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# Enhancing Ulos Batik Pattern Recognition through Machine Learning: A Study with KNN and SVM

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**Abstract**

This research aims to develop an automated classification system to accurately identify and classify Ulos batik patterns using K-Nearest Neighbors (K-NN) and Support Vector Machine (SVM) techniques. The method is based on computer vision technology and texture analysis using the Gray-Level Co-occurrence Matrix (GLCM). The dataset consists of 1,800 images of Ulos fabric categorized into six main motif classes. The preprocessing process involves converting images to grayscale and extracting features with GLCM. Two classification algorithms, K-NN and SVM, were used for modeling, with evaluation using confusion matrix metrics and Area Under Curve (AUC). Evaluation results show that the K-NN model has an accuracy of 82%, while SVM has an accuracy of 57%. The analysis also highlights the superiority of K-NN in distinguishing Ulos fabric patterns. This research highlights the importance of automatic classification of Ulos batik patterns in supporting cultural preservation and the creative industry. An automated system can significantly speed up the identification and documentation process of Ulos batik patterns, preserving their diversity and promoting innovation in the creative industry. The study demonstrates the effectiveness of using K-NN and SVM for this purpose, with K-NN showing superior performance. It provides insights into the significant difference in accuracy between the two methods.

Keywords: image classification, Ulos batik, computer vision, K-Nearest Neighbors, Support Vector Machine.

***Abstrak***

*Penelitian ini bertujuan untuk mengembangkan sistem klasifikasi otomatis untuk mengidentifikasi dan mengklasifikasikan corak batik ulos dengan akurasi tinggi menggunakan teknik K-Nearest Neighbors (K-NN) dan Support Vector Machine (SVM). Metode ini didasarkan pada penggunaan teknologi computer vision dan analisis tekstur menggunakan Gray-Level Co-occurrence Matrix (GLCM). Dataset terdiri dari 1.800 gambar kain ulos yang dikategorikan ke dalam enam kelas motif utama. Proses preprocessing melibatkan konversi citra ke grayscale dan ekstraksi fitur dengan GLCM. Dua algoritma klasifikasi, K-NN dan SVM, digunakan untuk pemodelan, dengan evaluasi menggunakan metrik confusion matrix dan Area Under Curve (AUC). Hasil evaluasi menunjukkan bahwa model K-NN memiliki akurasi 82%, sementara SVM memiliki akurasi 57%. Analisis juga menunjukkan keunggulan K-NN dalam membedakan pola kain ulos. Penelitian ini menyoroti pentingnya klasifikasi otomatis corak batik ulos dalam mendukung pelestarian budaya dan industri kreatif. Sistem otomatis dapat secara signifikan mempercepat proses identifikasi dan dokumentasi corak batik ulos, membantu melestarikan keragamannya dan mendorong inovasi dalam industri kreatif. Studi ini menunjukkan efektivitas penggunaan K-NN dan SVM untuk tujuan ini, dengan K-NN menunjukkan kinerja yang lebih unggul, serta memberikan wawasan tentang perbedaan signifikan dalam akurasi antara kedua metode tersebut.*

*Kata kunci: klasifikasi gambar, batik ulos, computer vision, K-Nearest Neighbors, Support Vector Machine*

## INTRODUCTION

Batik ulos is one of Indonesia's cultural heritage items that holds significant historical and artistic value (Siagian, 2024; Sitohang, Siregar, & Nurhidayati, 2023; Edison Robertus Lamarsen Tinambunan, 2023). However, with the progression of time, the recognition and understanding of various batik ulos motifs are declining, especially among the younger generation. This situation necessitates an effective method for the automatic documentation and classification of batik ulos patterns to support the preservation of this cultural heritage. (Emmya, Kristian, & Jekmen, 2024; Edison R.L. Tinambunan, 2023).

