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YOLO26 for automated batik pattern classification: Preserving cultural heritage through advanced computer vision

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ABSTRACT

Batik is an important cultural heritage of Indonesia, characterized by diverse motifs reflecting regional identity, philosophy, and historical background. Manual identification requires expert knowledge and is time-consuming, making automated classification a valuable research challenge. This study proposes an automated batik motif classification system using YOLO26, a modern deep learning architecture optimized for end-to-end inference without Non-Maximum Suppression. The removal of post-processing stages enables a simpler and more efficient classification pipeline, suitable for lightweight and scalable deployment. A dataset of 20 batik motif classes, including Batik Bali, Batik Parang, Batik Mega Mendung, and Batik Kawung sourced from Kaggle, was constructed and preprocessed using standardized image resizing and normalization techniques. Data augmentation strategies such as geometric and photometric transformations improved model robustness. The system was trained using GPU acceleration to ensure efficient experimentation and reproducibility. Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. Experimental results show the proposed system achieved 86.44% overall classification accuracy with balanced macro and weighted F1-scores, indicating consistent performance across all batik categories. Results demonstrate that YOLO26 effectively captures fine-grained texture details and high-level motif structures, enabling discrimination between visually similar patterns. This approach contributes to automated batik recognition systems and supports digital preservation, cultural education, and practical applications in batik authentication and classification.

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1. INTRODUCTION

Batik is a culturally rich textile art form with a history spanning more than a thousand years across Southeast Asia, particularly Indonesia, Malaysia, and the Malay Archipelago [1]. Recognized by UNESCO in 2009 as a Masterpiece of the Oral and Intangible Heritage of Humanity, Indonesian batik reflects regional identities, artistic traditions, and symbolic meanings passed down through generations [2]. Batik motifs are inspired by philosophical values, nature, social structures, and spiritual beliefs [3], [4], while the traditional wax-resist dyeing technique produces distinctive regional patterns [5], [6] such as Parang, Kawung, Megamendung, Tambal, and Sido Mukti, each with unique characteristics and historical significance [7], [8]. Despite its diversity, batik preservation and authenticastion face growing challenges due to modernization [9], [10], mass-produced imitations, and the declining number of expert artisans [11], [12]. Museums and cultural institutions require systematic cataloging and verification of batik collections [13], yet traditional identification methods still depend heavily on expert judgment, making the process time-consuming, subjective, and difficult to scale efficiently.

Advancements in image classification technologies offer a promising solution to these challenges [14]. Automated batik classification systems can support faster and more consistent pattern identification, assist in distinguishing authentic traditional batik from reproductions, and enable large-scale digital preservation of cultural assets [15], [16]. In addition, such systems can enhance educational tools by providing instant motif recognition for learners and improve market transparency for consumers and collectors seeking verified batik products [17]. The You Only Look Once (YOLO) family of algorithms introduced a major shift in object detection and image classification when first proposed by Redmon et al. in 2016 [18]. Unlike conventional two-stage detection methods, YOLO formulates detection as a single regression problem, allowing images to be processed in one forward pass through a convolutional neural network [19]. This design enables real-time inference while maintaining strong accuracy, making YOLO well suited for applications that demand both speed and precision [20]. Successive versions of YOLO have continuously evolved to improve model efficiency and inference performance [21], [22]. YOLO26, as the latest iteration, introduces a fundamental architectural change by eliminating the Non-Maximum Suppression (NMS) stage from the inference pipeline, enabling a native end-to-end prediction process [23], [24]. This design reduces inference latency and minimizes the need for manually tuned post-processing hyperparameters, such as Intersection-over-Union (IoU) thresholds, which are commonly required in traditional detection frameworks 25]. As a result, YOLO26 is optimized for lightweight deployment scenarios, including edge computing, mobile devices, and low-power systems, while maintaining competitive classification accuracy [25]. These characteristics make YOLO26 particularly well-suited for batik image classification tasks. Batik motifs exhibit complex visual characteristics across multiple spatial scales, ranging from fine-grained texture patterns to larger repetitive and structural elements [26]. The end-to-end inference mechanism of YOLO26 enables efficient learning of both low-level texture information and higher-level motif representations without additional post-processing steps [24]. Consequently, the model is capable of distinguishing between visually similar yet culturally distinct batik patterns with improved consistency and computational efficiency [23].

