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AN INTEGRATED APPROACH TO TEXTURE CLASSIFICATION USING RULE-BASED MOTIFS AND MAGNITUDE TEXTONS

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ABSTRACT

Texture classification plays a significant role in computer vision that affects many fields, including medical image analysis, content-based image retrieval, face recognition, industrial inspection, etc. The effectiveness of texture classification relies on the extensiveness of the features extracted from the image data. Despite advancements in texture classification, many existing methods still struggle with ambiguous pattern representation and insufficient integration of local and global texture features, leading to decreased classification performance on complex datasets. To address these challenges, in this paper, we proposed a novel framework for texture classification by integrating rule-based motifs with magnitude textons. The method begins by transforming the input image into a complete magnitude-based texton-indexed (CMT_i) image by examining the local pixel intensity relationships on a 2x2 grid, which precisely encapsulates structural features. Further, it applies an average filter to the 2x2 grids of the CMT_i image, then calculates the absolute difference between each pixel of the CMT_i image and the average of the 2x2 grid. Later, on the image derived average rule-based motif (ARM_i^{CMT}) indexed image through predefined rules, ensuring consistent and unique motif indexing even in cases of ambiguous intensity values, it is named as the average rule-based motif on complete magnitude texton (ARM_i^{CMT}) indexed image. Subsequently, the Gray Level Co-occurrence Matrix (GLCM) is computed on the ARM_i^{CMT} indexed image at various angles. This operation yields six spatial features: energy, contrast, entropy, angular second moment, correlation, and homogeneity. The feature vector integrates local descriptors with global spatial relationships, resulting in a holistic representation of texture. This strong feature extraction method enhances accuracy and robustness in texture classification, making it highly effective for diverse applications.

Keywords - *Magnitude Textons, Complete Magnitude-based Texton Indexed (CMT_i) Image, Rule-based Motifs, Average Rule-based Motif on Complete Magnitude Texton (ARM_i^{CMT}) Indexed Image, Average Rule-based Motif on Complete Magnitude-based Texton Co-occurrence Matrix (ARM_i^{CMT}-CM)*

1. INTRODUCTION

Texture serves as a fundamental feature for interpreting and understanding images. Unlike color, texture refers to the spatial arrangement of basic elements or primitives, which may or may not have well-defined structures. These act as the building blocks of natural images and crucial components of preattentive human visual perception. Textured regions exhibit distinct statistical properties, typically involving the periodic repetition of patterns with some variability in appearance and positioning. Since the 1960s, texture analysis has been recognized as one of the most fundamental and challenging problems in computer vision and pattern recognition [1], owing to its significance in both understanding human texture perception and its wide-ranging applications. The field encompasses several critical tasks, including classification, segmentation, synthesis, and shape-from-texture analysis [2], with substantial progress made in classification, segmentation, and synthesis since the 1990s. However, the area of shape-from-texture has received less attention. Applications of texture analysis span across multiple domains, including medical image analysis [3], quality inspection [4], content-based image retrieval [5], satellite and aerial analysis [6], face recognition [7], [8], biometrics [9], object recognition [10], and texture synthesis for computer graphics and image compression [11]. Furthermore, it is crucial for robot vision and autonomous navigation, particularly considering the rapidly produced image and video data by surveillance systems, portable devices, medical imaging, and robotics, therefore offering infinite possibilities for further developments.

Texture classification, in particular, has garnered significant attention over recent decades due to efforts to understand how the human brain processes textures. In this context, texture classification relies on identifying unique features that define each texture class and assigns an unknown image to one of several predefined texture classes. However, real-world textures are often non-uniform and vary in orientation, scale, and other visual parameters, posing a major challenge in classification. Moreover, texture measurement is computationally demanding. To address these challenges, various methods have been developed with a focus on achieving invariance to rotation and spatial scale, though these approaches have limitations. Later, researchers introduced a modified Markov Random Field (MRF) model, incorporating three statistical methods to further enhance texture invariance [12].

Texture classification has two steps. i) feature extraction; ii) classification. Feature extraction requires representing the features in a meaningful, semantically interpretable format. Generally, feature representation techniques are divided into two categories: global descriptors, which analyze the entire image, and local descriptors, which partition the image into smaller sub-images or patches to extract relevant information. As the field of computer vision evolves, texture analysis continues to grow in importance, with applications spanning across various industries. A wide range of methods has been devised in the literature to evaluate texture and extract features [13]. The most utilized techniques include scale-invariant feature transformation (SIFT) [14], model-based methods [15], texton-based methods [16], filter-based methods [17], and local binary patterns (LBP) [18], [19]. Model-based techniques have also been widely used in detecting and recognizing textures in computer vision.

In recent years, deep learning techniques [20] have shown exceptional performance across various computer vision tasks. However, they are often associated with higher computational complexity, increased data requirements, and a reliance on extensive training data. While traditional learning descriptors, such as those dependent on training databases, face challenges related to versatility, hand-designed local feature descriptors provide a simpler yet robust solution. These descriptors have a number of benefits, such as not being dependent on large databases, lower computational complexity, and better time efficiency, particularly with low-dimensional descriptors. As a result, they are still valuable tools in a wide variety of computer vision applications.

2. RELATED WORK

The extraction of statistical features and the construction of statistical models were the primary goals of the initial classification methods. The gray-level co-occurrence matrix model [21], one of the benchmark models for texture classification, remains in use today alongside several other models. The Gray Level Co-occurrence Matrix (GLCM) features are derived from variants of local neighborhood methods in the literature [22] [23], and these methods produced significant results in texture classification. In most natural images, a range of conditions are captured, such as various lighting conditions, positions, rotations, reflections, shadows, and more. Consequently, rotation, scale variations, and grayscale should all be included in the texture classification. Various methods had been developed in the literature to study gray-scale invariant texture classification. The most commonly used techniques are multi-resolution [19], Gaussian Markov random field [24], hidden Markov model [25], Gabor filtering [26], simultaneous auto-regressive modal [20], and wavelet decomposition [27]. Shape plays a significant role in many image processing applications. To deal with shape characteristics, the literature [28] widely used techniques such as moment invariants, fourier transform coefficients, and edge curvature.

