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Article Reviews

Deep Learning Approaches for Batak Script Recognition: A Literature Review

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Abstract

The Batak script, one of Indonesia's ancient writing systems, has recently garnered increasing attention in the fields of digital preservation and pattern recognition. However, the complexity of its character structures and the limited availability of annotated datasets pose significant challenges to automated recognition. This paper presents a comprehensive literature review on deep learning approaches for Batak script recognition. We analyze existing studies that apply convolutional neural networks (CNNs), recurrent neural networks (RNNs), hybrid models, and transfer learning to character recognition tasks. Furthermore, we highlight the strengths and limitations of these methods in addressing challenges such as character similarity, dataset scarcity, and noise in historical manuscripts. The review also discusses research gaps and potential future directions, including the integration of attention mechanisms, data augmentation strategies, and multimodal approaches. By synthesizing recent developments, this study provides valuable insights for researchers aiming to advance Batak script recognition and contributes to the broader effort of preserving Indonesia's cultural heritage through deep learning technologies.

Keywords *Batak Script, Deep Learning, Character Recognition, Literature Review, Cultural Heritage*

INTRODUCTION

Indonesia is renowned for its rich cultural diversity, comprising over 1,300 ethnic groups dispersed across the archipelago (Badan Pusat Statistik, 2022). One of the ethnic groups from North Sumatra with a particularly rich cultural heritage is the Batak, which encompasses diverse traditions ranging from music and dance to ancient literacy in the form of Batak script used in traditional manuscripts such as *Pustaha Laklak* (Hutabarat, 2024). The Batak script is part of a writing system that has been passed down through generations. *Pustaha Laklak*—made from the bark of a wood—is an important cultural artifact containing records of spells, traditional medicines, and customary laws (Sihombing et al., 2020). However, knowledge of the Batak script has become increasingly rare in society due to the lack of formal education teaching the script, limited digital documentation, and the influence of globalization that shifts interest away from local culture (Hasibuan, 2019). Preserving Batak script is crucial for maintaining local cultural heritage and national identity (Wiyatiningsih et al., 2023).

Automatic recognition of the Batak script can provide a practical solution to facilitate the transliteration and interpretation of these ancient manuscripts. Previous studies have developed traditional character recognition systems using deep learning methods such as Convolutional Neural Networks (CNN) for recognizing Javanese script (Pratama et al., 2021) and Balinese script (Widnyana et al., 2022). However, these approaches generally focus on recognizing individual

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characters in static images, whereas *Pustaha Laklak* often contains complex scripts with textured wooden backgrounds.

To address these challenges, approaches capable of detecting and recognizing Batak script in real-time under more dynamic conditions are needed. YOLO (You Only Look Once) is a well-known object detection algorithm due to its speed and accuracy in real-time object detection (Redmon et al., 2016). The latest version, YOLOv11, has shown significant improvements in detection speed and accuracy compared to its predecessors (Jocher et al., 2023). YOLOv11 has been successfully applied in various fields, including license plate detection (Zhang et al., 2018) and object recognition in ancient manuscripts (Chen et al., 2023). Previous research on traditional script recognition using YOLO includes the work of Wijaya and Sutoyo (2023), who applied YOLOv5 to detect Sundanese script in paper documents. However, this study did not evaluate YOLO's capability in recognizing scripts on more complex media, such as *Pustaha Laklak*. Moreover, no research has implemented YOLOv11 for real-time Batak script recognition, which could provide an efficient solution for digitizing ancient manuscripts.

This literature review paper is therefore important as it synthesizes existing studies on deep learning-based Batak script recognition, identifies gaps in current methodologies, and highlights potential directions for future research. By providing a comprehensive overview, this paper aims to support the development of effective solutions for preserving Batak cultural heritage through the use of advanced digital technologies. To ensure transparency, this review applied a systematic literature review approach. Relevant studies were collected from IEEE Xplore, SpringerLink, Scopus, and Google Scholar using keywords such as "Batak script recognition," "deep learning manuscript recognition," and "YOLO for ancient scripts." The inclusion criteria covered studies from 2015 to 2025 that focused on Batak or similar Southeast Asian scripts, while irrelevant or non-technical papers were excluded. Each study was analyzed for methods, datasets, evaluation metrics, and results, allowing a structured comparative synthesis.