This study develops and evaluates a YOLO26-based framework for automated batik pattern classification, aiming to assess whether YOLO26 can accurately classify diverse Indonesian batik motifs and match or surpass existing approaches. Secondary objectives include building a comprehensive annotated batik dataset, optimizing YOLO26's architecture for batik imagery, comparing performance against traditional machine learning and earlier deep learning methods, and identifying limitations while proposing applications for cultural heritage preservation. Here, we address key questions about YOLO26's classification accuracy across batik motif categories, its ability to distinguish visually similar regional patterns, optimal training configurations and preprocessing strategies, comparative performance in accuracy and efficiency against previous approaches, and identification of challenging pattern characteristics with potential solutions.

2. METHOD

Development Environment and Dataset Information

The discussion begins with an overview of the system design and development environment, including the use of the Kaggle platform, which provides cloud-based GPU resources, integrated dataset management, and notebook-based experimentation to support model training and evaluation. The dataset used in this study consists of RGB batik images representing 20 distinct batik classes in 983 images in total. The batik patterns including Batik Bali, Batik Betawi, Batik Celup, Batik Cendrawasih, Batik Ceplok, Batik Ciamis, Batik Garutan, Batik Gentongan, Batik Kawung, Batik Keraton, Batik Lasem, Batik Mega Mendung, Batik Parang, Batik Pekalongan, Batik Priangan, Batik Sekar, Batik Sidoluhur, Batik Sidomukti, Batik Sogan, and Batik Tambal sourced from the Kaggle public dataset titled "Indonesian Batik Motifs" which can be accessed via https://www.kaggle.com/datasets/dionisiusdh/indonesian-batik-motifs. This dataset was selected because it contains a wide range of categories, ensuring diverse regional and stylistic representation.

Data Processing and Augmentation

Data processing and augmentation were implemented using a customized dataset class based on Ultralytics YOLO augmentation to integrate preprocessing into the training and validation pipelines. All images were resized to a fixed input resolution for uniform batch processing. During training, augmentation techniques such as random horizontal and vertical flipping, RandAugment transformations, and color jittering were applied to improve generalization by simulating variations in fabric orientation, lighting, dye intensity, and fabric aging, as shown in Figure 1. Images were then converted into tensors, normalized, and subjected to random erasing to encourage learning of global pattern structures. For validation and testing, only deterministic preprocessing steps including resizing, tensor conversion, and normalization were applied to ensure unbiased evaluation. The proposed method is designed to handle visual variations in batik images, including differences in orientation, lighting, color intensity, and texture complexity [27].

