Classification of Batik Cual Bangka Belitung Based on Deep Learning: YOLOv11 Approach

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ABSTRACT

The rapid growth of artificial intelligence, particularly deep learning, has enabled significant advancements in computer vision and automated image recognition. However, the application of these technologies to traditional cultural artifacts remains limited, especially within the domain of Indonesian textile heritage. Batik Cual Bangka Belitung, which features intricate ornamentation and visually similar motifs, presents unique classification challenges that conventional Convolutional Neural Network (CNN) models struggle to address effectively. To overcome these limitations, this study introduces an automatic motif classification system using the YOLOv11 architecture, a state-of-the-art object detection model capable of identifying and distinguishing fine-grained visual patterns. The research follows a systematic pipeline consisting of dataset collection, curation, manual motif labeling, image preprocessing, model configuration, training, and testing. A curated dataset of Batik Cual images was augmented and divided into training, validation, and testing subsets to ensure robust evaluation. Experimental results demonstrate strong model performance, achieving a precision of 0.934, recall of 0.808, mAP50 of 0.950, and mAP50–95 of 0.8172. These findings confirm that YOLOv11 can accurately detect motif regions and classify them under varying structural and textural conditions. The study contributes not only a reliable technical framework for recognizing Batik Cual motifs but also supports digital preservation efforts and future cultural computing applications.

Keywords: Batik Cual, deep learning, computer vision, image classification; YOLOv11

1. INTRODUCTION

The rapid advancement of artificial intelligence over the past two decades has stimulated significant changes in visual data processing, particularly through deep learning. Rather than relying on handcrafted features, deep learning models are capable of learning hierarchical feature representations directly from raw image inputs, enabling more efficient and scalable analysis (Taralathasri et al., 2021). Within this development, computer vision has emerged as a core foundation in supporting tasks such as object recognition, pattern identification, and complex image classification across diverse domains (Khanam & Hussain, 2024; Mao & Hong, 2025).

As visual datasets become more complex, Convolutional Neural Networks (CNNs) have gained prominence as the primary architecture for image classification due to their capacity to capture spatial correlations and textural patterns at multiple abstraction levels. Prior studies consistently report strong CNN performance when dealing with objects featuring varied shapes, colors, and structural repetition (Arifin & Nurfaizah, 2024; Dani & Handayani, 2021; Oktarino et al., 2024). Nevertheless, motif-rich and visually similar images continue to pose challenges, especially when inter-class distinctions rely on subtle, fine-grained features that are difficult to separate through global representation learning (Aras et al., 2022; Fitriani et al., 2023). To address these limitations, object detection frameworks such as You Only Look Once (YOLO) have emerged as an alternative that not only classifies but also pinpoints object locations in a single inference step, thereby enhancing discrimination in visually dense environments (Ramadhani & Widyaningrum, 2025; Taralathasri et al., 2021).

The development of the YOLO architecture has been comprehensively mapped in a survey tracing the evolution of YOLOv1 through YOLOv11, which highlights significant advancements in backbone components, multiscale detection mechanisms, and computational efficiency across each model generation (Kotthapalli et al., 2025). These findings demonstrate that the YOLO family has become increasingly competitive in handling objects with complex patterns and varying scales, making it highly relevant for application to batik imagery characterized by dense motifs and repetitive visual structures. Moreover, the YOLO-pest study also shows that YOLO variants can effectively adapt to specialized visual domains and small objects with highly similar pattern characteristics, a phenomenon closely aligned with the primary challenges of recognizing Batik Cual motifs (Dong et al., 2022).

On the other hand, developments in image processing technology have opened strategic opportunities for digitizing and preserving visual cultural heritage. Cultural artifacts presented in image form—particularly traditional textiles represent valuable historical, aesthetic, and identity-based knowledge, yet remain highly vulnerable to degradation and intergenerational loss. Computer vision–driven digitization supports systematic and standardized documentation, analysis, and recognition of traditional motifs, enabling more sustainable preservation initiatives (Evita et al., 2021; Kurniawan et al., 2023; Sri Arsa et al., 2022). In practical terms, automated motif recognition systems enable scalable cultural documentation by allowing large batik collections to be indexed, categorized, and archived without manual inspection. For example, digital batik archives can automatically label motif types, assist museums in cataloging textile collections, and support educational platforms by providing real-time motif identification for students and researchers. Such systems also facilitate long-term preservation by creating structured digital records that can be efficiently searched, analyzed, and reused across generations.

Batik, recognized as one of Indonesia's intangible cultural heritage, is a visually rich artifact characterized by symbolic meaning, diverse motif structures, and intricate textural variations, making it a relevant subject for the advancement of deep learning–based image classification systems.

