Journal of Innovative Image Processing (ISSN: 2582-4252)
www.irojournals.com/iroiip/

Texture Segmentation Method Based on Multivariate New Symmetric Mixture Model and Log-DCT Features Derived from Local Binary Patterns

Prasanthi Mandha[1], Vamsidhar Enireddy[2]

Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Guntur(D), Andhra Pradesh, India.

E-mail: [1]dhavalaprasanthi3@gmail.com, [2]enireddy.vamsidhar@gmail.com

Abstract

In the proposed methodology, explore the superiority of different texture regions in an image along with log DCT and LBP. The image entirely metamorphoses into a local binary pattern domain using this technique. The ensuing step is to generate non-overlapping blocks based on the LBP image. The DCT coefficients are obtained in a zigzag pattern from each subsequent block. The EM technique is used to evaluate the model parameters, under the assumption that the feature vectors follow a new multivariate symmetric mixture model. The model parameters are initialized using the moment estimation technique and the hierarchical clustering approach. A Bayesian framework and the maximum likelihood method were used to develop the texture segmentation algorithm. In the Brodatz set's database, randomly selected images were used to implement the proposed algorithm using performance metrics like GCE, PRI, and VOI. Considering the performance metrics, this technique is better than the current texture segmentation algorithms. The segmentation accuracy is quantified via metrics like GCE, PRI, VOI, accuracy, precision, recall, F-measure, enhanced correctness, and enhanced model performance. Comparative studies show that integrating both LBP and log-DCT increases reliability and precision in texture segmentation.

Keywords: MNSMM, PRI, GCE, DCT Coefficients, Local Binary Patterns.

1. Introduction

As per the world scenario in research, texture segmentation is the main challenge. The most critical applications in image processing, which is connected to computer vision, include medical imaging, remote sensing, and various engineering applications. The main objective of this segmentation is to divide the image into regions that have textural properties. In the development of texture segmentation, it is most convoluted to determine metrics to evaluate illumination, complex patterns, and edges. To solve these, feature methodologies are becoming increasingly significant. Strengths of internal and external computations segment textures. In this proposal, we introduce discrete cosine transform (DCT) and local binary patterns for the segmentation of textures; these are most efficient in estimating the texture features with respect to all blocks. Additionally, the transformed DCT is evaluated well in this proposed model of the Multivariate New Symmetric Mixture Model to represent the complex distribution of these

DOI: https://doi.org/10.36548/jiip.2025.3.018
Received: 18.07.2025, received in revised form: 21.08.2025, accepted: 04.09.2025, published: 19.09.2025

curved features. The EM algorithm approach is implemented for finding the parameters in MNSMM's. This approach addresses fast convergence and maximum precision. The proposed model delivers extensive results compared to traditional texture segmentation methods on guaranteed texture datasets like the Brodatz dataset. This method has proven to have very low complexity in evaluating various texture blocks. The boundaries of the segments of blocks are also evaluated. The proposed method supports many regular implementations in research, whereas the accuracy is maximized. This method analyzes lightning computations heavily in all aspects. It will perform with metrics of GCE, PRI, and VOI on datasets like the Brodatz dataset. Its core strength lies in image decomposition, in which more complex blocks are deepened, while lower-order blocks are considered lesser identifications. Hence, the application of DCT achieves dimensionality reduction. Every image consists of pixels that encompass a range of frequencies, which convey information across micro and macro levels. In a texture image, while performing data operations, DCT preserves only the major effective macro information and removes most of the minimal and micro information. The micro level confines the inter-pixel associations; it is the fundamental aspect. Therefore, leaning exclusively on DCT might result in significant information being lost. This study applies the pixels' local binary patterns (LBP) to define the complexity in internal linkages of pixels. The main strength of texture segmentation lies in complicated blocks that are most involved in depth when less ordered blocks are considered as having fewer identifications. Mainly, the DCT leads to dimensionality reduction and evaluates each image's pixels and frequencies at the micro and macro levels. The selected texture image is first processed with LBP to derive binary patterns, which are then input to the DCT. The Log-DCT transformation on LBP is more effective than using LBP or DCT alone because it combines the strengths of both methods. LBP captures local micro-patterns and is robust to illumination changes, while DCT captures compact, global frequency-domain features. However, relying solely on DCT can lead to a loss of important local, micro-level information. Among the various features, texture is chiefly valued for its ability to discriminate pixels based on these patterns; hence, texture features are emphasized [1]. [19]. The features computed using LBP and DCT are then supplied to the proposed Multivariate New Symmetric Mixture Model. Experiments are performed on a benchmark dataset namely, Brodatz textures with performance evaluated through image and segmentation quality metrics, including precision, recall, sensitivity, specificity, F-measure, GCE, PRI, and VOI.

The experimental work is further extended by incorporating the log DCT. To reduce the illumination effects caused by images obtained from multiple calibrated cameras, log DCT is employed to minimize these variations [3], [5]. We use the mentioned performance metrics to compare the results from the two models against previous findings. The article mostly addresses texture-based image segmentation, which is a key component of processes like medical imaging, satellite image analysis, and pattern identification. The method involves applying LocalBinaryPatterns (LBP) to capture local texture, using the transformed discrete cosine transform (DCT) to extract macro-level features, and employing the Multivariate New Symmetric Mixture Model (MNSMM) to classify textures based on probability. The proposed solution addresses real-world challenges such as high-dimensional feature spaces and varying light levels by employing techniques like taking the logarithm of DCT coefficients. It applies a number of conventional segmentation measures to assess performance, including GCE, PRI, VOI, accuracy, precision, recall, and F-measure. While the Brodatz dataset serves as a crucial benchmark, it might not fully capture the diverse range of textures present in real-world images. LBP, DCT, and MNSMM jointly.

2. Literature Survey

In order to enhance precision and robustness against noise, several statistical and model-based methods have been put forward for the classical computer vision problems of image texture segmentation and analysis. One of the earliest attempts at this utilized doubly truncated GMMs in terms of DCT coefficients for face recognition by highlighting the role played by statistical distributions in feature representation [1]. To optimize segmentation efficiency, Jyothirmayi et al. [2] took it a step further and integrated hierarchical clustering and generalized Laplace mixture models. To provide a basis for comparing segmentation algorithms, objective evaluation paradigms such as Unnikrishnan et al.'s [3] were needed, and simple statistical methods such as the EM algorithm [4] and cluster distance measures [5] remain extremely useful in segmentation pipelines.

