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PRESERVATION OF THROUGH PATTERN RECOGNITION USING A COMBINATION OF GLCM, LBP, AND SVM MULTICLASS

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Abstract—*This study proposes an automatic method to recognize traditional Timorese weaving patterns using machine learning techniques. Timorese weaving image data is processed through pre-processing stages and its features are extracted using the Gray Level Cooccurrence Matrix (GLCM) and Local Binary Pattern (LBP) methods, which function to capture the characteristics of texture and design in the weaving patterns. The classification model is built with the Support Vector Machine (SVM) algorithm using the One Versus One (OVO) and One Versus All (OVA) approaches with several kernels, including Linear, Polynomial, and Radial Basis Function (RBF). The best results were obtained with the Linear kernel and the OVO method, resulting in an accuracy of 88.66%, a precision of 88.66%, a recall of 88.80%, and an F1-score of 88.73%. This approach shows great potential in preserving and documenting Timorese weaving patterns automatically and efficiently, with accurate classification results. This study explores a machine learning approach for identifying Timorese weaving patterns. By leveraging GLCM and LBP for texture analysis and SVM with OVO and OVA for classification, the method achieves high accuracy. The findings support digital preservation efforts and cultural heritage conservation.*

Keywords: *classification, GLCM, LBP, SVM, timor weaving.*

Intisari— *Penelitian ini mengusulkan metode otomatis untuk mengenali pola tenun tradisional Timor menggunakan teknik machine learning. Data citra tenun Timor diproses melalui tahap pra-pemrosesan dan fitur-fiturnya diekstraksi menggunakan metode Gray Level Cooccurrence Matrix (GLCM) dan Local Binary Pattern (LBP), yang berfungsi untuk menangkap karakteristik tekstur dan desain pada pola tenun. Model klasifikasi dibangun dengan algoritma Support Vector Machine (SVM) menggunakan pendekatan One Versus One (OVO) dan One Versus All (OVA) dengan beberapa kernel, termasuk Linear, Polynomial, dan Radial Basis Function (RBF). Hasil terbaik diperoleh dengan kernel Linear dan metode OVO, menghasilkan akurasi sebesar 88,66%, presisi 88,66%, recall 88,80%, dan F1-score 88,73%. Pendekatan ini menunjukkan potensi besar dalam melestarikan dan mendokumentasikan pola tenun Timor secara otomatis dan efisien, dengan hasil klasifikasi yang akurat. Penelitian ini mengeksplorasi pendekatan machine learning untuk mengidentifikasi pola tenun Timor. Dengan memanfaatkan GLCM dan LBP untuk analisis tekstur serta SVM dengan OVO dan OVA untuk klasifikasi, metode ini mencapai tingkat akurasi yang tinggi. Temuan ini mendukung upaya pelestarian digital dan konservasi warisan budaya.*

Kata Kunci: *klasifikasi, GLCM, LBP, SVM, tenun Timor.*

INTRODUCTION

Timorese weaving cloth is a cultural heritage from the province of Nusa Tenggara Timur (NTT) that reflects historical values and creativity passed down from generation to generation [1]. However, with time, interest in this cultural heritage has declined, thus threatening the continuation of the existing Timorese weaving patterns [2], [3]. In response to this challenge, researchers propose an innovative approach by utilizing machine learning to document and automatically recognize Timorese weaving patterns. Through this approach, researchers seek to synchronize cultural traditions with technological advances in order to preserve traditional Timorese weaving.

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This study aims to address the challenges in preserving the cultural heritage of Timorese weaving by combining machine learning technology and image feature extraction methods, through an innovative approach by combining the Gray Level Cooccurrence Matrix (GLCM) and Local Binary Pattern (LBP) methods and using the multiclass Support Vector Machine (SVM) algorithm to develop a more efficient and accurate model in recognizing traditional Timorese weaving patterns. This approach also prioritizes representative data collection and complex model development.