In the local context, Batik Cual Bangka Belitung represents a distinctive traditional textile form with a unique visual identity expressed through motif structure, color choices, and embedded philosophical interpretations. Typical Cual patterns integrate geometric repetition and decorative elements associated with Bangka Malay culture, often expressed through contrasting hues and densely textured ornamentation. Such characteristics render Batik Cual a challenging object for automated classification, particularly when motif differences are subtle and difficult to discern visually (Sri Arsa et al., 2022).

Unlike Javanese batik, which is produced using wax-resist techniques such as canting or stamping, Batik Cual Bangka Belitung is traditionally woven using sungkit techniques with gold threads and natural dyes derived from materials such as sappan wood and turmeric, and features distinctive local flora–fauna motifs, spice-related elements, and Arabic calligraphy that reflect aristocratic Malay culture since the 18th century; these unique material, structural, and ornamental characteristics require a different analytical approach for automated motif recognition (Harikiswanto, 2023).

Despite this cultural significance, studies on automated recognition and classification of Batik Cual Bangka Belitung remain limited. Existing research has predominantly addressed motifs from the major batik-producing regions, Yogyakarta (Dani & Handayani, 2021), Garut (Fitriani et al., 2023), Semarang (Afifah & Lusiana, 2025), Papua (Aras et al., 2022), and West Sumatra (Azmi et al., 2023) while only a few works touch on related textile traditions more broadly (Ihdal, 2021).

Previous studies on batik image processing have predominantly employed Convolutional Neural Network (CNN) approaches that focus on global image classification without considering the specific locations of motifs within the fabric (Girsang, 2021). Even when refinements are introduced through ensemble CNN architectures such as model voting and aggregated predictions, the resulting outputs still rely on whole-image classification and do not distinguish motif regions spatially (Azhar et al., 2021). Research on analogous traditional textiles, such as Batak Ulos, likewise applies conventional CNN-based classification without incorporating detailed object localization mechanisms (Muliono et al., 2023). The absence of bounding-box-based detection approaches in both batik and traditional woven fabrics reveals a significant innovation gap that can be addressed through the adoption of YOLOv11, enabling more precise motif-level classification.

Until now, the identification and classification of Batik Cual motifs have largely relied on subjective assessments carried out by artisans and cultural experts, a process that introduces variability, potential misinterpretation, and limited scalability. Manual visual inspection is time-consuming, requires specialized expertise, and remains impractical for broader digital adoption. Several studies have attempted to integrate Convolutional Neural Networks (CNNs) into batik motif recognition, including work on Yogyakarta, Garut, and South Kalimantan fabrics (Arifin & Nurfaizah, 2024; Fitriani et al., 2023; Ihdal, 2021), as well as on more generalized regional textile datasets (Azmi et al., 2023). However, these studies remain restricted to global image classification and do not incorporate motif localization, underscoring the need for a more adaptive, accurate, and fine-grained automated framework capable of reflecting the intricate visual complexity of Batik Cual.

A review of the existing literature indicates that research on batik motif recognition continues to focus primarily on conventional CNN architectures and transfer learning approaches, while exploration of more advanced object detection frameworks remains limited. Recent works have begun to consider the integration of the YOLO model family within textile-related studies—particularly YOLOv11 as demonstrated in emerging analyses on environmental imagery and patterned fabric datasets (Khanam & Hussain, 2024; Ramadhani & Widyaningrum, 2025). In parallel, broader discussions on object detection performance have highlighted YOLOv11's technical contributions in multiscale feature extraction and real-time inference (Mao & Hong, 2025). However, despite these developments, the application of YOLOv11 to traditional textile domains, especially indigenous cultural fabrics, remains notably scarce at both national and international levels. The absence of studies specifically addressing Batik Cual Bangka Belitung, therefore, underscores a meaningful and relevant research gap that merits systematic investigation. From a methodological perspective, batik motif classification presents several technical challenges, including limited dataset size, high intra-class variation, non-uniform motif distribution, and inconsistent lighting conditions during image acquisition. Variations in fabric folds, color fading, and background interference further complicate feature extraction, particularly when motifs share similar geometric structures. These challenges motivate the use of robust object detection architectures capable of learning localized and multiscale visual features rather than relying solely on global image representations.

Therefore, this study aims to develop a deep learning-based classification system for Batik Cual Bangka Belitung motifs with the YOLOv11 approach. The main contribution of this research lies in the application of the latest generation object detection architecture to classify Batik Cual motifs automatically and more precisely, while enriching the study of computer vision in the domain of visual cultural heritage. Practically, this research is expected to support efforts to preserve Batik Cual Bangka Belitung through the use of AI technology, as well as become a reference for the development of a deep learning-based regional batik classification system in the future.

