# A Mid-Level Feature Fusion Framework Integrating PHLF and VGG16 for Robust Batik Pattern Detection

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*Abstract*—**Javanese batik is characterized by distinctive motif patterns. The rapid evolution of designs through motif combination has introduced increased complexity, posing challenges for the community. People are increasingly less familiar with traditional Javanese original batik patterns. Many studies using CNN have been conducted to recognize batik patterns. However, it is important to improve object detection performance by strengthening explicit local features. To answer this question, our study aims to improve the detection of batik patterns that have local texture patterns and complex orientations that are in harmony with batik geometry with an integrated fusion scheme. To improve detection, an integrated fusion schema model was developed using the PHLF hybrid framework as a geometrically oriented local feature with VGG16 as a deep feature extractor for object detection. According to research, although VGG16 is reliable on large benchmarks such as ImageNet, VGG16 is less reliable for subtle intra-motif variations, which can suppress accuracy. Evidence from the results of the study shows that in the eight-class dataset consisting of 6,400 images for training data and 1.600 images for test data, a mid-level feature fusion approach on VGG16 with integrated PHLF improves resistance to data variations such as lighting, fabric deformation, and background complexity. The experimental results showed that the model achieved an mAP value of 0.68 at IoU = 0.5 and 0.2846 at IoU = 0.7. The significant difference between mAP@0.5 and mAP@0.7 suggests that the model still has limitations in the precision of the localization of the boundary box.**

***Keywords—A Mid-level feature; detection; fusion framework; phlf; traditional javanese batik***

## I. Introduction

Batik, an intangible cultural heritage with spiritual value, a deep history, and philosophy [1][2]. However, the characteristics of batik that are complex, repetitive, and have a high resemblance between classes are a challenge in batik detection [3][4]. To answer the challenge, various studies have been conducted, from the use of Deep Learning models such as Convolutional Neural Network (CNN) using VGG16, ResNet, and EfficientNet architectures, proven to be effective in capturing fine texture details [3][5]. Research shows that the Transfer Learning Technique and Hybrid models of VGG16 and XGBoost can achieve up to 89.83% accuracy in recognizing traditional motifs [3][6]. However, the research that has been conducted has not answered the problem, considering that Batik has undergone such rapid development. The use of CNN architecture is the dominant method in batik analysis because of its ability to automatically learn features directly from the data used [7][8]. Other architectures, such as Inception ResNetV2, have proven their effectiveness by achieving an average accuracy of 98.19% in the classification of batik patterns [9], while the VGG16 and MobileNetV2 models also show high results in detecting complex visuals [10]. For real-time detection, the Yolov11 model enhanced with an attenuation mechanism was able to achieve an mAP (mean Average Precision) value of 0.748. Provides a balance between localization accuracy and computational efficiency [11].

Although CNN excels in extracting global semantic features, this model has limitations in representing the subtle textures that characterize batik [12][13][14][15]. In contrast, feature selection such as the Gray Level Co-occurrence Matrix (GLCM) is highly effective in describing local texture characteristics through the spatial relationships between pixels [16][17][18][19]. However, this method often faces the challenge of semantic gaps and is less adaptive to large data variations in real time [20]. To answer the challenge, several studies with a hybrid approach and feature fusion were conducted, combining models is a crucial strategy to improve the performance of automatic detection [3][20]. One of the models is the combination of VGG16 and XGBoost, which managed to achieve the highest accuracy in Batik Keraton at 89.83% compared to the CNN model [3]. The integration of features in latent space, as implemented in the Deep Convolutional Autoencoder (DCAE) model, has been shown to produce a more discriminatory, clean representation of noise with an accuracy of up to 99% [21]. Commonly used fusion strategies include concatenation at the feature level, which is considered more advantageous because it can store different information from each extraction method [20]. In addition, the use of dual-attention modules that combine spatial attention and channel attention significantly strengthens the model's focus on the most informative motif regions [12]. Hybrid-based detection models that integrate VGG16 for high-level semantic features with local texture orientation features are strongly aligned with the finding that the combination of shape and texture features results in greater accuracy (90.48%) than Single features [22][9]. The multi-task learning approach that performs simultaneous bounding box regression and classification, as applied to the YOLO series, is an effective solution to the dense and complex challenge of localizing batik objects [11].

