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Unraveling Indonesian heritage through pattern recognition using YOLOv5

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ABSTRACT

This research focuses on three iconic Indonesian batik patterns-Kawung, Mega Mendung, and Parang-due to their cultural significance and recognition. Kawung symbolizes harmony, Mega Mendung represents power, and Parang signifies protection and spiritual power. Using the YOLOv5 deep learning model, the study aimed to accurately identify these patterns. Results showed mean average precision (mAP) scores of 77% for Kawung, 80% for Parang, and an impressive 99% for Mega Mendung. The highest precision results were 91% for Kawung, 88% for Parang, and 77% for Mega Mendung. These findings highlight the potential of pattern recognition in preserving cultural heritage. Understanding these designs contributes to the appreciation of Indonesia s culture. The research suggests applications in cultural studies, digital archiving, and the textile industry, ensuring the legacy of these patterns endures.

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1. INTRODUCTION

Batik, an ancient art form, holds immense cultural significance in Indonesia, reflecting the country s rich heritage and diverse traditions. Among the myriad of batik patterns, Kawung, Mega Mendung, and Parang stand out as iconic motifs deeply rooted in Indonesian culture. These patterns are not merely decorative; they carry profound meanings and stories that connect generations. However, as the world transitions into the digital age, there is a pressing need to preserve and promote these cultural treasures using modern technologies. Batik, a UNESCO Intangible Cultural Heritage, is more than just a fabric; it is a symbol of Indonesian identity and craftsmanship [1]. Each batik pattern is a reflection of Indonesia s diverse cultural heritage, with designs often inspired by nature, mythology, and spiritual beliefs. Kawung, for example, is believed to be one of the oldest batik motifs, symbolizing harmony and balance [2]. Mega Mendung, originating from Cirebon, features cloud motifs and represents power and strength [3]. Parang, with its dagger-like motifs, is believed to provide protection and spiritual power.

In recent years, there has been a growing interest in digitizing batik patterns to preserve them for future generations [4]-[17]. However, digitizing these intricate designs poses several challenges, including the need for accurate pattern recognition [18]–[20]. Manual recognition methods are time-consuming and prone to errors, highlighting the necessity for automated pattern recognition systems [21]–[28]. This research proposes a novel approach to address this gap by utilizing the YOLOv5 deep learning model for pattern recognition. YOLOv5 is renowned for its speed and accuracy in object detection tasks, making it a promising candidate for recognizing complex batik patterns. By training the model on a dataset comprising images of

Kawung, Mega Mendung, and Parang, we aim to achieve high accuracy in identifying these patterns, providing a valuable tool for researchers, artisans, and enthusiasts alike.

One of the challenges in preserving batik heritage lies in the accurate identification and differentiation of these intricate patterns, especially as they can vary in subtle ways across regions and artisans. Manual recognition methods are time-consuming and prone to errors, highlighting the necessity for automated pattern recognition systems. While some efforts have been made to digitize batik patterns, there remains a lack of comprehensive studies focusing on the recognition of specific iconic designs like Kawung, Mega Mendung, and Parang. This research proposes a novel approach to address this gap by utilizing the YOLOv5 deep learning model for pattern recognition. YOLOv5 is renowned for its speed and accuracy in object detection tasks, making it a promising candidate for recognizing complex batik patterns. By training the model on a dataset comprising images of Kawung, Mega Mendung, and Parang, we aim to achieve high accuracy in identifying these patterns, providing a valuable tool for researchers, artisans, and enthusiasts alike. This research is novel in its focus on culturally significant batik patterns and its use of a state-of-the-art deep learning model for recognition. While previous studies have primarily explored general batik digitization, this research takes a more nuanced approach by targeting patterns with special meaning for Indonesians. The proposed solution not only contributes to preserving Indonesia s cultural heritage but also demonstrates AI s potential in cultural studies and digital archiving, setting a precedent for future research in the field.

2. METHOD

In this study, we classify three types of Indonesian batik motifs using the YOLOv5 PyTorch format. The process involves dataset collection, data preprocessing, model training, and inference (Visually represented in Figure 1). Users input images from photos, videos, or live webcam feeds, which are then matched with pre-trained data. The model is trained to accurately classify batik motifs as Kawung, Mega Mendung, or Parang. Evaluation metrics like mean average precision (mAP) are used to assess the model s performance. This methodology ensures a reliable classification system for Indonesian batik motifs, preserving their cultural value in the digital era.