Building on these, researchers developed unsupervised segmentation based on hybrid clustering techniques and generalized Gaussian distributions [6]. In the detection of bacteria from images, Satyanarayana et al. [7] employed asymmetric distributions and k-means, demonstrating statistical model variations for work specific to an application area. Textural features for classification were offered by early texture-based approaches, such as Amadasun and King's work [8], which still hold sway in the literature. Probabilistic models enhance medical imaging applications, as evidenced by recent combinations of Laplace mixture models with hidden Markov random fields for MR brain segmentation [10] and hierarchical clustering [9]. By coupling advances in clustering, statistical modeling, and feature-based methodology, comparative reviews [11,12] provided in-depth perspectives on segmentation methods.

Gaussian mixture models have also remained particularly relevant, with applications spanning from model-based clustering [15], pixel labeling in the context of spatial neighborhood relations [14], to color and texture segmentation [13]. Theoretical and empirical work has also been extended in doubly truncated bivariate mixtures of Gaussians [16] and even in EM application handbooks in GMMs [17]. In clinical applications, segmentation of brain MRI was performed with biased Gaussian mixture models combined with fuzzy clustering and EM [18], allowing greater flexibility in modeling complicated data distributions.

Recent research combined advanced statistical and machine learning methods to move beyond the traditional GMM methods. For example, Karakaya et al. [20] applied segmentation to geological texture, whereas Tiwari et al. [19] addressed the problem of robustness and achieved improvements in fractal texture segmentation with Gaussian noise. Kinge et al. [21] combined probabilistic models with image reconstruction and employed Markov random fields in recovering texture. To reduce reliance on labeled data, self-supervised deep learning techniques such as the K-textures clustering algorithm [22] provide a new way of data-driven segmentation. In the same vein, the incorporation of segmentation into higher-level scene understanding is delineated by the semantic segmentation of textured mosaics [23]. The conventional statistical approaches and newer deep learning-based approaches are integrated in texture image analysis surveys [24], which emphasize the shift of the field from probabilistic schemes to data-driven and hybrid models. Fatima and Ram [25] proposed a GAN-enhanced framework for real-time deepfake video detection, demonstrating the capacity of generative models to identify manipulated content in dynamic environments.

3. Methodology

The proposed approach incorporates a logarithmic domain to combine Discrete Cosine Transform (DCT) and Local Binary Patterns (LBP) features to make texture segmentation simpler. First, the texture image is transferred to the LBP domain so that it can identify micro-patterns that remain constant when the illumination changes. Subsequently, 2D DCT is applied to each of the image's non-overlapping segments. After forming feature vectors derived from DCT coefficients in a zigzag manner, further processing is performed in the logarithmic domain to reduce the impact of illumination.

Multivariate New Symmetric Mixture Model (MNSMMs) are used to represent these feature vectors. This logarithmic transformation of DCT coefficients is a key technique for addressing real-world challenges like illumination variation. The combination of LBP and log-DCT features, modeled by the MNSMM, enhances texture discrimination and improves segmentation boundaries even with subtle variations in pattern, orientation, or illumination. The EM method is used to improve the model parameters, which are initially determined via hierarchical clustering. Maximum likelihood is used in the segmentation process within a Bayesian framework.

3.1 Extraction of Features based on DCT Coefficients under Logarithmic Domain & LBP

In the process, the DCT transform efficiently minimizes the error ratio in texture blocks, while local binary patterns achieve the finest texture qualities [5], [7], [12]. The combination of DCT coefficients with local binary patterns provides the best feature vector for segmentation. Local binary patterns transform each intensity of pixels into a decimal value by encoding the entire local structure. In this method, the center pixel intensity value is deducted and compared with its neighboring pixels (Huang et al. (2011) and Chi et al. (2007)). The negative differences are encountered as 0, and all remaining values become 1, forming a binary number in clockwise order. Additionally, the computation is initialized with the left-to-right neighborhood of pixel intensities [4],[9]. The process is illustrated in Figure 1.

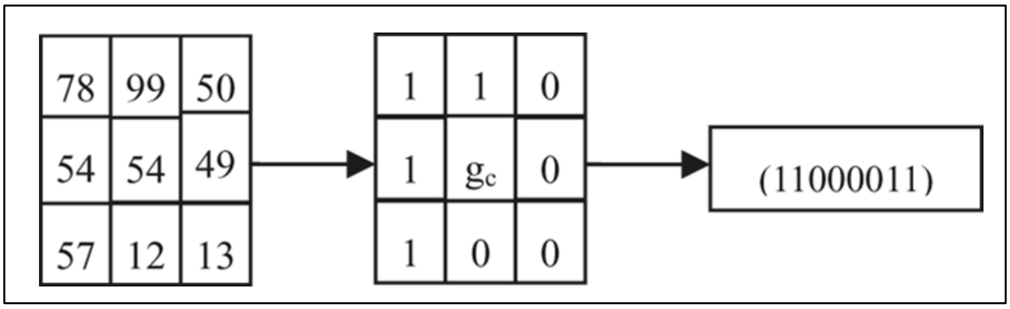


Figure 1. Extraction of LBP Code from Grey Scale Texture Image

A key limitation of the LBP operator is its inability to capture large-scale structures due to its restricted 3×3 neighbourhood. To capture texture information at various scales, the operator was extended to incorporate neighborhoods of varying dimensions (Ojala. T et al. (2004)). Given a pixel at (x_c,y_c), the resulting LBP is represented as a decimal s, which defines a threshold function as follows:

$$LBP_{P,R}\left(x_c, y_c\right) = \sum_{p=0}^{p-1} q(i_p - i_c)2^p \tag{1}$$

$$\text{q(x)=}\begin{cases} 1, & \textit{if } x \geq 0 \\ 0, & \textit{otherwise} \end{cases} \tag{2}$$

The standard LBP operator remains unaffected by monotonic gray-level changes, as long as the relative order of pixel intensities within the local neighbourhood is maintained. The operator LBP(P,R) generates 2P distinct output values, which correspond to 2P unique binary patterns created by P pixels within the neighborhood. The DCT features obtained from LBP images generally exhibit a lower ratio compared to those extracted from raw intensity values. [10][12] As a result, feature extraction is performed using two strategies: DCT+LBP and a logarithmic domain version of DCT+LBP.

