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A human-in-the-loop framework for generative batik design: integrating computer vision, cultural constraints, and IPR metadata

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ABSTRACT

Generative artificial intelligence (AI) can rapidly produce motifs and designs at scale, but its application to Indonesian batik requires consideration of cultural meaning and artisans' intellectual property rights (IPR). This study presents a hybrid, human-in-the-loop AI-native framework that integrates computer vision, artisan-provided cultural and IPR permission metadata, constraint-based filtering, and external multimodal generative models. A proof-of-concept evaluation was conducted using 447 images representing nine Lumbini batik motif categories, with 357 images (80%) used for training and 90 images (20%) for validation. ResNet-50 achieved 100% accuracy, precision, recall, and F1-score on the validation dataset. The framework subsequently classified motif inputs into Generation Allowed, Generation Prohibited, and Uncertain Pending Manual Verification based on a 0.70 confidence threshold and permission metadata. Generated designs for permitted motifs were further examined through human-in-the-loop cultural validation by Lumbini batik artisans and garment mockup assessment. The findings demonstrate the feasibility of integrating artisan-defined cultural constraints into a generative batik design workflow. However, the results are limited to the Lumbini motif collection and validation dataset, as no separate held-out test set or external validation across other batik collections was conducted.



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Introduction

The global fashion industry is undergoing a major transformation toward personalization and sustainability. According to a market analysis report by Grand View Research, the global fashion technology market reached USD 239.65 billion in 2024 and is projected to grow at a compound annual growth rate (CAGR) through 2030 (Moniruzzaman, Zaman, & Newaz, 2026). Within this transformation, traditional batik presents a distinctive design domain in which digital innovation must be balanced with cultural meaning, authenticity, and intellectual property protection (Agudelo et al., 2025).

The traditional batik industry, which is dominated by micro, small, and medium enterprises (MSMEs), faces changes in consumer preferences and the challenge of aligning cultural authenticity with modern fashion market demand. Although the national batik industry generates substantial export value, many batik MSMEs continue to rely heavily on manual design and production processes, which can limit the scalability and speed of design exploration when responding to rapidly changing market preferences (Agbaakin, 2025; Baburaj, Islam, & Tan, 2026; Juwarso, 2022). This situation does not diminish the cultural and artistic value

of traditional craftsmanship; rather, it indicates an opportunity to develop computational tools that assist artisans while retaining human control over culturally sensitive design decisions.

Similar challenges arise in the context of UMKM Batik Lumbini. Traditional batik motifs embody not only visual characteristics but also philosophical meanings and cultural values that require protection from inappropriate reproduction and cultural appropriation. Some motifs may also be subject to intellectual property rights (IPR) and artisans' customary rules governing their use rules (Ardhianto, Susanto, Regina, Mulyanto, & Almeyda, 2024). Therefore, a computational system for batik design generation cannot be evaluated solely on its visual similarity or classification accuracy. It must also incorporate mechanisms that distinguish motifs that can be regenerated from those requiring prohibition or human verification.

Recent advances in artificial intelligence (AI), particularly deep learning, provide opportunities to support computational analysis and generation of fashion designs. Deep learning models can learn complex visual representations from image data and can therefore support motif classification, feature extraction, and design variation variations (Choi et al., 2023; Giri, Jain, Zeng, & Bruniaux, 2019; Mohammadi & Kalhor, 2021). Compared with conventional rule-based approaches, deep learning is particularly relevant to batik because motifs contain complex visual patterns, shapes, and spatial relationships that can be represented directly from images. Convolutional neural network architectures have consequently been applied to recognize and extract visual features from complex motifs motifs (Girshick, 2015; Sumit, Joshi, & Rana, 2024). These learned representations can subsequently support generative models for producing visually coherent design variations (Bandara et al., 2026; Chu & Ko, 2020; de Rosen, 2025).

However, existing AI-based fashion and batik studies predominantly emphasize visual generation, classification performance, or design automation, while the cultural and licensing dimensions of generative design remain insufficiently integrated into the computational pipeline (Hidayat, Rudianto, & Sarwono, 2024; Raya et al., 2021). In particular, a technically accurate model may still generate a motif that should not be reproduced because of cultural restrictions, IPR ownership, or artisan-specific licensing rules. This creates a methodological gap between visual intelligence and culturally responsible generation. Ethical concerns surrounding generative AI have further emphasized the need for mechanisms that regulate the use and reproduction of cultural content (Association, 2025; Subrahmanyam, 2026; Wahid, Mero, & Ritala, 2025).

The unresolved issue is therefore not simply how to generate visually plausible batik motifs, but how to connect motif recognition and generative capabilities with explicit cultural and IPR constraints while retaining human oversight. Previous approaches have not adequately integrated these components into a single decision pipeline in which motif classification informs an IPR-based filtering mechanism before digital regeneration. This study addresses this gap by developing a human-in-the-loop framework that combines deep learning-based motif classification, cultural constraints, IPR metadata, and an external generative engine. The human-in-the-loop design is intended to ensure that computational generation does not operate as an autonomous replacement for artisan judgment, particularly when the system encounters motifs categorized as restricted or uncertain (Chairiyani, 2014; Morabito, Adorante, Mousannif, & Pau, 2025; Nur et al., 2026; Shukla, 2026).

This study adopts a design-oriented computational approach involving the development and validation of a hybrid AI framework. The framework uses ResNet-50 to classify Lumbini batik motifs and applies IPR metadata-based filtering to assign motifs to three decision categories: Generation Allowed, Generation Prohibited, and Uncertain Pending Manual Verification. This design enables visual classification to function as an initial decision stage before generative processing, while human verification remains available for culturally or legally ambiguous cases. Model performance is evaluated through motif classification accuracy, while the generated outputs are examined for their ability to retain the primary motif associated with the cultural identity of Lumbini batik.