Based on the results of the study, although the multi-task learning approach, such as the YOLO series, is considered effective, there are some fundamental weaknesses when applied to the dense and complex detection of batik motifs. This is important to underline the need for the development of a mid-level feature fusion framework that integrates PHLF's handcrafted features with VGG16's deep learning features. Therefore, the integration of PHLF to capture local geometric orientations and VGG16 for high-level semantic features through intermediate-level fusion is a crucial solution to improve the identification accuracy as well as the precision of bounding box localization on batik objects.

## II. Previous Research Study

Research shows that pure deep learning models often struggle with rotational and scale variations in dense batik motifs. In the study conducted by [23], the MU2ECS-LBP and Mulwin-LBP algorithms were developed specifically designed to be invariant to scale and rotation, as well as in the studies [24] and [25]. This study proves that the handling of geometric orientation specifically is crucial because shooting batik in the real world often involves inconsistent zoom and angle changes. Research conducted by [26] and [27], uses Geometric Invariant Moment (GIM) as a shape-based feature extractor to detect the Broken Parang motif. This supports the argument that geometric information and local shapes are formidable descriptors for recognizing the structure of a particular motif.

VGG16 is recognized in many studies as having the ability to extract very deep spatial features for intricate patterns. As in the research conducted [3], it is explained that the architecture of VGG16 is very effective in capturing the delicate textures and intricate ornaments of batik through its deep and dense convolutional structure. The VGG16 model is able to capture subtle differences in texture that traditional models often fail to identify. Likewise, in the study [28], utilizing VGG16 to study the unique characteristics of batik spatially through the convolution process proves that visual-based feature extraction is far superior to simple color-based methods. The integration between traditional features and deep learning features has been shown to mask the weaknesses of each method, as in studies conducted [29] and [24], it was found that the combination of texture features and shape features resulted in much higher accuracy (90.48%) than using only one type of feature. Similarly, in the study [16], it was emphasized that relying only on artificial neural networks can lead to the loss of important local textural information. Therefore, fusion between handcrafted texture features and deep learning models (such as ResNet or VGG) is strongly recommended to create a more robust classification system [30]. In the research conducted [20], it is hypothesized that various image features (geometry, points, parallel lines) complement each other in representing the properties of batik motifs, and the fusion of features consistently outperforms the performance of individual features.

To identify the limitations of standard detection models in handling the density of batik motifs, the research conducted by [11], explains that object detection architectures such as the standard YOLO have limitations in the local receptive field, making it difficult to model the long-range spatial relationships that define the composition of batik culture. In addition, very small and dense batik objects often exceed the detection capabilities of the baseline model, thus requiring the extraction of higher-quality features to improve the precision of localization. Research by [3], showed that combining the extraction of VGG16 in-depth features with the XGBoost classifier resulted in the highest accuracy of 89.83% on Keraton Batik, outperforming the standard CNN model. The study by [2], [28] and [31], utilized VGG16 to study the unique characteristics of batik spatially through convolution and used Random Forest to achieve 97.58% accuracy on a dataset with 50 classes. VGG16 Modified (Web-Based), as in the study [32], modified VGG16 for the classification of Demak Batik and managed to achieve 98.72% accuracy in just 5 epochs.

The problem with the research that has been conducted is that standard *deep learning* models, including CNN and detection architectures such as YOLO, tend to lose crucial micro-texture details in batik due to repeated downsampling processes [12], fine line details are often erased or become blurred, requiring additional handcrafted features that are more sensitive to local textures to retain the information [33]. Although CNN excels in global semantic features, it often struggles to cope with extreme rotation and scale variations without the support of massive augmented data or specific geometric features [22] [3]. There is a gap between the visual representation of humans of batik motifs that are rich in cultural significance and the low-level features stored in digital databases [22][20]. Single models often fail to bridge this gap, deep learning features are too abstract for the technical details of the craftsman, while traditional features are too rigid for visual variation [16].

To address these gaps, this study proposes a hybrid approach that integrates PHLF's handcrafted texture features with the deep learning features of VGG16 through a mid-level feature fusion strategy. This approach allows for a more effective interaction between texture features and semantic features in latent spaces, resulting in more discriminatory representations for batik motif detection.

## III. Proposed Research Methodology

The methodology for this study is illustrated in Fig. 1.

