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Hybrid Approach for Image Retrieval Using Local Directional Texton Histograms (LDTH) and Color Features

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ABSTRACT

The texton based methods played a significant role in retrieving the relevant objects from the given data bases. The textons in the literature are mostly derived on a 2*2 grid. This paper attempted to derive the 1*3 texton patterns on 3*3 windows. These textons are derived on different directions. This paper initially divides the image into an overlapped grids of same 3*3. The four directional triangular textons and four line directional textons are computed on each window. A ternary pattern is computed on each of the texton grid and corresponding texton unit is derived. The texton unit replaces the center pixel. This process transforms the image into 2 images, i.e., one with local triangular textons units and the other with local line texton units, each of which ranging from 0 to 80. A combined histogram named local directional texton histogram is derived from these transformed images and integrated with color histograms. This process derives the image features. These features are used for CBIR and the results indicate high performance when compared with other texton based methods.

Keywords: Triangular textons, Line patterns, directional textons, textons of 1 x3 , ternary patterns.

1. Introduction

Information retrieval together with storage has experienced radical changes due to rapid advancements in computer and communication technology systems. The search methodology of image retrieval allows users to identify database images that share similar characteristics with their query input to retrieve suitable photographs. The utilization of content-based image retrieval systems has significantly increased across data mining operations together with medical imaging technologies as well as educational and crime prevention initiatives during the last ten years. There exist two primary types of image retrieval systems which include text-based (TBIR) and content-based (CBIR). Text-based image retrieval utilizes keywords annotated within the images [1, 2]. However, this method presents several challenges. First, it is impractical to manually annotate large-scale databases. Second, the annotations are subjective to the individual performing them, making the process susceptible to human perception biases. Third, the annotations are often language-specific, limiting accessibility.

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CBIR, on the other hand, has gained popularity for overcoming the limitations associated with text-based retrieval systems [3]. The advantage of CBIR lies in its ability to leverage image descriptors like shape, color, and texture to represent an image [4].

CBIR predominantly focuses on color as an essential feature for retrieval. For instance, CH (Color Histogram) is commonly used to represent color features in CBIR [5-8]. In [9], Guang-Hai Liu et al. introduced a novel method for content-based image retrieval using the Color Difference Histogram (CDH). The distinctive feature of CDH is that it measures the perceptual uniformity of color differences between two points under different backgrounds, taking into account both color and edge orientations within the Lab* color space. The algorithm utilizes two histograms: one captures uniform color differences between neighboring pixels' edge orientations, while the other captures differences between color indices and edge orientation data. Metty Mustikasari et al. [10] proposed an image retrieval method based on local histograms. The RGB image is first converted to the HSV color space, after which it is divided into nine sub-blocks of equal size. The color of each sub-block is extracted by quantifying the HSV color space into a histogram. The local 3D histogram is computed and later converted into a 1D histogram for further processing. Studies have highlighted the benefits of CH, such as simplicity, ease of use, and robustness against image transformations like rotation [11–13]. Meanwhile, texture features are regarded as one of the most practical approaches within CBIR [14, 15].

Texture provides essential information about the structural arrangement of surfaces and objects within an image. It describes the distribution of light intensity across the image, making it a significant feature for determining image content. The texture plays a crucial role in face recognition [16, 17], age classification [18 19 20 21 22], texture Classification [23, 24, 25, 26]. Nevertheless, CBIR methods relying solely on texture struggle to account for the spatial relationship between colors and to overcome these, integrated approaches are proposed in the literature. [27- 30]. In many cases, relying solely on texture or color information is not sufficient for effective image retrieval. To address this limitation, combining multiple features has proven to be more efficient. This section reviews several studies that have employed hybrid approaches in image retrieval, highlighting their unique advantages and limitations. Ayan Kumar Bhunia et al. in [31] proposed a novel set of feature descriptors that integrate both color and texture information. Their approach focuses on the inter-channel relationship between the Hue (H) and Saturation (S) channels in the HSV color space, a feature that had not been previously explored. The Hue channel is divided into bins, and votes are cast based on saturation values, and vice versa. The texture component of their method, known as the Diagonally Symmetric Local Binary Co-occurrence Pattern, captures relationships between pixels located symmetrically along the diagonals of a 3 × 3 window. This method was tested across five databases, yielding competitive results in both feature vector length and retrieval accuracy. Anu Bala et al. in [32] introduced a new feature descriptor called Local Texton XOR Patterns (LTxXORP) for content-based image retrieval. Their method starts by converting the RGB image into the HSV color space and uses seven distinct Texton shapes to form a Texton image. This image is then divided into 2 × 2 non-overlapping blocks, where each block is encoded with a label based on the desired Texton pattern. After performing an XOR operation on the Texton image, the resulting feature vector is constructed from LTxXORP and HSV histograms. The experimental results showed that this approach significantly improves image retrieval performance compared to other methods.

In [33], a new feature descriptor called Correlated Primary Visual Texton Histogram Features (CPV-THF) was proposed for image retrieval. CPV-THF combines visual

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Research Article

content and semantic information by finding correlations among color, texture orientation, intensity, and local spatial structure. The co-occurrence matrix is used to represent these correlated attributes, and experiments demonstrated that CPV-THF outperformed several other descriptors.

Another hybrid approach was presented in [34], where three types of feature descriptors namely spatial, frequency, and hybrid were combined to develop an efficient CBIR algorithm. This method incorporates spatial domain features like the color auto-correlogram, color moments, and HSV histograms, along with frequency domain features such as wavelet transform moments and Gabor wavelet features. Feature extraction using the BSIF method involves converting the input RGB image to grayscale, selecting patches, and performing component whitening before estimating ICA components. The authors of [35] developed Multi-Direction and Location Distribution of Pixels in Trend Structure (MDLDPTS) which represents a variation of multi-trend structure descriptor (MTSD) specifically designed for content-based image retrieval systems. The HSV color space features extraction process contains two stages of fuzzy linking that improves precision levels. A discrete Haar wavelet transform applies up to level 3 to grey scale images and RGB images simultaneously.

. The method combines these features and applies dimensionality reduction, resulting in improved performance for retrieving natural, textural, and medical images.

Research has shown that relying solely on features like texture, shape, or color does not provide a comprehensive description of an image's content. As a result, recent studies have focused on hybrid approaches that combine multiple features to improve image representation.

This paper proposes a powerful hybrid approach, that transforms the given input image into two texture-featured images with structural, edge and directional features. These local texture features in the form of histograms are combined with global color information to represent image content more effectively. For texture feature extraction, the method uses Local directional texton Histogram (LDTH), while color feature extraction involves separating the input color image into three channels (H, S, V) and constructing a color histogram for each. The extracted texture and color features are then merged to form a unified feature vector, which is used in the similarity matching process with appropriate weighting for each feature group. The proposed method is evaluated using different datasets, showing improvements in both precision and recall compared to existing methods.

2. Related Work

Texton played a significant role in content based Image retrieval (CBIR) and also in texture classification [36-42]. Textons are derived initially on a micro grid of 2x2, whereas the local neighborhood features are mostly derived an a 3x3 window. The motifs are also derived on a 2x2 grid and has wide variety of image processing applications [30; 28; 27 ; 43 ;44]. The prominent models of textons were derived on a 2x2 grid are texton co-occurrence matrix (TCM) [45] , Multi texton histogram (MTH) [46], Complete texton matrix (CTM) [39], Full texton Matrix (FTM) [41]. These models, contributed significantly in retrieving the similar images. Further the texons also played a significant role in texture classification. The Motifs are derived on a 2x2 window based on a scan direction and achieved good classification and CBIR results [30,28,]. The combination of Motifs and textons are introduced for CBIR and achieved a high success rate [43]. The textons of TCM , MTH, CTM , FTM and other variants derived the texton patterns (i) on a 2x2 grid only (ii) they have not derived textons on 3x3 window. The reason for not attempting the derivation of textons on a 3x3 window by the researchers is mainly due to the high complexity involved. This paper overcomes this by dividing the 3x3 window into two types of texton grids each of 3 pixels.