The use of machine learning technology in the recognition of weaving patterns is rapidly developing along with advances in digital image processing. Several studies have shown that the multiclass Support Vector Machine (SVM) method, combined with feature extraction techniques such as Speeded Up Robust Features (SURF), can be used for woven motif classification with fairly good results. However, the use of the SURF method often requires a fairly long computing time, which is one of the obstacles in its application [4].

In order to improve the efficiency and accuracy of textile motif classification, previous studies have shown that feature extraction using Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) in the context of multikernel SVM shows effective performance. Both methods are able to provide good features for batik image classification, with more efficient computing time and higher accuracy [3]. The results of this study are in line with previous studies that also reported positive results in batik pattern recognition using the GLCM as well as LBP [5], [6], [7].

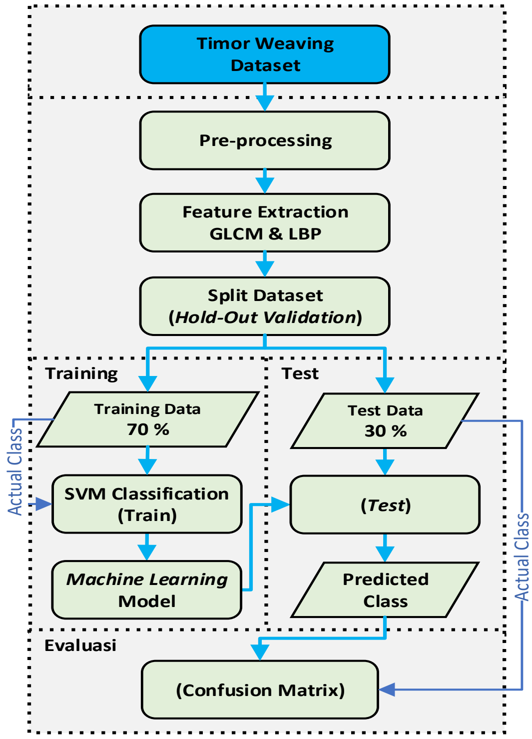
Based on the description of previous research, the researchers propose several advantages and novelties in the recognition of Timorese weaving patterns, with an approach focused on the combination of GLCM and LBP feature extraction algorithms. By combining these two feature extraction methods, it can present a more comprehensive representation of Timorese weaving images, taking into account that GLCM pays attention to the global relationship between pixels [8], [9], while LBP focuses on local patterns [10], [11]. The combination of the two algorithms allows for increased effectiveness and efficiency of the system in better recognizing variations in texture and patterns in Timorese weaving. In addition, the exploration of machine learning techniques using the multiclass SVM algorithm reflects the novelty in developing models to accurately recognize weaving patterns [12].

Previous studies faced limitations due to suboptimal use of weaving data and the complexity of models, which hindered performance. To address this, this study enhances the role of machine learning by expanding data collection and developing more sophisticated models.

Despite advancements in textile pattern recognition, most existing studies rely on single-feature extraction techniques, which may restrict classification accuracy. This research proposes a hybrid feature extraction approach combining GLCM and LBP, integrated with a multiclass SVM model, to improve the efficiency and accuracy of Timorese weaving pattern recognition.

MATERIALS AND METHODS

This study proposes an innovative approach in preserving traditional Timorese weaving art through the application of machine learning to recognize weaving design and patterns. This approach involves several stages starting from data collection, preprocessing, feature extraction, dataset division, classification model formation, testing, as well as model evaluation. The research method flow is presented in Figure 1.



