Journal of Applied Informatics and Computing (JAIC)
Vol.10, No.1, February 2026, pp. 462~467
e-ISSN: 2548-6861

Identification and Classification of Cracks in Traditional Pottery from West Sumatra Using Digital Image Processing

Raja Ayu Mahessya [1]*, Firna Yenila [2]**
* Teknik Informatika, Universitas Putra Indonesia YPTK Padang
** Sistem Informasi, Universitas Putra Indonesia YPTK Padang
ayumahessya@upiyptk.ac.id [1], firnayenila@upiyptk.ac.id [2]

Article Info

Article history:

Received 2026-01-02
Revised 2026-01-29
Accepted 2026-02-03

Keyword:

Cultural Heritage,
Digital Image Processing,
Image Segmentation,
Morphological Operation,
Pottery Crack Detection.

ABSTRACT

Cracks in traditional West Sumatran pottery are a major challenge in preserving this cultural heritage. With age and the manual manufacturing process, pottery becomes highly susceptible to physical damage, particularly cracks on the surface and internal structure. These cracks not only affect the functional and aesthetic value but also reduce the cultural and economic value of the pottery. Therefore, an accurate early identification system is crucial to ensure the survival and preservation of this culture. This study developed a digital image processing-based system to detect and classify cracks in traditional pottery. The system integrates image preprocessing, including cropping, resizing, grayscale conversion, contrast stretching, and histogram equalization to improve image quality and highlight thin and irregular cracks. Image segmentation was performed using the Multi-Threshold Otsu method to separate cracks from the background, while classification was performed using a convolutional neural network (CNN). Experimental results show that this system is able to achieve an accuracy of 94.8%, precision of 93.5%, recall of 92.3%, and F1-score of 92.9%, indicating the system's ability to accurately detect cracks. Comparisons with other segmentation and classification methods are needed to provide a more comprehensive picture of the effectiveness of this approach. The implementation of this system is expected to support the preservation of traditional Minangkabau pottery through digitalization, provide an ornament database that can be accessed by researchers, artists, and the general public, and assist in more efficient cultural documentation and archiving.

I. Introduction

Traditional West Sumatran pottery holds high historical, aesthetic, and economic value, and serves as a symbol of local cultural identity passed down through generations. As a cultural product, pottery is used both as a household item and as a representation of local wisdom. With age and the manual production process, which requires specific techniques, pottery is highly susceptible to physical damage, particularly cracks in its surface and internal structure [1]. These cracks can reduce the functional, aesthetic, and economic value of pottery. Early identification of cracks is crucial for the continuity and preservation of this culture. Digital image processing technology offers an efficient and non-destructive solution for detecting cracks in pottery, using techniques such as image segmentation and feature exploration to detect very fine and irregular cracks [2]. In this study, a digital image processing-based system was developed to detect and classify cracks in traditional West Sumatran pottery using the Multi-Threshold Otsu method and Convolutional Neural Network (CNN) [3]. Cracks in pottery can be caused by various factors, including natural factors such as age, weather, and manual manufacturing processes that require specific techniques. When pottery experiences cracks, whether small or large, this not only affects its functionality but also reduces its aesthetic value. These cracks can decrease its economic and historical value, as cracked pottery is often considered less valuable, even if the damage is not visually detectable [4].

Cracks in pottery can have very fine and irregular patterns, often resembling the natural texture of the pottery's surface. This phenomenon makes crack detection a very challenging task, especially in the supervision and maintenance of pottery that has high cultural value. If not promptly detected and addressed, these cracks can develop into larger damage that can damage the entire structure of the pottery, even destroying its distinctive aesthetic elements [5]. Therefore, early identification of cracks in pottery is crucial. By accurately understanding the condition of the pottery, maintenance and conservation efforts can be carried out more effectively. Digital image processing technology is a potential solution for detecting cracks in pottery more objectively, efficiently, and non-destructively. Image processing allows for detailed analysis of texture, shape, and surface patterns that are often difficult to observe with the naked eye. Through image segmentation and feature extraction, image processing systems can help detect very fine and irregular cracks, even under less than ideal lighting conditions [6].

