Deep learning utilization in Sundanese script recognition for cultural preservation

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ABSTRACT

This study addresses the challenge of preserving the Sundanese script, a traditional writing system of the Sundanese community in Indonesia, which is at risk of being forgotten due to technological advancements. To tackle this problem, we propose a deep learning approach using the YOLOv8 model for the automatic recognition of Sundanese characters. Our methodology includes creating a comprehensive dataset, applying augmentation techniques, and annotating the characters. The trained model achieved a precision of 95% after 150 epochs, demonstrating its effectiveness in recognizing Sundanese characters. While some variability in accuracy was observed for certain characters and real-time applications, the results indicate the feasibility and promise of using deep learning for Sundanese script recognition. This research highlights the potential of technological solutions to digitize and preserve the Sundanese script, ensuring its continued legacy and accessibility for future generations. Thus, we contribute to cultural preservation by providing a method to safeguard the Sundanese script against obsolescence.

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1. INTRODUCTION

The Sundanese script, known as Aksara Sunda, is a traditional writing system used by the Sundanese people of Indonesia. It holds significant cultural and historical value, reflecting the rich heritage of the Sundanese community [1]. Aksara ngalagena (depicted in Figure 1), or consonant letters, represent consonant phonemes in the Sundanese script that syllabically contain the vowel sound /a/. There are eighteen types of these ancient Sundanese characters, arranged according to articulatory positions such as guttural (throat), palatal (palate), lingual (tongue), dental (teeth), and labial (lips). These consonant letters are fundamental to the Sundanese script, as they form the basis for writing words and conveying meaning. Each letter represents a specific sound, and when combined with vowel diacritics, they create syllables. The Sundanese script is an abugida, where each consonant letter carries an inherent vowel sound, which can be modified by diacritics to alter the vowel sound. This systematic arrangement aids in understanding the phonetic structure of the Sundanese language and supports accurate pronunciation.

Field studies [2] highlight how traditional systems like Aksara Sunda can adapt and remain relevant in today's era. This adaptability is a testament to the enduring utility of traditional knowledge systems, which can be integrated with modern technologies to address contemporary challenges. The Sundanese script, Aksara Sunda, serves as a powerful example of how traditional systems can be preserved and adapted for modern use. Aksara Sunda is a structured and systematic script with each consonant letter carrying an inherent vowel sound that can be modified by diacritics to convey different meanings. This structured approach ensures accurate pronunciation and understanding of the Sundanese language, reflecting a deep cultural heritage. Similarly, Fianty *et al.* [3] illustrates the potential for combining traditional knowledge with advanced technology. Artificial intelligence (AI) models can process vast amounts of data from community health centers to identify nutritional deficiencies and trends among toddlers. By analyzing patterns in dietary intake, growth metrics, and health outcomes, these AI systems can provide actionable insights for healthcare providers.

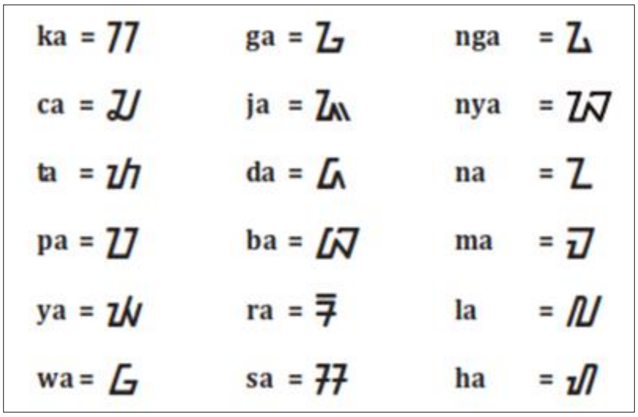

Figure 1. Consonant letters in Sundanese script “ngalagena”

With the advent of digital technology and the prevalence of Latin script, the Sundanese script faces the risk of marginalization, threatening the preservation of Sundanese culture and language. This shift highlights the urgent need for innovative solutions to effectively digitize and safeguard the script for future generations [4]-[6]. One primary challenge in this preservation effort is the lack of efficient methods for recognizing and digitizing Sundanese text. Manual transcription is labor-intensive and prone to inaccuracies, making it impractical for large-scale preservation. Traditional optical character recognition (OCR) systems also struggle with the unique characteristics of Sundanese handwriting, as the script’s complex and diverse shapes pose significant hurdles, leading to suboptimal accuracy and reliability.

