Cirebon Batik Pattern Classification using Convolutional Neural Network and Fusion Texture Features-Based Approach

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Abstract – *The classification of batik Cirebon motifs presents challenges due to their complex geometric patterns and rich textures. This study proposes a hybrid approach integrating a Convolutional Neural Network (CNN) with Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) texture feature extraction methods. The model was tested to classify four primary motifs: Megamendung, Sawat Pengantin, Paksi Naga Liman, and Singa Barong. The process includes image preprocessing, feature extraction using LBP and GLCM, and CNN-based classification. Experimental results show an overall classification accuracy of 79%. The Megamendung motif achieved the highest performance with 90% precision, 99% recall, and a 94% F1-score. Conversely, the Singa Barong motif yielded the lowest performance (46% across all metrics), attributed to its high visual similarity with other motifs and limited sample availability. Combining traditional texture feature extraction with deep learning proved effective in improving classification accuracy for cultural heritage datasets. This framework offers a solution for the automated recognition of Indonesian batik motifs and contributes to the digital preservation of cultural heritage.*

Keywords: Batik Cirebon, Convolutional Neural Network (CNN), Gray Level Co-occurrence Matrix (GLCM), Image Classification, Local Binary Pattern (LBP)

I. INTRODUCTION

Batik is one of Indonesia's most prominent cultural heritages, officially recognized by UNESCO as an Intangible Cultural Heritage of Humanity in 2009 [1]. Beyond its aesthetic value, batik holds symbolic meaning and philosophical depth that reflects the cultural identity and values of the Indonesian people [2]. With hundreds of motifs originating from various regions and techniques ranging from handcrafted to printed recognizing and distinguishing specific patterns remains a challenging task for the public [3].

Cirebon batik, in particular, is known for its intricate patterns and rich philosophical meanings that reflect local wisdom passed down through generations [4]. However, the complex geometric structures and detailed textures of these motifs pose significant challenges in the automated classification process, especially when introduced to wider audiences such as the younger generation and international communities [5].

In the digital era with its rapid technological development, digital image processing has become an important field in informatics [6]. Recent research shows that approaches based on artificial intelligence can assist in the preservation and documentation of cultural heritage, including batik [7]. Image classification has remained a fundamental area of study in recent years and serves as a cornerstone of computer vision, underpinning many aspects of visual recognition. Enhancing the performance of classification networks often leads to substantial advancements in their practical applications [8].

In the context of recognizing batik motifs, which have complex variations in patterns and visual characteristics, methods capable of effectively recognizing these patterns are needed. Over the past few decades, the evolution of machine learning methodologies has led to the development of numerous techniques capable of addressing complex problems across diverse domains. Driven by advancements in computational hardware, deep learning has emerged as a highly promising branch of machine learning, offering superior performance in a wide range of applications [9].

One widely used approach is Deep Learning, particularly using Convolutional Neural Network (CNN) [10]. CNN has the ability to recognize visual patterns in images through the feature extraction process performed in its convolutional layers. Using CNN, unique elements of batik motifs, such as geometric details and floral patterns, can be identified [11]. This makes CNN a relevant method for overcoming the challenges in classifying Cirebon batik motifs, which are rich in pattern variations [12].

Although CNN can perform feature extraction automatically, this approach still has several weaknesses, especially in capturing more specific texture information. Cirebon batik motifs have rich textural details, with variations in intensity and complex local structures. Therefore, a combination of feature extraction methods more focused on texture, such as Local Binary Pattern (LBP) and Gray-Level Co-occurrence Matrix (GLCM), is required to improve the accuracy of batik motif classification.

LBP is chosen because it is a texture descriptor that can efficiently capture micro-patterns in batik motifs. This method works by calculating the intensity difference between a central pixel and its neighbors, yielding a texture representation that is robust against changes in illumination [13]. LBP also possesses high computational speed and is capable of detecting detailed elements in batik motifs that contain fine textures and regular patterns [14].

Meanwhile, GLCM is used as a tool to obtain second-order statistics from two-dimensional textured images [15]. The coordinates of pixel pairs are determined based on a distance and an angular orientation. The distance is measured in pixels, while the orientation is represented in degrees. This method is recognized as one of the most effective and widely used algorithms for texture analysis. Typically, it utilizes four specific directional angles to construct the GLCM, which are: 0^o, 45^o, 90^o, and 135^o [16].

