

A Multilevel Image Processing Approach for Minangkabau Ornament Detection Using CLAHE, Multi Threshold Otsu, and CNN

Suci Wahyuni¹, Yogi Wiyandra², Firna Yenila³
^{1,2,3} Universitas Putra Indonesia YPTK, Padang, Indonesia

Article Info

Article history:

Received Jan 24, 2026

Revised Feb 21, 2026

Accepted Mar 29, 2026

Keywords:

Minangkabau Ornaments

Image Processing

CLAHE

Multi-Threshold Otsu

Convolutional Neural
Network

ABSTRACT

Traditional Minangkabau ornaments such as pucuk rabuang, itiak pulang patang, kaluak paku, and rabuang sanjo represent a form of visual cultural heritage with high aesthetic and philosophical value. However, the digital documentation and preservation of these ornaments still face significant challenges, particularly due to variations in media, fine surface textures, uneven illumination, and complex image backgrounds. These conditions complicate the separation of ornament motifs from the background and consequently affect the accuracy of identification and classification processes. This study aims to develop an image processing approach for the detection and identification of Minangkabau ornaments through image quality enhancement and multi-level segmentation. The proposed method begins with a preprocessing stage that includes motif area cropping, image size normalization, noise reduction through filtering, contrast stretching, and Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance local contrast. Subsequently, segmentation is performed using the Multi-Threshold Otsu method to divide the image into multiple intensity classes, enabling a more detailed separation of ornament structures. The segmentation results are evaluated using morphological analysis and further tested using a Convolutional Neural Network (CNN) to assess classification performance. Experiments were conducted on a dataset of 1,024 images, with a training-testing split of 70% and 30%, respectively. The experimental results demonstrate that the proposed approach produces representative motif segmentation and achieves a classification accuracy of 99.67%. These findings indicate that the integration of systematic preprocessing, multi-threshold segmentation, and CNN-based classification is effective in supporting the digital preservation of Minangkabau ornaments.

This is an open access article under the [CC BY-SA](#) license.



Corresponding Author:

Suci Wahyuni,
Universitas Putra Indonesia YPTK Padang,
Lubuk Begalung, Padang, Indonesia
Email: suci_wahyuni@upiyptk.ac.id

1. INTRODUCTION

Traditional Minangkabau ornaments such as pucuk rabuang, itiak pulang patang, kaluak paku, and rabuang sanjo represent a form of visual heritage that carries cultural identity and high-value aesthetic knowledge [1]. In this study, these four ornament motifs represent the primary target categories for motif identification, which are determined through morphology-based similarity analysis after segmentation. The deep learning component is designed as a complementary validation stage rather than a direct multi-class motif classifier. These ornaments appear across multiple media, particularly Rumah Gadang wood carvings and songket textile motifs, meaning that their visual characteristics are strongly influenced by material properties, relief structures, micro-textures, surface reflections, and illumination conditions during acquisition [2]. Media variation, material aging, non-uniform lighting, and complex backgrounds make

consistent digital documentation difficult, even though technology-based preservation requires motifs to be separated from the background with high precision so that they can be detected, classified, digitally cleaned, and archived in a standardized manner [3].

Previous studies have reported important progress in detecting and classifying visual objects related to ornaments and cultural heritage. In surveillance contexts, a YOLOv7-based system has been developed to detect ornaments and devices in real time during CCTV-based exam check-in, emphasizing fast and accurate localization of target objects [4]. In the domain of traditional ornaments, another study classified Balinese architectural pepatran patterns using Learning Vector Quantization with Sobel edge features, thereby relying on edge-based representations as the primary pattern descriptor [5]. From a data availability perspective, a data article introduced OrnAsia, a dataset of 1088 Asian ornament images focusing on traditional jewelry for image classification and cultural identification, highlighting the importance of labeled datasets and diverse real-world conditions to support computer vision model development [6].

In architectural cultural heritage, research published in Heritage Science proposed detecting and recognizing porcelain inlay patterns in traditional Lingnan architectural decoration using YOLOv4, including data collection and annotation of cultural patterns and training detection models for multiple traditional pattern types [7]. Another study in Sensors addressed the challenge of detecting small and densely distributed elements in complex Thangka images and proposed an enhanced YOLO-based approach using frequency feature reinforcement as well as color and texture fusion to capture local details and global structure [8]. These five works indicate that machine learning-based detection and classification methods are rapidly advancing and effective across diverse domains. However, most contributions remain focused on object localization or classification, rather than the core requirement of traditional ornament preservation, which demands clean and stable motif separation from complex backgrounds under varying illumination and highly fine-grained textures. Furthermore, ornament images frequently contain repetitive or visually similar motif structures that may increase the risk of data redundancy. Therefore, dataset preparation and partitioning must carefully consider artifact-level separation to avoid near-duplicate samples between training and testing subsets, which may otherwise artificially inflate classification performance.

