Optimizing Javanese script recognition using fine-tuned ResNet-18 and transfer learning

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ABSTRACT

Javanese script, known as *aksara Jawa*, is an ancient script used in historical and cultural texts. However, its complex character structure poses challenges for accurate recognition in modern digital applications. This study proposes an optimized classification approach for *aksara Jawa* using a fine-tuned residual network (ResNet)-18 model combined with the adaptive moment estimation (Adam) optimization algorithm and transfer learning on the hanacaraka image dataset. By leveraging the residual learning framework of ResNet-18, the model effectively captures deep spatial features of the script while reducing vanishing gradient issues. Fine-tuning is applied to enhance model adaptability, ensuring robust feature extraction specific to Javanese characters. Experimental results demonstrate that the fine-tuned ResNet-18 outperforms conventional deep learning architectures in recognizing *aksara Jawa* characters, achieving 93% precision, 91% recall, 91% F1-score, and 91% accuracy. The study further explores the impact of hyperparameter tuning, data augmentation, and dropout regularization on model performance. The findings highlight the effectiveness of transfer learning in resource-limited scenarios, making it a feasible solution for optical character recognition (OCR) applications in Javanese script digitization. This research contributes to the preservation of cultural heritage through advancements in deep learning-based script recognition.

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1. INTRODUCTION

The Javanese script, also known as *aksara Jawa* or hanacaraka, is a cultural heritage of significant historical and identity value in Indonesia, particularly on the Island of Java [1], [2]. For centuries, it has been used in literature, historical records, and official documents [3], [4]. However, with the advancement of modern technology, the use and interest in learning the Javanese script have significantly declined. This situation underscores the urgency of preserving and enhancing the recognition of the Javanese script to remain relevant in the digital era. Traditional approaches, such as optical character recognition (OCR), have been used to recognize Javanese script characters. However, these methods face limitations in handling variations in handwriting styles, distortions, and suboptimal image quality [5]. With the rapid progress in deep learning technology, deep learning-based approaches have shown promising potential in improving character recognition accuracy [6].

Transfer learning has also emerged as an effective approach to enhance the performance of deep learning models, particularly when the available training data is limited [7]. By leveraging pre-trained models, transfer learning allows the knowledge gained to accelerate training and improve the performance of new models on specific tasks [8]. Although research has been conducted on Javanese script character recognition, current approaches still face several limitations, such as insufficient accuracy under varying image conditions and the need for large training datasets [9]. Therefore, there is a need to develop more effective and efficient classification models to address these limitations. Existing research on *aksara Jawa* recognition is still in its early stages, with a limited number of studies focusing on this specific script. While some promising results have been achieved using techniques like convolutional neural networks (CNN), several key gaps remain [10]. Figure 1 shows hanacaraka.

Figure 1. Hanacaraka Javanese script

These include the need for larger and more diverse datasets, the development of robust pre-processing techniques to handle variations in handwriting styles, and the exploration of advanced deep learning architectures tailored for complex scripts like *aksara Jawa* [11], [12]. Additionally, research on real-time recognition systems and integration with other language technologies, such as machine translation and text-to-speech, is still in its infancy [13]. Addressing these gaps will be crucial for advancing the field of *aksara Jawa* recognition and ensuring its preservation and accessibility. Existing approaches to Javanese script recognition have faced three fundamental challenges: i) most studies used basic CNN architectures that struggle with the script's complex graphemes, ii) methods required impractically large datasets, and iii) systems showed poor generalization to real-world variations in handwriting quality and style. For instance, Susanto *et al.* [14] achieved only 85% accuracy despite using a deep 12-layer CNN.

ResNet-18, a variant of the residual network (ResNet) architecture, has significantly contributed to advancements in deep learning, particularly in computer vision tasks such as image classification, object detection, and medical image analysis. It consists of 18 layers, including convolutional layers, batch normalization, and rectified linear unit (ReLU) activation functions. The key feature of ResNet architectures is the use of skip connections or residual connections, which facilitate gradient flow and help mitigate the vanishing gradient problem [15]. The effectiveness of ResNet-18 has been demonstrated across various applications. It has also been successfully applied in fruit image classification, where multiple ResNet-18 models enhanced performance significantly [16]. Additionally, it has been utilized for detecting medical conditions such as brain tumors and colorectal cancer, yielding reliable and reproducible results [17], [18]. We implement the first application of ResNet-18 with skip connections specifically optimized for Javanese script's structural challenges, overcoming vanishing gradient issues that plagued earlier CNN approaches.