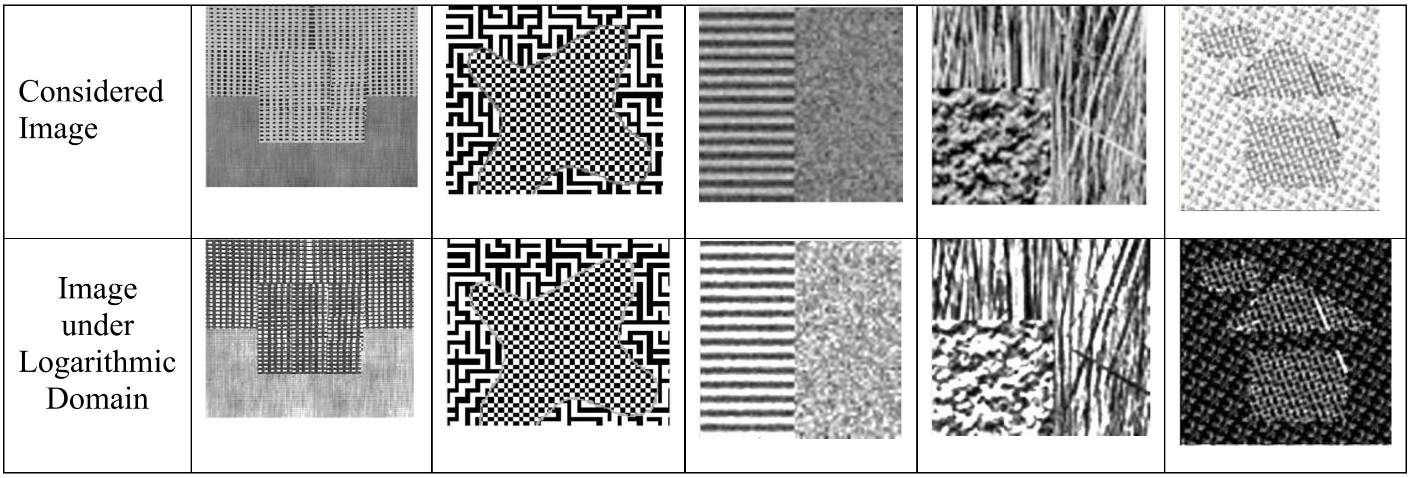


Figure 2. Actual Texture Images and Texture under Loc-Bi Patterns Domain

In the initial approach, the input image is transformed into the Loc-Bi-Patterns (LBP) domain. The resulting LBP-transformed image is subsequently arranged in non-overlapping segments of dimensions M×N. A two-dimensional Discrete Cosine Transform (2D DCT) is applied to each block, and the obtained coefficients are arranged using a zig-zag scanning pattern. [5][3]. These arranged coefficients are then concatenated to construct the feature vector.

In the second approach, to account for illumination changes, log-DCT features are employed. This is based on the observation that small variations in local features representing fine texture details or micro-level patterns play a crucial role in texture representation. To enhance feature extraction performance, both macro- and micro-level information are integrated under optimal conditions, resulting in a more generalized and robust method. The MNSMM was chosen because its flexible, symmetric distribution is better suited to model these complex data distributions, leading to improved segmentation accuracy and lower misclassification rates.

The overall steps involved in the feature vector retrieval process include converting the image into the LBP domain, dividing it into fixed-size blocks, applying the DCT on each block, arranging the coefficients in zig-zag order, and using these coefficients as the texture feature descriptors.

3.2 Multivariate New Symmetric Mixture Model (MNSMM)

In this analysis, the main component is interpreted as a composition of recurrent layouts, commonly referred to as textures. These textures are best described using feature vectors encompassing attributes such as shape, size, color, texture, and density. Incorporating multiple features enhances the accuracy of segmentation. The segmentation procedure involves analyzing the coefficients corresponding to each pixel, where these coefficients are derived from feature vectors computed using the logarithmic Discrete Cosine Transform (log DCT). These vectors serve as input to the model, specifically the Multivariate New Symmetric Mixture Model (MNSMM). The overall PDF representing every analyzed component region is formulated as follows:

$$p(\vec{x}_r / \theta) = \sum_{i=1}^{M} w_i g_i \left(\vec{x}_{r,} \theta\right) \tag{3}$$

Where $\vec{x}_r = (x_{rij})$, is a D dimensional arbitrary vector for j=1,2,3...D values, depicting the feature vector; i = 1,2,..M denotes the image's domains, and i=1,2,3..T values denote the pixels [1][4][6]. The parametric set is $\theta = (\mu, \sigma, \beta)$, w_i is the mixing weight such that $\sum_{i=1}^{M} w_i = 1$, Given the image's texture feature vector and the Multivariate New Symmetric Model of D-dimension, the likelihood of the ith pixel belonging to that vector is

$$\vartheta_i(\bar{x}_r, \theta) = \prod_{j=1}^{D} \left[\frac{2 + \left[\frac{(x_j - \mu_j)}{\sigma_j}\right]^2}{3\sigma_j\sqrt{2\pi}} \right] e^{-\frac{1}{2}\left[\frac{(x_j - \mu_j)}{\sigma_j}\right]^2} \tag{4}$$

Where μ_j , σ_j are the Parameters

The mixture model is

$$p\left(\frac{\bar{x}_r}{\theta}\right) = \sum_{l=1}^{m} w_i \, \vartheta_i(\bar{x}_r, \theta) \tag{5}$$

where, μ_j, σ_j, β_j are location, scale and shape parameters

$\beta_j \geq 0$ is the parameter that controls the shape of MNSMM distribution.

3.3 Application of EM Algorithm for Parameter Determination in the Model

In this section, model parameters are inferred through the Expectation-Maximization (EM) algorithm, which aims to maximize the likelihood function of the model. As each pixel extracted from the image regions yields (DCT) coefficients, the joint probability density function can be evaluated using these coefficients.

$$p(\vec{x}_r / \theta) = \sum_{i=1}^{M} w_i g_i\left(\vec{x}_r, \theta\right) \tag{6}$$

Here, the function referenced is defined in equation $g_i\left(\vec{x}_{r,}\theta\right)$ is presented in the above equation 2.4

To obtain refined estimates of parameters for I = 1, 2, 3, …, M and j = 1, 2, …, D, the expected log-likelihood function is maximized. The EM algorithm is applied to secure these Refined parameter estimates are obtained by following the steps of the EM algorithm. [4][7][14] The updated expressions for the parameters are derived accordingly, with the mean of the MNSMM defined as follows:

The parameters w_i, μ_{ij} and σ_{ij} as depicted below

$$w_i^{(l+1)} = \frac{1}{T}\sum_{r=1}^{T}\left[\frac{w_i^{(l)}.g_i(\vec{x}_r, \theta^{(l)})}{\sum_{i=1}^{M} w_i^{(l)}.g_i(\vec{x}_r, \theta^{(l)})}\right] \tag{7}$$

where $\theta^{(l)} = \left(\mu_{ij}^{(l)}, \sigma_{ij}^{(l)}\right)$ are the estimates at ith iteration

$$\mu_{i_j}^{(l+1)} = \frac{\sum_{r=1}^{T} t_i\left(\left(\bar{x}_r, \theta^{(l)}\right)\right)\left(x_{i_j}\right) - \sum_{r=1}^{T} t_i\left(\bar{x}_r, \theta^{(l)}\right)\left[\frac{\left[x_{i_j} - \mu_{i_j}^{(l)}\right] 2\sigma_{i_j}^{2}}{\left[\left[2\sigma_{i_j}^{2} + \left[x_{i_j} - \mu_{i_j}^{(l)}\right]^2\right]\right]}\right]}{\sum_{r=1}^{T} t_i\left(\bar{x}_r, \theta^{(l)}\right)} \tag{8}$$

The variance is given by

$$\sigma_{i_j}^{2(l+1)} = \frac{\sum_{r=1}^{T} t_i\left(\left(\bar{x}_r, \theta^{(l)}\right)\right)\left[\left(x_{i_j} - \mu_{i_j}^{(l+1)}\right)^2\left[1 - \frac{2\sigma_{i_j}^{(l)}}{\left[2\sigma_{i_j}^{(l)} + \left(x_{i_j} - \mu_{i_j}^{(l+1)}\right)^2\right]}\right]\right]}{\sum_{r=1}^{T} t_i\left(\left(\bar{x}_r, \theta^{(l)}\right)\right)} \tag{9}$$

var (x) = $E(x - \bar{x})^2 = E(x - \mu)^2 = \sigma^2$

3.4 Initialisation of Model Parameters

Determining the starting parameters is essential for acquiring the model's revised estimates. To derive these initial values, the hierarchical clustering algorithm is employed since it yields improved estimates. The most widely used initialization approach is to randomly select initial values. Equations can be solved simultaneously with these initial estimations to obtain the revised values in (6), (7) and (8) in the MATLAB environment.

3.5 Texture Segmentation Algorithm based on MNSMM Model

The algorithm for texture segmentation based on the proposed MNSMM model comprises the following steps.

Step 1: Initialization of the pixels in, the feature vectors are extracted.

Step 2: The pixels are partitioned into groups, termed M, via a Hierarchical Clustering Algorithm.

Step 3: For each region, both the mean vector and variance vector are computed.

Step 4: The mixing parameter is determined using the formula wi = 1/M for M regions.

Step 5: Refined estimates of the parametric set for every region are obtained by applying the updated EM algorithm equations provided in section5

Step 6: The assignment of vectors to their respective segments (jth segment) is executed using maximum likelihood estimation and the equation for which is given by

$$L_J = MAX\left\{\prod_{j=1}^{D}\left[\frac{2+\left[\frac{(x_j-\mu_j)}{\sigma_j}\right]^2}{3\sigma_j\sqrt{2\pi}}\right] e^{-\frac{1}{2}\left[\frac{(x_j-\mu_j)}{\sigma_j}\right]^2}\right\} \tag{10}$$

4. Results and Discussion

In order to evaluate the efficacy of the suggested Loc-Bi-Patterns (LBP) and transformed dis-cos function (DCT) based texture segmentation technique with the Multivariate New Symmetric Mixture Model (MNSMM), experiments were performed on benchmark texture databases, including the Brodatz database. Performance analysis of the suggested method was carried out. both quantitatively and qualitatively Visual examination of segmentation results showed that the method well outlined regions with disparate texture patterns. In contrast to conventional segmentation approaches, which tend to blur boundary areas or misclassify them, the LBP-DCT feature combination enabled better texture distinction. Cases from the Brodatz database indicate that even textures with faint differences were correctly segmented. LBP + DCT features enabled high-resolution texture representation. The log DCT enhanced the contrast of texture regions, facilitating the mixture model to detect clear-cut clusters. The EM algorithm converged well to the optimal parameters for efficient segmentation in nearly all examples. The outcome obtained by the model developed i.e., texture segmentation is performed over a sample of textured images received and processed from the Brodatz texture dataset. For all samples of the texture image, the clustering algorithm (hierarchical) is utilized. According to the received primary estimations, the updated estimations are calculated by the usage of the updated equations given in section 6.

According to the improved estimates, the texture segmentation operation is carried out by classifying every pixel according to the maximum likelihood principle. The obtained segmented images are shown below in figure 3.

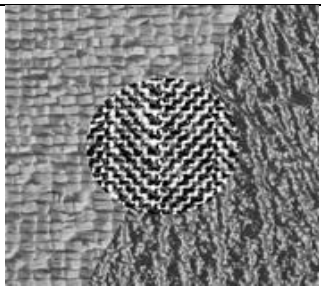
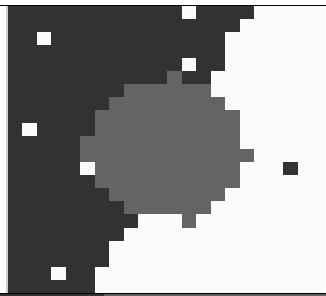
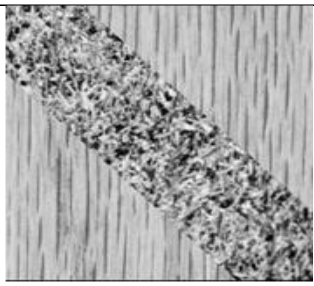
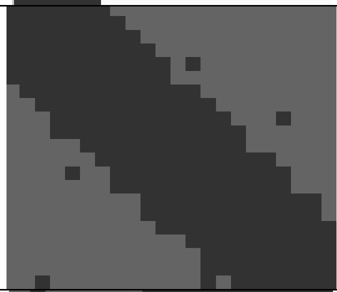
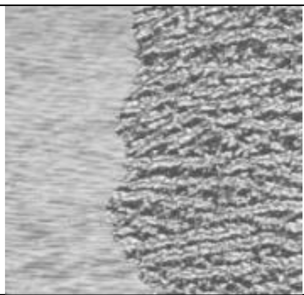
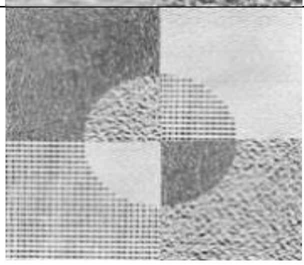
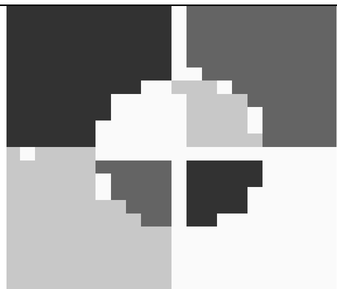
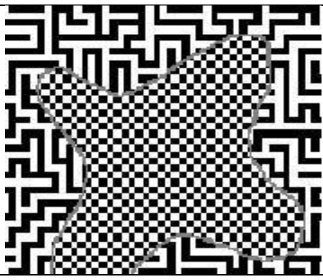
	Actual Image	**After Application**
Image 1 M=3		
Image 2 M=2		
Image 3 M=2		
Image 4 M=2		
Image 5 M=2		