In the context of Minangkabau ornaments, a critical technical challenge is how to prepare images so that the motif is truly “lifted” from the background before segmentation and classification [9]. Therefore, this study treats preprocessing as a foundational component rather than a secondary step. The process begins with targeted acquisition and selection of ornament images, followed by Region of Interest extraction through cropping to make the motif dominant and reduce background interference. The images are then normalized in size using resizing with aspect ratio preservation to avoid geometric distortion and to ensure consistency for subsequent processing, including CNN input [10]. To improve visual quality, filtering is applied to reduce noise while preserving edges, followed by contrast stretching to expand the intensity range and strengthen light–dark differences [11]. Next, CLAHE is used to enhance local contrast adaptively and in a controlled manner, making subtle carving details and fine motif textures more visible without excessively amplifying noise, especially under non-uniform illumination or reflective surface conditions [12].

After preprocessing strengthens the image representation, this study applies segmentation using Multi Threshold Otsu. Unlike a single threshold that separates only two classes, multi-threshold segmentation partitions the image into multiple intensity classes, which is more suitable for ornament motifs that naturally contain layered brightness due to relief, shadows, and material reflectance variation [13]. The segmentation output is then evaluated through heuristic scoring based on shape and morphological features to estimate similarity across motif categories, and further tested using a Convolutional Neural Network on datasets split into training and testing subsets to assess classification generalization [14]. In this study, the CNN is implemented as a binary validation mechanism to confirm the presence of valid ornament structures and to filter out non-ornament or incorrectly segmented patterns before multi-class motif identification is finalized through morphological similarity scoring. This pipeline is designed so that segmentation outputs are not only visually satisfactory but also measurably improve data readiness for automated

detection and classification, while supporting digital preservation goals such as standardized archiving and the development of a searchable ornament database. Overall, the proposed approach contributes a hybrid hierarchical recognition framework that integrates controlled preprocessing, multi-level segmentation, morphology-based motif identification, and CNN-based ornament validation to improve robustness and reproducibility in traditional ornament analysis.

2. RESEARCH METHOD

This section describes the research methodology employed to develop and evaluate an image processing framework for the detection and identification of Minangkabau traditional ornaments. The proposed method is designed to address challenges related to complex backgrounds, fine surface textures, and non-uniform illumination commonly found in ornament images. The overall workflow consists of image acquisition, preprocessing, multi-level segmentation, feature-based evaluation, and deep learning-based classification. In this study, motif categorization into four ornament types is primarily determined through morphology-based similarity evaluation, while the deep learning component is implemented as a binary validation mechanism to confirm the presence of valid ornament structures. Each stage is structured to ensure that the resulting image representation is suitable for accurate motif separation and reliable classification, thereby supporting the objectives of digital ornament preservation.

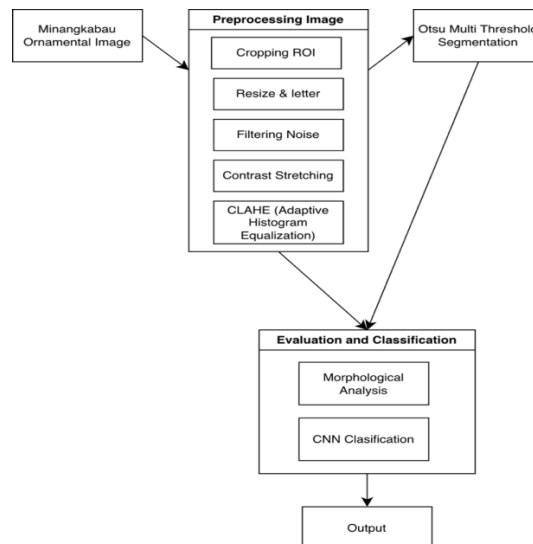


Figure 1. Research Methodology

2.1. Image Acquisition and Input Data

The initial stage of this study involves the acquisition of images of traditional Minangkabau ornaments used as the objects of analysis, including pucuak rabuang, itiak pulang patang, kaluak paku, and rabuang sanjo. The images were obtained through direct documentation of ornaments applied to various media, particularly wood carvings and textile motifs. During the acquisition process, variations in shooting angles, lighting conditions, and surface details of the ornaments were carefully considered. This stage aims to construct an image dataset that accurately represents real-world conditions, ensuring that the proposed method can be evaluated under realistic visual variations relevant to cultural heritage preservation [15]. The dataset consists of 1,024 images distributed across the four ornament motif categories. Each image was annotated using predefined visual identification guidelines, and the labeling process was cross-checked to reduce subjectivity. To reduce the risk of data leakage caused by repetitive ornament patterns, images originating from the same ornament artifact or object source were grouped prior to dataset partitioning, ensuring that visually similar samples were not simultaneously included in both training and testing subsets.

2.2. Preprocessing Image

Image preprocessing is conducted to enhance visual quality and reduce variability caused by differences in illumination, noise, and background complexity [16]. This stage begins with cropping to extract the Region of Interest (ROI), allowing the ornament motif to become the dominant visual element while minimizing background interference [17]. The cropped images are then resized to a uniform resolution using a letterbox padding technique to preserve the aspect ratio and prevent geometric distortion of the ornament shapes [18]. All images were normalized to a fixed input dimension of 224×224 pixels to ensure compatibility with CNN input requirements and consistent feature extraction across samples.

