JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8323

ENHANCING YOLOV8 PERFORMANCE FOR TASIKMALAYA BATIK CLASSIFICATION USING CLEO-BASED HYPERPARAMETER OPTIMIZATION

Teuku Mufizar[1*], Evi Dewi Sri Mulyani[1], Aso Sudiarjo[1], Ayu Djuliani[1], Egi Rahmatulloh[1], Rinaldi Satia Aulia Rahmat[1]

Perjuangan Tasikmalaya University, Tasikmalaya, Indonesia[1]
https://unper.ac.id/[1]
fizargama@gmail.com*, eviajadech@gmail.com, asosudiarjo@unper.ac.id, 2203010102@unper.ac.id, 2203010126@unper.ac.id, 2303010149@unper.ac.id

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

The creation is distributed under the Creative Commons Attribution-NonCommercial 4.0 International License

Submitted: 26 February 2026, **Revised:** 24 June 2026, **Accepted:** 31 August 2026, **Published:** 13 November 2026.

Abstract— *This study addresses the limitations of manual identification, specifically subjectivity and inefficiency in the digital preservation of Tasikmalaya Batik, a distinct cultural heritage of Indonesia. The primary objective is to enhance motif classification performance by proposing YOLOv8-CLEO, a hybrid framework that integrates deep learning-based object classification with metaheuristic optimization. The research methodology encompasses four key phases: (1) Data Acquisition of original Tasikmalaya batik imagery; (2) Preprocessing, utilizing data augmentation (geometric transformations) and labeling via LabelImg; (3) Implementation, where the YOLOv8 architecture undergoes automated hyperparameter fine-tuning using the Chimpanzee Leader Election Optimization (CLEO) algorithm to maximize the Top-1 validation accuracy; and (4) Evaluation, assessing performance via accuracy, precision, recall, and ROC curve analysis. The findings indicate that while both the standard YOLOv8 and the hybrid YOLOv8-CLEO models achieved a peak Top-1 Accuracy of 1.00, the proposed hybrid model demonstrated superior computational efficiency. The YOLOv8-CLEO architecture exhibited significantly faster convergence, achieving optimal accuracy benchmarks with fewer training epochs and greater stability compared to the conventional baseline. Future work will focus on validating this model on larger, more diverse datasets to further assess its scalability and generalization in real-world applications. The novelty lies in integrating CLEO with YOLOv8 for traditional textiles. However, this study is limited by the small dataset size (163 images), necessitating future external validation.*

Keywords: *CLEO algorithm, deep learning, hyperparameter optimization, Tasikmalaya batik, YOLOv8.*

INTRODUCTION

Tasikmalaya Batik represents a distinct cultural heritage of the Indonesian archipelago, characterized by unique features [1] and specific motifs such as payung geulis, merak ngibing [2], kujang, and other patterns inspired by the natural richness of the Sunda region [3]. However, the manual identification and classification of these motifs by artisans or experts are often subjective and labor-intensive. In the current digital era, the development of automated systems has become an urgent necessity to preserve and verify the authenticity of Tasikmalaya batik, particularly to support the competitiveness of local Micro, Small, and Medium Enterprises (MSMEs) [4].

In the context of traditional textile digitization, the combination of deep learning and computer vision has proven effective for image analysis, including motif segmentation and pattern classification [5]. Prior studies have leveraged conventional machine learning approaches, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), for batik motif

classification [6]. Recent developments demonstrate the utilization of more advanced deep learning architectures. For instance, Aras et al. proposed the use of EfficientNet and transfer learning for Papua batik motif classification [7], while Abd Manap et al. compared various deep learning models to distinguish between Malaysian and Indonesian batik designs, highlighting the importance of specialized approaches for cultural textiles [8]. Furthermore, Helen Sastypratiwi et al. developed a batik recognition system using MobileNet [9], whereas Andrian et al. compared the performance of AlexNet and EfficientNet for Lampung batik identification, demonstrating that modern architectures yield superior results [10].

In our previous work, we explored the classification of Tasikmalaya batik motifs using various Convolutional Neural Network (CNN) architectures, including VGGNet, ResNet, and GoogLeNet [11]. While that study achieved promising results with the GoogLeNet architecture, it highlighted challenges related to manual hyperparameter tuning and model complexity, which often led to overfitting during the initial training phases.

While classification methodologies have advanced, these approaches possess limitations regarding specific object localization within complex motif variations. Consequently, recent research has explored object detection architectures such as YOLO to achieve more precise identification [12]. Fiqrullah evaluated the performance of YOLOv10-based detection methods for identifying Lampung Batik motifs, indicating the significant potential of YOLO architectures in traditional textile analysis [13]. In this context, YOLOv8 was selected as the baseline architecture: although originally developed for real-time object detection [14], it also offers a lightweight classification variant (YOLOv8-cls) capable of high-accuracy image classification. The CSPDarknet backbone in YOLOv8 is capable of capturing multi-scale features from detailed batik motifs, contributing to its overall classification precision [15].