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Research Article

The other end the 3x3 local neighborhood approaches have become popular in texture classification. The basic and fundamental approach of local neighborhood methods is the Local Binary Pattern (LBP), derived by ojala et al[47]. The LBP and its variants are preferred by many researchers due to i) Its speed, due to non-requirement to tune the parameters, ii) Its success rate iii) Simplicity in integrating with statistical frameworks. The LBP initially derives a binary relationship between the centre pixel and each of its neighbouring pixel. This relationship is based on the grey level intensities between centre pixel and neighbouring pixel. Each of the neighbouring pixel is transformed into to a binary value i.e., one or zero. This grey level relationship also defines the edges in the 3x3 window or local neighbourhood (LN). The LBP derives a LBP unit ranging from 0 to 255. The LBP derivation is shown in the following Figure 1

G_1	G_2	G_3
G_8	G_c	G_4
G_7	G_6	G_5

(a)3x3sample window

➔

92	98	102
94	100	112
104	100	96

(b)

➔

0	0	1
0		1
1	1	0

(c)

*

2^3	2^2	2^1
2^4		2^0
2^5	2^6	2^7

(d)

➔ 99

Fig 1 : The LBP unit computation process

The G_1 to G_8 represents the neighboring pixels, whereas G_c is the center pixel. In the above Fig 1 : (a) represents a LN (3x3 window) patch of the image; (b) is the derivation of binary values for each pixels of the neighborhood; (c) The assigned binary weights; (d) is the derivation of LBP unit. The derived LBP unit replaces the center pixel. The same process is adopted on the entire image in an overlapped manner and this transforms the image into an LBP unit image. The histograms of LBP unit or the GLCM features computed on the transformed LBP image window are used for texture classification or CBIR applications. The main disadvantage of LBP is (1) limited discrimination power due to binary patterns. (ii) fails in handling complex patterns (iii) unable to capture the localized patterns of other shapes like triangular or line etc., on the 3x3 windows. To enhance the discrimination power of LBP the LTP is proposed and it derives the ternary relationship by comparing the center pixel with the neighboring (G_i) pixels of the 3x3 local window, and they are multiplied by the corresponding ternary weights. The LTP unit is derived by summation of the above.

$$Ti = \begin{cases} 0 \text{ if } g(Gi) < g(Gc) \\ 1 \text{ if } g(Gi) == g(Gc) \\ 2 \text{ if } g(Gi) > g(Gc) \end{cases} \qquad (1)$$

$$LTP_G = \sum_{i=1}^{8} T_i * 3^{i-1} \qquad (2)$$

The process of assigning for every pattern (T_i) to each of G_i and the derivation of LTP_U is summarized in the following Figure 2.

78	76	75
75	75	70
72	74	74

(a)

➔

2	2	1
1		0
0	0	0

(b)

*

3^3	3^2	3^1
3^4		3^0
3^5	3^6	3^7

(c)

➔ 155

(d)

Fig 2: The LTP-unit calculation procedure

The LTP is an enhanced version of LBP with ternary encoding scheme that gives a better discrimination power than LBP, however the LTP is not used widely due to high complexity i.e., the LTP_U ranged from 0 to 3^8-1, i.e., generates o to 3561 different LTP_u. Thus, it is difficult

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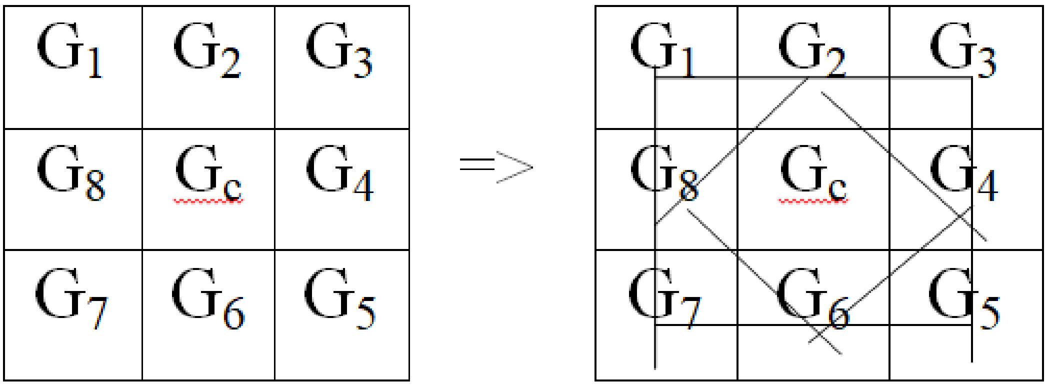
to integrate with statistical texture descriptions like GLCM etc..,. Further both LBP and LTP have not considered the inter relationship between neighboring pixel.

3. Proposed method

To enhance the capabilities of both LBP, LTP and earlier texton based methods, this paper derives **local directional textons (LDT)** on a 3x3 neighborhood, to augment the discrimination power of CBIR system. The 3x3 window is named as Local neighborhood (LN). This paper derived two different LDT's using 3 pixels, by considering dual directions on a LN. The two derived directional textons are i) the Local triangular Texton's (LTT) ii) the Local Line Texton's (LLT). The two approaches initially divide the image in to an overlapped 3x3 grid patch. The process of deriving LTT is given below: The LTT divides the 3x3 window into four Triangular texton grids (TTG) of 1 x3 (3 pixels of the 3x3 window). In this paper a grid is considered as three pixels. The TTG's are derived by considering neighborhood pixels of LN. From each of TTG, this paper derives Local triangular texton - ternary pattern (LTT-tp). The formation of TTG is shown in Fig 3.



a) 3x3 window b). Formation/ Derivation of four TTG

Fig 3 The TTG derivation from a LN

$$\textbf{LTT-tp(Gi,Gj,Gk)} = \begin{cases} 0 & \text{if } ((G_i \neq G_j) \text{ AND } (G_i \neq G_k) \text{ AND } (Gj \; \# \; G_k)) \\ & \text{else} \\ 1 & \text{if } ((G_i == G_j) \text{ AND } (G_i == G_k)) \\ & \text{else} \\ 2 & \text{if } ((G_i == G_j) \text{ OR } (G_i == G_k) \text{ OR } (G_j == G_k)) \end{cases} \quad (3)$$

Let the 3 neighboring pixels representing the TTG of LN are denoted of (G_i, G_j, G_k). The pixel Gj is one of the diagonal pixel of LN (the odd pixel of the LN) (Figure C). Thus, the TTG of the 3x3 are derived around the diagonal pixel. The relationship among the pixels

Journal of Information Systems Engineering and Management
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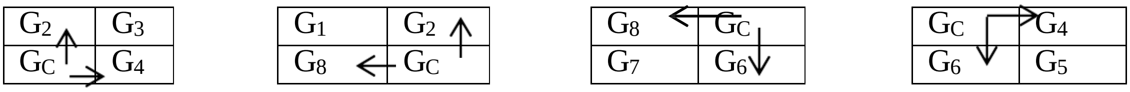
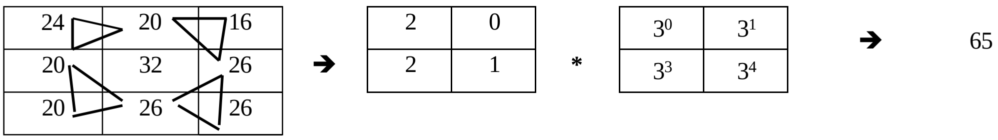
Research Article

of TTG of 1x3 can be derived as $G_k = G_{j+1}$ and $G_i = G_{j-1}$. This paper derived the LTT-tp on each of TTG as given in the equation B. The ternary values are assigned to LTT-tp as follows: A value zero is assigned if all three grey levels of Gi, Gj, Gk is unequal. A value 1 is assigned if all three grey levels are equal and a value 2 is assigned if any of the two grey levels of Gi, Gj and Gk are equal. The LTT-tp transforms the 3x3 window into a 2x2 grid, where each point of the 2x2 grid represents the LTT-tp, derived on one of the TTG. The LTT-tp are multiplied by the corresponding ternary weights and it results a unit value for LTT (LTTu). The LTTu ranges from 0 to 80. The center pixel of the LN is replaced by this LTTu value in an overlapped manner. *The triangular texton grids (TTG) are in fact derives the directional grids on LN with respect to the center pixel. The four TTG directions are given in the 4.*The entire process of deriving LTTu Unit is with an example is given in Fig 4.



a) b) c) d)

Fig 4: Directional TTG over G_c of LN (a) 0^0 to 90^0 together (b). 90^0 and 180^0 together (c). 180^0 and 270^0 together (d) 0^0 and 270^0.

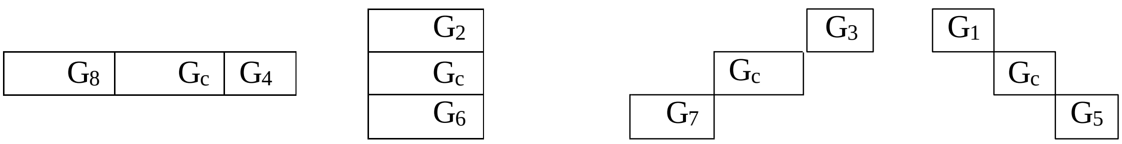


a) b) c) d)

Fig 5: The derivation of a LTTu from a 3x3 image patch.

