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JAVANESE SCRIPT HANACARAKA CHARACTER PREDICTION WITH RESNET-18 ARCHITECTURE

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Abstract: This study aims to train computers to recognize Javanese script characters known as Hanacaraka. The evaluation was conducted on the use of Convolutional Neural Network (CNN) with the ResNet-18 architecture in recognizing these characters. The research objective is to overcome traditional character recognition barriers and improve accuracy. The method employed includes building a CNN model with the ResNet-18 architecture and using diverse datasets. The results show a training accuracy of 100%, validation accuracy of 98.01%, and accuracy, precision, recall, and F1-score each at 100%. This study concludes that the developed model successfully achieves a high level of accuracy and contributes positively to the development of Javanese Hanacaraka character recognition technology.

Keywords: convolution neural network (CNN); javanese hanacaraka script; resnet-18

Abstrak: Penelitian ini bertujuan melatih komputer untuk mengenali huruf aksara Jawa Hanacaraka. Evaluasi dilakukan terhadap penggunaan Convolutional Neural Network (CNN) dengan arsitektur ResNet-18 dalam pengenalan karakter tersebut. Tujuan penelitian adalah mengatasi hambatan pengenalan karakter tradisional dan meningkatkan akurasi. Metode yang digunakan mencakup pembuatan model CNN dengan arsitektur ResNet-18 dan penggunaan dataset yang beragam. Hasilnya menunjukkan akurasi pelatihan 100%, validasi 98.01%, dan akurasi, presisi, recall, dan F1-score masing-masing sebesar 100%. Simpulan penelitian ini adalah bahwa model yang dikembangkan berhasil mencapai tingkat akurasi yang tinggi dan memberikan kontribusi positif pada pengembangan teknologi pengenalan karakter Hanacaraka Jawa.

Kata kunci: convolution neural network (CNN); huruf aksara jawa hanacaraka; resnet-18

INTRODUCTION

The development of computer-based learning media has entered a rapid phase, offering a variety of applications to enhance interactivity and the effec tiveness of the learning process. In this dynamic movement, digital image processing is a field that has seen significant advancements, and the implementation of Artificial Neural Network (ANN) technology has become a primary choice. Digital image processing offers various possibilities, including character recognition[1], alphanumeric characters[2], hand writing[3], and special characters such as Javanese script Hanacaraka characters. These applications leverage technological advancements to develop character reco gnition systems that are increasingly accurate and adaptable to various character formats.

Artificial Neural Networks, as information processing models inspired by the human neural network, prove to be an effective approach for understanding and analyzing image data [4]. The use of neural network models to solve specific problems requires sophisticated processes. The main advantage of ANN is its

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ability to recognize patterns by learning from the trained image data [5].

CNN are neural networks tailored for visual pattern recognition, inspired by how the human brain processes visual data[6]. CNN uses convolutional layers to extract local features from input data [7]. CNN with ResNet-18 architecture has proven to be an efficient method for pattern recognition tasks in image data [8][9]. The ResNet-18 architecture, a type of CNN, excels in overcoming the problem of vanishing gradients, enabling the training of deeper models [10]. However, there are still many challenges regarding the recognition of Javanese Hanacaraka script characters, which hold significant historical and cultural value, as shown in Figure 1. The continuous preservation and development of Java nese script require a character recognition system that is not only effective but also efficient.

Some differences between this res earch and previous studies using CN Ns include the study by A. Budiman et al., who identified Javanese script patterns using the Ngaglena script method and Histogram Chain code. However, the current research focuses on the Javanese scri pt Hanacaraka, known as the classical Jav anese script, which presents a unique cha llenge[11]. Muhdalifah et al., who compared pooling methods in the CNN met hod for Javanese script characters[12], and Rasyidi et al. investigated Javanese script characters using the random forest algorithm with 6000 data points, while the current study employs 12000 data points[13].

Therefore, the implementation and development of CNN, especially Res Net-18, are crucial to improving the quality and accuracy of recognizing Javanese Hanacaraka script characters. This research aims to evaluate the effectiveness of the CNN method with ResNet-18 architecture in recognizing Javanese Hanacaraka script characters and addressing variations in writing and classic character recognition challenges.