The combination of LBP and GLCM is implemented to overcome the respective limitations of each method in texture feature extraction. LBP is used to handle complex texture patterns and fine details, such as those found in batik motifs [15], whereas GLCM plays an important role in analyzing the spatial relationships between pixels in an image, which can be utilized to identify differences in batik motifs [17].

The novelty of this research lies in the integration of handcrafted texture features LBP and GLCM with a CNN-based classifier to improve the classification of traditional batik motifs, particularly for classes with high inter-class similarity. This fusion approach contributes to the growing body of knowledge on cultural heritage digitization by offering an efficient yet robust alternative to purely deep learning models.

II. RESEARCH METHODS

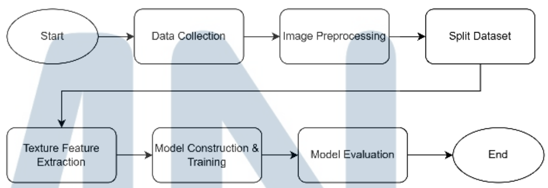

Figure 1 Methodology flowchart

The experimental methodology used in this research is summarized in the pipeline illustrated in Figure 1. This study implements a hybrid approach to classify Cirebon batik motifs by combining a Convolutional Neural Network (CNN) with two texture feature extraction methods: Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM). As depicted in the flowchart, the process is structured into six main stages: data collection, image preprocessing, dataset splitting, texture feature extraction, model construction, and finally, model evaluation.

Each stage is designed to systematically build and validate the classification system.

A. Data Collection

A dataset of 266 images representing four traditional Cirebon batik motifs: Megamendung (72 images), Paksi Naga Liman (68 images), Sawat Pengantin (63 images), and Singa Barong (63 images) was compiled from various publicly available online sources. The selection of these motifs was based on their visual distinctiveness, cultural significance, and the availability of sufficient image data to support model training and evaluation. The distribution of images across each class is summarized in Table 1.

Table 1 Dataset distribution

No	Motif	Number of Images
1.	Megamendung	100
2.	Paksi Naga Liman	71
3.	Sawat Pengantin	50
4.	Singa Barong	45

B. Image Preprocessing

To ensure data consistency and enhance image quality for feature extraction, a mandatory pre-processing workflow was applied to every image in the dataset. This workflow consisted of three sequential operations:

1. Image Resizing: Using the `cv2.resize()` function to change image dimensions to 256×256 pixels with `INTER_AREA` interpolation method.
2. Grayscale Conversion: Images are converted from RGB (Red-Green-Blue) format to grayscale using `cv2.cvtColor()`.
3. Histogram Equalization: Using `cv2.equalizeHist()` to enhance image contrast by redistributing pixel intensity values.

The visual transformation of an image as it moves through this workflow is illustrated in Figure 2.

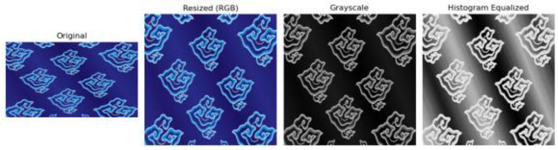

Figure 2 The sequential stages of the image pre-processing workflow

C. Texture Feature Extraction

Texture feature extraction was performed using two main methods, Local Binary Patter (LBP) and Gray Level Co-occurrence Matrix (GLCM).

- *Local Binary Pattern (LBP)*

Local Binary Pattern (LBP) is a statistical texture descriptor that captures local contrast variations. It encodes the relationship between a central pixel and its surrounding neighbors by comparing their intensity levels. If a neighboring pixel's intensity is greater than or equal to the center pixel, it is assigned a value of one; otherwise, it is given a zero. This comparison generates a binary pattern, which is then converted to a decimal value to capture the texture characteristics. Finally, these decimal values are compiled into a histogram that provides a compact and effective summary of the image's texture [18].