2. RESEARCH METHOD

This systematic literature and network analysis (SLNA) employed a two-component design integrating systematic review methodology with bibliometric network analysis. The systematic review component followed PRISMA 2020 guidelines (Page et al., 2021) for transparent reporting of systematic reviews, while the bibliometric component utilized established network analysis procedures for keyword co-occurrence mapping (Liu & Prajapati, 2022). The study protocol was developed a priori, specifying search strategies, selection criteria, data extraction procedures, and synthesis methods for both components, consistent with best practices in educational research synthesis (Maynard, 2025). No protocol pre-registration was conducted as narrative synthesis rather than meta-analysis was planned from study inception.

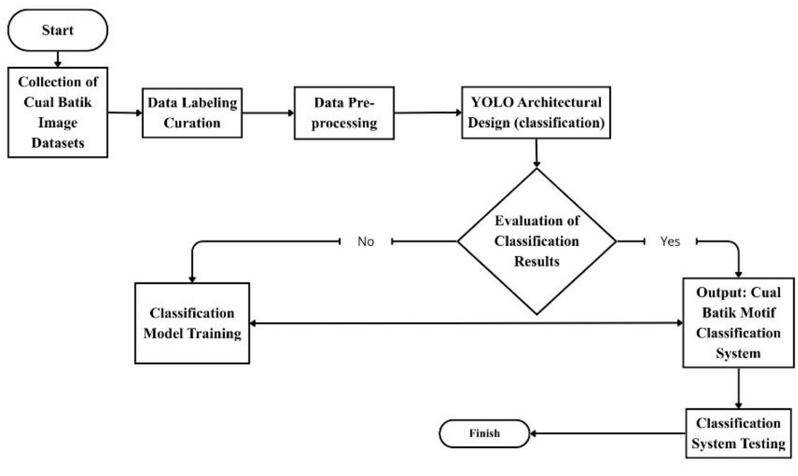

Figure 1. System Flowchart

2.1. RESEARCH DESIGN

This research is designed as a deep learning-based experimental research to build an automatic classification system for Batik Cual motifs in Bangka Belitung using the YOLOv11 architecture. The research design follows the process flow shown in the system flowchart, which starts from the collection of the Batik Cual image dataset, followed by data curation and labeling, pre-processing, designing the YOLO architecture for classification, model training, evaluation of classification results, implementation of the model into the system, to testing the classification system. The flowchart shows that the model training and evaluation process is iterative, where the model will be retrained if the evaluation results do not meet the set performance criteria. This approach ensures that the resulting classification system has an optimal level of accuracy and stability before it is implemented into the final platform.

2.2. COLLECTION OF CUAL BATIK IMAGE DATASET

The stage of collecting the Batik Cual image dataset is the initial phase of research and corresponds to the "Collection of Cual Batik Image Dataset" block shown in the flowchart. The dataset was obtained through visual documentation of Batik Cual Bangka Belitung sourced from local artisans, cultural archives, and field-based image acquisition. A total of 248 raw images were collected, consisting of 152 images from Ishadi Cual Gallery, 54 images from Shanti Cual Gallery, and 42 images from Destiani Gallery, representing 14 Batik Cual motif categories. The image collection process was conducted with careful consideration of lighting, shooting angle, and motif clarity to ensure that the visual characteristics of Batik Cual were captured optimally. The compiled dataset consists of several variations of Batik Cual motifs that differ in pattern structure, color composition, and levels of visual complexity. Incorporating such variation is important to represent real-world data conditions and support effective learning, enabling the model to generalize across motif categories (Afifah & Lusiana, 2025; Dani & Handayani, 2021; Harikiswanto, 2023).

2.3. DATA CURATION AND LABELING

After all Batik Cual images were successfully collected, the data were filtered and organized according to the curation and labeling stages described in the flowchart. The curation process was conducted by evaluating the visual suitability of each image, including pattern sharpness, detail clarity, and the absence of distracting background elements, to ensure that only representative samples progressed to the next stage. Images that passed the selection process were subsequently grouped into predefined Batik Cual motif categories. Consistent class labeling is essential, as annotation inconsistencies have the potential to disrupt the model's learning process and negatively impact the stability of deep learning training outcomes (Arifin & Nurfaizah, 2024; Fitriani et al., 2023). Thus, curation and labeling form critical foundations that ensure the model receives clean, structured, and reliable data input.

2.4. PRE-PROCESSING OF DATA

The next stage is image pre-processing, which involves several operations applied to the dataset before it is fed into the model. This process includes resizing images to achieve uniform dimensions compatible with YOLOv11 input requirements, normalizing pixel values, and applying augmentation when necessary. Augmentation techniques such as rotation, scaling, and lighting adjustment are designed to synthetically expand data variability and enable the model to better handle motif appearance differences that may occur in real-world scenarios. This strategy also helps mitigate overfitting risks, particularly when visual similarities between motifs are high and class boundaries are subtle (Aras et al., 2022; Fitriani et al., 2023). Through effective pre-processing, the dataset becomes more stable, structured, and ready for use in the training phase. All images were resized to 512 × 512 pixels to meet YOLOv11 input requirements. Data augmentation included rotation (±15°), horizontal and vertical flipping, brightness adjustment (±20%), and contrast enhancement. These operations were applied uniformly across classes to improve generalization and reduce overfitting.