Source: (Research Results, 2025)

Figure 1. Research Methods

1. Data Collection

Data collection of Timorese weaving images was carried out from various sources, covering a variety of representative patterns, there are 10 weaving motifs that represent tribes and weaving

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motifs from 5 districts on the island of Timor. The collected data can reflect the wide variety of Timorese weaving patterns, so that the model can recognize the patterns more accurately. Figure 3 displays the variety of weaving patterns used in this study, which consists of 10 types of Timorese weaving patterns. Each pattern has 250 image samples, so the total dataset used reaches 2,500 images. This data was obtained directly from weaving craftsmen through a documentation process using a digital camera with natural lighting to maintain the authenticity of the color and texture of the fabric. In addition, additional references were obtained from local community woven fabric collections and regional textile museums to validate the accuracy of the patterns in this study.

Source: (Research Results, 2025)
Figure 2. Variety of Timor Weaving Patterns
(a) Nunkollo; (b) Biboki; (c) Futus Pelangi;
(d) Kaimafafa; (e) Mabuna; (f) Weulun; (g) Biklusu;
(h) Kemak; (i) Kauniki; (j) Naisa

2. Timorese Weaving Pre-processing Data Set

The initial stage in image-based pattern recognition is pre-processing, which aims to improve image quality. Pre-processing stages include resizing, image format conversion, and contrast adjustment. These processes are essential to ensure that the resulting image has good quality for the subsequent feature extraction process.

3. Feature Extraction

Feature extraction is the process of obtaining distinctive features from an image, in this instance, the image of a Timorese weaving pattern. Two feature extraction methods used in this study are Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP). GLCM is used to extract texture features by calculating the probability of the intensity relationship between two adjacent pixels [13][14]. Some of the key features extracted from GLCM include:

a. Contrast: Contrast in GLCM measures the intensity difference between a pixel and its neighbors, indicating the extent of texture variation in an image.

$$Contrast = \sum_i \sum_j (i-j)^2 \, p_{(i,j)} \quad (1)$$

Whereas $p_{(i,j)}$ is the probability of occurrence of a pair of pixels with *i* and *j* intensity.
High contrast indicates a coarse texture with a large difference in intensity, while low contrast indicates a fine texture with a small difference.

b. Correlation: measures the linear relationship among pixel intensity.

$$Correlation = \sum_i \sum_j \frac{(i-\mu_i)(j-\mu_j)\, p_{(i,j)}}{\sigma_i \, \sigma_j} \quad (2)$$

Whereas *i* and *j* is the intensity level of the pixel, $p_{(i,j)}$ is the probability of occurrence of a pixel pair with intensity *i* and *j, and* μ_i and μ_j are average intensity, and σ_i and σ_j are standard deviation for the intensity of i and j.
High correlations indicate regular texture patterns, while low correlations indicate random or unstructured patterns.

c. Energy: measures the similarity of intensity in images.

$$Energy = \sum_i \sum_j p\,(i,j)^2 \quad (3)$$

This energy feature is high if the images have the same level of intensity.

d. Homogeneity: measures intensity consistency in images

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$$Homogeneity = \sum_i \sum_j \frac{p(i,j)}{i+|i-j|} \quad (4)$$

This Homogeneity feature is high if the pixel values in the image are at the same level.

Furthermore, LBP is used to capture local texture patterns by comparing the intensity values of the central pixel with its surrounding [15], [16]. Formula for LBP is:

$$LBP(x,y) = \sum_{i=0}^{P-1} sgn\,(I_i + I_c) \cdot 2^i \quad (5)$$

Whereas; P is the number of surrounding (using 8 for window 3×3). I_i is surrounding pixel intensity value to $-i$. I_c is the center pixel intensity value. $sgn(x)$ is the sign function that produces $1\ if\ x \geq 0\ and\ 0\ if\ x < 0$. LBP helps capture local texture patterns, focusing on the fine details in each Timorese weaving patterns.

GLCM analyzes global relationships between pixels, while LBP focuses on local patterns. The combination of the two allows the system to better recognize variations in texture and motifs of Timorese weaving. The combination of these methods results in a more comprehensive image representation, so that weaving motifs can be distinguished based on their texture. The results from feature extraction are then used as a basis to train a classification model, enabling the system to accurately classify and recognize Timorese weaving patterns.

