Contents lists available at IdNNS

Journal of Intelligent Systems for Community Development

Volume 1 ; Issue 1

journal homepage: https://journal.idnns.org/index.php/jiscode

Detection and Classification of Indonesian Batik Motifs Using YOLOv11

Mochamad Galih Pradipta[a], Herlawati Herlawati[a,*] and Rakhmat Purnomo[a]

[a]*Informatics, Faculty of Computer Science, Universitas Bhayangkara Jakarta Raya, Jl. Perjuangan No. 81, Marga Mulya, Bekasi Utara, Bekasi, 17143, West Java, Indonesia*

ARTICLE INFO

Keywords:
Batik Nusantara
YOLOv11
CRISP-DM
Object Detection
Web-based System

ABSTRACT

The complexity of asymmetric visual patterns and overlapping ornaments on batik motifs often causes difficulties in automatic identification for modern society. The limitations of previous conventional classification methods raised the need for computer-vision technology capable of precise object localization. This study aimed to detect and classify multiple motifs of Indonesian Batik in real time using the YOLOv11 model. The methodology employed was CRISP-DM, which encompasses six structured phases from business understanding to system deployment. The object of this research focused on the main batik-motif variations found across Indonesia, with model performance measured using the mean Average Precision (mAP) metric. The main results showed that: 1) the YOLOv11 model achieved an mAP50 of 77%; 2) the data-augmentation phase effectively prevented model overfitting; and 3) the detection system was successfully integrated into a web-based platform for direct image testing.

1. Introduction

The preservation of Indonesia's original cultural heritage, particularly batik, which has been recognized by UNESCO, faces increasingly urgent socio-cultural challenges in the modern era. Recent socio-cultural research indicates that the failure rate among young people in identifying complex batik motifs reaches 82%, largely due to low visual literacy (Midyanti et al., 2024). In addition, the rise of international cultural-ownership claims over traditional motifs underscores the urgency of massive, structured digital documentation (Hasanah et al., 2025). These problems indicate that, without technological intervention, the risk of eroding the sociological knowledge underlying the philosophy of Nusantara ornamentation will continue to grow.

Fast and accurate motif recognition is essential to support the protection of intellectual-property rights, cultural documentation, and the verification of the originality of commercial products. Inaccurate batik identification can obscure the philosophical value of regional ornaments, encourage motif counterfeiting, undermine the competitiveness of the local creative industry, and hinder intergenerational cultural-preservation campaigns (Susanti et al., 2024; Winarno et al., 2024). Therefore, artificial-intelligence-based digitalization is an appropriate strategy for automating the recognition of ornamental patterns efficiently, integrating contemporary techniques with efforts to preserve intangible heritage (Wesnina et al., 2025).

However, one of the biggest challenges in current batik-motif recognition systems is the limited ability of the technology to handle the physical condition of fabric in real-world settings. Conventional motif identification still largely relies on the manual expertise of senior batik experts, which is vulnerable to subjectivity, time-consuming, and difficult for the general public to access (Winarno et al., 2025). In addition, the physical characteristics of the fabric, such as folds, variation in the camera angle, diverse textures, and inconsistent lighting, often obscure the visual detail of the original ornament (Herlawati and Handayanto, 2026). As a result, the accuracy of independent identification by the public becomes low, hindering the optimization of Nusantara heritage mapping.

The You Only Look Once (YOLO) method has been widely used in various object-detection studies and is well known for its speed and precision in identifying multiple types of objects within digital images simultaneously. Several studies have shown that the YOLO architecture achieves more optimal bounding-box localization accuracy and training speed compared with conventional region-based detection models (Ramadhan and Ramadhani, 2024). YOLO has proven superior in several respects, including high-speed processing performance with a competitive precision level for real-time interaction needs. The YOLO model is also

*Corresponding author: herlawati@ubharajaya.ac.id
ORCID(s):