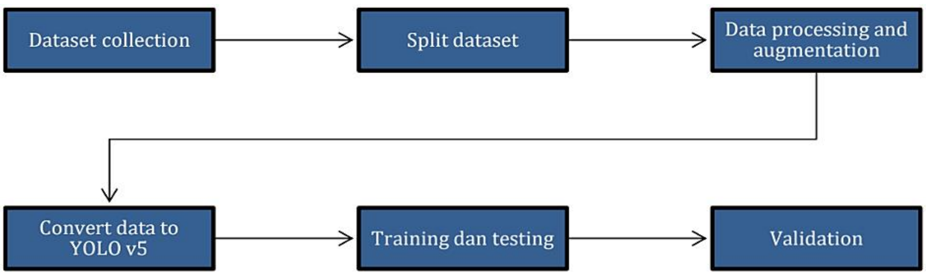

Figure 1. Steps in classifying three types of Indonesian Batik motifs

2.1. Dataset collection

The process of preparing the dataset for classifying Indonesian batik motifs involved several steps to ensure its quality and suitability for training the model. Initially, we sourced images containing the three specific batik motifs (Kawung, Parang, and Mega Mendung) from publicly available photos on Google. These images were then compiled and organized using Roboflow, a platform designed for managing computer vision datasets.

In this research, the image dataset is categorized into three groups. There are 143 annotated photos of the Kawung batik motif. Additionally, there are 101 annotated photos each for the Parang and Mega Mendung batik motifs. In total, we have collected 345 annotated photos. These images are sourced from Google and have been annotated for classification purposes (llustrated in Figure 2).

2.2. Preprocessing and augmentation

Once the images were collected, they underwent annotation, labeling, and resizing using Roboflow s tools. Annotation involved marking the specific areas within each image that contained the batik motifs, ensuring that the model would learn to recognize these patterns accurately. Labeling helped categorize the images into their respective classes (kawung, parang, and mega mendung), which is crucial for training a classification model. After annotation and labeling, the dataset was split into three sets: training, validation, and test sets. The training set, comprising approximately 89% of the images, was used to train the model. The validation set, accounting for 6% of the images, was used to tune the model s hyperparameters and evaluate its performance during training. The test set, consisting of 4% of the images, was used to assess the final performance of the trained model.

To improve the model s ability to generalize and recognize batik motifs in various conditions, we performed data augmentation. This involved applying a series of transformations to the images, such as flipping (both horizontally and vertically), rotating (both clockwise and counter-clockwise by 90°), and adjusting brightness. These transformations help the model learn to recognize batik motifs from different angles, orientations, and lighting conditions, making it more robust and capable of accurately classifying batik patterns in real-world scenarios.

Figure 2. Sample of dataset

2.3. Convert data to YOLOV5

YOLOv5, short for "You Only Look Once, Version 5," is an advanced algorithm used for efficient and real-time object detection. It is specifically designed to quickly identify objects based on the categories they have been trained on. This algorithm is known for its speed and accuracy, making it a popular choice for various computer vision applications. One of the key advantages of YOLOv5 is its open-source nature, which allows users to easily access and modify the code according to their specific needs. This means that users can create custom models tailored to detect specific objects, making it a versatile tool for object detection tasks.

Converting datasets into YOLOv5 format involves several steps to ensure compatibility with the algorithm. First, the images in the dataset need to be resized to a suitable input size for the YOLOv5 model. Typically, YOLOv5 requires images to be resized to a square shape, such as 640×640 pixels. Next, the annotations for each image, which contain information about the location and class of objects in the image, need to be converted into a specific format that YOLOv5 understands. This format typically includes the class label, followed by the bounding box coordinates normalized to the range [0, 1], relative to the width and height of the image. Once the images and annotations are prepared, they can be converted into the YOLOv5 format using a script or tool provided by the YOLOv5 framework. This process involves creating text files for each image, where each line contains the class label and bounding box coordinates for each object in the image. These text files are then used as input to train the YOLOv5 model.