4. Data Set Division

Data set is split using the Hold-out Validation method, which randomly separates the data into two parts: a training set and a testing set. Two-thirds of the data is used to train the model, while the remaining one-third is used to test the model that has been formed. This technique helps to avoid overfitting, to enable the model to evaluate performance more objectively [17].

5. Formation of Classification Model

In this study, the Support Vector Machine (SVM) algorithm was used to form a classification model for Timorese weaving patterns. SVM is known to be effective for high-dimensional data classification and separates classes accurately. However, since SVM by default can only perform binary classification, two approaches were used to address multiclass classification, namely One Versus One (OVO) and One Versus All (OVA) [18]. The OVO approach builds an SVM model for each pair of classes; for example, for three classes, three models will be built: A vs B, A vs C, and B vs C. This approach involves $\frac{N(N-1)}{2}$ model for N class, which is more complex but often gives very good results [19]. In contrast, the OVA approach builds an SVM model to distinguish one class from all other classes; for three classes, three models will be built: A vs (B and C), B vs (A and C), dan C vs (A and B). This approach is simpler as it only requires N models, and also found effective [20].

In order to handle data that cannot be separated linearly, SVM uses various kernel functions [21]. Kernel Linear, which is the point product of two feature vectors, is used when the data can be separated by a straight line. Polynomial Kernel, which is polynomial functions of the point product added with a constant, is used to capture more complex non-linear relations. Kernel Radial Basis Function (RBF), or Gaussian, maps the data to an infinite-dimensional feature space by using a Gaussian function to handle complex non-linear relations [22], [23], [24]. Kernel function can be observed in the following equation:

$$K(x_i, x_j) = x_i, x_j \quad (6)$$

$$K(x_i, x_j) = (x_i, x_j + c)^d \quad (7)$$

$$K(x_i, x_j) = exp\left(\frac{\|x_i, x_j\|^2}{2_{\sigma^2}}\right) \quad (8)$$

By using various types of Kernel Linear, Polynomial, and RBF, as well as the multiclass OVO (One Versus One) and OVA (One Versus All) methods, this study aims to find the most effective classification method for recognizing Timorese weaving design patterns.

6. Model Testing and Evaluation

After the model is formed, the testing phase is carried out by entering new data that has never been used in the training process. This stage aims to measure the extent to which the model is able to recognize weaving patterns images accurately. Evaluation on the model performance is carried out using the Confusion Matrix, which compares the actual classification results with the predicted results [25]. Confusion Matrix provides important information about accuracy, precision, recall, and other evaluation aspects that describe the extent to which the model is capable of soundly recognizing the weaving patterns [26].

Through this research stage, machine learning techniques are used to accurately recognize Timorese weaving patterns. The multiclass Support Vector Machine (SVM) algorithm is used to classify various weaving patterns, while feature extraction using Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) provides in-depth texture and pattern information. SVM works by separating data classes using an optimal hyperplane in feature space, where the selection of kernel function plays an important role in mapping the data to higher dimensions to improve class separation. In this study, One-Versus-One (OVO) and One-Versus-All (OVA) approaches are used to handle multiclass classification, where OVO compares each pair of classes, while OVA compares each class with all other classes. The linearly separable characteristics of the data allow the Linear kernel to produce weaving pattern classification with optimal performance. This combination aims to classify weaving patterns automatically and accurately, as well as to provide innovative solutions in preserving the cultural heritage of Timorese weaving tradition.

RESULTS AND DISCUSSION

In this study, the process of image-based classification of Timorese weaving patterns starts with the pre-processing stage, in which Timorese weaving images, originally in RGB format, are converted into grayscale images. This step is necessary since the feature extraction methods used, namely Gray Level Cooccurrence Matrix (GLCM) and Local Binary Pattern (LBP), work more optimally on grayscale images. After pre-processing, the features extracted from GLCM include Contrast, Correlation, Energy, and Homogeneity, which are then used to train the classification model. Next, the Support Vector Machine (SVM) model is applied with two multiclass methods, namely One Versus One (OVO) and One Versus All (OVA), using several types of kernels: Linear, Polynomial, and Radial Basis Function (RBF). The classification performance results of each kernel are presented in Table 1.