Beyond image processing, ResNet-18 has been explored in genomics for disease detection and treatment optimization, demonstrating its versatility across different domains [19]. Its skip connections play a crucial role in training deeper networks by addressing the vanishing gradient problem [20]. Techniques such as gradient amplification and optimized training strategies can further enhance its performance by reducing training time and improving accuracy [15], [21]. Although ResNet-18 is less complex than deeper models like ResNet-50 and ResNet-101, it still requires substantial computational resources, especially in multi-model setups. Fine-tuning parameters like input resolution and quantization precision is essential for optimal performance but can be a resource-intensive and complex process. As a powerful and adaptable deep learning model, ResNet-18 has achieved notable success in various applications, particularly in computer vision and medical imaging. Its residual connection-based architecture supports the training of deeper networks, while its versatility ensures its continued popularity despite its computational demands.

The recognition of *aksara Jawa* presents a significant challenge in the field of OCR due to its intricate character structures and limited digital resources [22]. This study highlights the importance of applying deep learning techniques, specifically a fine-tuned ResNet-18 model, to address these challenges and enhance the digitization of Javanese script [23]. By leveraging transfer learning and adaptive optimization techniques, this research contributes to the preservation of cultural heritage while advancing Indonesian language technology. The successful classification of *aksara Jawa* with high accuracy demonstrates the potential of deep learning-based OCR systems in automating the recognition and digital documentation of historical scripts, paving the way for broader applications in linguistic preservation, education, and cultural studies.

2. METHOD

2.1. Dataset description

This study employs a fine-tuned ResNet-18 model with adaptive moment estimation (Adam) optimization and transfer learning to classify *aksara Jawa* characters. The methodology consists of several key stages, including data preprocessing, model fine-tuning, training, and evaluation. The hanacaraka dataset is a valuable resource for *aksara Jawa* character recognition research. It consists of a collection of handwritten *aksara Jawa* characters, sourced from various online platforms and digital surveys. The dataset is composed of 1562 images, each representing a unique character from the *aksara Jawa* script. More details can be seen in Figure 2.

