

Batik Motif Recognition Using the BGP-Model: A Hybrid GLCM-PCA Approach with Machine Learning Classifiers

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ABSTRACT

This study proposes the Batik-GLCM-PCA Model (BGP-Model), a hybrid feature-engineering framework that integrates the Gray Level Co-occurrence Matrix (GLCM) for texture feature extraction with Principal Component Analysis (PCA) for dimensionality reduction. The BGP-Model was evaluated under two scenarios: classification using raw GLCM features and classification using PCA-reduced features, tested across three classifiers Naïve Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM). Experimental results demonstrate that the BGP-Model significantly improves classification performance, particularly for SVM (accuracy improved from 56.11% to 94.44%) and NB (from 78.33% to 85.00%). Although RF achieved its best performance (98.61%) with raw GLCM features, it experienced a slight decrease (93.89%) after dimensionality reduction. These findings confirm that the hybrid GLCM-PCA approach in the BGP-Model enhances classification accuracy, especially for algorithms sensitive to high-dimensional features, and contributes to the advancement of automated Batik motif recognition and the digitization of cultural heritage.

Keywords-BGP-Model; Batik motif recognition; GLCM; PCA; machine learning classifiers; cultural heritage digitization

I. INTRODUCTION

Batik is a traditional Indonesian textile art form, renowned for its intricate motifs and symbolic meanings [1], as well as its deep cultural significance in Indonesian heritage [2]. Among the diverse Batik designs, the Parang motif is one of the oldest and most iconic, distinguished by its diagonal repetition and structured visual rhythm [2]. Due to these distinctive visual patterns, the Parang motif is particularly suitable for texture-based image classification tasks, especially when using analytical techniques such as Gray Level Co-occurrence Matrix (GLCM) [3] and orientation-aware feature extraction [4]. The three Parang motifs used in this study are shown in Figure 1.

Driven by the digital transformation of Industry 3.0 and 4.0, advanced technologies such as Computer-Aided Design (CAD), Augmented Reality (AR), and digital archiving have been increasingly employed to preserve and promote Batik heritage [2]. This digital shift has also stimulated research in automated Batik recognition systems, particularly for cultural documentation [3], e-commerce authentication, and education platforms [5]. In this context, the proposed Batik-GLCM-PCA Model (BGP-Model) supports real-world applications such as

Batik authentication, heritage recognition, and educational tools through automated motif classification.

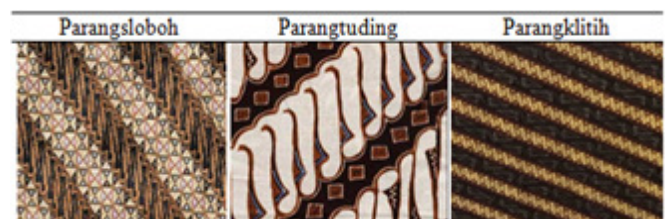


Fig. 1. Batik Parang motifs, including Parangsloboh, Parangtuding, and Parangklitih.

Texture analysis plays a central role in Batik classification, with the GLCM being one of the most widely used feature extraction methods [6]. GLCM captures second-order statistical texture features based on pixel spatial relationships [7] and has shown effectiveness across domains, including Batik recognition [3, 4], and texture-rich image analysis [8]. However, GLCM often produces high-dimensional feature spaces, which may introduce redundancy and lead to

overfitting in machine learning models [6]. To address this limitation, dimensionality reduction techniques such as Principal Component Analysis (PCA) are commonly employed to preserve significant variance while reducing dimensionality [9-11].

The integration of GLCM and PCA has shown promising results in several texture-rich domains [8, 9, 11], including traditional textile recognition [12]. Building upon these findings, this study introduces the BGP-Model as a novel, domain-specific framework for Batik motif classification.