The Figure 5.a represents the LN patch and the formation of four directional-TTG's. The derivation of the corresponding LTT-tp are computed and given in figure 5.b, followed by the corresponding weights in Fig. 5.c. By multiplying the LTT-tp with corresponding ternary weights and resulted the LTTu as given in Fig.5.d.

The next step is the derivation of the Local Line Textons(LLT). The LN is divided into four line texton grids (LTG), of 3 pixels each and shown in Fig 6.



(a) (b) (c) (d)

Fig 6: The representation of LTG of a LN.

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/
Research Article

The Four LTG are named as a vertical line texton (Fig 6.a), horizontal line texton (Fig 6.b), and two diagonal line textons (Fig 6.c and 6.d). The derived LTG comprises a dual degree textons with respect to the center pixel Gc as follows: 0° and 180° (Fig 6.a); 90° and 270°(Fig 6.b) ; 135°and 315° (Fig 6.d); 45° and 225° (Fig 6.c) for horizontal and vertical line texton, and diagonal line textons respectively.The local line texton (LLT) ternary patern (LLT-tp) is derived on each LTG in the same way as given in equation B. Thus, the LN is transformed into an LLT-tp grid, where each pixel value corresponds to the LLT-tp, derived from the corresponding LTG. The transformed LLT-tp grid is multiplied with the ternary weights to derive LLT unit (LLTu) and this value ranges from 0 to 80. The LLTu value replaces the center pixel. This process is carried out in an overlapped manner, thus this process transforms the original image into LLTu image. The values in LLTu image ranges from 0 to 80. The derivation process of LLTu is shown on an image patch of 3*3 in the Fig 7.

46	46	44
47	46	46
45	74	46

➔

2	2
1	0

=

30	31
33	32

➔ 35

(a) 9b) c d

Fig 7: Derivation Process of LLTu from a LN

Finally, the original image is transformed into two images namely LTTu and LLTu. For histogram calculation the LLTu values are measured from 81 + LLTu as given below. The final histogram is named as local directional texton histogram (LDTH). The proposed CBIR framework algorithm is given below.

The LDTH is computed as: H(LTTu , LLTu) = H(LTTu ; (81 + (LLTu)))

Algorithm :

Input: color image (query image)
Output: Retrieval images or similar images from the database image
begin

1. Transform the given image in to HIV color image
2. Compute the individual histograms of the color components
3. Select the 3x3 window patch from V plane of the image
4. Divide the window into four TTGs and into four LTGs separately.
5. Compute the LTT-tp and LLT-tp on each of the TTG and LTG respectively
6. compute LTTu and LLTu.
7. Replace the center pixel with the computed LTTu and LLTu in an overlapped manner. This process transforms the image in to two separate index images with LTTu and LLTu values.
8. Compute the LDTH (local directional texton histogram): for this the histogram of LTTu image ranging from 0 to 80 and histogram of LLTu from 81 to 161.

Journal of Information Systems Engineering and Management
2025, 10(43s)
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https://www.jisem-journal.com/
Research Article

9. Construct the feature vectors by concatenating the color histograms with the derived histograms of LDTH feature values.
10. Compare the features of query image with the features of the database image using distance functions.
11. Retrieve the similar images from the database images

End of the algorithm

4. Results and discussions

This study evaluated the proposed Content-Based Image Retrieval (CBIR) frameworks using several widely recognized natural image databases, including Corel-1K [48], Corel-10K [49], MIT-VisTex [51], Brodatz [50], and CMU-PIE [52], all of which are also commonly employed in computer vision applications.

4.1 Database description

The Corel-1K and Corel-10K image databases were sourced from the Corel photo gallery and contain natural images. The Corel-10K database features a diverse collection of images, including categories such as bonsai, dogs, icebergs, elephants, aviation, autumn, tigers, steam engines, and waterfalls. It contains 10,800 images across 80 different categories, with a varying number of images per category, but each category includes at least 100 images. The images in Corel-10K are sized at 120x86 pixels. The Corel-1K database, on the other hand, contains 1,000 images divided into 10 categories, with 100 images per category. Both the Corel-1K and Corel-10K databases are well-suited for image retrieval research due to their large, varied, and homogeneous image sets within each category.The MIT-VisTex database, consisting of high-quality texture images, was created as an alternative to the older and now partially unavailable Brodatz texture database. The MIT-VisTex images are representative of real-world texture conditions, offering a modern resource for texture-based image analysis.The CMU Multi-PIE database contains facial images and is one of the largest facial image datasets, featuring 337 subjects and a total of 750,000 images. It covers four sessions with a 15-month gap between them, offering 15 viewpoints and 19 illumination conditions, totaling more than 300 GB of image data. For this research, 15 categories of facial images were selected, with each category containing 150 images.Additionally, this study utilized the Holidays dataset, which consists of 500 image groups, primarily comprising personal holiday photographs.The image samples of these databases are shown from Fig. 8 to Fig. 12.

Fig. 8: The illustration of Corel-1K images

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/

Research Article

Fig. 9: A few example images of Corel-10K

Fig. 10: A few instance from MIT-VisTex

Journal of Information Systems Engineering and Management
2025, 10(43s)
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Research Article

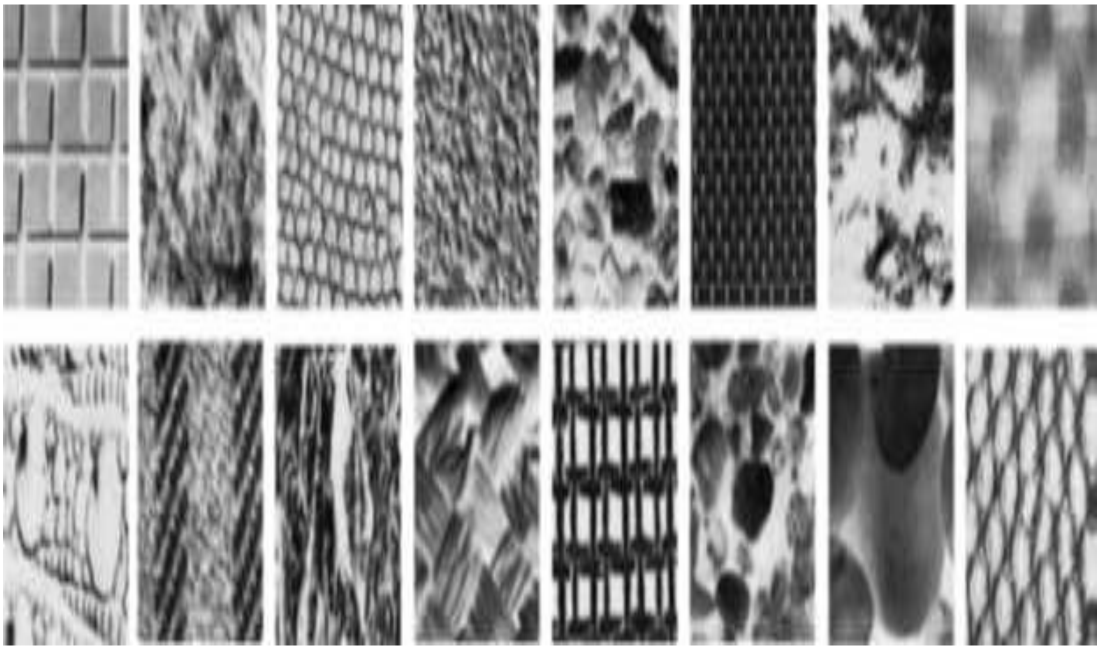

Fig. 11: A few Broadatz textures

Fig. 12: A few CMU-PIE facial images

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/
Research Article

4.3 Distance Measures

In this work, the similarity of pictures was evaluated using two commonly used distance measures: Manhattan and Euclidean distances. Euclidean distance between two feature vectors $A=(a_1,a_2,\ldots,a_n)$ and $B=(b_1,b_2,\ldots,b_n)$ has a formula:

$$d_{\text{Euclidean}}(A,B)=\sqrt{\sum_{i=1}^{n}(a_i-b_i)^2} \tag{4}$$

Here, n is the number of dimensions (features), and ai and bi are the corresponding feature values for the two images. The Euclidean distance measures the direct geometric distance between the points in the feature space.

The formula for Manhattan distance between two feature vectors $A=(a_1,a_2,\ldots,a_n)$ and $B=(b_1,b_2,\ldots,b_n)$ is:

$$d_{\text{Manhattan}}(A,B)=\sum_{i=1}^{n}|a_i-b_i| \tag{5}$$

This measure calculates the total distance by adding the absolute differences between the corresponding features of the two images. Both distance measures are used to determine how closely related the query image is to the images in the database based on their extracted feature vectors. The choice of distance measure can influence the retrieval performance depending on the nature of the data and the specific requirements of the image retrieval task.