Accordingly, this research makes three main contributions. First, it proposes a human-in-the-loop framework for generative batik design that integrates computer vision with cultural constraints and IPR metadata. Second, it develops a ResNet-50-based motif classification and filtering mechanism that separates motifs according to their permitted use and the need for human verification. Third, it provides an empirical validation of the framework using nine Lumbini batik motif classes and evaluates generated fashion mockups in terms of their retention of the primary motif and its associated cultural identity. Through this approach, the study extends existing AI-based batik research from visual generation toward a more controlled framework for culturally responsible generative design.

Method

The research methodology follows an end-to-end framework designed to integrate generative artificial intelligence with cultural constraints and artisan-defined permissions. The overall workflow, illustrated in Figure 1, consists of four interconnected phases: data preparation and dataset collection, data processing and constraint encoding, AI architecture implementation, and generation, validation, and output.

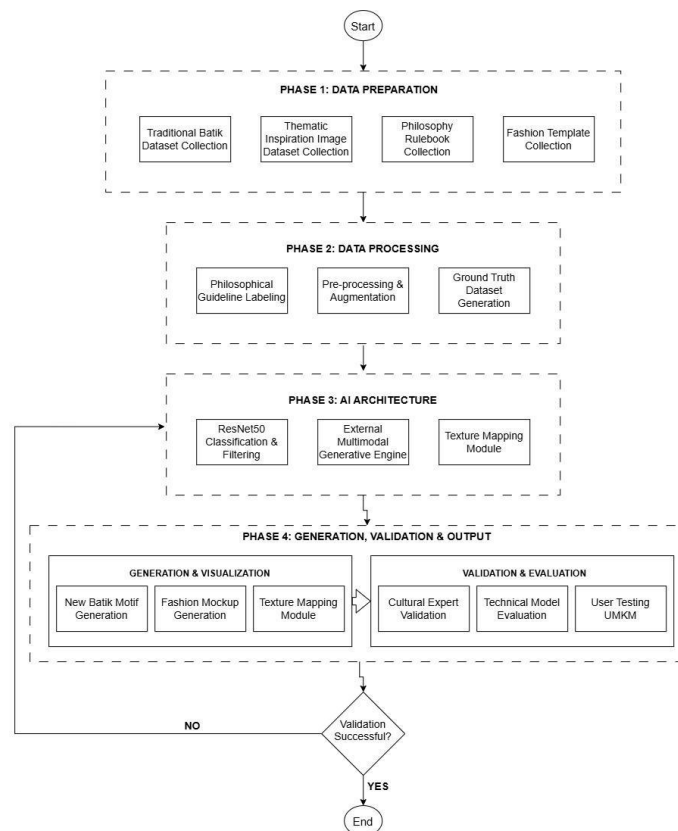


Figure 1. AI-Native Generative Pipeline for Traditional Batik

Data Preparation and Dataset Collection (Phase 1)

The dataset comprises multimodal assets for generative modeling governed by cultural constraints and artisan permissions (Figure 2). Data acquisition covers four main categories: (1) photographs of original Lumbini batik motifs provided by the artisans of Omah Batik Lumbini; (2) thematic reference images depicting Indonesian flora and fauna; (3) standard garment templates serving as texture-mapping targets; and (4) IPR and cultural permission metadata documenting the usage status of each motif.

The primary motif collection consisted of 447 digital images representing nine core batik motif categories provided by the artisans of Omah Batik Lumbini. These motifs were treated as the reference collection for model development and evaluation rather than as a researcher-selected sample. The dataset was divided into 357 images for training and 90 images for validation.



Figure 2. Multimodal Input Assets for the Generative Framework: (a) Lumbini Traditional Batik Motif Collection, (b) Thematic Pattern Inspirations, and (c) Fashion Templates

Data Processing and Constraint Encoding (Phase 2)

Following acquisition, the raw dataset underwent three processing stages to produce standardized inputs for the proposed framework. First, philosophical guideline labeling codified the philosophical meaning and principal cultural characteristics of each motif based on information provided by the artisans of Omah Batik Lumbini. These guidelines were used to define the cultural and usage constraints associated with the nine motif categories.

Second, the cultural constraints were encoded into a structured, machine-readable representation containing motif identity, principal visual elements, philosophical meaning, and permission status. Third, IPR and cultural permission metadata were integrated into the database used during classification and filtering.

The image data were resized to 224×224 pixels. Data augmentation was applied to the training images using random horizontal and vertical flipping with a probability of 0.5, rotation, and color jitter. Image normalization followed the ImageNet mean values of [0.485, 0.456, 0.406] and standard deviations of [0.229, 0.224, 0.225]. The validation images were subjected only to resizing and normalization to maintain consistent evaluation conditions.