At the classification stage, algorithms such as Naïve Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM) are extensively applied. SVM is well-suited for high-dimensional data such as GLCM features [3, 4], and has been successfully applied in Batik classification tasks [3, 12]. RF, with its ensemble learning mechanism, enables robust generalization across diverse datasets [13], whereas NB remains a practical choice in scenarios requiring computational efficiency or where training data are limited [14]. Table I provides a summary of selected studies on Batik classification using these techniques.

TABLE I. RELATED WORKS ON BATIK CLASSIFICATION

Study	Feature	Reduction	Classifier	Motif(s)	Accuracy (%)
[12]	GLCM + PCA	PCA	SVM-RBF	Troso	92.00
[15]	GLCM	None	KNN, SVM	Batik (unspecified)	87.23
[3]	GLCM	None	SVM (multiclass)	Batik	90.00
[14]	Statistical	None	NB, RF	Batik (binary)	89.00
This study	BPG-Model GLCM + PCA	PCA (24→4 comps.)	NB, RF, SVM	3 Parang motifs	98.61

SVM-RBF: SVM with a Radial Basis Function (RBF), KNN: k-Nearest Neighbors.

Table I highlights that most prior studies focused on limited motif types or applied only a single classifier, leading to restricted generalization of their findings. In contrast, this study introduces a multi-motif dataset comprising three Parang motifs and evaluates multiple classifiers using features derived from the optimized BGP-Model. While the integration of GLCM and PCA has demonstrated promising results in other domains [8, 9, 11], its potential for handling the complex and repetitive structures of Parang Batik motifs remains underexplored.

To address these gaps, this study proposes the BGP-Model, a hybrid feature engineering framework that integrates GLCM and PCA for optimized texture representation. The processed features are classified using SVM, RF, and NB, enabling comparative evaluation on a grayscale dataset comprising three Parang motifs.

The novelty of this work lies in three main contributions. First, a dedicated grayscale dataset of three distinct Parang motifs was constructed to provide a reliable basis for experimentation. Second, the BGP-Model formalizes the integration of GLCM features with PCA as a domain-specific framework for Batik recognition. Third, a comprehensive

comparative evaluation was conducted using multiple classifiers on both raw and PCA-reduced features.

These contributions not only support the development of intelligent Batik recognition systems for heritage digitization, textile authentication, and educational applications, but also introduce a methodologically novel integration of GLCM and PCA as a unified, task-specific feature-engineering pipeline for texture-based classification.

II. RESEARCH METHODOLOGY

A. Dataset Description

This study uses a dataset consisting of 1,200 grayscale images of three Parang Batik motifs (Parangsloboh, Parangtuding, and Parangklitih), collected from Kaggle [16, 17], GitHub [18], and publicly available digital repositories, including the Batik Nitik 960 dataset [19], the Batik Lasem Motifs dataset [20], and Batik 300 [21]. Every image was individually tagged, reduced to 64×64 pixels, and divided into two sets: 70% for training and 30% for testing. Although the 80:20 ratio is frequently adopted in the literature [22], a 70:30 split was selected in this study. This decision was motivated by the relatively moderate dataset size (1,200 images), where allocating a larger portion for testing helps reduce bias in performance measurement and ensures a more reliable assessment of the model's generalization ability.

B. Preprocessing

The preprocessing phase included two steps:

- **Grayscale conversion:** The RGB images were converted into grayscale using the standard luminance formulation [23]. This approach assigns different weights to the red, green, and blue components, reflecting the human visual system's varying sensitivity to these colors. Specifically, the eye is most sensitive to green, moderately sensitive to red, and least sensitive to blue. In light of this, the transformation uses the coefficients 0.299 for red, 0.587 for green, and 0.114 for blue, producing the equation that follows:

$$G = (0.299 \cdot \text{Red} + 0.587 \cdot \text{Green} + 0.114 \cdot \text{Blue}) \quad (1)$$

This ensures that the grayscale image preserves perceptual brightness in a way that aligns with human vision rather than treating all three-color channels equally.