Unresolved problems include the limited effectiveness of existing OCR systems in handling the complex and varied shapes of Sundanese characters, particularly in real-time applications. Current approaches often fail to provide accurate recognition under varying conditions, such as different lighting or image quality. Moreover, integrating Sundanese script recognition into practical applications, like mobile translation tools, remains challenging due to these limitations. In response, this research introduces a novel approach by leveraging YOLOv8, a deep learning model renowned for its precision in object detection, to enhance Sundanese script recognition. YOLOv8's architecture allows for more accurate and efficient recognition of Sundanese characters by handling complex shapes and diverse image conditions. This research aims to improve both the accuracy and robustness of character identification, offering a significant advancement in digitizing and preserving Sundanese texts. This approach addresses gaps left by previous methodologies and enables practical applications, such as real-time mobile translation tools.

Previous research on Sundanese script recognition has explored various methodologies, including traditional machine learning and deep learning approaches [7]-[21]. You only look once (YOLO) has gained prominence in real-time applications due to its exceptional speed and accuracy [22]-[24]. YOLO’s unique neural network design enables it to predict multiple bounding boxes and class probabilities simultaneously, allowing for real-time processing of video frames with high precision. YOLOv8, the latest iteration, builds upon its predecessors with enhancements that improve performance, accuracy, and efficiency in detecting objects [25]. While YOLOv8 has been applied to real-time Sundanese script detection in video streams [26], its predominant use has been in car plate recognition [27], [28]. This demonstrates YOLOv8's versatility in handling complex character recognition tasks with high accuracy and speed, positioning it as a powerful tool for diverse real-world applications.

2. METHOD

The methodology for the research on deep learning utilization in Sundanese script recognition for cultural preservation using YOLOv8 involves several key steps. Firstly, data collection will involve gathering a diverse dataset of Sundanese script images, ensuring representation of various styles and contexts. Preprocessing steps will include image normalization and augmentation to enhance model generalization. Next, the YOLOv8 architecture will be implemented for object detection, customized to recognize Sundanese script characters. Transfer learning will be employed using a pre-trained model on a large dataset to expedite training on the Sundanese script dataset. The model will be fine-tuned using the collected dataset, with hyperparameter tuning to optimize performance. Evaluation will be conducted using metrics such as precision, recall, and F1 score, with a focus on accuracy in Sundanese script character detection. The model will also be tested on a separate validation dataset to assess generalization. Lastly, the research will include a qualitative analysis of the cultural impact of Sundanese script recognition, considering factors such as the preservation of heritage and accessibility of the script in digital environments.

2.1. YOLO object detection algorithm

YOLO, created by Joseph Redmon and Ali Farhadi, is a renowned model for object detection and image segmentation, first introduced in 2015. YOLOv8, the latest version, incorporates new features and enhancements to improve performance and flexibility. YOLOv8 features a backbone and head as core components of its convolutional neural network (CNN). It builds on the CS architecture, with thirty-five convolutional layers and cross-stage partial connections that facilitate efficient data transfer between layers. YOLOv8's head predicts bounding boxes, evaluates objects, and determines class probabilities using the following formula for bounding box prediction:

$$Bounding\ Box = (x, y, w, h) \tag{1}$$

where, x and y are calculated as:

$$x = \sigma(\hat{x}) + c_x \tag{2}$$

$$y = \sigma(\hat{y}) + c_y \tag{3}$$

Here, σ is the sigmoid function that maps the output to a [0, 1] range. $\hat{x}$ and $\hat{y}$ are the model's raw predictions for the center coordinates, and c_x and c_y are the coordinates of the grid cell.
w and h are calculated as:

$$w = p_w . exp(\widehat{w}) \tag{4}$$

$$h = p_h . exp\left(\hat{h}\right) \tag{5}$$

Here, p_w and p_h are anchor box dimensions, and $\widehat{w}$ and $\hat{h}$ are the model's raw predictions for width and height.