Huang et al. made the Gray Level Co-occurrence Matrix (GLCM) work better in the generalized co-occurrence matrix [29] so that the distribution of local maxima could be used to find useful feature space. In [30], GLCM using Prewitt edge images was derived instead of the original image and then computed statistical parameters from the GLCM. Moreover, researchers enhanced GLCM in [31] to improve feature extraction in texture characterization. Jhanwar et al. proposed the Motif Co-occurrence Matrix (MCM) [32]. One way to construct a motif-transformed image is to divide the entire image into non-overlapping 2x2 pixel blocks and apply a peano scan from the top left corner of the 2x2 grid in an incremental direction. This led to the formation of the MCM. The MCM using color combinations was developed by applying the MCM process independently to the image's red (R), green (G), and blue (B) channels. Lin et al. used the k-mean color histogram (CHKM) [33], the motif co-

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occurrence matrix (MCM), and the difference between pixels of a scan pattern (DBPSP) to make texture and color data that can be used together. Using this probability as a feature of the altered motif picture, the MCM assesses the likelihood of neighboring motifs being similar. Using motif sequences in scan patterns, the DBPSP approach evaluates pixel differences and converts them into a likelihood of recurrence throughout the image. The CHKM feature effectively clusters all picture pixels into k clusters by assigning the nearest color from a specified palette to each pixel. To improve image retrieval, Vadivel et al. suggested the Integrated Color and Intensity Co-occurrence Matrix (ICICM) [34]. They started by studying the properties of the HSV color space, and then they added weight functions to measure the relative importance of color and grayscale levels in individual pixels. These weight values between a pixel and its surrounding pixels form the foundation of the ICICM construction.

Abdullah et al. introduced a technique for picture retrieval, utilizing a salient spot cluster correlogram and fixed partitioning. In Deng et al., they integrated the texton histogram with the motif co-occurrence matrix [35] for content-based image retrieval. S. Murala et al. proposed a modified color motif co-occurrence matrix (MCMCM) [35], and Obulesu et al. proposed a multi motif co-occurrence matrix (MMCM) [36]; both captured more discriminative texture information than the Motif Co-occurrence Matrix (MCM) by deriving Peano scan motifs in different directions. In both content-based image retrieval and texture classification, the motif-based approaches demonstrated strong performance.

Local binary descriptors, in particular, have received significant attention for their efficiency in capturing essential image features. These descriptors provide compressed representations of local neighborhoods within an image, and the Local Binary Pattern (LBP), introduced by Ojala et al., is a well-recognized binary descriptor for capturing local contrast in images [18]. Numerous extensions of LBP have been proposed to enhance both quantitative and qualitative performance, including Local Directional Patterns (LDP) [8], and Local Ternary Patterns (LTP) [37] have further expanded the capabilities of local descriptors by improving the relationships between pixels, thereby enhancing texture analysis performance. Following LBP and LTP, Local Tetra Patterns were introduced to include second-order derivatives in the horizontal and vertical directions, forming tetra patterns that are further converted into binary patterns [38]. The Robust Local Binary Pattern (RLBP), which includes sign and magnitude local patterns, was also developed and extended using Gabor wavelets for enhanced feature extraction [39]. Local patterns have additionally been adapted to three-dimensional formats for analyzing dynamic textures, including the extension of LBP to three-dimensional patterns for dynamic texture recognition. The method demonstrates enhanced classification accuracy compared to traditional LBP. Advanced methods used over the past few years have greatly improved the accuracy and robustness of texture and image classification. Gabor Contrast Patterns (GCP) [40] incorporates Gabor filters and LBP for accuracy, and Local Triangular Coded Pattern (LTCP) [41] improves classification with noise immunity. Neighborhood Influenced LBP (NLBP) [42] merges multi-neighborhood information to enhance the noise robustness and compactness, respectively.

Texton-based methods have been proven to yield effective outcomes in the classification of textures and in Content-Based Image Retrieval (CBIR). If at least two pixels within a grid have intensities that are comparable to each other, then a texton has been identified. There are various kinds of textons within images. The TCM [43] derives only five texton types on a 2x2 microgrid. The TCM scans the texture image five times and detects one texton pattern since it overlaps on a 2x2 grid. The TCM fuses the five texton type images to produce the final image. Multi Texton Histogram (MTH) [44] simplifies TCM fusing procedures. A few textons with two identical gray level values and three and four identical pixels were defined by MTH. To prevent TCM fusion, MTH divided the image into 2X2 grids earlier. Subsequently, several texton-based techniques were developed for image classification and CBIR. Complete Texton Matrix (CTM) [45] and Full Texton Index Co-Occurrence Matrix (FT_iCM) [46] were developed based on textons. Recently, in [47], authors developed a complete magnitude-based texton co-occurrence matrix (CMT-CM) that derived a comprehensive relationship between textons and non-textons in 2×2 grid.

Most existing texture descriptors either emphasize local or global features but hardly ever both effectively. Furthermore, motif representation ambiguity caused by identical pixel intensities compromises performance. Our method bridges this gap by combining rule-based motifs with magnitude-based textons.

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3. PRELIMINARY METHODS

3.1. Complete Magnitude-based Texton Indexed (CMT_i) Image

In our earlier study [47], we proposed a complete magnitude-based texton indexed (CMT_i) image for texture classification. It extends the earlier texton-based methods (like Texton Co-occurrence Matrix (TCM), Multi Texton Histogram (MTH), and Complete Texton Matrix (CTM)) by inclusion of the magnitude relationship among the pixels in 2x2 grids. The CMT_i is derived by dividing the whole image into non-overlapping 2x2 pixel patterns. Each 2x2 grid is replaced by a magnitude texton (MT) index based on the magnitude relationship as shown in Figures 1 to 5. This generates a full set of 40 unique magnitude textons (MT) that cover all possible pixel intensity setups. This method replaced the original 2x2 grid with magnitude texton indices from 0 to 39 and transformed the image into a CMT_i image. The magnitude-based texton generation for three identical pixels is shown in Figure 1. The textons with two identical pixels are shown in Figure 2; the magnitude-based texton generation for two identical pixels (X!=Y) is shown in Figure 3; for two identical pixels (X==Y), it is shown in Figure 4; and for all identical and zero identical pixels, it is shown in Figure 5.