2.5. YOLOV11 ADAPTATION AND TRAINING PROCESS

The model was developed using the YOLOv11 architecture, a state-of-the-art evolution within the YOLO algorithm family. This model was selected due to its capability to perform rapid object detection and classification through an efficient multiscale feature extraction mechanism (Khanam & Hussain, 2024; Wang et al., 2025). At this stage, the baseline structure of YOLOv11 was adapted to recognize the predefined Batik Cual motif categories. Custom configurations included adjusting the number of output classes and tuning network parameters to emphasize inter-motif visual distinctions. With these modifications, the model is expected to capture subtle variations in Batik Cual motifs, which often share overlapping structural and textural characteristics (Mao & Hong, 2025; Wang et al., 2025). Model training was conducted for 200 epochs using the Adam optimizer with an initial learning rate of 0.001 and a batch size of 16. Training was performed on a GPU-enabled environment to ensure computational efficiency.

The use of YOLOv11 in this research is further supported by a technical evolution survey of the YOLO family, which highlights substantial enhancements in multiscale detection, explicit separation between classification and localization heads, and more stable loss optimization compared to its predecessors (Kotthapalli et al., 2025). In addition, the capability of YOLO to generalize effectively toward non-natural visual domains, particularly those containing textured and repetitive patterns, has been demonstrated in YOLO-pest, where YOLOv4 successfully detected small-scale agricultural pests with highly similar visual structures across classes (Dong et al., 2022). These findings reinforce YOLOv11 as an appropriate model for this study, particularly in extracting fine-grained visual features and motif boundaries within Batik Cual fabrics that display high intra-class resemblance.

The training process was conducted using the pre-processed dataset, which was divided into three subsets training, validation, and testing, in proportions that ensured a structured and systematic learning workflow. The model was trained using several parameters, including the number of epochs, batch size, learning rate, and optimizer selection, each adjusted to the characteristics of the dataset and the objectives of the experiment. Training proceeded iteratively through network weight updates informed by loss function values, while the validation subset was used to track model progress and mitigate the risk of overfitting tendencies (Ramadhani & Widyaningrum, 2025; Wang et al., 2025).

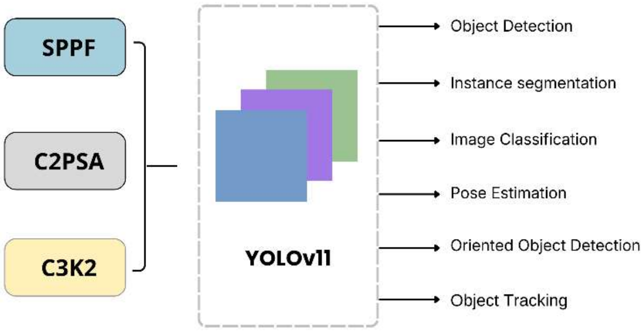

Figure 2. Key architectural modules in YOLO11
Source :(Khanam & Hussain, 2024)

2.6. EVALUATION OF CLASSIFICATION RESULTS

After training was completed, the model's performance was evaluated using several standard classification metrics, including accuracy, precision, recall, and mean Average Precision (mAP). This evaluation phase aimed to measure the capability of the YOLOv11 model in recognizing and classifying Batik Cual motifs accurately (Mao & Hong, 2025; Taralathasri et al., 2021). The assessment process also functioned as a key decision-making point within the research workflow, determining whether the model had achieved the expected performance. If the evaluation results did not meet the predefined criteria, adjustments to the configuration would be performed, and the model would be retrained to obtain improved results. This cycle reflects the inherent iterative nature of deep learning–based system development.

To formally define the metrics used in this study, the formulation for Accuracy is presented in (1) :

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

where TP(True Positive) refers to correctly detected motif instances, TN(True Negative) denotes correct predictions for non-existing objects, FP(False Positive) represents incorrect detections of motifs that do not appear in the image, and FN(False Negative) indicates real motifs missed by the model.

Next, Precision is defined in (2) :

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

while Recall is given in (3) :

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

The mean Average Precision (mAP), which serves as the primary indicator of overall detection performance, is computed as shown in (4) :

$$mAP = \frac{1}{N}\sum_{i+1}^{N} AP_i \quad (4)$$

where N represents the total number of motif classes evaluated.

In addition, the YOLOv11 evaluation incorporates a stricter metric known as mAP50–95, which is calculated as the average AP across IoU thresholds ranging from 0.50 to 0.95 in increments of 0.05. This formulation enables the assessment of model performance not only in terms of class recognition but also with respect to bounding box localization quality. The evaluation stage thus served as a decisive checkpoint in the research workflow. Whenever the model performance failed to meet the desired standards, modifications such as hyperparameter tuning, class weighting, or data augmentation were applied, and the training cycle was repeated. This iterative refinement continued until the model achieved optimal and stable performance on Batik Cual motif classification.