Table 1. Cultural Constraints and Philosophical Guidelines

Motif Name	Main Motif Elements	Philosophical Meaning	Permission
<i>Heliconia-pisang pisang Sidoluhur mbuduran</i>	Bali banana (<i>heliconia</i>), dragonflies, and <i>tumpal</i> ornaments with stylized flowers and leaves Paired diamond shapes (<i>sido luhur</i>), Borobudur Temple/stupas, <i>kawung</i> motifs, and clouds	Life is lived only once and should be used to do good before its cycle ends Those who live in harmony with their surroundings receive divine help in attaining nobility of character	Public domain (generation allowed) Generation prohibited
<i>Jatilan</i>	<i>Jathilan</i> dancers, Barongan, and <i>tumpal</i> ornaments with curls resembling <i>wayang</i> /Buddha hair	Without steadfast faith, happiness can lead people to lose self-awareness and become vulnerable to their ego	Generation prohibited
<i>Liman sarimbit</i>	Paired earth-colored/black elephants, trees, clouds of hope, stupa/ <i>gunungan tumpal</i> ornaments, and an orange background	People live as couples, trust one another, share their hopes, and remain faithful throughout life	Generation prohibited
<i>Mandala bumi</i>	Mandala, stylized trees, stupas, and natural elements	Humanity and culture endure when balance and harmony with nature are maintained	Public domain (generation allowed)
<i>Kalpataru</i>	Stylized <i>kalpataru</i> trees, <i>kinnara-kinnari</i> creatures, <i>kalpataru</i> flowers, and floral <i>tumpal</i> ornaments	The tree of life must be protected so that life's cycles and the seeds of goodness can continue	Generation prohibited
<i>Liman kembar jiwo</i>	Elephants facing toward/away from one another, mandala, stylized bodhi trees, and an earth-toned background	Wise people consistently reflect on themselves, remain self-aware, and act with care	Generation prohibited
<i>Mandala kencana</i>	Mandala as a cosmological center, red lotus flowers, and green tendrils	A harmonious life is achieved when all living beings care for and respect one another	Generation prohibited
<i>Pinisi</i>	<i>Pinisi</i> ships characteristic of Borobudur reliefs, clouds, and/or waves	Life is dynamic and should be lived with optimism and resilience	Generation prohibited

AI Architecture (Phase 3)

Classification and Artisan-Informed Generative Filtering

The proposed framework employs artisan-informed generative filtering, which links motif classification results to permission statuses established by the artisans of Omah Batik Lumbini. The ResNet-50 architecture serves as the feature extraction and classification backbone (He, Zhang, Ren, & Sun, 2016), with the residual connection mechanism expressed as:

$$H(x) = F(x) + x \quad (1)$$

where x represents the input feature map, $F(x)$ denotes the residual mapping learned by the network, and $H(x)$ represents the resulting feature representation. Following feature extraction and classification, the network output logits are converted into class probabilities using a temperature-scaled softmax function:

$$P(y = k | x) = \frac{\exp(z_k/T)}{\sum_{j=1}^C \exp(z_j/T)} \quad (2)$$

where z_k denotes the logit for class k , T represents the temperature parameter, and C denotes the number of motif classes. In this study, the temperature parameter was set to 0.5. The class with the highest probability was selected as the predicted motif class.

The predicted class was then matched with the IPR and cultural permission metadata provided by the artisans of Omah Batik Lumbini. A confidence threshold of 0.70 (70%) was applied. Predictions with confidence equal to or above 0.70 were processed according to their permission status, whereas predictions below 0.70 were assigned an “UNCERTAIN” status and temporarily blocked for manual verification. The filtering decision was formally defined as:

$$S(x) = \begin{cases} \text{Generation Allowed,} & p_{\max}(x) \geq 0.70 \text{ and } M(x) = \text{Permitted} \\ \text{Generation Prohibited,} & p_{\max}(x) \geq 0.70 \text{ and } M(x) = \text{Restricted} \\ \text{Uncertain,} & p_{\max}(x) < 0.70 \end{cases} \quad (3)$$

where $p_{\max}(x)$ denotes the highest predicted class probability for input image x , and $M(x)$ represents the permission status associated with the predicted motif in the artisan-provided IPR and cultural permission metadata. Predictions classified as Uncertain are blocked and forwarded for manual verification, whereas Generation Allowed outputs may proceed to the external multimodal generative engine. This mechanism integrates artisan-defined cultural permissions into the computational generation pipeline and prevents restricted motifs from being automatically forwarded to the generative stage.

External Multimodal Generative Engine and Texture Mapping

Motifs assigned permitted status and meeting the confidence threshold were forwarded to an external multimodal generative engine. Google Gemini and OpenAI GPT were used as proof-of-concept generation engines to evaluate the feasibility of applying the proposed generative constraints using available multimodal generative models.

The generative engines received semantic motif descriptions, thematic reference images, and garment templates to produce visual variations subject to the defined cultural constraints. The generated motif was subsequently applied to the prepared garment templates through texture mapping. Restricted motifs were not forwarded to the generative stage, while uncertain classifications remained blocked pending manual verification.

Generation, Validation, and Output (Phase 4)

The final phase consisted of output synthesis, automated evaluation, human-in-the-loop cultural validation, and garment mockup verification. First, generated motifs were evaluated against the predefined construction parameters, including principal motif elements, structural arrangement, *isen-isen* characteristics, line properties, and other encoded design constraints.

Second, the generated outputs underwent human-in-the-loop assessment by the artisans of Omah Batik Lumbini. The assessment focused on the retention of primary visual elements, thematic characteristics, philosophical meaning, and construction rules established for the corresponding motifs. This assessment was used to determine whether the generated variations remained within the cultural constraints defined by the artisans.

Third, validated motifs were applied to digital garment templates to verify their visual and aesthetic compatibility in the resulting fashion mockups. Outputs that did not satisfy the predefined technical or cultural constraints were subject to revision, whereas outputs meeting the specified criteria were retained as validated design outputs.

The overall framework therefore combines automated motif recognition, artisan-defined permission filtering, multimodal generative synthesis, and human-in-the-loop cultural validation to control the use of traditional batik motifs in generative design.

Results and Discussions

This study uses external multimodal generative models, namely Google Gemini and OpenAI GPT, as proof-of-concept generation engines to assess the feasibility of the proposed generative constraints. Evaluation covers three main components: (1) deep learning-based motif recognition; (2) permission mapping and constraint filtering; and (3) generative synthesis and cultural validation.

Deep Learning-Based Motif Recognition

A total of 447 images representing nine motif categories were used to evaluate deep learning-based recognition, with 357 images allocated to training (80%) and 90 to validation (20%). The ResNet-50 model was trained for 20 epochs using the Adam optimizer and a learning rate of 0.001. Figure 3 presents the training and validation accuracy and loss curves over the 20 epochs.