METHOD

This research utilizes the CNN method with ResNet-18 architecture, using a dataset provided by Hannan Hunafa through the Kaggle website at https://www.kaggle.com/datasets/ hanna hunafa/javanese-script-aksara-jawa augm ented.

The dataset comprises 20 labels of Javanese script characters, totaling 12,000 data points as shown in Table 1.

Table 1. Data on Javanese Script Character Images

No	Character	Amount of Data
1	Ha	600
2	Na	600
3	Ca	600
4	Ra	600
5	Ka	600
6	Da	600
7	Ta	600
8	Sa	600
9	Wa	600
10	La	600
11	Pa	600
12	Dha	600
13	Ja	600
14	Ya	600
15	Nya	600
16	Ma	600
17	Ga	600
18	Ba	600
19	Tha	600
20	Nga	600
Amount		12000

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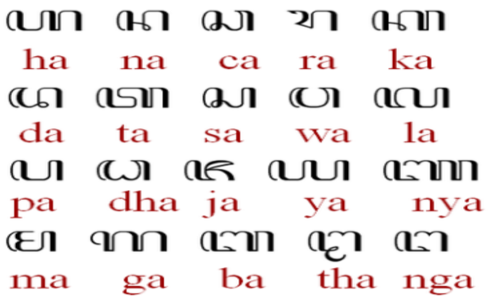

Image 1. Javanese Script Characters

Which are divided into 8,400 training data, 2,400 validation data, and 1,200 test data. The dataset allocation can be seen in Table 2.

Table 2 Data Distribution of Javanese Script Character Images

Character	Training Data	Validation Data	Test Data
Ha	420	120	60
Na	420	120	60
Ca	420	120	60
Ra	420	120	60
Ka	420	120	60
Da	420	120	60
Ta	420	120	60
Sa	420	120	60
Wa	420	120	60
La	420	120	60
Pa	420	120	60
Dha	420	120	60
Ja	420	120	60
Ya	420	120	60
Nya	420	120	60
Ma	420	120	60
Ga	420	120	60
Ba	420	120	60
Tha	420	120	60
Nga	420	120	60
Amount	8.400	2.400	1.200

Convolutional Neural Network

CNN is a feed-forward neural network that specializes in image recognition tasks inspired by biological visual recognition. It has deep learning capabilities [14]. As seen in Figure 2, CNN is composed of input, convolutional, pooling, fully connected, and output layers, in contrast to classic neural networks. In order to create a deeper network, CNN usually consists of multiple convolutional and pooling layers. Fully connected layers may also have a multi-layered structure [15].

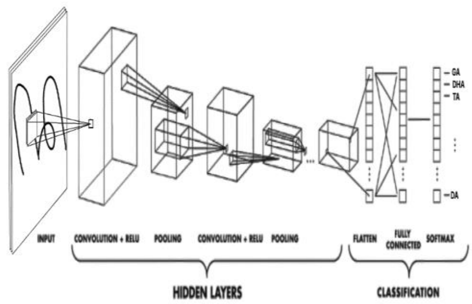

Image 2. Convolutional Neural Network adapted

The core component of CNN is the convolutional layer. Multiple feature maps, each made up of many neurons, are present in each convolutional layer. In order to extract picture features, the convolutional layer uses convolutional kernels to scan the image and completely utilizes information from nearby regions[16].

After entering the data, the CNN method with the resnet-18 architecture is used to train the data, then the test data is entered to carry out classification or detection. To display the resulting image, you must enter validation data, this process is as shown in Figure 3. Some commonly used CNN architectures include ResNet-18[17], MobileNet[18], AlexNet[19], InceptionV3 [20], and other architectures[21].