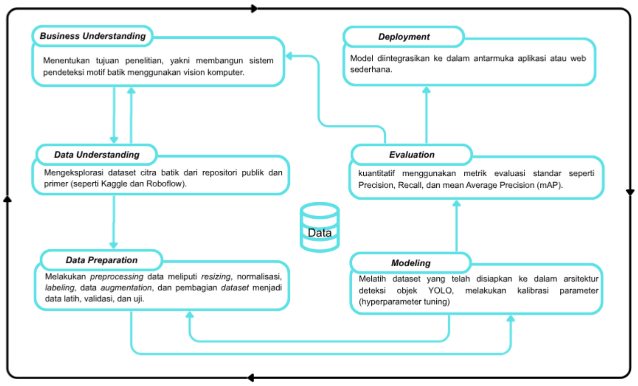


Figure 1: Stages of CRISP-DM. Source: research results (2026).

able to minimize the rate of background false positives because it accounts for the entire image globally, while its superior generalization capability makes this architecture more adaptive to irregular field data (Aldughayfiq et al., 2023).

Various deep-learning algorithms have been applied in previous studies to identify traditional patterns using different model architectures, such as pure CNN-based image-classification architectures, VGG16, and ResNet50 (Alya et al., 2023; Elvitaria et al., 2025; Mawan and Al Fatta, 2020; Nabila et al., 2025), which demonstrate strong feature-extraction capability. However, most of those studies remain confined to single global image classification, and therefore fail entirely to localize spatial coordinates when multiple motifs are combined on a single piece of fabric (Oktarino et al., 2024). In addition, model testing in prior studies is generally still limited to a local development environment without any downstream deployment as publicly accessible software. Therefore, this research aims to apply the You Only Look Once version 11 (YOLOv11) method within the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework to detect and classify multiple Indonesian Batik motifs spatially, through the integration of a web-based system.

2. Research Method

This research uses the Cross-Industry Standard Process for Data Mining (CRISP-DM) method as a reference for the data-processing workflow used to detect and classify batik, together with You Only Look Once (YOLO) as the object-detection modeling algorithm.

2.1. Cross-Industry Standard Process for Data Mining (CRISP-DM)

The Cross-Industry Standard Process for Data Mining (CRISP-DM) was introduced in 1996 and is used as an industry-analysis framework for designing business problem-solving strategies (Pete et al., 2026).

This methodology consists of six main, iterative stages, so that they can be repeated to improve system performance based on evaluation results.

2.2. You Only Look Once (YOLO)

You Only Look Once (YOLO) is a state-of-the-art object-detection algorithm that revolutionized the way machines perceive objects by formulating the detection task as a single spatial regression problem (Aldughayfiq et al., 2023).

The working principle of You Only Look Once (YOLO) involves dividing the input image into an $S \times S$ grid. Each cell in the grid is responsible for producing a confidence value and a number of bounding boxes. If no object is present in a given cell, the resulting confidence value will be zero. Once the confidence values for every cell have been obtained, these values are then compared using Intersection over Union (IoU) to determine the best predicted bounding box for each detected class, computed as (Nabila et al., 2025):

$$\text{Confidence} = \Pr(\text{Object}) \times \text{IoU}(\text{GT}, \text{pred}) \tag{1}$$

where Pr denotes probability, IoU is the Intersection over Union, GT is the ground truth, and pred is the prediction.

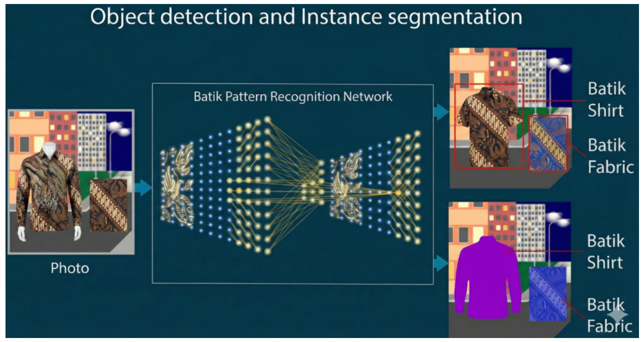


Figure 2: How YOLO works. Source: research results (2026).

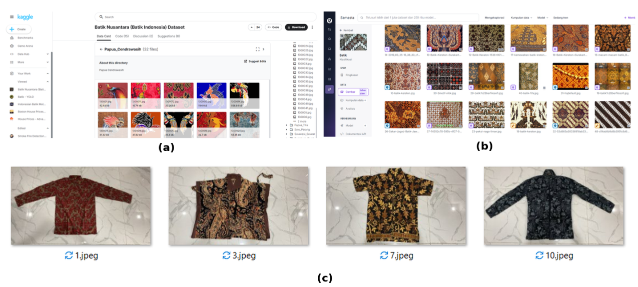


Figure 3: (a) Secondary Kaggle dataset, (b) secondary Roboflow dataset, (c) primary dataset. Source: research results (2026).