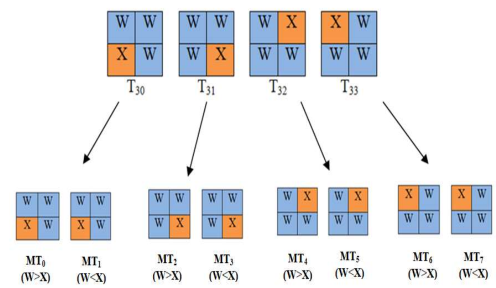

Figure 1: Magnitude-based Textons Generation For Three Identical Pixels

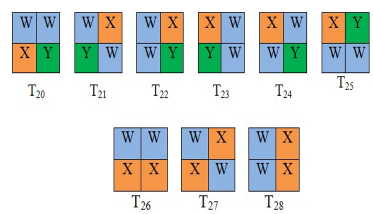

Figure 2: Textons With Two Identical Pixels

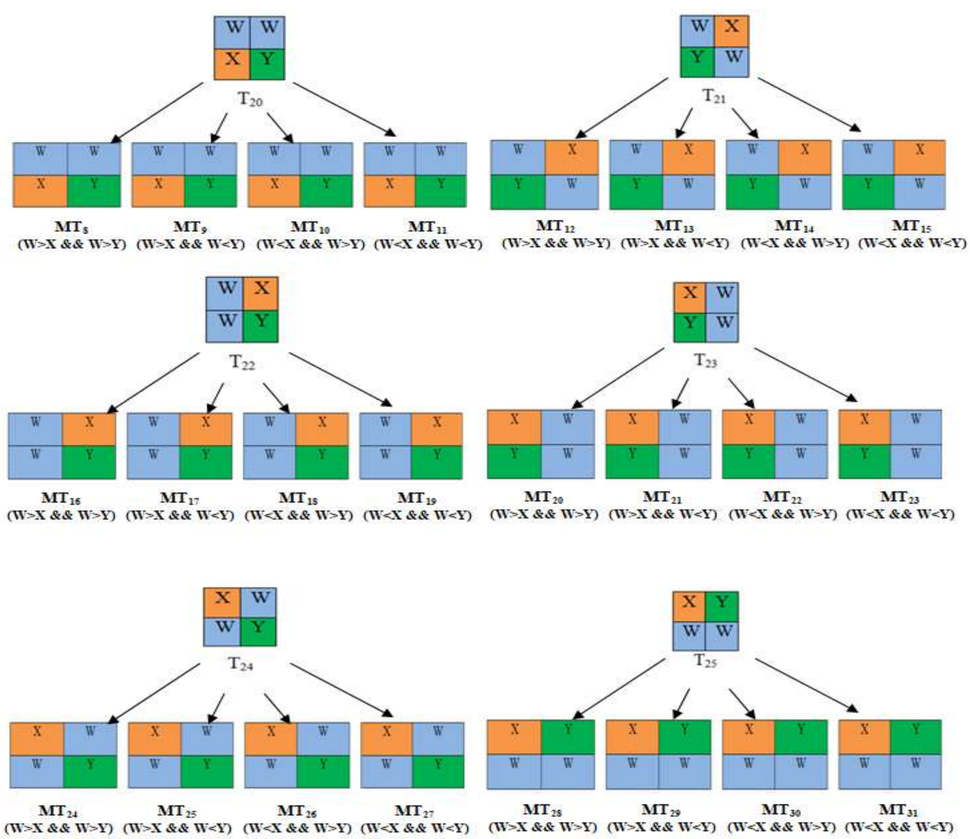

Figure 3: Magnitude-based Textons Generation For Two Identical Pixels (X!=Y)

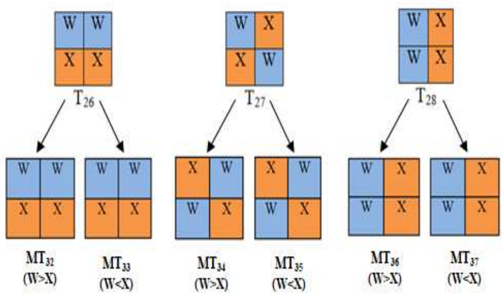

Figure 4: Magnitude-based Textons Generation For Two Identical Pixels (X==Y)

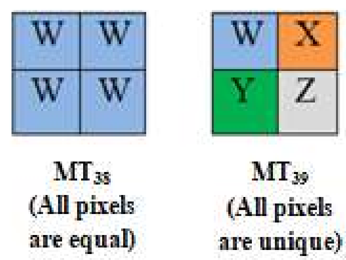

Figure 5: Magnitude-based Textons For All Identical And Unique Pixels

3.2. Motif Co-occurrence Matrix (MCM)

A motif is a distinct local pattern or structure created by the spatial arrangement of pixel intensities inside a small neighborhood. Often used for feature extraction and classification, it is a basic unit of texture that captures pixel relationships. The Motif Co-occurrence Matrix (MCM)[32], one of the earliest studies on motifs, scans a 2x2 grid from the top-left corner and moves progressively through the remaining three pixels depending on incremental deviations from the beginning point. As shown in Figure 6, this procedure creates six different motifs, each of which denotes a different configuration of pixels inside the grid. The procedure turns the image into an indexed image with six different possible values by choosing a particular motif and giving it an index value (0 to 5) based on the texture contrast features of the 2x2 grid. The motif index image is next employed to generate a co-occurrence matrix, called the Motif Co-occurrence Matrix (MCM), which is subsequently used for content-based image retrieval (CBIR). The MCM is considered static since the scanning position always begins from top left corner. To make it dynamic, Dynamic Motif (DM) [30] is proposed in the literature.

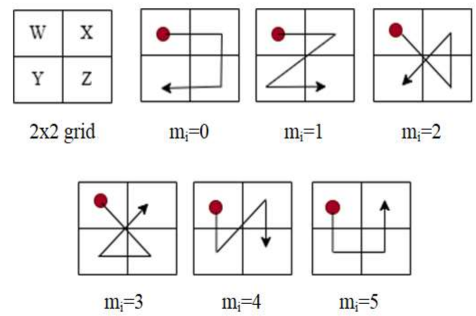

Figure 6: Six Peano Motifs On A 2x2 grid

3.3. Dynamic Motifs (DM)

Dynamic Motifs (DM) were presented in the literature [48] to address the limitation of fixed scanning position at the top-left corner, preventing it from capturing all possible motif configurations in a 2x2 grid. The DM does not have any fixed starting point like that of MCM. It initiates the scanning from the pixel of the lowest gray level in the 2x2 grid. This dynamic approach enables exploring a wider range of motifs by adjusting the scanning process depending on the pixel intensity values. Consequently, DM picks up 24 unique motif indices (0 to 23) that represent diverse structural arrangements within the 2x2 grid, which are shown in Figure 7. These indices result in a more significant manifestation of motif information rather than MCM.

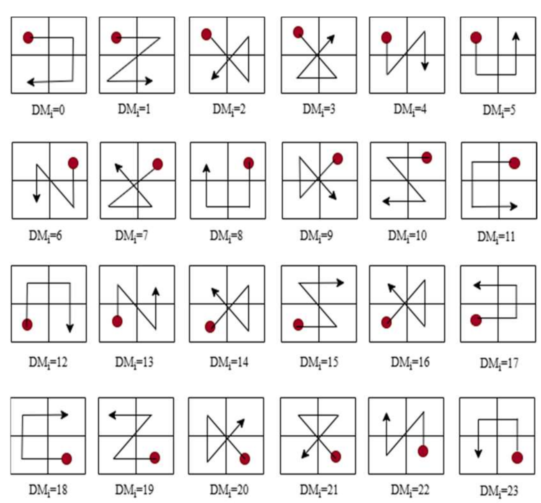

Figure 7: 24 Dynamic Motifs On A 2x2 Grid

4. PROPOSED METHODOLOGY

The proposed method introduces a robust framework that integrates Average Rule-based Motif (ARM) with Complete Magnitude Texton indexed (CMT_i) images to enhance the texture representation and classification.

