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Batik Classification using Microstructure Co-occurrence Histogram

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***Abstract*— Batik Nitik is a distinctive form of batik originating from the culturally rich region of Yogyakarta, Indonesia. What sets it apart from other batik styles is its remarkable motif similarity, a characteristic that often poses a considerable challenge when attempting to distinguish one design from another. To address this challenge, extensive research has been conducted with the primary objective of classifying Batik Nitik, and this research leverages an innovative approach combining the microstructure histogram and gray level co-occurrence matrix (GLCM) techniques, collectively referred to as the Microstructure Co-occurrence Histogram (MCH). The MCH method offers a multi-faceted approach to feature extraction, simultaneously capturing color, texture, and shape attributes, thereby generating a set of local features that faithfully represent the intricate details found in Batik Nitik imagery. In parallel, the GLCM method excels at extracting robust texture features by employing statistical measures to portray the subtle nuances within these batik patterns. Nevertheless, the mere fusion of microstructure and GLCM features doesn't inherently guarantee superior classification performance. This research paper has meticulously examined many feature fusion scenarios between microstructure and GLCM to pinpoint the optimal configuration that would yield the most accurate results. The dataset used consists of 960 Batik Nitik samples, comprising 60 categories. The classifiers employed in this study are K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Tree (DT), Naïve Bayes (NB), and Linear Discriminant Analysis (LDA). Based on the experimental results, the fusion of microstructure and GLCM features with the (LDA) classifier yields the best performance compared to other scenarios and classifiers.**

***Keywords*— Batik Nitik, classification; gray level co-occurrence matrix; feature fusion; Microstructure Co-occurrence Histogram**

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I. INTRODUCTION

Batik is a traditional fabric that has been integral to Indonesian culture for centuries. The word "batik" originates from the Javanese language "amba titik," which means "writing dots," referring to the technique of creating patterns by applying wax to fabric and then coloring it. One of the oldest forms of batik in Yogyakarta, developed during the reign of Sultan Hamengkubuwono VII, is Batik Nitik. Batik Nitik features a distinctive motif composed of arranged dots forming patterns. The evolution of Nitik motifs, resulting in diverse patterns, has made it increasingly challenging to identify Batik Nitik due to its variety.

Several studies have proposed research on batik using feature extraction approaches and machine learning techniques such as Local Binary Pattern (LBP) [1], [2], [3]–[5], Gray Level Co-occurrence Matrix (GLCM) [6], [7], [8], [9], [10], [11], Support Vector Machine (SVM) [12], [13], K-Nearest Neighbor [14], Linear Discriminant Analysis (LDA), Naïve Bayes, Decision Tree [15], Deep Neural Network [16], [17], Transfer Learning [18], [19], Generative Adversarial Network [20], and texton-based [21], [22], [23]. Research [24]–[26] discusses the recognition and automatic classification of batik motifs using deep learning and Convolutional Neural Networks (CNN). Two datasets are used, with a new dataset replacing the anomaly data in the old dataset. The use of deep learning and the pre-trained ResNet-18 model achieved the best accuracy of 88.88% ±0.88 on the new dataset, and on the old dataset, the best accuracy was found in patch-based testing at 66.14% ±3.7. Despite data augmentation, the significant increase in accuracy was only 1.22%.

Khaldi et al. [15] proposed a texton-based method, a Complete Multi-Texton Histogram (CMTH), contributing by adding new types of textons to extract features. CMTH combines information about color, edge orientation, and textons in images. The CMTH method has been extensively tested on five publicly available datasets, including Vistex, Outex, Batik, Corel10K, and UKBench. Evaluation results show that the proposed descriptor significantly outperforms the state-of-the-art methods. Research [27] explores image representation in content-based image retrieval (CBIR) and proposes a new color scheme called Stack Color Histogram (SCH) to generate descriptors for image indexing. In experiments using the Coil100, Outext, Batik, and Corel10K datasets, the SCH descriptor significantly improves classification performance compared to relevant descriptors.