3. Results and Discussion

This research applies the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology integrated with a state-of-the-art computer-vision algorithm, namely You Only Look Once Version 11 (YOLOv11). The modeling workflow was carried out systematically through a series of computational stages to produce the model with the most optimal performance. The best-evaluated final model was then integrated into a web-based batik-motif detection and classification system built with the Flask framework. This system is designed to identify 27 (twenty-seven) types of Indonesian Batik motifs informatively, while also serving as a technological foundation for the digitalization and preservation of culture within the textile industry.

3.1. Business Understanding

The initial stage of this research focused on analyzing the functional requirements of an automatic detection system to address the visual complexity of Indonesian Batik motifs. This research aims to build a web-based batik-motif detection and classification system using the YOLOv11 method to automate the identification of both geometric and non-geometric patterns of considerable complexity. The implementation of this technology is expected to become a new standard for the adoption of artificial-intelligence technology, particularly within the textile industry, digital data collection, and the broader preservation of cultural heritage. The output of this system is projected to support the curation, sorting, and documentation of batik motifs through technology, accurately and in real time.

3.2. Data Understanding

The dataset used in this research was obtained from two sources: secondary data from Kaggle[1] and secondary data from Roboflow[2], as well as primary data obtained through manual photography, as shown in Figure 3.

This dataset covers a total of 27 representative Indonesian Batik motif classes. To ensure the stability of the model's generalization process, each class was strictly limited to 40 high-quality sample images, so that the overall accumulated data amounted to 1,080 images, as illustrated in Figure 3.

3.3. Data Preparation

The data-preparation stage in this research involved several steps, as follows.

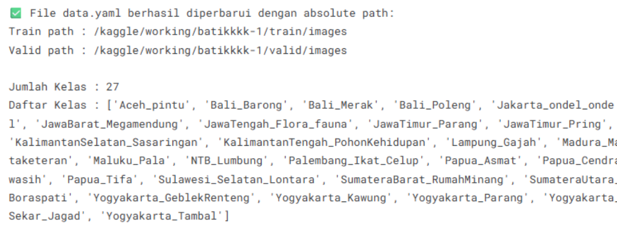
a. Annotation checking. This stage aims to check and identify the bounding-box annotations across the entire dataset, verifying whether they correctly and consistently represent the corresponding objects. This stage also aims to preliminarily identify whether any objects were annotated inaccurately, mislabeled, or not annotated at all.

b. Empty-label checking. This stage involves checking and removing data that has no label or is unannotated, in order to maintain annotation consistency for each class, as shown in Figure 4.

c. Identification of the data split and data volume. This stage involves identifying the size of the data split, the class distribution, and the total amount of clean data to be

[1] https://www.kaggle.com/datasets/hendryhb/batik-nusantara-batik-indonesia-dataset

[2] https://app.roboflow.com/lih-workspace/batikkkk/2



```
✅ File data.yaml berhasil diperbarui dengan absolute path:
Train path : /kaggle/working/batikkkk-1/train/images
Valid path : /kaggle/working/batikkkk-1/valid/images

Jumlah Kelas : 27
Daftar Kelas : ['Aceh_pintu', 'Bali_Barong', 'Bali_Merak', 'Bali_Poleng', 'Jakarta_ondel_onde
l', 'JawaBarat_Megamendung', 'JawaTengah_Flora_fauna', 'JawaTimur_Parang', 'JawaTimur_Pring',
'KalimantanSelatan_Sasaringan', 'KalimantanTengah_PohonKehidupan', 'Lampung_Gajah', 'Madura_Ma
taketeran', 'Maluku_Pala', 'NTB_Lumbung', 'Palembang_Ikat_Celup', 'Papua_Asmat', 'Papua_Cendra
wasih', 'Papua_Tifa', 'Sulawesi_Selatan_Lontara', 'SumateraBarat_RumahMinang', 'SumateraUtara_
Boraspati', 'Yogyakarta_GeblekRenteng', 'Yogyakarta_Kawung', 'Yogyakarta_Parang', 'Yogyakarta_
Sekar_Jagad', 'Yogyakarta_Tambal']
```

Figure 4: Result of the per-class data check. Source: research results (2026).