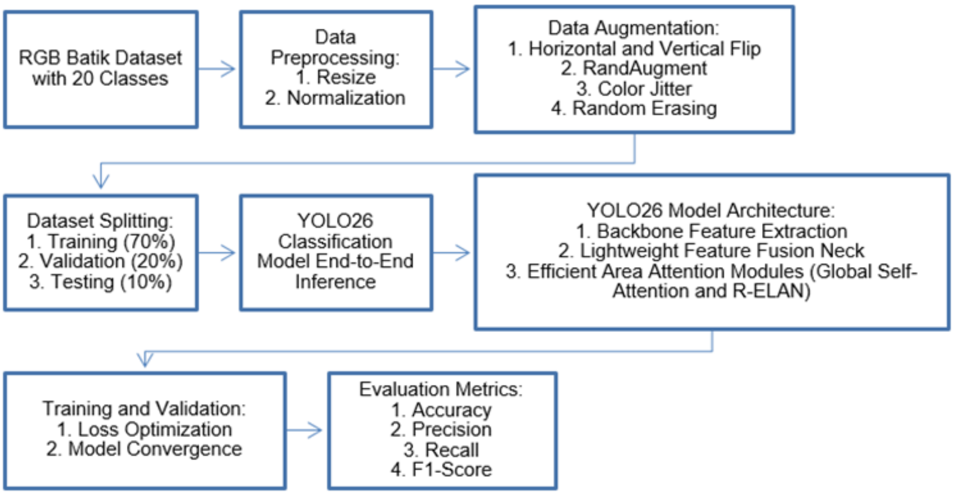

Figure 1. End-to-end batik classification pipeline

The YOLO26 model was trained using SGD optimizer with a learning rate of 0.001 to ensure stable convergence and computational efficiency [28], [29]. Training was performed for 100 epochs with a batch size of 32, while convolutional layers used default YOLO26 weight initialization to support effective gradient flow [30], [31], [32], [33]. Input images were resized to 640×640 pixels to match YOLO26 specifications and ensure consistent feature extraction [23]. The classification process uses an end-to-end inference pipeline in which preprocessed batik images are analyzed by the convolutional backbone to learn hierarchical features, including fine-grained textures and motif structures, before producing final classification outputs without additional post-processing. Model parameters were optimized through classification loss minimization, with validation conducted each epoch to monitor generalization and prevent overfitting. YOLO26, derived from the YOLO family for real-time object detection and adapted for image classification, employs convolutional backbones and feature aggregation layers to extract multi-scale visual features while eliminating Non-Maximum Suppression (NMS) for simpler and faster inference [23], [25]. Compared to traditional detection pipelines requiring IoU thresholds and NMS [34], [35], YOLO26 reduces inference latency, simplifies deployment, and supports low-power devices such as edge and mobile AI systems [23], [36]. For batik classification, the model is configured for single-label classification and enhanced with attention mechanisms and varying receptive field convolutions to capture both detailed textures and large-scale motif structures, enabling accurate recognition of visually similar batik patterns with high computational efficiency.

Evaluation Metrics

To evaluate the proposed batik classification model, standard metrics including accuracy, precision, recall, and F1-score were employed to provide overall and class-wise performance analysis, particularly for visually similar motifs [37]. Accuracy measured the proportion of correctly classified images across all categories using TP, TN, FP, and FN values [38], [39]. Precision evaluated the reliability of positive predictions and resistance to false positives [40], [41], while recall measured the model’s ability to correctly identify all relevant batik samples and minimize missed classifications [42], [43]. The F1-score, defined as the harmonic mean of precision and recall, balanced both metrics by considering false positives and false negatives equally [44], [45], [46]. Collectively, these metrics provide a comprehensive assessment of the model’s effectiveness in distinguishing visually similar and culturally distinct batik motifs.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

3. RESULTS AND DISCUSSIONS

Overall Classification Performance

The proposed system achieved strong classification performance across 20 batik motif categories with an overall accuracy of 86.44%. The macro-averaged precision, recall, and F1-score reached 0.8667, 0.8649, and 0.8649, indicating balanced performance across all classes despite visual similarities among batik patterns. The weighted F1-score of 0.8641 further demonstrates stable performance considering variations in class sample sizes, while the micro-averaged metrics remained consistent at 0.8644, confirming the robustness and reliability of the model. Overall, these results show that the YOLO26 model effectively learns discriminative visual features from complex batik images and performs efficient multi-class classification without requiring complex post-processing.

Table 1. Result of the model's performance

	Accuracy	Precision	Recall	F1-Score
Result	0.8644	0.8667	0.8649	0.8649

Confusion Matrix Analysis

The confusion matrix and its normalized version show that most misclassifications occur between batik motifs with similar structural patterns or color compositions, particularly regional variants sharing cultural influences. Nevertheless, the strong diagonal dominance in the normalized confusion matrix confirms that correct classifications greatly outnumber incorrect ones across most classes, as shown in Figure 3. These results demonstrate the effectiveness of YOLO26's hierarchical feature learning in capturing fine-grained textures and higher-level motif structures without requiring post-processing methods such as Non-Maximum Suppression.