Minarno et al. [28] proposed a feature extraction method using Multi Texton Co-Occurrence Descriptor (MTCD) and validated it with the SVM classifier, which was further validated with Logistic Regression (LR). Testing was conducted using the Batik 300 and Batik 41k datasets, and the experimental results showed that the combination of MTCD and SVM achieved high accuracy when validated with LR. Therefore, MTCD, SVM, and LR can effectively and reliably classify batik images. Irawan et al. [29] discussed Lasem batik, one of Indonesia's traditional batiks known for its artistic and economic value. The research aimed to analyze the number of GLCM features during the classification process of Lasem batik images using the K-Nearest Neighbor (KNN) method. The test results showed that using four or five types of GLCM features yielded the same accuracy in each experiment, indicating that four features are sufficient for accelerating the classification calculations.

Many studies have achieved high performance using texton-based, GLCM, and various classifiers such as SVM, NB, DT, and KNN. However, these studies can still be optimized for selecting the appropriate GLCM features and classifiers. Research [15] only uses local features, specifically 11 textons, as descriptors. On the other hand, [28] uses only four GLCM features combined with texton-based features. Irawan et al. [29] reported that using four or five GLCM features (energy, entropy, contrast, correlation, homogeneity) with the KNN classifier did not significantly affect the classification performance measured by accuracy. Based on previous experiments conducted in several studies, it is evident that the selection of GLCM features, combined with texton-based features and the appropriate classifier, dramatically affects the performance and remains an interesting area for further investigation. Therefore, this research aims to examine GLCM features, combine them with texton-based features, and test several relevant classifiers based on previous studies. The results of this research will be compared with the state-of-the-art research. The contributions of this research are as follows: (a) Six GLCM features, including energy, entropy, contrast, correlation, homogeneity, and dissimilarity; (b) Six types of textons rich in color, textures, and edges; (c) Combining GLCM and microstructure features to generate robust descriptors; (d) Proposing (LDA) as the classifier for MCH, which outperforms other relevant classifiers.

The remainder of this paper is organized as follows:

- Section 2 presents related research.
- Section 3 discusses the proposed MCH method.
- Section 4 provides the evaluation results and discussion.
- The last part is the concluding section presents the conclusions based on the test results.

II. Material and Method

A. *Microstructure Co-occurrence Histogram*

In our research on batik classification using microstructure co-occurrence histogram, we delved into the intricacies of GLCM (Gray-Level Co-occurrence Matrix) and texton-based methodologies, each offering unique advantages in the feature extraction process. The strength of GLCM lies in its ability to identify textures through statistical features globally. This method analyzes the frequency of pixel intensity pairs, capturing the spatial distribution of gray levels and providing a robust texture descriptor. It is particularly effective in highlighting the global textural features of batik patterns, which is crucial for classifying their intricate designs.

Complementing this, the texton-based methodology, which initially utilized 4 Textons, stands out for its simplicity and accuracy. Textons, being fundamental micro-structures in textures, are used in our study to represent the diversity of patterns in batik. These are characterized by properties such as orientation, scale, or contrast. The simplicity of this approach makes it highly effective for accurate feature extraction.

Advancing further, we enhanced our methodology by including 11 Textons in the Co-occurring Microtexture and Texton Histogram (CMTH). This extension significantly boosts the discriminatory power of our feature extraction process. With more Textons, we can achieve a more detailed and nuanced representation of batik patterns, combining the strengths of microtexture analysis with texton frequency distribution. This results in a more robust and comprehensive histogram, essential for adequate classification.

We observed a marked performance improvement by comparing CMTH with the Microstructure Texton Histogram (MTH). This suggests that a larger variety of Textons, integrated with microtexture features, yields a more accurate and efficient classification system.

During our research, we comprehensively analyzed GLCM (Gray-Level Co-occurrence Matrix) and texton-based methodologies, recognizing that each approach offers unique advantages in the feature extraction process. GLCM demonstrates its strength in globally identifying textures through statistical features, while texton-based methods excel in simplicity and accuracy, particularly with the utilization of 4 Textons. Moreover, including 11 Textons in CMTH (Co-occurring Microtexture and Texton Histogram) enhances the capabilities of MTH (Microstructure Texton Histogram) and has been claimed to outperform it in previous studies.

However, limitations were observed when employing 4 Textons in MTH, primarily due to a non-overlapping stride scheme, leading to significant information loss. Additionally, incorporating 11 Textons, as highlighted by Khaldi et al. in their previous study, increases computation time. To address these limitations, our research proposes a novel approach called the Microstructure Co-occurrence Histogram (MCH), building upon our previous work [28]. The MCH approach integrates six types of textons and 6 GLCM features, including energy, entropy, contrast, correlation, dissimilarity, and homogeneity, to enhance the feature extraction process.

