JURNAL INFORMATIKA, Vol. 11 No. 2 October 2025, Page 97-105
ISSN (Print) 2355-6579 | ISSN (Online) 2528-2247
DOI: https://doi.org/10.31294/inf.v12i2.25855

Batik Pattern Classification Using Logistic Regression, SVM, and Deep Learning Features

Ratih Addina Hapsari[1], Imam Yuadi[2]

[1,2] Universitas Airlangga
Jalan Airlangga No. 4 - 6 Surabaya, Indonesia

Correspondence e-mail: ratih.addina.hapsari-2024@pasca.unair.ac.id

Submission:	Revision:	Acceptance:	Available Online:
15-05-2025	04-07-2025	20-07-2025	01-10-2025

Abstract

This study presents the integration of deep learning-based feature extraction with conventional machine learning classifiers for automatically categorizing Indonesian batik patterns. The research utilizes five traditional motifs: Alas Alasan, Kokrosono, Semen Sawat Gurdha, Sido Asih, and Sido Mulyo. Feature extraction was conducted using three deep learning models: Inception V3, VGG16, and VGG19, followed by classification through Logistic Regression and Support Vector Machines (SVM), with data processing performed in Orange. Experimental results show that Inception V3 combined with Logistic Regression achieved the highest classification performance, reaching 99.2% classification accuracy and an F1-score of 0.992. These results confirm the effectiveness of deep feature embeddings in improving the automatic classification of batik motifs. The study contributes to developing intelligent classification frameworks, offering a scalable approach to cultural heritage preservation through technology. Future work will focus on enhancing feature extraction methods and expanding the dataset to address motif overlap challenges.

Keywords: Deep Learning, Batik Pattern Classification, Machine Learning Integration

1. Introduction

Batik, an Indonesian cultural heritage, has garnered global recognition for its elaborate designs and symbolic meaning, representing a blend of craftsmanship and tradition. Nevertheless, the accurate identification and classification of batik patterns remain challenging because of their diverse and complex designs. We widely employ logistic regression and support vector machines (SVM) for classification tasks due to their robustness in handling diverse data types. Adding features from deep learning models that have already been trained, such as VGG16, VGG19, and Inception V3, makes it easier to spot complicated visual patterns, which leads to a significant boost in model performance. Using Orange, a visual programming tool for data mining, allows researchers to employ complex approaches without extensive programming expertise, thus rendering advanced analytics more accessible to a broader audience (Alzahrani, 2022). This study tackles the urgent requirement for an effective and precise batik categorization system by combining deep learning attributes with conventional classification techniques in Orange, bridging a gap in existing research methodologies (Ishak et al., 2020).

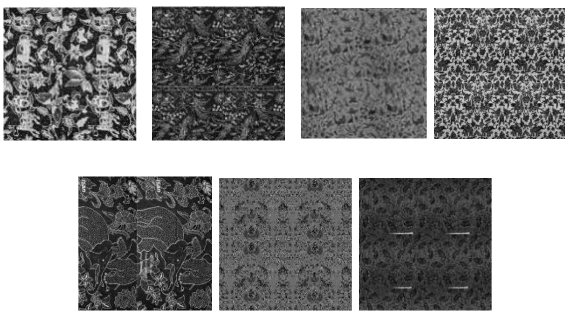
Initial studies focused on texture and colour feature extraction using traditional image processing techniques, achieving significant outcomes in distinguishing basic patterns (Meranggi et al., 2022)(Salsabila et al., 2023). Batik classification studies through image processing continue to be developed (Winarno et al., 2022). Machine learning, on the other hand, has made it easier to use classifiers like Support Vector Machines (SVM) and Decision Trees to improve accuracy by using extracted characteristics (Winarno et al., 2022)(Azhar et al., 2021)(Divyanth et al., 2022). Moreover, deep learning has transformed the domain, with convolutional neural networks (CNNs) facilitating automatic feature extraction and pattern identification, enhancing performance on intricate designs. CNNs are a special type of deep learning often applied to image processing (Rasyidi et al., 2021). Using pre-trained models like VGG16, VGG19, and Inception V3 for transfer learning has improved performance by using many visual features for batik-specific datasets. VGG is a popular CNN architecture for classifying batik (Filia et al., 2023). Consequently, these improvements highlight the necessity of combining traditional and contemporary methods to tackle the intricacies of batik image processing, thus safeguarding and promoting this cultural heritage.

Research on batik pattern classification has significantly progressed, highlighting several methodologies to address the issues posed by the complexity and diversity of batik designs (Minarno et al., 2023), (Meranggi et al., 2022), (Maiyang & Taqyuddin, 2021). A preliminary study used standard image processing methods, such as texture and colour feature extraction, along with classifiers, such as k-Nearest Neighbors (k-NN) and Decision Trees, but the results were not very good at telling patterns apart. Deep learning has established convolutional neural networks (CNNs) as pivotal instruments for automatically extracting complex patterns from images. People frequently employ pre-trained models like VGG16, VGG19, and Inception V3 due to their ability to leverage transfer learning, which modifies generic image features for batik classification (Alahmadi et al., 2022)(Divyanth et al., 2022)(Rasyidi et al., 2021)(Rasyidi & Bariyah, 2020). Hybrid approaches that combine deep learning attributes with traditional classifiers, such as SVM and logistic Regression, have enhanced classification efficacy (Rasyidi et al., 2021).