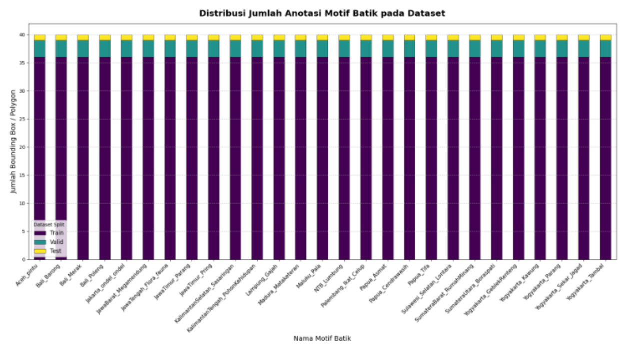


Figure 5: Data-split distribution. Source: research results (2026).

used in the subsequent training process. The data split and the total clean data are shown in Figure 5.

The data-splitting process was carried out consistently for each class with a proportion of 36 images as the training set, 3 images as the validation set, and 1 image as the testing set. Mathematically, this split forms a percentage ratio of 90% for training (972 images in total), 7.5% for validation (81 images in total), and 2.5% for final testing (27 images in total). This balanced dataset distribution served as the primary foundation before proceeding to the pre-processing and bounding-box-annotation stages.

3.4. Modeling

The modeling stage constitutes the core stage within the computational architecture, encompassing the application of the You Only Look Once Version 11 (YOLOv11) algorithm. The specific model implemented in this research is the YOLOv11n (nano) variant, using a transfer-learning approach. This approach was chosen to optimize training efficiency by leveraging pre-trained weights obtained from a large-scale dataset, which were then extracted and applied to the new dataset used in this research. The dataset used is a secondary dataset from the Roboflow Universe platform, comprising a total of 1,080 digital images for the detection and classification of 27 (twenty-seven) Indonesian Batik motif classes. The modeling stage was carried out through the following systematic steps.

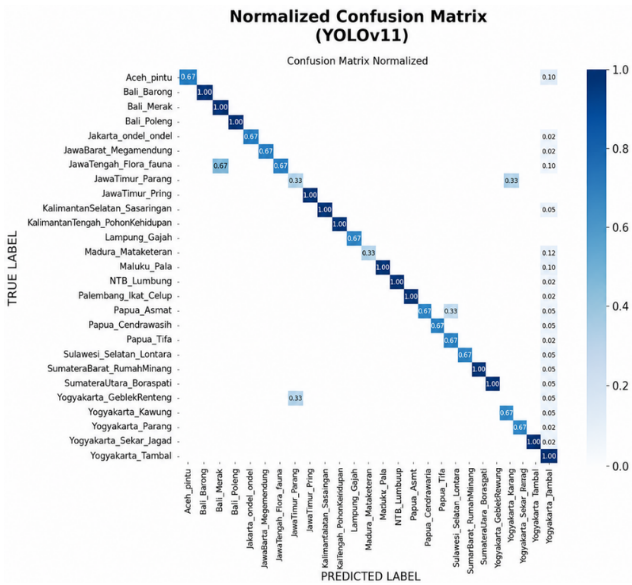
a. Downloading and importing the modeling library. The initial modeling stage involved configuring the computational working environment by downloading and installing the primary open-source library, namely *ultralytics*. After the installation was successfully completed, the main module named YOLO was imported. This step ensures that all functions, dependencies, and basic architectural elements of the YOLOv11 neural network can be accessed directly within the programming environment, enabling optimal use of the YOLOv11 model without having to build the object-detection algorithm architecture from scratch.

Table 1
Hyperparameter configuration used during training.