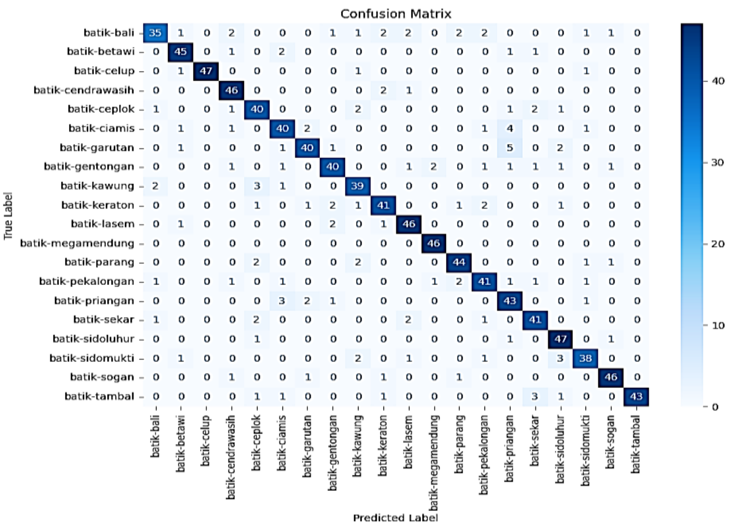

Figure 2. Confusion matrix of the relationship between classes

Training and Validation Curve Analysis

The training results in Figure 3 demonstrate effective convergence and strong performance of the YOLO26 model for batik classification. Training loss decreased sharply from approximately 3.0 to below 0.5

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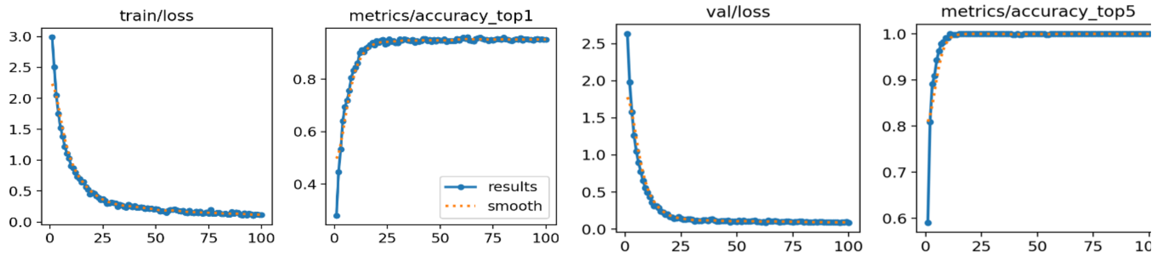
within the first 25 epochs and stabilized around 0.1 by epoch 100, while validation loss similarly declined from 2.7 to approximately 0.1, indicating good generalization without significant overfitting. The top-1 accuracy improved rapidly from near 0% to approximately 0.85 by epoch 10 and stabilized around 0.95 (95%) by epoch 50 through epoch 100. Meanwhile, top-5 accuracy reached 0.99 (99%) by epoch 20 and remained stable for the rest of training. The smooth training curves and close alignment between training and validation results indicate stable learning dynamics, effective feature extraction, and reliable classification performance for practical deployment.



Training Validation

Figure 1. Training and validation curve

Visual Result

Figure 4 presents visual validation results using 16 representative batik samples annotated with predicted labels and confidence scores. All samples achieved a confidence score of 1.0, consistent with the previously reported quantitative results. The samples include various batik categories such as parang, keraton, Lasem, Betawi, and Priangan, demonstrating strong generalization capability. The model accurately recognized motifs such as batik-sekar, batik-sogan, batik-parang, and batik-priangan despite variations in color, garment type, and photographic context, indicating that classification relies on structural pattern characteristics rather than superficial attributes. The successful classification of the complex batik-keraton Taman Teratai motif further demonstrates the model's ability to handle intricate compositions. Overall, these results confirm the effectiveness and robustness of the proposed method in addressing intra-class variation, inter-class similarity, and real-world image diversity for Indonesian batik motif recognition.