LITERATURE REVIEW

Batak Script and *Pustaha Laklak*

The Batak script is a traditional writing system used by the Batak people in North Sumatra. This script belongs to the Brahmi family, which developed across South and Southeast Asia. Several Batak script variants have evolved among different Batak sub-ethnic groups, including Mandailing, Toba, Karo, Pakpak, Simalungun, and Angkola (Siregar, 2017). Structurally, the Batak script is syllabic, where each character represents a syllable consisting of a consonant and an inherent vowel. It also employs diacritical marks to modify the basic vowel sound of each letter (Uli, 2015). In practice, the Batak script is written from left to right, with the primary medium being bamboo or tree bark, known as *Pustaha Laklak* (Hutagalung, 2020). With modernization, the use of the Batak script has declined, although revitalization efforts have been carried out by various parties, including local governments and cultural communities (Simanjuntak, 2021).

Pustaha Laklak is an ancient Batak manuscript made from the bark of the alim or agarwood tree (*Aquilaria malaccensis*). This manuscript was traditionally used by the datu—local spiritual and customary leaders—to record traditional knowledge, including mantras, medicine, divination, and customary law (Sianipar, 2018). The structure of the *pustaha* consists of a hard wooden cover and accordion-folded bark pages. Text in the pustaha is usually written with natural ink made from soot and sugarcane sap. The script employed in these manuscripts is the Batak script, which has been handed down through generations of datu (Saragih, 2019). *Pustaha Laklak* serves not only as a religious and scholarly document but also reflects the intellectual level and belief systems of the Batak society in the past. To this day, the pustaha remains an important object of study in philology and anthropology due to its rich information on Batak history and culture (Harahap, 2022).

Object Detection

Object detection is a branch of computer vision that aims to identify specific objects within images or videos, such as humans, vehicles, or buildings, by marking their location and assigning a classification. The main objective is to detect objects of interest and annotate them using bounding boxes, which are rectangular boxes that enclose the object. Each bounding box is defined by position coordinates (x, y), width, and height of the object, along with a class label indicating the object category (e.g., “car” or “pedestrian”) and a confidence score representing the detection accuracy (Amjoud & Amrouch, 2023a).

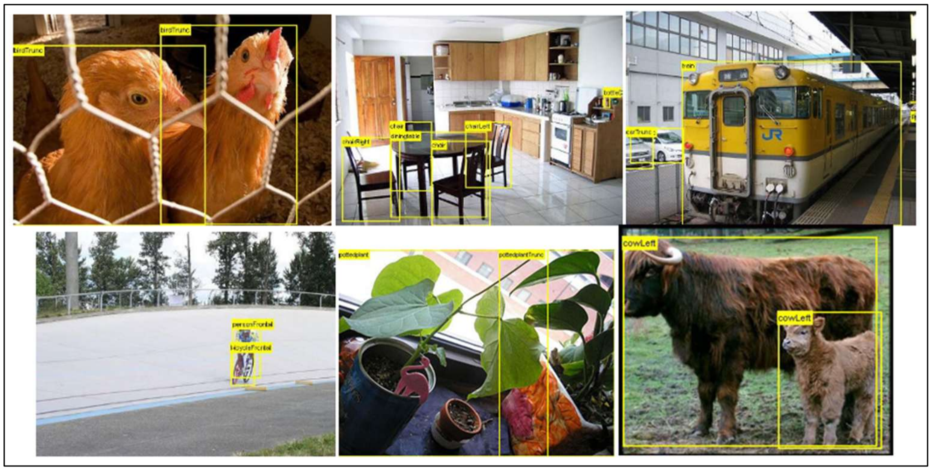

Figure 1. Example of Object Detection Application
Source: Amjoud and Amrouch (2023a)

In object detection, there are two main approaches: single-stage and two-stage detectors. Single-stage detectors (e.g., YOLO, SSD) combine detection and classification in a single step, where the model directly predicts the bounding boxes and object classes. This approach is faster and more efficient, making it suitable for real-time applications such as surveillance systems. On the other hand, two-stage detectors (e.g., Faster R-CNN) operate in two steps: first, generating region proposals—potential regions that may contain objects—then performing classification and bounding box refinement on these regions. Although more accurate, two-stage approaches require heavier computation, making them less optimal for real-time applications (Amjoud & Amrouch, 2023b).