To further suppress visual disturbances, a filtering process is applied to reduce noise without removing the primary edges of the ornaments [19]. In this study, filtering was implemented using a Gaussian filter with a kernel size of 5×5 to suppress small disturbances while preserving motif edge information. Subsequently, contrast stretching is performed to expand the pixel intensity range, thereby enhancing the distinction between bright and dark regions [20]. The preprocessing stage is completed with the application of Contrast Limited Adaptive Histogram Equalization (CLAHE), which adaptively enhances local contrast in a controlled manner. CLAHE is particularly important for traditional ornament images, as it effectively highlights fine carving details and texture patterns without excessively amplifying noise, especially in images with uneven illumination [21]. The CLAHE process was configured using a clip limit of 2.0 and a tile grid size of 8×8 , selected empirically to balance contrast enhancement and noise control.

2.3. Segmentation Using Multi-Threshold Otsu

Following image enhancement, segmentation is performed using the Multi-Threshold Otsu method. Unlike binary Otsu thresholding, which divides an image into only two intensity classes, the multi-threshold approach automatically separates the image into multiple intensity classes based on histogram distribution [22]. This method is more suitable for Minangkabau ornaments, which exhibit complex visual structures characterized by intensity variations among the background, shadows, primary motifs, and bright regions resulting from relief and material reflectance. The segmentation process produces a more detailed and representative separation of regions, making the results suitable for subsequent analysis. In this implementation, the segmentation process was configured using 3 threshold levels to produce four intensity classes, enabling separation of background regions, shadow layers, primary ornament structures, and reflective components.

2.4. Morphological Analysis-Based Evaluation

The segmented images are then evaluated through morphological analysis to assess the shape characteristics of the ornament motifs. At this stage, morphological features such as area, perimeter, shape ratio, and contour characteristics relevant to the distinctive properties of each ornament type are extracted. These features are used to compute similarity scores between the test images and reference ornament patterns [23]. This approach provides an initial geometry-based interpretation, enabling the system to identify the most closely matching ornament motif based on its visual form. This morphology-based evaluation serves as the primary multi-class motif identification stage by assigning similarity scores to the four ornament categories and selecting the motif label with the highest similarity score.

2.5. Classification Using Convolutional Neural Network

In addition to morphology-based evaluation, this study performs classification testing using a Convolutional Neural Network (CNN) to assess performance from a deep learning perspective [24]. In this study, the CNN is implemented as a binary validation mechanism to distinguish valid ornament structures (positive class) from non-ornament or incorrectly segmented patterns (negative class), thereby reducing segmentation noise before final motif identification is derived from morphological similarity scoring. The processed dataset is divided into training and testing subsets and used to train the CNN model to automatically recognize ornament patterns. Evaluation is conducted on unseen test data to measure the model's generalization capability. Classification

performance is assessed using metrics such as accuracy, allowing direct comparison with the results obtained from morphological analysis. To improve reproducibility, the CNN configuration includes architecture specifications such as convolutional layers, filter sizes, pooling operations, and dense layers, as well as training settings including optimizer selection, learning rate, batch size, number of epochs, and regularization strategies such as early stopping and data augmentation where applicable.

2.6. Ornament Identification Output

The final stage of the study produces an output in the form of identified Minangkabau ornament types based on the input images. The identification results are derived from the combined outcomes of multi-threshold segmentation, morphological analysis, and CNN-based classification. The CNN validation stage ensures that only structurally valid ornament segments proceed to motif categorization, thereby improving identification reliability. This output not only indicates the detected ornament category but also reflects the readiness of the proposed method to support digital cultural heritage preservation, including ornament archiving, visual database development, and the creation of interactive educational materials.

3. RESULTS AND DISCUSSION

This section presents and discusses the results obtained from the implementation of the proposed image processing and classification framework for Minangkabau ornament identification. The discussion focuses on evaluating the effectiveness of each processing stage, including image preprocessing, multi-threshold segmentation, morphological analysis, and convolutional neural network-based classification. Experimental results are analyzed to assess how the proposed approach improves the separation of ornament motifs from complex backgrounds and enhances the reliability of the identification process. The findings are further interpreted in relation to the characteristics of traditional Minangkabau ornaments, particularly their complex textures, relief structures, and sensitivity to illumination variations. In this study, motif categorization into four ornament types is primarily determined through morphology-based similarity evaluation, while CNN classification is employed as a binary validation stage to confirm the presence of valid ornament structures. Through this analysis, the section highlights the contribution of the proposed method to accurate ornament detection and its potential application in digital cultural heritage preservation.

3.1. Image Preprocessing Result

The preprocessing stage begins with Minangkabau ornament images that still exhibit repetitive patterns and complex visual backgrounds. Under these conditions, the main motif information is not yet well isolated, making it necessary to apply a cropping process to define the analysis region and reduce background interference.



Figure 2. Original Minangkabau Ornament Image

This figure represents the original image prior to any processing, displaying ornament patterns with repetitive compositions and accompanying background elements. Visually, the main motif is not yet isolated, as multiple curved primary forms are arranged sequentially within a single image plane, accompanied by dotted background textures and decorative lines in the upper and

lower regions. This condition reflects a realistic challenge in ornament documentation, where information relevant for motif identification is mixed with irrelevant elements such as repeated patterns, other ornaments, and background structures. As a result, if this image were directly used for feature extraction or model training, the system would tend to learn background patterns or repetitive elements rather than the target motif, thereby increasing the risk of segmentation errors and reducing classification accuracy. Additionally, repetitive ornament structures may introduce near-duplicate visual patterns, which further emphasize the importance of controlled region extraction during preprocessing.

