Bulletin of Electrical Engineering and Informatics
Vol. 14, No. 2, April 2025, pp. 1290~1297
ISSN: 2302-9285, DOI: 10.11591/eei.v14i2.8747

Handwritten Kaganga script classification using deep learning and image fusion

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Article Info

Article history:

Received May 27, 2024
Revised Oct 17, 2024
Accepted Nov 19, 2024

Keywords:

Contrast-limited adaptive histogram equalization
Convolutional neural network
Discrete wavelet transform fusion
Top-hat transform
Traditional script

ABSTRACT

Classification of traditional handwriting script and to preserve many cultures have been developed in some parts of the world, including image classification of handwriting Kaganga script. This study aims to propose a new combination model by implementing top-hat transform (THT) and contrast-limited adaptive histogram equalization (CLAHE) with discrete wavelet transform (DWT) to support the performance of the convolutional neural network (CNN) in Kaganga script classification. The top-hat transform and contrast-limited adaptive histogram equalization with discrete wavelet transform Fusion L2 convolutional neural network (DWT-THCL L2 CNN) models get the best accuracy from the CNN with L1 regularization, CNN with dropout regularization, CNN with L2 regularization and CNN with L2 regularization and CLAHE models. Based on the experimental results, the DWT-THCL L2 CNN model successfully increased training accuracy by 7.76%, validation accuracy by 5.11%, and testing accuracy by 3.73% from the CNN L1 model. The DWT-THCL L2 CNN model received a training accuracy of 99.87%, validation accuracy of 82.61%, and testing accuracy of 82.61%, while the CNN model with L1 regularization (L1 CNN) only received a training accuracy of 92.11%, validation accuracy of 77.50%, and testing accuracy of 78.88%.

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1. INTRODUCTION

Rejang language and Kaganga script are symbols of identity and diversity of an ethnicity, a means of communication, and enrich the variety of cultural languages in Indonesia. However, with time, these functions are slowly experiencing a reduction in terms of knowledge for the current generation. In addition, only a small number of schools in Bengkulu Province include local script learning in the curriculum of local content subjects. This situation assembled learning how to write Kaganga script letters for local people themselves is still very difficult to understand even though the daily language used is derived from Kaganga script letters [1], [2].

Therefore, the preservation of Kaganga script culture is needed with the introduction of Kaganga script so that all circles can understand it. This issue is urgent because the script is an essential asset as cultural heritage. The local government has registered the Kaganga script as an intangible heritage with the educational, scientific, and cultural organization The United Nations Educational, Scientific, and Cultural Organization (UNESCO) [3]–[7].

Several studies of script and handwriting identification to preserve many cultures have been developed in some parts of the world, including image classification of handwriting traditional script. Based on previous research, the convolutional neural network (CNN) method [8]–[15] is a better performing method for image recognition than MobileNet methods [16], [17], dan VGG16 [18], [19]. For example, in a study by Maliki and Prayoga [20], Sundanese script image classification was done from the results of augmentation data using flipping, rotation, and translation. The classification method proposed in this study is CNN, with a success rate of 80% [20].

However, script recognition models using the CNN method are prone to overfitting due to the large number of parameters and the small amount of training data used to train the model. As a result, the model may work well on training samples, but results on validation or testing samples are poor [21]–[23]. Classification of script images using CNN alone still obtains model performance that is not optimal, so there needs to be research with a combination of methods that can identify Kaganga script recognition accurately and in a short time even though it has images that have lighting and noise problems such as scribbles and ink marks [24]–[26].

The contrast-limited adaptive histogram equalization (CLAHE) method is suitable for cases where contrast enhancement is required in an image, especially in low-image imagery scenarios. CLAHE is a local histogram equalization method that overcomes the limitations of histogram equalization by effectively increasing contrast through the adaptive processing of image regions. This is particularly useful in enhancing image contrast and legibility in limited lighting conditions [27]–[29].

