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IMAGE SEGMENTATION OF YOGYAKARTA BATIK PATTERN USING SEGNET

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Abstract

Batik is an Indonesian intangible cultural heritage with high artistic value. However, the complexity of classical Yogyakarta patterns, particularly Parang and Kawung, characterized by intricate structures, color variations, and indistinct boundaries, poses significant challenges for automated image processing. Therefore, image segmentation becomes a crucial step in batik identification and digitalization. This study aims to develop an efficient segmentation model for Yogyakarta batik patterns using a modified SegNet architecture. The dataset comprises 720 RGB images, consisting of 360 Parang pattern images and 360 Kawung pattern images. All images were processed into binary ground truth masks through a combination of K-Means Clustering and morphological operations. The SegNet architecture was modified into three encoder and decoder blocks, employing Conv2DTranspose for upsampling and a sigmoid activation function in the output layer. The model was trained for 50 epochs using the Adam optimizer and binary cross entropy loss function. Based on evaluation on the test dataset, the modified SegNet model achieved strong performance with an accuracy of 91.72%, a mean Intersection over Union of 77.23%, and a mean Dice Coefficient of 87.07%. Visual inspection of the prediction results further confirms the model's ability to accurately separate pattern regions from the background. These findings demonstrate that the modified SegNet architecture performs well in segmenting Parang and Kawung batik patterns and shows strong potential for supporting future batik recognition and digitalization systems.

Keywords: Batik Yogyakarta; Deep Learning; Images Segmentation; Image Processing; SegNet.

Abstrak

Batik merupakan warisan budaya takbenda Indonesia dengan nilai seni yang tinggi. Namun, kompleksitas pola batik klasik Yogyakarta, khususnya motif Parang dan Kawung yang ditandai dengan struktur rumit, variasi warna, serta batas yang tidak jelas, menjadi tantangan signifikan dalam pemrosesan citra otomatis. Oleh karena itu, segmentasi citra menjadi tahapan krusial dalam identifikasi dan digitalisasi batik. Penelitian ini bertujuan untuk mengembangkan model segmentasi yang efisien untuk pola batik Yogyakarta menggunakan arsitektur SegNet yang dimodifikasi. Dataset yang digunakan terdiri dari 720 citra RGB, yang mencakup 360 citra motif Parang dan 360 citra motif Kawung. Seluruh citra diproses menjadi ground truth mask biner melalui kombinasi K-Means Clustering dan operasi morfologi. Arsitektur SegNet dimodifikasi menjadi tiga blok encoder dan decoder, dengan menerapkan Conv2DTranspose untuk upsampling serta fungsi aktivasi sigmoid pada lapisan output. Model dilatih selama 50 epoch menggunakan optimizer Adam dan fungsi loss binary cross entropy. Berdasarkan evaluasi pada dataset uji, model SegNet yang dimodifikasi mencapai performa yang kuat dengan akurasi sebesar 91,72%, mean Intersection over Union sebesar 77,23%, dan mean Dice Coefficient sebesar 87,07%. Inspeksi visual pada hasil prediksi memperkuat bukti kemampuan model dalam memisahkan area pola dari latar belakang secara akurat. Temuan ini menunjukkan bahwa arsitektur SegNet yang dimodifikasi berkinerja baik dalam menyegmentasi pola batik Parang dan Kawung serta memiliki potensi besar untuk mendukung sistem pengenalan dan digitalisasi batik di masa depan.

***Kata kunci**: Batik Yogyakarta; Deep Learning; Segmentasi Citra; Pemrosesan Citra; SegNet.*

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INTRODUCTION

Batik is an Indonesian intangible cultural heritage with high artistic value, deeply rooted in the nation's historical, philosophical, and artistic traditions. It has developed over centuries and become an inseparable part of Indonesian cultural identity, particularly within Javanese society (Rohmani Taufiqoh et al. 2018). Etymologically, the word batik originates from the Javanese terms to write (*amba*) and dot (*titik*), referring to the traditional process of applying wax (*malam*) to fabric using repetitive dot and line patterns (Widayanti and Handayani 2024). Global recognition of batik's cultural significance was officially granted in 2009 through its inclusion by UNESCO in the Representative List of the Intangible Cultural Heritage of Humanity, which subsequently led to the establishment of National Batik Day celebrated annually on October 2 (Kasim et al. 2022). This international acknowledgment reinforces the obligation of Indonesian society to safeguard batik not only as a cultural emblem, but also as an important intellectual and artistic heritage.