Convolutional Neural Networks

A Convolutional Neural Network (CNN) is a deep learning architecture specifically designed to process visual data with a grid-like structure, such as images (Albawi et al., 2017). CNN differs from conventional feature extraction techniques because it does not require manual feature engineering. Its design is inspired by the human visual system, where biological neurons are connected similarly to artificial neurons. Compared to a standard artificial neural network, CNN offers advantages such as local connectivity, weight sharing, and dimensionality reduction through down-sampling. These features enable a reduction in the number of parameters without losing critical information (Pang et al., 2002).

A CNN architecture consists of multiple stages that can be trained for specific tasks. The layers commonly found in CNNs include convolutional layers, pooling layers, and fully connected layers (Pujiati & Rochmawati, 2022). The convolutional layer applies filters (kernels) that slide across the input image to produce feature maps through a dot product operation. This process involves parameters such as stride (the step size of the filter) and padding (the addition of border pixels) to preserve the spatial dimensions of the output.

Following the convolution process, an activation function is applied to the convolution output. Activation functions help the model handle non-linearities, allowing it to learn and predict more complex patterns. The most commonly used activation function in convolutional networks is the Rectified Linear Unit (ReLU). ReLU maps negative values to zero while preserving positive values, providing efficient and effective nonlinear transformations for deep learning tasks.

You Only Look Once (YOLO)

You Only Look Once (YOLO) is a CNN-based object detection method designed to quickly and accurately detect objects (Virgiawan et al., 2024). Unlike traditional approaches, YOLO divides the input image into an S × S grid, where each grid cell is responsible for detecting objects whose center falls within the cell. Each grid cell predicts bounding boxes and confidence scores that represent the detection accuracy (Ramdan & Asriyanik, 2024). Since its initial introduction, YOLO has undergone several developments, with YOLOv8 being the latest version that significantly improves both accuracy and speed. As a successor to YOLOv5, YOLOv8 is designed to enhance computational efficiency and adaptability across diverse applications, including object detection, image segmentation, pose estimation, and classification. The YOLOv8 architecture integrates state-of-the-art machine learning techniques and consists of three main components: backbone, neck, and head. The backbone extracts feature from the input image using a Feature Pyramid Network (FPN), allowing the detection of objects of various sizes by combining features from different convolutional layers. Early layers focus on identifying basic patterns, such as edges and textures, during initial processing. The confidence score is calculated using the following equation:

$$Confidence = \Pr(Object)\, x\, IoU(GT, Pred) \ldots (1)$$

Where:
Pr : Probability
IoU : Intersection Over Union
GT : Ground Truth

Evaluation Metrics

To evaluate a model, proper measurements are necessary to assess the quality of the developed model. The confusion matrix is a common evaluation metric used to assess the performance of a classification model. A confusion matrix presents the number of correct (true) and incorrect (false) predictions in a tabular form. In object detection, the confusion matrix consists of three main components: True Positive (TP), False Positive (FP), and False Negative (FN). True Positive (TP) represents the number of positive cases correctly predicted by the model, meaning the model predicts an instance as positive, and it truly is positive. False Positive (FP) represents the number of negative cases incorrectly predicted as positive. False Negative (FN) refers to the number of positive cases that the model fails to predict (Hossin & Sulaiman, 2015).