Parameter	Value	Technical function
Epochs	150	Determines the total number of complete learning iterations.
Image size	800	Standardizes the input image resolution to balance accuracy and FPS.
Batch size	8	Determines the number of samples processed before the model weights are updated.
Optimizer	Auto (AdamW)	Optimization algorithm used to adaptively minimize the loss function.

b. Hyperparameter configuration. The experimentation process was carried out gradually through variations in hyperparameter configuration to evaluate the impact of parameter combinations on accuracy and on the model's generalization performance. The details of the hyperparameter combinations tested in this research are presented in Table 1.

Based on Table 1, this research tested several training scenarios in order to find the most optimal parameter composition. The input image size was standardized at a resolution



(a)

```
Validating /kaggle/working/runs/detect/Batik_Project/YOLOv11_Small_v3/weights/best.pt...
Ultralytics 8.4.48 ⚡ Python-3.12.12 torch-2.1.0+cu128 CUDA:0 (Tesla T4, 14913MiB)
YOLOv11s summary (fused): 101 layers, 9,423,249 parameters, 0 gradients, 21.4 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 5/5 2.10it/s 1.6s
                   all         74         81      0.682      0.926      0.770      0.778
            Aceh_pintu          3          3      0.537      0.618      0.618      0.537
           Bali_Barong          3          3      0.631      0.995      0.995      0.631
            Bali_Merak          3          3      0.333      0.333      0.333      0.333
           Bali_Poleng          3          3      0.691      0.731      0.731      0.691
     Jakarta_ondel_ondel          3          3      0.483      0.913      0.913      0.483
   JawaBarat_Megamendung          3          3      0.940      0.995      0.995      0.940
  JawaTengah_Flora_Fauna          3          3      0.117      0.333      0.333      0.117
       JawaTimur_Parang          2          3      0.279      0.533      0.533      0.279
        JawaTimur_Pring          3          3     0.0919      0.443      0.443     0.0919
 KalimantanSelatan_Sasaringan          3          3      0.720      0.843      0.843      0.521
KalimantanTengah_PohonKehidupan          3          3      0.863      0.995      0.995      0.863
         Lampung_Gajah          3          3      0.738      0.863      0.954      0.738
      Madura_Matakteran          3          3      0.102      0.172      0.172      0.102
           Maluku_Pala          3          3     0.0439     0.0995     0.0995     0.0439
           NTB_Lumbung          3          3      0.425      0.495      0.495      0.425
    Palembang_Ikat_Celup          3          3      0.714      0.913      0.913      0.714
           Papua_Asmat          3          3      0.567      0.706      0.706      0.567
      Papua_Cendrawasih          3          3      0.482      0.806      0.806      0.482
            Papua_Tifa          3          3      0.739      0.913      0.913      0.739
  Sulawesi_Selatan_Lontara          3          3     0.0195     0.0279     0.0279     0.0195
 SumateraBarat_RumahMinang          3          3      0.499      0.665      0.667      0.499
 SumateraUtara_Borasapati          3          3      0.439      0.863      0.863      0.439
 Yogyakarta_GeblekRenteng          1          3    0.00838      0.012      0.012    0.00838
      Yogyakarta_Kawung          3          3      0.000      0.000      0.000      0.000
      Yogyakarta_Parang          3          3      0.544      0.995      0.995      0.544
   Yogyakarta_Sekar_Jagad          2          3    0.00479     0.0239     0.0239    0.00479
      Yogyakarta_Tambal          2          3      0.357      0.445      0.445      0.357
-------------------------------------------------------------------------------------------
mAP50 (overall average)                       0.770  (77.0%)
Speed: 0.4ms preprocess, 6.2ms inference, 0.0ms loss, 5.4ms postprocess per image
Results saved to /kaggle/working/runs/detect/Batik_Project/YOLOv11_Small_v3
✅ Training selesai! Model dievaluasi dengan hasil terhubung ke confusion matrix yang diperoleh.
```

(b)

Figure 6: (a) Confusion matrix of the YOLOv11 Indonesian Batik model, (b) evaluation-metric summary. Source: research results (2026).

of 800×800 pixels to balance the resolution detail of micro batik patterns against inference speed. The number of epochs was varied gradually to track the model's learning curve and to anticipate the risk of overfitting. The optimizer and learning-rate components were left at their default system settings to allow automatic, adaptive adjustment based on the characteristics of the batik dataset being trained.