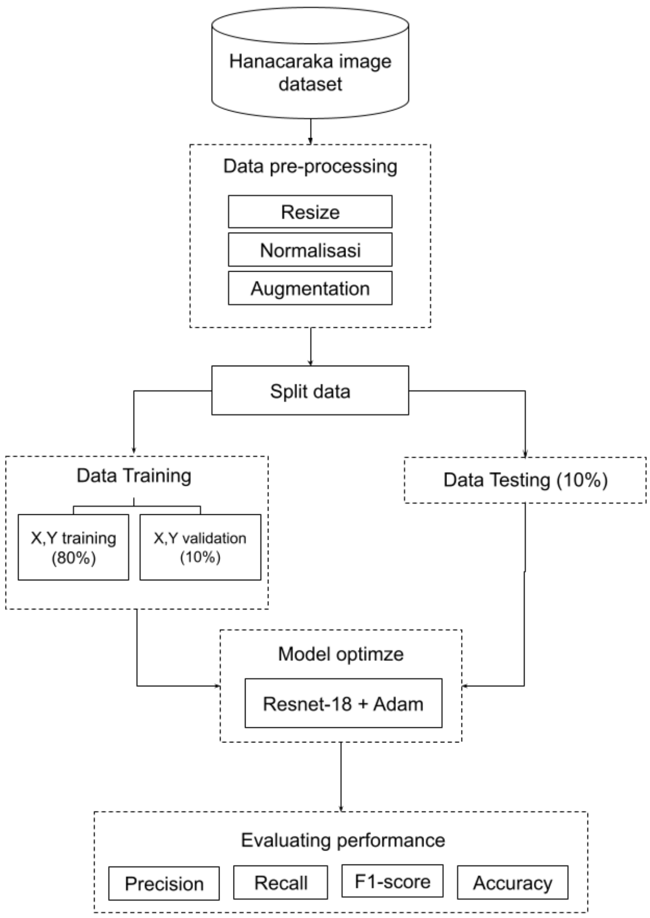

Figure 2. Research flowchart

The research flowchart illustrates the step-by-step process of *aksara Jawa* character classification using a fine-tuned ResNet-18 model with Adam optimization. The process begins with the hanacaraka image dataset, which undergoes preprocessing steps such as resizing, normalization, and data augmentation to enhance image quality and improve model generalization. The dataset is then split into training (80%), validation (10%), and testing (10%) subsets to ensure robust model evaluation. The training data is used to fine-tune the ResNet-18 model, where the final fully connected (FC) layer is modified to match the number of hanacaraka classes, and the Adam optimizer is employed for efficient parameter updates. The model's performance is then evaluated using precision, recall, F1-score, and accuracy, ensuring that the trained model is optimized for Javanese script recognition. The results and discussion should analyze the effectiveness of this approach, highlighting improvements in accuracy and robustness in recognizing *aksara Jawa* characters.

2.2. Model selection and fine-tuning

ResNet-18, a deep CNN model known for its residual learning mechanism, is chosen due to its efficiency in extracting hierarchical features. The model is pretrained on ImageNet and fine-tuned by replacing the FC layer to match the number of hanacaraka character classes. Only the final layers are trained while earlier convolutional layers remain frozen to retain pretrained knowledge. ResNet-18 is a CNN architecture designed to address the vanishing gradient problem in deep learning models [20], [24]. Unlike traditional CNNs, ResNet introduces skip connections (shortcut connections) that allow the gradient to flow directly through layers, preventing degradation in deep networks.

ResNet-18 consists of 18 layers, including convolutional layers, batch normalization, ReLU activation, and residual blocks [25]. The residual learning framework enables the model to learn identity mappings, making it more efficient in capturing hierarchical features from images. The network is pretrained on large-scale datasets like ImageNet, allowing it to extract robust features for transfer learning applications. Mathematically, a residual block in ResNet can be expressed as (1).

$$y = F(x, \{W_i\}) + x \tag{1}$$

Where x is the input; $F(x,\{W_i\})$ represents the learned transformation (series of convolutional layers); and the addition of x allows the model to learn an identity mapping, preventing degradation in deeper networks.

Due to its efficient feature extraction capabilities, ResNet-18 is chosen for this study to recognize the complex shapes of *aksara Jawa* while mitigating vanishing gradient issues. The Adam algorithm is an advanced optimization technique that combines the benefits of momentum-based optimization (e.g., root mean square propagation (RMSprop) and stochastic gradient descent (SGD) with momentum). Adam is widely used due to its adaptive learning rates, which help stabilize training across different datasets can show on (2). Adam updates the model’s parameters using first-order and second-order moment estimates.

$$\begin{aligned} M_t &= \beta_1 m_{-1} + (1-\beta_1) g_t \pi r^2 \\ v_t &= \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \\ \theta_t &= \theta_{t-1} - \frac{\eta}{\sqrt{v_t + \epsilon}} m_t \end{aligned} \tag{2}$$

Where m_t is the exponentially decaying average of past gradients; v_t is the exponentially decaying average of squared gradients; β_1 beta β2 are hyperparameters (typically set to 0.9 and 0.999); η is the learning rate; and ϵ is a small constant to prevent division by zero.

Adam is chosen in this study due to its fast convergence and ability to handle sparse gradients, making it suitable for fine-tuning pretrained ResNet-18 without extensive hyperparameter tuning. The algorithm dynamically adjusts learning rates for each parameter using moving averages of gradients and squared gradients, which stabilizes training. This adaptive approach proves particularly effective for Javanese script recognition, where character complexity demands precise weight updates during backpropagation.

2.3. Training process

The model is trained using the Adam optimization algorithm with a learning rate of 0.001, batch size of 32, and cross-entropy loss function. The training is conducted for 50 epochs, and early stopping is applied to prevent overfitting. During training, dropout regularization is used to enhance generalization, and batch normalization is applied to stabilize learning. The training process involves fine-tuning a pretrained ResNet-18 model for *aksara Jawa* classification using the Adam optimizer. First, the dataset is preprocessed by resizing images to 224×224 pixels, normalizing pixel values, and applying augmentation techniques like rotation and contrast adjustment. The dataset is split into training (80%), validation (10%), and testing (10%)

subsets to ensure robust learning. During training, the ResNet-18 model undergoes forward propagation, where input images pass through convolutional layers for feature extraction, followed by classification using a modified FC layer. The loss function, cross-entropy loss, evaluates prediction errors, and backpropagation updates weights using the Adam optimizer, which adjusts learning rates adaptively for efficient convergence. Regularization techniques like dropout are applied to prevent overfitting, and the model is trained for up to 50 epochs with early stopping to prevent unnecessary computations. Performance is evaluated using precision, recall, F1-score, and accuracy, ensuring optimal recognition of *aksara Jawa* characters. Finally, the best-performing model is selected for testing and later deployed for OCR applications, enabling automated recognition of Javanese script.