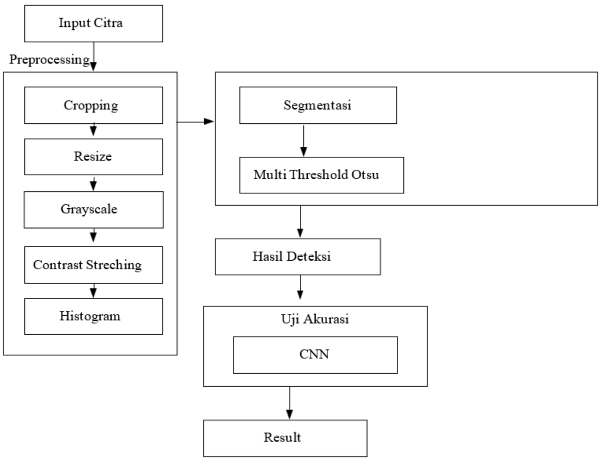
Digital image processing techniques that have been widely applied in cultural heritage conservation, such as image segmentation and morphological analysis, enable the detection of physical damage to cultural artifacts with a high degree of accuracy [7]. Recent research shows that using imaging technology to detect cracks in cultural artifacts, such as ceramics and pottery, can improve the quality of documentation and archiving [8]. The use of Convolutional Neural Networks (CNNs) in image classification has proven effective in recognizing complex patterns on material surfaces, such as fine cracks in traditional pottery. Using a CNN trained on a dataset of ceramic and pottery images, the system can learn the visual characteristics of thin, irregular cracks with excellent accuracy [9]. This opens up great opportunities for the application of similar technology to the identification and classification of cracks in traditional West Sumatran pottery [10].

The application of image processing technology to detect cracks in traditional pottery still faces several challenges. The complex natural texture of pottery surfaces, inconsistent lighting variations, and limited representative datasets are the main challenges [11]. Cracks in pottery are often very thin, irregular, and barely visible, which can lead to misdetection if not using the right method. Therefore, an approach is needed that is able to combine effective image segmentation, more sophisticated morphological analysis, and an understanding of the cultural material context to produce more accurate crack identification. [12].

This research aims to develop a digital image processing-based system that can accurately identify and classify cracks in traditional West Sumatran pottery. By using this technology, it is hoped that this system can assist in the pottery quality inspection process, as well as function as a digital documentation tool that can be used for inventory, preservation, and promotion of the traditional craft industry in the digital era. The developed system also aims to bridge the use of modern technology in efforts to preserve local cultural values sustainably, and provide an ornament database that can be accessed by researchers, artists, and the general public [13]. This research is expected to bridge the use of modern technology with efforts to preserve local cultural values in a sustainable manner [14].

II. METHOD

To identify cracks in traditional West Sumatran pottery using a digital image processing approach, there are several main stages that must be carried out, as shown in Figure 1.



Gambar 1. Alur Penelitian

Figure 1 illustrates this flowchart explaining the key stages in the digital image processing process for identifying and classifying cracks in traditional West Sumatran pottery, with a focus on improving the accuracy and precision of the results.

A. Image Input

These images consist of photographs taken from various sources such as private collections, museums, or cultural literature. This input serves as the initial step for initiating a series of subsequent image processing steps.

B. Preprocessing

The preprocessing stage involves a series of processes to improve image quality before segmentation. The first process is cropping, which ensures only relevant portions of the image are processed, eliminating unnecessary portions[15]. The image is then resized to fit the standard input size required by the segmentation and classification algorithms. The image is then converted to grayscale to reduce data complexity and speed up analysis, followed by contrast stretching to increase the contrast between elements within the image. This process concludes with histogram equalization to clarify the distribution of color intensities, making the ornamental pattern more visible [16].

C. Segmentasi

The Otsu Multi-Threshold method is used to separate ornaments from the background by automatically determining the optimal threshold. The basic formula used to find the optimal threshold for an image with k classes is as follows [17] :

$$\sigma_b^2\left(t_{1,}t_{2,\dots\dots}t_k\right) = \sum_{i-1}^{k} W_{i\,.}\,(\mu_{i-}\ \mu)^2$$

Dimana :

- **t1, t2, ..., tk** are the thresholds used to separate the image into k classes..
- **W_i** is the weight of the i-th class, which is the proportion of the number of pixels in that class to the total number of pixels.
- **μ_i** is the average pixel intensity in the i-th class.
- **μ** is the average intensity of the entire image.