The feature extraction stages in the MCH approach are as follows:

1) Step 1: Edge orientation features are extracted using the Sobel operator applied to each channel (R, G, and B) of the images. These features are then quantized into 18 bins.

2) Step 2: Texton detection is performed by convolving the images obtained from Step 1 with the 6 Textons. The resulting convolution outputs are stored in vector form and combined into a single vector comprising 18 features.

3) Step 3: Color features are quantized separately on each channel (R, G, and B) using four bins, resulting in a total of 64 bins.

4) Step 4: Texton detection is performed by convolving the images obtained from Step 3 with the 6 Textons. The convolution results are stored in vector form and combined into a single vector with 64 features.

5) Step 5: GLCM feature extraction involves calculating energy, entropy, contrast, correlation, homogeneity, and dissimilarity. Each feature is computed for four orientations (0, 45, 90, and 135 degrees), resulting in a total of 24 GLCM features in vector form.

6) Step 6: The final stage combines all 18 edge features, 64 color features, and 24 GLCM features to create the MCH histogram.

By incorporating these steps, the proposed MCH approach aims to enhance the overall performance of feature extraction in batik image classification. This novel methodology addresses the limitations observed in previous approaches and seeks to improve the accuracy and efficiency of feature extraction, ultimately contributing to more effective batik image classification outcomes.

B. Gray level Co-occurrence Matrix

The proposed enhancement to the Microstructure Texton Co-occurrence Descriptor (MTCD) involves integrating the Gray Level Co-Occurrence Matrix (GLCM) feature, which encompasses six specific features: energy, entropy, contrast, correlation, homogeneity, and dissimilarity. Calculating these GLCM features follows a series of steps to ensure accurate and informative representation.

Firstly, the RGB image is converted into grayscale to simplify the subsequent computations. This conversion ensures that the GLCM feature extraction operates on the intensity values of the image, rather than color information. Secondly, a co-occurrence matrix is generated, capturing the statistical relationships between neighboring pixels. This matrix represents pixel pairs with specific intensity values at a given distance and angular orientation.

Next, the spatial relationship between the reference pixels and their neighbors is determined, considering parameters such as the angle (θ) and distance (d). These parameters define the neighborhood characteristics and influence the co-occurrence matrix generation. To symmetrize the matrix, the co-occurrence matrix is added to its transpose in the fourth step. This step ensures that both the horizontal and vertical relationships are considered, providing a comprehensive representation of pixel co-occurrence. In the fifth step, matrix normalization is performed by calculating the probability of each matrix element. This normalization step accounts for image size and intensity distribution variations, allowing for fair comparisons across different images. Finally, in the sixth step, the GLCM features are computed. Each feature utilizes a distance of 1 pixel and four directions (0°, 45°, 90°, and 135°) to detect co-occurrence patterns in the image. These features quantify different aspects of the texture, such as the distribution of intensity values, the level of contrast, and the correlation between neighboring pixels.

The GLCM matrix has a size of L x L, where L represents the number of gray levels in the original image. The number of occurrences or the probability (P) of one pixel (i) being a neighbor to another pixel (j) at a specific distance (d) and angular orientation (θ) is calculated. Using Equations 1-6, as indicated below, the energy, entropy, contrast, correlation, homogeneity, and dissimilarity features can be derived:

$$Energy = \sum_{i,j=0}^{L-1} P^2(i,j,d,\theta) \tag{1}$$

$$Ent = \sum_{i,j=0}^{L-1} P(i,j,d,\theta).\log P(i,j,d,\theta) \tag{2}$$

$$Cont = \sum_{i,j=0}^{L-1} (i-j)^2.P(i,j,d,\theta) \tag{3}$$

$$Corr = \sum_{i,j=0}^{L-1} \frac{(i-\mu_x)(j-\mu_y)P(i,j,d,\theta)}{\sigma_x\sigma_y} \tag{4}$$

$$Hom = \sum_{i,j=0}^{L-1} \frac{P^2(i,j,d,\theta)}{1+(i-j)^2} \tag{5}$$

$$Dis = \sum_{i,j=0}^{L-1} P^2(i,j,d,\theta)|i-j| \tag{6}$$

Where:$\mu_x = \sum_{i,j=0}^{L-1} i.P(i,j,d,\theta)$,$\mu_y = \sum_{i,j=0}^{L-1} j.P(i,j,d,\theta)$ $\sigma_x = \sum_{i,j=0}^{L-1}(i-\mu_x)^2.P(i,j,d,\theta)$ $\sigma_y = \sum_{i,j=0}^{L-1}(j-\mu_y)^2.P(i,j,d,\theta)$