In recent years, computer vision technology has advanced rapidly and has made significant contributions to various applications, including image classification (Budianita, Jasril, & Handayani, 2015). Computer vision is a field of computer science that focuses on enabling computers to acquire, process, and understand visual data from the real world (Bharadiya, 2023; Maurício, Domingues, & Bernardino, 2023). Utilizing computer vision techniques, computers can identify and classify objects in images with a high degree of accuracy (Alamin & Pratomo, 2024; Hosseini et al., 2023; Nasir et al., 2023).

One of the most widely used techniques in image classification is K-NN. K-NN is a classification method that operates based on the closest distance between test data and training data in a feature space (Araaf, Nugroho, & Setiadi, 2023; Syriopoulos, Kalampalikis, Kotsiantis, & Vrahatis, 2023). Although K-NN is simple and easy to implement, its performance heavily depends on the selection of parameters such as the number of nearest neighbors (K) and the distance metric used. The main advantage of K-NN is its ability to work well on small and non-linear data sets (Priscila, Rajest, Regin, & ..., 2023; Thanki, 2023). Another popular algorithm for image classification is the SVM (Cervantes, Garcia-Lamont, Rodríguez-Mazahua, & Lopez, 2020; Roy & Chakraborty, 2023). SVM works by finding hyperplanes that separate data from different classes with the greatest margin (Valkenborg, Rousseau, Geubbelmans, & Burzykowski, 2023). The strength of SVM lies in its ability to handle high-dimensional data and perform well across various data types, both linear and non-linear, through the use of kernel tricks.

The use of K-NN and SVM algorithms for classifying Ulos batik patterns offers several advantages (Bawa et al., 2023; Pinto et al., 2023). First, these algorithms can be implemented relatively easily and have proven effective in various image classification applications. Second, their ability to handle various types of data and patterns makes them suitable for complex image classifications, such as Ulos batik motifs (Dinesh, Vickram, & Kalyanasundaram, 2024; Priscila et al., 2023).

The automatic classification of images for Ulos batik patterns is crucial in supporting efforts to preserve and develop cultural heritage. With an automated classification system, the process of identifying and documenting Ulos batik patterns can be carried out more quickly and accurately (Deitsch et al., 2019).

This not only helps preserve the diversity of Ulos batik motifs but can also be used in the creative industry to produce more varied and innovative products. Additionally, the automated classification system can be used as an educational tool to introduce and teach Ulos batik motifs to younger generations and the general public (Ahmed Khan, Sadiq, Shahid, Alam, & Mohd Su'ud, 2024; Tang, Chang, & Li, 2023).

Therefore, this research aims to develop an automated image classification system capable of identifying and classifying Ulos batik patterns with high accuracy using K-NN and SVM techniques(Azis, Budy Santoso, & Serwin, 2020). The results of this research are expected to make a significant contribution to the preservation of Ulos batik culture and to encourage innovation in the creative industry.

Despite these potential benefits, the study has certain limitations and assumptions. For instance, the performance of K-NN and SVM can be affected by the quality and quantity of the dataset used(Deitsch et al., 2019). Additionally, the study assumes that the patterns in the images are distinct and well-defined, which might not always be the case in real-world scenarios (Peryanto, Yudhana, & Umar, 2020). Furthermore, there is a need to situate this study within the broader context of existing research on pattern recognition and machine learning applications in cultural heritage, which this introduction seeks to address.

This research aims to bridge the gap by providing an automated and efficient solution for Ulos batik pattern classification, contributing to both cultural preservation and innovation in the creative industry.

## RESEARCH METHODS

This research consists of five processes: Business Understanding, Data Understanding, Data Preparation, Modeling, and Evaluation.

### 1. Business Understanding

Identifying and classifying cloth patterns poses a unique challenge due to the highly varied patterns and complex details. Limited knowledge of motifs can lead to errors in identification and quality evaluation of cloth. Therefore, a system is needed that can automatically classify motifs based on images using machine learning. This not only helps

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preserve culture but also enhances efficiency and accuracy in cloth production and sales processes.