However, a critical challenge in deep learning deployment remains the determination of optimal hyperparameters. The Chimpanzee Leader Election Optimization (CLEO) algorithm offers strategic advantages in adaptive hyperparameter optimization [16]. Introduced by Ferry Wahyu Wibowo et al., CLEO is based on chimpanzee social behavior. Comprehensive evaluations against various metaheuristic algorithms, including Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), have proven CLEO's superiority in achieving faster convergence and better stability across multi-dimensional objective functions (Table 1). Furthermore, its efficacy has been validated in complex classification tasks, demonstrating high accuracy without the need for exhaustive manual hyper-tuning.

Table 1. Theoretical and Empirical Comparison of Optimization Algorithms

No	Feature / Metric	CLEO	PSO	Grid Search
1	Hyperparameter Requirements	None	Moderate	High
2	Convergence Speed	Very Fast	Moderate	Very Slow
3	Avoidance of Local Optima	High	Moderate	High
4	Suitability for Classification	Highly effective without complex manual tuning	Effective but requires parameter tuning	Extremely time-consuming for deep learning

Source: (Wibowo, 2022 [16])

The effectiveness of this integration has been substantiated in other domains; Nandal et al. utilized YOLO-NAS with a CLEO optimizer for real-time object detection in autonomous vehicles [17], and in separate research applied a CLEO-optimized YOLOv8 for skin cancer detection, achieving significant accuracy improvements [18]. Mufizar et al. [11] demonstrated that deep learning approaches, specifically CNNs, significantly outperform traditional methods in classifying complex batik patterns. However, their study primarily focused on image-level classification and relied on grid search or manual adjustments for optimization. This current research advances that methodology by adopting the YOLOv8 classification framework (YOLOv8-cls) and integrating the CLEO metaheuristic algorithm for automated and adaptive hyperparameter optimization.

Based on this literature review, a distinct research gap is evident. Although various approaches have been tested for traditional textile analysis, there is a notable absence of studies specifically synergizing the YOLOv8 architecture with CLEO optimization for the classification of Tasikmalaya batik motifs. Most prior research has focused solely on classification tasks (Aras et al. [7], Sastypratiwi et al. [9]) or utilized traditional CNN architectures (Andrian et al. [10]). The integration of CLEO with YOLOv8 in this study is expected to mitigate overfitting issues[18] and enhance classification performance, in terms of both accuracy and speed, thereby providing a more

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

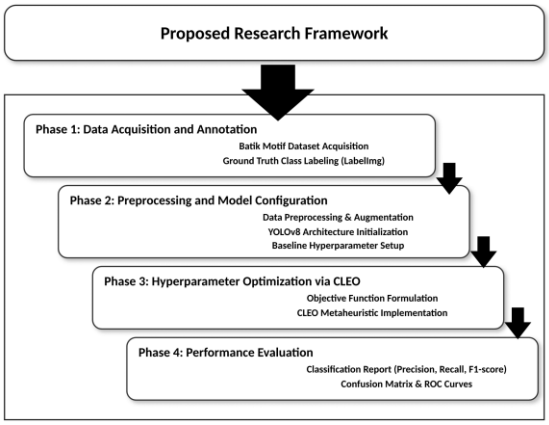
VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8323

precise and efficient digital preservation solution for Tasikmalaya batik.

The novelty of this study lies in the synergistic integration of the YOLOv8 classification framework with the CLEO metaheuristic algorithm, explicitly adapted to optimize the hyperparameters (learning rate, momentum, and weight decay) for the complex spatial characteristics of Tasikmalaya batik motifs. This provides a more dynamic and adaptive alternative to conventional grid-search methods. Therefore, the objective of this research is to evaluate the enhancement of YOLOv8's classification performance when optimized with the CLEO algorithm. The primary research question addressed is: How does the integration of CLEO-based hyperparameter tuning affect the convergence speed, stability, and accuracy of the YOLOv8 model compared to its baseline configuration?

MATERIALS AND METHODS

The proposed research framework for Tasikmalaya Batik classification using the hybrid YOLOv8-CLEO architecture is presented in Figure 1.



Source: (Research Results, 2026)

Figure 1. The Proposed Methodology

As illustrated in Figure 1, Phase 1: Data Acquisition and Annotation establishes the foundational ground truth required for the deep learning framework. This initial stage entails the systematic collection of high-resolution imagery capturing a diverse range of Tasikmalaya Batik motifs to construct the primary dataset. Subsequently, ground truth labeling is performed by assigning a specific class label to each motif image using LabelImg, ensuring that the model receives accurate categorical information essential for supervised learning.