The subsequent step involves cropping to extract a Region of Interest focused on a single primary motif.



Figure 3. Cropped Image Result

This figure illustrates the result of the cropping process, which focuses the analysis area on a single primary motif along with its curved edges and internal filling details. Methodologically, cropping aims to increase the ratio of motif information relative to the background, ensuring that shape, texture, and intensity features computed in subsequent stages originate primarily from the ornament to be identified. In the cropped image, interference from surrounding repetitive patterns is reduced, contour edges become easier to trace, and the motif region appears more dominant. This condition is critical, as the success of segmentation and morphological analysis strongly depends on how cleanly the motif region is separated from irrelevant background elements.

The cropped image is then normalized in size using a resize process with aspect ratio preservation.



Gambar 4. Resized Image Result

This figure shows the image after size normalization into a uniform working dimension. The resize process is performed while preserving the aspect ratio to prevent geometric distortion of the motif, followed by padding on the remaining sides to ensure consistent final dimensions. This size normalization stabilizes computational processing and allows subsequent analysis parameters to operate on a comparable scale across all samples. At this stage, motif details remain well preserved, while the image dimensions become suitable for further processing such as contrast

enhancement, segmentation, and use as input for CNN-based models that require fixed input sizes. The use of standardized input dimensions also supports stable CNN training and improves consistency in feature extraction.

3.2. Filtering and Contrast Enhancement Results

The resized image is subsequently converted into a grayscale representation and processed using filtering techniques to reduce noise.



Figure 5. Grayscale Image

Figure 5 shows the result of converting the color image into a single-channel intensity image. Grayscale conversion is performed to simplify data representation, allowing the analysis to focus on intensity structures, edges, and textures without being influenced by color variations. At this stage, the ornament motif begins to appear as variations of light and dark intensities; however, coarse textures, sharp intensity differences in certain regions, and fine noise are still present, which may interfere with accurate threshold determination during segmentation. The grayscale image serves as an essential foundation for subsequent processing stages, including filtering, contrast stretching, CLAHE, and Otsu thresholding, as all these methods rely on the distribution of pixel intensity values.



Figure 6. Filtered Image

Figure 6 illustrates the image after filtering has been applied to the grayscale image. The primary purpose of filtering is to reduce noise or small disturbances caused by surface material textures, camera sensor artifacts, or lighting irregularities, while preserving the main shape of the ornament motif. In the filtered result, intensity variations appear smoother and cleaner compared to the grayscale image, while major contours and structural elements of the motif remain intact. This effect is critical because threshold-based segmentation is highly sensitive to noise; the presence of noise can generate small spots or holes that may be misinterpreted as separate regions, resulting in irregular segmentation masks and complicating morphological feature extraction. The application of Gaussian filtering effectively suppresses local disturbances while maintaining essential ornament edge structures required for accurate segmentation.

To further enhance the visibility of motif structures, contrast stretching is applied. Contrast stretching is an image processing technique used to improve visual quality by expanding the range of pixel intensity values. Its primary objective is to emphasize the differences between bright and dark regions, enabling previously indistinct motif details to become more prominent. Images with low contrast typically exhibit pixel intensity values concentrated within a narrow range, for example between 100 and 150 on a scale of 0–255, which causes the image to appear dull or grayish. Through contrast stretching, this intensity range is expanded toward the full range of 0–255, resulting in a sharper image with more distinguishable motif details and improved readiness for subsequent segmentation stages. The pseudocode for the contrast stretching process used in this study is presented below.

Pseudocode contrast stretching

```

INPUT : I ← grayscale image of size M × N
OUTPUT : O ← contrast-enhanced image

1. r_min ← minimum intensity value in I
2. r_max ← maximum intensity value in I
3. L_min ← 0
4. L_max ← 255

5. For i ← 1 to M do
6.   For j ← 1 to N do
7.     O(i, j) ← ((I(i, j) - r_min) / (r_max - r_min))
      × (L_max - L_min) + L_min
8.   End For
9. End For
10. Return O
  
```

The contrast stretching pseudocode enhances image quality by expanding the range of pixel intensity values. First, the minimum and maximum intensity values in the grayscale image are identified. These values are then linearly mapped to a wider target range, typically 0 to 255. By applying this transformation to each pixel, the differences between dark and bright regions become more pronounced, allowing fine structural details of the motif to appear more clearly and improving the image's suitability for subsequent segmentation and classification stages.



Figure 7. Contrast Stretching Result

Figure 7 presents the result of global contrast enhancement using contrast stretching. In many ornament images, the initial intensity range is often confined to a narrow interval, causing the image to appear pale or lacking definition. Contrast stretching expands the intensity range toward a wider scale, making the differences between dark and bright regions more pronounced. In this result, the boundary between the motif and the background becomes clearer, and the main structural elements of the motif are more easily distinguishable. However, because this technique operates globally, certain regions affected by uneven illumination may still appear less detailed. Therefore, further local contrast enhancement is required. The contrast enhancement stage is continued by applying CLAHE.