2.7. CLASSIFICATION SYSTEM TESTING

The final stage of the research involved testing the classification system, as represented in the *"Testing of the Classification System"* block within the flowchart. This phase aimed to evaluate overall system performance, including both functional behavior and the accuracy of classification outcomes. Testing was conducted by validating system outputs against the designated test set, analyzing prediction consistency, and assessing the model's responsiveness to variations in Batik Cual imagery. The outcomes of this evaluation served as the basis for determining the effectiveness and reliability of the proposed YOLOv11-based Batik Cual Bangka Belitung motif classification system.

3. RESULT AND ANALYSIS

The results obtained from model development and experimentation are reported in this section. The presentation includes dataset characteristics, training progression, quantitative evaluation metrics, class-wise performance analysis, and system demonstration outcomes.

3.1. RESULT

3.1.1. Dataset Acquisition and Composition

The dataset utilized in this research was sourced directly from three Batik Cual producers in Bangka Belitung Ishadi Cual Gallery, Shanti Cual Gallery, and Destiani Gallery, each contributing motif variations authentic to their production styles. A total of 248 raw images representing 14 distinctive motif categories were collected. These images exhibited substantial differences in color composition, motif density, and geometric structure, providing rich visual diversity for model training. To compensate for the limited number of samples and ensure better generalization, a series of augmentation techniques, including rotation, horizontal flipping, vertical flipping, and adaptive contrast adjustment, was employed, successfully expanding the dataset to 621 images. All images were standardized to 512 × 512 pixels to maintain compatibility with YOLOv11 input requirements.

Table 1. Motif Batik Cual

Gallery	Quantity	Motif Name
Ishadi Cual Gallery	9 Motifs	 Bebek, Burung Hong + Kembang Cina, Garuda, Kembang Cempaka, Kembang Gaja, Kembang Seroja, Kepiting, Kupu-Kupu + Kembang Cina, Mawar
Shanti Cual Gallery	3 Motifs	 Gajah Mada, Kembang Sepatu, Kembang Setangkai

Destiani Cual Gallery	2 Motifs	 Kantong Semar  Lebah Pelawan

3.1.2. Pre-processing and Data Labeling

After augmentation, each image underwent manual labeling using the Roboflow platform to annotate motif class locations accurately. This labeling process ensured consistency across samples and enabled the model to learn the distinctive visual regions associated with each Batik Cual motif class. The curated dataset was then partitioned into training 90% (560 images), validation 7% (41 images), and testing 3% (20 images) subsets. This distribution strategy was selected to maximize learning while preserving sufficient samples for unbiased model validation and final performance evaluation. The combination of controlled augmentation, Roboflow-assisted labeling, and systematic partitioning ensured that the model was exposed to diverse image variations while preventing data leakage between phases.

3.1.3. Training Progression

Model training was conducted incrementally until convergence.Throughout training, YOLOv11 exhibited steady learning behavior, shown by the continuous decline in box loss, classification loss, and DFL loss during successive epochs. Around epoch 163, all learning indicators stabilized, marking a plateau where the model ceased showing significant error reduction. This indicates that the model had successfully captured the relevant distinguishing features within the dataset and that further training would produce diminishing returns or risk overfitting.