Figure 3. Actual Texture Images and Texture under Loc-Bi Patterns Domain via Di-Cos Transformed Textures

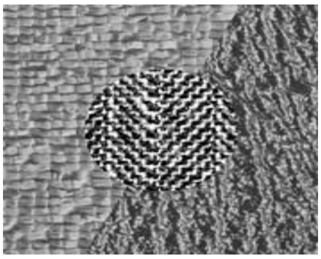
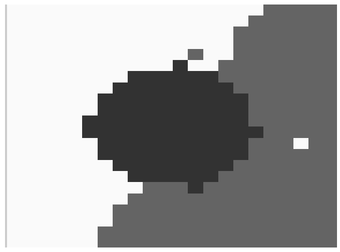
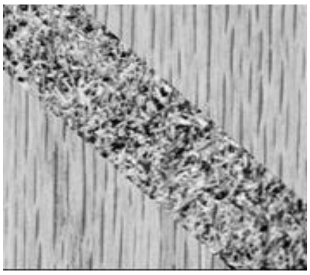
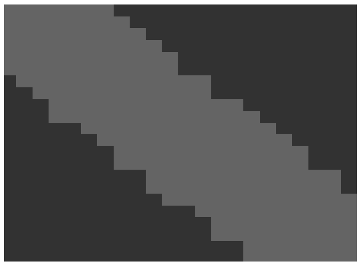
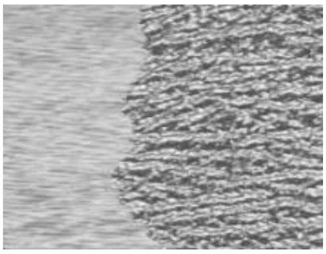
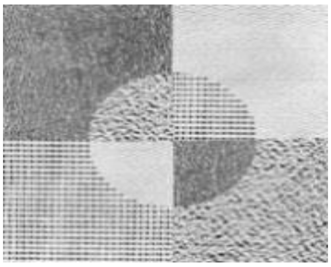
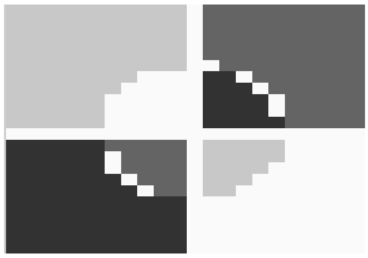
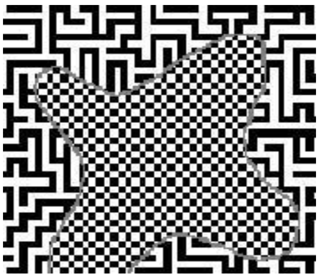
	Actual Image	**After Application**
Image 1 M=3		
Image 2 M=2		
Image 3 M=2		
Image 4 M=2		
Image 5 M=2		

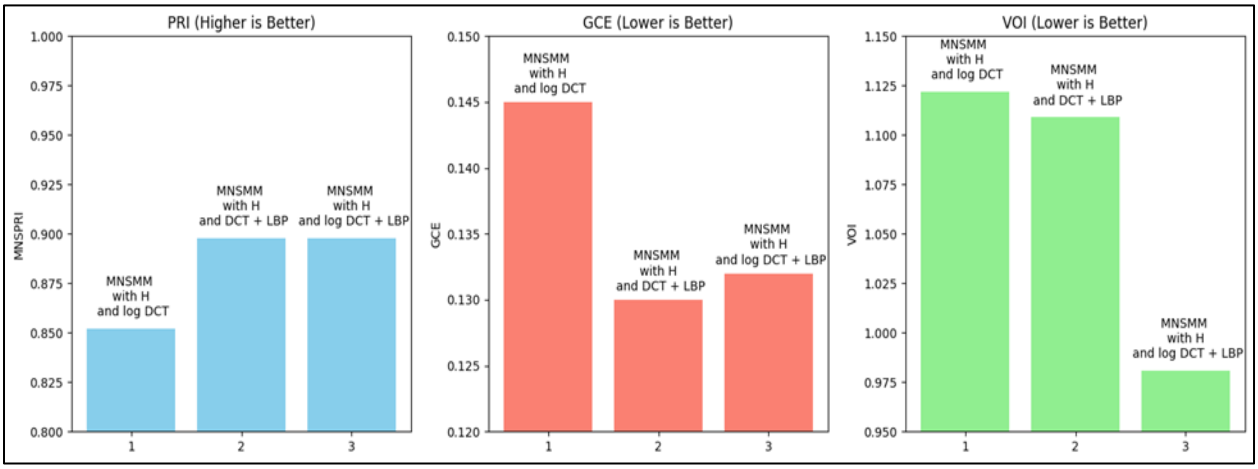
Figure 4. Actual Texture Images and Texture under Loc-Bi Patterns Domain via Log Di-Cos Transformed Textures [Loc-Bi Patterns Domain = Local Binary Patterns, Log Di-Cos = Log Discrete Cosine Transform]