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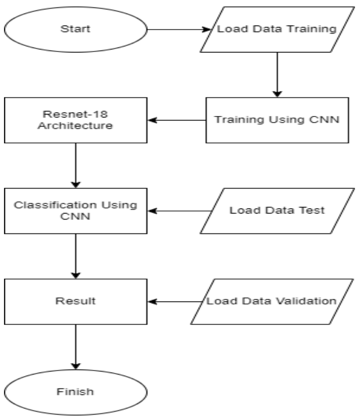

Image 3. Flowchart CNN Method Working System

Residual Network (ResNet-18)

ResNet-18 is a variant of the ResNet architecture with 18 layers, emphasizing the use of residual blocks to address training challenges in neural networks. With two 3x3 convolutions and a shortcut connection, ResNet-18 becomes efficient and performs well[22]. Starting with the initial convolutional layer, this model concludes with global pooling and fully connected layers for classification tasks, as illustrated in Figure 4. Despite its simplicity, ResNet-18 remains effective and can train networks without significant performance degradation[23]. Its main advantage lies in its good generalization ability, especially in image classification tasks.

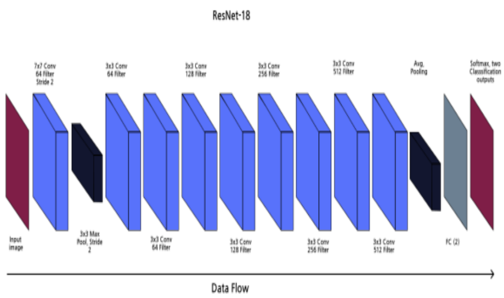

Image 4. ResNet-18 Architecture adapted

At the end of training, an evaluation will be conducted using metrics to measure the detection and classification performance of each CNN model. The metrics used include accuracy, precision, recall, and F1-Score[24]. Below are the formulas used to calculate each metric:

$$Accuracy\,(\%) = \frac{TP+TP}{TP+FP+FN+TN}\; X\; 100\% \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1-score = 2\left(\frac{Precision \text{ x } Recall}{Precision+Recall}\right) \quad (4)$$

True Negative (TN) indicates accurate negative forecasts, whereas True Positive (TP) indicates right positive predictions. False positives, also called false alarms, are denoted by the acronym FP (False Positive). Mistakes, often known as misses, are represented by the symbol FN (False Negative).

RESULTS AND DISCUSSION

In the results phase, the use of Convolutional Neural Network (CNN) techniques and ResNet-18 architecture in recognizing Javanese Hanacaraka script characters shows impressive outcomes.

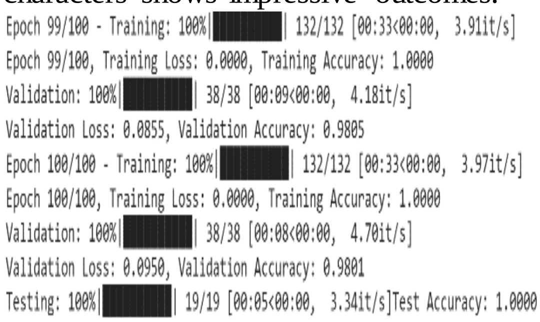
```
Epoch 99/100 - Training: 100%|██████████| 132/132 [00:33<00:00,  3.91it/s]
Epoch 99/100, Training Loss: 0.0000, Training Accuracy: 1.0000
Validation: 100%|██████████| 38/38 [00:09<00:00,  4.18it/s]
Validation Loss: 0.0855, Validation Accuracy: 0.9805
Epoch 100/100 - Training: 100%|██████████| 132/132 [00:33<00:00,  3.97it/s]
Epoch 100/100, Training Loss: 0.0000, Training Accuracy: 1.0000
Validation: 100%|██████████| 38/38 [00:08<00:00,  4.70it/s]
Validation Loss: 0.0950, Validation Accuracy: 0.9801
Testing: 100%|██████████| 19/19 [00:05<00:00,  3.34it/s]Test Accuracy: 1.0000
```

Image 5. Training Results

As seen in Image 5 with 100 epochs, The model achieved 100% training accuracy after 100 epochs, with 98.01% validation accuracy and 0.0950 validation loss. In testing, it reached

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100% accuracy. To determine the accuracy, precision, recall, and F1-score, plug equations (1)-(4) into the confusion matrix provided in Figure 8 to achieve 100% accuracy, precision, recall, and F1-score. This model successfully overcomes traditional obstacles in character recognition. This success will contribute positively to the development of character recognition technology in a specific cultural context.