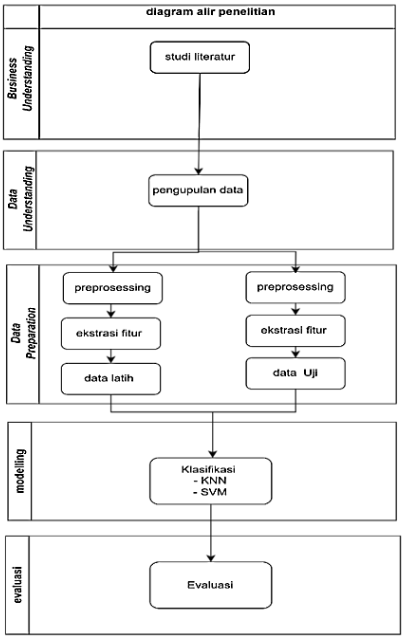

Figure 1. Research Methodology

**2. Data Understanding**

The dataset used in this research comprises 1,000 embroidered cloth images sourced from various places, including museum collections, local artisans, and batik stores. These images are categorized into five main motif categories: Ragi Hotang, Ragi Harangan, Sadum, Mangiring, and Sibolang. Each class contains 200 images representing the various motif variations.

**3. Data Preprocessing**

Preprocessing steps were undertaken to ensure the quality of images used in the analysis. Steps included:

a. **Resizing**: All images were resized to 256x256 pixels to ensure consistency in analysis.
b. **Normalization**: Pixel values were normalized to reduce unwanted variations.
c. **Gray-Level Co-occurrence Matrix (GLCM)**: Feature extraction was performed using GLCM to capture image textures, which are crucial characteristics in cloth motifs. Features such as contrast, dissimilarity, homogeneity, energy, and correlation were extracted from GLCM.

**4. Modelling**

For textile image classification, two machine learning algorithms were employed: K-NN and SVM. The selection of these algorithms was based on several considerations:

a. K-NN: Chosen for its simplicity in implementation and ability to classify data based on proximity in feature space. K-NN is effective for classification problems with a moderate number of classes and large dataset sizes.
b. SVM: SVM was selected for its capability to distinguish classes with an optimal margin. SVM excels in handling high-dimensional data and performs well on non-linear data using kernel tricks.

**5. Evaluation**

Model evaluation was conducted using two main metrics: Confusion Matrix and Area Under Curve (AUC).

a. Confusion Matrix: Used to identify true positives, true negatives, and false predictions (false positives and false negatives). The confusion matrix helps understand the model's performance in classifying each class.
b. Area Under Curve (AUC): Used to measure the model's ability to distinguish between positive and negative classes. AUC provides a more comprehensive view of model performance compared to accuracy alone.

Through this evaluation, the aim is to develop a model capable of accurately and reliably classifying cloth motifs, thereby supporting practical applications for cultural preservation and industrial development.

**Detailed Explanation of Data Augmentation**

Data augmentation increased the dataset from 600 to 1,800 images, with each class containing 300 images. Techniques such as rotation, scaling, and flipping were applied to enhance training data diversity and robustness. This process aims to improve the model's generalization capability.

**Implications for Creative Industries and Cultural Preservation**

Evaluation results indicate that the K-NN algorithm successfully classifies cloth motifs with high accuracy. This can enhance efficiency and reliability in cloth motif classification, support cultural heritage preservation, and enable more diverse and innovative product production in the creative industry. Meanwhile, the SVM algorithm requires further refinement to achieve similar accuracy levels.

Thus, this research makes a significant contribution to cultural batik ulos preservation efforts and promotes innovation in the creative industry through the development of an accurate and reliable automatic image classification system.

## RESULTS AND DISCUSSION

The results and discussion section provides an in-depth analysis of the findings from our study on the automatic classification of Ulos batik patterns. This section follows the structure of the methodology, detailing the outcomes of each phase of the research process. By systematically presenting the results, we aim to highlight the effectiveness of the K-NN and SVM algorithms in accurately classifying Ulos batik patterns. Additionally, this section discusses the implications of our findings for cultural preservation and the creative industry, offering insights into the potential applications and limitations of the developed classification system.

