposed method is compared with the state of art local based approaches.

Index Terms*: Cross and Diagonal units, GLCM features, Gradient, Rank, 2 X 2 grid, 3 X 3 grid.

I. INTRODUCTION

Texture analysis has become one of the important branches of computer vision and image processing and this fact has been well known from decades [1]. Texture analysis has become one of the significant areas of computer vision and it has attracted many researches from the past decades due to its wide range of applications from medical image processing to face recognition [2]-[4] etc.

The term texture refers to the surface property and all images contain texture and this has lead to the interest in texture analysis by researchers. Further the continuous development and research in image acquisition technology made the possibility for acquiring a very high resolution images and thus it had made to analyze the texture attributes more critically. This has improved the importance of texture analysis and today texture based properties are playing very significant role in Machine Learning problems, including Medical image analysis to detect and analyze various abnormalities, Surface inspection, Texture classification [5], [6], host image detection etc.

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The literature in texture analysis is rich and abundant due to the extensive research carried out by many researchers over the past 30 to 40 years. There is no unique definition of texture; however it is easy to understand. In the literature many researchers tried to give a precise definition, however these definitions of textures are based on the application they were intended. That is researchers were published various qualitative definitions of texture; however this research identified there is no universal quantitative definition of texture. In the literature many researchers defined texture and they are reviewed by many researchers based on the application they have used. The common points from those definitions are identified in [7] and noted as (i) The textures contain the presence of repetitive patterns with same size (ii) The spatial and non random organization of these primitives in a region are larger than the primitive size itself (iii) The texture is a neighborhood property that is the intensity of a pixel depends also on the grey levels of the surrounding pixels.

In the literature a variety of quantitative texture descriptors are proposed during the last forty years and they are mostly based on the local neighbourhoods, few of them derived region based and global based descriptors. Histogram of equivalent patterns is derived to classify the most relevant texture descriptors and has provided discrimination between local and global methods. The global methods derive the texture attributes and feature vector by considering the entire image as one region.

This paper adapted the local based approach for texture classification, and the local based methods have advantages over global based methods. This paper reports the most popular and most used local approaches of texture analysis and classification. One of the most popular methods for texture analysis that measures the joint probability of grey levels at two pixels located at fixed relative positions is popularly known as Grey Level Co-occurrence Matrix (GLCM). The Haralick [1] derived set of features on GLCM with different distances and different rotations. These features are later combined with other local descriptors and structural operators. Later neighborhood methods are derived, these methods are mainly based on a local neighborhood of Square, Circle, Rectangle shapes. The features are derived on these structural neighborhoods by shifting one column position then by one row (overlapped manner) mostly.

The research on neighborhood methods and the derivation of texture descriptors on local neighborhood has become more prolific from the nineties. The popular ones of this category are texture spectrum [8] and its simplified version [9].

The texture spectrum methods derived the ternary relationship among central verses sampling pixels of the 3 X 3 neighborhood and they derived the popular Texture Unit, Black and White Symmetry [BWS] etc. Later Ojala et al., [10] extended the texture spectrum concept and derived more versatile texture descriptor known as Local Binary Patterns [LBP] and it has played a significant role in various applications. Many extensions are proposed to LBP like Local Ternary Pattern [LTP][4], Local Quinary Patterns [LQP][11], Complete Local Binary Patterns [CLBP][12] and other variants [13]. All these local based methods are derived on circular neighbourhood, however recently researchers derived texture features based on circular and elliptical neighbourhood and it has resulted a better classification than LBP variants [6]. In the literature texture primitives are derived using 2 X 2 grid and known as Texton [14], [15] and Motif based [16], [17] approaches. The popular motif based methods are Motif Co-occurrence Matrix (MCM) [16].

The organization of the paper is as follows: Section 1 presents a comprehensive introduction to texture classification and its applications followed by the related work done in this area. The frame work of the proposed system is presented in Section 2. In Section 3 the experimental results are offered and discussed. The paper is concluded with the summary in Section 4.