Figure 8. CLAHE Result

Figure 8 shows the result of applying CLAHE, which enhances contrast locally across different regions of the image. Unlike contrast stretching, CLAHE operates on small image blocks, enabling it to highlight fine details that were previously obscured in darker or shadowed areas. In ornament images, the effect of CLAHE is evident in the increased sharpness of internal motif details and the clearer definition of texture variations along curved structures and inner motif regions. The use of a contrast limit (clip limit) ensures that the enhancement remains controlled and does not introduce excessive noise. This result is particularly important as a preparation step for multi-threshold segmentation, since intensity class separation becomes more stable when motif details are evenly enhanced across the entire image.

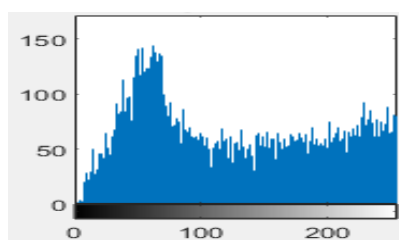


Figure 9. Intensity Histogram After CLAHE

Figure 9 illustrates the pixel intensity distribution after CLAHE has been applied. The histogram shows a more evenly distributed intensity range compared to images prior to local enhancement, where pixel values tend to cluster within limited intensity intervals. This broader histogram distribution indicates increased contrast and clearer intensity variation between background regions, shadows, and motif structures. From a segmentation perspective, such a histogram condition is advantageous because Otsu-based methods can more easily determine optimal thresholds that maximize inter-class variance, particularly in multi-threshold segmentation approaches.

3.3. Multi-Threshold Otsu Segmentation Results

The preprocessed images are subsequently segmented using the Multi-Threshold Otsu method.

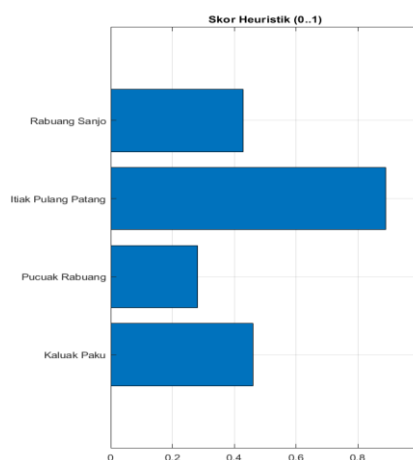


Figure 10. Multi-Threshold Otsu Segmentation Result

Figure 10 presents the segmentation results obtained using the Multi-Threshold Otsu method, which partitions the image into multiple intensity classes. Different colors represent pixel groups with distinct brightness levels, such as background regions, shadowed areas, the main ornament motif, and brighter motif components. These results demonstrate that the ornament structure can be separated in greater detail compared to binary Otsu segmentation, as ornament motifs typically consist of more than a single intensity level. Multi-class segmentation is particularly relevant for carved or textured ornaments, where relief depth and light reflection generate layered intensity patterns that must be preserved to prevent motif structures from being lost or merged with the background. The use of three threshold levels produces four intensity classes, enabling clearer separation between structural ornament layers and background regions.

3.4. Evaluation Results Based on Morphological Analysis

The segmentation results are used as input for morphological analysis and heuristic assessment.



Ornamen Figure 11. Heuristic Score Graph for Ornament Identification

Figure 11 presents heuristic scores ranging from 0 to 1 for several ornament motif categories, namely Kaluak Paku, Pucuak Rabuang, Itiak Pulang Patang, and Rabuang Sanjo. The scores reflect the degree of shape similarity between the segmentation results and reference ornament patterns based on morphological features such as circularity, eccentricity, solidity, as well as skeleton-based characteristics including the number of endpoints. The Itiak Pulang Patang motif achieves the highest score, approaching 0.9, indicating that the segmented shape is most consistent with the defining characteristics of this motif, such as its elongated form with distinctive curved structures. The variation in scores across categories demonstrates that morphological features are capable of capturing relevant shape discriminators, while also indicating that the segmentation quality is sufficient to support reliable shape-based ornament identification.

3.4. CNN Classification Results

Classification testing was conducted using a Convolutional Neural Network (CNN) on a total of 1,024 ornament images. In this study, CNN is implemented as a binary validation stage to distinguish valid ornament structures from non-ornament or incorrectly segmented patterns.