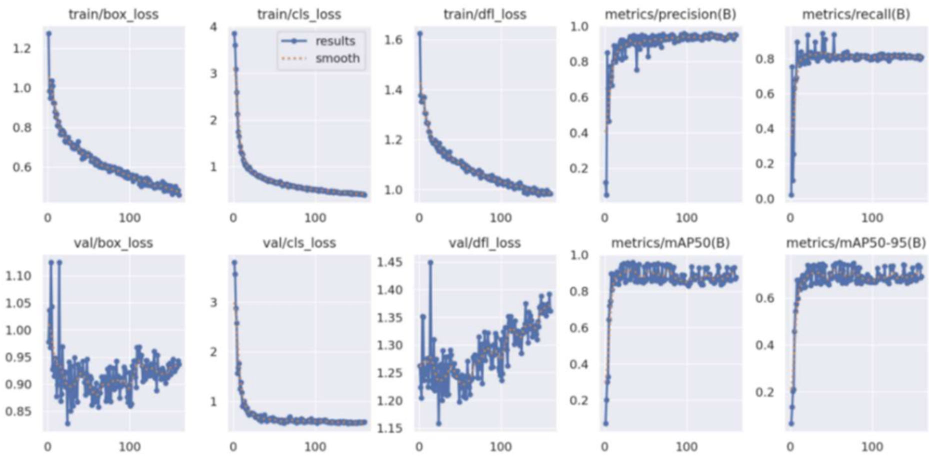

Figure 3. Loss Curve

3.1.4. Quantitative Performance Evaluation

The trained model was evaluated using standardized metrics widely adopted in object detection benchmarks, and the results demonstrated strong performance across all indicators. On the test set, the model achieved a precision of 0.934, a recall of 0.808, a mAP50 score of 0.950, value of 0.8172. The high precision score confirms the model's ability to minimize false positive classifications, indicating that most predicted motifs correspond accurately to their actual classes. Meanwhile, the elevated recall value reflects the model's strong capacity to detect nearly all motif instances present in the evaluation images, ensuring minimal missed detections. Taken together, these metrics suggest that YOLOv11 demonstrates a well-balanced trade-off between sensitivity and specificity, even when applied to the visually complex and densely patterned characteristics of Cual Batik motifs.

Table 2. Result of the evaluation of the YOLOv11 Model on the Batik Cual Dataset

Class	Box(P)	R	mAP50
all	0.934	0.808	0.950
Bebek	1.000	0.000	0.995

Gajah Mada	0.714	0.767	0.800
Garuda	0.834	1.000	0.995
Kantong Semar	1.000	0.700	0.934
Kembang Cina	1.000	0.922	0.995
Kembang Gajah	1.000	0.659	0.863
Kembang Sepatu	0.926	0.895	0.935
Kembang Setangkai	0.963	1.000	0.995
Kepiting	0.905	0.941	0.943
Kupu-Kupu Kombinasi Kembang Cina	0.934	0.934	1.000
Lebah Pelawan	0.994	1.000	0.995

For the Burung Hong Kembang Cina, Kembang Cempaka, Kembang Seroja, and Mawar classes, the Box(P), Recall, and mAP50 values were estimated using the AP50–95 scores because these classes did not appear in the mAP50 evaluation.

3.1.5. Class-Wise Performance Analysis

A more granular inspection of per-class results revealed varying levels of model confidence and class separability. Motifs with bold shapes and distinctive visual features, such as Bebek, Kembang Sepatu, and Kantong Semar, achieved near-perfect AP50–95 values, approaching 0.99. Conversely, motifs displaying denser textures and overlapping graphic elements, particularly the combination Kembang Cina Kupu-Kupu, displayed lower AP values due to structural similarity with neighboring motif classes.

This highlights the inherent difficulty of distinguishing visually similar motifs and underscores the importance of balanced dataset representation.

Table 3. AP50-95 Value per Batik Cual Motif Class

class_name	**AP50–95**
Bebek	0.995000
Burung Hong Kombinasi Kembang Cina	0.817236
Gajah Mada	0.736597
Garuda	0.751200
Kantong Semar	0.995000
Kembang Cempaka	0.710267
Kembang Gajah	0.890024
Kembang Sepatu	0.995000
Kembang Seroja	0.817236
Kembang Setangkai	0.812429
Kepiting	0.796000
Kupu-Kupu Kombinasi Kembang Cina	0.602579
Lebah Pelawan	0.883950
Mawar	0.638782

3.1.6. Precision & Recall Confidence Trends

Analysis of confidence-based performance trends revealed that the model maintained strong predictive behavior across varying confidence thresholds. The precision–confidence curve demonstrated high precision throughout most operating regions, particularly above a confidence value of 0.6, indicating that predictions made with moderate to high certainty were highly reliable and associated with minimal false positives. Complementing this trend, the recall–confidence curve showed similarly stable behavior, maintaining values above 0.9 across confidence levels. This indicates that the model consistently detected the majority of motif occurrences even as the confidence threshold increased, demonstrating its ability to minimize missed detections. Together, these findings confirm that YOLOv11 is capable of distinguishing relevant visual features with robustness and generalization, without generating excessive misclassification noise or overlooking motif objects within the dataset.