These equations capture different statistical properties and relationships within the GLCM matrix, providing valuable information about the texture characteristics of the image. By incorporating these GLCM features into the MTCD framework, the enhanced descriptor offers a more comprehensive and discriminative representation of the image texture. The integration of GLCM further enriches the feature set and contributes to improved performance in various texture analysis and recognition tasks.

C. Dataset

Batik Nitik is one of the oldest traditional motifs from Yogyakarta, developed by members of the Yogyakarta Palace under BRAy. Brongtodiningrat on February 19, 1940. In our research, we utilized the Batik Nitik 960 dataset as used in the study [30]. The Batik Nitik dataset consists of 60 augmented categories to produce 960 images. Each image has dimensions of 512 x 512 pixels with a 24-bit RGB color depth in JPG format. Fig. 1 showcases a sample of the Nitik Batik fabric displaying 60 different motifs, and Table I shows a sample of metadata batik nitik 960.

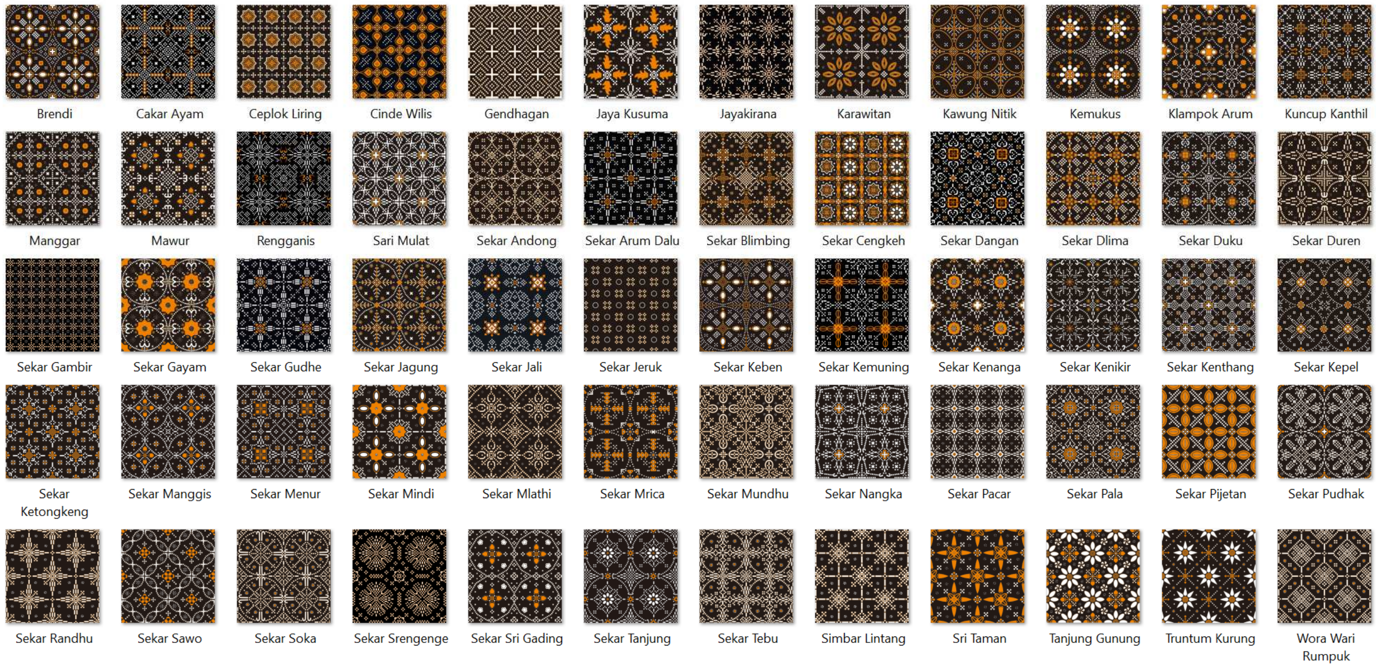
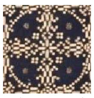


Fig. 1 Sample of batik Nitik 960 Dataset [25]

TABLE I
SAMPLE OF METADATA BATIK NITIK DATASET 960.