In mathematical terms, the LBP value at a given pixel *(x, y)* is determined using circular neighborhoods and bilinear interpolation. The Local Binary Pattern for a pixel is defined as [19]:

$$LBP_{P,R}(x,y) = \sum_{P=0}^{P-1} s(g_P - g_c)2^P \quad (1)$$

$$s\,(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases} \quad (2)$$

The LBP operator was applied using a list of three different radius: [3, 5, 8]. The number of sampling points was set to 8 * radius for each respective radius. The 'uniform' LBP variant was utilized, which reduces the number of possible patterns by grouping non-uniform patterns, thereby decreasing the feature vector's length and improving its stability against noise. After generating the LBP image for each scale, a normalized histogram was computed to quantify the frequency of each texture pattern. These three histograms were then concatenated to form the final LBP feature vector.

- *Gray Level Co-occurrence Matrix (GLCM)*

Gray-Level Co-occurrence Matrix (GLCM) technique is commonly used to evaluate and transform gray-level values into texture-related data, offering valuable insights for texture analysis and feature extraction. By capturing structural details of texture patterns across various scales and directions, this method enhances both efficiency and ease of implementation [20].

The values within the normalized co-occurrence matrix serve as the basis for computing GLCM texture features. Haralick proposed 14 features derived from the GLCM, consisting of 7 core features and 7 additional ones that are extensions of the main features. These include Angular Second Moment, Correlation, Contrast, Variance, Sum Variance, Inverse Difference Moment, Sum Entropy, Entropy, Maximum Correlation Coefficient, Difference Entropy, Difference Variance, Sum Average, and two Information Measures of Correlation (1 and 2) [21].

In this research, GLCMs were calculated using a set of distances [1, 3, 5] pixels and four angles [0°, 45°, 90°, and 135°] to provide a comprehensive texture analysis. GLCM method consists of 14 Haralick features, but this research focuses on only five of those characteristics.

- CON: Represents the difference in brightness between a pixel and its neighboring pixels; the more prominent the texture grooves, the higher the contrast value [22].
- COR: evaluates the similarity of GLCM elements across rows or columns, indicating the degree of linear correlation in the image's gray-level values [23].
- HOM: measures the similarity of elements in the GLCM by evaluating how close they are to the diagonal elements within the same row [23].
- DIS: Dissimilarity quantifies local variations in an image using a linear scale [24].
- ENT: Entropy quantifies the amount of information contained in an image and reflects the irregularity or complexity of its texture. Higher entropy values indicate greater randomness or noise within the image [22].

D. *Feature Fusion*

After the extraction process, the feature vectors from both LBP and GLCM were combined to create a single, unified feature representation for each image. The individual vectors were concatenated to form a final feature vector with a dimensionality of 194 (134 from LBP and 60 from GLCM). This fused vector, containing rich information about both local micro-patterns and broader spatial textures, served as the definitive input for the neural network classifier.

E. *Model Construction*

The classification model is built with flexibility through a technique known as hyperparameter tuning. The model begins with the first Dense layer, which contains a number of neurons (units) dynamically determined using the Int function from Keras Tuner, ranging from 32 to 256, and uses the ReLU activation function. This layer serves as the initial processor for input features derived from the image extraction process, with a vector length of 194.

Following the first Dense layer, a Batch Normalization layer is added to normalize outputs between layers, along with a Dropout layer with a probability ranging from 0.1 to 0.5 to reduce the risk of overfitting. The model also provides an option to include a second hidden layer, depending on a boolean configuration set via Keras Tuner. If enabled, this layer introduces an additional Dense layer with 64 to 128 neurons and ReLU activation, followed by similar normalization and dropout processes.

The final layer (output layer) consists of 4 neurons, corresponding to the number of classes to be classified. This layer uses the Softmax activation function to produce outputs in the form of class probabilities. The model compilation process uses the Adam optimizer, with a learning rate dynamically set between 10^{-4} and 10^{-2} on a logarithmic scale. The loss function applied is categorical crossentropy. Figure 3 shows the flowchart of the model development based on the described structure.

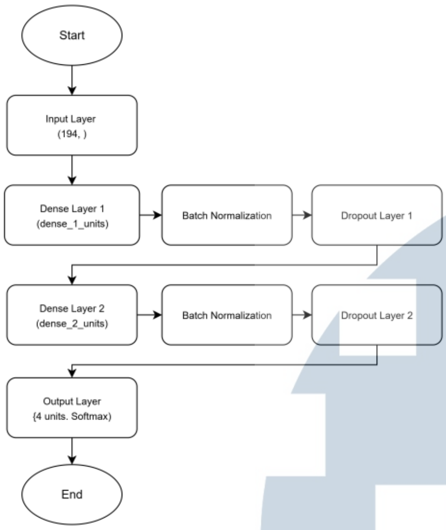

Figure 3 Flowchart model construction

F. Model Evaluation

During the evaluation phase, the trained model is tested using validation data to measure its performance in classifying Batik Cirebon patterns. The evaluation methods used include accuracy, precision, recall, and F1-score. Additionally, a confusion matrix is employed to analyze classification errors.