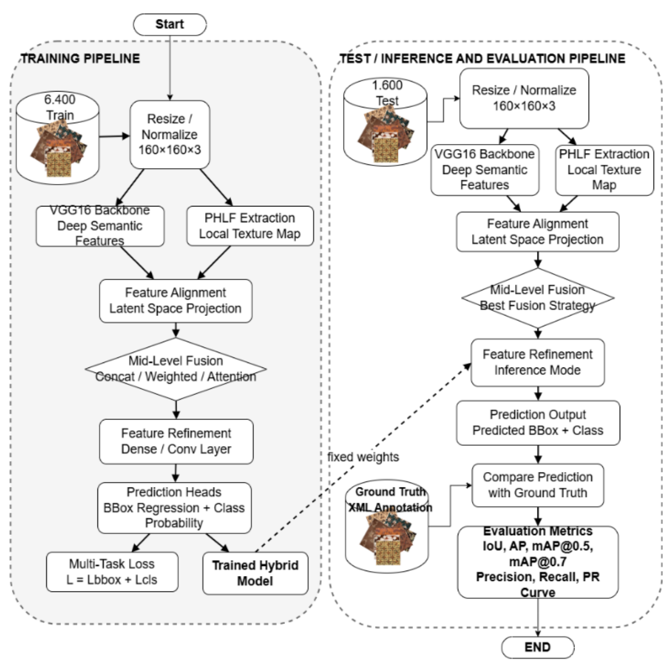


Fig. 1. Proposed method.

This study proposes a hybrid-based batik motif detection framework that integrates the handcrafted texture features of

Parallelogram Haar-Like Features (PHLF) with the deep learning features of VGG16. This approach is designed to overcome the limitations of a single method in representing the complexity of batik patterns, especially in capturing microtextures and semantic structures simultaneously.

## A. Data Processing

This study uses the Batik Keraton dataset consisting of eight pattern classes, each containing 800 original images (a total of 6,400 images) for training data and 200 (a total of 1,600 images) for testing data. Fig. 2 shows the eight patterns of Batik classes used.


Fig. 2. Eight batik classes patterns used.

## B. Input Processing

Given an input batik image, shown in Eq. (1):

$$I \in \mathbb{R}^{HxWx3} \tag{1}$$

The image is first normalized, shown in Eq. (2):

$$I_{norm} = \frac{I}{255} \tag{2}$$

And resized to a fixed dimension, shown in Eq. (3):

$$I_{resized} \in \mathbb{R}^{160x160x3} \tag{3}$$

A grayscale version of the image is also generated for texture feature extraction, shown in Eq. (4):

$$I_{gray} = 0.299R + 0.587G + 0.144B \tag{4}$$

Remarks:

$I$ = original input batik image, $H$ = height image, $W$ = image width, 3 = number of color channels, $I_{norm}$ = image of normalization results, $I_{resized}$ = image resized, $I_{gray}$ = image grayscale, $R, G, B$ = color channels red, green, blue.

## C. PHLF-Based Texture Feature Extraction

The first branch focuses on extracting local texture features using Parallelogram Haar-Like Features (PHLF). This method captures directional patterns and geometric structures inherent in batik motifs.

The convolution operation is defined as shown in Eq. (5),

$$F_k(x,y) = (I_{gray} * K_k)(x,y) \tag{5}$$

where, $K_k$ represents the PHLF kernels. The final PHLF map is computed as shown in Eq. (6),

$$PHLF(x,y) = \sum_{k=1}^{K} |F_k(x,y)| \tag{6}$$

Followed by normalization, shown in Eq. (7),

$$PHLF_{norm} = \frac{PHLF - min}{\max - min} \tag{7}$$

The resulting feature map is shown in Eq. (8).

$$X_{phlf} \in \mathbb{R}^{HxWx1} \tag{8}$$

Remarks:

$x, y$ = pixel coordinates in the image, $K_k$= Colonel Philf K-K, $K$ = total number of PHLF kernels, $F_x(x,y)$ = the characteristic response of the result of the convolution of the kernel k at position (x,y), $PHLF(x,y)$= PHLF feature value at position (x,y), $PHLF_{norm}$ = Normalized PHLF, $min$ = Minimum values on feature maps, $max$ = Maximum value on the feature map, $X_{phlf}$ = feature map of PHLF extraction results.

## D. Deep Feature Extraction Using VGG16

The equation for showing the convolution process at the CNN layer is shown in Eq. (9).

$$F^{(l)} = \sigma(W^{(l)} * F^{(l-1)} + b^{(l)}) \tag{9}$$

Remarks:

$F^{(l)}$ = feature map at layer $l$. $F^{(l-1)}$ = feature map from the previous layer, $W^{(l)}$ = convolutional weights at layer $l$. $b^{(l)}$= bias term at layer $l$. $\sigma$ – activation function (e.g., ReLU, sigmoid).