The uniqueness of batik lies in its rich diversity of motifs, each of which embodies distinct philosophical meanings and cultural narratives. Among the most prominent traditional batik centers in Indonesia are Yogyakarta and Surakarta, both of which played a crucial role during the Mataram Kingdom era (Rohmani Taufiqoh et al. 2018). This study focuses specifically on classical Yogyakarta batik motifs, namely Kawung and Parang, which are strongly associated with royal and philosophical symbolism. The Kawung motif, regarded as one of the oldest batik patterns, consists of repeated elliptical shapes symbolizing purity, balance, and moral integrity, reminding the wearer to become a virtuous individual beneficial to society (Anastasia Desmeria Br Ginting et al. 2024). In contrast, the Parang Rusak motif is characterized by diagonal, wave-like patterns resembling repeated "S" shapes inspired by ocean waves striking rocks, representing strength, perseverance, self-control, and resilience (Penelitian Multidisiplin et al. 2024; Saputra, Supriyati, and Listyorini 2024).

Despite its cultural and aesthetic value, batik presents significant challenges in the context of digital documentation and automated pattern analysis. The complexity of batik motifs, characterized by dense ornamentation, overlapping geometric structures, and subtle texture transitions, makes it difficult to distinguish boundaries between pattern regions and background areas (Mardani, Pranowo, and Santoso 2020). These challenges are further compounded by variations in fabric texture, color intensity, and handcrafted irregularities, which often result in ambiguous region transitions (Padmo 2016). Furthermore, the presence of intricate and overlapping motifs, along with mixed patterns frequently found in real-world textile datasets, significantly complicates the extraction of distinct features and the identification of clear pattern boundaries(Abd Manap et al. 2024; Gede et al. 2022). As a result, accurate image segmentation becomes a fundamental prerequisite for subsequent tasks such as pattern recognition, classification, and digital archiving. Effective segmentation enables the partitioning of an image into homogeneous regions based on shared characteristics such as texture, shape, or intensity, thereby supporting reliable pattern identification and cultural heritage preservation (Kasim et al. 2022).

Image segmentation methods can generally be categorized into traditional approaches and Deep Learning-based techniques. Traditional segmentation methods rely on pixel-level discontinuities or similarity measures, such as edge detection, thresholding, and region-based clustering (S, Sravani, and Jiji 2024). Techniques such as K-Means clustering and texture feature extraction using the Gray Level Co-occurrence Matrix (GLCM) have been widely applied to patterned images, including batik, due to their simplicity and interpretability (Padmo 2016). However, these methods depend heavily on handcrafted features and predefined parameters, which limits their robustness and generalization capability when dealing with complex and highly variable batik textures (S et al. 2024). Consequently, traditional approaches often struggle to accurately segment intricate motifs with overlapping structures and subtle boundary transitions.

Recent developments in deep learning, particularly those involving Convolutional Neural Networks (CNNs), have brought substantial changes to image segmentation by allowing feature representations to be learned automatically from data (Chen et al. 2020). Within semantic segmentation, various CNN-based frameworks have been widely applied to perform pixel-level labeling in diverse application domains, including architectures derived from FCN, U-Net, SegNet, and DeepLab (Zhang et al. n.d.). The introduction of FCN-based models marked an important shift

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toward dense prediction, as conventional fully connected layers were restructured into convolutional operations, enabling inference over entire images in an end-to-end manner (Hu et al. 2021). Subsequent improvements, such as FCN+, expanded the receptive field using global convolutional layers to capture broader contextual information without increasing the number of trainable parameters (Ren et al. 2025).

U-Net has also gained widespread adoption, particularly in tasks requiring high boundary precision, as a result of its balanced encoder–decoder design combined with skip connections that retain detailed spatial features (Annafii et al. 2022). This architecture has demonstrated high accuracy in medical image segmentation, such as blood cell identification, achieving performance levels above 94% (Boly and Akbar 2024). However, the extensive use of skip connections and feature concatenation can increase memory consumption, which may limit its efficiency when applied to high-resolution images or resource-constrained environments. Among existing segmentation architectures, SegNet is often regarded as an efficient solution for semantic segmentation. It adopts an encoder–decoder framework in which spatial resolution is restored using pooling index information transferred from the encoder, rather than storing complete feature maps (Badrinarayanan, Kendall, and Cipolla 2017). This design significantly reduces memory usage while preserving spatial boundary information, making SegNet well-suited for segmenting images with complex textures and fine structural details (Minaee et al. 2022). Recent studies have demonstrated that SegNet can be further optimized through architectural modifications and backbone customization to achieve faster convergence and improved boundary delineation in complex visual environments (Priya et al. 2022; Zhang et al. n.d.). In parallel, the DeepLab family has advanced semantic segmentation by introducing dilated convolution operations together with multi-scale context aggregation mechanisms (Wang et al. 2021). Enhanced variants such as DeepLabV3+ have shown improved robustness under challenging imaging conditions by integrating advanced normalization strategies to strengthen feature representation (Memon et al. 2022). Despite their strong performance, these models tend to be computationally expensive and may not be optimal for applications requiring efficiency and simplicity.