II. PROPOSED METHOD

This Paper initially divides the texture image into micro regions of size 2 X 2 in a non-overlapped manner. This research derives a rule based gradient rank position for each pixel location based on the grey level values of gradients. A 2 X 2 grid will have four pixels represented by $\{b_1, b_2, b_3, b_4\}$. The $b_1,\ldots,b_4$ represents the grey level value associated with each pixel location. This research derives a gradient value 'g_i' for each pixel location by computing the difference between the average grey level value of the 2 X 2 grid 'a' with individual grey level value 'b_i' in the following manner.

$$a = \mathrm{int}\left(\left(\sum_{i=1}^{4} b_i \right) / 4 \right) \qquad (1)$$

$$g_i = b_i - a \qquad (2)$$

The g_i values can be positive if $a < b_i$ or negative if $a > b_i$ or zero if $a = b_i$. This research derives rule based gradient rank (RGR) for each gradient of the 2 X 2 neighborhood as follows. The ranks are assigned to each gradient pixel in ascending order on the 2 X 2 window. From this a gradient rank vector (GRV) $\{gr_1, gr_2, gr_3, gr_4\}$ is generated. The gradient rank vector (GRV) is generated in a clock wise direction from top leftmost pixel as shown in Fig. 2.

The gradients ranks are initiated from 1 to 4. Therefore the gr_i can have value ranging from 1 to 4.The process of generating rank vectors for a 2 X 2 grid with grey level values is shown in Fig. 3.

b_1	b_2
b_4	b_3

(a)

g_1	g_2
g_4	g_3

(b)

Fig. 1: (a): A 2 X 2 grid; (b): Gradient grid.

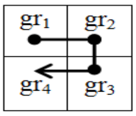

Fig. 2: The generation of gradient rank vector.

20	18
28	32

(a)

=> a = 24

(b)

-4	-6
4	8

(c)

2	1
3	4

(d)

=> {2, 1, 4, 3}

(e)

Fig. 3: (a): The 2 X 2 grid with grey values; (b): The average value 'a'; (c): The gradient grid of (a); (d): The gradient rank (GR); (e): The gradient rank vector (GRV).

The average grey level value 'a' of the 2 X 2 grid of Fig. 3(a) is computed using (1) and the 'a' value is noted as 24 (Fig. 3(b)). The gradient is computed using (2) (Fig.3(c)). The GR are assigned in the Fig. 3(c). The gradient rank vector (GRV) is derived on the Fig. 3(d) by evaluating rank sequences in clock wise manner initiating from top left most corner of the 2 X 2 grid. This research observed there is an ambiguity in generating rank vector if two or more GR are similar as shown below.

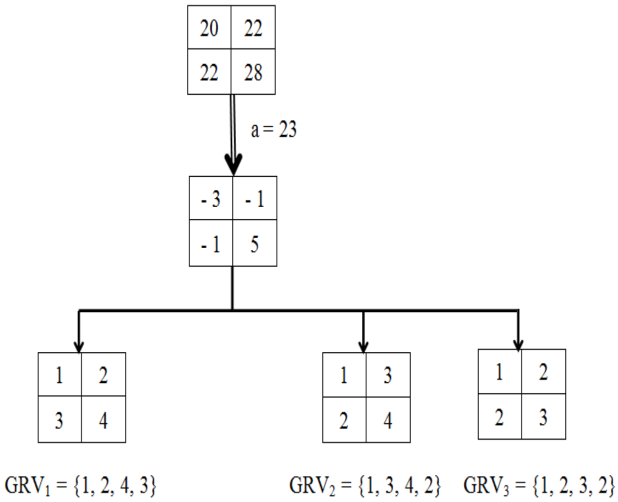

Fig. 4: The Ambiguity in generating GRV for the same 2 X 2 grid.

The 2 X 2 grid of the above Fig. 4 generates an average grey level value 'a' = 23. And this process generates three different GRV's : GRV_1, GRV_2 and GRV_3: {1,2,4,3} or {1,3,4,2} or {1,2,3,2}as shown above. This is mainly due to the following reasons:

1) Whenever two or more pixels in the 2 X 2 grid exhibits the similar gradient values it leads to ambiguity in assigning ranks as shown in GRV_1 and GRV_2.
2) The GRV_3 is not possible due to the basic definition of gradient rank: the rank positions must be unique i.e. no two positions of the grid should exhibit the similar rank.

To address this, this research assigns different ranks even though two or more pixel locations exhibit the same GR's.