2.4. Evaluation metrics

The trained model is evaluated on the test set using precision, recall, F1-score, and accuracy to measure its effectiveness in recognizing Javanese script. To assess the performance of the fine-tuned ResNet-18 model for *aksara Jawa* classification, several evaluation metrics are used, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive understanding of the model's effectiveness in distinguishing between different Javanese characters. Accuracy measures the overall correctness of the model's predictions, calculated as the ratio of correctly classified samples to the total number of samples as shown in (3).

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FP+FN)} \tag{3}$$

Where true positives (TP): correctly predicted *aksara Jawa* characters; true negatives (TN): correctly predicted non-target characters; false positives (FP): incorrectly classified characters that do not belong to the class; and false negatives (FN): misclassified characters that should belong to the class.

Precision indicates how many of the predicted positive classifications were correct, measuring the model's ability to avoid FP. It is calculated as the ratio of TP (correctly classified *aksara Jawa* characters) to all predicted positives (TP+FP). This metric is particularly crucial for Javanese script recognition, where misclassifying similar-looking characters (e.g., 'ha' vs 'na') could distort historical document interpretations. It is calculated as (4).

$$\text{Precision} = \frac{TP}{(TP+FP)} \tag{4}$$

A higher precision means that the model produces fewer FP, which is crucial when misclassification can lead to incorrect OCR recognition. In the context of Javanese script digitization, high precision ensures that characters like "da" and "dha"—which differ by only a single stroke—are not confused during transcription. This metric becomes especially important when processing historical manuscripts where preservation accuracy is paramount. It is calculated as (5).

$$\text{Recall} = \frac{TP}{(TP+FN)} \tag{5}$$

A high recall value means the model correctly identifies most of the true characters but may still misclassify some as negatives. This is particularly important for preserving rare Javanese script variants that appear infrequently in historical documents. While high recall ensures comprehensive character detection, it may come at the cost of accepting some FP in the results. It is the harmonic mean of precision and recall.

$$\text{F1} - \text{score} = \frac{2\times(Precision\times Recall)}{(Precision + recall)} \tag{6}$$

A high F1-score indicates a good balance between identifying correct characters and minimizing false classifications. This harmonic mean of precision and recall becomes particularly valuable when evaluating Javanese script recognition. Where both accurate identification (precision) and complete detection (recall) of characters are equally important.

3. RESULTS AND DISCUSSION

Data preprocessing played a vital role in enhancing the performance of the ResNet-18 model for *aksara Jawa* classification. As outlined in Algorithm 1, the dataset underwent multiple preprocessing steps, including image resizing (224×224 pixels), normalization, and augmentation such as rotation and contrast adjustment. These steps ensured consistency in input data, reduced noise, and improved the model's ability to generalize across different character variations. Augmentation techniques helped address the challenge of limited training data by artificially expanding the dataset and introducing variations in character appearance, making the model more robust.

```
Algorithm 1. Fine-tuned ResNet-18 with Adam optimization
Input: X_train, Y_train, X_test, Y_test (Testing dataset), lr, epochs, batch_size
Output: ResNet18* (Fine-tuned ResNet-18 model)
Begin
   Load pretrained ResNet-18
   Freeze initial convolutional layers
   Replace the fully connected (FC) layer:
        FC_input = ResNet18.fc.in_features
        ResNet18.fc = FullyConnected(FC_input, num_classes)
  Preprocess Dataset
   - Resize images to 224×224
   - Normalize pixel values
   - Apply data augmentation (rotation, flipping, contrast adjustment)
   - Split into train (80%), validation (10%), test (10%)
  Define training components
   - Loss function: CrossEntropyLoss()
   - Optimizer: Adam (ResNet18.parameters(), lr)
  While stopping criterion not met do
     For each batch (X_b, Y_b) in training set:
        - Forward pass: output = ResNet18(X_b)
        - Compute loss: loss = CrossEntropyLoss(output, Y_b)
        - Zero gradients: optimizer.zero_grad()
        - Backpropagation: loss.backward()
        - Update weights: optimizer.step()
     - Validate model on validation set
     Evaluate model
     - Compute precision, recall, F1-score, and accuracy on test set
  Return fine-tuned model ResNet18*
End
```