However, the effectiveness of CLAHE in enhancing contrast must be adaptable to the shape and characteristics of the script image [30], [31]. Excessive contrast will eliminate the lines that form the script so that there is a need for an approach to morphological analysis techniques such as top-hat transform (THT) to maintain the shape of the morphological form of the script [32]. Get maximum results, the advantages of CLAHE and THT must be combined by image fusion methods such as discrete wavelet transform (DWT), which can combine several images to produce one image by maintaining all the necessary features of the original image [33]. Based on the background, several important points were made in the research analyzed, including:

- Classification of script images using the CNN method will cause overfitting, so regularization methods are needed to reduce their impact on accuracy.
- The image to be classified has direct contrast and noise problems from handwriting, so it can use CLAHE and optimized THT methods to maintain the shape of the morphological form of the script.
- CLAHE and THT models must produce one image by maintaining all the necessary features of the original image, which can be obtained by applying the image fusion method with DWT.
- This study carried out a combination of THT and CLAHE with DWT (DWT-THCL) to support the performance of CNN in Kaganga script classification accurately and in a short time, even though the image has contrast and noise-like strokes and traces of ink.

2. METHOD

This research will compile the stages of research formed in a research framework. This research framework has six stages that must be completed: literature study, data collection, experiment with regularization, experiment with preprocessing, experiment with image fusion, and evaluation measurement. These stages can be seen in Figure 1.

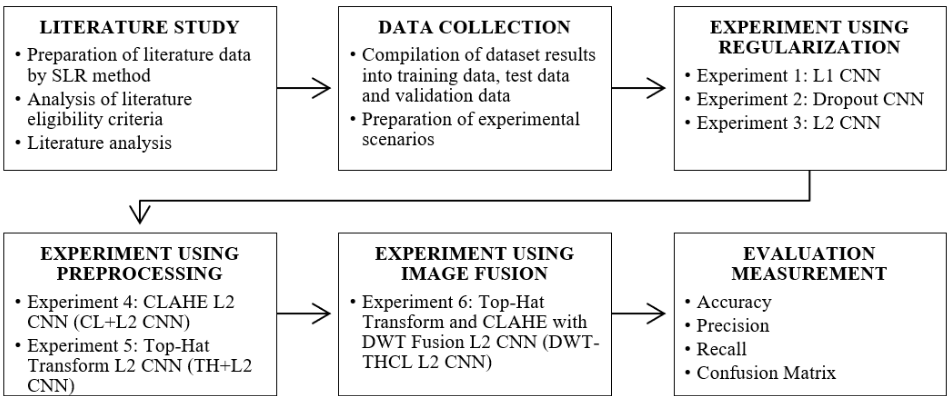

Figure 1. Research method

The first stage was completed by conducting the results of a systematic literature review (SLR) on introducing Kaganga Bengkulu characters. The data used to complete the SLR is taken from several existing libraries and research databases such as Scopus, ScienceDirect, Web of Science, and Google Scholar. This literature review aims to obtain a more in-depth study of improving the accuracy of character images. The second stage is data collection. Primary data collection of the Kaganga script was conducted by involving 50 respondents. Each respondent was asked to write a Kaganga script on the paper provided. This data collection involves organizations related to cultural heritage research, namely digital script research (RAD) by Yayasan Sejahtera Bersama (Bengkulu), cultural and digital research by Yayasan Insani Mandiri Santani (Bengkulu) and Yayasan Budaya Nusantara Digital (Jakarta). An example of Kaganga script data that is a class in this dataset can be seen in Figure 2.