D. Detection Result

The results of the segmentation process proceed to the detection stage, where the segmented images are further analyzed. This detection stage is crucial in assessing and verifying the physical condition of the detected pottery. The use of the CNN method for classification and bounding box for crack locations allows for more precise and efficient analysis.

E. Accuracy Testing

This process involves accuracy testing using a Convolutional Neural Network (CNN) for crack classification. CNNs were chosen because of their ability to recognize complex patterns and features in images, allowing them to identify ornament types with high accuracy. The CNN model was trained with preprocessed ornament image data to ensure the system could recognize pottery cracks.

F. Result

Identification and classification results from the system. These results display identification along with accuracy and related information, which can then be used for digital documentation. With accurate detection results, this system can assist in pottery preservation by providing information about the physical condition of the pottery that can be used for maintenance, renovation, or even digitization for cultural archives.

III. Results And Discussion

The result of this research is the development of a crack detection and classification system in traditional West Sumatran pottery using a digital image processing approach combined with rule-based analysis and a Convolutional Neural Network (CNN) [18]. Sistem yang diusulkan It is designed to classify pottery into two main classes, namely normal pottery and cracked pottery, based on the visual characteristics of the pottery surface. This approach aims to improve the objectivity and consistency of the pottery quality inspection process, which has so far been carried out manually [19].

A. Dataset Collection

The data sources for this study were obtained from various sources relevant to cultural preservation, including photographic documentation taken directly at cultural museums, the personal archives of pottery collectors and artisans, and online digital sources from libraries and cultural repositories. Overall, the dataset used in this study consists of 500 images of traditional West Sumatran pottery, encompassing a wide variety of shapes, textures, and surface conditions. This dataset is divided into two main classes: normal pottery and cracked pottery, which reflect the physical condition of the pottery before and after damage, respectively. The data distribution for each class is as follows:

- Training data: 350 images (175 images of normal pottery, 175 images of cracked pottery)
- Validation data: 74 images (37 images of normal pottery, 37 images of cracked pottery)
- Test data: 76 images (38 images of normal pottery, 38 images of cracked pottery)

The dataset also includes a variety of lighting conditions and shooting angles, which aim to ensure the model's generalizability and reduce potential classification bias. This variation is important to increase the model's validity in real-world conditions. The dataset is divided into two categories: normal pottery and cracked pottery, which represent the physical condition of the pottery before and after damage, respectively.

The CNN architecture used in this study consists of several convolutional layers followed by a pooling layer for feature extraction. This model has four convolutional layers with a 3x3 kernel in each layer, followed by a fully connected layer. The activation functions used were ReLU in the convolutional layer and Softmax in the output layer for classification. Dropout was applied to the fully connected layer to reduce overfitting, with a dropout value of 0.5. This model was trained using an optimizer with a learning rate of 0.001 and a batch size of 32.

The diversity of image sources and conditions in this dataset aims to ensure that the developed system has good generalization capabilities in detecting cracks under various lighting conditions, shooting angles, and crack severity levels. Examples of images from the dataset collection are shown in Figure 2, which demonstrates the visual differences between pottery in normal condition and pottery with cracks.

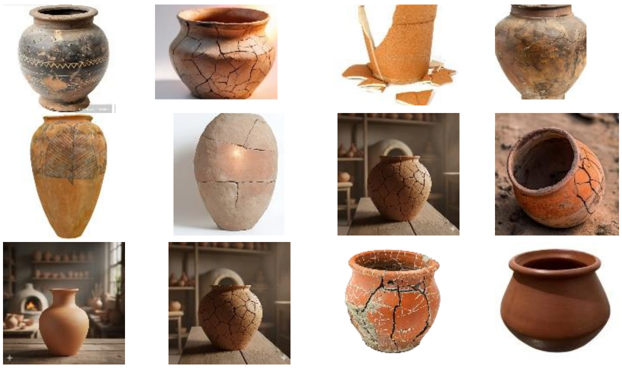


Figure 2. Example Image Dataset

Figure 2 shows that, before the preprocessing stage, the dataset in this study was divided into three subsets: training data, validation data, and testing data. The dataset was divided into 70% training data, 15% validation data, and 15% testing data. This division was intended to ensure that the model had sufficient data for the learning process and to provide sufficient data for system performance evaluation and testing.