Figure 4. Visual result of the trained model

Discussion

The experimental results show that the YOLO26-based approach performs competitively for multi-class batik motif recognition. By eliminating Non-Maximum Suppression, YOLO26 reduces inference complexity, latency, and memory overhead while maintaining robust classification accuracy, making it suitable for resource-constrained environments such as mobile, embedded, and cloud-based cultural heritage systems, as shown in Table 2. The results confirm the feasibility of YOLO26 for applications including digital archiving, cultural preservation, educational tools, and batik authentication. Future improvements may involve expanding datasets, using higher-resolution images, applying advanced textile-specific augmentation, and integrating attention-based feature enhancement methods. Compared with previous studies, the proposed YOLO26 system achieved 86.44% accuracy on 20 batik classes with 983 images, outperforming HOG-MLP [48] with 84.2% accuracy and KNN-GLCM [49] with 75% accuracy. Against YOLOv11 [50], the proposed method achieved competitive recall (86.49% vs. 80.8%) while maintaining balanced precision across all classes. The model also achieved consistent performance with precision of 86.67%, recall of 86.49%, and F1-score of 86.49%, demonstrating robust and unbiased classification. Its end-to-end architecture without Non-Maximum Suppression further simplifies deployment by eliminating manual hyperparameter tuning and complex post-processing while maintaining computational efficiency and strong classification performance.

Table 2. Comparison with related domain of studies

Study	Model / Approach	Dataset & Classes	Reported Performance	Comparison to Our Proposed Method
[47]	HOG-MLP	50 types of batik and 6 pictures for each type	Accuracy: 82.6%, Precision: 82.7%, Recall: 82.6% for 10 kFold. Accuracy: 84.2%, Precision: 84.1%, Recall: 84.2% for 5 kFold. Written metrics above were weighted average of each metrics.	Lower reported accuracy, precision, and recall. The study also used fewer dataset than our proposed method
[48]	KNN-GLCM	Total dataset size was not reported, and the dataset was described as "still dirty" because it contained non-batik images.	Accuracy: 75%. Precision and recall were defined but no actual results are reported.	Lower reported accuracy and dirty dataset.
[49]	YOLOv11	248 raw Batik Cual Bangka Belitung images	Precision: 93.4%, Recall 80.8%, mAP50: 95.0 %, and mAP50–95: 81.72%	Lower reported Recall with fewer image classes
Proposed method	YOLO26 (End-to-End Classification)	Batik images, 20 motif classes with 983 images in total	Accuracy: 86.44%, Precision: 86.67%, Recall: 86.49%, F1-Score: 86.49%	Highest number of classes; balanced performance across all metrics; single unified architecture without NMS

4. CONCLUSION

This study successfully developed an automated batik classification system using the YOLO26 model to recognize 20 traditional batik motif classes. By employing an end-to-end classification framework without Non-Maximum Suppression, the proposed approach achieved efficient inference while maintaining strong classification performance. The experimental results demonstrate that YOLO26 is capable of learning both fine-grained texture details and high-level motif structures that characterize diverse batik patterns. Based on evaluation using accuracy, precision, recall, and F1-score metrics, the proposed system achieved an overall classification accuracy of 86.44%, with balanced macro and weighted F1-scores. These results indicate that the model performs consistently across multiple batik categories, including motifs with high visual similarity. The per-class analysis further shows that motifs with distinctive structural and color characteristics achieved higher performance, while more visually overlapping patterns presented greater classification challenges. The use of a cloud-based GPU environment provided by Kaggle enabled efficient model training and evaluation, demonstrating the practicality of the proposed system for research and scalable deployment. Moreover, the elimination of post-processing steps such as Non-Maximum Suppression simplifies the inference pipeline and enhances suitability for lightweight and low-power applications. In conclusion, this research confirms that YOLO26 is an effective and efficient solution for automated batik motif classification. The proposed system contributes to digital cultural heritage preservation by supporting batik documentation, authentication, and educational applications. Future work may focus on expanding the dataset, improving class balance, and exploring hybrid or multimodal approaches to further enhance classification accuracy and robustness.

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CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Moch. Sjamsul Hidajat: Conceptualization, Methodology, Software, Project administration. Dibyo Adi Wibowo: Conceptualization, Methodology, Software, Review. Zudha Pratama: Editing, Validation, Supervision.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

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Data can be accessed via Kaggle website: https://www.kaggle.com/datasets/dionisiusdh/indonesian-batik-motifs/data.

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