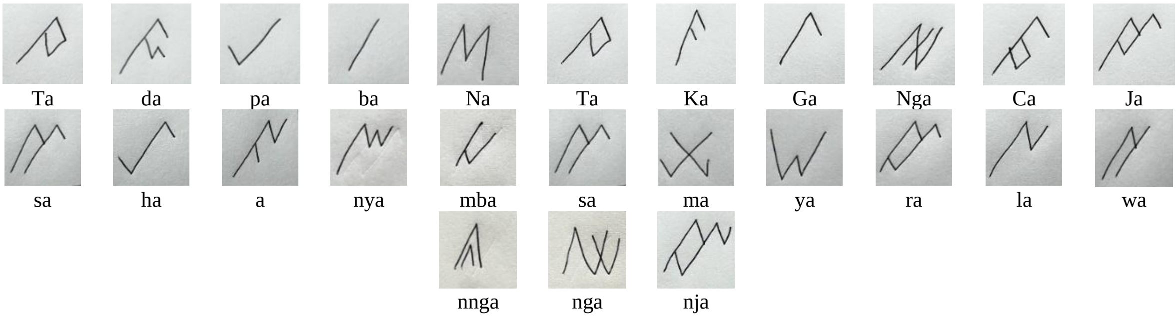

Figure 2. Example of aksara Kaganga dataset

To get the appropriate image size, process editing individually to get an image with the exact resolution. After the editing process is complete, the dataset labeling process follows. Each image of a Kaganga character is labeled according to its respective class. This image data labeling process is done manually by grouping the same Kaganga characters into a folder with 23 Kaganga characters. The dataset used is a Kaganga script image dataset with handwritten images for each character. This dataset totals 1,150 images with a file size of 65.5 MB. Each image is 500 pixels x 500 pixels with the format. *JGP. In this dataset, there are 23 classes, namely "a", "ba", "ca", "da", "ga", "ha", "ja", "ka", "la", "ma", "mba", "na", "nda", "nga", "nja", "nnga", "nya", "pa", "ra", "sa", "ta", "wa", and "ya". Kaganga's image data has a white paper background and precise handwritten strokes. The data is divided into training, validation, and testing, with the most data comparison based on the experimental results ratio of 60:20:20.

The third stage is an experiment for character classification using deep learning architecture with a CNN method model. This experiment aims to see the effect of regularization methods on the overfitting and accuracy of models. Dropout regulation techniques, L1 and L2, were compared in this experiment to determine which regularization performed best. The fourth stage is experimentation using preprocessing. This experiment used the CLAHE method and the THT method. The experiment's results were analyzed to determine the impact on classification accuracy. The fifth stage is experimentation with image fusion. The results of the CLAHE method and THT method will be processed using the image fusion method with DWT. Applying this DWT image fusion is essential in maintaining all the necessary features of the images to be merged.

The final stage is the calculation of the evaluation. This evaluation calculation is needed to see how much performance the model obtains in classifying Kaganga characters. Model performance is measured based on a confusion matrix, and accuracy values and F1-score are used to measure classification model performance by utilizing the sklearn.metrics library. This study will use an evaluation model of accuracy, precision, F1-score, recall, and confusion matrix to measure the performance of the proposed model.

3. RESULTS AND DISCUSSION

This research has conducted experiments for character classification using a CNN. This experiment applied dropout regulation techniques, L1 and L2, to see the effect of regularization methods on overfitting and model accuracy. Each experiment result is compared to determine which regularization has the best performance. Results from experiments using dropout regulation techniques, L1 and L2, can be seen in Table 1.

Table 1. Accuracy result of CNN with dropout, L1 and L2

Model	Abbreviation	Training (%)	Validation (%)	Testing (%)
CNN with L1 regularization	L1 CNN	92.11	77.50	78.88
CNN with Dropout regularization	DO CNN	98.75	86.25	78.88
CNN with L2 regularization	L2 CNN	100.00	86.34	80.12

Based on comparing accuracy results from dropout regulation techniques, L1 and L2, the highest accuracy was obtained using CNN architecture with L2 regularization with a training accuracy of 100.00%, validation accuracy of 86.34%, and testing accuracy of 80.12%. The dropout regularization technique (DO) received a training accuracy of 98.75%, validation accuracy of 86.25%, and testing accuracy of 78.88%. The L1 regularization technique received a training accuracy of 92.11%, validation accuracy of 77.50%, and testing accuracy of 78.88%.

In the training and validation process, the L2 CNN model has a normal distribution of values with an upward curve at accuracy and a descending curve at loss. The difference in lines for values at the training and validation stages in the accuracy and loss models is not very significant, so the model performs well. The accuracy calculation of the L2 CNN model is calculated based on the value of the confusion matrix. The confusion matrix helps visualize the amount of Kaganga script data that is correctly and incorrectly classified by the L2 CNN model based on a predetermined script class. The confusion matrix results of the L2 CNN model can be seen in Figure 3.

a	6	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ba	0	4	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
ca	0	0	6	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
da	1	0	0	4	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ga	0	0	0	1	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ha	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ja	0	0	1	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	3	0	0	0	0
ka	0	0	0	0	2	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
la	0	0	0	0	1	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ma	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0
mba	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0
na	0	0	0	0	0	0	0	0	0	0	0	6	1	0	0	0	0	0	0	0	0	0	0
nda	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0
nga	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0
nja	1	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	1	0	0	0	0
nnga	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	6	0	0	0	0	0	0	0
nya	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0
pa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0
ra	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	3	1	0	0	0
sa	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	4	0	2	0
ta	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	5	0	0
wa	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	6	0
ya	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
	a	ba	ca	da	ga	ha	ja	ka	la	ma	mba	na	nda	nga	nja	nnga	nya	pa	ra	sa	ta	wa	ya

Figure 3. Confusion matrix L2 CNN

Further experiments were conducted using the CLAHE method and the THT method. The experiment's results were analyzed to determine the impact on classification accuracy. Based on the study's results, the CLAHE L2 CNN model (CL+L2 CNN) received a training accuracy of 100.00%, validation accuracy of 85.00%, and testing accuracy of 80.75%. The THT L2 CNN (TH+L2 CNN) model received a training accuracy of 98.50%, validation accuracy of 79.38%, and testing accuracy of 77.64%.