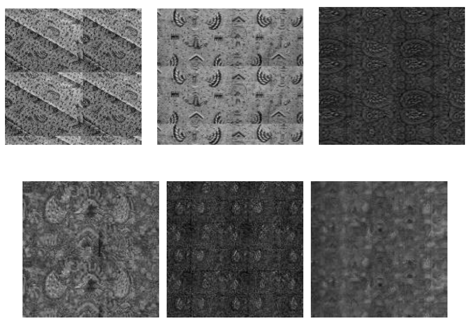
Moreover, technologies like Orange have optimized complex workflows, enabling researchers to employ sophisticated data mining techniques without requiring extensive coding proficiency. The gains underscore the necessity of integrating conventional and contemporary approaches for precise batik pattern classification, greatly aiding cultural preservation and industrial innovation. This study explores the classification of batik patterns, incorporating traditional and modern methods to enhance the use of technology in cultural heritage preservation. This study combines deep learning features from VGG16, VGG19, and Inception V3 into conventional classifiers, such as logistic Regression and SVM, implemented through Orange. By combining pre-trained models for feature extraction with traditional machine learning, this study aims to create an accessible and user-friendly framework.This study seeks to tackle the difficulties of batik pattern categorization by combining sophisticated deep learning attributes with conventional machine learning classifiers within an accessible platform, Orange. This project aims to improve the accuracy and efficiency of batik classification systems by utilizing pre-trained models such as VGG16, VGG19, and Inception V3, alongside robust classifiers like Logistic Regression and SVM. This strategy promotes the development of innovative classification techniques while concurrently supporting the preservation of Indonesia's cultural heritage in the digital era. The outcomes of this study are expected to provide significant insights for academics and professionals in cultural and technological fields while offering a scalable solution for practical applications.

2. Research Methods

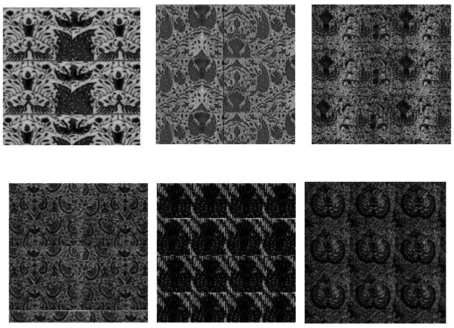
This study uses an extensive dataset of batik patterns featuring five unique motifs, namely Alas-alasan, Kokrosono, Semen Sawat Gurdha, Sido Asih, and Sido Mulyo. Multiple patterns exemplify each motif, each comprising ten photographs obtained using a variety of cropping approaches, thereby creating diversity and enhancing the robustness of the dataset. The Alas-alasan motif consists of seven distinct patterns, each including ten cropped photographs for seventy images. The Kokrosono motif consists of six patterns, each represented by ten cropped photographs, resulting in sixty images. The Semen Sawat Gurdha motif consists of six patterns, each with ten cropped photographs, resulting in sixty images. The Sido Asih motif includes a comprehensive array of ten patterns, each comprising ten photographs, culminating in a dataset of one hundred images. The Sido Mulyo motif consists of ten patterns, each containing ten photos, making a total of one hundred images for this motif. This curated dataset encapsulates each batik design’s subtle nuances and distinctive features, offering a comprehensive basis for categorising and studying traditional Indonesian batik patterns (Minarno et al., 2023). The images in Figure 1 to Figure 5 include comprehensive illustrations of each motif design.



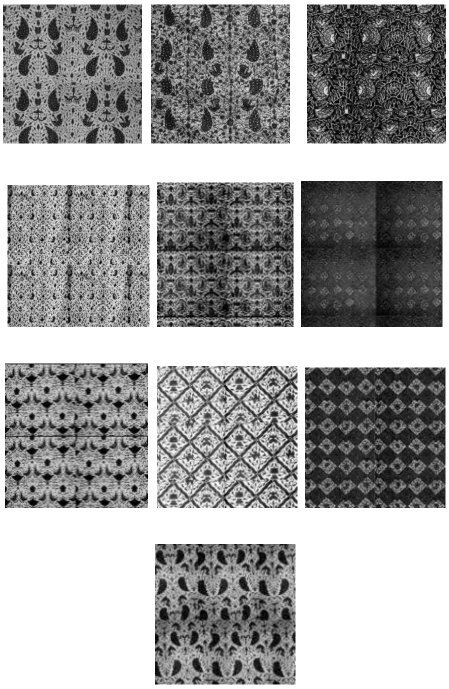
Source: Research Process
Figure 1. Alas-alasan Batik Pattern