Based on the reviewed studies, a research gap exists regarding computationally efficient deep learning-based segmentation specifically designed for traditional batik motifs with limited manually annotated data. Many existing works primarily emphasize classification tasks rather than accurate pixel-level segmentation, or depend on manually annotated datasets that require substantial effort and resources to construct. Therefore, the present study introduces a modified SegNet architecture for semantic segmentation of classical Yogyakarta batik motifs, specifically Parang and Kawung, by employing automatically generated binary ground-truth masks. These masks are obtained through a combination of K-Means clustering and morphological operations, addressing the challenge of limited labeled data while improving boundary detection accuracy. This research aims to implement a modified SegNet architecture for the semantic segmentation of batik motifs by effectively distinguishing pattern regions from background areas. The proposed approach is evaluated using standard segmentation metrics, namely Accuracy, Intersection over Union (IoU), and Dice Similarity Coefficient (DSC), to assess the quality of segmentation (Violeta Vlăsceanu et al. n.d.). The findings are expected to provide academic contributions to the utilization of deep learning techniques within the domain of cultural heritage image analysis and to support initiatives focused on the digital preservation and protection of Indonesian batik motifs.

RESEARCH METHODS

The stages in this research consist of six stages shown in Figure 1, namely: literature study, data collection, data preprocessing, SegNet model development, model implementation, and model evaluation.

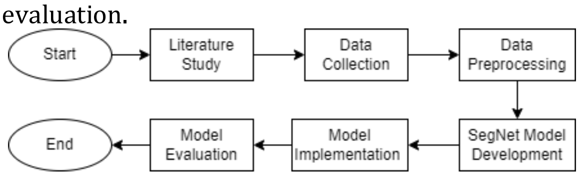

Figure 1. Research stages

Literature Study

A systematic review was carried out to identify previous studies related to semantic segmentation, encoder–decoder architectures, and batik pattern analysis. The review focused on research involving SegNet, convolutional neural networks for textile pattern recognition, and segmentation metric evaluation. Insights obtained from the literature served as the scientific basis for

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determining the model architecture, preprocessing strategy, and evaluation metrics used in this study.

Data Collection

The data for this study were obtained from the open dataset platform Kaggle (Stefaron 2025). The dataset originally contained four types of Batik patterns: Kawung (506 images), Mega Mendung (472 images), Parang (426 images), and Truntum (395 images). However, this research focuses on the Parang and Kawung patterns as representations of Yogyakarta Batik patterns that possess strong geometric qualities suitable for developing the segmentation method.

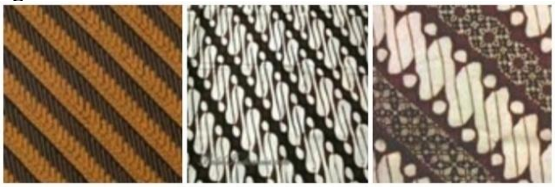

Figure 2. Example of batik parang

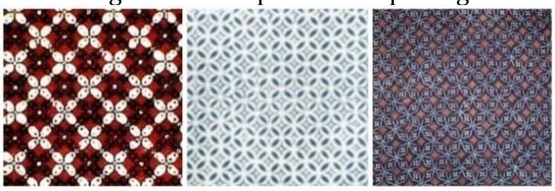

Figure 3. Example of batik kawung

To maintain class balance and prevent model bias, the number of images used was limited to 360 Parang images and 360 Kawung images. The acquired dataset consists only of RGB images without annotation masks and thus could not be directly used for segmentation model training. Therefore, an automated process for generating label masks was required, as detailed in the data preprocessing section.

Data Preprocessing

The acquired dataset required intensive preprocessing as it lacked the necessary ground truth masks for supervised training. The entire data pipeline started by uniformly resizing all RGB images to 256×256 pixels. Subsequently, an automated mask generation method using unsupervised K-Means Clustering was applied. In this approach, two clusters were employed to segment the pattern area from the background based on pixel color similarity. In this process, the RGB color space was utilized as the feature representation, where each pixel was defined by its Red, Green, and Blue intensity values. Prior to clustering, pixel values were normalized to the range [0, 1] to ensure balanced distance computation and to prevent bias toward higher intensity values. The cluster exhibiting the lowest average brightness was automatically designated as the object (pattern) area, based on the assumption that patterns are generally darker than the background.

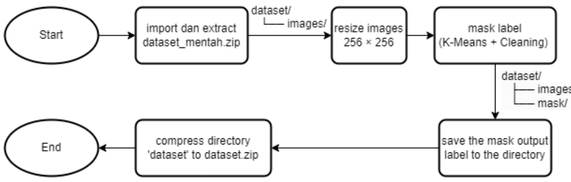

Figure 4. Data preprocessing flowchart

This process generated a binary mask (0 for background, 255 for pattern). To finalize the mask quality, morphological operations, specifically opening (to remove small noise) and closing (to fill minor gaps), were applied to ensure the resulting mask possessed a clean and continuous shape, making the dataset ready for model training.