Phase 2: Preprocessing and Model Configuration focuses on data preparation and architectural initialization to ensure robust learning. The dataset undergoes rigorous preprocessing and augmentation—including geometric transformations (rotation, flipping) and scaling to enhance generalization and mitigate overfitting. Concurrently, the YOLOv8 architecture is initialized utilizing the CSPDarknet backbone. Baseline hyperparameters are established at this stage to create a performance benchmark, while the dataset is partitioned into training and validation subsets (129 and 34 images, respectively, as detailed in the Results and Discussion section). Owing to the limited dataset size, the validation subset also serves as the testing set.

Phase 3: Hyperparameter Optimization via CLEO introduces a metaheuristic approach to elevate model performance beyond standard configurations. In this phase, a candidate solution representing the YOLOv8 hyperparameter set is denoted as a vector:

$$X = \{learning_rate, momentum, weight_decay\} \quad (1)$$

The optimization problem is mathematically formulated to find the optimal X by dynamically fine-tuning these critical hyperparameters. The Chimpanzee Leader Election Optimization (CLEO) algorithm is integrated directly into the training pipeline. CLEO updates each candidate's position through two mathematical processes based on chimpanzee behavior: cognitive capability and social interaction. First, the candidate's capability performance (X^+) is updated using an inverted U-shaped cognitive model based on age:

$$X^+ = r_a X + 4(r_a - r_a^2)(X_{best} - X) \quad (2)$$

Where $r_a \in [0,1]$ is a random age factor, and X_{best} is the local best configuration. Second, the social relationship update (X^*) is formulated to balance exploration and exploitation by considering male (X_M), female (X_F), and the global best (X_{Gbest}) candidate configurations:

$$X^* = X + r_1(X_M - X) + r_2(X_F - X) + r_3(X_{Gbest} - X) \quad (3)$$

Where r_1, r_2, r_3 are random coefficients representing social interactions, such that $r_1 + r_2 + r_3 = 1$. Finally, each candidate configuration X is evaluated using a fitness function. To map this

CC BY NC

metaheuristic into the YOLOv8 deep learning process, the fitness function $f(X)$ evaluates the YOLOv8 model's validation performance over short sub-epochs. The objective is to maximize the model's Top-1 validation accuracy:

$$f(X) = Accuracy_{Top-1}(YOLOv8|X) \quad (4)$$

Accordingly, the fitness function *f(X)* is defined as the Top-1 validation accuracy of the YOLOv8 model trained with candidate configuration *X*. If multiple candidate configurations achieve identical accuracy, the validation loss is used as a secondary tie-breaker to select the most robust configuration. This adaptive mechanism identifies globally optimal parameter settings that manual tuning might overlook.

Phase 4: Performance Evaluation concludes the framework by assessing the efficacy of the optimized model on the held-out validation subset (34 images), which also serves as the testing set. This phase employs comprehensive analytical metrics, specifically focusing on the Confusion Matrix to analyze classification distribution and Receiver Operating Characteristic (ROC) curves to evaluate discriminatory power. These quantitative assessments are essential for validating the model's accuracy, stability, and readiness for practical implementation in digital preservation tasks.

RESULTS AND DISCUSSION

Dataset

The dataset utilized in this study is based on the collection established in our prior research [11], comprising high-resolution imagery of four distinct Tasikmalaya batik motifs: Kujang, Kumeli, Payung Geulis, and Merak Ngibing. Detailed preprocessing steps, including initial segmentation techniques discussed in [11], served as a foundation for the data augmentation strategies employed in this YOLOv8 framework.

Table 2. Distribution of the Tasikmalaya Batik Dataset Across Four Motif Classes

No	Class	Record
1	Kujang	23
2	Kumeli	50
3	Payung Geulis	24
4	Merak Ngibing	66

Source: [11]

As detailed in Table 2, the dataset comprises a total of 163 distinct samples. The distribution of images across classes is as follows: the Merak Ngibing class contains the highest number of samples (66 images), followed by Kumeli (50 images), Payung Geulis (24 images), and Kujang (23 images).

These 163 samples were explicitly partitioned into 129 training images and 34 validation images. Due to the extreme limitation of the dataset, the 34 validation images concurrently serve as the testing set to evaluate the final model. The class distribution reveals a mild-to-moderate imbalance with a majority-to-minority ratio of 2.87:1. Although the imbalance is not extreme, the relatively small sample size necessitated rigorous data augmentation strategies to prevent majority class bias.

To mitigate potential bias and enhance representativeness from the limited 163 samples, rigorous data augmentation strategies (such as geometric transformations, rotation, and scaling) were applied to ensure the model learns robust features invariant to orientation and size. To address the class imbalance between the majority class (Merak Ngibing, 66 samples) and the minority class (Kujang, 23 samples), the YOLOv8 loss function intrinsically utilizes a weighted loss mechanism. Additionally, the data augmentation strategies applied in Phase 2 served as an oversampling technique to ensure minority classes were adequately represented during training.