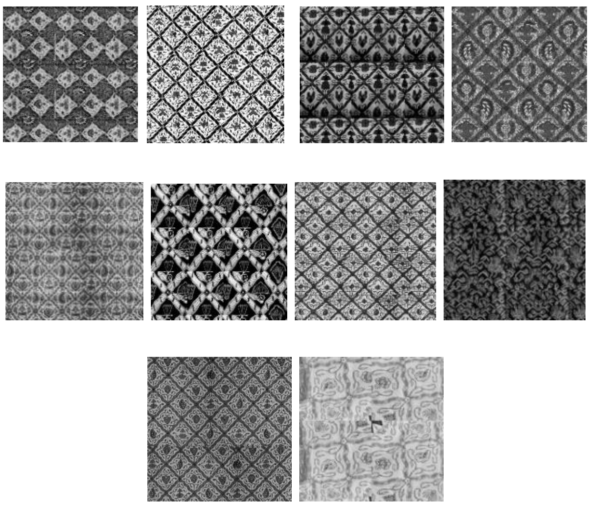
Source: Research Process
Figure 2. Kokrosono Batik Pattern



Source: Research Process
Figure 3. Semen Sawat Gurdha Batik Pattern

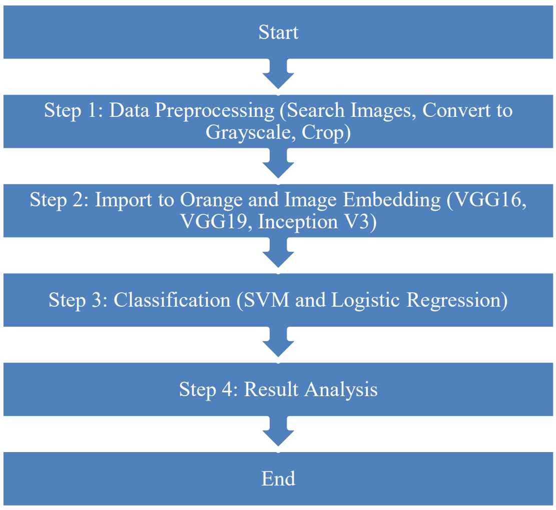


Source: Research Process
Figure 4. Sido Asih Batik Pattern



Source: Research Process
Figure 5. Sidho Mulyo Batik Pattern

This dataset encompasses the intricate characteristics of batik patterns, providing a robust basis for feature extraction and classification. Step 1: Data Processing commences by gathering batik pictures, turning them to grayscale to emphasize patterns and textures, and cropping them to preserve perspective diversity (Trisakti Akbar et al., 2023)(Minarno et al., 2023)(Adelin & Sri Handayani, 2020). Step 2: Import into Orange, and Image Embedding involves integrating the produced photos into the Orange data mining platform. Step 3: Classification consists of categorising the extracted features using two machine learning algorithms: Support Vector Machines (SVM) and Logistic Regression. Step 4: Evaluate the classification performance outcomes with accuracy, F1 score, precision, recall, and Matthews correlation coefficient (MCC) (Danquah et al., 2025). Techniques like t-SNE illustrate results by analyzing motif clustering and confirming pattern distinctiveness. This systematic approach creates a robust framework for classifying batik patterns, utilizing deep learning and machine learning to get enhanced accuracy and significant insights into the characteristics of Indonesian batik (Lô et al., 2020).



Source: Research Process
Figure 6. Flowchart Batik Pattern Classification Process

Step 1: Data Processing

Data processing is an essential phase in batik image categorization. The procedure commences with acquiring photos from three distinct places to enhance the data and evaluate the dataset representation utilizing various traditional batik motifs. The chosen motifs originate from the island of Java, specifically from Central Java (Sido Mulyo and Alas-Alasan motifs), West Java (Kokrosono motifs), and Yogyakarta (Semen Sawat Gurdha and Sido Asih motifs). We then transform the collected images to grayscale to highlight patterns and textures while reducing computational complexity ; . Then, we cluster batik from different viewpoints to generate pattern variants. The more pattern variants, the more the machine learns from the data, thus improving the recognition of data variability and complexity. These joint pretreatment steps ensure the dataset is robust, diverse, and optimized for efficient feature extraction and classification (Xu et al., 2023).