4.4 Evaluation Measures

The efficiency of the proposed CBIR framework is evaluated in this study using precision and recall. Precision is defined as the ratio of relevant pictures obtained to the total number of images retrieved (denoted as n) (Eqn. 6). Recall, on the other hand, evaluates, for a given query picture (denoted as Nic), the ratio of relevant photos retrieved to the total number of relevant images in the database where Nic denotes the number of relevant images in each category cc in the database (Eqn. 7).

$$\mathrm{P(i,n)} = \text{Number of relevant images retrieved}/_{\mathrm{n}} \tag{6}$$

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Research Article

$$R(i,n) = \text{Number of relevant images retrieved} / N_{ic} \tag{7}$$

Average precision and recall are given in equation 8 and 9.

$$P_{avg}(J,n) = \frac{1}{N_{ic}} \sum_{i=1}^{Nic} P(i,n) \tag{8}$$

$$R_{avg}(J,n) = \frac{1}{N_{ic}} \sum_{i=1}^{Nic} R(i,n) \tag{9}$$

Where, J denotes the number of categories. The total precision and total recall for the entire database are calculated as.

$$P_{total}(n) = \frac{1}{N_c} \sum_{i=1}^{N_c} P_{avg}(J,n) \tag{10}$$

$$R_{total}(n) = \frac{1}{N_c} \sum_{i=1}^{N_c} R_{avg}(J,n) \tag{11}$$

Where N_c is the total number of categories exist in the database.

VV.4 MAIN CONTRIBUTION OF THIS RESEARCH

1. Extraction of local directional textons on a 3 x3 grid without any ambiguities.
2. Transforming the 3x3 image patch in to two types of directional texton units of 3 pixels instead of a regular 2 x 2 grid.
3. Derivation of ternary patterns on the triangular and line directional texton patterns.
4. Integrating triangular and line texton units under one histogram for better discrimination.

vv.5 DISCUSSIONS on the results

The proposed LDTH system implements retrieval performance assessment using five popular database standards. The databases contain multiple types of photos which makes them efficient for analyzing CBIR-based applications. Every category in these databases presents distinct characteristics because they contain varying lighting conditions with their specific backgrounds and viewpoint angles. The proposed LDTH framework's performance evaluation relies on both Euclidean and Manhattan distances together with APR and ARR metrics as

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https://www.jisem-journal.com/
Research Article

10 pictures. High Euclidean distance retrieval. The evaluation data from these tables functions as the key metric to assess the proposed LDTH method against different frameworks. Regardless of databases including Corel-1k, Corel-10k, MIT-VisTex, Brodatz, and CMU-PIE, the proposed LDTH descriptor achieves accuracy rates of 91.02%, 49.53%, 90.26%, 89.92%, and 92.05%.

Table X.1. APR (%) for the top 10 Matches of LDTH Descriptor

Distances/Database	Corel-1k	Corel-10k	MIT-VisTex	Brodatz	CMU-PIE	Average
Manhattan	90.15	81.51	89.15	89.64	91.32	81.588
Euclidean	91.02	82.58	90.26	89.92	92.05	82.536

Table X.2. ARR (%) for the top 10 Matches of LDTH Descriptor

Distances/Database	Corel-1k	Corel-10k	MIT-VisTex	Brodatz	CMU-PIE	Average
Manhattan	0.225	0.235	0.215	0.236	0.256	0.2334
Euclidean	0.232	0.247	0.226	0.251	0.267	0.2446

A set of results appears in Fig. 13 through Fig. 22. Each query image in Fig..24 to Fig. 28 leads to retrieval of the best 20 images from their respective databases according to the LDTH descriptor.

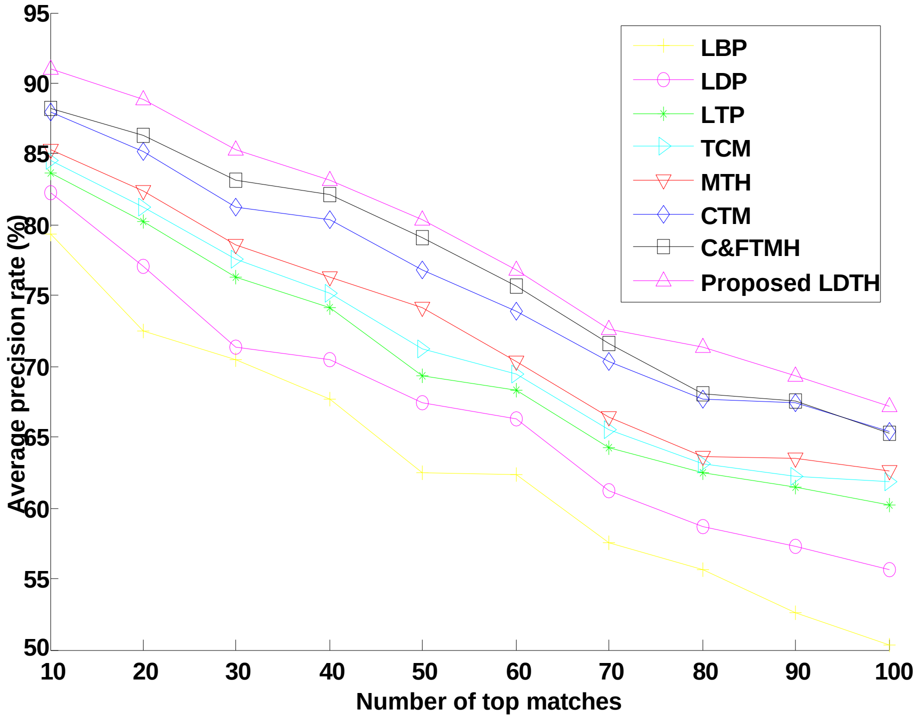

Fig. 13. Corel 1 K on APR: Existing descriptors vs LDTH descriptor

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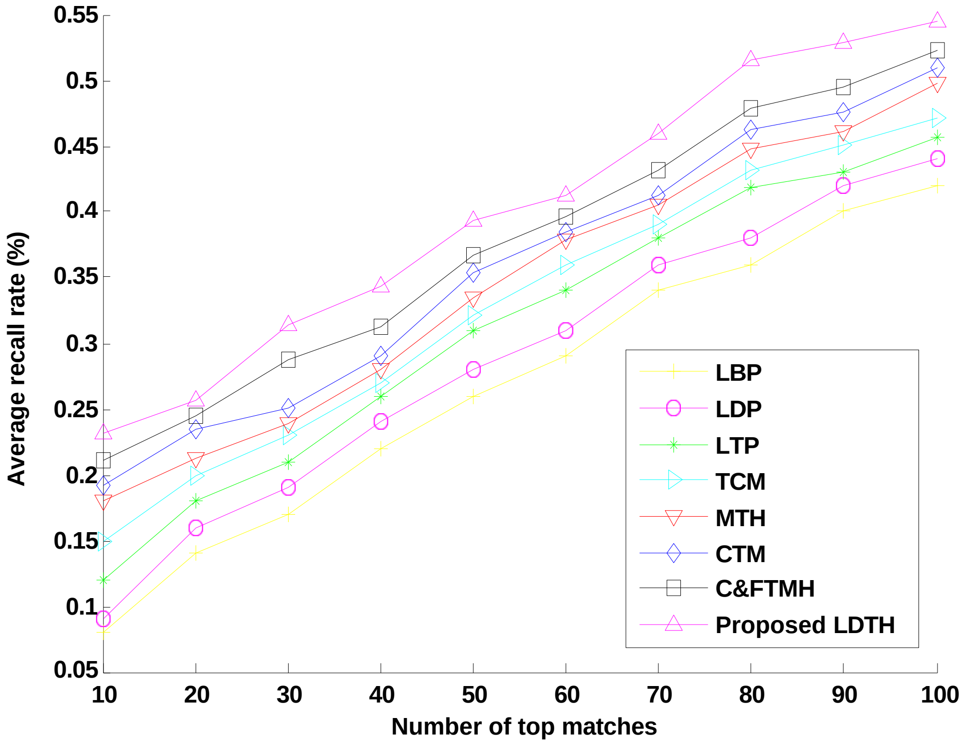