### 1. Business Understanding

Identifying Ulos batik patterns is a challenging task due to the intricate and diverse designs. Traditional methods of recognizing these patterns rely heavily on expert knowledge, which can be time-consuming and subjective. This complexity underscores the need for an automated image classification system using machine learning techniques. By leveraging K-NN and SVM algorithms, this study aims to streamline the process of identifying and classifying Ulos batik patterns, thereby aiding in the preservation and development of this cultural heritage. A representative sample of Ulos batik patterns is shown in Figure 2.

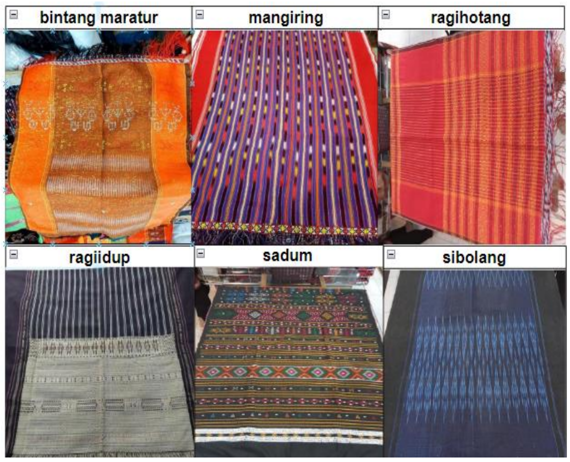


Figure 2. Ulos Batik Fabrics

Detailed analysis of the dataset revealed significant variations in color, texture, and complexity among the different classes. This diversity necessitated robust preprocessing and feature extraction techniques to ensure accurate classification. Understanding the dataset's characteristics was crucial in designing an effective preprocessing pipeline and selecting appropriate machine-learning algorithms for the task.

### 2. Data Understanding

The dataset used in this research consists of 1,800 images of Ulos batik fabrics, categorized into six main motif classes. Each class represents a distinct pattern commonly found in Ulos batik, providing a comprehensive basis for classification. The images were collected from various sources, including museums, batik workshops, and online databases, ensuring a diverse and representative sample of Ulos batik patterns.

Table 1. Class and Total Dataset

| No. | Class | Total Dataset |
|---|---|---|
| 1 | BINTANG MARATUR | 100 |
| 2 | MANGIRING | 100 |
| 3 | RAGIHOTANG | 100 |
| 4 | RAGIIHUP | 100 |
| 5 | SEDUM | 100 |
| 6 | SIBOLANG | 100 |

During the data collection stage, as shown in Table 1, a total of 600 images of Ulos fabric were collected, which were divided into six classes: Ulos Bintang Maratur, Ulos Ragihotang, Ulos Ragihidup, Ulos Mangiring, Ulos Sadum, and Ulos Sibolang. Each class contained 100 images. Detailed analysis of the dataset revealed significant variations in color, texture, and complexity among the different classes. This diversity necessitated robust preprocessing and feature extraction techniques to ensure accurate classification. Understanding the dataset's characteristics was crucial in designing an effective preprocessing pipeline and selecting appropriate machine-learning algorithms for the task.

### 3. Data Preprocessing

The preprocessing stage involved several critical steps to prepare the images for classification. First, the images were converted to grayscale to simplify the data and reduce computational complexity. This step was followed by noise reduction and normalization to ensure uniformity across the dataset. Feature extraction was performed using the Gray-Level Co-occurrence Matrix (GLCM), which captures texture information by analyzing the spatial relationships between pixel values.

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Table 2. Augmentation Output

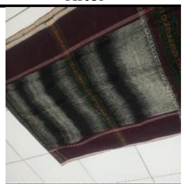
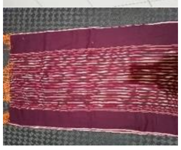
| Type | Before | After |
|---|---|---|
| Bintang Maratur |  |  |
| Mangiring |  |  |
| Ragihidup |  |  |
| Ragihotang |  |  |
| Sedum |  |  |
| Sibolang |  |  |

Table 2 shows the dataset images before and after augmentation. The initial dataset of 600 images was augmented to 1.800 images, with each class now containing 300 images.