Step 2: Import to Orange and Image Embedding

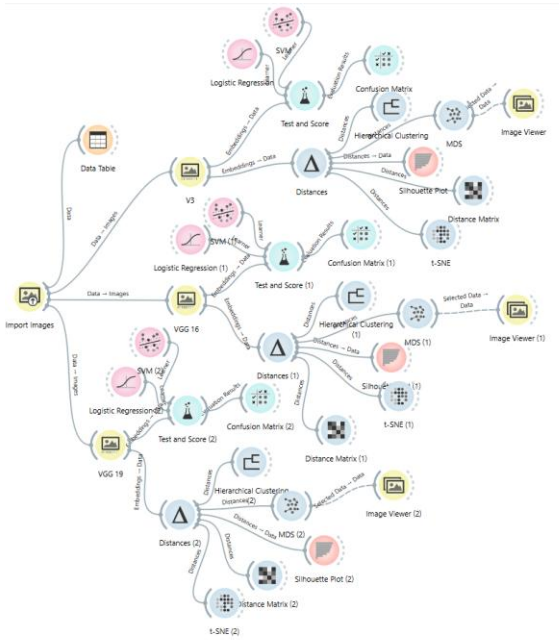
Next, the processed images are sent to the Orange data mining platform. Importing grayscale batik images. For image embedding in Orange using unsupervised learning models, namely VGG16, VGG19, and Inception V3. Inception V3, VGG 16, and VGG 19 provide unique benefits for classifying batik patterns. Inception V3 demonstrates proficiency in managing complicated and varied patterns owing to its multi-scale feature extraction and computational efficiency, rendering it suitable for elaborate batik motifs. VGG 16, recognized for its efficient architecture, is appropriate for repetitive or straightforward batik designs, but VGG 19 offers enhanced feature extraction for intricate patterns but demands more processing resources. Researchers employ the three models to analyze the outcomes of their image evaluation.

Step 3: Classification

In stage 3 of the batik pattern classification procedure, each model (Inception V3, VGG 16, and VGG 19) is evaluated using logistic Regression and an SVM through test scoring; findings are represented in confusion matrices. This stage assesses the models' learning efficacy by comparing actual and expected results. Next, we calculate and analyze the distance between data points using techniques of hierarchical clustering, t-SNE, distance matrix, silhouette plots, and MDS (Multidimensional Scaling). These approaches improve understanding of model performance by making it possible to see data structures and interactions between patterns. Figure 7 shows the data classification results, which can later be shown using plot images, charts, and statistical data.

Step 4: Result Analysis

During the result analysis phase, the efficacy of the classification model is evaluated utilizing standard statistical metrics: accuracy, precision, recall, and F1 score for each model (V3, VGG 16, and VGG 19). This document aims to deliver a thorough evaluation of the efficacy of each model in data processing. The confusion matrix results from the logistic Regression and SVM investigations are shown as a comparative prediction table matrix for each batik pattern.



Source: Research Process

Figure 7. Processing Data in Orange

The probability value ranges from 0 to 1. The predictive value mapping caps the outcomes at 100% and produces precise and reliable findings. Forecasted outcomes: We use the t-SNE plot image to observe the subsequent analysis findings and assess the proximity between patterns. We compare the V3, VGG 16, and VGG 19 classification models using standard metrics, prediction matrix tables, and graphs to look at the modelling results.

End

The objective of finalizing this process is to consolidate the principal findings of the research, encompassing a thorough analysis of the results and their implications. This phase demonstrates the optimal combinations of embedding models (VGG16, VGG19, and Inception V3) and classifiers (SVM and logistic Regression) for classifying batik patterns, emphasizing their efficacy with diverse and intricate designs. We document all results and analyses from this study as vital resources for academic inquiry, establishing a foundation for subsequent research. We advocate for enhancing the data mining-based batik classification system to advance the textile industry and optimize the recording of Indonesian culture.

3. Results and Discussion

This methodology allows the study to clarify the effectiveness of Inception V3, VGG16, and VGG19 embedding in improving the classification accuracy and uniqueness of batik patterns, as indicated by the measures of AUC, CA, F1 score, Precision, Recall, and MCC. This methodology connects intricate feature representation with practical classification, showcasing the efficacy of integrating deep learning embeddings with conventional classifiers through a case study of batik. The results compare the efficacy of Logistic Regression and SVM classifiers utilizing features derived from three pre-trained deep learning models: Inception V3, VGG16, and VGG19. Logistic Regression significantly outperforms SVM across all measures (AUC, CA, F1, Precision, Recall, and MCC) when utilized with the Inception V3 model, achieving an AUC of 0.998 and a classification accuracy (CA) of 0.992. Conversely, SVM attains a somewhat reduced AUC of 0.997 and a CA of 0.974. In the context of VGG16, Logistic Regression surpasses SVM, achieving an AUC of 0.998 versus 0.992 and a CA of 0.967 compared to 0.91, demonstrating the efficacy of Logistic Regression with VGG16 features. Nonetheless, with VGG19, SVM attains commendable results but fails to exceed Logistic Regression, which retains an AUC of 0.996 and a CA of 0.959, in contrast to SVM's AUC of 0.994 and CA of 0.941.