No	Batik Nitik Motif	Description
1	 Sekar Menur	*Menur* (*Clerodendrum chinese*) flowers are pure white and overlap each other. The white color symbolizes piled-up purity. The meaning is to do good things as much as possible without expecting anything in return.
2	 Sekar Tebu	*Sekar tebu*. Sugarcane (*Saccharum officinarum*) has flowers that, in Javanese, are called *gleges. Gleges* in Javanese means prolonged laughter, in this case, either because it is fun or because it is funny. The meaning of this motif is advice for someone not to judge or to do things excessively. Thus, you should be careful and full of calculations so as not to fall into unwanted conditions.
3	 Sekar Manggis	It is only seen from the shape of the mangosteen (*Garcinia mangostana*) flower as an idea to make a *nitik* batik motif. Mangosteen is the queen of fruits. It tastes very refreshing, balanced between the sweet and sour flavors. The meaning of this motif is a hope that the wearer will become the best human being physically and mentally for the community.
4	 Sekar Randu	*Sekar randu. Randu* (*Ceiba pentandra*) is a plant that produces fibres called *kapuk. Kapuk* is useful as a filling material for the mattresses of the nations in the world, thus providing enjoyment. Apart from that, *randu* flowers also spread a light fragrance. The meaning of this motif is that the best person should give enjoyment to others and always maintain a good name to maintain honor.

III. RESULT AND DISCUSSION

In the extensive research study focused on image analysis, a team of researchers dedicated their efforts to evaluating the performance of the Microstructure Co-occurrence Histogram (MCH) method. This evaluation was set against the backdrop of existing state-of-the-art methods in the field. The primary goal was to understand the effectiveness of MCH, particularly in image classification, a pivotal task in various image analysis applications.

The study was structured around various scenarios to achieve a comprehensive evaluation, each meticulously designed to test MCH under different conditions. These scenarios were critical in determining the robustness and versatility of MCH. Central to these tests were the different combinations of Texton types, specifically using 6 and 11 Texton sets. Textons, the fundamental micro-structures in textures, are integral to how an image's texture is analyzed and interpreted. The variation in the number of Textons was strategic, aimed at assessing how MCH performs under different levels of textural complexity.

Furthermore, the study evaluated the impact of using either 4 or 6 features from the Gray-Level Co-occurrence Matrix (GLCM). GLCM, a method that assesses the spatial relationship of pixel intensities, is widely used in texture analysis. By varying the GLCM features, the researchers intended to explore how different levels of detail in texture representation influence the performance of MCH in classifying images.

For the classification aspect of the study, four classifiers were chosen: K-nearest neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), and Linear

Discriminant Analysis (LDA). These classifiers were selected based on their widespread usage and established efficacy in handling various data types in classification tasks. Integrating these classifiers with MCH provided insights into how well MCH can differentiate and classify images based on their visual features. This aspect was particularly crucial because accurate image classification is essential in many image analysis applications, such as medical imaging, digital libraries, and content-based image retrieval systems.

To quantify the performance of MCH in these classification tasks, the researchers employed an accuracy metric, as detailed in Equation 7. This metric was pivotal in evaluating the classification performance of MCH quantitatively across the different scenarios. Accuracy as a metric provides a straightforward yet comprehensive measure of the percentage of correctly classified instances, allowing for a direct comparison between different methods and configurations. This is essential in determining the effectiveness of any classification technique.

The study's approach was comprehensive, covering a wide range of scenarios to ensure that the evaluation of MCH was as thorough as possible. This included examining MCH's performance under different texture complexity levels and with various GLCM features. The selection of classifiers was also a key decision, as each classifier has its strengths and weaknesses, and their performance with MCH could provide valuable insights.

The research also extended to understanding the practical utility of MCH in real-world applications. The effectiveness of MCH in accurately classifying images is crucial in many digital applications where rapid and precise image analysis is required. The study's findings have the potential to significantly contribute to the field of image analysis, offering insights into the effectiveness of MCH and guiding future developments in image classification methods.

