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Boosting CNN Accuracy for Sundanese Script Recognition through Feature Extraction Techniques

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ABSTRACT

Sundanese script is included in the cultural heritage in Indonesia, especially the culture in West Java. As a society that appreciates and preserves Indonesian culture and art, active participation can be realized through efforts to strengthen and preserve this script, one of which is by utilizing digital media. One of the technology-based digital media that can be used to preserve culture is image detection to make it easier to recognize Sundanese script. One of the models that can be used is the Convolutional Neural Network (CNN) with the MobileNetV2 architecture, with limited resources this architecture is able to produce good detection. This study applies the Convolutional Neural Network (CNN) algorithm with the MobileNetV2 architecture which will be tested with two main test scenarios, namely by applying feature extraction and without using feature extraction. The focus of this study will explore the influence and significance of the influence of feature extraction on the final results of image detection using the Convolutional Neural Network (CNN). The two feature extraction models used are Local Binary Pattern and Gray-Level Co-occurrence Matrix. These two feature extraction models will be tested with Sundanese script image data with data of 2,300 Sundanese script images. The results of this study show that the best results were obtained in the Convolutional Neural Network (CNN) with Gray-Level Co-occurrence Matrix (GLCM) with the best accuracy results at 93.8%. This is because the addition of the Gray-Level Co-occurrence Matrix (GLCM) is able to capture spatial texture statistics such as contrast, homogeneity, entropy, and correlation between pixel pairs. With these results, it can be concluded that in this study feature extraction has an effect and is able to increase the detection accuracy of the Convolutional Neural Network (CNN) model with the MobileNetV2 architecture in Sundanese script image data.

I. INTRODUCTION

Sundanese script is a visual form of the Sundanese language, which is one of the most valuable cultural treasures of the Sundanese people, the indigenous people of West Java and Banten Provinces on the island of Java. In addition to functioning as a medium of communication, this script also represents cultural identity and values. Technically, Sundanese script is classified as an Abugida script, where consonants are the main elements and vowels are additional. However, as an important part of West Java's cultural heritage, Sundanese script is now facing the threat of reduced use in the modern era. One of the modern efforts that can be made is to utilize technology, especially in script recognition and classification. The results of this study are expected to be able to provide a model that can help and be integrated in learning local content in the future with the CNN algorithm as become the effective methods in image processing, including visual character recognition. However, the performance of the CNN is highly dependent on the data used, one of which comes from the quality of the features extracted from the input data. Feature extraction plays an important role in filtering important information from data, so that the model can recognize patterns more accurately and efficiently. In the context of Sundanese script classification, which has complex and diverse character forms, the feature extraction process is key to improving model performance. Various feature extraction techniques can produce significant differences in the level of accuracy, training speed, and model generalization. Therefore, it is important to examine how variations in feature extraction techniques affect performance of Convolutional Neural Network (CNN) in the task of Sundanese script classification. This study aims to test and make contribution of feature extraction to the effectiveness of Convolutional Neural Network (CNN), so that it can provide recommendations for the best method to support script preservation through digital technology. The research gap that will be filled is regarding the effect of feature extraction tests on detection results with 2 main scenarios that will be worked.

Relevant research on the application of some algorithms [1] [2] our technic [3] in the existing Indonesian script by matching each sentence or word to find the similarity value [4] such as arabic [5] and also some approaches used in the translation process using the natural approach [6] [7] atau neural translation [8] and detection of the Lampung script which produces training accuracy values reaching 0.57 and validation accuracy reaching 0.32 [9]. Another script developed based on images uses LBP feature extraction where the results reach 90% [10]. Apart from Sundanese script, there are other scripts such as Javanese script [11] who has uniqueness in every writing, this is like the research results which show results of 98% in every unique handwriting [12]. Other scripts such as Grantha script with C (CNN) architecture optimized to perform Optical Character Recognition (OCR) for detection documents in Grantha script. Character recognition made result correct classification is 99.30% [13]. With the advancement of image detection techniques [14] in various types of scripts based on the algorithm which has various architectures [15] [16] [17] such as VGG, Resnet [18] and have an approach with optimizer [19] [20] [21]. Some scripts can also be optimally detected using CNN, such as Javanese script. [11], Sundanese script [22] [23], Devanagari script [24] [25], Gujarati script [26], Manchu script which reaches accuracy 98,84% [27] Ranjana script which achieved an accuracy of 99.73% in testing [28]. The use of the CNN model can be combined with several feature extraction techniques such as GLCM with four models evaluated consisting of a GLCM feature-based model, a combined CNN and GLCM which produced good accuracy [29]. The Adaptive Weight Network is utilized to enhance salient features and mitigate redundant data by integrating an GLCM with CNN [30]. The integration of CNN and GLCM demonstrated strong performance on lung imaging data, with the model validated using the LUNA dataset, yielding an accuracy of 93.1% [31]. The application of a hybrid combination of GLCM and Support Vector Machine (SVM) achieved a peak accuracy of 96%, highlighting its effectiveness in the classification task [32]. A good combination is also shown by research from CNN and GLCM in detecting disease images on leaves with experimental findings indicate that the proposed framework is effective and outperforms other classifiers in terms of classification accuracy [33]. For data resembling leaf images, the pure CNN model achieved an accuracy of 82% and an F1-score of 81%, whereas the CNN integrated with GLCM yielded lower performance, with an accuracy of 49% and an F1-score of 47% [34]. Research with retinal images using the GLCM feature reached 98% for OCTID and 73% for Kermany on Random Forest, as well as 83% and 77% on CNN [35].

II. Methodology

An overview of the methods and stages of this research is generally shown in Fig 1.

