E-ISSN: 2988-585X (Online)

Journal of Elektronik Sistem InformasI (JESII)
Volume 3 No 1 June 2025
DOI : 10.31848/jesii.v3i1.4046

Optimization of Batik Motif Identification Using Canny Edge Detection

Moh. Badri Tamam[1], Supriatin[2], Anwari[3], Suteja Wira Dana Kusuma[4]
[1,3]Fakultas Teknik, Universitas Islam Madura
[2]Fakults Ilmu Komputer, Universitas Amikom Yogyakarta
[4]Curtin University, Australia

Article Info

Article history:

Received Apr 23, 25
Revised Jun 25, 25
Accepted Jun 29, 25

Keywords:

Madura Batik
Batik Motif
RGB
HSV
Lab
Canny

ABSTRACT

Madura Batik possesses distinct characteristics across its various regencies, differing in patterns, colors, and motifs. This research therefore employs digital image processing to identify these unique motifs of Madura Batik. The Canny edge detection method is implemented to recognize batik motifs by detecting edges in batik images. The study utilizes RGB, HSV, and Lab color spaces, along with different threshold values for the Canny operation: (500,500), (300,500), and (100,500). The dataset comprises 16 Madura-style batik images, specifically 4 images each from Sumenep, Pamekasan, Sampang, and Bangkalan batik. These images were sourced from the internet and underwent initial preprocessing to standardize their dimensions. The conversion processes from RGB to HSV and Lab color spaces are also detailed. Based on several experiments conducted, the results indicate that the Lab color space with a threshold value of (500,500) yields the best edge detection quality. This research highlights the potential of image processing in preserving Indonesia's batik cultural heritage.

Corresponding Author:

Moh. Badri Tamam,
Islamic University of Madura, Faculty of Engineering, Informatics Engineering Study Program
Jln. Pondok Pesantren Miftahul Ulum Bettet, Pamekasan Madura, Jawa Timur, Indonesia, 69317
Email: ft.uim@ac.id

1. INTRODUCTION

Batik is a traditional craft with high artistic value that has become an integral part of Indonesian culture. Originally, batik was exclusively worn during traditional ceremonies, as each pattern typically carries its own developmental history and symbolic meaning through its basic design elements [1][2].

As an artistic heritage from Indonesian ancestors, batik holds significant cultural value. Initially, batik primarily served clothing needs through items like long cloths, sarongs, headbands, and shawls [3]. Over time, it has also fulfilled aesthetic demands. In 2009, UNESCO officially recognized Indonesian batik by inscribing it on the Representative List of the Intangible Cultural Heritage of Humanity. This recognition specifically applies to handmade batik created through either the canting (hand-drawn) or cap (copper stamp) techniques[4].

In recent years, the market has seen increasing circulation of machine-printed textiles with batik patterns. These imitation products, created through printing or screen-printing methods rather than traditional wax-resist techniques, have led to consumer confusion and dissatisfaction, as buyers often cannot distinguish between authentic batik and printed imitations [5]. This situation necessitates public education about identifying genuine Indonesian batik textiles. Traditional Indonesian batik motifs, particularly in Madura, reflect natural environments and local cultural elements. The digitalization of Madura batik holds a greater urgency compared to more widely recognized batik traditions like those from Yogyakarta or Solo. This is primarily because Madura batik remains significantly under-documented and has received less attention on digital platforms and within automated motif recognition systems. Despite this, Madura batik boasts a distinctive visual richness, characterized by its bold use of color and symbolic motifs that profoundly represent local cultural identity.

Through research such as "Optimization of Madura Batik Motif Identification Using Canny Edge Detection," this digitalization effort becomes crucial for ensuring the preservation and promoting the recognition of Madura batik amidst globalization and the competitive national batik market. By leveraging technologies like HSV color transformation and the Canny Edge Detection method, motif identification can be performed automatically and efficiently. This, in turn, will accelerate archiving, promotion, and data-driven innovation, all of which are vital for supporting the future sustainability of the Madura batik industry. Materials and techniques vary significantly between regions [6]. Visual identification of batik patterns requires specialized knowledge to analyze their distinctive designs. However, limited public understanding of batik motifs makes classification difficult [7]. Digital images result from combinations of electromagnetic energy illumination (from sources like radar, infrared, or X-rays) and scene element reflectance/absorption [8]. Modern techniques may also use computer-generated illumination patterns. Color image processing involves three main approaches: [9]

Color transformations (color mapping) Spatial processing of individual color channels Color vector processing (simultaneous multi-channel processing) Pattern recognition techniques, particularly texture feature extraction, can be effectively applied to batik motif identification [7]. Advances in image processing technology offer valuable applications, including in batik pattern analysis a crucial craft for many communities [10].