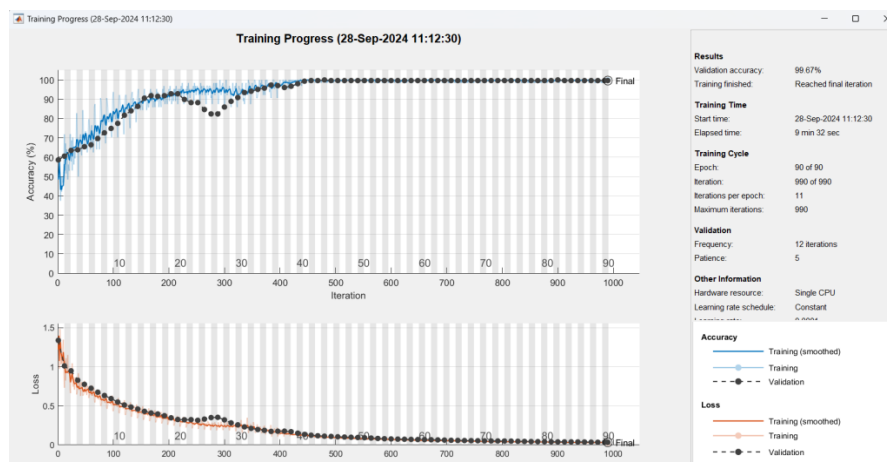


Figure 12. CNN Training Progress Graph

Figure 12 illustrates the CNN training progress on the ornament dataset. The training curve typically shows an increasing accuracy trend and a decreasing loss trend across epochs, indicating that the model progressively learns the visual feature patterns from the training data. Stable convergence suggests that the input images, which have undergone preprocessing and segmentation, provide a strong and consistent representation, thereby preventing sharp fluctuations during learning. Methodologically, this graph serves as evidence that the preprocessing–segmentation pipeline produces consistent training data and helps reduce disturbances that may trigger overfitting or training instability.

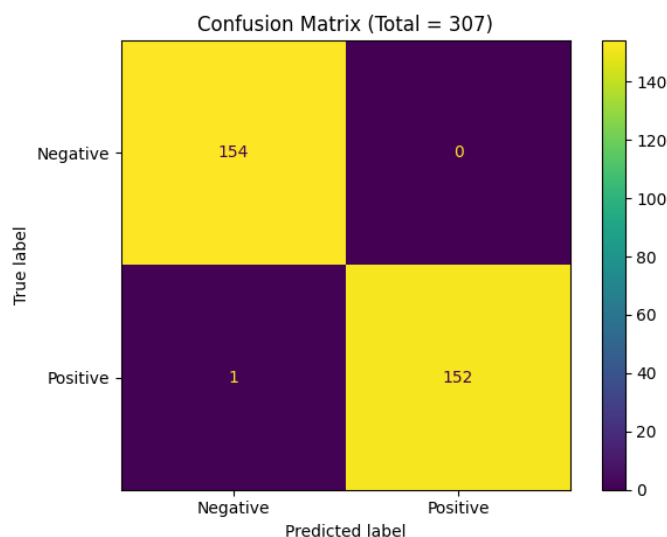


Figure 13. Confusion Matrix

A confusion matrix is a performance evaluation tool for classification models that compares actual labels with predicted labels. It reports the number of correctly and incorrectly classified samples within each category, providing a clear view of the model's error patterns. In Figure 13, the True Negative value (154) indicates the number of negative samples correctly classified, while the True Positive value (152) represents the number of positive samples correctly predicted. In this context, negative samples represent non-ornament or invalid segmented patterns, while positive samples correspond to valid ornament structures used for further motif identification. No False Positives are observed, meaning that all positive predictions match the ground truth. A single misclassification appears as a False Negative, where one positive sample is predicted as negative. This pattern indicates excellent class separability with only minimal classification errors.

	precision	recall	f1-score	support
Negative	0.9935	1.0000	0.9968	154
Positive	1.0000	0.9935	0.9967	153
accuracy			0.9967	307
macro avg	0.9968	0.9967	0.9967	307
weighted avg	0.9968	0.9967	0.9967	307

Figure 14. Classification Report

The classification report summarizes key evaluation metrics, including precision, recall, F1-score, and support for each class. Precision measures how accurate the model is when predicting the positive class, recall indicates how effectively the model identifies all true positive samples, and the F1-score is the harmonic mean of precision and recall, reflecting their balance. As shown in Figure 14, precision, recall, and F1-score for both classes remain at very high levels, and the overall accuracy reaches 99.67%. These results demonstrate that the model is not only highly accurate overall but also consistently classifies each class reliably, supporting its suitability for the ornament identification task in this study. The high validation accuracy further strengthens the reliability of the hybrid recognition pipeline by ensuring that only structurally valid ornament objects proceed to morphology-based motif classification.

4. CONCLUSION

This study successfully developed a structured image processing pipeline to support the detection and identification of traditional Minangkabau ornaments through image quality enhancement and multi-level segmentation. The results demonstrate that a disciplined preprocessing stage, including motif area cropping, image size normalization, filtering, contrast stretching, and the application of Contrast Limited Adaptive Histogram Equalization (CLAHE), significantly improves the readability of ornament structures, particularly in images affected by uneven illumination, reflective surfaces, and complex fine textures.

The application of Multi-Threshold Otsu segmentation proves to be more adaptive than binary thresholding in separating ornament images into multiple intensity classes representing background regions, shadows, primary motifs, and bright components. This approach preserves internal motif structures and achieves better isolation, resulting in segmentation outputs that are more representative for subsequent shape-based analysis and deep learning applications. In this implementation, three threshold levels were used to produce four intensity classes, enabling layered separation that aligns with the visual characteristics of relief-based ornaments. Morphological analysis further confirms that the shape features extracted from the segmentation results are capable of distinguishing ornament categories with consistent similarity to reference patterns. Accordingly, multi-class identification of the four target motifs (pucuak rabuang, itiak pulang patang, kaluak paku, and rabuang sanjo) is primarily achieved through morphology-based similarity scoring.