The above case generates the ambiguity in generating GRV. To address this, this paper derived Rule based Gradient Rank (RGR) Scheme. The GR must be unique, that is two or more pixel locations should not have the similar ranks, even though they have exactly similar values. To derive unique GR this paper introduced Rule based Gradient Rank (RGR) based on the scan direction of the Rank Vector generation.

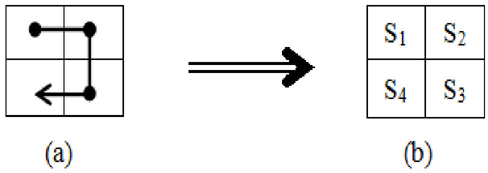

Fig. 5: The scan direction of the Rank Vector (RV).

The above Fig. 5 represents the scan direction of the RV and S_1, S_2, S_3 and S_4 represents the scan position. The RGR assigns unique rank values based on scan directions. That is whenever two or more ranks are similar then this research assigns the rank values $R_i < R_j$ if and only if $S_i < S_j$ positions. That is if the scan positions S_2 and S_4 represents the same ranks then the rank of $S_2 < S_4$ according to RGR. The above RGR derives a unique RGRV for figure 4 which is {1, 2, 4, 3}, based on the derived rule. By this the RGRV will have N! Combinations for N number of ranks or N-positional grid.

This research also derives Rule based Rank Word Matrix (RRWM). In our case with N number of unique ranks (1 … N) the dimension of RRWM will be N X N!, Where N represents the number of rows and N! represents the number of columns. Each word W_i of RRWM represents the column entry of RRWM, which represents the RGRV. This research replaces the 2 X 2 grid with the Rule based Rank Word (RRW) position index W_i (column index) of the RRWM. The range of column positions of RRWM or RRW will be 1 … N! and in our case 1 … 4! (i.e. 1 to 24). Thus the dimension of the RRWM will be 4 X 24. This process transforms the entire texture image into a RRW image, where the range of each word W_i ranges from 1 to 24. The entire process of this transformation is shown below in Fig. 6.

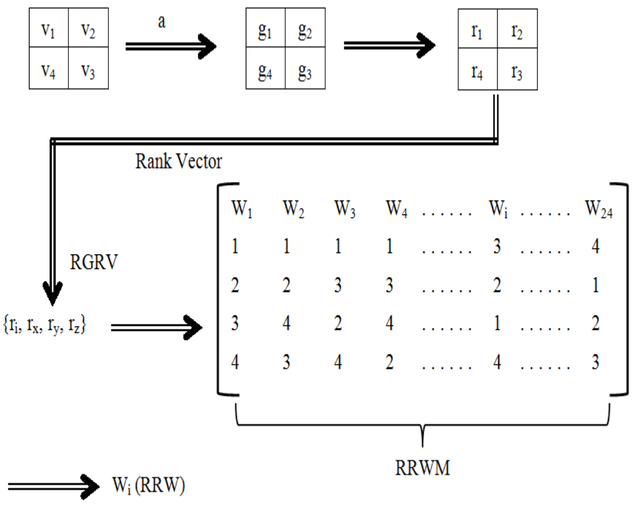

Fig. 6: The framework for generation of RRWM and derivation of W_i (RRW).

In the above Fig 6 the v_1, v_2, v_3, v_4; g_1, g_2, g_3, g_4 represents the grey levels of a 2 X 2 grid and their corresponding gradients derived from equation 1and 2. And the r_1, r_2, r_3, r_4 represents the corresponding Rule based Gradient Ranks. This research searches the RGRV position in the RRWM and replaces the 2 X 2 grid with RRW i.e., W_i.

This research divides Rule based Rank Word (RRW) texture image into a 3 X 3 overlapped grids. This research derives a ternary pattern for each sampling point of 3 X 3 RRW grid by comparing it with the centre pixel as given in (3).

$$W_j = \begin{cases} 0 & \text{if } W_i < W_c \\ 1 & \text{if } W_i = W_c \\ 2 & \text{if } W_i > W_c \end{cases} \qquad (3)$$

Where W_j and j = 1 to 8 are the sampling points and W_c is the centre pixel of the 3 X 3 RRW window.