Model Training

The experimental framework evaluates two distinct models using the stratified training subset: the standard YOLOv8 baseline and the proposed Hybrid YOLOv8-CLEO. Both implementations utilize PyTorch on a GPU-enabled workstation with fixed random seeds for reproducibility.

1) Baseline YOLOv8: The baseline model utilizes the standard YOLOv8 architecture with the CSPDarknet backbone. It is trained using default hyperparameters established in image classification literature and the Stochastic Gradient Descent (SGD) optimizer. The objective function is the cross-entropy loss used for image classification, without adaptive metaheuristic intervention, serving as a benchmark for performance comparison.
2) Hybrid YOLOv8-CLEO: The proposed method integrates the CLEO algorithm into the training loop to dynamically optimize critical hyperparameters, specifically learning rate, momentum, and weight decay. The process follows an iterative strategy: (1) Initialization of candidate hyperparameter sets; (2) Fitness Evaluation based on the Top-1 validation accuracy over short sub-epochs (two epochs per candidate, Table 3), with validation loss as a secondary tie-breaker; and (3) Parameter

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8323

Updates utilizing CLEO's social incentive mechanism to balance exploration and exploitation. This adaptive tuning continues until convergence, yielding a model configuration tailored to the specific complexities of the Tasikmalaya Batik dataset.

To ensure the reproducibility of the experiments and to facilitate a fair comparison between the baseline and the hybrid models, specific configuration parameters were established. The CLEO optimizer was initialized with a distinct set of hyperparameters designed to balance the search for the global optimum. Table 3 details the configuration used for the optimization process, including population size, iteration limits, and the defined search space.

Table 3. The Configuration Table of the CLEO Optimizer

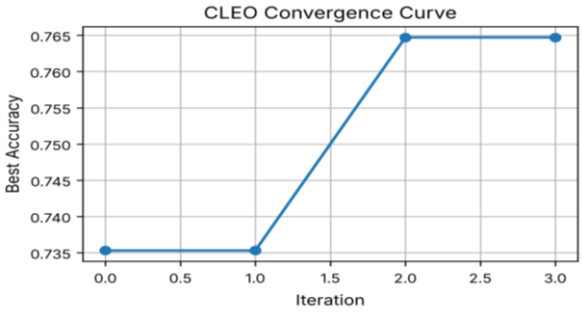
Parameter	Data Type	Value / Default	Description
search_space	dict	contains: lr0, momentum, weight_decay	Defines the search space bounds: learning rate (lr0) = [0.0001, 0.1], momentum = [0.6, 0.98], and weight_decay = [0.0, 0.001].
population_size	int	5	Number of individuals (parameter candidates) generated in each iteration.
max_iteration	int	3	Number of evolutionary iterations (generations) performed to update the population and find the best parameters.
random seed	int	0	Random seed value to ensure the optimization process is reproducible with identical results.
fitness_function	function	Created using make_fitness_fn()	Evaluation function that briefly trains the YOLOv8 model and returns the *accuracy_top1* value as the fitness score.
base_model	str	'yolov8n-cls.pt'	The base YOLOv8 model used as the starting point for training during fitness evaluation.
fitness epochs	int	2	Number of short training epochs used to speed up the fitness evaluation for each parameter combination.
device	str	'cuda'	Specifies the computing device used (GPU or CPU).

Source: (Research Results, 2026)

Training and Analysis

1) Training Stability and Convergence Analysis

The training dynamics of the proposed framework were evaluated against the baseline model, as visualized in Figure 2 and 3. Both architectures demonstrate effective learning capabilities, characterized by a steady reduction in loss functions without signs of overfitting.



Source: (Research Results, 2026)

Figure 2. CLEO Convergence Curve

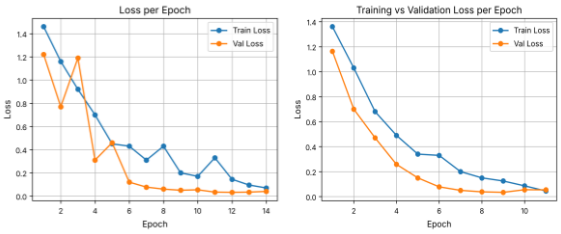
Figure 2 shows the CLEO Convergence Curve, demonstrating how the metaheuristic dynamically interacts with the training loop. Within just 3 iterations, CLEO successfully optimized the hyperparameters, elevating the base fitness accuracy from approximately 0.735 to 0.765 before finalizing the training parameters. As shown in Figure 3(a), Training vs Validation Loss curve, the CLEO-optimized model exhibits a smooth, non-intersecting validation loss trajectory compared to the baseline's fluctuating curve, suggesting better generalization on this validation set. The standard YOLOv8 model achieves convergence with a validation loss below 0.05. However, the trajectory exhibits minor oscillations before stabilizing. Conversely, the YOLOv8-CLEO model (Figure 3(b)) demonstrates significantly improved training stability and efficiency. The integration of the CLEO optimizer facilitated a steeper convergence gradient, allowing the model to reach optimal performance benchmarks in fewer epochs (11 epochs) compared to the baseline (14 epochs).