The dataset, consisting of 1,562 images of *aksara Jawa* characters, was split into three subsets to ensure effective training and evaluation of the ResNet-18 model. Following a standard data division strategy, 80% (1,250 images) were allocated for training, allowing the model to learn character patterns efficiently. A separate 10% (156 images) was reserved for validation, enabling the fine-tuning of hyperparameters and preventing overfitting by monitoring model performance during training. The remaining 10% (156 images) was designated for testing, providing an unbiased assessment of the model's generalization ability on unseen data. After splitting the dataset, the ResNet-18 model was initialized with pretrained weights from ImageNet to leverage its existing feature extraction capabilities. The first convolutional layers were frozen to retain previously learned low-level features such as edges and textures, while the FC layer was replaced to match the number of *aksara Jawa* classes. The input images, resized to 224×224 pixels, passed through multiple convolutional layers, batch normalization, and ReLU activations, enabling deep hierarchical feature extraction. Max pooling layers helped reduce dimensionality while preserving critical features. The modified FC layer utilized SoftMax activation to classify images into respective *aksara Jawa* characters. This initial phase prepared the model for optimization, ensuring that the backbone architecture was effectively adapted to the new dataset before applying Adam optimization to fine-tune the model's parameters.

The model undergoes forward propagation, where input images pass through convolutional, batch normalization, and pooling layers to extract hierarchical features. The final classification layer applies SoftMax activation to assign probabilities to each character. The model is trained using cross-entropy loss, with weight updates performed using the Adam optimization algorithm, which adaptively adjusts learning rates for faster convergence. Training continues for a maximum of 50 epochs, incorporating early stopping to prevent overfitting. Once trained, the model is evaluated on the test set using accuracy, precision, recall, and F1-score, ensuring its effectiveness in recognizing *aksara Jawa* characters. It can be seen in Figure 3.

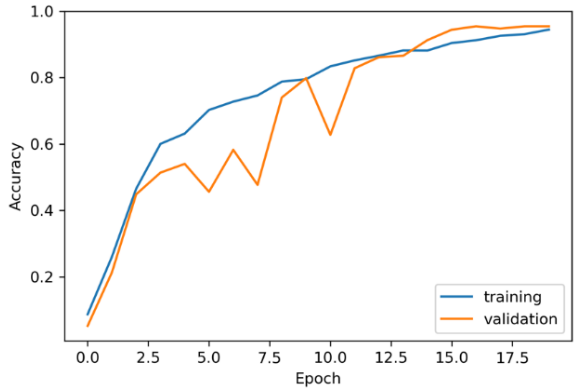

Figure 3. Training accuracy graph

The fine-tuned ResNet-18 algorithm for *aksara Jawa* classification follows a structured pipeline, beginning with data preprocessing, where images are resized to 224×224 pixels, normalized, and augmented to enhance generalization. The dataset of 1,562 images is then split into training (80%), validation (10%), and testing (10%) sets to ensure balanced learning and evaluation. The ResNet-18 model, pretrained on ImageNet, is modified by freezing the initial convolutional layers while replacing the FC layer to match the number of *aksara Jawa* classes. Training accuracy graph illustrates the model's learning progression over multiple epochs, showing both the training accuracy (blue line) and validation accuracy (orange line). Initially, both curves exhibit a steep upward trend, indicating that the ResNet-18 model is quickly learning and improving its ability to classify *aksara Jawa* characters. However, the validation accuracy fluctuates, suggesting that the model occasionally overfits to the training data, leading to performance variations on unseen validation samples. Around epoch 12 onward, both curves stabilize and converge near 0.9 (90%) accuracy, demonstrating that the model has effectively learned the patterns in the dataset. The fluctuations in the validation curve indicate sensitivity to specific batches, which could be mitigated by regularization techniques such as dropout or further hyperparameter tuning. Overall, the graph confirms the model's strong generalization ability, with consistent training and validation accuracy after sufficient epochs. It can be seen in Figure 4.