The morphological operations were implemented using a square structuring element with a kernel size of 3×3. The opening operation (erosion followed by dilation) was applied to remove small isolated noise regions, while the closing operation (dilation followed by erosion) was used to fill small holes and gaps within the segmented motif regions. Both operations were applied with a single iteration to preserve the overall structure of the pattern while improving mask continuity.

SegNet Model Development

In this study, a modified SegNet architecture was developed to perform binary semantic segmentation of Yogyakarta batik motifs. The developed model builds upon the original SegNet framework introduced by Badrinarayanan et al. (Badrinarayanan et al. 2017), which adopts an encoder–decoder structure for pixel-wise image segmentation. However, several architectural modifications were introduced to improve computational efficiency while maintaining segmentation accuracy, particularly for the characteristics of batik motif patterns.

The encoder–decoder structure was simplified by reducing the encoder path to three downsampling blocks with filter progression of 64, 128, and 256, respectively. Each block consists of 3×3 convolutional layers followed by the Rectified Linear Unit (ReLU) activation function and 2×2 max-pooling operations for spatial downsampling. In this architecture, the encoder is responsible for

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extracting hierarchical feature representations that capture the complex geometric and textural characteristics of Batik motifs

$$f(x) = \max(0, x) \quad (1)$$

The ReLU activation function is defined as equation 1, which introduces non-linearity into the network while maintaining computational efficiency. ReLU facilitates faster convergence during training and mitigates the vanishing gradient problem, thereby supporting stable learning of intricate pattern structures present in Batik images (Kechris et al. 2025). In contrast to the original SegNet design that relies on max-pooling indices for unpooling, the decoder path in this study employs Conv2DTranspose layers with a stride of 2×2 to perform upsampling and restore spatial resolution.

This modification simplifies the decoding process while maintaining effective feature reconstruction for pixel-wise prediction. The network concludes with a final 1×1 convolution operation combined with a Sigmoid activation to generate a single-channel binary segmentation mask, corresponding to pattern and background classes. This architectural adaptation significantly reduces model complexity and improves training efficiency, making it well-suited for binary Batik pattern segmentation. The detailed configuration of the proposed SegNet architecture is presented in Table 4.

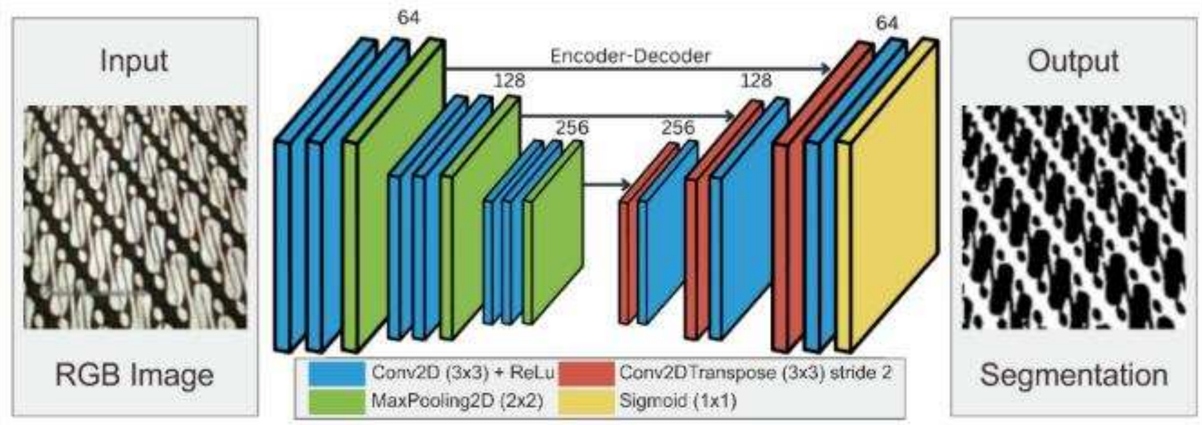

Figure 5. SegNet Modified Architecture

Model Implementation

The The model implementation was conducted based on the predefined architectural design and executed using the TensorFlow/Keras deep learning framework on the Google Colab environment with NVIDIA T4 GPU acceleration. The implementation process included data loading, generator construction, model compilation, and training configuration. The normalized dataset, consisting of RGB images and their corresponding generated binary masks, was divided into training (80%), validation (10%), and testing (10%) subsets.