Table 1. SVM Performance

No	Metrik	Metode		*Kernel*
		OneVsOne	*OneVsAll*	
1	*Accuracy*	**88.66**	87.73	*Linear*
	Precision	**88.66**	87.73	
	Recall	**88.80**	87.81	
	F1-score	**88.73**	87.77	
2	*Accuracy*	79.86	84.26	*Polynomial*
	Precision	79.86	84.26	
	Recall	86.22	89.44	
	F1-score	82.92	86.77	
3	*Accuracy*	43.20	43.20	*RBF (Radial Basis Function)*
	Precision	43.20	43.20	
	Recall	91.08	91.08	
	F1-score	58.60	58.60	

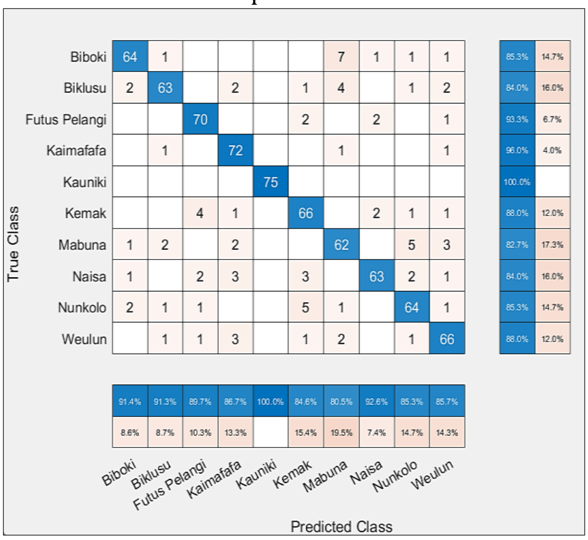
Source: (Research Results, 2025)

Based on the above table, the Linear kernel with OVO method provides the best performance compared to the other kernels. This model achieves an accuracy of 88.66%, a precision of 88.66%, a recall of 88.80%, and an F1-score of 88.73%. The Polynomial kernel produces lower performance with the highest accuracy of 84.26%, while the RBF kernel shows the lowest performance with an accuracy of only 43.20%. This shows that the Linear kernel is more suitable for the classification of Timorese weaving patterns, especially in handling relatively non-complex data set.

In the application of RBF kernel, although the recall value is high (91.08%), the accuracy and precision are low, which indicates overfitting. The RBF model often misclassifies samples, resulting in low overall accuracy.

The poor performance of the RBF kernel compared to the Linear kernel could be due to the characteristics of the data set that do not require mapping to higher dimensions. RBF kernels usually excel in handling data with complex non-linear patterns, but in this case, the Timor weaving texture pattern is more suitable for linear separation. In addition, the sensitivity of the gamma parameter may lead to overfitting, hindering the generalization of the model.

Confusion Matrix resulted from the SVM classification with Linear kernel and OVO method is presented in Figure 3. This Confusion Matrix describes the number of correct and incorrect predictions of each weaving pattern class, enabling to evaluate the model performance in detail.