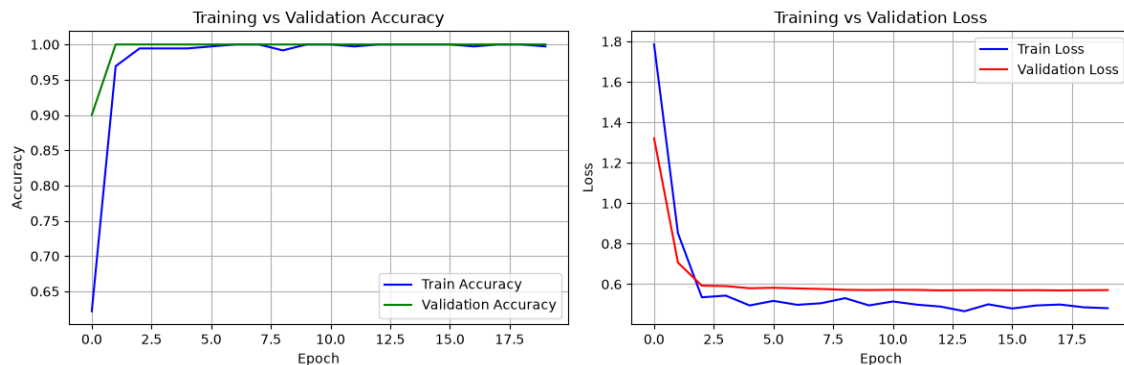


Figure 3. Training and Validation Accuracy (Left) and Loss (Right) over 20 Epochs for the ResNet-50 Model

The training accuracy increased from 62.18% to 96.92% over the training period, while validation accuracy reached 100% during the early training stage and remained at that level in the subsequent epochs. The validation loss remained approximately within the range of 0.569–0.593 during the later training stages without a sustained increase. Evaluation used a confusion matrix and four principal metrics: accuracy, precision, recall, and F1-score (Davis & Goadrich, 2006). The metrics were calculated as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (7)$$

where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives. The confusion matrix is presented in Figure 4.

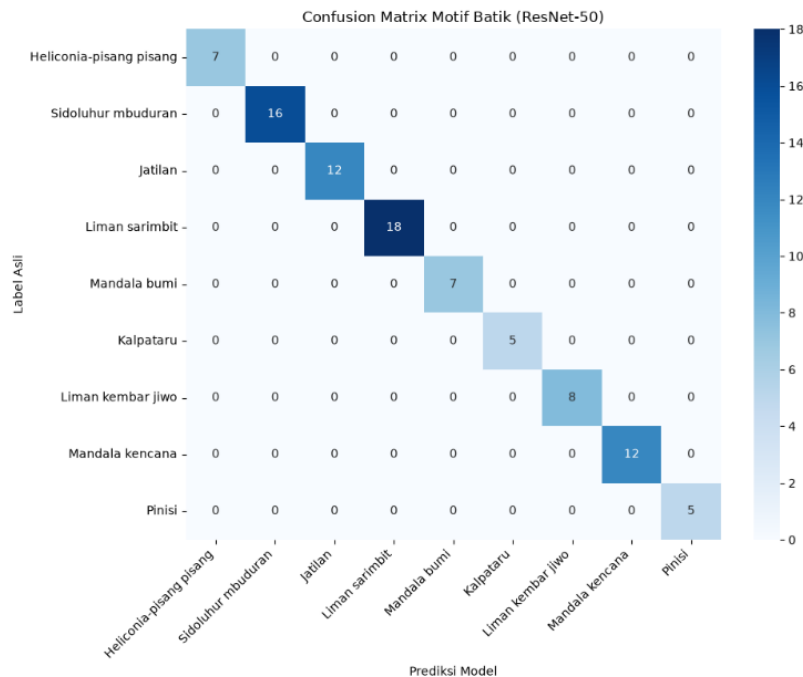


Figure 4. Confusion Matrix (Label Asli: True Label; Prediksi Model: Model Prediction)

On the validation dataset, all nine classes achieved precision, recall, and F1-scores of 1.00, with macro-averaged and weighted-averaged scores also equal to 1.00, as shown in Figure 4. These results indicate that ResNet-50 correctly classified all motif categories represented in the validation dataset.

The confidence analysis provides an additional perspective on the classification results. As shown in Table 2, eight motif categories produced confidence values above 70%, whereas *Sidoluhur mbuduran* produced a confidence of only 44.93%. Although the predicted class was correct, the confidence value was below the operational threshold and therefore required manual verification.

Table 2. Model Classification On The Validation Dataset

Motif Category	Status	Confidence (%)	Prediction Result
<i>Heliconia-pisang pisang</i>	Valid	90.37	Correct
<i>Sidoluhur mbuduran</i>	Manual verification required	44.93	Correct; review required
<i>Jatilan</i>	Valid	99.53	Correct
<i>Liman sarimbit</i>	Valid	99.28	Correct
<i>Mandala bumi</i>	Valid	99.89	Correct
<i>Kalpataru</i>	Valid	99.98	Correct
<i>Liman kembar jiwo</i>	Valid	99.98	Correct
<i>Mandala kencana</i>	Valid	85.63	Correct
<i>Pinisi</i>	Valid	99.32	Correct

The perfect validation metrics should be interpreted within the characteristics of the dataset. The images originated from the artisan-provided Lumbini collection and represented nine predefined motif categories. Therefore, the results demonstrate successful recognition within the available validation dataset but should not be interpreted as evidence of universal generalization to other batik collections.