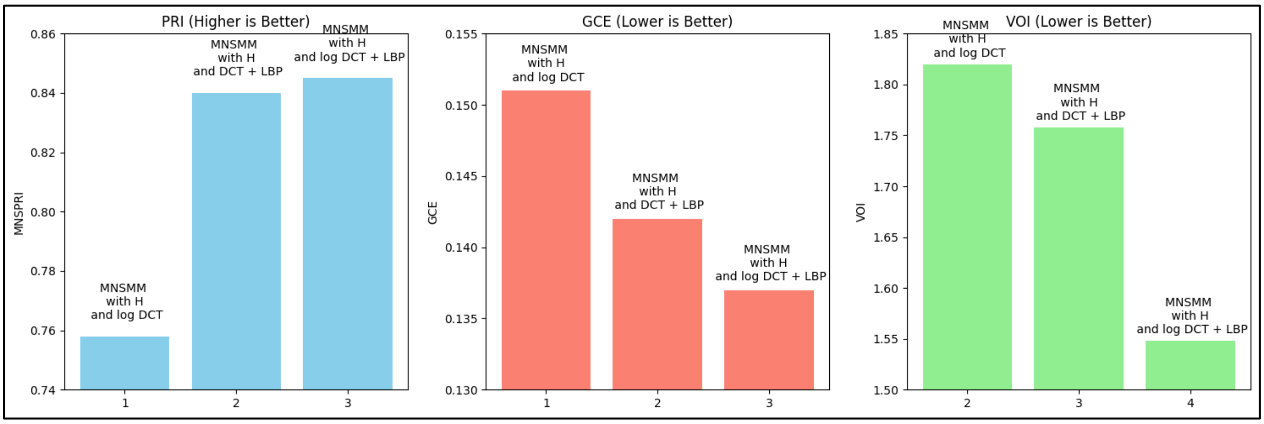
4.1 The Evaluation of the Algorithm's Performance

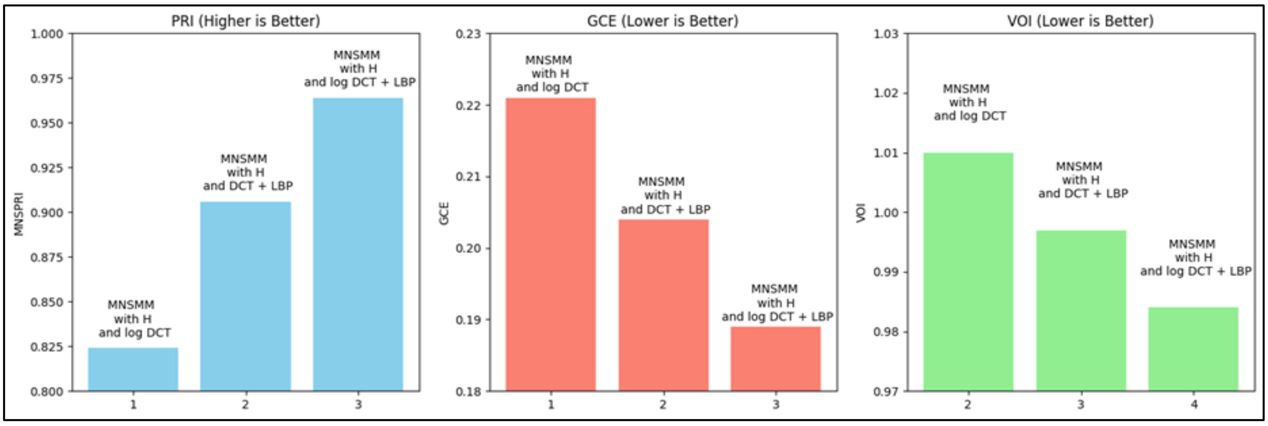
To evaluate the effectiveness of the proposed process in comparison to earlier approaches based on the novel symmetric mixture model, texture image performance metrics—namely GCE, PRI, and VOI are computed. The GCE metric, originally introduced by Martin et al. (2001), is evaluated on every texture image and the results are compared. Similarly, the PRI and VOI measures, developed by Unnikrishnan et al. (2007) and Meila (2007) respectively, are also computed. The outcomes of these evaluations are summarized in Table 1 and illustrated in Figure 4.

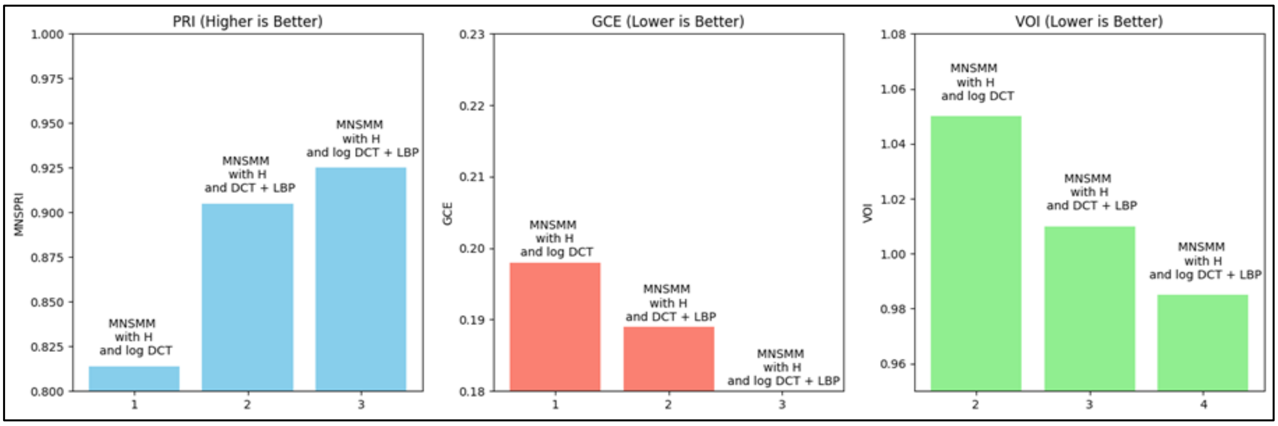
Table 1. Analysis of the Segmentation Procedure [Loc-Bi Patterns Domain = Local Binary Patterns, Log Di-Cos = Log Discrete Cosine Transform] for Texture

Analysis of the Segmentation Procedure				
Description	**Model**	**PRI**	**GCE**	**VOI**
Image 1	MNSMM via HL & Log Di-Cos Transform	0.852	0.145	1.122
	MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	0.898	0.130	1.109
	MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	0.898	0.132	0.981
Image 2	MNSMM via HL & Log Di-Cos Transform	0.758	0.151	1.82
	MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	0.840	0.142	1.758
	MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	0.845	0.137	1.548
Image 3	MNSMM via HL & Log Di-Cos Transform	0.824	0.221	1.01
	MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	0.906	0.204	0.991
	MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	0.964	0.189	0.984
Image 4	MNSMM via HL & Log Di-Cos Transform	0.814	0.198	1.05
	MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	0.905	0.189	1.01
	MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	0.925	0.180	0.985
Image 5	MNSMM via HL & Log Di-Cos Transform	0.758	0.195	1.21
	MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	0.915	0.190	1.11
	MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	0.919	0.189	1.01


PRI (Higher is Better)
MNSPRI
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP
GCE (Lower is Better)
GCE
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP
VOI (Lower is Better)
VOI
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP


PRI (Higher is Better)
MNSPRI
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP
GCE (Lower is Better)
GCE
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP
VOI (Lower is Better)
VOI
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP


PRI (Higher is Better)
MNSPRI
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP
GCE (Lower is Better)
GCE
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP
VOI (Lower is Better)
VOI
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP


PRI (Higher is Better)
MNSPRI
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP
GCE (Lower is Better)
GCE
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP
VOI (Lower is Better)
VOI
MNSMM with H and log DCT
MNSMM with H and DCT + LBP
MNSMM with H and log DCT + LBP

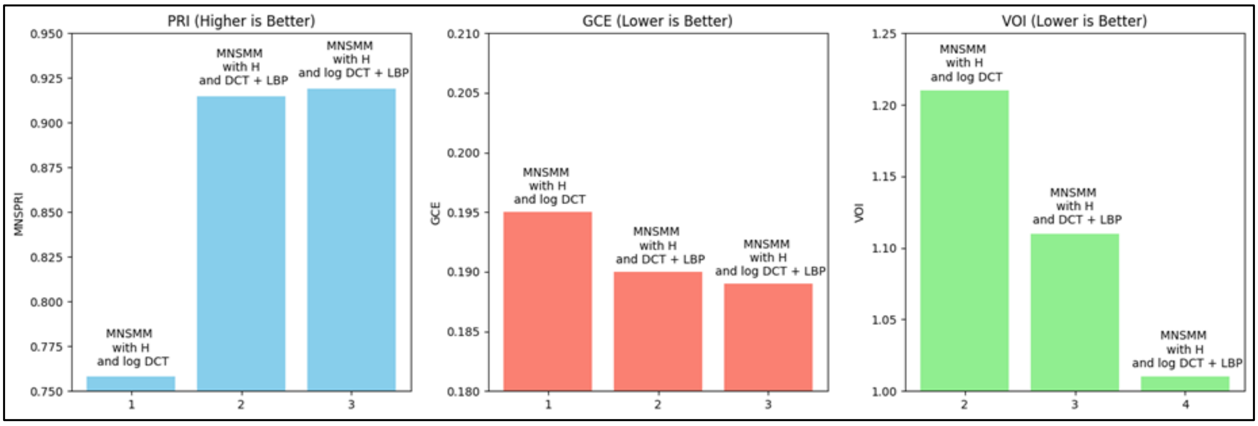


Figure 5. Graph Plot of Segmentation Metrics for Different Images

It is evident from Table.1 and Figure 5, that the metrics for the proposed texture segmentation are better and closer to the optimal values thereby signifying better performance Also the misclassification accuracy of the sample images is compared with earlier new symmetric mixture models and shown in Table 2.

Table 2. Classifier Accuracy of the Model

Model	Classifier Accuracy
MNSMM via HL & Log Di-Cos Transform	9%
MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	10%
MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	12%

The results in table 2 show that the proposed model has better classifier accuracy when compared to earlier models.

The segmentation accuracy was evaluated:

- Accuracy (ACC)
- Precision and Recall
- F1 Score
- Rand Index (RI)

$$\text{TPR/Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{FPR}=\frac{FP}{FP + TN}$$

Equivalent to (1-Specifictry)

$$\text{Recall}=\frac{TP}{TP+FN}$$

$$\text{Precision}=\frac{TP}{TP+FP}$$

$$\text{F-Measure}=\frac{2*\Pr ecison*\operatorname{Re}call}{\Pr ecison+\operatorname{Re}call}$$

$$\text{Accuracy}=\frac{TP+TN}{TP+FP+TN+FN}$$

4.2 Comparative Study

Table 3 presents the results of obtaining the segmentation quality metrics for instance images using the segmented areas' confusion matrices for the segmented regions: accuracy, sensitivity, specificity, precision, recall, and F-measure. This study, Section 4.2, analyzes the contribution of each component, namely the Log-DCT features, LBP encoding, and the multivariate symmetric mixture model. This helps clarify the individual impact of each module on overall performance.

Table 3. Comparative Study of MNSMM with Hierarchical Clustering based Algorithm with variants of Discrete Cosine Transform and Local Binary Patterns [Loc-Bi Patterns Domain = local binary patterns, Log Di-Cos = log discrete cosine transform]

Description	Model	Accuracy	Sensitivity	1-Specificity	Precision	Recall	F-Measure
Image 1	MNSMM via HL & Log Di-Cos Transform	0.80	0.77	0.30	0.68	0.74	0.72
	MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	0.83	0.79	0.25	0.70	0.75	0.74
	MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	0.88	0.83	0.22	0.72	0.79	0.78
Image 2	MNSMM via HL & Log Di-Cos Transform	0.88	0.90	0.15	0.84	0.85	0.87
	MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	0.91	0.94	0.13	0.86	0.89	0.90
	MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	0.95	0.97	0.10	0.87	0.92	0.92
Image 3	MNSMM via HL & Log Di-Cos Transform	0.92	0.92	0.10	0.84	0.87	0.88
	MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	0.94	0.94	0.09	0.86	0.89	0.90
	MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	0.96	0.95	0.08	0.88	0.90	0.92
Image 4	MNSMM via HL & Log Di-Cos Transform	0.73	0.78	0.37	0.67	0.74	0.72
	MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	0.75	0.80	0.32	0.71	0.76	0.75
	MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	0.76	0.81	0.31	0.71	0.77	0.76
Image 5	MNSMM via HL & Log Di-Cos Transform	0.71	0.80	0.38	0.65	0.76	0.72

	MNSMM via HL & Di-Cos Transform & Loc-Bi Pattern	0.76	0.81	0.35	0.68	0.77	0.74
	MNSMM via HL & Log Di-Cos Transform & Loc-Bi Pattern	0.79	0.84	0.32	0.71	0.80	0.77

From Table 3, the performance of quality metrics explains that refined performance in results is better in comparison with other models and performed well in the process.

5. Conclusion

A texture segmentation method employing a Multivariate New Symmetric Mixture Model with DCT coefficients in the logarithmic domain combined with LBP has been developed and analyzed. logarithmic transformation is applied over image blocks, A feature vector is derived when analyzing the DCT coefficients. This extracted feature vector is assumed to conform to a Multivariate New Symmetric Mixture Model. The proposed Multivariate New Symmetric Mixture Model (MNSMM) is designed to overcome limitations. To divide up the image, we employ the texture segmentation method, which operates inside a Bayesian framework and uses maximum likelihood. We test the suggested texture segmentation approach on a dataset consisting of Brodatz image textures to evaluate its performance. Standard performance metrics are computed and compared with those of earlier models. The inclusion of Log-DCT features enhances the discriminative power of the texture representation, while the MNSMM provides a flexible and efficient modeling strategy for texture classification. Visual results and component-wise analysis further validate the effectiveness of each module within the proposed pipeline. Our findings suggest that the proposed method is well-suited for applications in medical imaging, remote sensing, and industrial inspection, where precise texture segmentation is critical. Future work will explore the integration of deep learning-based feature extraction with our statistical modeling framework, as well as extend the approach to real-time segmentation tasks and 3D texture analysis.