3.5. Evaluation

To analyze model performance in depth for each of the 27 Indonesian Batik motif classes, evaluation metrics were visualized using a confusion matrix and performance-metric curves. The overall evaluation-visualization results for the tested YOLOv11n model are shown in Figure 6.

After the evaluation stage was carried out for the 27 (twenty-seven) Indonesian Batik motif classes, the primary metric used was mean Average Precision (mAP), defined as follows.

a. Mean Average Precision (mAP). mAP is used to assess the overall performance of the object-detection model. Its value ranges from 0 to 1, where a value closer to 1 represents an increasingly perfect model capability in both classification and spatial object localization. The mAP value is obtained by averaging the Average Precision (AP) values across all evaluated object classes, formulated mathematically as follows.

$$\mathrm{mAP} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{AP}_i \tag{2}$$

where N is the total number of evaluated batik-motif classes, and AP_i is the Average Precision value for class i.

b. Readability analysis of the system and object-extraction performance. To evaluate the mapping accuracy of the YOLOv11 model integrated into the web-based system, a comparative analysis was carried out on the detection success rate across batik-motif classes. The evaluation focused on grouping the 5 (five) batik-motif classes with the highest readability (top-5 easiest) and the 5 (five) batik-motif classes with the highest visual obstruction (top-5 hardest),

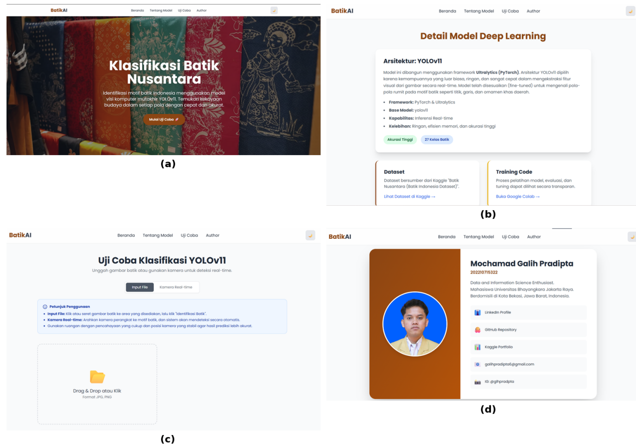


Figure 7: (a) Top view of the home page, (b) about the model, (c) detection trial page, (d) developer information. Source: research results (2025).

Table 2
Comparison of detection performance values.

No.	Batik motif	AP (%)
1	Batik Megamendung	94.8
2	Batik Cendrawasih	93.2
3	Batik Barong	91.5
4	Batik Asmat	89.7
5	Batik Pring	88.0
6	Batik Parang	66.6
7	Batik Kawung	62.1
8	Batik Sekar Jagad	60.8
9	Batik Lontara	58.4
10	Batik Mataketeran	57.0

based on the individual Average Precision (AP) scores that make up the overall mAP value, as shown in Table 2.

Based on Table 2, the YOLOv11 model is generally able to optimally recognize macro-motif variations with sharp edge contours and high color contrast, as shown by the top-5-easiest group. The consistent geometric structure of these motifs makes it easier for the network architecture to precisely localize object coordinates when accessed through the web platform. Conversely, testing on the top-5-hardest group shows a decrease in accuracy for traditional motif variations with dense, complex micro-patterns. Localization obstacles in this category are driven by high visual ambiguity caused by densely overlapping patterns and physical creases in the fabric image, which increase the risk of classification bias and create gaps that lead to detection errors (false positives).

3.6. Deployment

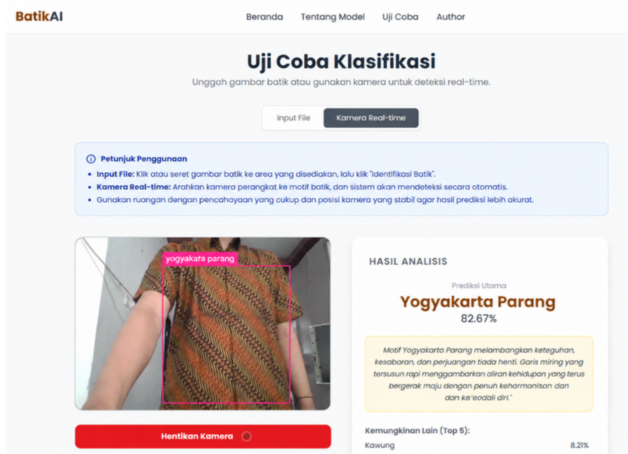
The deployment stage is the final phase within the CRISP-DM methodology and aims to implement the trained model into a real-world environment so that its functionality can be used directly by end users. The best-performing YOLOv11n model in this research was deployed to the Hugging Face Spaces cloud-hosting platform and can be accessed publicly online through the official link: https://glhpradipta-klasifikasi-batik-nusantara.hf.space.