The equation used to convert the PHLF and VGG16 features to compatible latent dimensions is shown in Eq. (10)-(11).

$$Z_{phlf} = f_{phlf}(X_{phlf}) \tag{10}$$

$$Z_{cnn} = f_{cnn}(X_{cnn}) \tag{11}$$

Remarks:

$Z_{phlf}$ = Latent representation of PHLF features, $Z_{cnn}$ = Latent representation of CNN features, $f_{phlf}(.)$ = Projection function for PHLF features, $f_{cnn}(.)$= Projection function for CNN features.

## E. Concatenation Fusion

Combines features by stacking them, shown in Eq. (12).

$$F = [Z_{cnn}, Z_{phlf}) \tag{12}$$

Balances contributions from CNN and PHLF features, shown in Eq. (13).

$$F = \alpha Z_{cnn} + (1-\alpha) Z_{phlf} \tag{13}$$

Dynamically weight feature importance using attention, shown in Eq. (14)-(15).

$$A == \alpha(W_\alpha . Z_{cnn}) \tag{14}$$

$$F = A \odot Z_{cnn} + (a - A) \odot Z_{phlf} \tag{15}$$

Enhances feature representation before prediction, as shown in Eq. (16).

$$F_{ref} = \sigma(W_f . F + b_f) \tag{16}$$

### F. Evaluation

Bounding Box Loss measures localization error using L1 loss, shown in the following Eq. (17).

$$L_{bbox} = ||B - \hat{B}||_1 \tag{17}$$

Intersection over Union (IoU), shown in the following Eq. (18).

$$IoU = \frac{|B_{pred} \cap B_{gt}|}{|B_{pred} \cup B_{gt}|} \tag{18}$$

Average Precision (AP), shown in the following Eq. (19).

$$AP = \int_0^1 Precision(Recall)dRecall \tag{19}$$

Mean Average Precision (mAP), shown in the following Eq. (20).

$$mAP = \frac{1}{C}\sum_{C=1}^{C} AP_C \tag{20}$$

## IV. Experimental Results and Analysis

The evaluation of the performance of the VGG16 technique with integrated PHLF was verified based on a dataset of 8 batik patterns of Kawung, Parang, Satriomanah, Sidoasih, Sidomukti, Tambal, Truntum, and Wahyutumurun. The batik data set consists of 8,000 images of batik patterns, each consisting of 1,000 data points. The images are categorized according to batik patterns. Evaluation was also carried out on 1,600 data points before augmentation.

TABLE I. Train Results of 8 Batik Classes

| Method | Task | Accuracy / mAP | Limitation |
|---|---|---|---|
| VGG16 + XGBoost | Classification | 89.83% | No localization |
| VGG16 + RF | Classification | 97.58% | Not detection-based |
| Modified VGG16 | Classification | 98.72% | No bounding box |
| YOLO | Detection | 0.174 mAP | Weak for dense patterns |
| CNN only | Classification | – | Loss of texture detail |
| PHLF + VGG16 | Detection | 0.208 mAP@0.5 | Localization still limited |

A detailed description of the test results of the augmentation is shown in Table I. Fig. 3 shows the results of Accuracy and Loss, Precision, and Recall of Model VGG16 with integrated PHLF. Fig. 3 shows that the PHLF-VGG16 Hybrid model experienced a rapid increase in accuracy during the initial and stable period around 10 years of age. Training accuracy and validation remained aligned with minimal deviations, indicating effective learning with no signs of overfitting. The loss curve showed an equally consistent decrease, with validation loss tracking training loss closely, confirming good generalization to unseen data. These patterns showed a stable and efficient convergence process, supporting the conclusion that integrating PHLF with VGG16 improved feature extraction quality and improved overall training stability.