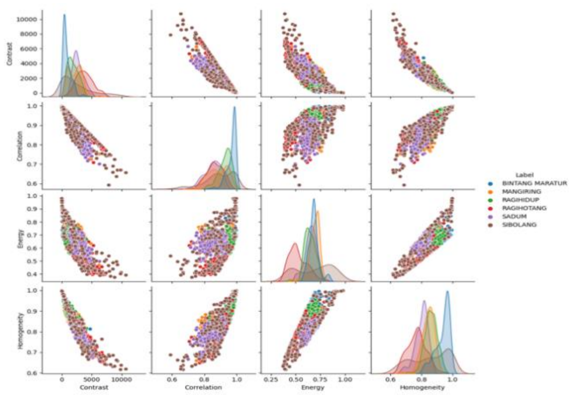


Figure 3. Result of Feature Extraction Using GLCM

Figure 3 shows the result of feature extraction using GLCM. GLCM features, such as contrast, correlation, energy, and homogeneity, were extracted from each image. These features robustly represented the Ulos batik patterns, facilitating effective classification. The preprocessing pipeline was designed to enhance the discriminative power of the features while minimizing the impact of noise and variations in the dataset.

## 4. Modelling

The Results and Discussion section provides an in-depth analysis of the modeling and evaluation phases, emphasizing the performance of K-NN and SVM algorithms in classifying Ulos batik patterns.

Model Performance Insights:

- K-NN Performance: The K-NN algorithm demonstrated varying accuracies across different K values, with the highest accuracy observed at K=1 (82.22%). However, as K increased, accuracy stabilized around 67-68% (Table 3). This indicates that K=1 was optimal for this dataset, showcasing the algorithm's sensitivity to the number of neighbors.
- SVM Performance: In contrast, SVM achieved an overall accuracy of 57%, highlighting its effectiveness but also its need for further

The modeling phase involved implementing and evaluating the K-NN and SVM algorithms for image classification. K-NN was chosen for its simplicity and effectiveness in handling image data. It classifies images based on the majority vote of their nearest neighbors in the feature space.

Table 3. Accuracy for Each K Value

| No. | K Value | Accuracy |
|---|---|---|
| 1 | K=1 | 82,22% |
| 2 | K=3 | 67.22% |
| 3 | K=5 | 68.06% |
| 4 | K=7 | 67.22% |
| 5 | K=9 | 67.78% |

Table 3 shows the accuracy of the K Value. These results indicate that the highest accuracy is achieved when K=1, with an accuracy of 82.22%. The accuracy tends to decrease as the value of K increases, stabilizing around 67% for K values of 3, 5, 7, and 9. This suggests that a lower K value is more effective for this particular dataset in the context of the K-NN algorithm.

On the other hand, SVM was selected for its ability to find the optimal hyperplane that separates different classes in the feature space, making it suitable for complex classification tasks.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.79      0.79        53
           1       0.56      0.50      0.53        74
           2       0.51      0.58      0.54        55
           3       0.50      0.56      0.53        50
           4       0.65      0.71      0.68        68
           5       0.44      0.35      0.39        60