While a reduction of 3 epochs (from 14 to 11) may appear marginal for a single training run, it becomes highly significant in the context of metaheuristic optimization. With a CLEO population size of 5 evaluated over 3 maximum iterations, the algorithm processes 15 candidate models. Saving 3 epochs per candidate translates to a total reduction of 45 training epochs during the hyperparameter search phase, substantially decreasing the overall computational time and memory footprint.

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8323

JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)



(a) (b)

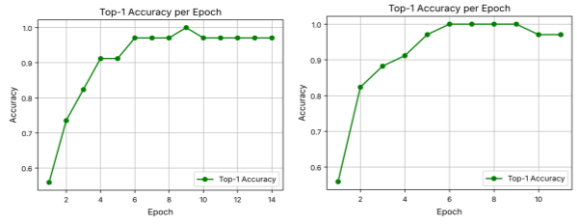
Source: (Research Results, 2026)

Figure 3. Comparative Analysis of Loss Trajectories During the Training Phase: (a) Baseline YOLOv8 Model Utilizing Early Stopping; and (b) Proposed Hybrid YOLOv8 Model Optimized via the CLEO Algorithm.

Based on the learning curves, there is no significant indication of overfitting. Both training and validation losses exhibit a consistent downward trend until the end of training, without any divergence where validation loss increases while training loss decreases, a classic hallmark of overfitting. Furthermore, in the CLEO-optimized model, the phenomenon where the validation loss tracks slightly below the training loss in most epochs is primarily attributed to the rigorous data augmentation applied exclusively during the training phase, which artificially increases the difficulty of the training set. Additionally, this phenomenon suggests that the adaptive hyperparameter tuning balanced the model's complexity, although the small validation set limits how far this can be generalized.

2) Accuracy and Convergence Analysis

The progression of Top-1 Accuracy for both the baseline and the hybrid models is presented in Figure 4. Both architectures demonstrated exceptional learning capabilities, initializing at approximately 0.55 (55%) in the first epoch and swiftly ascending to high-performance thresholds. As illustrated in Figure 4(a), the baseline YOLOv8 model exhibits a rapid learning curve, surpassing 0.90 (90%) accuracy by the fourth epoch. However, the trajectory indicates slight fluctuations before stabilizing at approximately 0.97 after a single peak of 1.0 at Epoch 9. In contrast, the YOLOv8-CLEO model (Figure 4(b)) displays a more robust convergence behavior. While the YOLOv8-CLEO model reached a peak accuracy of 1.0 (100%) around Epoch 6, the Top-1 Accuracy curve demonstrates a slight adjustment to approximately 0.97 in Epochs 10 and 11 before early stopping occurred. This minor fluctuation indicates that the CLEO algorithm continuously attempts to regularize the weights and prevent the model from blindly overfitting the training data, ensuring better generalization.



(a) (b)

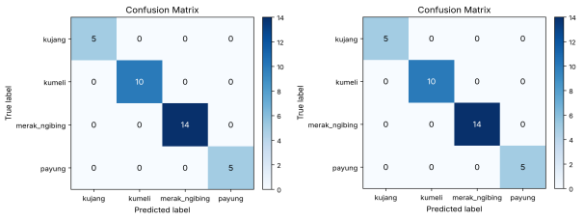
Source: (Research Results, 2026)

Figure 4. Comparative Analysis of Top-1 Accuracy Trajectories Over Training Epochs: (a) Baseline YOLOv8 Model With Early Stopping; and (b) Hybrid YOLOv8-CLEO model

This comparison suggests that the CLEO optimization successfully identified hyperparameter configurations that accelerate the feature extraction process. The ability of the hybrid model to reach and sustain peak accuracy earlier than the baseline confirms the efficiency of the proposed optimization strategy in minimizing computational overhead while maximizing classification performance.

Evaluation

To provide a granular analysis of classification performance, the confusion matrices for both the baseline and hybrid models are presented in Figure 5. The confusion matrix explicitly details the validation phase against 34 testing images (5 Kujang, 10 Kumeli, 14 Merak Ngibing, 5 Payung Geulis). The total absence of values outside the principal diagonal confirms zero instances of False Positives or False Negatives. As illustrated, both architectures achieved identical and flawless results on the validation dataset. Every sample is concentrated along the principal diagonal, indicating zero misclassifications across all categories.