Source: (Research Results, 2025)

Figure 3. Confusion Matrix resulted from SVM Multi Class OVO with Linear Kernel

Furthermore, the confusion matrix of the SVM classification results with the Linear kernel

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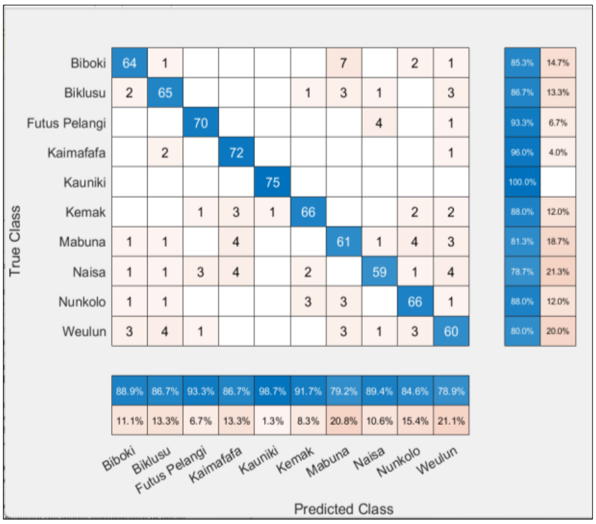
and the OVA method is presented in Figure 4. Compared to the OVO method, with an accuracy of 87.73%, precision of 87.73%, recall of 87.81%, and F1-score of 87.77%.

The analysis results show that Buna, Biklusu, and Naisa motifs have the highest misclassification rate due to their complex patterns and fine textures. The model often misclassified them as more uniformly textured motifs, possibly due to the extracted features not distinguishing enough fine details.



Source: (Research Results, 2025)

Figure 4. Confusion Matrix resulted from SVM Multi Class OVA with Linear Kernel

The use of OVO and OVA methods on SVM shows that OVO is superior in handling multiclass classification on Timorese weaving data. This is due to OVO's ability to compare each class separately, making it more effective in identifying differences among existing pattern classes. The Linear kernel proved to be better than other kernels in this context, possibly due to the characteristics of the data set which is more linear and does not require complex non-linear functions, as provided by the Polynomial or RBF kernels.

Additionally, these results show that the combination of GLCM and LBP methods in feature extraction is able to capture the texture design of Timorese weaving patterns well, producing feature representations that assist SVM in undertaking classification accurately.

The main contribution of this research lies in the combination of Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) feature extraction methods in weaving motif classification, which has not been applied in previous studies. Previous studies generally used a single extraction method, such as GLCM or LBP alone, which is less than optimal in capturing the complexity of weaving patterns.

In this study, the combination of GLCM and LBP resulted in a more accurate feature representation-GLCM analyzes the spatial relationships between pixels, while LBP captures the micro-texture patterns. This approach is in line with other research in the field of image processing which shows that combined feature extraction methods can improve classification accuracy.

Furthermore, the model was developed using a multiclass Support Vector Machine (SVM), with the One-Versus-One (OVO) method and linear kernel which proved superior to polynomial and RBF. These results support the theory that SVMs with linear kernels are more effective for data with relatively simple pattern distributions, such as Timorese weaving motifs.

Thus, this study offers a new approach in weaving motif classification with a combination of feature extraction and a more accurate SVM model. These results can serve as a reference in similar studies and open up opportunities for further exploration, including the application of deep learning for accuracy improvement.

CONCLUSION

This research develops an image-based classification model of Timorese weaving motifs by combining the GLCM and LBP feature extraction methods and the SVM multiclass algorithm. Unlike previous studies that used a single extraction method, this combination proved to be more effective in capturing the texture complexity of weaving motifs. The best results were obtained with the One Versus One (OVO) method and Linear kernel, achieving an accuracy of 88.66%, indicating that Timorese weaving motif patterns are better suited to linear separation than non-linear approaches such as the RBF kernel.

The main contribution of this research to science lies in the application of complementary feature extraction strategies to improve the classification accuracy of textile motifs, which can be applied to various types of traditional fabrics with complex patterns. This study successfully demonstrates the feasibility of combining GLCM and LBP for the automatic classification of Timorese weaving patterns using an SVM-based approach. The results highlight the potential of machine learning in preserving cultural heritage through digital means. Future work should explore deep learning models to further enhance classification accuracy and develop real-time applications for artisan communities

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