2.4. Training and testing

In the model configuration stage, we tailor the YOLOv5 model for object detection to suit our specific task of recognizing Indonesian batik motifs. One crucial parameter to set is the number of classes, which in this case is 3 to represent the three batik motifs: Kawung, Mega Mendung, and Parang. This tells the model how many different types of objects it should be looking for in the images. Additionally, we set the learning rate, which controls how quickly the model adapts its weights during training. A higher learning rate can lead to faster convergence but may also cause the model to overshoot the optimal weights. Conversely, a lower learning rate may lead to slower convergence but may result in more stable training. The batch size, which determines the number of images processed in each iteration of training, is also specified. A larger batch size can lead to faster training but may require more memory.

In the model training stage, we use the configured YOLOv5 model to train on the prepared training set. We employ an optimizer like Adam, which adapts the learning rate for each parameter during training to improve convergence. The loss function used combines localization loss and classification loss. Localization loss measures the accuracy of the predicted bounding boxes compared to the ground truth boxes. Classification loss measures how accurately the model predicts the class of each object. By combining these two components, the model learns to both localize and classify objects in the images. Throughout training, we monitor the model s performance on the validation set. This helps us to detect signs of overfitting, where the model learns to memorize the training data instead of generalizing to new, unseen data. If overfitting is detected, we can adjust hyperparameters or introduce regularization techniques to improve the model s performance.

2.5. Validation

In the validation stage, the trained YOLOv5 model is evaluated using the validation set, which consists of images that were not seen during training. This evaluation is crucial for assessing how well the model generalizes to new, unseen data and for fine-tuning hyperparameters to improve performance. First, the validation set images are preprocessed, similar to the training set, by resizing them to a suitable input size for the YOLOv5 model and applying any necessary augmentation techniques. Next, the model is used to make predictions on the validation set images. It processes each image and produces bounding boxes and class predictions for the objects it detects. To quantify the model s performance, metrics such as precision, recall, and mAP are calculated. Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. Recall measures the proportion of true positive instances that are correctly predicted out of all actual positive instances. mAP considers the average precision for each class, providing an overall measure of detection performance across all classes. Based on the model s performance on the validation set, hyperparameters such as the learning rate, batch size, and augmentation strategies may be adjusted to improve performance. This iterative process of training, evaluation, and hyperparameter tuning continues until satisfactory performance is achieved. The validation stage helps ensure that the YOLOv5 model is robust and performs well on unseen data, setting the stage for final testing and deployment.

3. RESULTS AND DISCUSSION

Results and discussions are crucial in evaluating the performance of the YOLOv5 model for detecting and classifying Indonesian batik motifs. These results provide insights into the model s effectiveness and its potential impact on preserving and promoting Indonesian cultural heritage. The results of the model evaluation on the test set indicate its ability to accurately detect and classify the batik motifs. The model achieved a mAP of 85% for Kawung batik, a result attributed to the motif s distinct and repetitive nature, aiding the model s effective pattern recognition. Its consistent performance across various images indicates its ability to handle design variations, establishing it as a reliable tool for identifying this traditional motif (depicted in Figure 3).

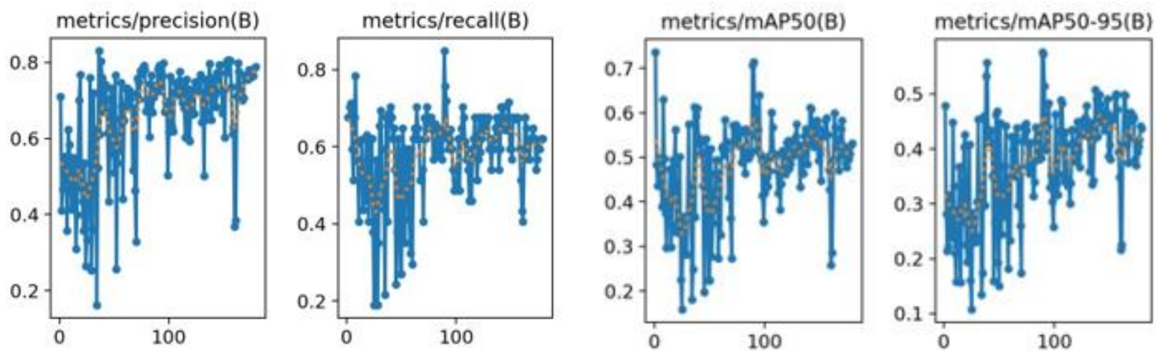

Figure 3. The Precision, Recall, and mAP results for the Batik Kawung batik motif