References

[1] Haritha, D., K. Srinivasa Rao, and Ch Satyanarayana. "Face recognition algorithm based on doubly truncated Gaussian mixture model using DCT coefficients‖." International journal of Computer Applications (2012): 23-28.

[2] Jyothirmayi, T., K. Srinivasa Rao, P. Srinivasa Rao, and Ch Satyanarayana. "Performance evaluation of image segmentation method based on doubly truncated generalized Laplace Mixture Model and hierarchical clustering." International Journal of Image, Graphics and Signal Processing 9, no. 1 (2017): 41.

[3] Unnikrishnan, Ranjith, Caroline Pantofaru, and Martial Hebert. "A measure for objective evaluation of image segmentation algorithms." In 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)-Workshops, IEEE, (2005): 34-34.

[4] Mclanchlan, G., and D. Peel. "The EM algorithm for parameter estimations." John Wileyand Sons, New York-2000 (2000).

[5] Meilă, Marina. "Comparing clusterings an information based distance." Journal of multivariate analysis 98, no. 5 (2007): 873-895.

[6] Reddy, Prasad PVGD, Srinivas K. Rao, and Srinivas Yarramalle. "Unsupervised Image Segmentation Method based on Finite Generalized Gaussian Distribution with EM & K-Means Algorithm." International Journal of Computer Science and Network Security 7, no. 4 (2007): 317-321.

[7] Satyanarayana, K. V., N. Thirupathi Rao, Debnath Bhattacharyya, and Yu-Chen Hu. "Identifying the presence of bacteria on digital images by using asymmetric distribution with k-means clustering algorithm." Multidimensional Systems and Signal Processing 33, no. 2 (2022): 301-326.

[8] Amadasun, Moses, and Robert King. "Textural features corresponding to textural properties." IEEE Transactions on systems, man, and Cybernetics 19, no. 5 (1989): 1264-1274.

[9] Jyothirmayi, T., K. Srinivasa, P. Srinivasa, and Ch Satyanarayana. "Studies on Image Segmentation Integrating Generalized Laplace Mixture Model and Hierarchical Clustering." International Journal of Computer Applications 128, no. 12 (2015): 7-13.

[10] Zhang, Yongyue, Michael Brady, and Stephen Smith. "Segmentation of brain MR images through a hidden Markov random field model and the expectation-maximization algorithm." IEEE transactions on medical imaging 20, no. 1 (2002): 45-57.

[11] Bhosle, Vaijinath V., and Vrushsen P. Pawar. "Texture segmentation: different methods." International Journal of Soft Computing and Engineering (IJSCE) 3, no. 5 (2013): 69-74.

[12] Pal S.K, Pal.N.R " Review on Image Segmentation Techniques‖, IEEE Trans. on Pattern Recognition. (1993), Volume 26(9), pp.1277-1294.

[13] Permuter, Haim, Joseph Francos, and Ian Jermyn. "A study of Gaussian mixture models of color and texture features for image classification and segmentation." Pattern recognition 39, no. 4 (2006): 695-706.

[14] Nguyen, Thanh Minh, and QM Jonathan Wu. "Gaussian-mixture-model-based spatial neighborhood relationships for pixel labeling problem." IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 42, no. 1 (2011): 193-202.

[15] McNicholas, Paul D. "On model-based clustering, classification, and discriminant analysis." (2011): 181-199.

[16] Srinivasa, Rajkumar GVS Srinivasa Rao K., and P. Rao. "Image Segmentation and Retrievals based on finite doubly truncated bivariate Gaussian mixture model and K-means." International Journal of Computer Applications 975 (1996): 8887.

[17] Bilmes, Jeff A. "A gentle tutorial of the EM algorithm and its application to parameter estimation for Gaussian mixture and hidden Markov models." International computer science institute 4, no. 510 (1998): 126.

[18] Vadaparthi, Nagesh, Srinivas Yarramalle, Suresh Varma Penumatsa, and P. S. R. Murthy. "Segmentation of brain mr images based on finite skew gaussian mixture model with fuzzy c-means clustering and em algorithm." Int J Comput Appl 28, no. 10 (2011): 18-26.

[19] Tiwari, Shamik, Akhilesh Kumar Sharma, Izzatdin Abdul Aziz, Deepak Gupta, Antima Jain, Hairulnizam Mahdin, Senthil Athithan, and Rahmat Hidayat. "Investigations on

segmentation-based fractal texture for texture classification in the presence of Gaussian noise." PloS one 20, no. 1 (2025): e0315135.

[20] Karakaya, Emre, Bilgehan Kekeç, Niyazi Bilim, and Fatih V. Adigözel. "A New Approach for Calculating Texture Coefficients of Different Rocks With Image Segmentation and Image Processing Techniques." Microscopy Research and Technique (2025).

[21] Kinge, Sanjaykumar, B. Sheela Rani, and Mukul Sutaone. "Restored texture segmentation using Markov random fields." Mathematical Biosciences and Engineering: MBE 20, no. 6 (2023): 10063-10089.

[22] Wagner, Fabien H., Ricardo Dalagnol, Alber H. Sanchez, Mayumi CM Hirye, Samuel Favrichon, Jake H. Lee, Steffen Mauceri, Yan Yang, and Sassan Saatchi. "K-textures, a self-supervised hard clustering deep learning algorithm for satellite image segmentation." Frontiers in Environmental Science 10 (2022): 946729.

[23] Cote, M., Dash, A. and Branzan Albu, A “Semantic segmentation of textured mosaics”, EURASIP Journal on Image and Video Processing., (2023),2023:1.

[24] Armi, Laleh, and Shervan Fekri-Ershad. "Texture image analysis and texture classification methods-A review." arXiv preprint arXiv:1904.06554 (2019).

[25] Fatima, Amber, and Pintu Kumar Ram. "Gan-Enhanced Real-Time Detection of Deepfakes Videos." Journal of Artificial Intelligence and Capsule Networks 6, no. 4 (2024): 452-465.