The determination of TP, FP, and FN in object detection considers the Intersection over Union (IoU) value. IoU measures the overlap between the predicted bounding box and the ground truth bounding box. Ground truth refers to the bounding box provided in the image, indicating the correct object position and class. If the IoU value exceeds a predetermined threshold, the prediction is considered a True Positive (TP). Conversely, if the IoU value is below the threshold but the model still provides a prediction, it is classified as a False Positive (FP). Objects that are present in the ground truth but not detected by the model are counted as False Negatives (FN).

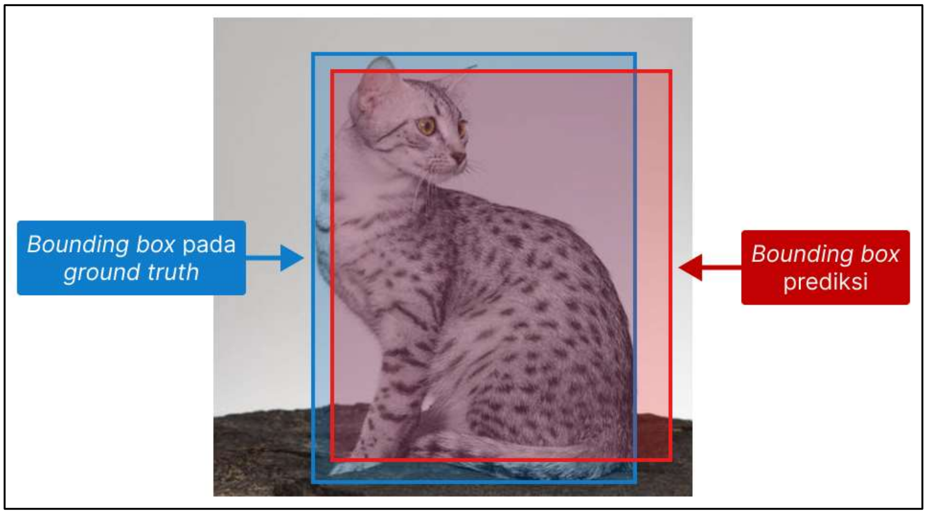

Figure 2. Illustration of Intersection over Union (IoU)

$$Intersection\ over\ Union\ (IoU) = \frac{A \cap B}{A \cup B} \ldots (2)$$

where:
A: Prediction bounding box
B: Bounding box on ground truth

Using TP, FP, and FN values from the confusion matrix, several evaluation metrics can be calculated, such as precision and recall. However, precision and recall are primarily used for classification models since they only measure how well the model classifies correct categories. For object detection, evaluation requires metrics that consider both correct classification and accurate object localization. The standard metric for object detection is mean Average Precision (mAP), which accounts for object classification and localization through bounding boxes (Carbonell et al., 2019). The mAP is obtained by averaging the Average Precision (AP) values for each class in a dataset. AP is calculated based on the two primary metrics in object detection, precision and recall, as follows:

$$precision_k = \frac{TP_k}{TP_k + FP_k} \ldots (3)$$

$$recall_k = \frac{TP_k}{TP_k + FN_k} \ldots (4)$$

$$AP = \int_{recall=0}^{1} precision(recall) \ldots (5)$$

where:
TP_k : True positive in class k
FP_k : False positive in class k
FN_k : False negative in class k

k : Class k

In object detection models, TP, FP, and FN are determined using IoU. The IoU measures the intersection between predicted bounding boxes and the ground truth boxes. The larger the IoU, the better the predicted bounding box represents the actual object. To classify a prediction as TP or FP, an IoU threshold is set. For example, if a model uses an IoU threshold of 0.5, predictions with IoU< 0.5 are considered FP, while predictions with IoU≥ 0.5 are considered TP (Rezatofighi et al., 2019). After calculating the AP values, the mAP can be computed as follows:

$$mAP = \frac{1}{n}\sum_{k=1}^{n} AP_k \ldots(6)$$

where:
AP_k : Average Precision for class k
n : Number of classes in the dataset

FINDINGS AND DISCUSSION

Research on script recognition has been conducted previously by Pasaribu and Hasugian (2017), who compared five feature extraction methods for handwritten Toba Batak script recognition: Elliptic Fourier Descriptor (EFD), Statistical, Directional, Boundary, and Skeleton. The results showed that Mahalanobis Distance (MD) yielded the highest accuracy across all methods, with the highest percentage reaching 96.88% for Directional and Boundary feature extraction. However, the Naive Bayes (NB) and 1-Nearest Neighbor (1-NN) classifiers demonstrated lower performance, particularly for Skeleton features, which only achieved 16.94%. This study emphasized the importance of selecting suitable classification algorithms to enhance character recognition accuracy.