The following experiment was an experiment with the image fusion approach. The results of the CLAHE method and THT method will be processed using the image fusion method with DWT. Based on the study results, the THT and CLAHE with DWT Fusion L2 CNN (DWT-THCL L2 CNN) model obtained a training accuracy of 99.87%, validation accuracy of 82.61%, and testing accuracy of 82.61%. To analyze the performance of DWT-THCL L2 CNN in more detail can be seen from the accuracy model and loss model at each epoch that has been done. The results of the accuracy model and loss model for DWT-THCL L2 CNN can be seen in Figure 4.

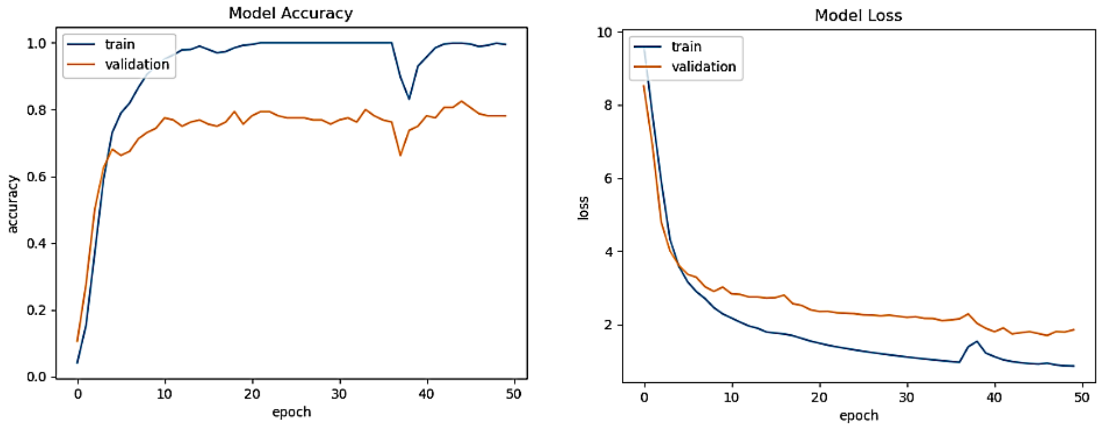

Figure 4. Accuracy and loss of DWT-THCL L2 CNN

In addition to accuracy and loss, a confusion matrix needs to be displayed to visualize the performance of the classification model in matrix form. This confusion matrix includes information about the class and class predictions that DWT-THCL L2 CNN performed on Kaganga script data. The matrix columns represent the predicted Kaganga script data class, while each row represents the predicted result of that class. The confusion matrix of Kaganga script data is in the form of a 23×23 matrix, which is used to visualize the amount of accuracy of the DWT-THCL L2 CNN algorithm in calcifying. The confusion matrix model of DWT-THCL L2 CNN can be seen in Figure 5.

a	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ba	0	4	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
ca	0	0	5	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
da	1	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ga	0	0	0	0	6	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ha	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ja	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0
ka	0	0	0	0	1	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
la	0	1	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ma	0	0	0	0	0	0	0	0	0	6	1	0	0	0	0	0	0	0	0	0	0	0	0
mba	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0
na	0	0	0	0	0	0	0	0	0	0	0	6	1	0	0	0	0	0	0	0	0	0	0
nda	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0
nga	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	1	0	0	0	0	0	0
nja	0	0	0	0	0	0	1	0	0	0	1	0	1	0	4	0	0	0	0	0	0	0	0
nnga	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0
nya	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0
pa	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0
ra	1	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	4	0	0	0	0
sa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	5	0	1	0
ta	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	5	0	0
wa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0
ya	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7
	a	ba	ca	da	ga	ha	ja	ka	la	ma	mba	na	nda	nga	nja	nnga	nya	pa	ra	sa	ta	wa	ya

Figure 5. Confusion matrix of DWT-THCL L2 CNN

The following process groups characters by selecting the number of true positives (TP) obtained in the confusion matrix. The result of the true positive (TP) value is calculated to determine the precision, recall, and F1 score. DWT-THCL L2 CNN results are based on precision value, and recall to F1-score can be seen in Table 2.