Table 1. Result Of Deep Learning

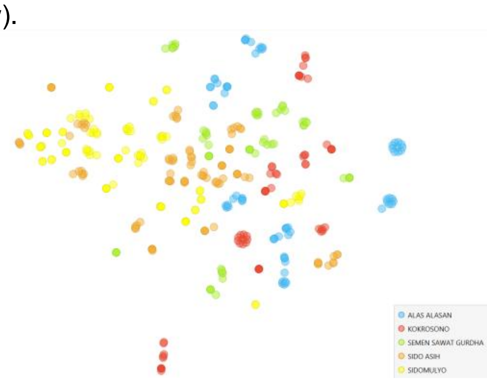
Model Deep Learning	Machine Learning	AUC	CA	F1	Prec	Recall	MCC
Inception V3	Logistic Regression	0,998	0,992	0,992	0,992	0,992	0,99
	SVM	0,997	0,974	0,974	0,976	0,974	0,968
VGG 16	Logistic Regression	0,998	0,967	0,967	0,967	0,967	0,958
	SVM	0,992	0,91	0,911	0,916	0,91	0,888
VGG 19	Logistic Regression	0,996	0,959	0,959	0,96	0,959	0,948
	SVM	0,994	0,941	0,94	0,942	0,941	0,926

Source: Research Process

Pairwise comparisons among models utilizing specific statistical methodologies underscore significant differences. In the context of Inception V3, Logistic Regression exhibits a considerable superiority over SVM, evidenced by a significance value of 0.052 in pairwise comparison, indicating that Logistic Regression yields more reliable outcomes. In VGG16 and VGG19, pairwise comparisons indicate a preference for Logistic Regression, evidenced by the lower comparison values (e.g., 0.066 for VGG16 and 0.214 for VGG19).

The findings indicate that Logistic Regression combined with features derived from Inception V3 exhibits the most robust performance, followed by its integration with VGG16 and VGG19. Although SVM yields competitive outcomes, Logistic Regression consistently exhibits superior accuracy and reliability in this investigation, establishing it as the optimal classifier for batik pattern categorization within this dataset.

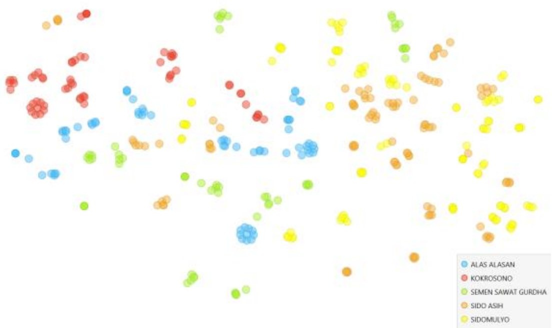
The t-SNE (t-Distributed Stochastic Neighbor Embedding) image illustrates the grouping of batik patterns derived from features retrieved with the Inception V3 model. Each data point represents a picture of a batik motif, with colours denoting the various motifs: Alas Alasan (blue), Kokrosono (red), Semen Sawat Gurdha (green), Sido Asih (Orange), and Sido Mulyo (yellow).



Source: Research Process

Figure 8. t-SNE Inception V3

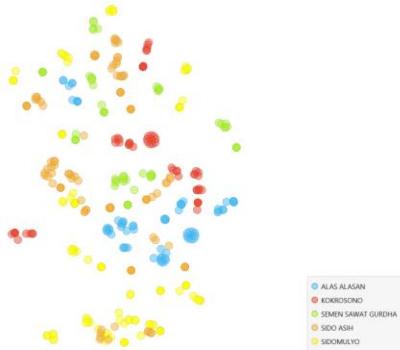
The t-SNE technique condenses the high-dimensional characteristics derived from Inception V3 into a two-dimensional space, maintaining local commonalities among data points. The visualization demonstrates that motifs are predominantly well-clustered, with specific groupings emerging for particular patterns like Kokrosono and Alas Alasan, indicating that Inception V3 proficiently captures the distinctive visual characteristics of these motifs. Nevertheless, several regions exhibit overlap among clusters, especially between motifs such as Sido Asih and Sido Mulyo, potentially indicating common design attributes or difficulties in distinguishing features. This clustering pattern underscores the efficacy of Inception V3 in embedding significant features while also revealing opportunities for enhancement in classification.



Source: Research Process
Figure 9. t-SNE VGG 16

The t-SNE image illustrates the clustering of batik patterns utilizing features derived from the VGG16 deep learning model. Each point represents a batik image, with colours indicating distinct motifs: Alas Alasan (blue), Kokrosono (red), Semen Sawat Gurdha (green), Sido Asih (Orange), and Sido Mulyo (yellow). The high-dimensional features obtained from VGG16 have been condensed to two dimensions by the t-SNE technique, maintaining the local associations among data points. The visualization illustrates distinctly defined clusters for many motifs, including Alas Alasan and Kokrosono, indicating that VGG16 proficiently captures the distinctive visual characteristics of these patterns. Nevertheless, several overlapping clusters, especially between Sido Asih and Sido Mulyo, indicate common traits or constraints in feature differentiation. This graphic underscores VGG16's potential to provide significant feature embeddings while indicating regions where further refining or feature improvement may be required to boost motif separability.