III. RESULTS AND DISCUSSION

The classification model for Cirebon batik motifs was implemented using Convolutional Neural Network (CNN) with feature engineering techniques, Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM). The dataset consisted of four main batik motifs: Megamendung, Sawat Pengantin, Paksi Naga Liman, and Singa Barong.

A. Model Configuration and Performance

The classification model was constructed by initially extracting a 194-dimensional texture feature vector from each image using a combination of LBP and GLCM techniques. This feature vector was then input into the model for classification. The optimal hyperparameters for this network, identified through a Keras Tuner Random Search, are detailed in Table 2. The search determined that a Dense layer with 160 units, a Dropout rate of 0.15, and an Adam optimizer with a learning rate of 0.00173 yielded the best performance on the validation data.

Table 2 Optimal hyperparameters

Hyperparameter	Optimal Value
First Dense Layer Units	160
Dropout Rate	0.15
Learning Rate	0.00173

The training process incorporated EarlyStopping and ReduceLROnPlateau callbacks to prevent overfitting and ensure stable convergence. As shown in the training curves in Figure 4 and Figure 5, the validation loss steadily decreased before plateauing around epoch 60, triggering the early stop at epoch 70. This behavior indicates that the model learned the patterns from the feature vectors effectively without significant overfitting, achieving an overall accuracy of 79% on the test set.

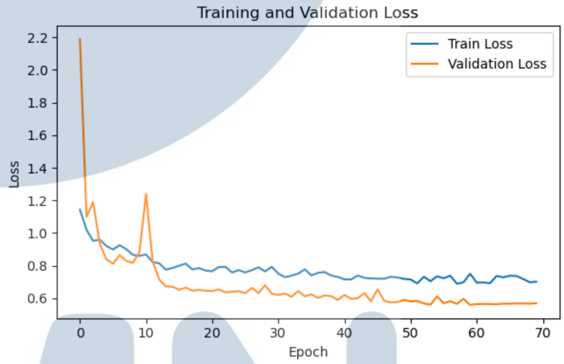

Figure 4 Training and validation loss curves

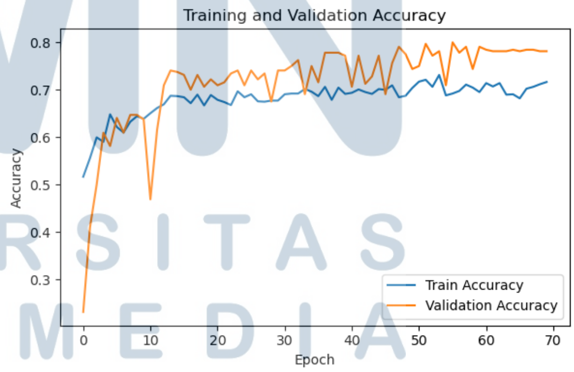

Figure 5 Training and validation accuracy curves

B. Evaluation Metrics

The model's performance on the four Cirebon batik motifs is detailed in the classification report in Table 3. The results show strong performance for two classes: Megamendung and Sawat Pengantin, which achieved high F1-scores of 0.94 and 0.90, respectively. The near-perfect recall of 99% for Megamendung demonstrates the model's exceptional ability to correctly identify instances of this class. In sharp contrast, the Singa Barong motif recorded the lowest F1-score of only 46%, indicating it posed a significant challenge for the model.

Table 3 Classification report

Class	Precision	Recall	F1-score	Support
Megamendung	0.90	0.99	0.94	120
Paksi Naga Liman	0.76	0.62	0.68	86
Sawat Pengantin	0.88	0.93	0.90	60
Singa Barong	0.46	0.46	0.46	54
Accuracy			0.79	320
Macro Avg	0.75	0.75	0.75	320
Weighted Avg	0.78	0.79	0.78	320

C. *Error Analysis*

A granular view of the classification errors, provided by the confusion matrix in Figure 5, highlights the model's primary weaknesses. The matrix confirms the strong performance on the Megamendung class, with only one sample being misclassified. However, it also visually exposes significant confusion between the Paksi Naga Liman and Singa Barong classes. For instance, 28 instances of Paksi Naga Liman and 29 instances of Singa Barong were misclassified, with a high degree of crossover between these two motifs.