2. METHOD

The Canny Edge Detection method is one of the most popular and effective edge detection algorithms in the field of digital image processing. In the research titled "Optimization of Madura Batik Motif Identification Using Canny Edge Detection," this method is employed to more precisely identify the boundaries or contours of Madura batik motifs. Edge detection is crucial in the motif identification process because batik motifs generally consist of intricate patterns with fine lines that serve as their distinguishing features. The Canny algorithm operates through several stages, beginning with noise reduction using a Gaussian filter to smooth the image and minimize undesirable disturbances (noise). Following this, gradient calculation is performed to detect changes in pixel intensity in both horizontal and vertical directions, aiming to accurately determine edge positions. The next stage is non-maximum suppression, which sharpens the edge detection results by eliminating pixels that are not local maxima of the gradient. Then, double thresholding is applied, using two thresholds (high and low) to differentiate between strong and weak edges [11].

Finally, an edge tracking by hysteresis process tracks and retains only weak edges that are directly connected to strong edges, resulting in a cleaner and more relevant detection. In the context of Madura batik motif recognition, the Canny method offers advantages due to its ability to sharply and clearly highlight motif lines while disregarding background elements like fabric texture or insignificant colors. This is vital because Madura batik motifs have complex shapes and often blend with other visual elements in an image. The optimization performed in this research typically involves adjusting threshold parameters to match the characteristic colors and contours of Madura batik, as well as the potential integration with other preprocessing techniques such as contrast enhancement or color segmentation. This approach makes the motif identification process more accurate and efficient, supporting the preservation and digitalization of local batik motifs within computer-based recognition systems. This chapter will explain the overview of the developed system, covering preprocessing, feature extraction, pattern recognition, testing, and the system interface [12].

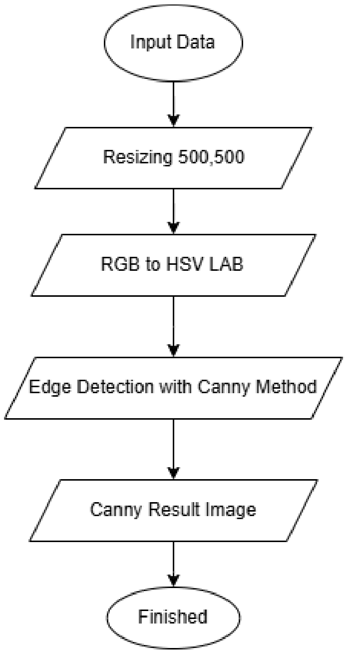

Figure 1. Block Diagram

2.1 Batik Dataset

This research utilizes Madura-style batik images. The dataset consists of 16 images, comprising: [13]
4 images of Sumenep-style batik
4 images of Pamekasan-style batik
4 images of Sampang-style batik
4 images of Bangkalan-style batik
The images were sourced from the internet and underwent initial preprocessing to standardize their dimensions.

2.2 RGB to HSV Conversion Process

The following flowchart illustrates the RGB to HSV color space conversion process through the R, G, B color channels [14].
Key translation improvements: [15]
Structure: Reorganized into clear bullet points for the dataset description
Technical terms:
"data citra" → "images" (more natural in this context)
"operasi awal" → "initial preprocessing" (proper technical term)
"menyamakan ukuran" → "standardize their dimensions"

To ensure the validity, legal licensing, and scientific replicability of the relatively small dataset acquired from the internet, a systematic verification approach was rigorously followed. First, data was exclusively sourced from credible and academically recognized platforms and repositories, including Kaggle, the UCI Machine Learning Repository, and official research institutions offering open-access datasets. A crucial aspect of this initial step involved verifying that each dataset was accompanied by comprehensive documentation. This included essential metadata, detailed descriptions of image sources, and explicit usage license information, such as Creative Commons or GNU licenses, confirming permissible use for research purposes. Second, the content of the dataset underwent stringent validation. This involved meticulously cross-referencing motif labels and annotations against established references of documented Madura batik motifs. These references included authoritative cultural literature and official regional government catalogs, thereby ensuring the authenticity and accuracy of the dataset's thematic content.