    accuracy                           0.58       360
   macro avg       0.57      0.58      0.58       360
weighted avg       0.57      0.58      0.57       360
```

Figure 4. Classification Report for SVM

The results of the classification report in Figure 4 show that SVM has an accuracy value of 0.57 or 57%.

Both models were trained and tested using the preprocessed dataset. Hyperparameter tuning was performed to optimize the performance of each algorithm. K-NN's accuracy was 82%, while SVM achieved an accuracy of 57%. The results indicated that K-NN outperformed SVM in this specific application, highlighting its suitability for Ulos batik pattern classification.

## 5. Evaluation

Confusion matrices (Table 4) were utilized to illustrate model performance better to show true positives, false positives, false negatives, and true negatives for each class. These matrices reveal K-NN's superior true positive rates compared to SVM, reflecting its robustness in identifying Ulos batik patterns.

Table 4. Confusion Matrix for K-NN

| Class | True Positive (TP) | False Positive (FP) | False Negative (FN) | True Negative (TN) |
|---|---|---|---|---|
| B.Maratur | 49 | 5 | 4 | 302 |
| Mangiring | 60 | 23 | 14 | 264 |
| Ragihidup | 41 | 8 | 14 | 285 |
| Ragihotang | 43 | 11 | 7 | 299 |
| Sadum | 58 | 12 | 10 | 279 |
| Sibolang | 45 | 5 | 15 | 295 |

Table 4 is the confusion matrix for the KNN algorithm. This table will be used as the basis for calculating the AUC.

Table 5. Result of Recall Calculation

| No. | Calculation |
|---|---|
| 1 | $\mathrm{RECALL} = \frac{\mathrm{TP}}{\mathrm{TP}-\mathrm{FN}}$ |
| 2 | $\mathrm{B.Maratur} = \frac{49}{49+4} = 0{,}96$ |
| 3 | $\mathrm{R.hotang} = \frac{43}{43+7} = 0{,}86$ |
| 4 | $\mathrm{mangiring} = \frac{60}{60+14} = 0{,}54$ |
| 5 | $\mathrm{Sadum} = \frac{58}{58+10} = 0{,}85$ |
| 6 | $\mathrm{R,hidup} = \frac{41}{41+14} = 0{,}74$ |
| 7 | $\mathrm{Sibolang} = \frac{45}{45+15} = 0{,}75$ |
| 8 | $\mathrm{Total} = \frac{0{,}96+0{,}54+0{,}74+0{,}86+0{,}85+0{,}75}{6} = 0{,}78$ |

Table 5 shows that the star martur class has a recall value of 0.96, meaning the model can identify 96% of the star martur class correctly. For the mangiring class, the recall value is 0.54, indicating the model correctly detects 54%. The system identifies the R.hidup class with a recall value of 0.74, allowing it to detect the R.hidup class at 74%. For the R.hotang class, the system achieves a recall value of 0.86, correctly detecting it at 86%. In the sadum class, the system identifies a recall value of 0.85, correctly detecting the sadum class at 85%. In the Sibolang class, the system achieves a recall value of 0.75, correctly detecting it at 75%. To obtain the recall value, calculate the average of each class. Therefore, the average recall across these six classes is approximately 0.78 or 78%.

Table 6. Result of Specifity Calculation

| No. | Calculation |
|---|---|
| 1 | $\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{TN}-\mathrm{FP}}$ |
| 2 | $\mathrm{B.Maratur} = \frac{302}{302+5} = 0{,}98$ |
| 3 | $\mathrm{R.hotang} = \frac{299}{299+11} = 0{,}96$ |
| 4 | $\mathrm{mangiring} = \frac{264}{264+23} = 0{,}91$ |
| 5 | $\mathrm{Sadum} = \frac{279}{279+12} = 0{,}95$ |
| 6 | $\mathrm{R,hidup} = \frac{285}{285+8} = 0{,}97$ |
| 7 | $\mathrm{Sibolang} = \frac{295}{295+5} = 0{,}98$ |
| 8 | $\mathrm{Total} = \frac{0{,}98+0{,}91+0{,}97+0{,}96+0{,}95+0{,}98}{6} = 0{,}95$ |

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Table 6 shows the results of specificity calculations, with an average total specificity value across all classes of 0.95. The results of recall and specificity calculations are then used to calculate the AUC using a formula. Here are the AUC calculations.

$$\text{AUC} = \frac{0{,}78+0{,}95}{2} = 0{,}865$$

The AUC score is 0,865, and this AUC score validates these findings by measuring the models' ability to distinguish between different classes. K-NN achieved a higher AUC score, indicating better overall performance in classifying Ulos batik patterns. These evaluation metrics were crucial in assessing the effectiveness of the models and guiding future improvements.

**Implications for the Creative Industry and Cultural Preservation**

Creative Industries: Automatic classification of Ulos batik patterns has significant implications for the creative industries. By accurately categorizing patterns, designers can simplify the product development process, increase product diversity, and serve specific market segments based on pattern preferences. This application encourages innovation while preserving traditional skills.