Classification experiments using a Convolutional Neural Network on the processed ornament dataset yield very high performance, achieving an accuracy of 99.67% with precision and recall values approaching perfection. To avoid ambiguity, the CNN component in this study is implemented as a binary validation stage that distinguishes valid ornament structures from non-ornament or invalid segmented patterns prior to final motif categorization. These findings confirm that preprocessing and segmentation quality directly influence model learning effectiveness and demonstrate that images prepared through multi-level segmentation provide more informative and stable visual representations for classification tasks. This validation stage strengthens the overall pipeline by reducing the propagation of segmentation artifacts into the multi-class motif identification process.

Overall, this study contributes a methodological end-to-end pipeline that positions image quality enhancement and multi-threshold segmentation as foundational components in traditional ornament identification. More specifically, the proposed method represents a hybrid hierarchical recognition framework that integrates controlled preprocessing, multi-level segmentation, morphology-based multi-class motif identification, and CNN-based binary ornament validation to

improve reliability and reproducibility. The proposed approach is not only technically effective but also highly relevant for supporting technology-based cultural preservation initiatives, including the development of standardized Minangkabau ornament databases, searchable visual archives, and the creation of objective and reproducible educational and conservation materials. Despite the strong results, this study acknowledges that further robustness evaluation (e.g., repeated runs with different random seeds and k-fold cross-validation) and broader dataset diversity would further strengthen generalization claims. Future work may extend this approach by expanding dataset diversity, integrating deep learning-based segmentation methods, and applying the framework to a broader range of Indonesian cultural ornaments.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to Universitas Putra Indonesia YPTK Padang for the academic support, facilities, and research environment provided, which enabled the successful completion of this study.

REFERENCES

- [1] Nofriah, P. Prihatin, and M. A. Laksono, "Ukiran Ornamen Tradisional Minangkabau pada Dekorasi Pelaminan," *Naskah Diterima Naskah Final Naskah Publish Corak: Jurnal Seni Kriya*, vol. 10, no. 2, pp. 153–168, Nov. 2021, doi: 10.24821/corak.v10i2.4581.
- [2] T. Akbar, I. Desra, N. Rahmanita, D. Yanuarmi, and I. Qomarats, "Representasi Nilai Multikultural dalam Desain Ornamen Songket 'Kambang Cino' Koto Gadang," *ANDHARUPA: Jurnal Desain Komunikasi Visual & Multimedia*, vol. 9, no. 3, pp. 326–342, Sep. 2023, doi: 10.33633/andharupa.v9i03.6996.
- [3] A. Bentkowska-Kafel and L. MacDonald, *Digital techniques For Documenting and preseving Cultural Heritage*. Arc Humanities Press, 2017.
- [4] P. S. Krishnapriya, G. Nikitha, K. V. U. Kiran, K. Aparna, and S. C. Priya, "A Deep Learning-based Smart System for Ornaments and Devices Detection during Check-In of Entrance Exams," in *Procedia Computer Science*, 2024, vol. 233, pp. 464–473. doi: 10.1016/j.procs.2024.03.236.
- [5] I. G. A. G. A. Kadyanan, N. Gunantara, I. B. G. Manuaba, K. O. Saputra, and W. F. Mahmudy, "Classification of Ornament or Papatran in Balinese Traditional Architecture Pattern Using Learning Vector Quantization Algorithm," in *ACM International Conference Proceeding Series*, Apr. 2024, pp. 90–96. doi: 10.1145/3669754.3669768.
- [6] Y. Li, M. Zhao, J. Mao, Y. Chen, L. Zheng, and L. Yan, "Detection and recognition of Chinese porcelain inlay images of traditional Lingnan architectural decoration based on YOLOv4 technology," *Herit Sci*, vol. 12, no. 1, pp. 1–41, Dec. 2024, doi: 10.1186/s40494-024-01227-z.
- [7] M. D. Nayeem, S. Z. Sraboni, S. S. Biswas, and M. M. Islam, "OrnAsia: A dataset of asian ornaments for image classification and cultural identification," *Data Brief*, vol. 63, pp. 1–6, Dec. 2025, doi: 10.1016/j.dib.2025.112195.
- [8] Y. Xian, Y. Lee, T. Shen, P. Lan, Q. Zhao, and L. Yan, "Enhanced Object Detection in Thangka Images Using Gabor, Wavelet, and Color Feature Fusion," *Sensors*, vol. 25, no. 11, pp. 1–22, Jun. 2025, doi: 10.3390/s25113565.
- [9] A. L. Sari and A. A. Yusuf, "Cultural Navigation and Multiple Roles: Study of Adaptation of Minangkabau People in Overseas Land in the Perspective of the Proverb 'Nan Sakuduang Jadi Saruik, Nan Salapeh Jadi Kambang,'" *INFLUENCE: International Journal of Science Review*, vol. 5, no. 2, pp. 419–425, 2023, doi: 10.54783/influencejournal.v5i2.170.
- [10] C. C. Andrianos *et al.*, "Development of a Fully Optimized Convolutional Neural Network for Astrocytoma Classification in MRI Using Explainable Artificial Intelligence," *J Imaging*, vol. 11, no. 10, pp. 1–22, Oct. 2025, doi: 10.3390/jimaging11100343.
- [11] D. I. Mulyana and M. A. A. Abyan, "Image Quality Improvement for Sign Language Gestures Through Gaussian Filter and Contrast Stretching Techniques," *International*