The research provided an in-depth and systematic evaluation of the Microstructure Co-occurrence Histogram method, focusing on its application in image classification tasks. The methodical approach, combined with a diverse range of scenarios and robust evaluation metrics, ensured a thorough understanding of MCH's capabilities and limitations. The insights gained from this study are expected to contribute to the field significantly, offering guidance on the practical application and future development of MCH in image analysis.

In conducting these scenarios, the researchers utilized robust evaluation metrics to ensure a thorough analysis of MCH's performance in classification tasks. Each scenario was carefully designed to test MCH's capabilities under varying conditions and with different types of images. The results from these scenarios were systematically compiled in Table II, which served as a critical reference for the study. This table facilitated consistency in the evaluation process and enabled meaningful comparisons between various feature extraction configurations.

TABLE II
SCENARIO OF FEATURE EXTRACTION

Feature Extraction	Number of Texton	GLCM Features
FE1	6	Energy, entropy, contrast, correlation
FE2	6	Energy, entropy, contrast, correlation, homogeneity, dissimilarity
FE3	11	Energy, entropy, contrast, correlation
FE4	11	Energy, entropy, contrast, correlation, homogeneity, dissimilarity
FE5	0	Energy, entropy, contrast, correlation
FE6	0	Energy, entropy, contrast, correlation, homogeneity, dissimilarity

These scenarios were utilized to evaluate the performance of MCH in classification tasks. The classifiers used were K-Nearest Neighbors, Support Vector Machine, Decision Tree, and Linear Discriminant Analysis for classification. The accuracy metric (Equation 7) was employed to measure the classification performance.

$$Accuracy = \frac{Correctly\ classified\ images}{Total\ images} \quad (7)$$

Based on the test results presented in Table III, it can be observed that there is an improvement in accuracy influenced by two factors: the addition of GLCM features and the selection of classifiers. The inclusion of homogeneity and dissimilarity features has a positive impact on accuracy improvement across all classifiers. This demonstrates the effectiveness of these two features in representing batik images. Among the classifiers tested, (LDA) exhibits the best performance compared to KNN, SVM, and DT. The results in Table III are compared to the findings of [30] for further analysis.

TABLE III
COMPARISON OF FEATURE EXTRACTION AND CLASSIFIER OF NITIK 960 BATIK

Feature Extraction	Accuracy								Time (s)
	KNN [30]					**SVM** [30]	**DT** [30]	**(LDA) (Proposed)**	
	1	**3**	**5**	**7**	**9**				
FE1	0.51	0.53	0.49	0.50	0.49	0.71	0.69	0.98	0.0262
FE2	0.51	0.53	0.49	0.50	0.48	0.71	0.64	0.99	0.0312
FE3	0.50	0.51	0.48	0.50	0.48	0.67	0.68	0.98	0.0300
FE4	0.50	0.51	0.48	0.50	0.48	0.68	0.68	0.99	0.0349
FE5	0.49	0.49	0.48	0.5	0.48	0.47	0.58	0.91	0.0159
FE6	0.49	0.49	0.48	0.5	0.48	0.58	0.67	0.94	0.0209

IV. Conclusion

This paper introduces a straightforward yet powerful feature extraction method that proves highly effective in representing Nitik Batik images. By combining local features through texton-based techniques and global features utilizing GLCM, the accuracy of the classification process is significantly enhanced, particularly when employing the Linear Discriminant Analysis. Several key findings emerge from this study, highlighting the factors that contribute most to the observed accuracy improvement. Firstly, including homogeneity and dissimilarity features within the GLCM plays a crucial role in enhancing the accuracy of the classification. These features capture important information about the spatial relationships and texture variations within the Nitik Batik images, enabling more precise discrimination between different classes. Secondly, the LDA classifier demonstrates impressive classification capabilities, improving overall accuracy. The LDA classifier is well-suited for handling high-dimensional feature spaces. It is particularly effective in scenarios where the number of samples is relatively small compared to the feature dimensionality. Its ability to effectively separate classes based on discriminant features greatly enhances the accuracy of the classification process.

The Microstructure Co-occurrence Histogram approach presented in this paper holds significant potential for the batik and texture-based datasets. Its simplicity in feature extraction and computational efficiency makes it a versatile method that can be easily applied to various texture recognition tasks. This adaptability allows researchers and practitioners to explore its performance and applicability in a wide range of texture-based image classification problems beyond the specific domain of Nitik Batik images.

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