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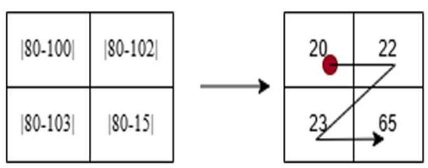
4.1. Average Rule-based Motif (ARM)

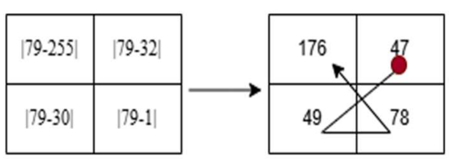
All the motif methods initiate the scanning process always either from the leftmost pixel or the pixel with the lowest intensity. None of the motif methods initiated the scan from the concentrated gray levels. The concentrated gray level means the property of exhibiting the similar range of gray levels by a majority of pixels. This characteristic is accomplished by the average filter. A few examples of concentrated gray levels, indicated in red color, are presented in Figure 8.

a. avg=80 *b. avg= 79*

Figure 8: 2x2 grid with concentrated gray levels



a. Average = 80

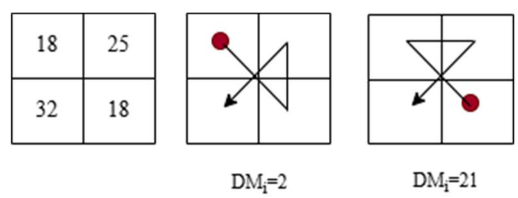


b. Average = 79

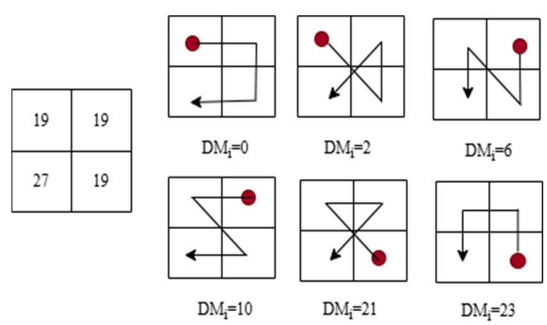
Figure 9: Average Motifs On The 2x2 Grid With Average Filter

In the above Figure 8, the dynamic motif starts from gray level 15 (Figure 8.a) and gray level 1 (Figure 8.b). To initiate the scan from the concentrated gray levels, propose Average Motif (AM). To derive this, initially an average filter is applied on the 2x2 grid. Later, calculate the absolute difference between the average and each pixel of the 2x2 grid, then start the peano scan from the minimum value. Sample Average Motifs on 2x2 grids are shown in Figure 9. The Average Motif (AM) initiates the scan position based on the distribution of concentrated gray levels within the 2x2 grid. The other advantages of the average filter are: i) it reduces intensity variations within small regions, making the image more locally uniform; ii) it provides moderate smoothing without excessively blurring edges or fine details in the image.

In the next step, on the average motif, this paper applied rules [5] to address the ambiguity issues. The ambiguity in any motif method arises when two or more pixels of the 2x2 grid exhibit identical gray level values. In such cases, it is not possible to derive unique patterns. The classification accuracy drastically falls down if there is no unique representation of peano scan / motif directions for exactly similar gray levels of the grid. These ambiguities in dynamic motifs (DM) are shown in Figure 10. For the same gray level pattern, there is no unique representation. If two pixels exhibit the same gray level, dynamic motifs exhibit two different scan directions (shown in Figure 10.a), i.e., derive two different motif indices (DM_i=2 and 21). In the same way, if three pixels exhibit the same gray level, a dynamic motif exhibits six different scan directions (shown in Figure 10.b), i.e., it derives six different motif indices (DM_i=0, 2, 6, 10, 21, and 23). This is addressed by applying rule-based motifs [5], which formulate a unique peano scan direction whenever two or more pixels of 2x2 grids exhibit the same gray level/index.



a. Ambiguities In Dynamic Motifs With Two Identical Pixels

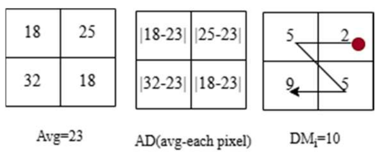


b. Ambiguities In Dynamic Motifs With Three Identical Pixels

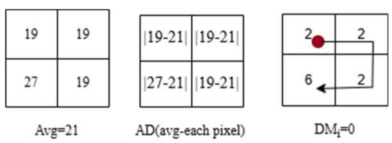
Figure 10: Ambiguities In Motif Methods When Pixels Have Identical Gray Values

The rules regarding dynamic motifs to prevent ambiguity are outlined below.

Rule 1: The pixel in the top row is prioritized for scanning if its value or code is identical to that of the pixel in the bottom row.
Rule 2: The leftmost pixel will be prioritized for scanning if the value of a pixel in the left column and the right column is identical.
The ambiguity issues are resolved and illustrated in Figures 11.a. and 11.b. following the application of the aforementioned principles.



a. Rule-based motif on 2 identical pixels



b. Rule-based motif on 3 identical pixels

Figure 11: Resolved Ambiguities In Motif-based Methods After Applying Rules

In order to resolve the ambiguities shown in Figure 10. Initially took the average of the 2x2 grid, calculated the absolute difference between the average and each pixel, and applied the rules. In Figure 11.a, after calculating the absolute difference between the average and each pixel, the values were 5, 2, 9, and 5. Here both pixels have the same value, one in the top row and the other in the bottom row. So, to overcome the ambiguity, rule 1 is applied, i.e., priority is given to the top row pixel, and it derives the unique motif index 10. Similarly, to resolve the ambiguities shown in Figure 11. b, got the values 2, 2, 6, and 2. These three have the same values. So, to overcome the ambiguities, first apply rule 1, which gives priority to the top row; later apply rule 2, which gives priority to the left column, and it derives the unique motif index 0.

The framework of the proposed Average Rule-based Motif on Complete Magnitude-based Texton Co-occurrence Matrix (ARM_i^{CMT}–CM) is shown in Figure 12, and the process is explained below.

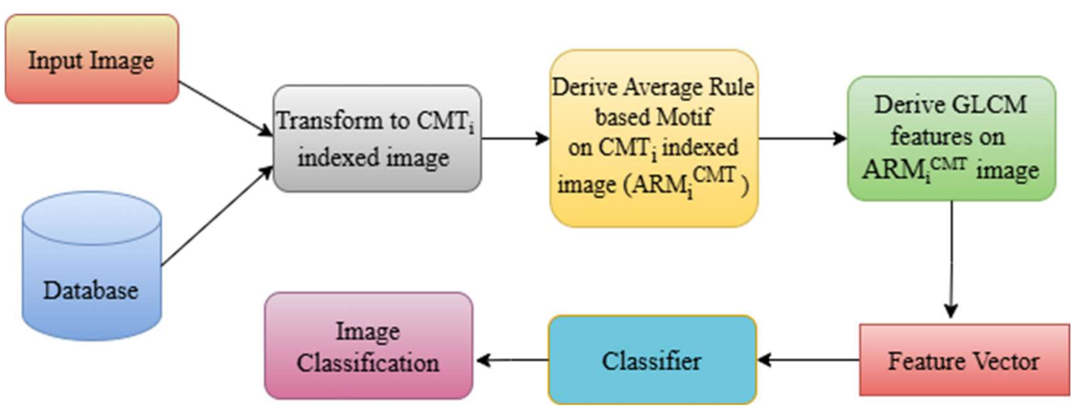


Figure 12: Framework Of Proposed Method Average Rule-based Motif on Complete Magnitude-based Texton- Co-occurrence Matrix (ARM_i^{CMT}-CM)