- **Data augmentation:** Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustments are widely used to improve data diversity and reduce overfitting [5]. Beyond these traditional methods, Generative Adversarial Network (GAN)-based augmentation approaches have also been shown to be effective in broader domains, including Batik [24] and medical imaging [25], and can be adapted to enrich Batik datasets.

C. Feature Engineering

The proposed BGP-Model formalizes feature engineering into two integrated stages:

- GLCM feature extraction: Texture information was extracted using the GLCM computed at four orientations: 0°, 45°, 90°, and 135°, with a pixel distance of 1. From each direction, six statistical features were derived: contrast, dissimilarity, homogeneity, correlation, Angular Second Moment (ASM), and energy [7, 26], resulting in 24 features per image. Multi-directional GLCM enhances the model's ability to capture complex variations, whereas the 0° orientation is particularly significant for Parang motifs due to their strong horizontal structures [4, 8].
- PCA-based dimensionality reduction: To minimize feature redundancy, PCA was applied to the 24-dimensional feature vectors [9, 10]. Features were standardized, and a covariance matrix was computed to normalize scale. The top four principal components were retained, cumulatively capturing over 95% of the dataset variance [9, 11]. This ensures a compact yet informative feature representation.

D. Classification Models

Three supervised classifiers were employed to evaluate features derived from the BGP-Model:

- NB: Based on Bayes' theorem, NB computes posterior probabilities from priors and likelihoods [14]:

$$\frac{P(X|H) \cdot P(H)}{P(X)} = P(H|X) \quad (2)$$

where $P(H|X)$ is the posterior, $P(X|H)$ is the likelihood, $P(H)$ is the prior, and $P(X)$ is the evidence.

- RF: An ensemble of decision trees using bagging and random feature selection for robust classification [13].
- SVM: Determines the optimal separating hyperplane in high-dimensional feature space [3, 4]. The following equation defines this decision boundary:

$$Wx + b = 0 \quad (3)$$

where W represents the weight vector, x is the input feature vector, and b is the bias.

E. System Workflow and Experimental Setup

1) System Architecture

The overall system architecture workflow of the BGP-Model is presented in Figure 2. A total of 1,200 grayscale images were preprocessed, features extracted via GLCM, and reduced with PCA into four principal components. Both raw GLCM features and PCA-optimized features derived from the BGP-Model were classified using NB, RF, and SVM. The predicted motif labels were then compared with the ground truth to compute accuracy, precision, recall, and F1-score.

2) Experimental Scenarios

Two experimental scenarios were designed:

- Path A: Classification using the raw GLCM features (24 features).
- Path B: Classification using PCA-optimized features derived from the BGP-Model (4 dimensions).

This setup enables comparative analysis of classification performance with and without dimensionality reduction.