The t-SNE image illustrates the clustering of batik patterns utilizing features derived from the VGG19 deep learning model. Each point signifies a batik image, with colours denoting various motifs: Alas Alasan (blue), Kokrosono (red), Semen Sawat Gurdha (green), Sido Asih (Orange), and Sido Mulyo (yellow). VGG19 generates a high-dimensional feature space that the t-SNE technique reduces to two dimensions, thereby preserving local similarities.



Source: Research Process
Figure 10. t-SNE VGG 19

This depiction delineates the clusters, particularly for motifs like Alas Alasan and Kokrosono, demonstrating that VGG19 effectively recognizes the unique attributes of these patterns. Nonetheless, considerable overlaps between specific motifs, particularly Sido Asih and Sido Mulyo, may suggest shared design characteristics or challenges in differentiating similar elements. This indicates that while VGG19 provides strong embeddings for classification, there is room for improvement in differentiating motifs with subtle visual similarities.

The graphic illustrates VGG19's capability in feature representation while identifying areas for improvement in pattern separability. The t-SNE representations of features from the Inception V3, VGG16, and VGG19 models show how well deep-learning embeddings can hold the complicated features of batik patterns. Each model exhibits robust clustering for specific motifs, such as Alas Alasan and Kokrosono, underscoring its capacity to discern diverse patterns. The overlap of motifs such as Sido Asih and Sido Mulyo illustrates the difficulty in distinguishing them due to their similar appearances. This indicates that feature refining or classifier optimization may be enhanced. Inception V3 and VGG16 demonstrate superior motif separability relative to VGG19, with each model providing significant insights into the distinctive characteristics of batik patterns. These findings demonstrate the potential utility of deep learning embeddings in analysing cultural assets. They illustrate the significance of continually enhancing the system to eliminate overlapping clusters and augment classification accuracy.

This research demonstrates the efficacy of integrating deep learning feature extraction with machine learning classifiers for classifying batik patterns. By using pre-trained VGG16 and VGG19 models for feature extraction and combining them with Support Vector Machines (SVM) and logistic Regression, the classification performance was better than that of many traditional methods and previous hybrid approaches. This work demonstrated a significant enhancement in classification accuracy (CA), F1-score, and Matthews Correlation Coefficient (MCC) relative to the last research employing handmade characteristics such as colour extraction and texture analysis (Meranggi et al., 2022)(Salsabila et al., 2023). This indicates that deep feature representations effectively capture the delicate features of batik patterns.

The results of this study are also in line with the new trend in the use of transfer learning in image classification. Basic machine learning models have been used frequently in previous studies, including k-nearest Neighbors (k-NN) and Decision Trees; however, they are ineffective due to the complex characteristics of batik designs. This study’s use of t-SNE visualization proved that VGG16 and VGG19 can embed patterns into a clear high-dimensional space, making it easier to group motifs like Alas Alasan, Kokrosono, and Sido Mulyo. Despite observing overlaps in specific clusters, particularly between analogous designs like Sido Asih and Sido Mulyo, the improved accuracy compared to earlier handcrafted techniques underscores the importance of utilizing deep learning in batik research.

This study demonstrated that SVM consistently outperformed logistic Regression across all metrics, including AUC, CA, and MCC, for both VGG16 and VGG19 features. These findings validate the efficacy of SVM in managing high-dimensional and intricate feature spaces produced by deep learning models. Moreover, the incorporation of logistic Regression facilitated a comparison, demonstrating that, although simpler classifiers can attain acceptable accuracy, they are inadequate for discerning complex patterns. This research broadens the application of deep learning in cultural heritage preservation by concentrating on batik patterns and assessing various motifs from different locations, in contrast to prior studies focusing on cloth pattern identification or traditional motifs (Jati & Hariyadi, 2021).

The study illustrates the accessibility of advanced data mining approaches by integrating tools such as Orange, allowing researchers lacking considerable programming skills to utilize cutting-edge methodologies. These findings contribute to advancing cultural heritage preservation and highlight the potential of integrating deep learning and machine learning in similar fields. Future research could concentrate on overlapping clusters to enhance the model’s generalizability. This research demonstrates the efficacy of integrating deep learning feature extraction with conventional machine learning classifiers for batik pattern categorization. Utilizing features from pre-trained models (Inception V3, VGG16, and VGG19), logistic Regression and SVM exhibited improved performance metrics, while the specific outcomes were contingent upon the embedding model employed. Inception V3 consistently produced exceptional results, with logistic Regression achieving the highest classification accuracy (CA) of 0.992 and an F1 score of 0.992, exceeding SVM in most metrics. This demonstrates the effectiveness of Inception V3 in recognizing complex batik pattern features. The strong performance of VGG16 with logistic Regression outperforms SVM in classification accuracy and precision, reflecting the ability to generate significant feature embeddings for classification. While effective, VGG19 performs worse than Inception V3 and V16, with overlap in the t-SNE visualization indicating difficulty distinguishing motifs with little similarity. Logistic Regression consistently outperformed SVM in all models, demonstrating its suitability for this dataset and task. The t-SNE visualizations validate these findings, revealing distinct groupings for particular motifs and highlighting areas of overlap that may necessitate additional refinement. The results demonstrate that integrating deep learning embeddings with traditional classifiers can improve the conservation of cultural artefacts. Their findings suggest that the categorization of batik motifs needs refinement.