Permission Mapping and Constraint Filtering Based on Artisan Knowledge

After ResNet-50 completes motif class recognition, the system automatically forwards the class representation to a filtering stage based on the Lumbini batik IPR and cultural metadata database. First, the system applies a minimum confidence threshold of 70% ($\text{CONFIDENCE_THRESHOLD} = 0.70$) using a temperature-scaled softmax activation function with a temperature value of 0.5. If the prediction confidence falls below this threshold, the sample is categorized as “Uncertain” and temporarily blocked pending manual verification by an artisan. Second, samples that meet the confidence threshold are evaluated against the permission metadata. The metadata assigns each motif to an operational status of either permitted or restricted. Permitted motifs can proceed to the generative engine, whereas restricted motifs are prevented from automatic generation.

The results of constraint filtering and permission mapping are summarized in Table 3. Based on the IPR and cultural metadata and confidence threshold, the system automatically assigns classification results to three operational decision categories: 1). Generation Allowed: Assigned to motifs with permitted status that meet the confidence threshold; 2). Generation Prohibited: Assigned to motifs with restricted status and sufficient classification confidence; and 3). Uncertain: Assigned to samples with confidence below 70%, which are temporarily blocked pending manual verification.

Table 3. Constraint Filtering

Motif Category	Threshold Status ($\geq 70\%$)	Confidence (%)	IPR/Cultural Status	Operational Decision
<i>Heliconia-pisang pisang</i>	$\geq 70\%$	90.37	Permitted (public domain)	Generation allowed
<i>Sidoluhur mbuduran</i>	$< 70\%$	44.93	Restricted (IPR-protected)	Uncertain (blocked/review)
<i>Jatilan</i>	$\geq 70\%$	99.53	Restricted (IPR-protected)	Generation prohibited
<i>Liman sarimbit</i>	$\geq 70\%$	99.28	Restricted (IPR-protected)	Generation prohibited
<i>Mandala bumi</i>	$\geq 70\%$	99.89	Permitted (public domain)	Generation allowed
<i>Kalpataru</i>	$\geq 70\%$	99.98	Restricted (IPR-protected)	Generation prohibited
<i>Liman kembar jiwo</i>	$\geq 70\%$	99.98	Restricted (IPR-protected)	Generation prohibited
<i>Mandala kencana</i>	$\geq 70\%$	85.63	Restricted (IPR-protected)	Generation prohibited
<i>Pinisi</i>	$\geq 70\%$	99.32	Restricted (IPR-protected)	Generation prohibited

The system tests representative samples covering the three main conditions illustrated in Figure 5: (a) permitted status, allowing progression to the generative engine; (b) restricted status, resulting in automatic blocking; and (c) uncertain status, requiring manual verification.

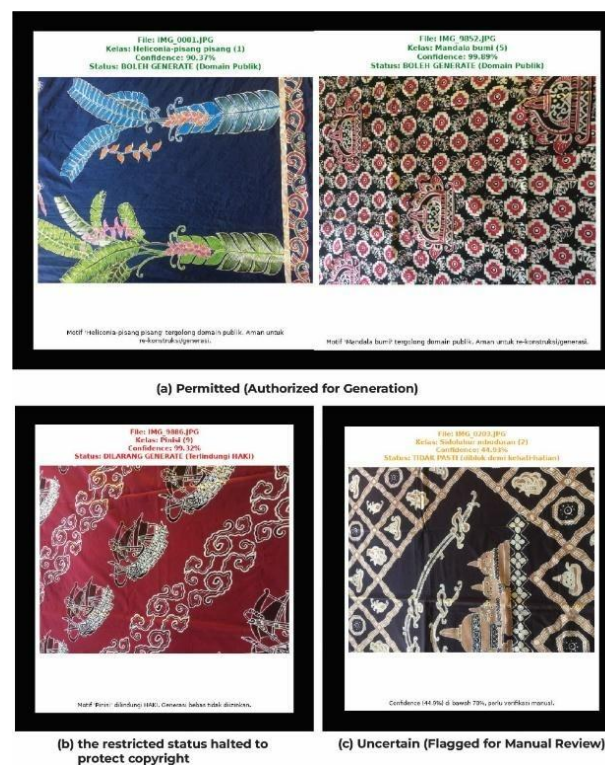


Figure 5. Representative Test Outputs of the Constraint-Filtering Framework: (a) Permitted, (b) Restricted, and (c) Uncertain. “Boleh Generate” means Generation Allowed; “Dilarang Generate” means Generation Prohibited; “Tidak Pasti” means Uncertain.

The results demonstrate that classification confidence and permission status operate as separate decision variables. A motif with high classification confidence is not automatically eligible for generation when its cultural status is restricted. Conversely, a motif with a confidence value below 70% is not forwarded to the generative engine even when its permission status would otherwise allow generation. This separation establishes a two-stage control mechanism consisting of computational recognition and artisan-defined cultural constraints.

Importantly, the *Sidoluhur mbuduran* result illustrates the distinction between classification performance and operational filtering. Although the motif was correctly predicted, its confidence was only 44.93%, so the framework categorized the sample as uncertain. Therefore, the perfect classification metrics in Figure 4 do not contradict the confidence-based decision shown in Table 3.

Visual Element Analysis and Motif Feature Construction

The system performs detailed element-wise decomposition of motifs assigned permitted status through permission mapping. It extracts the micro-level characteristics of each visual element and represents them as a parameterized motif structure that can be interpreted by the external generative engine.

Heliconia Motif Construction

Detailed element-wise decomposition was implemented through a case study of the permitted *Heliconia-Pisang Pisang* motif. Figure 6 illustrates the workflow for deconstructing this motif and extracting its parameters.