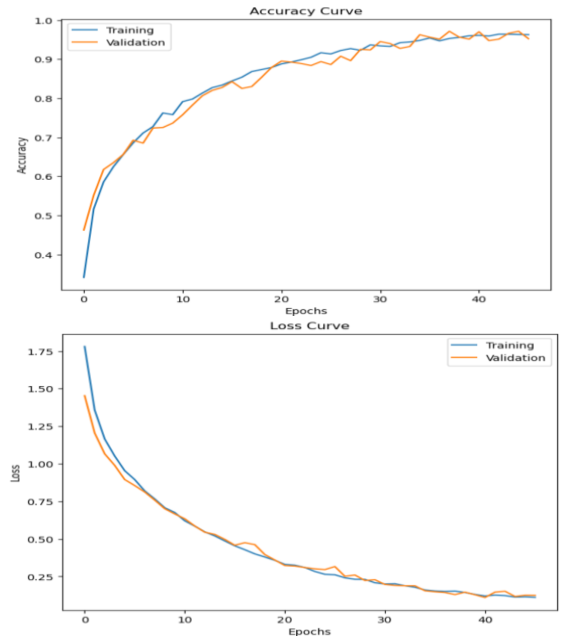


Fig. 3. Curve of accuracy and loss.

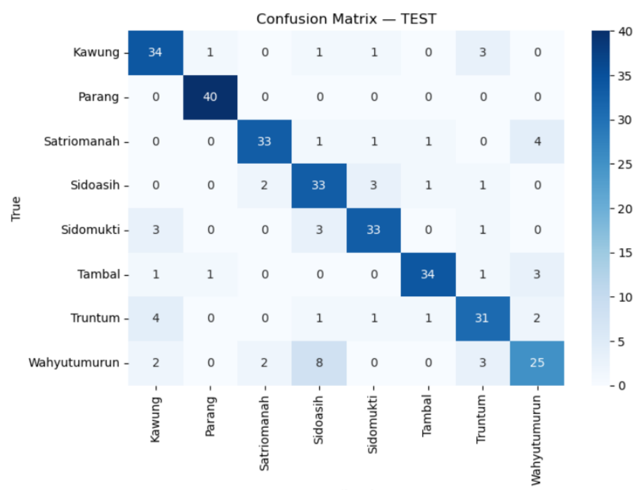


Fig. 4. Confusion matrix results test.

The Confusion Matrix shown in Fig. 4 provides strong evidence of the robustness and reliability of the VGG16 fine-tuning method using PHLF.

The sharp rise and stabilization of macro precision suggest that this method produces very few false positives, even when faced with visually similar batik motifs. This behavior suggests that the PHLF enhancement module effectively reinforces the local texture differentiation that is important for batik classification. Likewise, the convergence of F1's macro and macro graven towards unity reflects the model's ability to recognize diverse variations in motifs without systematically ignoring specific classes. This is especially important in datasets with rich intra-class variations such as Kawung, Parang, Truntum, and Tambal.

TABLE II. COMPARISON OF ACCURACY, PRECISION, RECALL, AND F1 SCORE RESULTS

| Model | Acc | Precision | Recall | F1-score |
|---|---|---|---|---|
| VGG + XGBoost | 89,83% | 92% | 92% | 92% |
| VGG16 Pretrained | 87,77% | 88% | 88% | 88% |
| VGG16 | 85% | 85% | 85% | 85% |
| VGG16 + PHLF | 98,72% | 97,6% | 97,5% | 97,55% |

Table II shows the results, showing a consistent trend: performance improves when explicit geometry features (PHLFs) are integrated into the VGG16. In other words, the scale of the data and the feature fusion strategy are decisive, especially as the number of classes grows and the variety of motifs becomes more complex. In the initial scenario, the VGG+XGBoost approach provides the highest accuracy (89.83%) compared to the standard VGG16 ($\approx$85 – 87%). These results indicate that in a simpler classification space, the output of VGG features combined with powerful classifiers such as XGBoost is quite effective in separating motifs that have a pronounced visual difference.

Meanwhile, VGG16 is in the F1 range of 85%: VGG16 is capable of capturing global textures and patterns, but is still less sensitive to the diagonal structure and geometric repetition that characterize some motifs. The advantages of the VGG16 approach using PHLF clearly reach F1 = 97.55%. This spike is proof that the PHLF really does add important information: it strengthens the response to repetitive geometric elements, allowing the model to become more stable in distinguishing motifs that rely on diagonals without losing the ability of VGG16 to capture the context of texture. These findings point to two points: first, VGG16 is indeed greatly aided by a mid-level feature fusion framework that integrates PHLF and VGG16 for strong batik pattern detection; second, PHLF still provides additional advantages even though the backbone of VGG16 is already strong, resulting in more stable and consistent performance. In summary, the results of the table confirm that the enhancements in VGG16 using PHLF result in the most complete and most effective representation, especially in multi-class scenarios.