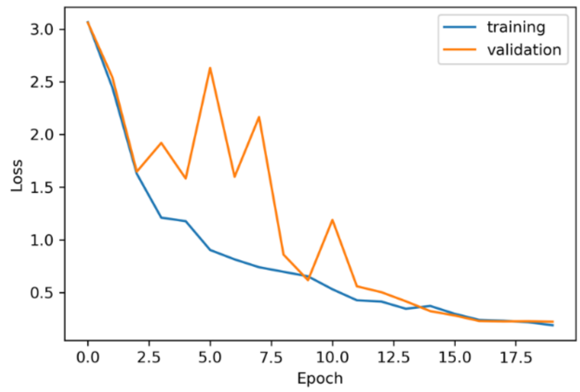

Figure 4. Training loss graph

Training loss graph depicts the reduction in training (blue line) and validation loss (orange line) over multiple epochs, demonstrating how well the ResNet-18 model minimizes classification errors during training. Initially, both losses are high, indicating that the model is learning to extract meaningful features from the *aksara Jawa* dataset. A sharp decline in the first few epochs suggests rapid improvement, followed by a more gradual decrease as the model converges. The validation loss fluctuates, reflecting occasional overfitting, where the model learns patterns in the training data that do not generalize well to unseen validation data. However, after approximately epoch 12, both curves stabilize near a low loss value, confirming that the model has achieved optimal convergence. The remaining fluctuations in validation loss could be mitigated with additional regularization techniques or increased training data. Overall, this graph demonstrates that the model is effectively learning while avoiding excessive overfitting.

Evaluation metrics presented in the Figure 5, which includes accuracy, precision, recall, and F1-score. These metrics are used to assess the effectiveness of the fine-tuned ResNet-18 model in classifying *aksara Jawa* characters. Accuracy represents the proportion of correctly classified images among the total test samples, providing an overall performance measure. Precision indicates the ratio of correctly predicted *aksara Jawa* characters to the total number of predicted instances, ensuring minimal FP. Recall measures the model's ability to correctly identify true instances of each character, highlighting its effectiveness in minimizing FN. F1-score, which is the harmonic mean of precision and recall, provides balanced assessment of the model's classification performance. Figure 6 presents these metrics to give a clear understanding of the model's reliability and effectiveness before proceeding to a detailed discussion of the results.