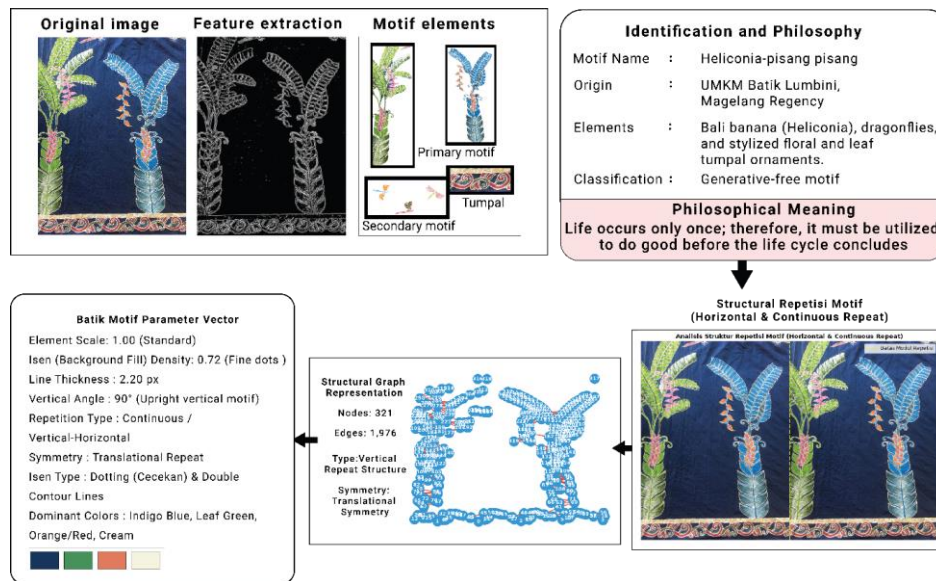


Figure 6. Overall Workflow of Visual Deconstruction and Parameter Extraction for the *Heliconia-Pisang Pisang* Batik Motif

The decomposition identifies the principal visual components and their relationships so that the motif can be represented semantically rather than solely as a raster image. This representation provides structured information for the subsequent multimodal generation stage.

Mandala Bumi Motif Construction

The *Mandala Bumi* motif was similarly decomposed into primary and secondary elements and represented as a parameterized motif structure. These parameters serve as semantic inputs to the external generative engine, as illustrated in Figure 7.

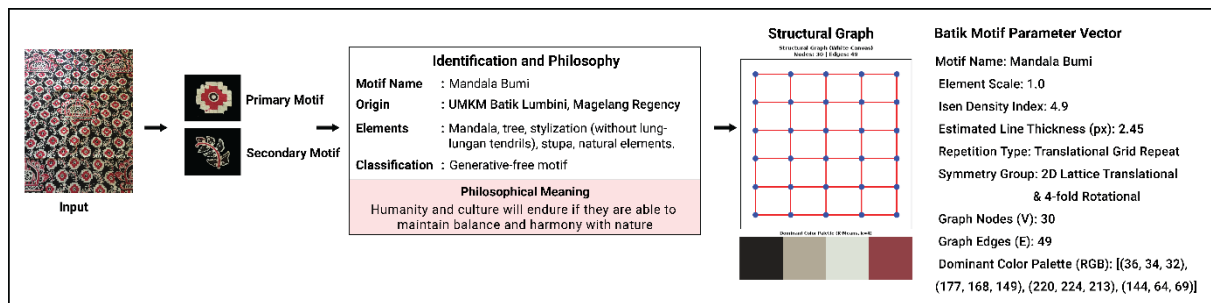


Figure 7. Deconstruction and Parameter Extraction for the *Mandala Bumi* Batik Motif

The two examples demonstrate that the framework can transform selected traditional motifs into structured visual descriptions before generation. This step is intended to retain important motif characteristics while allowing generative models to recombine the specified elements in new compositions.

Generative Synthesis and Multimodal Engine Evaluation

To evaluate integration performance, construction parameters and semantic descriptions were supplied to the external multimodal generative engines using original motif images, thematic visual references, and garment templates as multimodal inputs. Figure 8 shows batik motif synthesis using external multimodal models based on *Heliconia-Pisang Pisang* traditional visual rules and thematic flora and fauna references.



Figure 8. Batik Motif Synthesis Using External Multimodal Models Based on *Heliconia-Pisang Pisang* Traditional Visual Rules and Thematic Flora and Fauna References

The resulting output demonstrates the feasibility of combining structured motif parameters with external multimodal generation. The generative model is not given unrestricted access to the complete motif collection; instead, the generation process is conditioned by the output of the preceding recognition and permission-filtering stages. Figure 9 presents the synthesis of the *Mandala Bumi* motif using a peacock as the thematic reference.

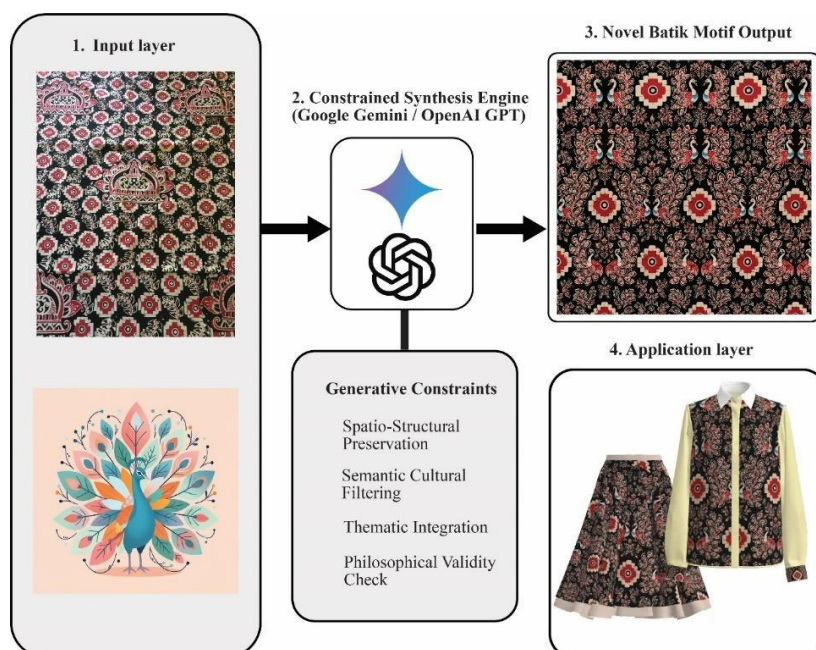


Figure 9. Batik Motif Synthesis Using External Multimodal Models Based on *Mandala Bumi* Traditional Visual Rules and a Thematic Peacock Reference

The outputs demonstrate that the external generative models can interpret semantic motif parameters together with thematic visual references and produce new design compositions. The results are therefore primarily evidence of the feasibility of the proposed workflow rather than a benchmark of the generative models themselves.