In this paper, the input image is initially transformed into a Complete Magnitude Texton (CMT_i) indexed image. The CMT_i indexed image is produced by replacing each overlapped 2x2 grid by its corresponding texton index from 0 to 39. Further, on the 2x2 grid of the complete magnitude texton indexed (CMT_i) image in an overlapped manner, the average rule-based motif (RAM) is applied, and the 2x2 grid is replaced with the indices from 0 to 23 based on the respective scan directions. This transforms the CMT_i indexed image (from indices 0 to 39) into an Average Rule-based Motif on Complete Magnitude-based Texton (ARM_i^{CMT}) indexed image (from indices 0 to 23); hence, each 2x2 grid gets uniquely indexed using a rule-based motif. The derivation of the proposed Average Rule-based Motif (ARM_i^{CMT}) index on an image patch of size 5x5 is shown in Figure 13.

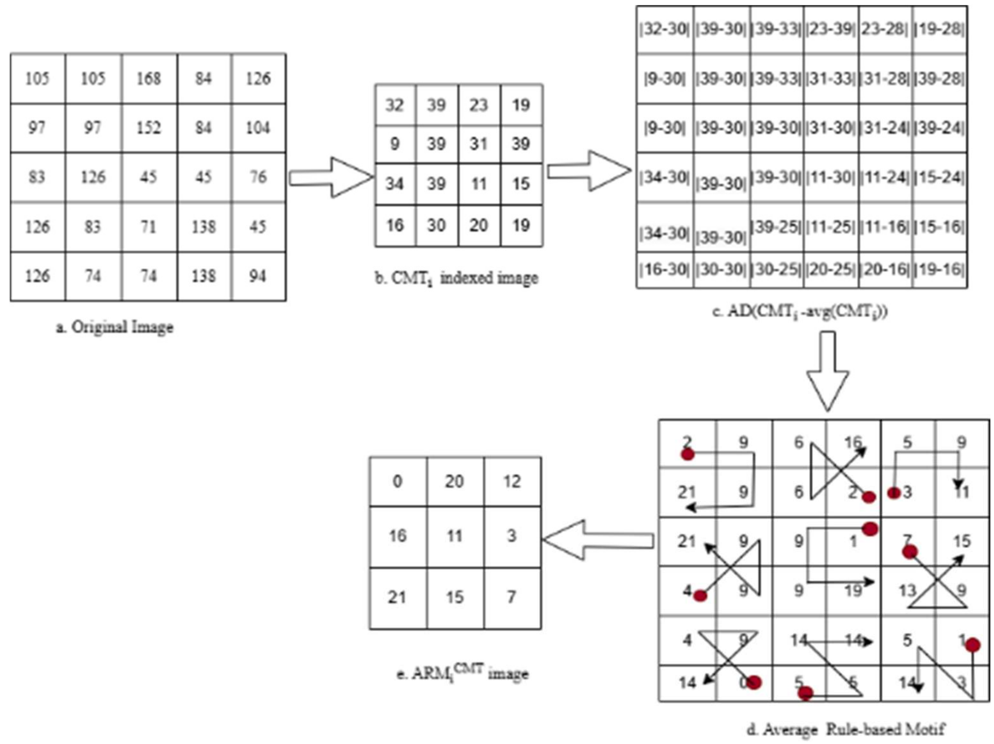


Figure 13: Derivation Of Average Rule-based Motif Indexed (ARM_i^{CMT}) Image

Further, from the ARM_i^{CMT} indexed image, a gray-level co-occurrence matrix (GLCM) is computed to capture spatial relationships between motif indices. Six GLCM features: energy, contrast, entropy, angular second moment, correlation, and homogeneity are calculated, with a distance (d) of 1. The method generates six ARM_i^{CMT}-CMs at rotation angles of 0°, 45°, 90°, 135°, 180°, and 225°, resulting in a total of 6×6=36 GLCM features for each image. A feature vector is created from aggregating six ARM_i^{CMT}-CM features, and that feature vector is used as the input for the classifier. This feature vector includes all the local texture information, which is in the form of ARM_i^{CMT} descriptors, while GLCM analysis collects the global spatial properties. This feature vector encompasses all the significant aspects of the texture present in the image. This kind of comprehensive feature positively affects both the accuracy and robustness of the classification process.

5. RESULTS AND DISCUSSIONS

To test the efficacy of the proposed method, six benchmark datasets are used: Colored Brodatz Texture, MIT-VisTex, Outex TC-00010, University of Illinois Urbana-Champaign (UIUC), Salzburg Texture Database (STex), and Flicker Material Dataset (FMD), and the performance of the proposed framework is computed on these databases. The proposed framework is tested with five different classifiers: i) Naive Bayes (NB), ii) K-Nearest Neighbors (KNN), iii) Decision Tree (DT), iv) Support Vector Machine (SVM), and v) Random Forest (RF), and the results are shown in Table 1 and Figure 14. It is evident that the SVM classifier has attained the best possible results. The SVM classifier results are used when compared with other methods.

The results are compared with the eight state-of-the-art texture descriptors: motif co-occurrence matrix (MCM)[32], rule-based dynamic motif matrix on full texton index images (RDMM-FTi) [5], cross diagonal complete Motifs matrix (CD-CMM)[50], multi motif co-occurrence matrix (MMCM)[36], Complete Magnitude-based Texton Co-occurrence Matrix (CMT-CM) [47], Local Triangular Coded Pattern (LTCP) [41], Gabor Contrast Patterns (GCP) [40], Neighborhood influenced Local Binary Pattern (NLBP) [42]. Comparison of proposed method ARM_i^{CMT}-CM with different texture descriptors on various databases is shown in Table 2 and Figure 15.

Table 1: Classification Accuracies Of Proposed Method ARM_i^{CMT}-CM On Various Databases Using Five Different Classifiers.