Of the 500 traditional West Sumatran pottery images used in this study, 350 images were allocated as training data, 74 images as validation data, and 76 images as testing data, as shown in Table 1. The dataset was divided equally between normal and cracked pottery classes, allowing the developed system to learn crack patterns fairly and reduce the potential for classification bias.

TABEL I
NUMBER OF TRAINING, VALIDATION, AND TEST DATA

Class	Training Data	Validation Data	Test Data
Normal Pottery	175	37	38
Cracked Pottery	175	37	38
Total	350	74	76

B. Preprocessing

The preprocessing stage was conducted before model training and testing, with the aim of improving image quality and ensuring uniformity of the data structure used in the pottery crack detection system. All images in this study were standardized to a size of 256 × 256 pixels, so that each image had the same dimensions and could be processed consistently throughout all image processing and classification stages.

After standardizing the size, the images underwent a series of preprocessing processes, including cropping to focus the analysis area on the pottery surface, converting to grayscale to simplify visual information, and contrast stretching to increase the intensity difference between the surface normal and the crack area. This process was followed by histogram equalization to improve the pixel intensity distribution and highlight the details of thin and elongated cracks [20]. Visualization of the preprocessing results shows that the main structure of the pottery remains intact, while the crack pattern becomes clearer and easier to recognize as seen in the image 3:

Figure 3. Result Preprocessing

Figure 3 shows the results of the dataset preprocessing, demonstrating the differences between the images before and after preprocessing.

C. Detection Result

Based on the test results of the crack detection system developed using MATLAB, the system was able to visually distinguish between cracked and normal pottery, as shown in Figure 4 below :

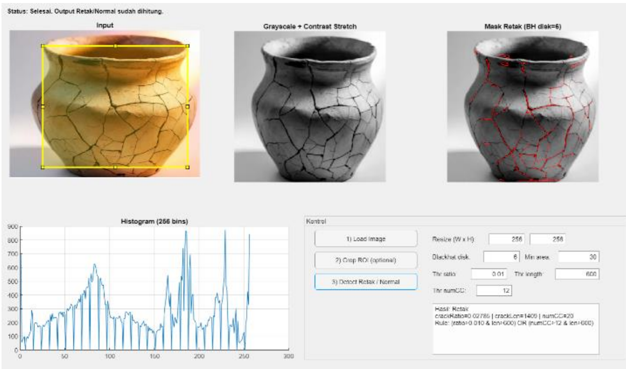


Figure 4. Cracked Pottery

Figure 4 shows an example of cracked pottery, where the crack pattern is clearly visible on the surface after preprocessing and segmentation [21]. Cracks appear as interconnected, longitudinal lines spread across several parts of the pottery's surface, indicating structural damage. Conversely, the detection results for pottery in normal condition can be seen in Figure 5 below:

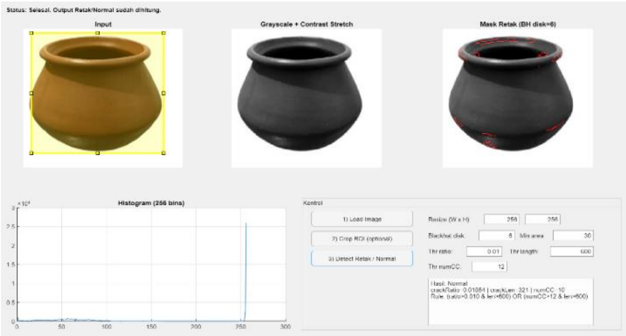


Figure 5. Normal Pottery

Figure 5 shows no significant crack patterns on the surface of the pottery. The areas detected by the system are relatively small and do not form a longitudinal line pattern, so they are still below the established classification threshold. Based on these results, the system returns a "Normal" rating.

These results demonstrate that the proposed crack detection system is capable of effectively identifying visual differences between cracked and normal pottery. By visualizing the detection results in images, users can easily understand the condition of the analyzed pottery, making this system potentially useful as a tool for inspecting pottery cracks.