During model training, the Adam optimizer was employed with a learning rate of 0.0001 to ensure stable convergence while preventing excessively large parameter updates during optimization. The learning process was carried out over 50 epoch with a batch size of 8, a setting that balances optimization stability and GPU memory constraints. Binary Cross-Entropy loss was utilized because of its effectiveness in binary segmentation scenarios that distinguish foreground (batik pattern) regions from background areas. To better evaluate segmentation performance, spatial overlap–based metrics, namely Intersection over Union (IoU) and the Dice Similarity Coefficient (DSC), were adopted, allowing comprehensive assessment of boundary accuracy between the predicted outputs and the corresponding reference masks.

To minimize overfitting and improve better model generalization, the ModelCheckpoint callback was employed during training to monitor validation loss and automatically preserve the model parameters associated with the best generalization performance (Wang et al. 2024). This checkpointing strategy allows the selection of the most effective model based on validation performance and is widely adopted in deep learning–based segmentation tasks as a standard approach for mitigating overfitting (Gygi, Kleinstein, and Guan 2023).

Model Evaluation

Model evaluation was carried out to examine the segmentation effectiveness and generalization capability of the proposed modified SegNet architecture. The evaluation process was performed on three data partitions, namely the training, validation, and testing datasets, to analyze the model's learning characteristics, robustness, and behavior when applied to previously unseen data. Segmentation quality was quantified using Accuracy, Intersection over Union (IoU), and Dice Similarity Coefficient (DSC), which collectively assess pixel-wise correctness, spatial overlap, and boundary agreement between the predicted segmentation outputs and the reference ground truth masks. In addition to numerical assessment, visual analysis was performed by comparing the original RGB images, the corresponding ground truth masks, and the predicted segmentation outputs to verify the model's ability to accurately delineate complex batik motif boundaries.

Accuracy measures the proportion of correctly classified pixels, including True Positive (TP) and True Negative (TN), relative to the total number of pixels in the image (Müller, Soto-Rey, and Kramer n.d.; Setiawan 2020). This metric provides an overall indication of segmentation correctness but may be less sensitive to class imbalance.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

Intersection over Union (IoU), also known as the Jaccard Index, evaluates the spatial overlap between the predicted segmentation and the ground truth mask by penalizing both False Positive (FP) and False Negative (FN) predictions, making it a stricter measure of segmentation performance (Badrinarayanan et al. 2017; Violeta Vlăsceanu et al. n.d.).

$$IoU = \frac{TP}{TP + FP + FN} \tag{3}$$

Dice Similarity Coefficient (DSC) is equivalent to the F1-score when applied to binary segmentation tasks and highlights consistency between predicted and ground truth regions by directly measuring overlap, which is particularly effective for evaluating boundary accuracy in complex patterned images (Chen et al. 2020; Müller et al. n.d.).

$$\text{DSC} = \frac{2TP}{2TP + FP + FN} \tag{4}$$

RESULTS AND DISCUSSION

After completing all methodological stages, ranging from dataset acquisition and preprocessing to network training and performance assessment, this section presents and discusses the experimental results in detail. The discussion begins with an analysis of the data preprocessing outcomes, followed by the implementation and architectural verification of the modified SegNet model. Subsequently, the training dynamics, performance trends, and final evaluation results are examined both numerically and visually to offer an in-depth understanding of the model's segmentation capability on Yogyakarta batik patterns.

Data Preprocessing Result

The data preprocessing stage produced a dataset that is suitable for training a deep learning–based semantic segmentation model. A total of 720 paired samples were obtained, each consisting of an RGB image and its corresponding binary mask. The dataset includes two classical Yogyakarta batik motifs, namely Parang and Kawung. The dataset was divided into training, validation, and testing sets using an 80:10:10 ratio, resulting in 576 samples for training, 72 samples for validation, and 72 samples for testing. The data split was performed randomly while maintaining a balanced distribution of motif classes across all subsets.

All RGB images were uniformly resized to a resolution of 256 × 256 pixels to maintain consistent input dimensions for the segmentation model. This resolution was selected as a trade-off between segmentation accuracy and computational efficiency. A higher resolution may preserve more fine-grained details of batik patterns, but it significantly increases memory usage and training time. Conversely, a lower resolution reduces computational cost but risks losing important structural information. The chosen resolution of 256 × 256 is sufficient to retain essential motif structures while enabling efficient model training.

Binary masks were generated automatically using K-Means Clustering and further processed using morphological operations. The resulting masks represent the foreground motif regions and background areas in binary form. Tables 1 and 2 present representative examples of the automatic masking results for the Parang and

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Kawung motifs, respectively, illustrating the correspondence between the original RGB images and the generated mask labels.