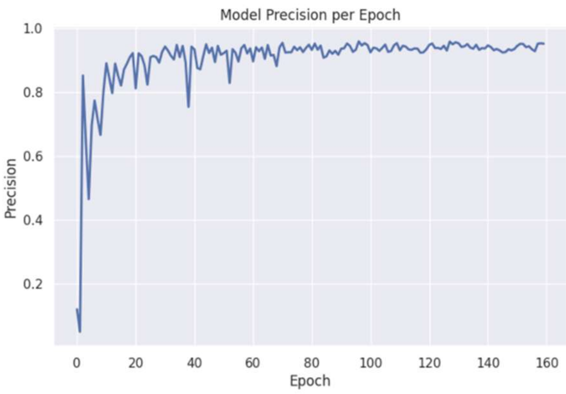

Figure 4. Precision Confidence Curve

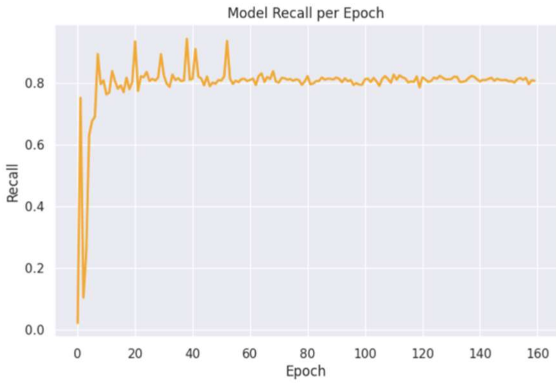

Figure 5. Recall Confidence Curve

3.1.7. Confusion Matrix Interpretation

Confusion matrix visualization provided insights into error distribution patterns. The majority of predictions correctly aligned with their intended motif classes, confirming consistent feature learning. Minor misclassifications occurred primarily between motifs sharing visual resemblance and decorative structure.

These findings suggest that improving the representativeness of motifs with subtle variations could further enhance performance.

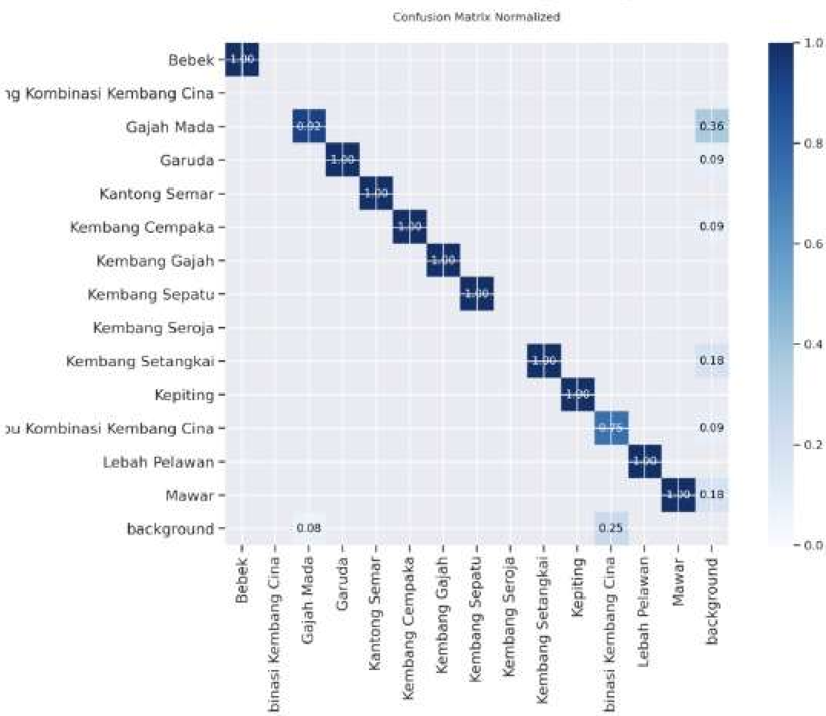

Figure 6. Confusion Matrix

3.1.8. Confusion Matrix Interpretation

Finally, the trained model was deployed and tested through a functional interface. The system successfully processed batik images uploaded by users, detecting motifs and returning class labels, confidence scores, and inference duration. A representative example showed the model correctly identifying the Gajah Mada motif with 91.83% confidence, validating real-time scalability and practical applicability.

Figure 7. System Output Display

3.2. ANALYSIS

The analysis section in a journal's abstract typically provides a concise summary of the methods used to analyze the data and the key findings derived from this analysis. It should briefly describe the analytical techniques or statistical methods employed, the scope of the analysis, and the most significant results that answer the research questions or hypotheses. The results affirm the effectiveness of the YOLOv11 architecture in addressing the classification challenges posed by Cual Batik motifs, which are characterized by intricate ornamentation and significant intra-class variation. The high precision demonstrates that false positive predictions are minimized, while the near-perfect recall indicates that the model successfully detects almost all motif instances present in the test images. This balance suggests that the model adequately captures salient visual characteristics required for robust classification.

Despite the strong overall performance, the dataset used in this study exhibits class imbalance, with several Batik Cual motifs represented by fewer samples compared to others. Data augmentation techniques contributed to increased visual diversity and improved model robustness; however, such synthetic expansion cannot fully substitute real-world data variability. As a result, motif classes with fewer original samples tended to demonstrate lower recall values, indicating that while augmentation mitigates imbalance-related issues, it does not entirely eliminate bias introduced by uneven class distribution.

The dataset was divided into 90% training, 7% validation, and 3% testing due to the limited availability of labeled Batik Cual images. Given the fine-grained visual complexity and high intra-class similarity of Batik Cual motifs, a larger proportion of training data was prioritized to ensure stable feature learning and effective model convergence. The relatively small test set was intended for preliminary performance evaluation as a proof-of-concept rather than for definitive statistical generalization. To mitigate potential bias, the evaluation was complemented by validation monitoring and detailed analysis of class imbalance and misclassification patterns. Future work is expected to incorporate larger and more diverse datasets to strengthen generalization assessment.