Fig.14. Corel 1 K on ARR: Existing descriptors vs LDTH descriptor

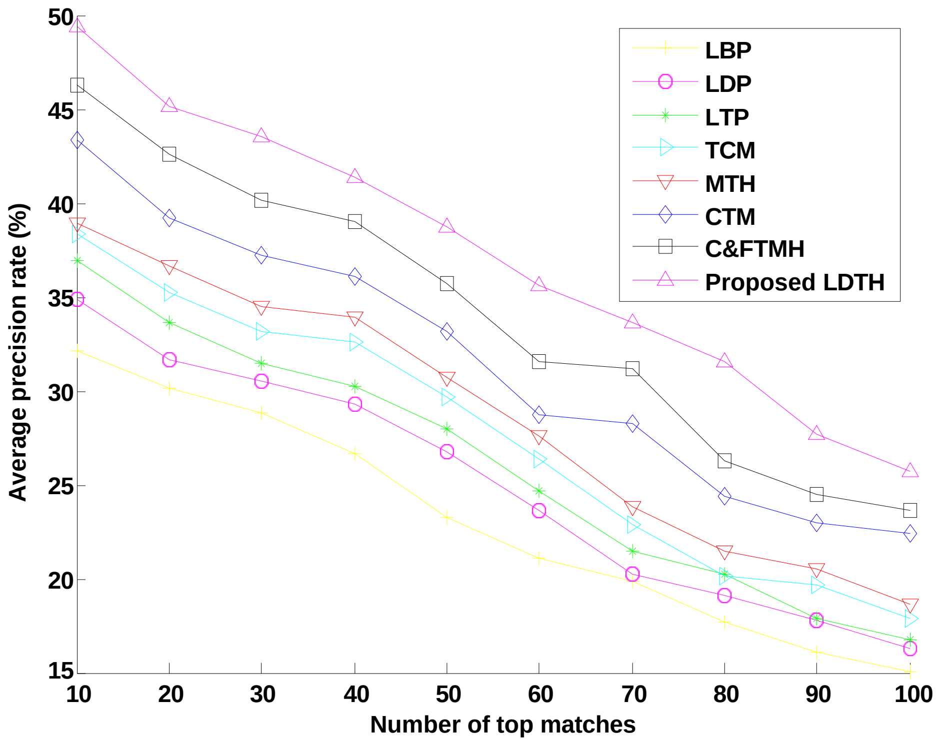

Fig. 15. APR on Corel 10K: Existing methods vs Proposed LDTH

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
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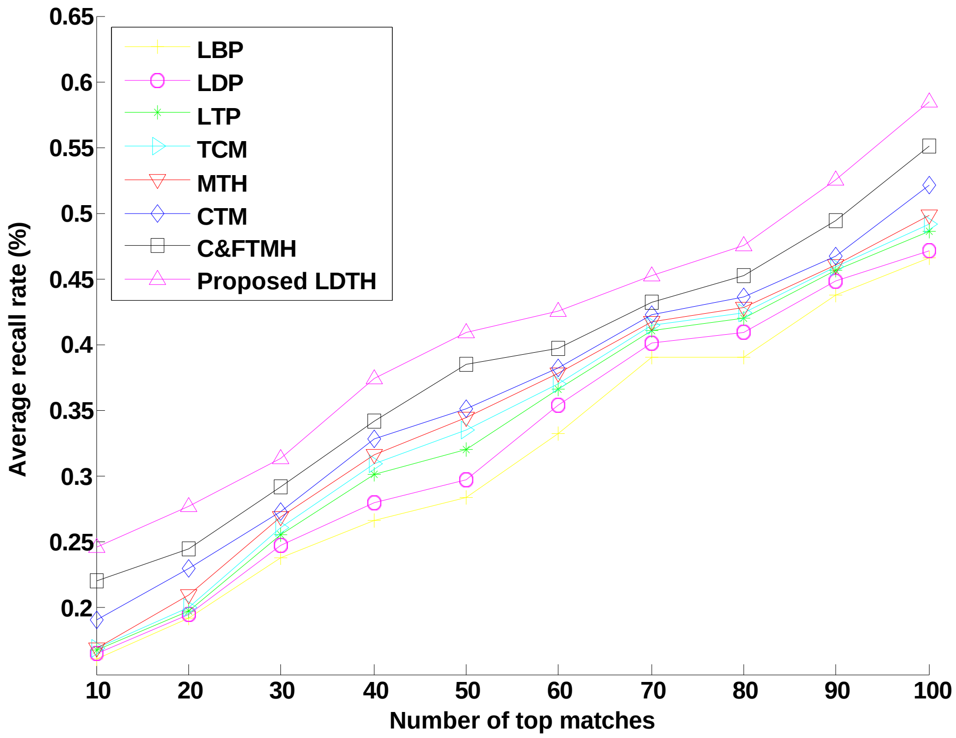

Fig. 16. ARR on Corel 10K: Existing methods vs Proposed LDTH

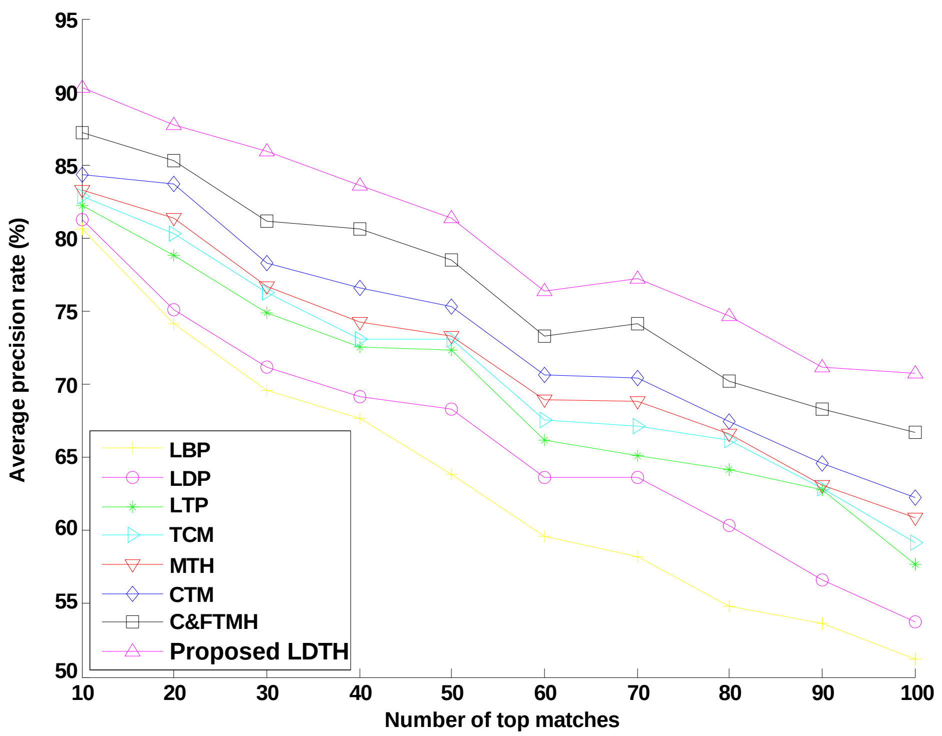

Fig. 17. MIT-VisTex: using APR : Proposed descriptor vs prevailing methods

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
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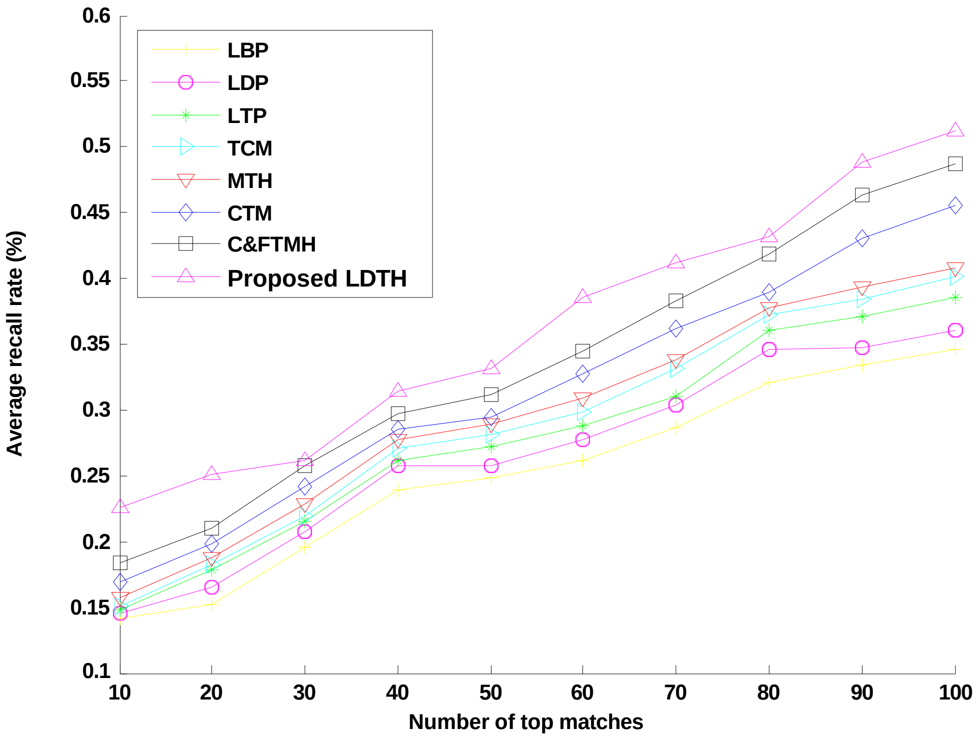