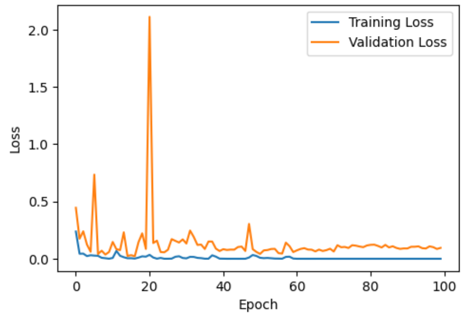

Image 6. Line Graph of Training and Validation Loss Results

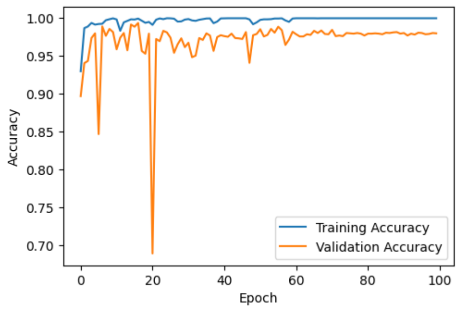

Image 7 Line Graph of Training and Validation Accuracy Results

It is noteworthy in Image 6 and Image 7 that this model can handle variations in letter shapes and the distinctive features of Javanese Hanacaraka script. The test results demonstrate the model's adaptability to the character recognition task commonly encountered in a specific cultural context. From a technology development contribution perspective, the model's reliability opens opportunities for integration into broader application systems.

This actively supports the preservation and development of local culture and offers innovative solutions to support cultural heritage. A detailed analysis provides a comprehensive overview of the quality of character recognition in the Javanese Hanacaraka script, as shown in the confusion matrix in Image 8.

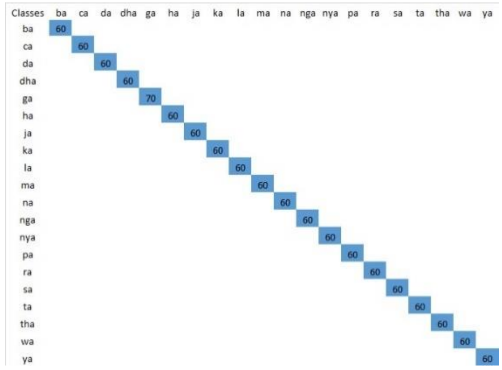

Image 8 Confusion Matrix

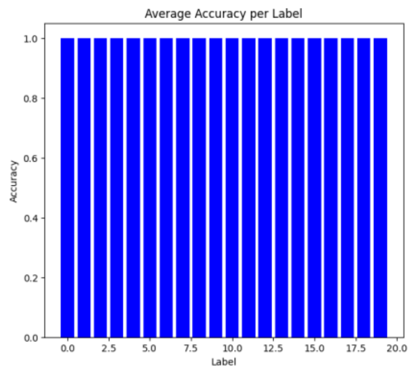

Image 9 Average Accuracy Bar Graph

Training results in Image 9, there are no problems with the ResNet-18 architecture in recognizing Javanese script letter patterns. and some results from the introduction of Javanese script letters are shown in table 3.

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Table 3. Prediction Results

Character	Prediction Results
Ha	
Na	
Ca	
Ra	
Ka	

CONCLUSION

This research demonstrates the effectiveness of using Convolutional Neural Network (CNN) techniques with ResNet-18 architecture for recognizing Javanese Hanacaraka script characters. The model successfully handled various challenges, including processing documents with writing style variations, surpassing traditional character recognition barriers.

In the training phase, the model achieved 100% accuracy, while in validation, it attained a loss of 0.0950 and accuracy of 98.01%, with all evaluation metrics at 100%.

Suggestions for future research include expanding the dataset, fine-tuning hyperparameters, exploring practical applications, and testing resilience to real-world conditions. Comparing the model with other techniques could offer further insights. Overall, future research is expected to enhance Javanese Hanacaraka script character recognition technology, contributing to local culture preservation and development.

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