Practical Validation of Cultural Constraints in Generative Fashion Mockups

As a final validation of the integration of traditional values into the digital workflow, permitted Lumbini batik motifs produced through constrained generation are applied to the prepared garment templates. Figure 10 presents design mockups demonstrating the feasibility of the constraint-based generative framework for traditional batik preservation.



Figure 10. Design Mockups Demonstrating the Feasibility of the Constraint-Based Generative Framework for Traditional Batik Preservation

The garment mockups demonstrate how generated motif compositions can be transferred from isolated visual outputs into apparel-oriented representations. The final output therefore connects motif recognition, cultural filtering, generative synthesis, and garment visualization within a single workflow.

Deep Learning-Based Motif Recognition

The ResNet-50 results demonstrate successful classification of the nine motif categories within the validation dataset. The model achieved 100% validation accuracy, while all classes obtained precision, recall, and F1-scores of 1.00. The result is consistent with previous studies demonstrating that convolutional neural networks can effectively distinguish batik motifs based on their visual characteristics. Filia et al. (2023) for example, demonstrated the usefulness of CNN-based approaches for batik pattern classification, particularly when combined with augmentation and oversampling. Khoirunnisa et al. (2025) also demonstrated the application of MobileNetV2 and data augmentation for Semarang batik classification.

The result is also comparable in methodological direction with Prayoga, Sukmasetya, Yudianto, & Hasani (2023), who applied CNN architecture to Yogyakarta batik classification, and Rangkuti, Harjoko, & Putra (2021), who developed a scale- and rotation-invariant image classification approach using MU2ECS-LBP. These studies collectively demonstrate that batik motif recognition can be approached using both deep-learning and feature-based image analysis. The present study extends this classification function by using the predicted motif category as an input to a subsequent cultural-constraint filtering stage.

Nevertheless, the 100% validation performance should not be interpreted as evidence that ResNet-50 universally outperforms other architectures. The dataset consisted exclusively of 447 images from the artisan-provided Lumbini collection, and the study did not include an independent external test set or cross-validation. Consequently, the result establishes performance on the available validation dataset but does not establish generalization across different batik producers, image acquisition conditions, geographical origins, or larger motif collections.

Training Behavior and Validation Performance

Figure 3 shows that the model learned the classification task rapidly. Validation accuracy reached 100% during the early training stage and remained stable, while the validation loss did not show a sustained upward trend. This indicates that, within the available validation data, the model maintained consistent classification performance throughout training.

The high validation result may partly reflect the controlled nature of the dataset. The nine categories originate from the same artisan-provided collection, and the visual characteristics within each category may be sufficiently distinctive for the model to separate them effectively. This differs from studies involving more heterogeneous datasets, where differences in image quality, motif presentation, imbalance, and visual variation can create additional classification challenges (Filia et al., 2023; Khoirunnisa et al., 2025)

The findings therefore support the feasibility of ResNet-50 as the recognition component of the proposed framework but also highlight the need for further validation. Future experiments should include an independent held-out test set, k-fold cross-validation, and comparisons with alternative architectures. Such

experiments would allow the classification performance to be evaluated more robustly and would clarify whether the observed performance is attributable primarily to the architecture, the dataset characteristics, or both.

Confidence Filtering as a Safety Mechanism

One important finding is the difference between prediction correctness and prediction confidence. The *Sidoluhur mbuduran* sample was correctly classified but produced only 44.93% confidence. This result does not contradict the perfect precision, recall, and F1-score because those metrics evaluate whether the selected class is correct, whereas confidence represents the model's probability distribution over possible classes.

The distinction is important for the proposed application. A model can select the correct class while still exhibiting substantial uncertainty relative to the alternative classes. The framework therefore does not use the classification result alone to determine whether generation should proceed. Instead, the 70% threshold provides an operational gate that separates sufficiently confident predictions from uncertain cases.

This approach is consistent with the broader development of AI-assisted fashion systems in which automated processing is integrated with human judgment. Choi et al. (2023) described an AI-based fashion design system that reflects the workflow of fashion designers rather than treating design as a completely autonomous computational process. In the present framework, confidence filtering provides the first control layer before cultural and artisan-defined constraints are applied.

Permission Mapping and Cultural Constraints

The results in Figure 5 demonstrate that motif classification and cultural permission are treated as separate processes. This distinction is important because visual recognition alone cannot determine whether a traditional motif is appropriate for unrestricted generative reuse. The system first identifies the most probable motif category and then evaluates its permission status using artisan-provided metadata.

This approach addresses the cultural and contextual dimensions of Indonesian batik, where the meaning and appropriate use of motifs may extend beyond their visual characteristics. Chairiyani (2014) for example, discussed restricted batik motifs within the Yogyakarta cultural context, illustrating how certain motifs may be associated with specific cultural meanings and usage conventions. Therefore, a computational system that focuses solely on visual similarity may be insufficient for determining whether a motif can be regenerated or reused.