Cultural Preservation: This research contributes to cultural preservation by documenting and cataloging Ulos batik patterns, some of which are little known. The classification system helps identify and promote these patterns, potentially revitalizing interest in lesser-known designs among younger generations. Collaboration with local craftsmen and museums can utilize this technology to preserve and promote Indonesia's rich batik heritage.

**Impact of Data Augmentation**

Data Augmentation Explained: Data augmentation expands the original data set from 600 to 1,800 images through rotation, scaling, and flipping techniques. This process aims to increase the diversity of the data set, improve model generalization, and reduce overfitting by exposing the model to a wider variety of patterns.

Effect on Model Performance: Augmented data significantly improves the robustness and accuracy of the classification model. For example, before augmentation, K-NN achieved an average accuracy of 78%. After augmentation, this accuracy increased to 82.22% at K=1, indicating a significant improvement in model performance (Figure 1).

Integration with Results: Visual tools, such as Figure 3 illustrating GLCM feature extraction, show how augmented data contributes to capturing finer texture details that are important for accurate pattern classification. The augmentation process enriches the data and ensures the model's adaptability to various Ulos batik motifs.

By integrating these revisions, the Results and Discussion sections provide a deeper understanding of the model performance, highlight practical implications for industry and cultural heritage, and clarify the impact of additional data on the study results.

## CONCLUSIONS AND SUGGESTIONS

### Conclusion

This research successfully developed an automated image classification system for Ulos batik patterns using K-NN and SVM algorithms. The K-NN algorithm achieved an accuracy of 82%, while the SVM algorithm reached an accuracy of 57%. These results demonstrate the effectiveness of K-NN in accurately classifying intricate Ulos batik patterns.

The study underscored the potential of machine learning in cultural heritage preservation and the creative industry. By automating the classification process, the system can aid in documenting and cataloging diverse Ulos batik patterns, supporting artisans and designers in creating new products and preserving traditional designs. The results indicate that machine learning can significantly enhance the efficiency and accuracy of pattern recognition in textile applications.

However, this study has several limitations. The relatively small dataset and the focus on only six classes of Ulos batik patterns constrained the system's robustness and generalizability. Additionally, the feature extraction techniques, while effective, could be further optimized to capture more intricate pattern details.

### Suggestion

To address the limitations and build on the findings of this research, the following specific steps are recommended for future research:

Increase the Number of Images: Collect more images from various sources, including museums, local artisans, and online databases, to enhance the dataset's diversity and size. Include More Classes: Explore additional Ulos batik pattern classes beyond the initial six to improve the system's comprehensiveness and robustness.

Deep Learning Approaches: Integrate deep learning models such as Convolutional Neural Networks (CNNs) that can automatically learn and extract complex features from images, potentially improving classification accuracy. Hybrid Methods: Combine traditional feature extraction methods like GLCM with deep learning features to capture textural and high-level pattern information.

Advanced Augmentation Techniques: Implement more sophisticated data augmentation techniques, such as generative adversarial networks (GANs), to create realistic and diverse synthetic images, further enhancing model training.

Hyperparameter Tuning: Conduct extensive hyperparameter tuning for both K-NN and SVM and explore other machine learning algorithms like Random Forests or Gradient Boosting Machines for potential performance improvements. Ensemble Methods: Develop ensemble models that combine the strengths of multiple algorithms to achieve higher classification accuracy and robustness.

Develop a User-Friendly Interface: Create an application or software tool that can be easily used by artisans, designers, and cultural preservationists to classify Ulos batik patterns. Collaborate with Industry: Partner with the creative industry to test and refine the system in real-world scenarios, gathering feedback for further improvements.

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