This paper divides the ternary RRW window into, two units named as cross unit (CU) and diagonal unit (DU). The ternary RRW-CU consists of cross pixels and the ternary RRW-DU consists of diagonal pixels. In the following Fig. 7 the cross pixels and diagonal pixels are represented in Red & Green colors respectively.

W_1	W_2	W_3
W_8	W_c	W_4
W_7	W_6	W_5

Fig. 7: The representation of cross and diagonal units of a 3 X 3 window.

This paper derives cross diagonal matrix of RRW in the following way: Initially this paper derives RRW-CU code and RRW-DU code using (4).

$$code = \sum_{i=1}^{4} w_i * 3^{i-1} \qquad (4)$$

The above (4) derives RRW-DU and RRW-CU for i = 1, 3, 5, 7 and i = 2, 4, 6, 8 respectively and the code for RRW-CU and RRW-DU is obtained respectively. The RRW-DU and RRW-CU code ranges from 0 to 81. This paper derived RRW cross and diagonal texture matrix (RRW-CDM) based on the relative frequencies of RRW-CU and RRW-DU codes in the following way. The dimension of the RRW-CDTM will be 81 X 81 (0 to 81 X 0 to 81). Initially the RRW-CDTM is initialized to zero. Then for each 3 X 3 window the following step is performed.

RRW-CDTM(c,d) = RRW-CDTM(c,d) + 1;

Where the c and d represents the RRW-CU and RRW-DU codes respectively (ranges from 0 to 81).

This research derived six Grey Level Co-occurrence Matrix (GLCM) features i.e. Contrast, Correlation, Entropy, Homogeneity, Inverse Difference Moment (IDM) and Prominence feature on the RRW-CDTM for distance value 1 and 2 with six degrees of rotation 0^0, 45^0, 90^0, 135^0, 180^0, and 225^0. Thus this research derived 6 feature vector values for each feature vector for each distance value and it results a total of 36 features. This research used the machine learning classifiers IBK, Multilayer perceptron, J48 and Naïvebayes for classification purpose.

The algorithm for the proposed RRW-CDTM is given below.

Step 1: Perform the pre-processing step on the input image if required.

Step 2: Divide the image into 2 X 2 grid and drive gradients of each pixel.

Step 3: Compute rule based gradient ranks for the each 2 X 2 grid.

Step 4: Formation of rule based gradient rank vector (RGRV) based on peano scan direction.

Step 5: Formation of RRWM with a dimension of 4 X 4!, and place the all 4! Rank sequences in RRWM.

Step 6: Match the derived RGRV with the column/ RRW entry W_i of RRWM.

Step 7: Replace the 2 X 2 grid with W_i.

Step 8: Repeat the process for entire image.

Step 9: Divide the image with W_i or RRW into 3 X 3 grids.

Step 10: Derive a ternary value for each sampling pixel of the 3 X 3 grid.

Step 11: Divide the 3 X 3 RRW-window into cross & diagonal units.

Step 12: Compute RRW-Cross Unit and RRW-Diagonal Unit value.

Step 13: create the RRW-CDTM with the dimensions of 81 x 81

Step 14: initialize the RRW-CDTM! with zero values.

Step 15: for each window perform RRW-CDTM(c,d) = RRW-CDTM(c,d) + 1.

Step 16: compute six GLCM features on RRW-CDTM with six degrees of rotation.

Step 17: Apply different machine learning classifiers for classification purpose.

End of the algorithm.

The Main contribution of this paper is listed below

1) Derivation of unique gradient ranks without any ambiguity by using rule based approach.

2) The derivation of rule based approach in assigning unique rank position based on peano scan direction.

3) Derivation of RRW matrix.

4) Derivation of cross and diagonal texture matrix by dividing the RRW indexed image into 3 X 3 overlapped windows.

III. RESULTS AND DISCUSSIONS

This paper conducted experiments on the popular databases to investigate the performance of the projected method RRW-CDTM. The databases considered are MIT Vision Texture database (Vistex) [18], Salzburg Texture database (Stex) [19], Colored Brodatz Texture database (CBT) [20], the USPtex [21], the Outex TC-00013 [22]. The sample images are displayed in the following figures.