Table 1. Automatic Masking Results on Parang Pattern

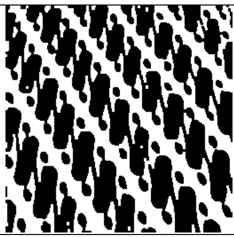
Original (RGB)	Mask Label
	

Table 2. Automatic Masking Results on Kawung Pattern

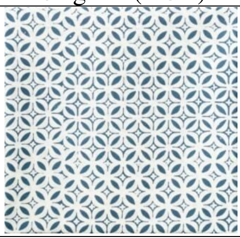
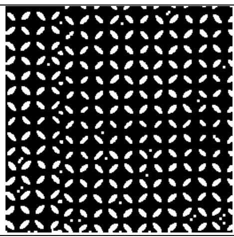
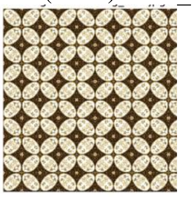
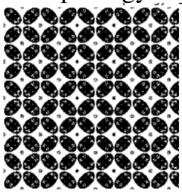
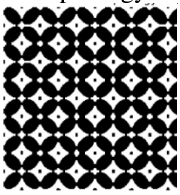
Original (RGB)	Mask Label
	

Table 3. Comparison of Original Image, Raw K-Means Mask, and Morphologically Refined Mask

Original (RGB)	Without Morphology	With Morphology
		

SegNet Model Development Result

The modified SegNet architecture proposed in this study was successfully implemented using the TensorFlow and Keras frameworks. The implemented model follows a simplified encoder–decoder structure consisting of three encoder blocks and three decoder blocks. Each encoder block contains two Conv2D layers followed by a MaxPooling operation, while each decoder block utilizes Conv2DTranspose layers for upsampling followed by Conv2D layers. The model summary generated by TensorFlow confirms that the spatial resolution of the input image is progressively reduced from 256 × 256 to 32 × 32 through the encoder pathway and subsequently restored to the original resolution through the decoder pathway.

Table 4. Summary architecture of SegNet model

Layers	Size
Input Layer	256 × 256 × 3
Conv2D	64 filter size 3×3, activation ReLU
Conv2D	64 filter size3×3, activation ReLU
MaxPooling2D	Pool size 2×2
Conv2D	128 filter size3×3, activation ReLU
Conv2D	128 filter size3×3, activation ReLU
MaxPooling2D	Pool size 2×2
Conv2D	256 filter size3×3, activation ReLU
Conv2D	256 filter size3×3, activation ReLU
MaxPooling2D	Pool size 2×2
Conv2DTranspose	256 filter size3×3, stride 2 (upsampling)
Conv2D	256 filter size3×3, activation ReLU
Conv2DTranspose	128 filter size3×3, stride 2 (upsampling)
Conv2D	128 filter size3×3, activation ReLU
Conv2DTranspose	64 filter size3×3, stride 2 (upsampling)
Conv2D	64 filter size3×3, activation ReLU
Output Conv2D	1 filter size1×1, activation Sigmoid

Table 4 presents the complete architecture of the modified SegNet model, covering the layer composition, output dimensions, and trainable parameter counts. Based on this configuration, the proposed model contains a total of 2,878,977 trainable parameters.

Model Implementation Result

The model training stage was carried in a Google Colab environment equipped with an NVIDIA T4 GPU. The implementation utilized TensorFlow, Keras, OpenCV, NumPy, and Matplotlib libraries. The dataset was partitioned into training, validation, and testing sets. The model underwent training over 50 epochs with a batch size of 8, using the Adam optimizer in combination with the Binary Cross-Entropy loss function. Segmentation performance was evaluated using Intersection over Union (IoU) and the Dice Coefficient.

Table 5. Training result

Epoch	Loss	Acc	IoU	DSC
1	0,6859	0,5346	0.3051	0,4669
10	0,2326	0,8989	0,7237	0,8388
20	0,1994	0,5327	0,3076	0,4698
30	0,1747	0,9247	0,7884	0,8809
40	0,1702	0,9277	0,7928	0,8835
46	0,1530	0,9349	0,8115	0,8953
49	0,1478	0,9371	0,8234	0,9026
50	0,1555	0,9338	0,8113	0,8951

Table 6. Monitoring Results on the Training Process (Validation Metrics)

Epoch	Loss	Acc	IoU	DSC
1	0,5896	0,6525	0,3171	0,4811
10	0,2463	0,8932	0,7061	0,8268
20	0,1931	0,9175	0,7772	0,8740
30	0,1722	0,9259	0,7926	0,8839
40	0,1756	0,9239	0,7836	0,8780
46	0,1602	0,9311	0,8112	0,8951
49	0,1715	0,9239	0,7983	0,8870
50	0,1739	0,9251	0,7937	0,8844

The lowest validation loss value of 0.1602 was achieved at epoch 46, indicating the point at which the model reached its best performance on the validation dataset during training. Accordingly, the model weights obtained at this epoch were saved and selected for subsequent evaluation on the training, validation, and testing subsets. Figures 6 and 7 show the learning curves observed during the training process. Figure 6 illustrates the development of loss and accuracy values for the training and validation datasets throughout the epochs. Meanwhile, Figure 7 shows the corresponding trends of the Intersection over Union (IoU) and Dice Coefficient metrics, providing an overview of the development of segmentation performance during the training process.