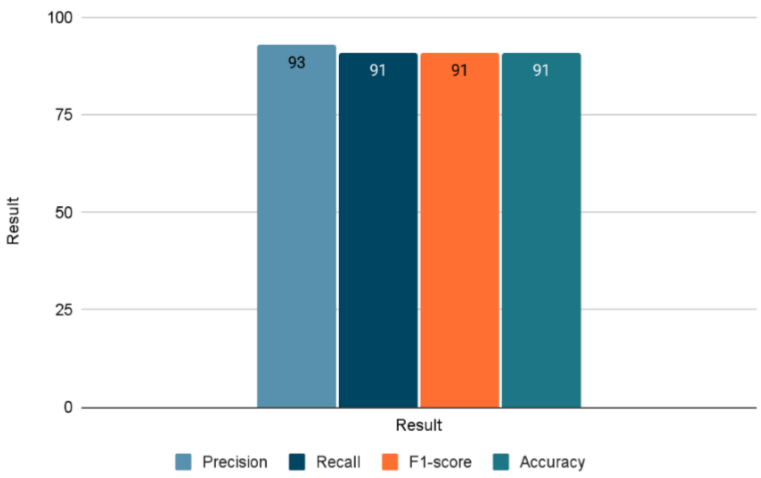

Figure 5. Evaluation of the fine-tuned ResNet-18

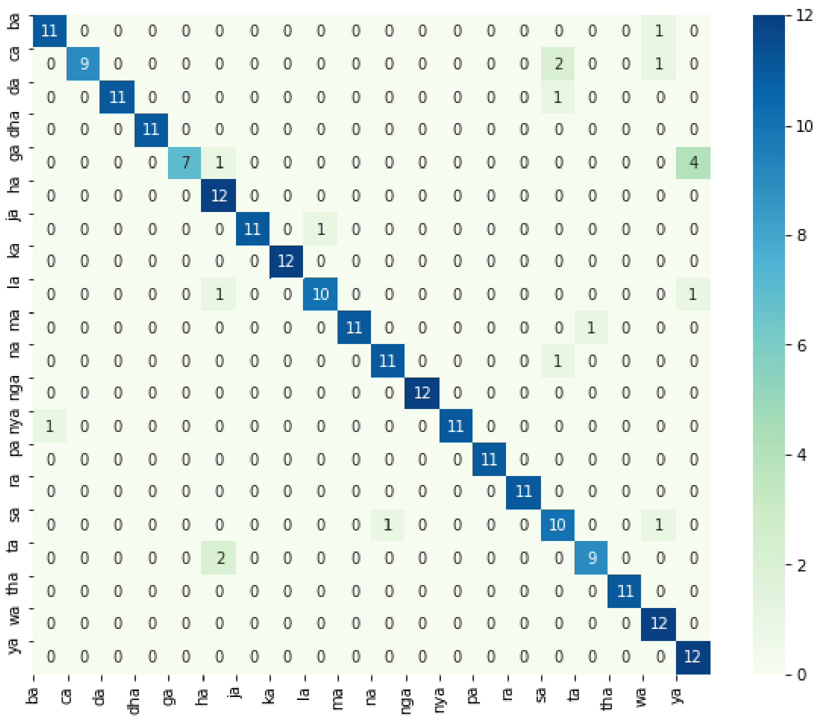

Figure 6. Confusion matrix

The confusion matrix provides a detailed breakdown of the ResNet-18 model's classification performance on the *aksara Jawa* dataset by displaying the number of correct and incorrect predictions for each character class. The diagonal values represent the correct classifications, where the model successfully identified the characters, with most values being high (10-12 occurrences per class), indicating strong classification accuracy. The off-diagonal values represent misclassifications, where some characters were confused with others, often due to visual similarities between certain *aksara Jawa* symbols. Misclassification instances are marked with lighter green shades, showing lower error counts, with occasional errors in the 'ha', 'ja', and 'sa' classes due to their structural resemblance to other characters. The matrix suggests that the model has high precision and recall, but further refinement—such as additional training data, feature extraction enhancements, or tuning hyperparameters—could reduce misclassification rates and further improve the model's robustness. More details in graphic form can be seen in Figure 5.

Evaluation of the fine-tuned ResNet-18 model for *aksara Jawa* classification demonstrates its high reliability and balanced performance across key metrics: precision, recall, F1-score, and accuracy. The model achieved an accuracy of 91%, indicating its overall effectiveness in correctly classifying characters. The precision score of 93% reflects the model's ability to minimize FP, ensuring that predicted characters are highly accurate. The recall score of 91% demonstrates that the model effectively identifies the correct characters while minimizing FN. The F1-score of 91%, which balances precision and recall, confirms that the model maintains strong classification performance across all character classes. These metrics collectively indicate that the ResNet-18 model, optimized with the Adam algorithm, effectively generalizes across different *aksara Jawa* characters, ensuring high recognition accuracy for OCR applications.

4. CONCLUSION

This study successfully implemented and evaluated a fine-tuned ResNet-18 model with Adam optimization for *aksara Jawa* character classification. The model demonstrated high performance, achieving 91% accuracy, 93% precision, 91% recall, and 91% F1-score, confirming its effectiveness in recognizing complex Javanese script. The data preprocessing steps, including resizing, normalization, and augmentation, significantly contributed to the model's robustness. Fine-tuning the pretrained ResNet-18 by freezing initial layers and modifying the FC layer enabled efficient feature extraction, while the Adam optimizer provided stable and adaptive weight updates, ensuring faster convergence and reduced overfitting. The confusion matrix and loss analysis further validated that the model effectively distinguishes between *aksara Jawa* characters, with minor misclassifications occurring in visually similar classes. Despite these promising results, some challenges remain, particularly in cases where similar character structures lead to misclassification errors. Future research can focus on enhancing the model by incorporating larger and more diverse datasets, experimenting with deeper architectures like ResNet-34 or ResNet-50, and integrating denoising techniques to improve image clarity. Additionally, real-world deployment can be explored by developing a mobile or web-based OCR application, enabling automatic digitization of Javanese script for historical and cultural preservation. These advancements will further refine the accuracy and usability of deep learning models for *aksara Jawa* recognition, contributing to the broader field of Indonesian language technology and digital heritage conservation.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data that support the findings of this study are available from Kaggle. Restrictions apply to the availability of these data, which were used under license for this study. Data are available at https://www.kaggle.com/datasets/vzrenggamani/hanacaraka/data with the permission of Kaggle.

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