A study by Muchtar (2020) developed a Batak manuscript digitization system using the Learning Vector Quantization (LVQ) method. The input data consisted of manuscript images in .jpg format that underwent preprocessing, including grayscale conversion, contrast enhancement, and segmentation. The system achieved 97.9% accuracy; however, poor image quality, noisy backgrounds, inconsistent character positions, and limited training data remained significant challenges. This study highlighted the necessity for more robust preprocessing techniques to handle the complexity of ancient manuscripts.

Another study by Dharma et al. (2022) compared the performance of Faster R-CNN and YOLOv3 for detecting the Toba Batak script. On a standard test dataset, YOLOv3 achieved 98.9% accuracy, outperforming Faster R-CNN at 97.3%. However, when tested on mixed data containing foreign symbols, YOLOv3's accuracy dropped drastically to 35.5%, whereas Faster R-CNN remained at 47.3%. This finding indicates that YOLO-based models are vulnerable to interference from foreign objects despite performing well under ideal conditions.

Another study by Zamzami et al. (2021) combined Diagonal-Based Feature Extraction (DBFE) with Backpropagation Neural Network (BPNN) for handwritten Toba Batak script recognition. Using 190 data samples (114 for training and 76 for testing), the model achieved an accuracy of 87.19%. Although lower than CNN-based approaches, this study demonstrated the potential of traditional methods such as BPNN when combined with effective feature extraction.

Alfael Maradu Andar Turnip, Nurul Fadillah, and Munawir implemented CNN to recognize handwritten Toba Batak characters with specific parameters: 3×3 kernels, 150×150 pixel images, and 300 epochs. Accuracy varied from 57.89% to 89.47%, depending on the complexity of the test data. The results indicated that variations in handwriting position and form significantly affect model performance, especially with unstructured characters.

Finally, a study by Muis et al. (2024) analyzed the influence of activation functions in CNN for Batak script recognition. Results demonstrated that using ReLU and eLU activation functions yielded the highest accuracy—94.11% for testing and 99.71% for training—compared to the lower performance of the tanh function. Additionally, the model with eLU achieved the lowest error (0.0108), indicating better training stability. This research emphasizes the importance of selecting activation functions for optimizing CNN models.

Table 1. State of The Art

No	Author & Year	Method	Result
1	Pasaribu and Hasugian (2017)	Feature Extraction (EFD, Statistical, Directional, Boundary, Skeleton) + Classification (MD, NB, 1-NN)	Highest accuracy 96.88% (MD on Directional & Boundary). Lowest 16.94% (NB on Skeleton)
2	Muchtar et al. (2020)	Learning Vector Quantization	97.9% accuracy on ideal data. Performance drops with noisy backgrounds
3	Dharma et al. (2022)	Faster R-CNN vs YOLOv3	YOLOv3: 98.9% (test), 35.5% (mixed data). Faster R-CNN: 47.3% (mixed data)
4	Zamzami et al. (2021)	BPNN + DBFE	87.19% accuracy with diagonal feature extraction
5	Andar et al. (2023)	Convolutional Neural Network	Accuracy varies 57.89%-89.47% depending on test data complexity
6	Muis et al. (2024)	CNN (ReLU, eLU)	ReLU: 94.11% testing. eLU: 99.71% training.