The application interface is designed as a web-based application using the Python ecosystem to ensure ease of accessibility. The system's working mechanism begins when the user inputs a batik-fabric image, either by uploading a file from the local gallery or by capturing an image directly through the device camera. The input image is then processed on the back end using the optimized YOLOv11n model weight file. The final output presented to the user is a visualization of the original image, complete with bounding boxes, the predicted label from among the 27 Indonesian Batik motif classes, and the accuracy level expressed as a real-time confidence score.

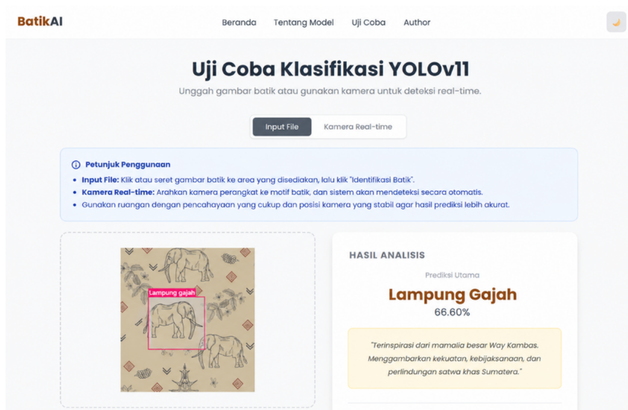
As shown in Figure 7, the home-page interface displays basic information about the system as well as a guide introducing the 27 Indonesian Batik motif classes. In addition, the system provides a real-time detection menu using the device camera, which automatically localizes, identifies, and displays the batik-motif label together with the confidence score instantly whenever a batik fabric object is presented to the camera.

Details regarding the real-time detection menu interface are presented in Figure 8. The web-based object-detection system implementation is divided into two main functionalities to accommodate variations in user input needs. The interface design and workflow visualization for the direct real-time detection menu and the static image-file detection menu are presented in sequence.

Meanwhile, in Figure 8(b), the static image-detection menu shares the same export-button functionality, but its mechanism focuses on processing local digital files. Users can use the Upload Image feature to input a fabric image from device storage, press the Process button to execute YOLOv11n model inference, and use the Reset button if they wish to clear the working canvas to reload a new motif test from the beginning. Both interface sub-systems ensure that the web application can operate flexibly across a variety of user devices.



(a)



(b)

Figure 8: (a) Real-time detection menu interface, (b) static image-upload detection menu interface. Source: research results (2025).

4. Conclusions

This research successfully implemented the YOLOv11s algorithm with a transfer-learning approach to classify 27 Indonesian Batik motif classes. Based on the testing results, the final model showed reasonably good overall performance, with an mAP of 77%, Accuracy of 77%, Precision of 68.2%, Recall of 75%, and an F1-Score of 76%. Nevertheless, minor limitations were found in several motif classes with high visual complexity, such as Yogyakarta Kawung and Yogyakarta Sekar Jagad, which are prone to misclassification due to the similarity of their micro-pattern structures. This best model was successfully deployed as an interactive web application called BatikAI, via the Hugging Face Spaces platform, which supports testing through both static image files and direct real-time camera capture. For future research, it is recommended to focus on adding more data-augmentation variation and balancing the sample distribution in order to improve detection accuracy for traditional motifs with a high degree of visual ambiguity.

Credit authorship contribution statement

Mochamad Galih Pradipta – Conceptualization, Methodology, Software, Data Curation, Investigation, Writing – Original Draft. Herlawati Herlawati – Supervision, Methodology, Validation, Writing – Review & Editing. Rakhmat Purnomo – Supervision, Validation, Writing – Review & Editing.

Funding: Not applicable.