Database / Classifier	Naive Bayes (NB)	Decision Tree (DT)	Random Forest (RF)	K-nearest neighbors (KNN)	Support Vector Machine (SVM)
Colored Brodatz Texture (CBT)	86.63	91.84	93.12	88.24	97.36
MIT Vision Texture (MIT-Vistex)	88.79	89.65	91.48	85.83	95.29
Outex TC-00010	88.36	86.79	89.74	92.16	95.87
University of Illinois Urbana-Champaign (UIUC)	85.41	92.67	91.46	93.27	93.86
Salzburg Texture (Stex)	86.37	88.91	93.35	87.46	94.12
Flickr Material Database (FMD)	78.42	78.63	82.51	76.38	86.58

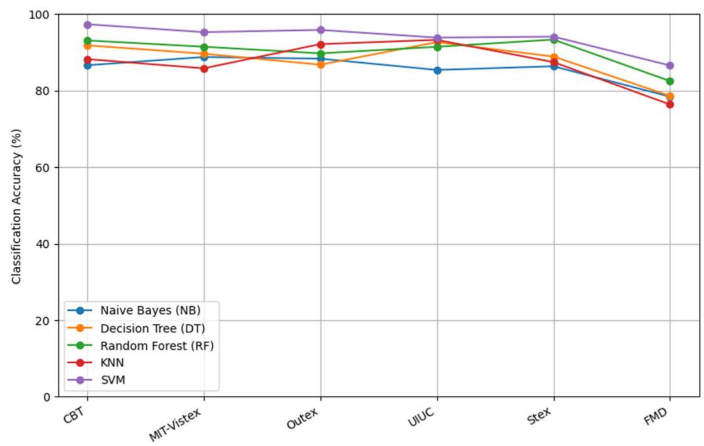


Figure 14: Classification Accuracies Of Proposed Method ARM_i^{CMT}-CM With Different Classifiers On Various Databases

Table 2: Comparison of proposed method ARM_i^{CMT}-CM with different texture descriptors on various databases.

State-of-art-methods and Proposed method	Databases					
	Colored Brodatz	MIT-Vistex	Outex TC-00010	UIUC	STex	FMD
Motif Co-occurrence Matrix (MCM)[32]	90.44	87.62	87.53	85.36	81.53	75.46
Multi Motif Co-occurrence Matrix (MMCM)[36]	92.42	90.82	89.25	86.42	85.44	75.48
Cross Diagonal Complete Motifs Matrix (CD-CMM)[50]	94.17	87.13	88.62	85.72	80.35	77.49
Rule based dynamic motif matrix on full texton index images ($RDMM-FT_i$) [5]	91.28	90. 78	90.36	89.76	86.43	77.24
Complete Magnitude-based Texton Co-occurrence Matrix (CMT-CM) [47]	96.47	94.63	95.37	92.58	93.65	83.79
Local Triangular Coded Pattern (LTCP) [41]	92.82	93.81	91.74	90.67	88.67	83.21
Gabor Contrast Patterns (GCP) [40]	92.65	94.38	91.63	84.15	86.64	78.62
Neighborhood influenced Local Binary Pattern (NLBP) [42]	87.77	82.19	86.74	81.3	85.57	76.19
Proposed method ARM_i^{CMT}-CM	97.36	95.29	95.87	93.86	94.12	86.58

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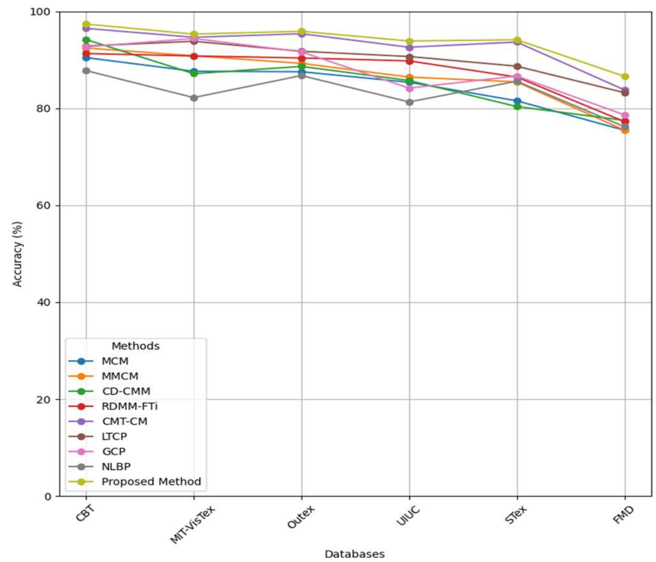

Figure 15: Comparison Of Proposed Method ARM_i^{CMT}-CM With Different Texture Descriptors On Various Databases

As shown in Figure 15, the proposed method ARM_i^{CMT}-CM consistently outperforms all other methods, achieving the highest accuracy across all datasets, with notable performance on Colored Brodatz (97.36%), MIT Vision (95.37%), UIUC (93.86%), Salzburg (94.12%), and Flickr Material Database (86.58%). The CMT-CM method also shows strong performance, particularly in the UIUC and Salzburg datasets, suggesting its effectiveness in capturing discriminative texture features. Although MCM and RDMM-FT_i work well in some datasets, such as Colored Brodatz Texture and MIT Vision, their performance decreases in more complex datasets, like Flickr Material Database. Similarly, GCP is effective for certain structured textures but fails in datasets with higher intra-class variations. On the other hand, NLBP showed poor performance in all datasets, and its accuracy is between 81.3% and 87.77%, which indicates its weakness in extracting robust texture features. In comparison with MCM and RDMM-FT_i, the novel ARM_i^{CMT}-CM framework prevents motif ambiguity via rule-based indexing, which is particularly important for noisy or intricate textures. In contrast to LTCP or GCP, our approach fuses both local motif features and spatial GLCM features and thus gives consistent performance improvements on all datasets. The superior performance of the proposed method is due to the ability to capture strong local texture information through a unique integration of average rule-based motifs and complete magnitude-based textons, making it highly robust for diverse texture patterns. These results suggested that fusion of local and global information from texture leads to a highly improved classification accuracy for the proposed method, making it eligible for real-world applications. To ensure the consistency of our results, we further tested a smaller subset of the feature set with single CMTi indices and classical Gabor filters. The trends in classification were consistent, demonstrating the reliability of our method.

The proposed Average Rule-based Motif on Complete Magnitude Texton Co-occurrence Matrix ARM_i^{CMT}-CM framework demonstrates its efficacy by addressing key limitations in traditional methods, such as motif ambiguity and limited feature representation. By combining advanced motif indexing rules with CMT and GLCM features, the method achieves a comprehensive representation of texture patterns, resulting in superior classification performance. Its scalability and adaptability across diverse datasets underline its robustness and potential for real-world applications. The results validate that ARM_i^{CMT}-CM is not only an improvement over existing motif-based and texton-based approaches but also establishes a new benchmark for texture classification accuracy on widely used datasets.

6. CONCLUSION

The proposed Average Rule-based Motif on Complete Magnitude Texton Co-occurrence Matrix (ARM_i^{CMT}-CM) method introduces a robust framework that combines Average Rule-based Motifs (ARM) with Complete Magnitude Texton indexed (CMTi) images to enhance the texture representation and classification. The usage of Complete Magnitude-based Texton indexing along

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with the Average Rule-based Motifs (ARM) ensures a unique and unambiguous motif representation, which overcomes the problems caused by repetition and ambiguity of texture patterns. The integration of motif-based descriptors with Gray-Level Co-occurrence Matrix analysis provides both local structural details and spatial relationships, resulting in a comprehensive feature representation. The methodology shows remarkable improvements in classification accuracy and robustness, especially when the texture is complex or ambiguous. Its rotational invariance and ability to reduce dimensionality without losing texture information make it a versatile solution for texture-based image analysis in many applications. Further work would optimize the computational efficiency and then apply it to multi-scale texture analysis or real-time systems, thereby potentially opening its application areas to more extended use.