Based on the study's results, the THT and CLAHE with DWT Fusion L2 CNN (DWT-THCL L2 CNN) models get the highest accuracy from the previous model. CNN's DWT-THCL L2 model received a training accuracy of 99.87%, validation accuracy of 82.61%, and testing accuracy of 82.61%. The comparison of DWT-THCL L2 CNN results with other models can be seen in Table 3.

Table 2. Evaluation of DWT-THCL L2 CNN based on precision, recall to F1-score

Class	Precision	Recall	F1-score	Class	Precision	Recall	F1-score
a	0.70	1.00	0.82	nda	0.70	1.00	0.82
ba	0.80	0.57	0.67	nga	1.00	1.00	0.82
ca	1.00	0.71	0.83	nja	0.80	0.57	0.67
da	1.00	0.86	0.92	nnga	1.00	1.00	1.00
ga	0.60	0.86	0.71	nya	0.88	1.00	0.93
ha	0.88	1.00	0.93	pa	1.00	0.86	0.92
ja	0.40	0.29	0.33	ra	0.44	0.57	0.50
ka	0.86	0.86	0.86	sa	1.00	0.71	0.83
la	1.00	0.86	0.92	ta	0.83	0.71	0.77
ma	1.00	0.86	0.92	wa	0.78	1.00	0.88
mba	0.78	1.00	0.88	ya	1.00	1.00	1.00
na	1.00	0.86	0.92				

Table 3. Comparation result of classification model

Model	Abbreviation	Training (%)	Validation (%)	Testing (%)
CNN with L1 regularization	L1 CNN	92.11	77.50	78.88
CNN with dropout regularization	DO CNN	98.75	86.25	78.88
CNN with L2 regularization	L2 CNN	100.00	86.34	80.12
CNN with L2 regularization and CLAHE	CL+L2 CNN	100.00	85.00	80.75
CNN with L2 regularization and THT-CLAHE-DWT	DWT-THCL L2 CNN	99.87	82.61	82.61

4. CONCLUSION

This study aims to perform a combination of THT and CLAHE with DWT to support the performance of the CNN in Kaganga script classification accurately even though the image has limited contrast and noise such as streaks and ink marks. The dataset used is a Kaganga script image dataset in handwritten images for each character. This dataset totals 1,150 images with an image size of 500 pixels x 500 pixels and 23 classes. The data is divided into training, validation, and testing with the most data comparison based on the experimental results ratio of 60:20:20. The THT and CLAHE with DWT Fusion L2 CNN (DWT-THCL L2 CNN) models get the highest accuracy from the CNN with L1 regularization, CNN with dropout regularization, CNN with L2 regularization and CNN with L2 regularization and CLAHE models. CNN's DWT-THCL L2 model received a training accuracy of 99.87%, validation accuracy of 82.61%, and testing accuracy of 82.61%. The CNN with L1 regularization (L1 CNN) model received a training accuracy of 92.11%, validation accuracy of 77.50%, and testing accuracy of 78.88%. CNN's DWT-THCL L2 model improved training accuracy by 7.76%, validation accuracy by 5.11%, and testing accuracy by 3.73% from the L1 CNN model.

Future work will concentrate on expanding the dataset size for the handwritten Kaganga script classification project by collecting a diverse range of handwritten samples from individuals of various ages. Incorporating responses from different demographics will enhance the robustness and accuracy of our classification model. A larger and more varied dataset will improve the model's ability to generalize across different writing styles and individual idiosyncrasies, as handwriting characteristics can vary significantly due to factors such as age, education level, and personal writing habits. Furthermore, this enriched dataset will facilitate more effective training of the CNN, leading to improved performance in recognizing and classifying Kaganga script. We also plan to integrate image fusion techniques to enhance the quality of the input images, ensuring the CNN receives clearer and more informative data. This improvement is crucial for achieving accurate classification, as high-quality images can significantly impact the model's overall performance.

ACKNOWLEDGEMENTS

This work is supported by Universitas Sriwijaya and Direktorat Riset, Teknologi, dan Pengabdian Kepada Masyarakat, Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia through research funding with number 090/E5/PG.02.00.PL/2024 cq. 0016.031/UN9/SB1.LP2M.PT/2024.

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