4. Conclusion

This research illustrates the potential of integrating deep learning feature extraction with conventional machine learning classifiers for batik pattern classification. The study attains excellent accuracy and robust classification performance by utilizing features derived from pre-trained models like Inception V3, VGG16, and VGG19, in conjunction with Logistic Regression and SVM. Inception V3 shows the highest accuracy, with logistic Regression achieving maximum classification accuracy (0.992) and F1 score (0.992). This indicates that Inception V3 can identify complex batik patterns. Meanwhile, VGG16 shows strong performance, especially with logistic Regression, which underlines its effectiveness in substantial feature extraction. VGG19, although efficient, encountered difficulties in distinctly differentiating motifs with nuanced visual similarities, as demonstrated by overlapping clusters in the t-SNE visualizations. Logistic Regression significantly surpassed SVM in all models, demonstrating its appropriateness for this dataset. The results underscore the significance of integrating models to enhance motif separability and precision, while t-SNE visualizations offer essential insights into clustering efficacy. This study enhances AI-driven cultural heritage preservation by providing a scalable framework for analysing and classifying batik motifs. Future studies may strengthen the embedding to resolve overlapping clusters, investigate alternative deep learning architectures, and optimise the dataset to augment generalization.

Reference

Adelin, & Sri Handayani, F. (2020). Object-Based Design and Modeling Batik Nusantara Catalog Wibatara.com. *Journal of Physics: Conference Series*, *1500*(1), 012124. https://doi.org/10.1088/1742-6596/1500/1/012124

Alahmadi, A., Hussain, M., & Aboalsamh, H. (2022). LDA-CNN: Linear Discriminant Analysis Convolution Neural Network for Periocular Recognition in the Wild. *Mathematics*, *10*(23). https://doi.org/10.3390/math10234604

Alzahrani, S. S. (2022). Data Mining Regarding Cyberbullying in the Arabic Language on Instagram Using KNIME and Orange Tools. *Engineering, Technology & Applied Science Research*, *12*(5), 9364–9371. https://doi.org/10.48084/etasr.5184

Azhar, Y., Mustaqim, M. C., & Minarno, A. E. (2021). Ensemble convolutional neural network for robust batik classification. *IOP Conference Series: Materials Science and Engineering*, *1077*(1), 012053. https://doi.org/10.1088/1757-899X/1077/1/012053

Danquah, L. K. G., Appiah, S. Y., Mantey, V. A., Danlard, I., & Akowuah, E. K. (2025). Computationally Efficient Deep Federated Learning with Optimized Feature Selection for IoT Botnet Attack Detection. *Intelligent Systems with Applications*, *25*(November 2024), 200462. https://doi.org/10.1016/j.iswa.2024.200462

Divyanth, L. G., Guru, D. S., Soni, P., Machavaram, R., Nadimi, M., & Paliwal, J. (2022). Image-to-Image Translation-Based Data Augmentation for Improving Crop/Weed Classification Models for Precision Agriculture Applications. *Algorithms*, *15*(11). https://doi.org/10.3390/a15110401

Feng, Z., & Hua, X. (2020). Pattern Recognition and Its Application in Image Processing. *Journal of Physics: Conference Series*, *1518*(1), 012071. https://doi.org/10.1088/1742-6596/1518/1/012071

Filia, B. J., Lienardy, F. F., Laksana, I. K. P. B., Jordan, J. A., Siento, J. G., Honova, S. M., Hasana, S., & Permonangan, I. H. (2023). Improving Batik Pattern Classification using CNN with Advanced Augmentation and Oversampling on Imbalanced Dataset. *Procedia Computer Science*, *227*, 508–517. https://doi.org/10.1016/j.procs.2023.10.552

Huang, Y., Su, J., Wang, J., & Ji, S. (2020). Batik-DG: Improved DeblurGAN for Batik Crack Pattern Generation. *IOP Conference Series: Materials Science and Engineering*, *790*(1), 012034. https://doi.org/10.1088/1757-899X/790/1/012034

Ishak, A., Siregar, K., Aspriyati, Ginting, R., & Afif, M. (2020). Orange Software Usage in Data Mining Classification Method on The Dataset Lenses. *IOP Conference Series: Materials Science and Engineering*, *1003*(1), 012113. https://doi.org/10.1088/1757-899X/1003/1/012113