7. LIMITATIONS AND FUTURE SCOPE

Though the ARM_i^{CMT}-CM method produces high classification accuracy, its fixed 2x2 grid dependence can restrict performance with larger-scale texture patterns. Also, rule-based motif calculation, though effective, can create computational overhead in high-resolution images. Future work may investigate adaptive grid sizing and multi-scale motif integration to represent hierarchical texture features. Further, integrating deep learning with the ARM_i^{CMT}-CM descriptors might also improve performance in real-time systems.

REFERENCES

[1] Julesz B. Visual pattern discrimination. IEEE Transactions on Information Theory. 1962 Feb 1;8(2):84–92. https://doi.org/10.1109/tit.1962.1057698

[2] Chen CH, Pau LF, Wang PS. Handbook of Pattern Recognition and Computer Vision. World Scientific; 1993.

[3] Depeursinge A. Multiscale and multidirectional biomedical texture analysis. In: Elsevier eBooks. 2017. p. 29–53. https://doi.org/10.1016/b978-0-12-812133-7.00002-8

[4] Jung SY, Tsai YH, Chiu WY, Hu JS, Sun CT. Defect detection on randomly textured surfaces by convolutional neural networks. 2022 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM) [Internet]. 2018 Jul 1;1456–61. https://doi.org/10.1109/aim.2018.8452361

[5] Madhavi G, Kumar VV. A new frame work for content based image retrieval based on rule based motifs on full Texton images. International Journal of Advanced Trends in Computer Science and Engineering [Internet]. 2019 Sep 7;8(1.4):1083–98. https://doi.org/10.30534/ijatcse/2019/15842019

[6] Naseer A, Jalal A. Efficient aerial images algorithms over multi-objects labeling and semantic segmentation. 2024 5th International Conference on Advancements in Computational Sciences (ICACS). 2024 Feb 19;1–9. https://doi.org/10.1109/icacs60934.2024.10473251

[7] Khoshnevisan E, Hassanpour H, AlyanNezhadi MM. Face recognition based on general structure and angular face elements. Multimedia Tools and Applications [Internet]. 2024 Mar 21; 83 (36): 83709–27. https://doi.org/10.1007/s11042-024-18897-3

[8] Mohan BV, Kumar VV. A method for face recognition based on rotational invariant Structural Texture primitives (RISTP) derived on local directional pattern (LDP). Journal of Computational and Theoretical Nanoscience. 2019 May 1; 16(5): 2571–80. https://doi.org/10.1166/jctn.2019.7933

[9] Jan F, Min-Allah N, Agha S, Usman I, Khan I. A robust iris localization scheme for the iris recognition. Multimedia Tools and Applications. 2020 Sep 30;80(3):4579–605. https://doi.org/10.1007/s11042-020-09814-5

[10] Bansal M, Kumar M, Kumar M. 2D object recognition: a comparative analysis of SIFT, SURF and ORB feature descriptors. Multimedia Tools and Applications. 2021 Feb 20;80(12):18839–57. https://doi.org/10.1007/s11042-021-10646-0

[11] Chang J, Zhao Z, Jia C, Wang S, Yang L, Mao Q, et al. Conceptual compression via deep structure and texture synthesis. IEEE Transactions on Image Processing. 2022 Jan 1;31:2809–23. https://doi.org/10.1109/tip.2022.3159477

[12] Yu H, Yang W, Hua G, Ru H, Huang P. Change detection using high resolution remote sensing images based on active learning and Markov random fields. Remote Sensing. 2017 Nov 29; 9(12):1233. https://doi.org/10.3390/rs9121233

[13] Liu L, Chen J, Fieguth P, Zhao G, Chellappa R, Pietikäinen M. From BOW to CNN: Two decades of texture Representation for texture Classification. International Journal of Computer Vision. 2018 Nov 8;127(1):74–109.

https://doi.org/10.1007/s11263-018-1125-z

[14] Lowe DG. Object recognition from local scale-invariant features. In Proc IEEE Int Conf Comput Vision. 1999 Jan 1;1150–7 vol.2. https://doi.org/10.1109/iccv.1999.790410

[15] Campisi P, Neri A, Panci G, Scarano G. Robust Rotation-Invariant texture classification using a model based approach. IEEE Transactions on Image Processing. 2004 May 13;13(6):782–91. https://doi.org/10.1109/tip.2003.822607

[16] Minarno AE, Soesanti I, Nugroho HA. Batik Image Representation using Multi Texton Co-occurrence Histogram. JOIV International Journal on Informatics Visualization. 2024 Nov 30;8(3–2):1582. https://doi.org/10.62527/joiv.8.3-2.3095

[17] Ouslimani F, Ouslimani A, Ameur Z. Robust directional median pattern for noisy texture classification. Multimedia Tools and Applications. 2024 Oct 15; https://doi.org/10.1007/s11042-024-20378-6

[18] Ojala T, Pietikainen M, Maenpaa T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2002 Jul 1;24(7):971–87. https://doi.org/10.1109/tpami.2002.1017623

[19] Alpaslan N, Hanbay K. Multi-Resolution intrinsic texture Geometry-Based local binary pattern for texture classification. IEEE Access. 2020 Jan 1; 8:54415–30. https://doi.org/10.1109/access.2020.2981720

[20] Xiong J 1, Liu G 2, Huang L, Wu C, Wu T, Mu Y, et al. Autoregressive Models in Vision: a survey. arXiv. 2024; https://arxiv.org/abs/2411.05902v1

[21] De Siqueira FR, Schwartz WR, Pedrini H. Multi-scale gray level co-occurrence matrices for texture description. Neurocomputing. 2013 Apr 2;120:336–45. https://doi.org/10.1016/j.neucom.2012.09.042

[22] Siradjuddin IA, Sophan MK, Kusumaningsih A, Santosa I. An Integrated Color and Intensity Co-Occurrence Matrix for batik image retrieval. Advanced Science Letters. 2016 Jul 1;22(7):1787–90. https://doi.org/10.1166/asl.2016.7044

[23] Garg M, Dhiman G. A novel content-based image retrieval approach for classification using GLCM features and texture fused LBP variants. Neural Computing and Applications. 2020 Jun 6;33(4):1311–28. https://doi.org/10.1007/s00521-020-05017-z

[24] Song T, Han Y, Li S, Zhao C. Grayscale-inversion and rotation invariant image description using local ternary derivative pattern with dominant structure encoding. Expert Systems With Applications. 2021 Dec 11;191:116327. https://doi.org/10.1016/j.eswa.2021.116327

[25] Xing Z, Qiao Y, Zhao Y, Liu W. Dynamic texture classification based on bag-of-models with mixture of student's t-hidden Markov models. Computer Vision and Image Understanding . 2023 Feb 15;230:103653. https://doi.org/10.1016/j.cviu.2023.103653

[26] Du Y, Weng Z, Li F, Ablat G, Wu D, Liu C. A novel approach for pavement texture characterisation using 2D-wavelet decomposition. International Journal of Pavement Engineering. 2020 Oct 1; 23(6):1851-66. https://doi.org/10.1080/10298436.2020.1825712.