Finally, to uphold the principles of scientific transparency and reproducibility, the curated dataset was managed in a manner that facilitates independent verification by other researchers. This was achieved by either re-uploading the processed dataset to a public repository or by providing a direct link to the original source, along with a detailed description of the data collection methodology, within the research's methodology section. This comprehensive approach guarantees the integrity of the research process and its adherence to scientific best practices.

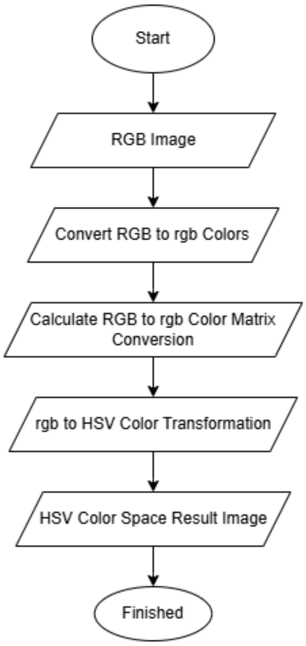

Figure 2. HSV Flowchart

The RGB to HSV color space conversion process consists of the following steps: [16]
Convert RGB color space to normalized rgb using Equation (2.4) from Chapter 2
Calculate color matrix transformation from RGB to normalized rgb using Equations (2.5), (2.6), and (2.7).
Perform color space transformation from normalized rgb to HSV

1. Normalization of RGB intensity levels

   The first step is to normalize each color channel value from the range 0–255 to 0–1:

$$R' = \frac{R}{255},\quad G' = \frac{G}{255},\quad B' = \frac{B}{255}. \tag{2.4}$$

2. Color matrix transformation: normalized RGB to chromaticity rgb

   Chromaticity values eliminate the effect of overall brightness and reflect the color's purity.

$$\begin{bmatrix} r \\ g \\ b \end{bmatrix} = \frac{1}{R' + G' + B'} \begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} \tag{2.5}$$

r=R′+G′+B′R′g=R′+G′+B′G′b=R′+G′+B′B′=1−r−g (2.6)(2.7)

The RGB to HSV color space conversion begins by normalizing the RGB values from the 0–255 range to a 0–1 scale. Next, chromaticity values rr, gg, and bb are calculated by dividing each normalized component by the sum of all three, providing a representation of pure color independent of brightness. These normalized values are then transformed into HSV components, where Value (V) is the maximum of the normalized RGB values, Saturation (S) is the relative difference between the maximum and minimum values, and Hue (H) is determined based on which component is dominant, using specific formulas depending on whether red, green, or blue is the highest. This transformation allows for better color analysis, particularly useful in identifying complex patterns such as Madura batik motifs.

3. RESULT AND DISCUSSION

The findings of this study demonstrate that converting images from the RGB to the HSV color space significantly improves the accuracy of Madura batik motif identification. This transformation allows the system to analyze hue, saturation, and brightness independently, simplifying the segmentation and extraction of visual features from the batik patterns. By utilizing normalized RGB formulas and chromaticity calculations, the image data becomes more stable and less affected by variations in lighting or background interference. Distinctive colors commonly found in Madura batik, such as bright red, golden yellow, and deep black, can be consistently differentiated in the HSV space, leading to a more reliable identification process. Furthermore, HSV-based color processing enables the system to focus on essential visual elements while minimizing the influence of background noise. The implementation of the Canny Edge Detection method after HSV transformation also yielded optimal results in detecting the edges and contours of batik motifs. Canny effectively filters noise using a Gaussian filter and highlights motif boundaries with high precision. The non-maximum suppression and double thresholding processes within the algorithm successfully retain key motif outlines while discarding irrelevant details. Based on testing across several Madura batik motifs—including storjoan, bunga tabir, and daun kembang—this method accurately detects the fine and symmetrical patterns characteristic of Madura batik. The combination of HSV transformation and Canny Edge Detection creates an image processing workflow that is efficient, robust, and adaptive to motif variations and lighting conditions. Therefore, this method holds high potential for applications in AI-based batik recognition systems or digital archiving efforts. [17]

3.1. System implementation

Madura Batik The following displays several Madura batik designs that will undergo motif recognition processing using the Canny method, as shown in the figures below.