Fig. 5 presents example visualizations of batik motif detection results using the hybrid PHLF–VGG16 model, comparing ground truth (GT) and predicted outputs with evaluation metrics including TP, FP, FN, and IoU. In the left image (Kawung), the model achieved strong localization performance with mIoU(TP) $\approx$ 0.84, TP = 1, FP = 0, and FN = 0, indicating accurate detection without missed or incorrect predictions. This result suggests that the regular and repetitive structure of Kawung is easier for the model to learn and localize. In contrast, the right image (Sidoasih) shows limitations in localization precision. Although the motif was detected (FN = 0), the presence of FP = 1 and an mIoU(TP) close to zero indicates weak overlap between the predicted bounding box and the ground truth. These results suggest that the model can recognize motif presence but still struggles to precisely estimate object boundaries. The comparison highlights that detection performance is highly influenced by motif characteristics, where denser and more complex textures increase localization difficulty.

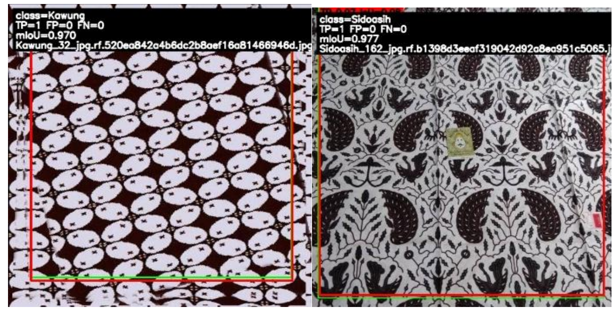


Fig. 5. Test results.

TABLE III. HASIL RATA-RATA IOU PER CLASS

| Name | meanIoU | IoU@0.5 |
|---|---|---|
| Kawung | meanIoU=0.538248 | IoU@0.5=60.69% |
| Parang | meanIoU=0.605074 | IoU@0.5=72.43% |
| Satriomanah | meanIoU=0.539754 | IoU@0.5=60.89% |
| Sidoasih | meanIoU=0.512537 | IoU@0.5=54.93% |
| Sidomukti | meanIoU=0.712856 | IoU@0.5=82.22% |
| Tambal | meanIoU=0.546839 | IoU@0.5=57.95% |
| Truntum | meanIoU=0.461856 | IoU@0.5=47.16% |
| WahyuTumurun | meanIoU=0.686640 | IoU@0.5=83.84% |

Table III presents the batik motif detection results using mean Intersection over Union (mIoU) and IoU@0.5 to evaluate localization performance based on the overlap between predicted bounding boxes and ground truth annotations. Overall, all classes achieved IoU@0.5 above 50%, indicating satisfactory localization capability despite performance variations caused by differences in texture, object scale, and pattern complexity.

The best results were achieved by WahyuTumurun (83.84%) and Sidomukti (82.22%), demonstrating strong localization accuracy, followed by Parang (72.43%) and Kawung (60.69%). In contrast, Satriomanah, Sidoasih, Tambal, and Truntum obtained lower IoU@0.5 values (54–61%), suggesting that although objects were successfully detected, the predicted bounding boxes were not yet fully aligned with the ground truth. This limitation is likely related to texture similarity across motifs, pattern variations, small object regions, and the tendency to predict broader fabric areas than the annotated regions.

## V. CONCLUSION

This study proposes a mid-level feature fusion framework that integrates handcrafted Parallelogram Haar-Like Features (PHLF) with deep semantic representations extracted by VGG16 for batik pattern detection. By combining local texture enhancement and high-level semantic learning, the framework improves feature discriminability and achieves effective detection and localization performance across all classes, with IoU@0.5 above 50% and average IoU exceeding 0.68. The best results were obtained for WahyuTumurun (83.84%) and Sidomukti (82.22%). However, performance declined at IoU = 0.7 (average IoU = 0.2846), revealing limitations in precise localization for dense and repetitive motifs due to texture similarity, scale variation, and background complexity. Overall, the proposed framework enhances texture representation and delivers more robust, accurate, and consistent batik detection, demonstrating strong potential for real-world automated batik identification. Future work will focus on integrating Feature Pyramid Networks (FPN), attention mechanisms, and IoU aware loss functions to further improve localization accuracy for visually similar motifs.

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