[27] Han J, Ma KK. Rotation-invariant and scale-invariant Gabor features for texture image retrieval. Image and Vision Computing. 2006 Dec 29; 25(9):1474–81. https://doi.org/10.1016/j.imavis.2006.12.015

[28] Du Y, Weng Z, Li F, Ablat G, Wu D, Liu C. A novel approach for pavement texture characterisation using 2D-wavelet decompo-sition. International Journal of Pavement Engineering . 2020 Oct 1; 23(6):1851–66. https://doi.org/10.1080/10298436.2020.1825712

[29] Davis LS, Johns SA, Aggarwal JK. Texture analysis using generalized Co-Occurrence matrices. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1979 Jul 1; PAMI-1(3):251–9. https://doi.org/10.1109/tpami.1979.4766921

[30] Zhang J, Li GL, He SW. Texture-Based Image Retrieval by Edge Detection Matching GLCM. 10th IEEE International Conference on High Performance Computing and Communications. 2008 Sep 1;2: 782–6. https://doi.org/10.1109/hpcc.2008.55

[31] De Siqueira FR, Schwartz WR, Pedrini H. Multi-scale gray level co-occurrence matrices for texture description. Neurocomputing. 2013 Apr 2;120: 336–45. https://doi.org/10.1016/j.neucom.2012.09.042

[32] Jhanwar N, Chaudhuri S, Seetharaman G, Zavidovique B. Content based image retrieval using motif cooccurrence matrix. Image and Vision Computing. 2004 Nov 8;22(14):1211–20. https://doi.org/10.1016/j.imavis.2004.03.026

[33] Lin CH, Chen RT, Chan YK. A smart content-based image retrieval system based on color and

texture feature. Image and Vision Computing. 2008 Jul 23;27(6):658–65. https://doi.org/10.1016/j.imavis.2008.07.004

[34] Siradjuddin IA, Sophan MK, Kusumaningsih A, Santosa I. An Integrated Color and Intensity Co-Occurrence Matrix for batik image retrieval. Advanced Science Letters. 2016 Jul 1;22(7):1787–90. https://doi.org/10.1166/asl.2016.7044

[35] Subrahmanyam M, Wu QMJ, Maheshwari RP, Balasubramanian R. Modified color motif co-occurrence matrix for image indexing and retrieval. Computers & Electrical Engineering]. 2012 Dec 25;39(3):762–74. https://doi.org/10.1016/j.compeleceng.2012.11.023

[36] Obulesu A, Kumar VV, Sumalatha L. Content based Image Retrieval Using Multi Motif Co-Occurrence Matrix. International Journal of Image Graphics and Signal Processing. 2018 Apr 8;10(4):59–72. https://doi.org/10.5815/ijigsp.2018.04.07

[37] Reddy KS, Kumar VV, Reddy BE. Face Recognition Based on Texture Features using Local Ternary Patterns. International Journal of Image Graphics and Signal Processing. 2015 Sep 8; 7(10):37–46. https://doi.org/10.5815/ijigsp.2015.10.05

[38] Murala S, Maheshwari RP, Balasubramanian R. Local Tetra Patterns: a new feature descriptor for Content-Based Image Retrieval. IEEE Transactions on Image Processing. 2012 Apr 11;21(5):2874–86. https://doi.org/10.1109/tip.2012.2188809

[39] Satpathy A, Jiang X, Eng HL. Human detection using Discriminative and Robust Local Binary Pattern. IEEE International Conference on Acoustics Speech and Signal Processing. 2013 May 1;2376–80. https://doi.org/10.1109/icassp.2013.6638080

[40] Muzaffar AW, Riaz F, Abuain T, Abu-Ain WAK, Hussain F, Farooq MU, et al. Gabor Contrast Patterns: a novel framework to extract features from texture images. IEEE Access. 2023 Jan 1;11:60324–34. https://doi.org/10.1109/access.2023.3280053

[41] Arya R, Vimina ER. Local Triangular Coded pattern: a texture descriptor for image classification. IETE Journal of Research. 2021 May 16;69(6):3267–78. https://doi.org/10.1080/03772063.2021.1919222

[42] Dev A V, Baskar A. NLBP - An Improved Local Binary Pattern for Texture Classification using Correlational Features of Neighboring Pixels. 2019 Innovations in Power and Advanced Computing Technologies (i-PACT). 2023 Dec 8;1–7. https://doi.org/10.1109/ipact58649.2023.10434916

[43] Liu GH, Yang JY. Image retrieval based on the texton co-occurrence matrix. Pattern Recognition. 2008 Jun 18;41(12):3521–7. https://doi.org/10.1016/j.patcog.2008.06.010

[44] Liu GH, Zhang L, Hou YK, Li ZY, Yang JY. Image retrieval based on multi-texton histogram. Pattern Recognition. 2010 Feb 20;43(7):2380–9. https://doi.org/10.1016/j.patcog.2010.02.012

[45] Kumari YS, Kumar VV, Satyanarayana Ch. Texture classification using complete Texton Matrix. International Journal of Image Graphics and Signal Processing. 2017 Oct 8;9(10):60–8. https://doi.org/10.5815/ijigsp.2017.10.07

[46] Madhavi G B, Kumar VV. Sasidhar K. Content based image retrieval using color and full Texton Index Co-occurrence Matrix (FTICM) features. International Journal of Recent Technology and Engineering (IJRTE). ISSN: 2277-3878 (Online). 2019;1(8):1262–75.

[47] Ujwala Bhoga, Kumar VV.Texture Classification based on Complete Magnitude Texton Co-occurrence Matrix using Machine Learning Classifiers. Nanotechnology Perceptions. 2024 Sep 26;20(S12). https://doi.org/10.62441/nano-ntp.v20is12.76

[48] Sarma KSRK, Ussenaiah M. Classification of color textures using regionb ased motif and color features. International Journal of Innovative Technology and Exploring Engineering. 2019 Jun 30;8(8):2185–91. https://www.ijitee.org/portfolio-tem/h7126068819

[49] Kishore B, Kumar VV, Shylashree N. Local texton centre symmetric pattern matrix (Ltcspm) on Wavelet domain for texture classification. International Journal of Innovative Technology and Exploring Engineering. 2018 Jan 1;8:440–5. https://manipal.pure.elsevier.com/en/publications/local-texton-centre-symmetric-pattern-matrix-ltcspm-on-wavelet-do

[50] Reddy AM, Krishna VV, Sumalatha L. Face Recognition based on Cross Diagonal Complete Motif Matrix. International Journal of Image Graphics and Signal Processing. 2018 Mar 6; 10(3): 59–66. https://doi.org/10.5815/ijigsp.2018.03.07