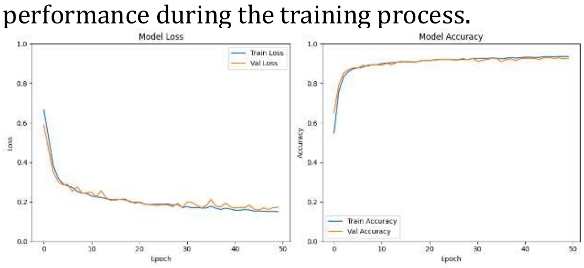


Figure 6. Loss and Accuracy Graph

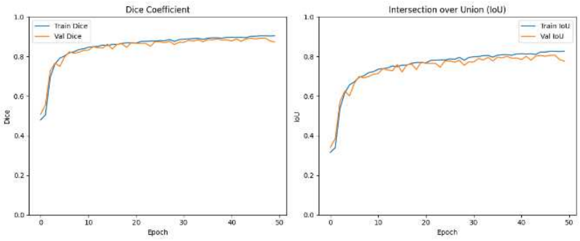


Figure 7. Dice Coefficient and Interction over Union (IoU) Graph

From these figures, it can be observed that the loss values exhibit a consistent decreasing trend, particularly during the early stages of training, indicating effective optimization and progressive error minimization. At the same time, accuracy, IoU, and Dice Coefficient show steady improvement, reflecting the model's increasing capability to correctly segment the batik motif regions. As training progresses, the rate of improvement gradually decreases and the curves begin to stabilize, indicating that the model is approaching convergence. Furthermore, the relatively small gap between training and validation curves suggests that the model maintains stable learning behavior and does not exhibit significant overfitting during the training process.

Model Evaluation Result

The final evaluation stage was carried out to examine overall performance of the modified SegNet model using three distinct data subsets: training, validation, and testing. Model performance was examined using four evaluation indicators, namely loss, accuracy, mean Intersection over Union (IoU), and mean Dice Similarity Coefficient (DSC). Unlike the per-batch IoU and Dice values monitored during training, the evaluation results were calculated as mean values across all images in each subset, allowing for a more representative assessment of segmentation performance.

Table 7. Summary SegNet Model Evaluation

Layer	Train	Validation	Test
Loss	0,1477	0,1602	0,1954
Accuracy	0,9368	0,9311	0,9172
mean IoU	0,8281	0,8127	0,7723
mean DSC	0,9054	0,8961	0,8707

On the training subset, the model achieved an accuracy of 93.68%, a mean Intersection over Union (mean IoU) of 82.81%, and a mean Dice

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Coefficient of 90.54%. These values summarize the segmentation performance obtained on the data used during the training process. On the validation subset, the model obtained an accuracy of 93.11%, a mean IoU of 81.27%, and a mean Dice Coefficient of 89.61%. The validation results are reported to provide an intermediate performance reference during model development. On the testing subset, the model achieved an accuracy of 91.72%, a mean IoU of 77.23%, and a mean Dice Coefficient of 87.07%. These results represent the final performance of the model on previously unseen data.

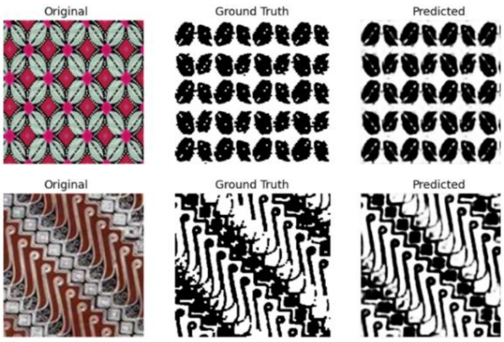

Figure 8. Visualization of Segmentation Results using SegNet modified

Figure 8 presents representative visualization results from the testing dataset. The illustration displays the input RGB images, their associated reference masks, as well as the segmentation predictions generated by the modified SegNet model.