These results are consistent with previous research confirming that batik motifs represent a challenging visual domain for conventional image classification models, particularly when class distinctions depend on subtle decorative elements and highly repetitive patterns (Girsang, 2021). Even ensemble-based CNN approaches, designed to strengthen prediction stability through model voting strategies, remain limited to whole-image judgment without differentiating the spatial origin of motifs, thereby leaving open opportunities for more localized object detection architectures such as YOLO (Azhar et al., 2021). The strong precision and mAP metrics achieved in this study further validate the ability of YOLOv11 to explicitly identify motif regions within Batik Cual fabrics—an advancement that conventional CNN models applied to batik and analogous cultural textiles, such as Batak Ulos, have not been able to achieve (Muliono et al., 2023).

The mAP50–95 value of 0.8172 reflects strong capability across multiple IoU thresholds, implying that YOLOv11 is not only able to identify motif regions accurately but also distinguish fine-grained textural differences that often define motifs with similar geometric structures. These findings highlight the suitability of object detection frameworks for cultural textile recognition—tasks where motif boundaries and subtle ornament details matter. Variation in class-wise performance further illustrates the association between visual separability and model accuracy. Distinct motifs such as Bebek and Kantong Semar were classified correctly with near-perfect scores, whereas motifs sharing overlapping design elements, such as combination Kembang Cina Kupu-Kupu, recorded reduced accuracy due to feature ambiguity. This trend is consistent with deep learning literature, where inter-class similarity and limited unique patterning typically increase confusion rates.

The confusion matrix supports this interpretation, as classification errors are predominantly concentrated among visually related motifs. Nonetheless, the low proportion of misclassification reveals that the YOLOv11 feature extraction pipeline effectively discriminates between complex textile patterns, even under limited training samples. The stability shown in the precision–confidence and recall–confidence curves further demonstrates that model generalization remains reliable across different confidence thresholds. This indicates robustness not only on controlled test datasets but also suggests acceptable behavior in more variable conditions, aligning with requirements for real-world deployment.

Several misclassifications occurred among motifs with overlapping decorative elements and dense textures, particularly in combination motifs involving floral and fauna patterns, such as the Kupu-Kupu–Kembang Cina combination motif and the Burung Hong–Kembang Cina combination motif. These errors are influenced by high inter-class visual similarity, limited sample availability for certain motifs, and partial overlap in bounding box annotations. In some cases, fine-grained ornamental details are difficult to distinguish at specific scales, leading the model to confuse visually similar regions. These findings indicate that although YOLOv11 effectively captures motif localization, its performance remains sensitive to dataset quality, annotation consistency, and the availability of truly distinctive visual features.

3.2.1. Future Work

Future research could address these limitations by expanding the dataset with field-captured images containing natural variations in lighting, folds, and background interference. Further performance improvements could be pursued by leveraging advanced augmentation strategies such as CutMix, Mosaic, or style transfer to better simulate real-world capture scenarios. Model enhancement avenues include exploring transformer-based detectors (e.g., DETR variants), large-scale pretraining, or hybrid CNN-Transformer approaches that may be more adept at extracting long-range texture dependencies common in traditional textiles. Additionally, deployment-oriented studies such as quantization, edge inference optimization, and mobile-friendly model design could broaden practical accessibility for cultural preservation initiatives and educational applications. Collectively, the results and subsequent analysis confirm that YOLOv11 represents a strong foundation for automated Cual Batik motif recognition while simultaneously identifying critical opportunities for methodological and dataset enhancements going forward.

4. CONCLUSION

This study successfully developed an automated Batik Cual motif classification system using the YOLOv11 deep learning architecture. Through a systematic workflow including dataset collection, curation, annotation, preprocessing, training, and evaluation, the model demonstrated the ability to learn and distinguish complex visual characteristics found in traditional Cual fabrics. Experimental results revealed strong performance, with precision reaching 0.934, recall 0.808, mAP50 at 0.950, and mAP50–95 at 0.8172, indicating robust detection accuracy and minimal misclassification. These outcomes confirm that YOLOv11 is capable of recognizing fine-grained patterns and handling motif diversity despite limited sample size and high intra-class similarity.

The successful implementation further highlights the advantage of object detection frameworks over conventional CNN-based classification, which typically analyzes images holistically without identifying motif regions. This research addresses a notable gap in existing scholarship, as Batik Cual, despite its cultural significance, has received minimal attention compared to batik from major Indonesian regions such as Yogyakarta and Garut. Beyond technical contributions in computer vision, the findings support cultural preservation efforts by enabling digital documentation and automated motif recognition using modern AI approaches. Future studies may expand the dataset, adopt transformer-based architectures, or optimize lightweight deployment for mobile devices, ensuring broader accessibility and practical field application.

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