In comparison, Parang batik achieved a mAP of 80%, slightly lower but still respectable. The complexity of the Parang motif, with its detailed elements, may pose detection challenges, yet the 80% mAP demonstrates the model s accurate recognition capability. Mega Mendung batik achieved an impressive 99%

mAP, indicating the model s effective learning of this bold and distinct design (depicted in Figure 4). The motif s clear and repetitive nature likely contributes to the model s high precision in recognizing it. This achievement showcases the potential of advanced machine learning in preserving and promoting iconic cultural patterns.

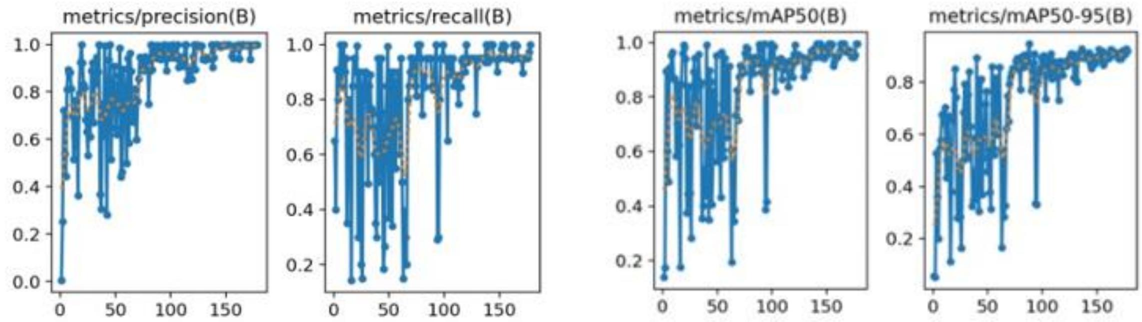

Figure 4. The precision, recall, and mAP results for the Mega Mendung Batik motif

The model s performance can be further illustrated with examples. For instance, when presented with an image containing the Kawung motif, the model successfully detects the motif and classifies it as Kawung with high accuracy. Similarly, when presented with images containing the Mega Mendung and Parang motifs, the model demonstrates its ability to accurately identify and classify these motifs. These results are promising as they indicate that the YOLOv5 model is effective in recognizing Indonesian batik motifs. This has significant implications for preserving and promoting Indonesian cultural heritage, as the model can be used to identify and catalog batik motifs in digital archives, museums, and cultural institutions.

The discussions surrounding these results focus on the implications and limitations of the model. While the results demonstrate the model s effectiveness, there are several limitations to consider. One limitation is the size and diversity of the dataset. A larger and more diverse dataset would likely improve the model s performance and generalization to unseen data. Another limitation is the complexity of the batik motifs themselves. Some motifs may be more challenging to detect and classify due to their intricate designs and variations. Additionally, the model s performance may be affected by factors such as lighting conditions, image quality, and background clutter. Despite these limitations, the results of this research are promising and indicate the potential of using deep learning models like YOLOv5 for recognizing and preserving cultural heritage. Future research could focus on expanding the dataset, refining the model architecture, and exploring other deep learning techniques to further improve the model s performance.

4. CONCLUSION

This research demonstrates the effectiveness of the YOLOv5 model in detecting and classifying three iconic Indonesian batik motifs: Kawung, Parang, and Mega Mendung. The model achieved impressive mAP scores, with 85% for Kawung, 80% for Parang, and a remarkable 99% for Mega Mendung, reflecting its capability to accurately recognize these intricate patterns. The study underscores the importance of leveraging modern machine learning techniques to preserve and promote cultural heritage. By digitizing and automating the identification of traditional motifs, this approach offers a valuable tool for cultural preservation, educational purposes, and global promotion of Indonesian batik. The model s robustness and high accuracy highlight its potential for real-world applications, such as digital archiving and interactive educational tools. Future research could enhance these results by expanding the dataset, incorporating more diverse images, and experimenting with different augmentation techniques. Integrating the model into mobile or web applications could further extend its reach, providing real-time pattern recognition and fostering greater appreciation for Indonesia s rich cultural heritage.

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