Discussion

The experimental findings indicate that the modified SegNet architecture developed in this study achieves effective segmentation performance while maintaining a relatively low computational burden. The architectural simplification introduced in this study, particularly the reduction of the encoder–decoder depth to three blocks, enables the model to focus on learning essential spatial and textural features of batik motifs without relying on excessively deep feature hierarchies. This design choice is appropriate for batik pattern segmentation, where repetitive structures and strong geometric elements are dominant visual characteristics. Compared to more complex segmentation architectures such as U-Net, DeepLab, and the original SegNet, which typically employ deeper networks or additional mechanisms to capture multi-scale contextual information, the proposed model offers a more computationally efficient alternative while still maintaining competitive performance for structured pattern data. However, it should be noted that a direct experimental comparison with these architectures was not conducted in this study, and the comparison is therefore based on architectural characteristics and computational considerations.

The preprocessing results indicate that the adopted automatic mask generation pipeline is able to produce segmentation labels with adequate consistency to support deep learning–based segmentation. The generated masks successfully represent motif regions across both Parang and Kawung patterns, allowing the model to learn meaningful spatial representations during training. Although minor boundary imperfections are visible in some mask samples, particularly in areas with complex textures or subtle foreground–background transitions, these variations do not significantly affect the model's ability to learn general motif structures. This implies that approximate masks generated through unsupervised methods can still be effectively utilized, although segmentation accuracy at fine boundaries remains dependent on mask quality. The implementation of the simplified SegNet architecture results in a considerable reduction in the number of trainable parameters compared with the original SegNet configuration (approximately 29 million parameters), while the proposed model employs only 2,878,977 parameters. This result highlights that reducing model complexity does not necessarily degrade performance when the data characteristics are relatively structured.

The overall training behavior reflects typical convergence characteristics of convolutional segmentation models. The model is able to learn meaningful representations efficiently in early training stages and gradually reaches a stable condition. The observed gap between training and validation performance at later stages indicates the presence of overfitting, where the model increasingly adapts to the training data while improvements on validation data diminish. To mitigate this issue, a validation-based model selection strategy was applied, in which the model with the lowest validation loss was selected as the final model to ensure optimal generalization performance. This confirms that selecting model weights based on validation loss is an effective strategy to maintain generalization capability. In addition, the applied training configuration contributes to stable convergence without causing excessive performance divergence.

Evaluation on the testing dataset indicates that the model is capable of generalizing to previously unseen data, although a slight decrease in performance is observed. This suggests that the model captures underlying structural patterns of batik motifs rather than memorizing training samples. However, the performance gap also indicates that variations in motif complexity and texture still present challenges, particularly in segmenting fine-grained details. This limitation further reflects the trade-off between computational efficiency and segmentation precision when compared to more complex architectures.

The observed segmentation behavior suggests that the model effectively captures global motif structures while exhibiting limitations in handling fine-grained boundary details under certain conditions. This outcome is closely related to both the simplified architectural design and the characteristics of the automatically generated masks used during training. While the model demonstrates strong consistency at the structural level, boundary precision may be influenced by the inherent variability in the training labels. Overall, the discussion of the experimental results indicates that the modified SegNet model achieves a balance between architectural simplicity and segmentation performance. The model demonstrates stable training behavior, controlled overfitting through validation-based checkpointing, and consistent segmentation outputs across different data subsets. Overall, these experimental outcomes demonstrate that the proposed method is well suited for the segmentation of classical Yogyakarta batik motifs within the defined experimental.

CONCLUSIONS AND SUGGESTIONS

Conclusion

This article presents image segmentation of Yogyakarta batik pattern using SegNet. Based on the result of this research, it can be concluded that the modified SegNet model is effective in performing segmentation of Yogyakarta batik patterns. The data preprocessing stage utilizing K-Means Clustering successfully generated consistent binary ground truth masks, enabling the use of the original dataset, which initially lacked labeled annotations, for supervised training. The SegNet architecture was simplified into a three block encoder and decoder structure with Conv2DTranspose for upsampling, resulting in a significantly lighter model with a reduced number of parameters while maintaining strong feature extraction and reconstruction capabilities. Implementation using TensorFlow and Keras demonstrated stable training behavior and good generalization without significant overfitting. Evaluation on the test dataset showed strong performance, achieving an accuracy of 91.65%, a mean Intersection over Union of 77.18%, and a mean Dice Coefficient of 87.06%. Visual inspection of prediction results further confirms that the model can accurately separate batik pattern regions from the background, particularly for patterns with clear structural contours.

Suggestion

Future studies are recommended to focus on several improvements. First, the quality of ground truth mask generation should be enhanced through more precise annotation methods, such as limited manual labeling or the use of GrabCut, to improve label accuracy and overall model performance. Second, further architectural exploration is necessary by comparing the modified SegNet with more advanced segmentation models, including U Net, DeepLabv3 plus, and attention based architectures, to assess performance trade offs. Finally, model generalization may be achieved by increasing dataset diversity through the inclusion of more complex and varied batik motifs, as well as by integrating transfer learning techniques. These improvements are expected to facilitate wider applications in batik motif segmentation, classification, and digital cultural preservation.

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