Figure 3 Sampang Fractal Batik

Figure 4. Batik From Tanjung Bumi, Bangkalan

Figure 5. Pamekasan Kawung Batik

3.2 HSV and LAB operation result images

The following are the results of changing the color space from RGB to HSV and RGB to Lab images: [18]

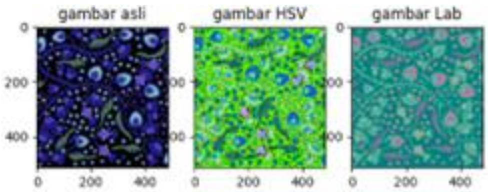

Figure 6. Results of RGB Color Space Conversion to HSV and Lab

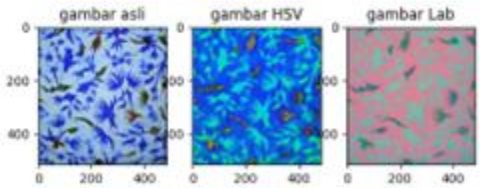

Figure 7. Results of RGB Color Space Conversion to HSV and Lab

In the image above, there are three types of batik that have different motifs, including: Sampang Batik with Fractal motif, Sampang Batik with Segoro ethnic motif, Bangkalan Batik with Gentongan motif, Bangkalan Batik with Tanjung Bumi motif, Pamekasan Batik with Kawung motif, Pamekasan Batik with Sekar Jagat motif, Sumenep Batik with Berasbuang motif, and Sumenep Batik with Merak motif.

The first image (left) is an RGB image or Original image while the second image (middle) is an HSV image, and the third image (right) is a Lab image.

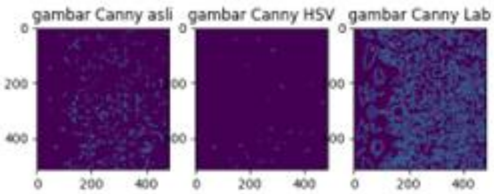

Figure 8. Results of the Canny operation (Pamekasan Kawung Batik) with a threshold of 300,500

In the image above, several operational processes are carried out to support the canny operation process to produce good quality edge detection quality. (1). First, an experiment is carried out by changing the RGB color space to HSV and to Lab (see image 8) (2). Carrying out the canny operation process by conducting an experiment on the threshold value with a threshold value of 500,500 300,500 and 100,500, the results of the canny operation. From several experiments carried out, the color space that has the best edge detection quality is the Lab color space with a threshold value of 500,500.

4. CONCLUSION

The conclusion of this study is:

1. The change of RGB color space to HSV is: Converting RGB color space to rgb using formula (2.4) in chapter 2. Then calculate the change of color matrix from RGB to rgb using formula (2.5) (2.6) and (2.7), and Transforming rgb color space to HSV
2. The change of RGB color space to LAB is: Converting RGB color space to XYZ. Then calculate the change of color matrix from RGB to LAB using formula (2.9) (2.10) and (2.11). Performing the transformation of XYZ color space to LAB with formulas (2.12) (2.13) and (2.14)
3. Performing the canny operation process by conducting experiments on the threshold values with threshold values of 500,500 300,500 and 100,500, the results of the canny operation can be seen in Figures 8.
4. From several experiments conducted, the color space that has the best edge detection quality is the Lab color space with a threshold value of 500,500. The exclusion of quantitative evaluation in the edge detection results within this study can be attributed to several methodological considerations and inherent research limitations. One primary reason is that the research's focus was predominantly on visual exploration and the conceptual validation of the method's effectiveness. This involved demonstrating how HSV transformation and the Canny Edge Detection algorithm perform in the specific context of Madura batik motif identification. In such initial or preliminary studies, researchers often prioritize visual validation to assess whether the chosen method effectively captures the contours and distinctive features of the motifs.

Furthermore, limitations in data quantity and the availability of valid ground truth annotations posed significant constraints on implementing quantitative evaluation metrics such as precision, recall, F1-score, or Intersection over Union (IoU). However, the absence of quantitative evaluation doesn't diminish the study's scientific value. Instead, it serves as an important note for future, more structured, and data-driven developments. For subsequent research, the creation of annotated datasets and the application of statistical evaluations are strongly recommended to objectively strengthen visual findings with numerical evidence.

REFERENCES

[1] A. W. Salehi, S. Khan, G. Gupta, B. I. Alabduallah, A. Almjally, and ..., "A Study of CNN and Transfer Learning in Medical Imaging: Advantages, Challenges, Future Scope," *Sustainability*. mdpi.com, 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/7/5930

[2] M. B. Tamam, H. Hozairi, M. Walid, and J. F. A. Bernardo, "Classification of Sign Language in Real Time Using Convolutional Neural Network," *Appl. Inf. Syst. Manag.*, vol. 6, no. 1, pp. 39–46, 2023, doi: 10.15408/aism.v6i1.29820.