(a) (b)

Source: (Research Results, 2026)

Figure 5. Confusion Matrices Evaluated on the Validation Dataset: (a) Baseline YOLOv8 Model; and (b) Hybrid YOLOv8-CLEO Model

Specifically, the models correctly identified all instances of the four distinct classes: Kujang (5 samples), Kumeli (10 samples), Merak Ngibing (14

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8323

samples), and Payung Geulis (5 samples). The absence of off-diagonal values confirms that both the standard YOLOv8 and the CLEO-optimized version attained 100% Precision, Recall, and F1-Score. This result validates that the proposed optimization maintained the high classification integrity of the baseline while, as previously discussed, enhancing convergence efficiency. Tables 4 and 5 present the comprehensive classification metrics: Precision, Recall, and F1-Score, evaluated on the validation dataset. Consistent with the confusion matrix analysis, both the baseline YOLOv8 and the hybrid YOLOv8-CLEO models achieved optimal performance metrics, reaching a value of 1.00 across all distinct motif classes (Kujang, Kumeli, Merak Ngibing, and Payung Geulis).

Table 4. Classification Report for the Baseline YOLOv8 Model

Class	Precision	Recall	F1-Score	Support
Kujang	1.00	1.00	1.00	5
Kumeli	1.00	1.00	1.00	10
Merak-Ngibing	1.00	1.00	1.00	14
Payung Geulis	1.00	1.00	1.00	5
Accuracy	1.00	1.00	1.00	34
Macro avg	1.00	1.00	1.00	34
Weight avg	1.00	1.00	1.00	34

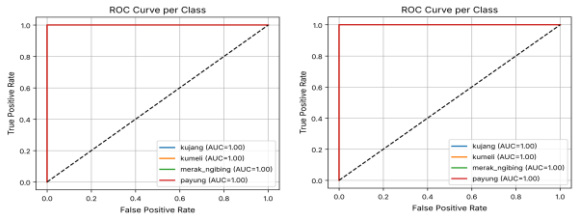
Source: (Research Results, 2026)

Table 5. Classification Report for the Hybrid YOLOv8-CLEO Model

Class	Precision	Recall	F1-Score	Support
Kujang	1.00	1.00	1.00	5
Kumeli	1.00	1.00	1.00	10
Merak-Ngibing	1.00	1.00	1.00	14
Payung Geulis	1.00	1.00	1.00	5
Accuracy	1.00	1.00	1.00	34
Macro avg	1.00	1.00	1.00	34
Weight avg	1.00	1.00	1.00	34

Source: (Research Results, 2026)

The Support column corroborates the dataset distribution used for validation, comprising a total of 34 instances. Specifically, the models successfully generalized across both minority classes (5 samples each for Kujang and Payung) and majority classes (10 for Kumeli and 14 for Merak Ngibing) without a single false positive or false negative. Consequently, the Macro Average and Weighted Average for all metrics also reached unity (1.00). While these results demonstrate the exceptional feature extraction capabilities of the YOLOv8 architecture for this specific task, they warrant cautious interpretation. The attainment of perfect classification scores is likely influenced by the limited cardinality of the validation set and high inter-class distinctiveness. While this confirms that the models have successfully learned the available data patterns, further evaluation on a larger, more diverse external testing dataset is recommended to definitively rule out overfitting and assess real-world robustness. To evaluate the models' capability to distinguish between classes at various threshold settings, the Receiver Operating Characteristic (ROC) curves are presented in Figure 6. The curves plot the True Positive Rate (Sensitivity) against the False Positive Rate (1-Specificity) for the four motif classes: Kujang, Kumeli, Merak Ngibing, and Payung.



(a) (b)

Source: (Research Results, 2026)

Figure 6. Receiver Operating Characteristic (ROC) Curves Evaluated on the Validation Dataset: (a) Baseline YOLOv8 Model; and (b) Hybrid YOLOv8-CLEO Model

As illustrated in both Figure 6(a) and Figure 6(b), the ROC trajectories for all categories exhibit an ideal characteristic, rising vertically to the top-left corner (0,1). This indicates that the models achieved a perfect Area Under the Curve (AUC) value of 1.00. Statistically, an AUC of 1.00 signifies that the classifiers possess optimal discriminatory power, successfully ranking all positive instances higher than negative instances without any overlapping distributions. Consequently, both the baseline and the CLEO-optimized models demonstrate flawless class separation on the validation dataset, confirming the high precision and recall metrics reported in the previous section.

CONCLUSION

This study proposed and evaluated a hybrid YOLOv8-CLEO architecture for the classification of Tasikmalaya Batik motifs. The experimental results confirm that the addition of the Chimpanzee Leader Election Optimization (CLEO) algorithm significantly improves the efficiency of the training process. The hybrid model demonstrated a superior convergence rate, with the Early Stopping mechanism triggering at Epoch 11, compared to Epoch 14 for the baseline. Furthermore, the loss analysis indicated that the CLEO-optimized model followed a smoother trajectory with minimal

CC BY NC

fluctuations, stabilizing more rapidly than the standard YOLOv8. Compared to the training dynamics observed in our previous CNN-based study [11], where manual tuning often resulted in fluctuating validation accuracy, the proposed YOLOv8-CLEO model demonstrates significantly superior stability and faster convergence speeds. In terms of accuracy, both models achieved a peak Top-1 Accuracy of 1.00.