YOLO predicts class probabilities for each bounding box. For each grid cell, YOLO outputs the probability of each class using a SoftMax function:

$$P(class_i) = \frac{exp(\widehat{p_i})}{\sum_j exp(\hat{p}_j)} \tag{6}$$

where $\widehat{p_i}$ is the raw score for class i and the denominator is the sum of exponentials of scores for all classes. This gives the probability distribution over all classes for the detected object.

YOLO also predicts a confidence score for each bounding box, indicating how confident the model is that the box contains an object and how accurate the box is:

$$Confidence = Objecness\ Score\ x\ Intersection\ over\ Union\ \text{(IoU)} \tag{7}$$

where objectness score represents the probability that the box contains an object and intersection over union (IoU) measures the overlap between the predicted bounding box and the ground truth bounding box. YOLOv8 detects objects at various scales through a hierarchical network structure, ensuring accurate identification of objects of different sizes within an image. Figure 2 depicts the structure of YOLOv8 [26].

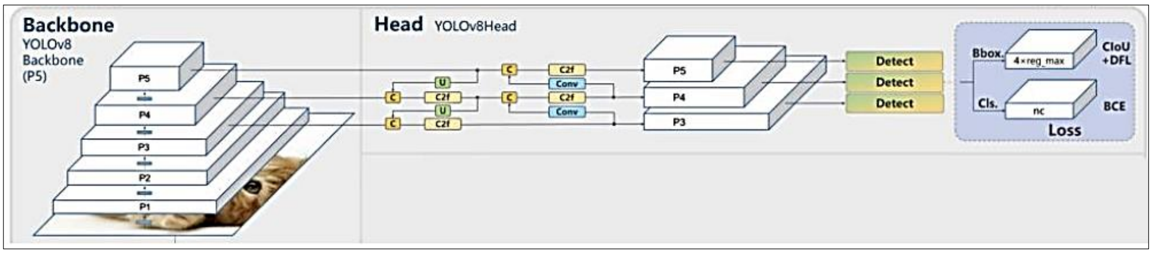

Figure 2. The structure of YOLOv8 [26]

2.2. Data collection and preparation

In the data collection and preparation phase, a diverse dataset of Sundanese script images was meticulously assembled to capture various styles and contexts of the script. This dataset includes 21 consonant letters and 10 numerals (0 to 9), amounting to a total of 31 distinct characters, as depicted in Figure 3.

Figure 3. The pictures of the generated Sundanese letters

To create the initial dataset, a Python script was used. This script generated images of each Sundanese character, ensuring that every character was represented in its basic form. To enhance the model's robustness and generalizability, several augmentation techniques were applied. These techniques introduce variations in size, position, and rotation, helping the model learn to recognize characters under diverse conditions. The augmentation techniques include:

Scaling: $Scale\ factor = scale\ x\ image$ (8)

Rotation: $Rotation\ matrix = \begin{bmatrix} cos(\theta) & -sin(\theta) \\ \sin(\theta) & cos(\theta) \end{bmatrix}$ (9)

Translation: $translation\ vector = \begin{bmatrix} t_x \\ t_y \end{bmatrix}$ (10)

The processes described in (8) to (10) resulted in 1,840 unique letter images. Each image was annotated using Roboflow, which labeled each Sundanese letter. Additional augmentation included:

$$Exposure\ adjustment: Exposure = original\ exposure\ \pm exposure\ range \quad (11)$$

Blurring: $Gaussian\ filter\ with\ kernel\ size\ up\ to\ 1.5\ pixels$ (12)

Noise: $random\ noise\ up\ to\ 6\%\ of\ pixels$ (13)

The augmentation processes described in (11) to (13) resulted in a final dataset of 4,410 images. This dataset was divided into training (3,855 images), validation (366 images), and test sets (189 images) to ensure comprehensive model training and evaluation.