Based on previous studies, the current research shares the same object of study, namely the Batak script in ancient manuscripts. However, it differs in methodological approach, data coverage, and technical innovations. Key distinctions include:

1. Pasaribu et al. (2017) relied on traditional feature extraction (Directional, Boundary) and single-class classification (MD), whereas this study adopts YOLOv8, a deep learning single-stage detection model capable of automatic feature extraction and real-time multi-object detection.
2. Muchtar et al. (2020) focused on manuscript digitization using LVQ with high accuracy on ideal data, but without transliteration. This study addresses that limitation by focusing on the transliteration of complex *Pustaha Laklak* manuscripts with textured or degraded backgrounds.
3. Dharma et al. (2022) compared Faster R-CNN and YOLOv3, where YOLOv3 struggled with mixed data (accuracy dropped to 35.5%). The current research utilizes YOLOv8 with an optimized anchor-free head and CSPDarknet backbone to enhance detection stability across diverse datasets.
4. Muis et al. (2024) and Andar et al. (2023) focused on isolated character classification with high accuracy (94.11%-99.71%) but were limited to single-character images. This research expands coverage with multi-object detection, enabling the simultaneous identification of multiple characters in a single image, and integrates mobile deployment for practical applications.

5. Zamzami et al. (2021) combined diagonal feature extraction with BPNN (87.19% accuracy). The present study eliminates the dependency on manual feature extraction by leveraging YOLOv8's hierarchical end-to-end feature extraction for improved efficiency and precision.

CONCLUSIONS

This literature review has examined various approaches to Batak script recognition, highlighting the evolution of methods from traditional feature extraction and statistical classifiers to modern deep learning-based models. Previous research demonstrates that classical methods, such as Mahalanobis Distance combined with Directional and Boundary features, can achieve high accuracy under controlled conditions (Pasaribu & Hasugian, 2017). However, these approaches are often limited by manual feature engineering and sensitivity to variations in handwriting and document quality.

Deep learning methods, particularly Convolutional Neural Networks (CNNs), have shown significant improvements in recognizing Batak script, with accuracies ranging from 57.89% to over 99%, depending on the architecture, activation functions, and preprocessing techniques (Andar et al., 2023; Muis et al., 2024). Object detection frameworks like YOLOv3 and Faster R-CNN have further extended the capabilities of these models to handle multi-character detection; however, their performance still drops when faced with complex or noisy manuscript backgrounds (Dharma et al., 2022).

By analyzing these studies, it is clear that automated recognition of Batak script remains challenging due to factors such as manuscript degradation, varying handwriting styles, and complex backgrounds found in *Pustaha Laklak*. While YOLO-based architectures show promise for real-time multi-object detection, further research is required to optimize their performance for historical manuscripts with diverse and textured media.

LIMITATIONS & FURTHER RESEARCH

This study has several limitations. First, the number of accessible works on Batak script recognition is still limited compared to other traditional scripts, which affects the generalizability of the findings. Second, most reviewed studies rely on small and imbalanced datasets, making comparisons across methods less robust. Third, evaluation metrics vary across studies (e.g., accuracy, precision, recall, *mAP*), which complicates direct benchmarking of results. Finally, since this work is limited to secondary analysis, no experimental validation with newly collected datasets was conducted. These limitations highlight the need for larger benchmark datasets, more consistent evaluation protocols, and future studies that integrate empirical validation with literature-based findings.

Future research directions may include:

1. Integration of YOLOv8 for real-time detection and transliteration: Implementing advanced anchor-free heads and optimized backbones can improve stability and accuracy for complex manuscripts.
2. Robust preprocessing techniques: Developing methods to mitigate noise, uneven lighting, and manuscript degradation to enhance model reliability.
3. Multi-modal approaches: Combining visual recognition with linguistic models or contextual information to increase transliteration accuracy.
4. Deployment on mobile or edge devices: Allowing practical applications for educational, cultural preservation, and archival purposes.
5. Dataset expansion: Curating larger, annotated datasets of *Pustaha Laklak* manuscripts to improve generalization and facilitate comparative studies.

In conclusion, this literature review highlights the importance of adopting modern deep learning techniques, such as YOLOv8, for recognizing the Batak script. The integration of multi-object detection, hierarchical feature extraction, and end-to-end training offers a promising avenue for preserving and digitizing Batak manuscripts while providing a foundation for future advancements in automated script recognition.

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