However, the hybrid approach reached this optimal performance earlier, highlighting its capability to balance exploration and exploitation effectively. These findings suggest that the YOLOv8-CLEO framework offers a robust solution for preserving cultural heritage through digital identification, particularly in scenarios involving complex patterns and limited datasets. Future work will focus on validating this model on larger, more diverse datasets to further assess its scalability and generalization in real-world applications. In practical terms, this optimized lightweight YOLOv8-CLEO architecture can be deployed as the backend engine for mobile-based applications, allowing local MSME artisans and consumers to instantly verify the authenticity and motif type of Tasikmalaya batik using smartphone cameras.

This current study serves as a preliminary Proof of Concept (PoC) for integrating CLEO with YOLOv8 in traditional textile classification. We acknowledge that the perfect 1.00 accuracy score is likely influenced by the limited cardinality of the validation/test set (34 images) and high inter-class distinctiveness. Moreover, because the same 34 images were also used to compute the CLEO fitness during hyperparameter selection, the reported accuracy may be optimistic, and evaluation on an independent test set is required. Consequently, extensive computational experiments such as k-fold cross-validation, ablation studies of CLEO components, and direct empirical comparisons with other optimizers (e.g., PSO or Genetic Algorithms), fell outside the current computational scope. These rigorous validations, along with testing on large-scale external datasets, remain imperative areas for future research to definitively confirm the model's real-world scalability.

DECLARATION OF AI USE

The authors declare that generative artificial intelligence (AI) tools were used in the preparation of this manuscript. Claude (Anthropic) was used to assist with English language editing and grammar improvement. The AI tool was not used to generate, analyze, or alter any experimental data or results. The authors reviewed and revised all AI-assisted content and take full responsibility for the accuracy, originality, and final content of the manuscript.

AUTHOR CONTRIBUTIONS

This journal uses the Contributor Roles Taxonomy (CRediT) to identify individual author contributions to the research and manuscript preparation.

Author	Contribution Roles
Teuku Mufizar	Conceptualization, Methodology, Software, Formal Analysis, Funding Acquisition, Project Administration, Writing – Original Draft, Writing – Review & Editing.
Evi Dewi Sri Mulyani	Conceptualization, Methodology, Validation, Resources, Supervision, Writing – Review & Editing.
Aso Sudiarjo	Methodology, Validation, Resources, Supervision, Writing – Review & Editing.
Ayu Djuliani	Investigation, Data Curation, Visualization.
Egi Rahmatulloh	Investigation, Software, Formal Analysis.
Rinaldi Satia Aulia Rahmat	Investigation, Data Curation, Formal Analysis.

ACKNOWLEDGMENTS

The authors would like to thank LPPM Perjuangan Tasikmalaya University for the research funding and administrative support.

FUNDING

This research was funded by the Institute for Research and Community Service (Lembaga Penelitian dan Pengabdian kepada Masyarakat, LPPM), Perjuangan Tasikmalaya University, through the internal research grant scheme Riset Keilmuan Dosen (Faculty Scientific Research, RKD), Contract No. 28, dated 8 October 2025.

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest related to the research, writing, or publication of this article.

REFERENCE

[1] I. Y. Aripin, N. Nurjanah, and R. Permana, "Tasikmalaya Batik," *IJoLaC: International Journal of Language and Culture*, vol. 1, no. 1, pp. 13–17, Jun. 2023, doi: 10.63762/ijolac.v1i1.3.

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

VOL. 12. NO. 2 NOVEMBER 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v12i2.8323

[2] E. Puspitasari, W. R. Husen, and A. T. Lestari, "Analisis Motif Batik Merak Ngibing Di Rizqi Batik Collection Cigeureung Kelurahan Nagarasari Kecamatan Cipedes Kota Tasikmalaya," *Magelaran: Jurnal Pendidikan Seni*, vol. 5, no. 1, pp. 197–206, 2022, doi: 10.35568/magelaran.v5i1.1797.

[3] S. M. Ulfah, "Analisis proses pembuatan batik tulis sukapura di desa janggala kecamatan sukaraja kabupaten tasikmalaya," *Realisasi: Ilmu Pendidikan, Seni Rupa dan Desain*, vol. 1, no. 3, pp. 96–109, 2024, doi: 10.62383/realisasi.v1i3.184.