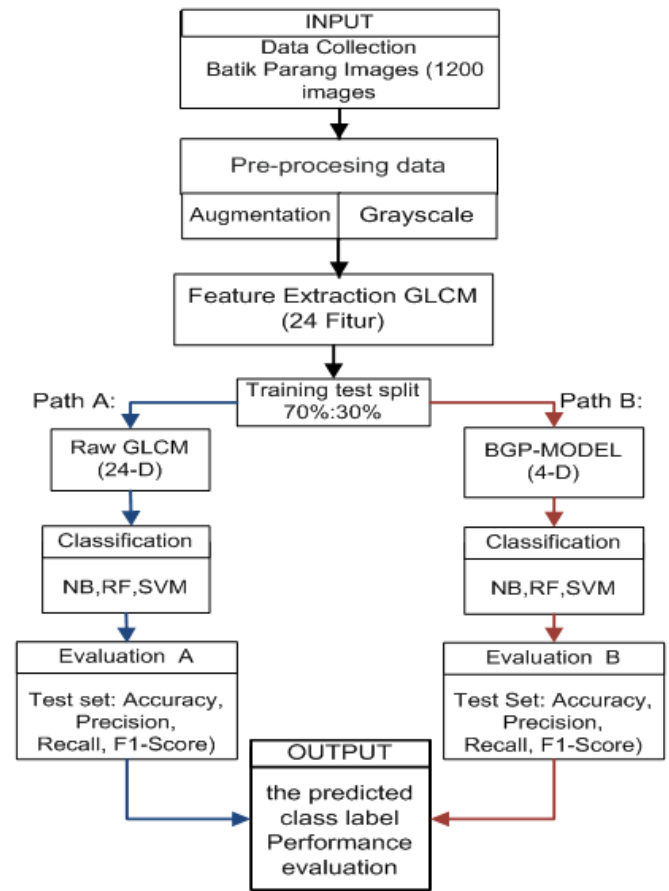


Fig. 2. System architecture: input-output workflow of the BGP-Model for Batik classification.

F. Model Training and Evaluation

All models were trained using 70% of the dataset, whereas 30% was reserved for testing [22]. Optimized classifier training was performed on both raw and BGP-Model-derived features to effectively represent Batik Parang characteristics.

G. Evaluation Metrics

The performance of the classification model was assessed using widely adopted metrics, namely accuracy, precision, recall, and the F1-score [27, 28]. Performance was evaluated using the following four standard metrics.

Accuracy measures the proportion of correct predictions relative to the total number of instances:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Precision quantifies the reliability of the model in identifying positive cases:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

Recall (or sensitivity) evaluates the model's capability to correctly detect all actual positive cases:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

In the case of uneven class distribution, the F1-score is the most appropriate evaluation metric, because it combines precision and recall values in the form of a harmonic mean:

$$F1 - \text{score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \quad (7)$$

The choice of metrics depends on the dataset characteristics. Accuracy is appropriate when classes are relatively balanced, whereas F1-score provides more reliable insights when dealing with imbalanced data [27].

H. Comparative Setup

The effectiveness of dimensionality reduction was assessed by comparing:

- Raw GLCM features (24-D)
- Optimized features derived from the BGP-Model (4-D)

Each classifier (NB, RF, SVM) was evaluated under both scenarios using accuracy, precision, recall, F1-score, and training time.

I. Output

The system outputs the predicted class label (Paranggloboh, Parangtuding, or Parangklitih) for each image. Comparative evaluation demonstrates the trade-off between feature complexity and classification performance, highlighting the effectiveness of the BGP-Model in optimizing recognition.

III. RESULTS AND DISCUSSION

A. Experimental Setup

The dataset used in this study consists of 1,200 grayscale images of three classes of Parang Batik motifs: Parangtuding, Paranggloboh, and Parangklitih, with 400 images per class [16]. All images were resized to 64×64 pixels to standardize input dimensions for the model.

During preprocessing, grayscale conversion and data augmentation techniques such as rotation, scaling, brightness adjustment, and shifting were applied to enhance data diversity and reduce overfitting. These augmentation steps ensure that the model can generalize better across variations in Batik patterns. Feature engineering was conducted using the BGP-Model, which integrates GLCM for texture feature extraction and PCA for dimensionality reduction. Subsequently, three supervised classifiers, NB, RF, and SVM, were employed for classification.

B. Classification Results

Three classifiers (NB, RF, and SVM) were trained using a 70:30 split. Comparative evaluations were conducted between raw GLCM features and features extracted and optimized through the BGP-Model, which integrates GLCM and PCA.

Table II presents the macro-averaged accuracy and training time for each classifier, whereas Table III presents precision,

recall, and F1-score, derived from the confusion matrices. RF performed best on raw GLCM features, whereas SVM benefited from PCA-optimized features generated by the BGP-Model.