D. *Accuracy Test*

Accuracy testing was conducted to evaluate the system's performance in classifying cracks in pottery based on segmentation and classification results using a Convolutional Neural Network (CNN)[22]. The dataset used consisted of 500 images, divided into 70% training data and 30% testing data. The testing data was used to measure the system's ability to recognize ornamental patterns in images that had not been previously trained. The classification results were compared with the actual labels to determine the system's accuracy level [23].

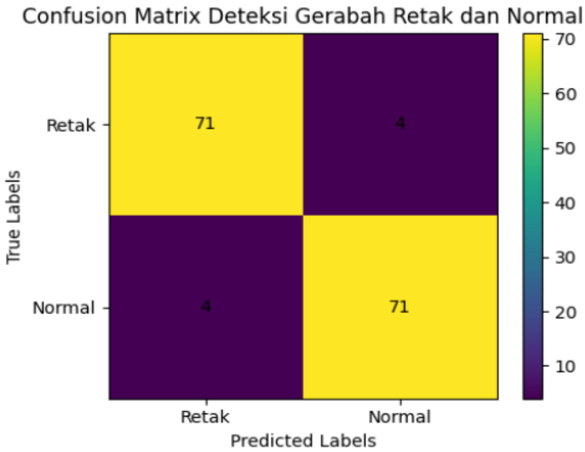


Figure 6. Confusion Matrix

Based on Figure 6, the test results show that the proposed system achieved an accuracy of 94.8%, with a precision of 93.5%, a recall of 92.3%, and an F1-score of 92.9%. These values indicate that the system is capable of classifying cracks with a high degree of accuracy.

TABEL II
CLASSIFICATION RESULTS

No	Comparison of classification model results based on accuracy values		
	Model	**Akurasi**	**Catatan**
1	Multi-Threshold Otsu + CNN	94.8	Uses Multi-Threshold Otsu segmentation to separate cracks from the background, followed by classification using CNN.
2	Adaptive Thresholding + CNN	88.2	Uses Adaptive Thresholding for segmentation based on local pixel averages, followed by CNN for classification.
3	K-Means + CNN	84.5	Uses K-Means for image clustering, followed by CNN for classification based on clustered features.
4	CNN Tanpa Segmentasi	91.2	Uses CNN directly to classify images without prior segmentation.

Table II provides a clearer picture of the effectiveness of each image processing approach for identifying pottery cracks. By comparing these models, we can better understand the contribution of segmentation techniques to the accuracy of the proposed detection system.

IV. CONCLUSION

This research has successfully developed a digital image processing-based system that can identify and classify cracks and ornaments on traditional West Sumatran pottery. By using Multi-Threshold Otsu for segmentation and a Convolutional Neural Network (CNN) for classification, this system can detect cracks with high accuracy. Evaluation results show an accuracy of 94.8%, a precision of 93.5%, a recall of 92.3%, and an F1-score of 92.9%. Implementation of this system can assist in the digitization of pottery, provide an accessible database for the preservation of Minangkabau culture, and support cultural education.

ACKNOWLEDGMENTS

The author would like to thank the Putra Indonesia University YPTK Padang for providing full support in funding this research through the SIMLIT UPI Batch 5 grant of 2025. This support is very meaningful so that this research can be carried out well. The author also expressed his appreciation to all parties who have helped, both directly and indirectly, in the process of preparing this research.

REFERENCES

[1] X. Wang and B. Chen, “Artificial intelligence for cultural heritage : digital processing-based techniques and research challenges Artificial intelligence for cultural heritage : digital image processing-based techniques and research challenges Xiaonan Wang and Baozhong Chen *,” no. May, 2025, doi: 10.1504/IJICT.2025.10070954.

[2] Y. Wu, S. Li, J. Li, Y. Yu, J. Li, and Y. Li, “Journal of Infrastructure Intelligence and Resilience Deep learning in crack detection : A comprehensive scientometric review,” vol. 4, no. February, 2025.

[3] M. A. Ilani, L. Amini, H. Karimi, and M. S. Kuhshuri, “CNN-based Labelled Crack Detection for Image Annotation”.