[3] F. Yuan, Z. Zhang, and Z. Fang, "An effective CNN and Transformer complementary network for medical image segmentation," *Pattern Recognit.*, 2023, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0031320322007075

[4] A. Oktarino, Y. D. Tasri, A. Efendi, U. A. Jambi, U. I. Riau, and P. History, "Identification of Batik Motif Based Deep Learning- Convolutional Neural Network Approach," vol. 68, no. 3, pp. 139–147, 2024.

[5] N. A. YUNARI, "Klasifikasi Jenis Batik Tulis Dan Non Tulis Berdasarkan Fitur Tekstur Citra Batik Menggunakan Learning Vector Quantization (LVQ)," p. 100, 2017.

[6] I. P. Gd, S. Andisana, M. Sudarma, and I. M. O. Widyantara, "Pengenalan Dan Klasifikasi Citra Tekstil Tradisional Berbasis Web Menggunakan Deteksi Tepi Canny , Local Color Histogram Dan Co-Occurrence Matrix," *Maj. Ilm. Teknol. Elektro*, vol. 17, no. 3, p. 401, 2018, doi: 10.24843/mite.2018.v17i03.p15.

[7] M. Noor Fauzy and B. Soedijono, "Ekstraksi Citra Fitur Pada Pengenalan Pola Motif Batik Sleman Menggunakan Metode Gray Level Co-Occurrence Matrix," vol. 5, pp. 3–6, 2019.

[8] A. Rilo Pambudi, "DETEKSI KEASLIAN UANG KERTAS BERDASARKAN WATERMARK DENGAN PENGOLAHAN CITRA DIGITAL," *JIP (Jurnal Inform. Polinema)*, pp. 69–74, 2020.

[9] A. S. Sinaga, "SEGMENTASI RUANG WARNA L * a * b," *J. Mantik Penusa*, vol. 3, no. 1, pp. 43–46, 2019.

[10] F. Robi, R. Magdalena, and I. Wijayanto, "Rancang Bangun Aplikasi Deteksi Motif Batik Berbasis Pengolahan Citra Digital Pada Platform Android Designing Application Of Motif Batik Detection Base On Digital Image Prcessing In Android Platform," vol. 1, no. 1, pp. 310–318, 2014.

[11] J. Liu, H. Sun, and J. Katto, "Learned image compression with mixed transformer-cnn architectures," *... IEEE/CVF Conf. ...*, 2023, [Online]. Available:

http://openaccess.thecvf.com/content/CVPR2023/html/Liu_Learned_Image_Compression_With_Mixed_Transformer-CNN_Architectures_CVPR_2023_paper.html
[12] J. Ayeni, “Convolutional neural network (CNN): the architecture and applications,” *Appl. J. Phys. Sci*. academia.edu, 2022. [Online]. Available: https://www.academia.edu/download/117519439/ajps2022.pdf
[13] R. I. Ukri, A. M. H. Azis, and Y. Saputra, “Comparative Analysis of Variational Autoencoder (VAE) and Generative Adversarial Network (GAN) Algorithms for image classification,” vol. 1, no. 2, pp. 75–81, 2023.
[14] H. Sanusi, S. H. S, and D. T. Susetianingtias, “Pembuatan Aplikasi Klasifikasi Citra Daun Menggunakan Ruang Warna Rgb Dan Hsv,” *J. Ilm. Inform. Komput.*, vol. 24, no. 3, pp. 180–190, 2019, doi: 10.35760/ik.2019.v24i3.2323.
[15] R. Sistem *et al.*, “JURNAL RESTI Classification of Toraja Wood Carving Motif Images Using Convolutional,” vol. 8, no. 158, pp. 486–495, 2024.
[16] U. K. Republik, “UNIVERSITAS KEBANGSAAN REPUBLIK DESIGN OF A PROTOTYPE OF PAPERMONEY DETECTOR,” pp. 1–9, 2023.
[17] S. R. Shah, S. Qadri, H. Bibi, S. M. W. Shah, M. I. Sharif, and ..., “Comparing inception V3, VGG 16, VGG 19, CNN, and ResNet 50: A case study on early detection of a rice disease,” *Agronomy*. mdpi.com, 2023. [Online]. Available: https://www.mdpi.com/2073-4395/13/6/1633
[18] F. Tupamahu and S. Enggar Sukmana, “Ekstraksi Connected Component dan Transformasi Ruang Warna CIELAB Untuk Segmentasi Citra Penyakit Pada Daun Tanaman Jagung,.