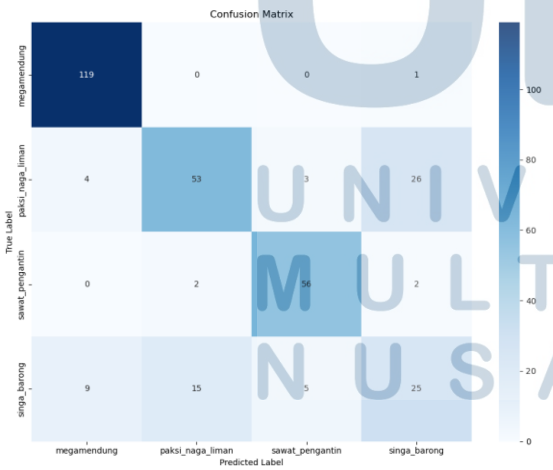

Figure 5 Confusion matrix

D. *Comparison with Baseline*

To evaluate the added value of feature engineering, a pure CNN model was also trained directly on raw pixel data without LBP or GLCM features. A comparative analysis of this pure CNN against the proposed hybrid model reveals a critical trade-off between predictive accuracy and operational efficiency, as summarized in Table 4. The pure CNN achieved a superior classification accuracy of 91%. However, this performance came at a significant cost to computational resources and model stability. The model required approximately 600 minutes to train and, during qualitative testing on new images, demonstrated a tendency to overfit, resulting in less stable predictions.

In contrast, the proposed hybrid model, which integrates LBP and GLCM features, offered superior efficiency and robustness. By utilizing pre-computed features, its training time was dramatically reduced to under one minute. While its accuracy of 79% is lower than the pure CNN's, it exhibited greater stability and reliability on unseen data. The trade-off between accuracy and computational cost must be considered, particularly in resource-constrained environments or real-time applications where the hybrid model's efficiency is a distinct advantage.

Table 4 Performance comparison between pure CNN and the hybrid model

Metric	Pure CNN (No Feature Engineering)	Model CNN eith LBP & GLCM
Accuracy	91%	79%
Training Time	600 min	< 1 min
Highest Precision	1.00	0.90
Lowest Recall	0.70	0.46
Testing Accuracy on New Samples	Low	High

E. *Discussion and Interpretation*

The results indicate that the hybrid model successfully captures texture patterns essential for classifying Cirebon batik motifs. Performance varied across different motifs, highlighting specific strengths and limitations. The Megamendung motif, characterized by its distinctive pattern, achieved the highest performance across all metrics.

Conversely, the Singa Barong motif consistently yielded the lowest scores. This is likely attributable to its high visual similarity with the Paksi Naga Liman motif, compounded by fewer available training samples. The confusion matrix confirmed that these two motifs were frequently misclassified, underscoring a key limitation of the current approach and reinforcing the need for strategies to handle class imbalance and visual ambiguity.

Despite achieving slightly lower accuracy than the pure CNN, the proposed hybrid model offers significant benefits in terms of training efficiency and robustness to overfitting. Its ability to train rapidly while delivering stable performance on new data makes it a more practical solution for many real-world classification scenarios.

IV. CONCLUSION

This study presents a hybrid classification method for Cirebon batik motifs that integrates Convolutional Neural Network (CNN) with texture feature extraction techniques, namely Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP). The proposed model achieved an overall accuracy of 79%, proving its effectiveness in recognizing complex texture patterns in traditional batik designs. Notably, motifs with distinct visual characteristics such as Megamendung were classified with high precision and recall, while motifs like Singa Barong showed lower performance due to inter-class visual similarity and limited data.

Despite its promising results, the model encountered challenges in distinguishing motifs with high visual similarity and class imbalance. Future work may involve expanding the dataset, applying advanced data augmentation techniques, and incorporating ensemble learning or alternative feature extraction strategies to improve accuracy across all motif classes. This hybrid framework provides a valuable foundation for the automated recognition and digital preservation of Indonesia's batik heritage.

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