Data Availability Statement: The secondary datasets used in this study are publicly available on Kaggle and Roboflow Universe (see Section 3.2 for links). The trained model and web application are available at https://glhpradipta-klasifikasi-batik-nusantara.hf.space. Additional data generated and analyzed during the current study are available from the corresponding author on reasonable request.

Acknowledgments

The authors would like to express their sincere appreciation to the peer reviewers for their constructive critique and suggestions, which significantly helped improve the quality of the articulation and substance of this scientific article. Deep gratitude is also extended to Universitas Bhayangkara Jakarta Raya for all forms of institutional support, computing-infrastructure facilitation, and academic guidance provided throughout the implementation of this research. All contributions from the various parties involved were highly valuable in supporting the smooth progress and successful completion of this publication manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

References

Aldughayfiq, B., Ashfaq, F., Jhanjhi, N. Z., and Humayun, M. (2023). Yolo-based deep learning model for pressure ulcer detection and classification. *Healthcare (Switzerland)*, 11(9):1–19.

Alya, R. F., Wibowo, M., and Paradise, P. (2023). Classification of batik motif using transfer learning on convolutional neural network (cnn). *Jurnal Teknik Informatika (JUTIF)*, 4(1):161–170.

Elvitaria, L., Fadzrin Ahmad, E., Azah Samsudin, N., Kamal Ahmad Khalid, S., and Indra, Z. (2025). International journal on informatics visualization. *International Journal on Informatics Visualization*, 9(January):115–119.

Hasanah, N. K., Nabila, D., Nina, Paska, M. Y., Wulandari, N., and Barella, Y. (2025). Malaysia's claim to indonesian batik: Background and conflict resolution. *Ilmiah Pendidikan, dan Ilmu Pendidikan Sosial*, 3(1):95–106.

Herlawati, H. and Handayanto, R. T. (2026). Performance evaluation of yolov8 and yolov11 for river waste detection. *Piksel*, 14(1):141–152.

Mawan, R. and Al Fatta, H. (2020). Pengaruh dimensi gambar pada klasifikasi motif batik menggunakan convolutional neural network. *Jurnal Teknologi Informasi*, 4(2).

Midyanti, H. I., Sukmayadi, Y., Sella, F., and Midyanti, D. M. (2024). Digital audio preservation for indonesian traditional vocal recognition based on machine learning: A literature review and bibliometric analysis. *SHS Web of Conferences*, 197:03002.

Nabila, M. S., Herlawati, H., and Hidayat, A. (2025). Pendeteksian dan klasifikasi sampah pada bank sampah berbasis web menggunakan yolov11. *Journal of Students' Research in Computer Science*, 6(1):99–112.

Oktarino, A., Desnita Tasri, Y., and Efendi, A. (2024). Mechanical and aerospace science and engineering, 30th edition. *Journal of Ocean, Mechanical and Aerospace – Science and Engineering-*, 68(3).

Pete, C., Julian, C., Randy, K., Thomas, K., Thomas, R., Colin, S., and Wirth, R. (2026). Crisp-dm 1.0. Technical report, CRISP-DM Consortium.

Ramadhan, D. A. and Ramadhani, D. (2024). Classification of riau batik motifs using the convolutional neural network (cnn) algorithm. *International Journal of Electrical, Energy and Power System Engineering*, 7(3):201–211.

Susanti, I. D., Winarno, S., and Zeniarja, J. (2024). Yogyakarta batik image classification based on convolutional neural network. *Advances in Sustainable Science, Engineering and Technology*, 6(1):1–9.

Wesnina, W., Prabawati, M., and Noerharyono, M. (2025). Integrating traditional and contemporary in digital techniques: The analysis of indonesian batik motifs evolution. *Cogent Arts and Humanities*, 12(1).

Winarno, E., Septiarini, A., Hadikurniawati, W., and Hamdani, H. (2024). The hybrid features and supervised learning for batik pattern classification. *Journal on Computing and Cultural Heritage*, 17(2).

Winarno, E., Solichan, A., Ramdani, A. P., Hadikurniawati, W., Septiarini, A., and Hamdani, H. (2025). Enhanced semarang batik classification using deep learning: A comparative study of cnn architectures. *Bulletin of Electrical Engineering and Informatics*, 14(5):3544–3557.