Jati, E. S., & Hariyadi, A. (2021). Form Finding Architectural Shading Device: Reinterpretation of Batik Pattern through Parametric Approach. *IOP Conference Series: Earth and Environmental Science*, *764*(1), 012002. https://doi.org/10.1088/1755-1315/764/1/012002

Kasim, A. A., Bakri, M., Hendra, A., & Septriani, A. (2022). Spatial and topology feature extraction on batik pattern recognition: a review. *Jurnal Informatika*, *16*(1), 1. https://doi.org/10.26555/jifo.v16i1.a25415

Lô, G., de Boer, V., & van Aart, C. J. (2020). Exploring West African folk narrative texts using machine learning. *Information (Switzerland)*, *11*(5). https://doi.org/10.3390/INFO11050236

Maiyang, F., & Taqyuddin. (2021). Assessment of Indramayu batik based on Outstanding Universal Value (OUV) and Geographical Indications (GI). *Journal of Physics: Conference Series*, *1725*(1), 012104. https://doi.org/10.1088/1742-6596/1725/1/012104

Meranggi, D. G. T., Yudistira, N., & Sari, Y. A. (2022). Batik Classification Using Convolutional Neural Network with Data Improvements. *JOIV : International Journal on Informatics Visualization*, *6*(1), 6. https://doi.org/10.30630/joiv.6.1.716

Minarno, A. E., Soesanti, I., & Nugroho, H. A. (2023). Batik Nitik 960 Dataset for Classification, Retrieval, and Generator. *Data*, *8*(4), 63. https://doi.org/10.3390/data8040063

Rachmayanti, S., Salim, P., Roesli, C., & Hartono, H. (2023). Vernacular Architecture Residential in Lasem with Batik Pattern Latohan in Interior. *IOP Conference Series: Earth and Environmental Science*, *1169*(1), 012060. https://doi.org/10.1088/1755-1315/1169/1/012060

Rajpal, S., Agarwal, M., Kumar, V., Gupta, A., &

Kumar, N. (2021). Triphasic DeepBRCA-A Deep Learning-Based Framework for Identification of Biomarkers for Breast Cancer Stratification. *IEEE Access*, *9*, 103347–103364. https://doi.org/10.1109/ACCESS.2021.3093616

Rasyidi, M. A., & Bariyah, T. (2020). Batik pattern recognition using convolutional neural network. *Bulletin of Electrical Engineering and Informatics*, *9*(4), 1430–1437. https://doi.org/10.11591/eei.v9i4.2385

Rasyidi, M. A., Handayani, R., & Aziz, F. (2021). Identification of batik making method from images using convolutional neural network with limited amount of data. *Bulletin of Electrical Engineering and Informatics*, *10*(3), 1300–1307. https://doi.org/10.11591/eei.v10i3.3035

Salsabila, A. P. B., Rozikin, C., & Adam, R. I. (2023). Klasifikasi Motif Batik Karawang Berbasis Citra Digital dengan Principal Component Analysis dan K-Nearest Neighbor. *Jurnal Sistem Dan Teknologi Informasi (JustIN)*, *11*(1), 20. https://doi.org/10.26418/justin.v11i1.46936

Susantio, M., & Widyasari, R. (2023). The Influence of Peranakan Culture on The Typology of The Kidang Mas Batik House, Lasem. *IOP Conference Series: Earth and Environmental Science*, *1169*(1), 012067. https://doi.org/10.1088/1755-1315/1169/1/012067

Trisakti Akbar, Muhammad Fajar B, Muhammad Akbar Amir, Andi Akram Nur Risal, Nur Azizah Ayu Safanah, & M. Miftach Fakhri. (2023). Sulsel Typical Batik Motif Classification Using Neural Network Method With Glcm Feature Extraction. *Journal of Deep Learning, Computer Vision and Digital Image Processing*, 24–33. https://doi.org/10.61255/decoding.v1i1.49

Widodo, T., Ishak, S. I., Haryato, T., & Santoso, A. B. (2023). Explorasi Pola Batik Baru dengan Deep Convolutional Algorithm Generative Adversarial Networks (DCGANs). *Informatika Mulawarman : Jurnal Ilmiah Ilmu Komputer*, *18*(1), 40. https://doi.org/10.30872/jim.v18i1.9531

Winarno, E., Hadikurniawati, W., Septiarini, A., & Hamdani, H. (2022). Analysis of color features performance using support vector machine with multi-kernel for batik classification. *International Journal of Advances in Intelligent Informatics*, *8*(2), 151. https://doi.org/10.26555/ijain.v8i2.821

Xu, M., Yoon, S., Fuentes, A., & Park, D. S. (2023). A Comprehensive Survey of Image Augmentation Techniques for Deep Learning. *Pattern Recognition*, *137*, 109347. https://doi.org/10.1016/j.patcog.2023.109347