TABLE II. ACCURACY AND TRAINING TIME OF CLASSIFIERS

Classifier	Feature set	Accuracy (%)	Training time (s)
NB	GLCM	78.33	0.0016
NB	BGP-Model	85.00	0.0014
RF	GLCM	98.61	0.3501
RF	BGP-Model	93.89	0.3254
SVM	GLCM	56.11	0.0417
SVM	BGP-Model	94.44	0.0205

TABLE III. PRECISION, RECALL, AND F1-SCORE (MACRO-AVERAGED) OF CLASSIFIERS

Classifier	Feature set	Precision (%)	Recall (%)	F1-score (%)
NB	GLCM	78.79	78.33	78.37
NB	BGP-Model	86.11	85.00	84.09
RF	GLCM	98.65	98.61	98.61
RF	BGP-Model	94.18	93.89	93.82
SVM	GLCM	63.54	56.11	57.18
SVM	BGP-Model	95.01	94.44	94.40

C. Performance Analysis

The BGP-Model significantly improved the performance of both SVM and NB classifiers, especially SVM, whose accuracy increased from 56.11% to 94.44%. NB achieved an increase from 78.33% to 85.00%. Figure 3 shows the comparative accuracy of all three classifiers, clearly illustrating the impact of the BGP-Model in optimizing simpler classifiers.

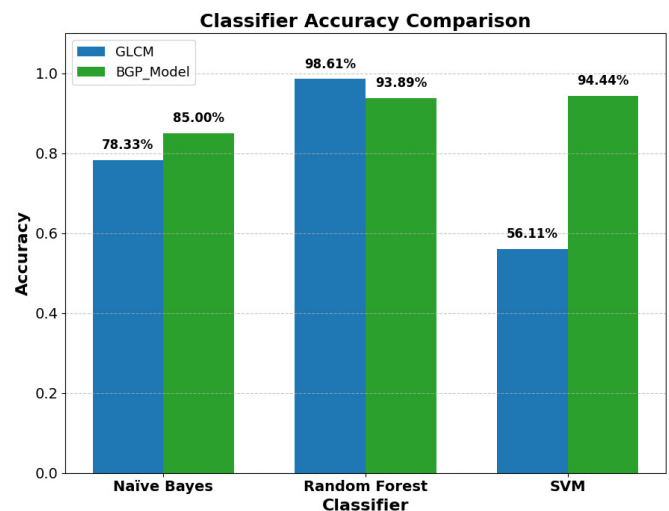


Fig. 3. Comparative accuracy of all three classifiers: NB, RF, and SVM.

In contrast, RF achieved its best performance using raw GLCM features (98.61%) and experienced a slight decrease after PCA (93.89%). This result highlights that while ensemble-based models like RF are inherently robust to

redundant features, the BGP-Model is more advantageous for classifiers that benefit from compact, discriminative representations such as SVM.

D. Confusion Matrix Analysis

To further validate classification performance, confusion matrices were constructed for each experimental setup. Figure 4 shows the SVM confusion matrix based on features extracted via the BGP-Model, in which 119 out of 120 Parangtuding samples were correctly classified. This demonstrates the BGP-Model's ability to reduce misclassifications across visually similar Parang motifs.

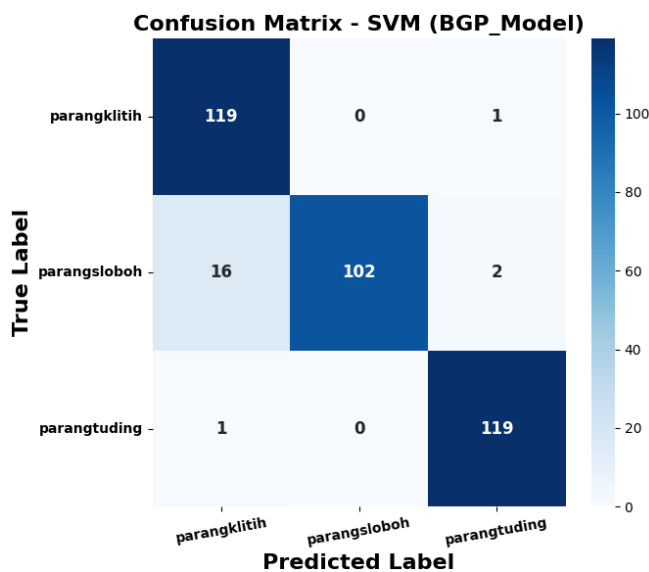


Fig. 4. Confusion matrix of the SVM classifier using features derived from the BGP-Model for Batik Parang motif classification.