2.3. Model selection and customization

The YOLOv8 model was trained using the augmented dataset, which included 4,410 images of Sundanese characters. The primary objective of the training process was to enhance the model's ability to accurately distinguish between the 31 different Sundanese characters, comprising 21 consonant letters and 10 numerals. The training was conducted iteratively over 150 epochs. An epoch represents one complete pass through the entire dataset during training. The iterative training process allows the model to gradually refine its parameters and improve its performance. The training loss function, which measures the model's error during training, is composed of three main components: the bounding box loss, the objectness loss, and the class loss. The overall loss function for YOLOv8 is given by:

$$Loss = Bounding\ Box\ Loss + Object\ Loss + Class\ Loss \quad (14)$$

Bounding box loss is used to measure the difference between the predicted and ground truth bounding boxes, computed as:

$$Bounding\ Box\ Loss = \alpha. IOU\ Loss + \beta. Localization\ Loss \quad (15)$$

where:
IOU loss is the IoU loss, calculated as: $IOU\ Loss = 1 - IoU$.
Localization loss measures the deviation of the predicted bounding box from the ground truth box.
Object loss is used to evaluate how well the model predicts the presences of an object within the bounding box:

$$Object\ Loss = Binary\ Cross - Entropy\ (Objectness\ Score, Ground\ Truth) \quad (16)$$

where the objectness score indicates the confidence that an object exists within the predicted box.

2.4. Training and evaluation

The model is trained using the augmented dataset, which includes 4,410 images of Sundanese characters, with a focus on optimizing its ability to distinguish among the 31 different Sundanese characters. The training process involves an iterative approach with a specified number of epochs. During each epoch, the model adjusts its internal parameters based on the training data to improve its performance in recognizing Sundanese characters. By training over multiple epochs, the model gradually learns to recognize Sundanese characters with higher accuracy. After training, the model's performance is evaluated using metrics such as precision, recall, and F1 score. Precision measures the proportion of correctly identified Sundanese characters out of all characters identified by the model.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (17)$$

Recall measures the proportion of correctly identified Sundanese characters out of all actual Sundanese characters in the dataset.

$$Recall = \frac{True\ Positives}{True\ Positive + False\ Negatives} \quad (18)$$

The F1 score is the harmonic mean of precision and recall, providing a balanced measure of the model's overall performance in recognizing Sundanese characters.

$$F1\ Score = 2.\frac{Precision.Recall}{Precision + Recall} \quad (20)$$

2.5. Cultural impact analysis

The cultural impact analysis assesses how the Sundanese script recognition model contributes to the preservation of Sundanese cultural heritage. It considers factors such as the script's accessibility in digital environments and its role in maintaining cultural identity. By enabling the recognition of Sundanese characters, the model helps digitize and preserve Sundanese texts and documents. This enhancement increases the accessibility of Sundanese culture to a wider audience, contributing to the longevity of the cultural heritage and ensuring that future generations can access and appreciate Sundanese literature and traditions. To quantify the cultural impact, the following metrics and formulas is used:

Digitization rate is used to measures the extent to which physical Sundanese texts have been converted into digital format:

$$Digitazion\ Rate = \frac{Number\ of\ Digitized\ Texts}{Total\ Number\ of\ Texts} x\ 100 \tag{21}$$

accessibility score is used to assesses how accessible Sundanese texts have become due to digitalization. This score could be based on factors like the number of digital platforms hosting Sundanese texts and the frequency of access:

$$Accessibility\ Score = \frac{Number\ of\ Platforms\ Hosting\ Sundanes\ Texts}{Total\ Number\ of\ Relevant\ Platforms} x\ 100 \tag{22}$$

cultural engagement index is used to measures the level of engagement with Sundanese cultural materials post-digitization, such as user interactions, educational use, and public interest:

$$Cultural\ Engagement\ Index = \frac{Number\ of\ User\ Interactions}{Total\ Digital\ Text\ Available} x\ 100 \tag{23}$$