Fig. 8: Sample images of Vistex-640 [18]

Fig. 9: Sample images of Stex-7616 [19]

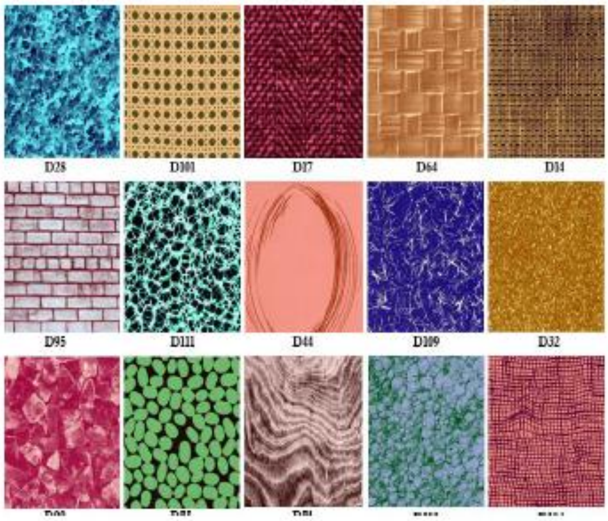

Fig. 10: Sample images of CBT-2800 [20]

Fig. 11: Sample images of USPtex-2292 [21]

Fig. 12: Sample images of Outex-1360 [22]

Table- I: classification rates of the proposed RRW-CDTM descriptor with different classifiers for d value 2.

Database	Multilayer Perceptron	Naivebayes	IBK	J48
MIT-VisTex	98.57	89.01	90.07	90.49
Stex	95.21	85.75	88.71	85.41
USPTex	99.74	91.05	91.74	89.51
CBT	99.01	89.81	91.45	88.02
Outex-13	99.01	90.10	90.56	91.27
Average	98.31	89.14	90.51	88.94

For classification purpose this paper considered four machine learning classifiers instead of distance functions. The four machine learning classifiers used on the proposed descriptor RRW-CDTM are IBK, Multilayer perceptron, J48 and Naïvebayes. The RRW-CDTM features are computed using distance function d=1 and 2 with six different rotations as specified above. The results indicated that the above classifiers exhibited high results for d value 2. When compared to the individual classifiers among the above four, it is noted from the Table- I that multilayer perceptron outperformed other three classifiers on all considered natural databases.

In the remaining section of this paper, this paper presents the classification rate of multilayer perceptron classifier on the proposed RRW-CDTM especially when compared with the other popular local descriptors.

To examine the efficacy of the projected descriptors RRW-CDTM, this research compared the classification rates of the popular descriptor of classification LBP [10], LTP [4], CLBP-SMC [12], CS-LBP [23] and the other counter parts of the motif based descriptors like MCM [16].

The ternary pattern frame work on 3 X 3 neighborhood i.e., LTP attained almost 4 to 5% high classification rate on average when compared to LBP. This is mainly due to the introduction of ternary pattern with a threshold and LTP is more resistant to noise when compared to LBP. The CS-LBP could not attain promising results due to non-consideration of center pixel value when computing symmetric relationship between sampling points. The motif based method MCM is different from LBP, LTP, CS-LBP and other variants of LBP such as LDP etc... The motif based methods are derived on a 2 X 2 neighborhood where as the basic LBP and its variants are derived on 3 X 3 window. The other difference is the motif based frameworks are based on the piano scan directions of the intensity levels, whereas the LBP and its variants derive the relationship between center pixel and sampling points and thus derives a unique code. The codes derived by LBP variants are huge when compared to motif based methods. The motif based attained high classification rate when compared to the basic versions of LBP based methods. The proposed RRW-CDTM attained high classification rate when compared to the existing LBP and motif based methods due to the derivation of gradient based rank vectors on a 2 X 2 grid, and replacing it with the word index of the RRWM and due to the derivation of CDTM grid and integration those with GLCM features. The Table- II and

Table- II: Classification rate (%) of proposed and state-of-art-methods on various databases

Database	LBP [10]	LTP [4]	CLBP-SMC [12]	CS-LBP [23]	MCM [16]	Proposed RRW-CDTM
MIT-VisTex	57.29	60.24	88.53	78.69	89.12	99.02
Stex	59.12	76.8	92.08	76.54	93.05	94.13
USPTex	59.04	79.12	93.54	77.67	94.76	99.72
CBT	66.37	69.04	90.74	78.07	91.39	98.78
Outex-13	67.87	69.82	93.74	75.17	92.06	99.03