For the Parangtuding class, performance metrics were calculated as follows:

- Precision = $119 / (119 + 3) = 97.54\%$
- Recall = $119 / (119 + 1) = 99.17\%$
- Accuracy = $340 / 360 = 94.44\%$

These results reinforce the effectiveness of the BGP-Model in producing reliable classification outcomes.

Note: This confusion matrix represents the performance of the SVM classifier using features derived from the BGP-Model. Similar matrices were generated for all classifier scenarios and were used to compute the performance metrics reported in Tables II and III.

E. Sample Classification Results

Figure 5 presents representative classification results produced by the SVM classifier using features derived from the BGP-Model. Each image is annotated with its ground truth label, predicted label, and classification outcome (correct or incorrect). The examples include both correct classifications (e.g., Parangsloboh, Parangtuding, Parangklitih) and misclassifications, such as Parangsloboh being misclassified as

Parangklitih. These visualizations demonstrate that although the BGP-Model substantially improves classification reliability, challenges remain in differentiating visually similar Batik motifs.

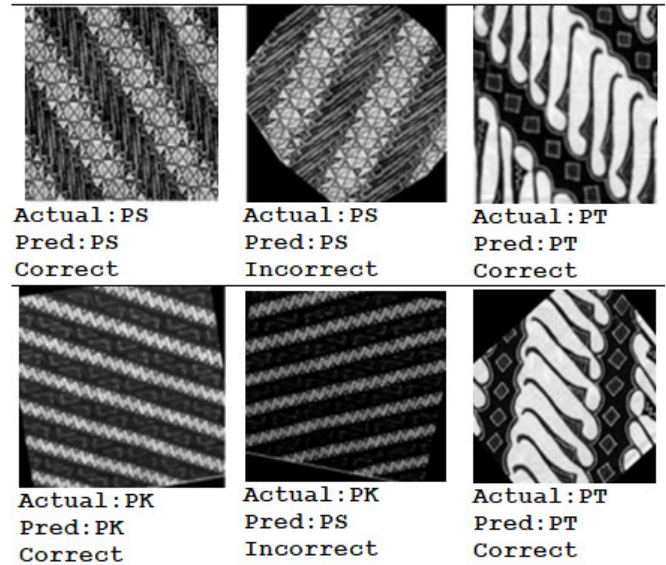


Fig. 5. SVM classification results using BGP-Model features. Each image shows actual and predicted labels with classification outcome (correct/incorrect). Abbreviations: PS = Parangsloboh, PK = ParangKlitih, PT = Parangtuding.

IV. CONCLUSION

This study introduced the Batik-GLCM-PCA Model (BGP-Model), which integrates the Gray Level Co-occurrence Matrix (GLCM) for texture feature extraction and Principal Component Analysis (PCA) for dimensionality reduction. Using a dataset of 1,200 grayscale images of three Parang motifs, the model reduced 24 GLCM features into 4 principal components while preserving over 95% of the variance.

Results show that the BGP-Model markedly improved Support Vector Machine (SVM) accuracy (56.11% → 94.44%) and Naïve Bayes (NB) accuracy (78.33% → 85.00%), whereas Random Forest (RF) achieved the highest accuracy (98.61%) using raw features. Compared to prior studies [3, 12, 14] that focused on limited motifs or single classifiers, this work provides a multi-motif dataset and demonstrates that the hybrid GLCM-PCA pipeline can outperform existing approaches, achieving up to 98.61% accuracy.

The novelty of this work lies in formalizing GLCM-PCA integration as a domain-specific feature engineering framework for Batik recognition and validating it across multiple classifiers. Future research may extend this framework to incorporate deep learning, larger motif collections, and real-time or mobile implementations to further support Batik digitization and heritage preservation.

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