- Journal Software Engineering and Computer Science (IJSECS)*, vol. 5, no. 3, pp. 1029–1044, Dec. 2025, doi: 10.35870/ijsecs.v5i3.5254.
- [12] F. Noor, Muhathir, Fadliansyah, and D. Syahputra, “Analysis of Combined Contrast Limited Adaptive Histogram Equalization (CLAHE) and Median Filter Methods for Enhancement of CCTV Screenshot Image Quality,” *JITE (Journal of Informatics and Telecommunication Engineering)*, vol. 8, no. 2, pp. 335–345, Jan. 2025, doi: 10.31289/jite.v8i2.14016.
 - [13] Y. Guo, Y. Wang, K. Meng, and Z. Zhu, “Otsu Multi-Threshold Image Segmentation Based on Adaptive Double-Mutation Differential Evolution,” *Biomimetics*, vol. 8, no. 5, pp. 1–22, Sep. 2023, doi: 10.3390/biomimetics8050418.
 - [14] R. Lu *et al.*, “Strategic sampling for training a semantic segmentation model in operational mapping: Case studies on cropland parcel extraction,” *Remote Sens Environ*, vol. 331, pp. 1–17, Dec. 2025, doi: 10.1016/j.rse.2025.115034.
 - [15] M. Abu Talib, I. Ibrahim, and M. Anwer Abusirdaneh, “Reusability and benchmarking potential of architectural cultural heritage datasets for generative AI: An analytical study,” *Expert Syst Appl*, vol. 309, pp. 1–21, May 2026, doi: 10.1016/j.eswa.2025.130916.
 - [16] H. Yenni, R. Muzawi, M. Khairul Anam, M. Kasaf, T. Rizqi Maysyarah Hadi, and D. Sari Wahyuni, “MYCD: Integration of YOLO-CNN and DenseNet for Real-Time Road Damage Detection Based on Field Images,” *Journal of Applied Data Sciences*, vol. 7, no. 1, pp. 384–395, 2026, doi: 10.47738/jads.v7i1.1040.
 - [17] H. G. Jeon and K. H. Lee, “Region-of-Interest Extraction Method to Increase Object-Detection Performance in Remote Monitoring System,” *Applied Sciences (Switzerland)*, vol. 15, no. 10, pp. 1–18, May 2025, doi: 10.3390/app15105328.
 - [18] D. Li, J. Zhang, and K. Huang, “Learning to Learn Cropping Models for Different Aspect Ratio Requirements,” in *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 12685–12694. doi: 10.1109/CVPR42600.2020.01270.
 - [19] M. Tsaqofah, L. S. Harahap, and D. S. Hasibuan, “Optimization of Digital Image Processing Through Gaussian Filtering for Noise Reduction,” *Journal of Artificial Intelligence and Engineering Applications*, vol. 4, no. 3, pp. 2808–4519, 2025, doi: 10.59934/jaiea.v4i3.1120.
 - [20] B. A. Rivera-Aguilar, E. Cuevas, A. Luque-Chang, J. López, and M. Pérez-Cisneros, “Pixel Interaction Model for Contrast Enhancement: Bridging Social Science and Image Processing,” *Applied Sciences (Switzerland)*, vol. 14, no. 23, pp. 1–20, Dec. 2024, doi: 10.3390/app142310887.
 - [21] M. S. Z. Ahmad, N. A. A. Aziz, H. S. Lim, A. K. Ghazali, and ‘Afif Abdul Latiff, “Impact of Image Enhancement Using Contrast-Limited Adaptive Histogram Equalization (CLAHE), Anisotropic Diffusion, and Histogram Equalization on Spine X-Ray Segmentation with U-Net, Mask R-CNN, and Transfer Learning,” *Algorithms*, vol. 18, no. 12, pp. 1–22, Dec. 2025, doi: 10.3390/a18120796.
 - [22] J. Zheng, Y. Gao, H. Zhang, Y. Lei, and J. Zhang, “OTSU Multi-Threshold Image Segmentation Based on Improved Particle Swarm Algorithm,” *Applied Sciences (Switzerland)*, vol. 12, no. 1, pp. 1–22, Nov. 2022, doi: 10.3390/app122211514.
 - [23] D. Yokokawa, K. Shikino, Y. Nishizaki, S. Fukui, and Y. Tokuda, “Evaluation of a Computer-Based Morphological Analysis Method for Free-Text Responses in the General Medicine In-Training Examination: Algorithm Validation Study,” *JMIR Med Educ*, vol. 10, no. 1, pp. 1–11, 2024, doi: 10.2196/52068.
 - [24] M. K. Anam, S. Sumijan, K. Karfindo, and M. B. Firdaus, “Comparison Analysis of HSV Method, CNN Algorithm, and SVM Algorithm in Detecting the Ripeness of Mangosteen Fruit Images,” *Indonesian Journal of Artificial Intelligence and Data Mining*, vol. 7, no. 2, pp. 348–356, May 2024, doi: 10.24014/ijaidm.v7i2.29739.