Fig. 18. ARR : MIT-VisTex database” Proposed vs existing methods

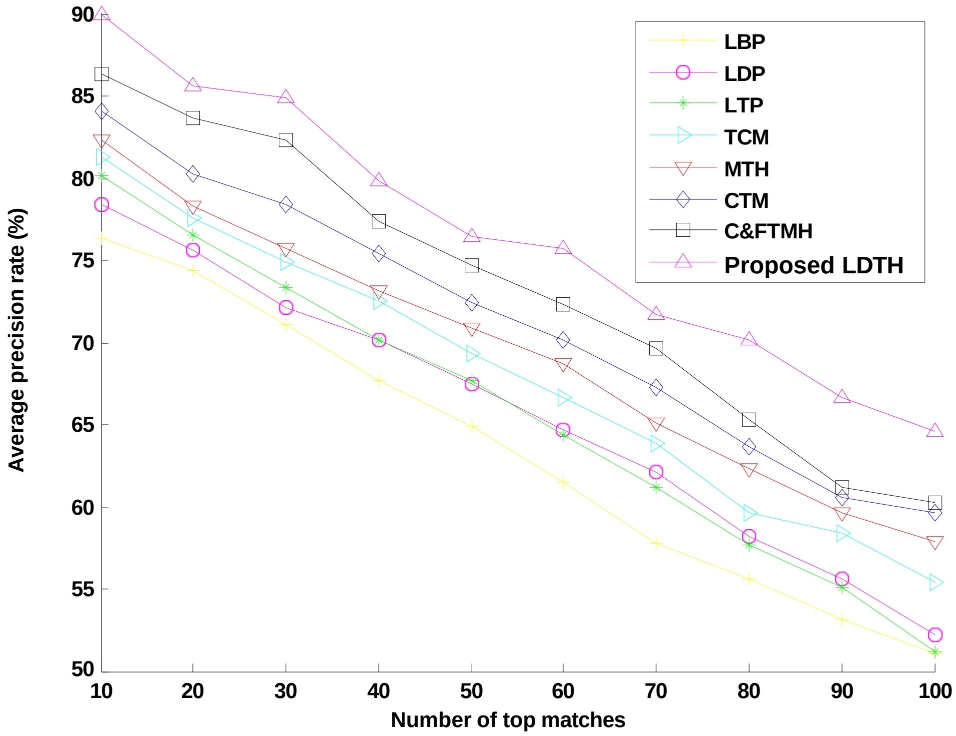

Fig. 19. The LDTH versus existing methods on Brodatz database using APR

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
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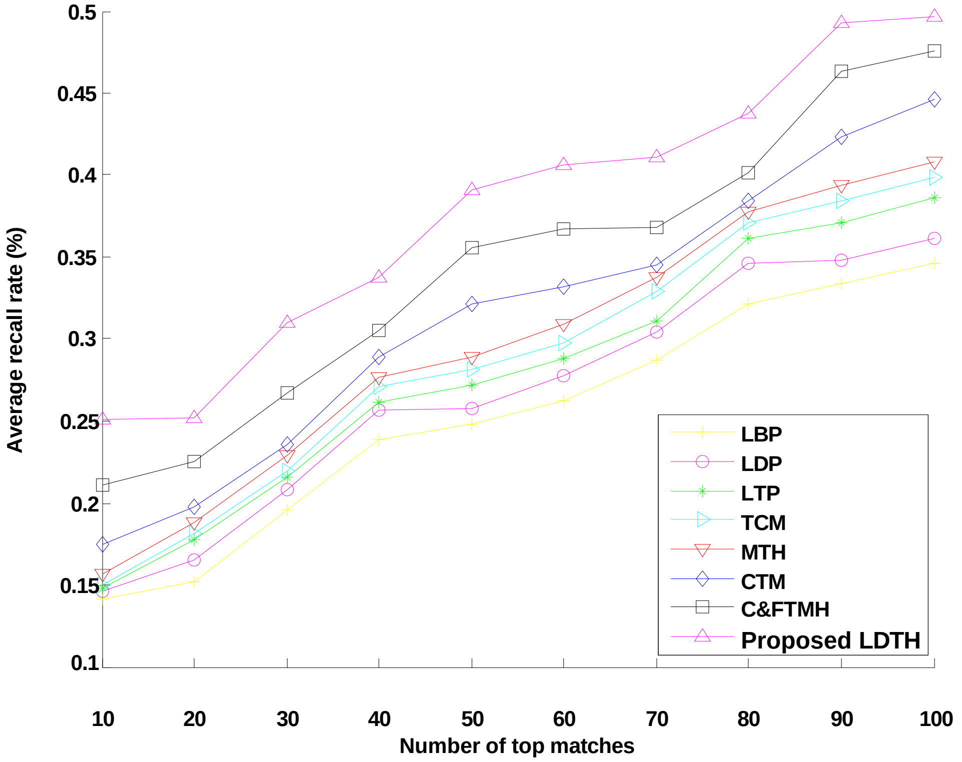