3. RESULTS AND DISCUSSION

The training of the YOLOv8 model on the curated and augmented Sundanese letter dataset resulted in a precision of approximately 95% after 150 epochs. Precision is a critical metric that reflects the accuracy with which the model correctly identifies Sundanese characters within images. This high precision demonstrates the model's effectiveness in distinguishing among the 31 unique Sundanese letters and numbers. Achieving a precision of 95% indicates that the model has a low false-positive rate, meaning it correctly identifies the majority of Sundanese characters in the dataset. This high level of accuracy is crucial for applications such as digitizing and preserving Sundanese texts and documents, where any errors in character recognition could lead to misinterpretation or loss of cultural information. The plot of the model's result summary, shown in Figure 4, visually represents the training progress and achieved precision, providing a clear overview of the model's performance over the training epochs.

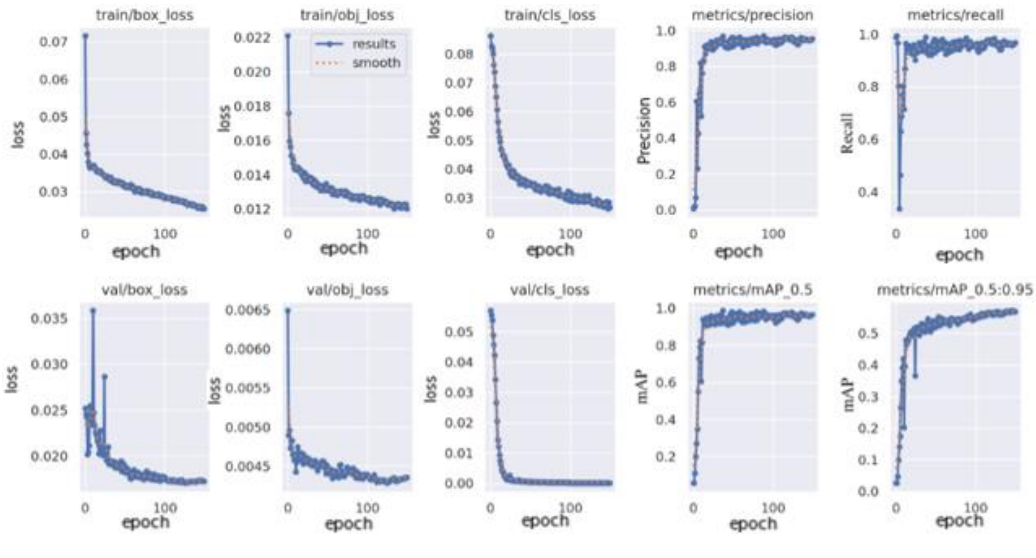

Figure 4. The plot of model result summary

Meanwhile, Figure 5 depicts the model's predictions on a given set of test images for the characters "za", "va", "da", "la", "fa", and "ja" along with their respective accuracies. The model achieved an accuracy of 70% for "za", 80% for "va", 70% for "da", 68% for "la", 60% for "fa", and 50% for "ja". These accuracies reflect the model's performance in correctly identifying each Sundanese character within the test images. While some characters have higher accuracies than others, the overall results demonstrate the model's capability to recognize Sundanese characters with varying degrees of accuracy. Further analysis may be needed to improve the model's performance, especially for characters with lower accuracies, to enhance its effectiveness in applications such as digitizing and preserving Sundanese texts and documents.