[4] M. Sabha, M. Saffarini, and R. Yousef, “Image classification in cultural heritage,” vol. 13, no. 4, pp. 4722–4735, 2024, doi: 10.11591/ijai.v13.i4.pp4722-4735.

[5] D. Shojaei, P. Jafary, and Z. Zhang, “Mixed Reality-Based Concrete Crack Detection and Skeleton Extraction Using Deep Learning and Image Processing,” 2024.

[6] S. Gokak, P. Khichade, N. Heggalagi, A. Billowria, and S. Hegde, “Defect Detection and Classification of Cultural Heritage Buildings Using Deep Learning Section II - Background :,” vol. 3, no. Incoft, pp. 619–626, 2025, doi: 10.5220/0013633700004664.

[7] S. Niu, “Image Processing Based on Convolution Neural Network,” pp. 1–8, 2025.

[8] J. Zhou, H. Li, L. Lu, and Y. Cheng, “Machine Vision-Based Surface Defect Detection Study for Ceramic 3D Printing,” pp. 1–15, 2024.

[9] M. Bahrami and A. Albadvi, “H ERITAGE B UILDINGS IN N EED OF C ONSERVATION U SING I MAGE C LASSIFICATION AND G RAD -CAM ∗,” 2023.

[10] J. Diao, H. Wei, Y. Zhou, and Z. Diao, “A Deep Learning-Based Algorithm for Ceramic Product Defect Detection,” pp. 1–19, 2025.

[11] N. Karimi, M. Mishra, and P. B. Lourenço, “Deep learning-based automated tile defect detection system for Portuguese cultural heritage buildings,” *J. Cult. Herit.*, vol. 68, pp. 86–98, 2024, doi: 10.1016/j.culher.2024.05.009.

[12] S. S. Zadeh, S. Aalipour, M. Khorshidi, and F. Kooban, “Concrete Surface Crack Detection with Convolutional-based Deep Learning Models,” vol. 10, no. 3, pp. 25–35, 2023.

[13] H. M. Structures, “Deep Learning-Based Automated Detection of Cracks in Historical Masonry Structures,” 2023.

[14] M. Ikhsan and M. Rahardi, “Image-Based Classification of Indonesian Traditional Houses Using a Hybrid CNN-SVM Algorithm,” vol. 9, no. 5, pp. 2303–2309, 2025.

[15] E. Ogun and Y. A. Voeurn, “A Real-Time Mobile Robotic System for Crack Detection in Construction Using Two-Stage Deep Learning,” pp. 1–28, 2026.

[16] S. Roy, B. Yogi, R. Majumdar, P. Ghosh, and S. Kumar, “Deep learning - based crack detection and prediction for structural health monitoring,” 2025.

[17] Y. Zhang, X. Liu, W. Sun, T. You, and X. Qi, “Multi-Threshold Remote Sensing Image Segmentation Based on Improved Black-Winged Kite Algorithm,” pp. 1–24, 2025.

[18] A. Raza, F. Hanif, and H. A. Mohammed, “Efficient crack and surface- type recognition via CNN-block development mechanism and edge profiling,” pp. 1–25, 2025.

[19] A. Nur, A. Thohari, A. Karima, K. Santoso, and R. Rahmawati, “Crack Detection in Building Through Deep Learning Feature Extraction and Machine Learning Approach,” vol. 8, no. 1, pp. 1–6, 2024.

[20] A. Ranieri, G. Palmieri, and S. Biasotti, “Artifacts Using Semantic Segmentation”.

[21] N. M. Pawar, “Deep Learning Framework for Infrastructure Maintenance: Crack Detection and High-Resolution Imaging of Infrastructure Surfaces,” pp. 1–14.

[22] S. Deshpande, V. Venugopal, M. Kumar, and S. Anand, “Deep learning - based image segmentation for defect detection in additive manufacturing : an overview,” *Int. J. Adv. Manuf. Technol.*, pp. 2081–2105, 2024, doi: 10.1007/s00170-024-14191-6.

[23] Y. Wang, L. Zhang, X. Zhao, B. Tang, and W. Yang, “Review of Research on Ceramic Surface Defect Detection Based on Deep Learning,” pp. 1–19, 2025.