Fig. 20. ARR: Brodatz database : Proposed versus existing approaches

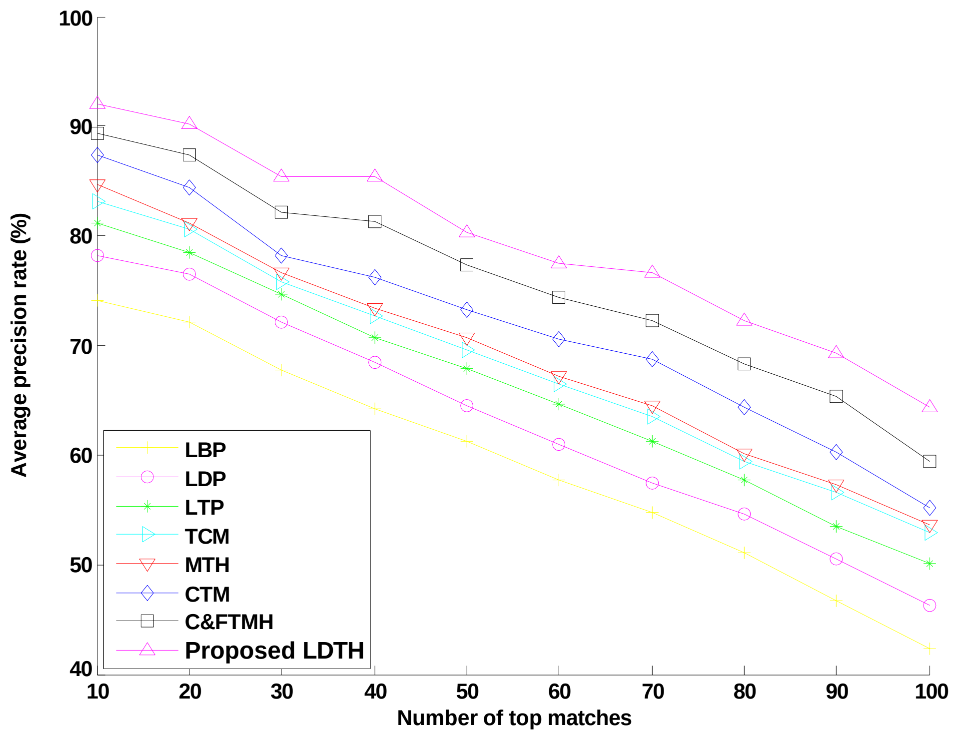

Fig. 21. Proposed LDTH vs existing descriptors: CMU-PIE database : APR

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
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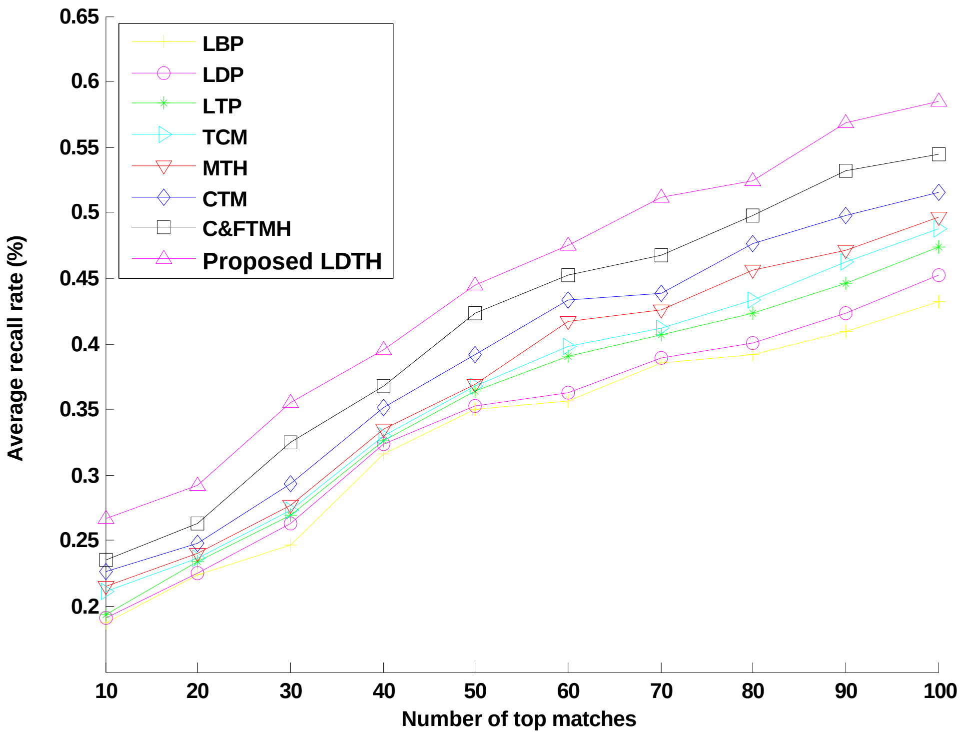

Fig. 22. ARR: LDTH versus existing methods: over CMU-PIE

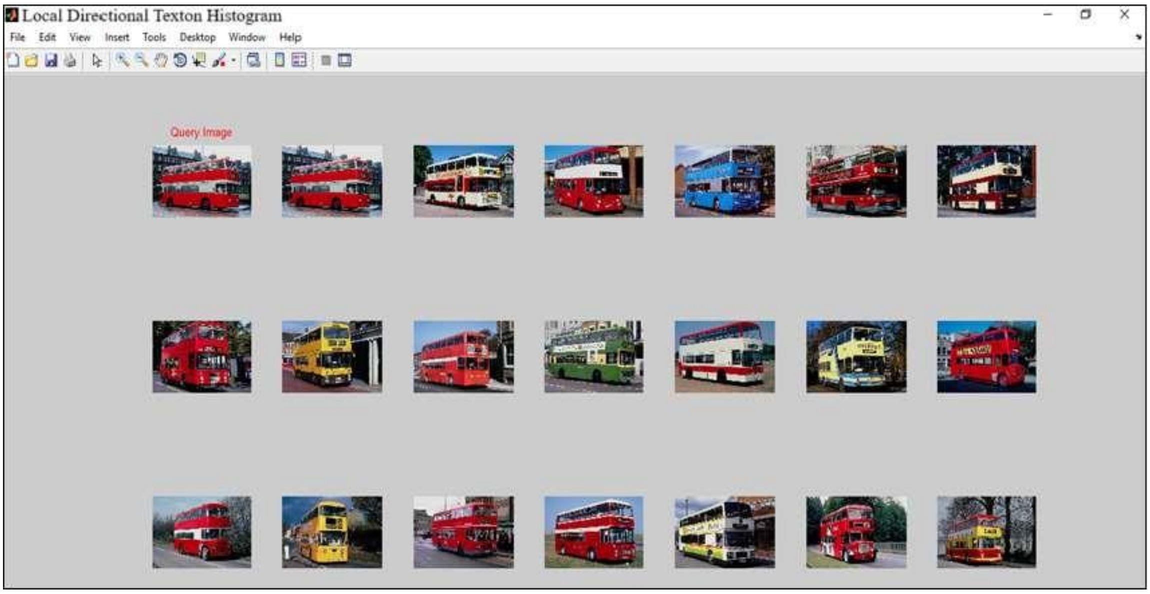

Fig. 23. Corel-1k : the top 20 retrievals by LDTH

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2025, 10(43s)
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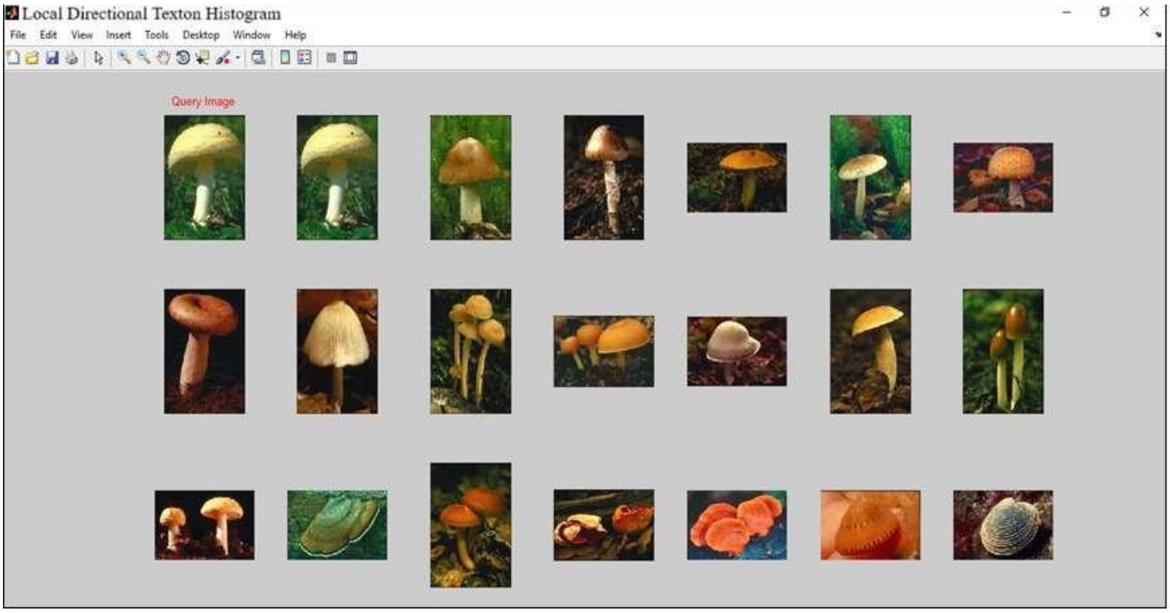