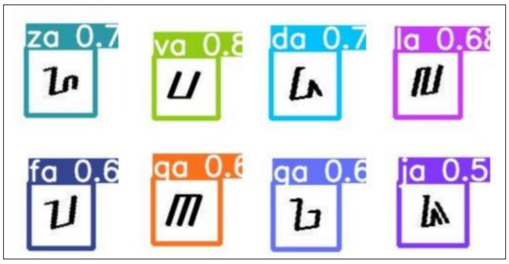

Figure 5. The model prediction on given sets of test images

Figure 6 showcases the model's predictions for the test phrase "nama saya raka" captured through a webcam. The model's accuracy for this task is reported to be less than 70%. This suggests that the model may struggle with accurately recognizing and distinguishing the Sundanese characters in the phrase when captured in real-time through a webcam. The lower accuracy could be attributed to various factors such as lighting conditions, camera quality, and image processing issues that affect the clarity and quality of the input images. Improving the model's performance for real-time applications may require additional preprocessing steps, model tuning, or training on a more diverse dataset that includes webcam-captured images to enhance its robustness and accuracy in such scenarios.

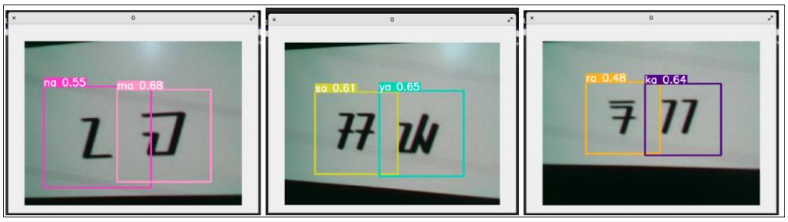

Figure 6. The model prediction on given “nama saya raka” test words through webcam

The Sundanese script recognition model has demonstrated significant potential in preserving and promoting Sundanese cultural heritage. By converting delicate historical manuscripts into digital formats, the model ensures that these valuable texts are preserved and accessible to future generations. This digitization process is crucial for researchers specializing in Sundanese literature, as it allows for easier analysis and deeper understanding of the script's cultural subtleties. Additionally, the model’s real-time recognition capabilities offer practical solutions, such as a mobile app that translates Sundanese text captured by a smartphone camera. This innovation not only facilitates communication but also promotes the integration of Sundanese script into daily use.

Despite these advancements, the cultural impact analysis, as detailed in Table 1, indicates that there is still substantial room for improvement. The digitization rate and user engagement with digital texts are relatively modest at 60%. However, the integration of Sundanese texts on digital platforms is lower, at 45%, reflecting limited online visibility. Additionally, the availability of translation tools and educational resources is not optimal, with scores of 50% and 55%, respectively. The cultural content representation is particularly weak, at 40%, suggesting that Sundanese cultural materials are underrepresented in digital formats. These results highlight the need for more focused efforts to enhance the accessibility, visibility, and engagement with Sundanese script in digital environments.

Table 1. Accessibility score result

Aspect	Score (%)
Digitization rate	60
Integration on digital platforms	45
User engagement with digital texts	60
Availability of translation tools	50
Educational resource availability	55
Cultural content representation	40

4. CONCLUSION

The application of deep learning, specifically the YOLOv8 model, in recognizing Sundanese script is a vital advancement for preserving cultural heritage. This model has demonstrated its capability by achieving a high precision of approximately 95% after 150 epochs, highlighting its effectiveness in accurately identifying 31 distinct Sundanese characters. This accuracy is crucial for digitizing and safeguarding Sundanese texts, which helps ensure their availability for future generations. Despite these promising results, the model's real-world performance reveals areas needing improvement. The digitization rate and user engagement are currently at 60%, and the integration of Sundanese texts on digital platforms is only 45%. Additionally, translation tools and educational resources are lacking, with scores of 50% and 55%, respectively. Most notably, cultural content representation is critically low at 40%, indicating a significant gap in the digital presence of Sundanese materials. To overcome these challenges, future research should aim to refine the YOLOv8 model for better real-time performance and robustness. There is also a need for enhanced visibility and integration of Sundanese texts online, along with the development of more effective translation tools and educational resources. Collaborative efforts from researchers, technology developers, and cultural organizations are essential to advancing these initiatives and ensuring the comprehensive preservation and promotion of Sundanese heritage in the digital era.

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