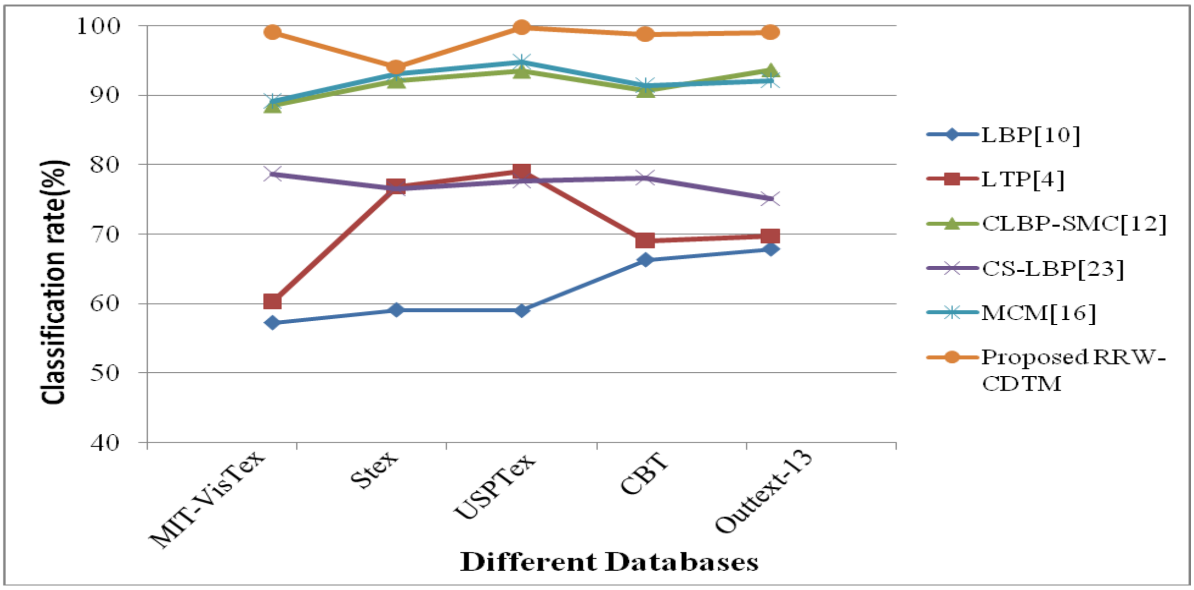

Fig. 13: Comparison of proposed method performance with existing methods on different database.

Fig. 13 reveal the same.

IV. CONCLUSIONS

This paper derived a new local descriptor called RRW-CDTM for efficient texture classification. The gradient of 2 X 2 grids derives more edge information, which basically inherits more texture information than grey level intensities. The derivation of rule based rank vectors overcomes the ambiguity in ordinary rank sequences. The advantage of proposed rule based rank vector frame work is, it is simple that is without increasing overall dimension of RRWM the proposed method addressed the drawback of ordinary rank sequence. The proposed rule based approach for rank sequence is based on the piano scan direction. That is this approach exhibits the properties of motif frame work in deriving rank vectors. This paper transforms the given texture image by replacing the 2 X 2 grid with column index of the RRWM, and further divides the texture image into 3 X 3 grid and then computes cross diagonal texture units and thus computing RRW-CDTM. The advantage of RRW-CDTM is it integrated the (i) Gradient features of a 2 X 2 grid. (ii) The rule based rank sequence in the form of piano scan direction. (iii) The derivation of cross of diagonal texture units of the rank sequences. (iv) The computation of GLCM features on the proposed RRW-CDTM. The proposed method used machine learning classifiers for the classification purpose on the derived integrated features. Thus the proposed approach is more significant in extracting texture features when compared to other local based approaches. The proposed method is tested with four machine learning classifiers and out of these multi-layer perceptron classifier has shown a little improvement in classification accuracy when compared to the other three classifiers. The proposed method has shown high classification rate when compared to the local based approaches of two popular domains like LBP and Motif based frame works.

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