Fig. 24. The Top 20 retrievals: Corel-10k database

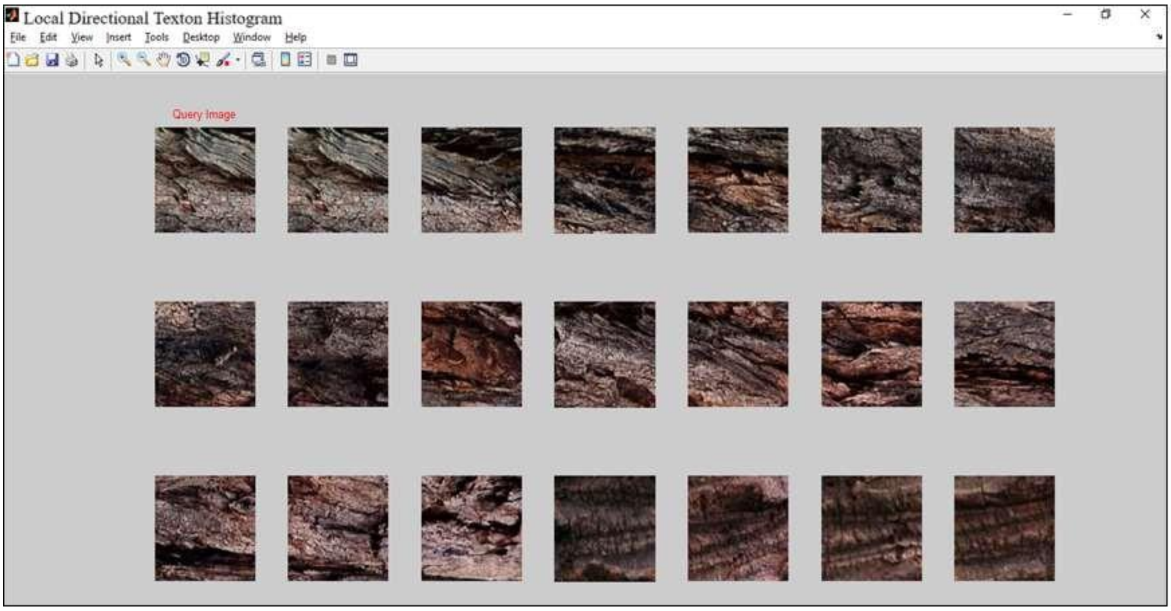

Fig. 25. The Top 20 retrievals from LDTH over MIT-VisTex

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
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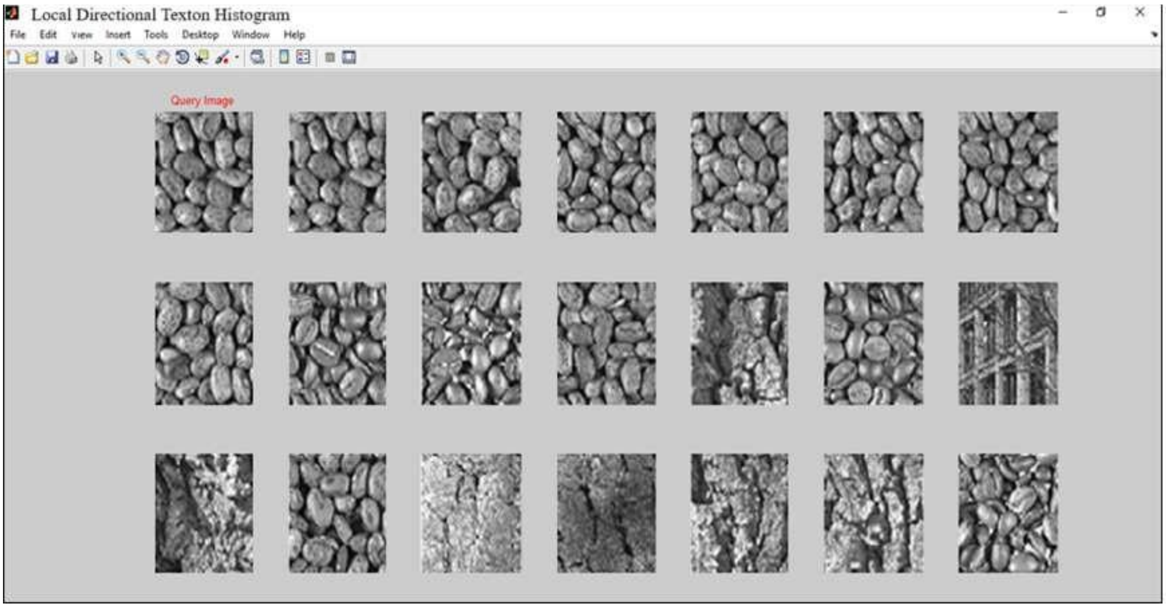

Fig. 26. Brodatz database: The top 20 retrievals

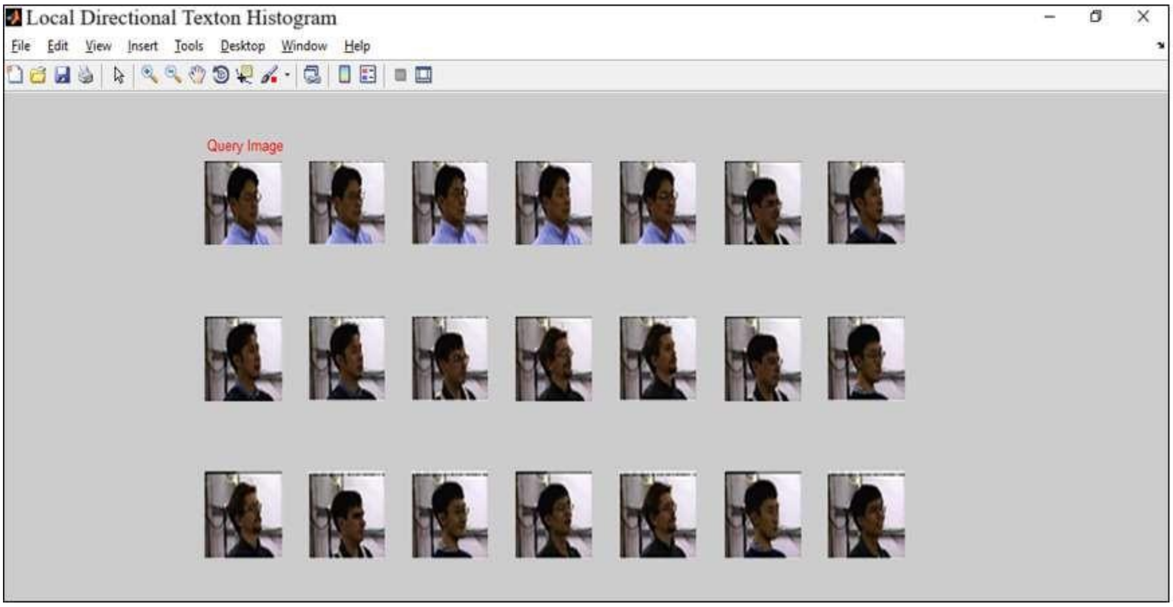

Fig. 27 Top 20 retrievals from CMU-PIE database

From the experimental data, this study observed the following:

1. The reason for slightly high retrieval rate by the Euclidean distance is as follows: The Euclidean distance performs better when the feature vectors are well-scaled and the image content has a strong geometric relationship (e.g., color histograms or texture features). Thats why the Euclidean distance, achieved higher precision and recall, indicating that it retrieves more relevant images. Though the Manhattan Distance offers slightly lower precision and recall, it offers faster retrieval times, which could be

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
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beneficial when processing large datasets or when the images contain noisy or sparse features.

2. The LDTH descriptor provides superior performance than established descriptors through its accuracy metrics for all databases.
3. The LDTH, achieved the good results: a) due to the directional aspects of the derived textons. B) The segmentation 3 x3 LN into triangular and line Patterns of 3 pixels each c) derivation of ternary texton patterns and the computation of LTTu and LLTu values d) the transformation of the given input image into LTTU and LLTU images and final derivation of a combined histogram. E) Integration of this combined histogram known as LDTH with color component histograms could able to derive the texture, edge and color features more prominently and significantly.
4. The suggested framework achieved better image retrieval rates and more precise discrimination on Corel-1k than Corel-10k because of its fewer categories and similar photo numbers per category.
5. The proposed LDTH has exhibited a) an 8 to 10% increase in ARR than the basic LBP variants. b) exhibited 4 to 6% of high ARR than LDP and LTP. This mainly due to the poor robustness performance of LBP and LTP, with respect to noise, rotation invariance, spatial information and further not well suited for histogram approaches due to their high unit size 256 and 3671. The main disadvantage of Local Directional Patterns (LDP) is its sensitivity to image rotation, meaning that even a slight rotation of the image can significantly change the extracted features, leading to inaccurate classification results; The main problem or the classification / retrieval performance of LDP depends on selecting the optimal number of edge response directions and how to select this optimal number is not defined.
6. Performance assessment demonstrated the proposed approach outperformed existing texton based approaches which included TCM and MTH and CTM and C&FTMH mainly because of two factors i) The TCM and MTH have not defined all possible textons; ii) The CTM & C&FTMH has defined all potential textons but fails to resolve ambiguity problems. All possible textons are defined within the CTM & C&FTMH framework yet they cannot provide a solution for ambiguity issues. The proposed technique defined every possible texton through triangular and linear patterns on three pixels across the center pixel of a 3x3 window while other textons from the above approaches were limited to the 2 x 2 grid. The addition of new texton definitions enhances the overall resistance of the proposed method.

Conclusion

This research derived a new approach for CBIR by deriving directional textons over a 3x3 local neighbourhood. The proposed LDTH transforms the 3x3 image patch in to two image patches of triangular and line texton pattern units. Thus, transforming the given image into two images in an overlapped manner, where the first image represents the local triangular texton units and the second one derives local line texton values. These two patches are derived based on the dual directions around the center pixel of the LN. The LTTu and LLTu are derived on neighbouring pixels (leaving the center pixel) and all pixels of LN respectively. The combination of histograms achieved high retrieval rate than other texton based methods and also against LBP and LTP is mainly due to the factor that they haven’t considered the directional textons around the LN. To reduce the complexity this research divided the 3 x 3 window into two units and further computed only histograms instead of computing cooccurrence matrix and later deriving GLCM features. Thus, the proposed The fast retrieval of LDTH framework occurs primarily because of its low-dimensional nature when compared to TCM and CTM and C&FTMH descriptors. The experimental evidence shows the proposed framework demonstrates better effectiveness in retrieving natural textures when compared with existing texton-based approaches as well as local-based alternatives.

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