Research on Indonesian batik SMEs also emphasizes the importance of local knowledge, innovation capability, and stakeholder engagement. Raya et al. (2021) highlighted stakeholder engagement and open innovation in craft SMEs, while Hidayat et al. (2024) examined the capabilities of Indonesian batik SMEs in product-design innovation. The present framework incorporates these principles technically by translating artisan knowledge into an operational filtering mechanism that determines whether a recognized motif can proceed to generative synthesis.

Visual Deconstruction and Parameterized Motif Representation

Figure 6 and 7 demonstrate the transformation of traditional motifs into structured visual parameters before they are supplied to the generative models. This stage is important because direct image-to-image generation may reproduce visual patterns without explicitly representing the relationships among motif components.

The decomposition approach is consistent with previous computational approaches to traditional textile design. Ratnadewi, Pandanwangi, & Prijono (2024), for example, used turtle-graphics algorithms to construct Batang batik motifs, demonstrating that traditional visual structures can be represented through computational procedures. Kang, You, & Xie (2025) similarly demonstrated how computational generative approaches can be combined with decision-making methods for traditional textile-pattern design.

In the present framework, parameterization serves a different but complementary function. Rather than attempting to replace the original motif with an entirely algorithmic reconstruction, it converts selected visual characteristics into semantic information that can guide multimodal generative models. This creates an intermediate representation between artisan-defined motif knowledge and AI-generated design.

Generative Synthesis and Multimodal AI

The outputs in Figure 8 and 9 demonstrate the feasibility of using external multimodal generative models to synthesize new batik design compositions from structured motif parameters and thematic visual references. The *Heliconia-Pisang Pisang* example demonstrates the combination of traditional motif characteristics with thematic flora and fauna references, while the *Mandala Bumi* example demonstrates the use of a peacock as an additional visual reference.

These findings are consistent with the broader development of generative approaches in fashion and traditional textile design. Chu & Ko (2020) demonstrated the use of BatikGAN for batik creation, while Ardianto et al. (2024) examined the integration of generative AI into Bakaran Batik and its implications for design and workflow efficiency. Choi et al. (2023) further demonstrated the potential of AI-based systems to support fashion-design processes.

The contribution of the present study differs from these approaches because generation is not treated as an independent design operation. Instead, the generative engine receives inputs only after motif recognition and constraint filtering. This architecture creates a conditional generation process in which cultural permission and recognition confidence precede synthesis.

Garment Mockups and Practical Design Feasibility

Figure 10 demonstrates the final translation of generated motifs into garment-oriented mockups. This stage is important because a generated motif may appear visually appropriate as an isolated pattern but produce a different visual effect when applied to an apparel surface.

The garment mockups therefore function as a practical visualization stage rather than as a separate classification or generative evaluation metric. They demonstrate how the proposed framework can connect motif-level generation with a potential fashion-design application. This is consistent with research emphasizing the use of AI to support fashion-design workflows rather than limiting AI applications to image classification alone (Choi et al., 2023; Giri et al., 2019).

The outputs should nevertheless be interpreted as proof-of-concept visualizations. The study did not conduct a formal consumer evaluation, commercial usability test, or quantitative aesthetic assessment of the garment mockups. Accordingly, the results demonstrate technical feasibility of the workflow rather than evidence of market acceptance or consumer preference.

Integrated Contribution of the Framework

The overall results indicate that the proposed framework integrates four sequential functions: motif recognition, confidence filtering, cultural permission mapping, and constrained generative synthesis. The classification component identifies the motif, the confidence threshold identifies uncertain predictions, the permission layer determines whether generation is operationally allowed, and the multimodal engine produces the design output. Human validation then provides an additional cultural oversight mechanism.

This integrated structure distinguishes the framework from approaches that focus exclusively on either classification or generation. Existing studies have demonstrated CNN-based batik recognition (Filia et al., 2023; Khoirunnisa et al., 2025; Prayoga et al., 2023), generative batik design Chu & Ko (2020), generative AI applications in batik Ardianto et al. (2024), and computational traditional-pattern design (Kang et al., 2025; Ratnadewi et al., 2024) the present study connects these functions through explicit confidence and cultural-constraint gates.

The framework therefore provides a proof-of-concept for human-in-the-loop generative batik design in which AI assists the design process without becoming the sole authority over cultural use. The findings support the technical feasibility of this integration while leaving broader questions of generalization, formal IPR verification, comparative model performance, and systematic cultural evaluation for future research.

Conclusions

This study designed and implemented a hybrid, human-in-the-loop AI-native framework that integrates deep learning-based batik motif classification, artisan-provided cultural and IPR permission metadata, constraint-based filtering, and an external multimodal generative engine. Using 447 images representing nine Lumbini batik motif categories, with 357 images for training and 90 images for validation, the ResNet-50 model achieved 100% accuracy, precision, recall, and F1-score on the validation dataset. The permission-mapping mechanism classified motifs into three operational categories: Generation Allowed, Generation Prohibited, and Uncertain Pending Manual Verification. The confidence threshold and permission metadata prevented restricted or low-confidence motifs from proceeding to the generative stage, while generated designs for permitted motifs retained the primary structural and semantic characteristics specified as generation constraints. Cultural appropriateness was further examined through human-in-the-loop validation by Lumbini batik artisans and visual assessment of garment mockups. These findings demonstrate the feasibility of integrating cultural constraints into a generative batik design workflow, but the 100% validation performance should be interpreted within the scope of the evaluated Lumbini dataset rather than as evidence

of generalizable classification performance. Future research should evaluate the framework using larger and more diverse datasets covering batik motifs from different regions, collections, and stylistic traditions, together with a separate held-out test set and cross-validation to assess generalization and robustness. Systematic cultural validation should also involve multiple qualified artisans or cultural experts using explicit criteria for motif identity, philosophical meaning, visual fidelity, and cultural appropriateness. Such extensions would provide stronger empirical evidence for the scalability and cross-cultural applicability of the framework while maintaining human oversight over culturally sensitive generative design.

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