[4] S. Suranto, R. Pratiwi, N. Nurgiyatna, A. Pratiwi, and R. A. Rahman, "Model pemasaran batik berbasis digital industri kreatif di Indonesia," *AKSES: Jurnal Ekonomi dan Bisnis*, vol. 18, no. 1, 2023, doi: 10.31942/akses.v18i1.8592.

[5] A. Majumdar, R. Bhattacharyya, and V. S. Yadav, "Deep learning applications in textile industry: A systematic review of current status and delineating future research agenda," *Archives of Computational Methods in Engineering*, vol. 33, no. 2, pp. 2205–2227, 2026, doi: 10.1007/s11831-025-10366-w.

[6] L. Hakim, H. R. Rahmanto, S. P. Kristanto, and D. Yusuf, "Klasifikasi citra motif batik banyuwangi menggunakan convolutional neural network," *Jurnal Teknoinfo*, vol. 17, no. 1, p. 203, 2023, doi: 10.33365/jti.v17i1.2342.

[7] S. Aras and A. Setyanto, "Deep Learning Untuk Klasifikasi Motif Batik Papua Menggunakan EfficientNet dan Transfer Learning," *Insect (Informatics and Security): Jurnal Teknik Informatika*, vol. 8, no. 1, pp. 11–20, 2022, doi: 10.33506/insect.v8i1.1865.

[8] N. Abd Manap, L. Xiao Xuan, K. Kumar Singh, A. Sheikh Akbari, and A. Putra, "Classification of Malaysian and Indonesian batik designs using deep learning models," *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, vol. 16, no. 4, pp. 23–30, 2024, doi: 10.54554/jtec.2024.16.04.004.

[9] H. Sastypratiwi, H. Muhardi, and Y. Yulianti, "Batik Recognition and Classification Using Transfer Learning and MobileNet Approach," *JOIV: International Journal on Informatics Visualization*, vol. 8, no. 4, pp. 2400–2410, 2024, doi: 10.62527/joiv.8.4.2407.

[10] R. Andrian, R. Taufik, D. Kurniawan, A. S. Nahri, and H. C. Herwanto, "Lampung Batik Classification Using AlexNet, EfficientNet, LeNet and MobileNet Architecture," *International Journal of Advanced Computer Science and Applications*, vol. 15, no. 11, pp. 930–935, 2024, doi: 10.14569/IJACSA.2024.0151191.

[11] T. Mufizar, A. Sudiarjo, E. D. S. Mulyani, A. A. Wakih, M. A. Kasyfurrahman, and L. A. Mahbub, "Classification of Tasikmalaya batik motifs using convolutional neural networks," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 14, no. 4, pp. 3287–3299, 2025, doi: 10.11591/ijai.v14.i4.pp3287-3299.

[12] U. Sirisha, S. P. Praveen, P. N. Srinivasu, P. Barsocchi, and A. K. Bhoi, "Statistical Analysis of Design Aspects of Various YOLO-Based Deep Learning Models for Object Detection," *International Journal of Computational Intelligence Systems*, vol. 16, no. 1, art. no. 126, 2023, doi: 10.1007/s44196-023-00302-w.

[13] A. Fiqrullah, "Evaluasi Kinerja Arsitektur Convolutional Neural Network (CNN) YOLOv10 untuk Identifikasi Motif Batik Lampung," Skripsi, Jurusan Ilmu Komputer, Fakultas MIPA, Universitas Lampung, Bandar Lampung, Indonesia, 2025. [Online]. Available: https://digilib.unila.ac.id/92008/

[14] M. Safaldin, N. Zaghden, and M. Mejdoub, "An improved YOLOv8 to detect moving objects," *IEEE Access*, vol. 12, pp. 59782–59806, 2024, doi: 10.1109/ACCESS.2024.3393835.

[15] X. Xu, Y. Jiang, W. Chen, Y. Huang, Y. Zhang, and X. Sun, "Damo-yolo: A report on real-time object detection design," *arXiv preprint arXiv:2211.15444*, 2022, doi: 10.48550/arXiv.2211.15444.

[16] F. W. Wibowo, E. Sediyono, and H. D. Purnomo, "Chimpanzee leader election optimization," *Mathematics and Computers in Simulation*, vol. 201, pp. 68–95, 2022, doi: 10.1016/j.matcom.2022.05.007.

[17] P. Nandal, S. Pahal, S. Malik, N. Sehrawat, and Mamta, "Enhancing real time object detection for autonomous driving using YOLO-NAS algorithm with CLEO optimizer," *International Journal of Information Technology*, vol. 17, no. 3, pp. 1321–1328, 2025, doi: 10.1007/s41870-024-02296-w.

[18] P. Nandal, N. Bohra, and P. Mann, "Real-time skin cancer detection: Optimizing YOLOv8 with CLEO for enhanced performance," *Intelligent Decision Technologies*, vol. 19, no. 3, pp. 1768–1782, 2025, doi: 10.1177/18724981241308218.

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.