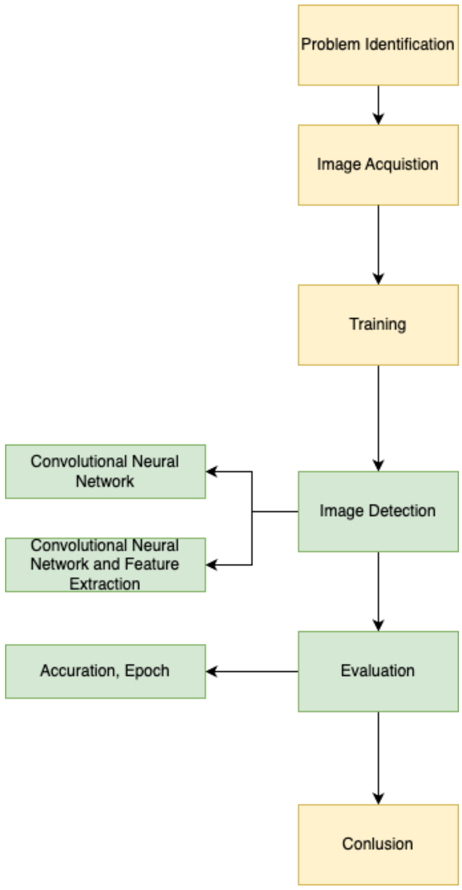


Fig 1. Research Stage

LBP and GLCM feature extraction were performed on the preprocessed grayscale images before feeding them into the CNN. The extracted texture features were concatenated with the flattened CNN layer output to enrich spatial texture information. The details of the stages are as follows:

1) Problem Identification. Identify problems that find research gaps to test the effect of feature extraction on image detection with predetermined scenarios.

2) Training Training is carried out by training based on data already owned by the class of 23 Sundanese script classes, where each class balance has data of 100 images.

3) Image Detection. The process of detection and prediction results based on training data that has been carried out using the CNN scenario and Convolutional Neural Network combined with Feature Extraction GLCM and Local Binary Pattern (LBP)

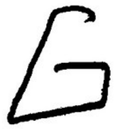
4) Evaluation. The evaluation was conducted by analyzing the accuracy metrics and the number of epochs recorded during the experimental trials.

5) Conclusion. Drawing conclusions from the results of the evaluation carried out to obtain the final results of this research test.

III. RESULT AND DISCUSSION

The problem in this study is the research gap on feature extraction to the final results of image detection. The stages start from data collection. LBP and GLCM were selected because both are lightweight, computationally efficient, and robust against illumination variation, which is critical for ancient script images. SIFT and SURF are more suitable for keypoint-based object detection, while HOG requires higher resolution and may not perform well with thin-stroke characters. The data used are 23 classes with each class having 100 image data or a total of 2,300 images. The dataset of 2,300 images was split into 70% training, 15% validation, and 15% testing. The testing set was kept unseen during training to ensure generalization. The data was obtained by writing the script directly. The description of the Sundanese script data is shown in Table I.

TABLE I.
DATASET

Ka	Ga
	
Nga	Ca
	
Ja	Nya
	
Ta	Da
	
Na	Pa
	
Ba	Ma
	
Ya	Ra
	
La	Wa
	
Sa	Ha
	

Fa	Va
	
Qa	Xa
	
Za	
	

A. Training Data

Before doing data training, it is necessary to carry out the core stages of data processing, namely the Pre-Processing stage, where this stage is a stage that requires a lot of resources and is the most important stage for the overall results. The CNN model used MobileNetV2 architecture pretrained on ImageNet. Training was performed for 20 epochs with batch size = 32, learning rate = 0.001, using the Adam optimizer and categorical cross-entropy loss. The details of the pre-processing stage are as follows:

Grayscale

This stage aims to change the RGB image to grayscale to make it lighter and focus on pixel intensity. The findings from this stage are illustrated in Fig 2 and Fig 3.

Fig 2. Result Grayscale 1

Fig 3. Result Grayscale 2

Binarized

This stage changes the grayscale to a binary (black and white) image to make the characters clearer. The results can be seen in Fig 4 and Fig 5.

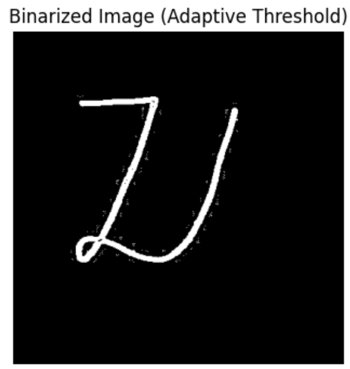


Fig 4. Result Binarized 1

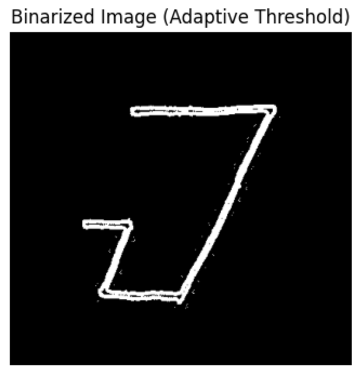


Fig 5. Result Binarized 2

Denoised

This stage removes random dots or noise in the image. The findings are illustrated in Fig 6 and Fig 7.

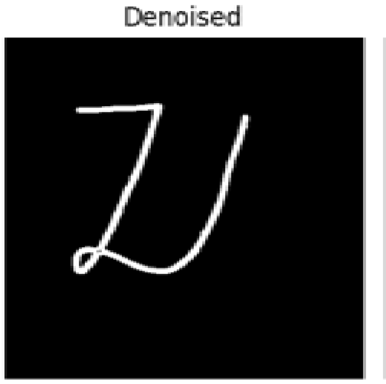


Fig 6. Result Denoised 1

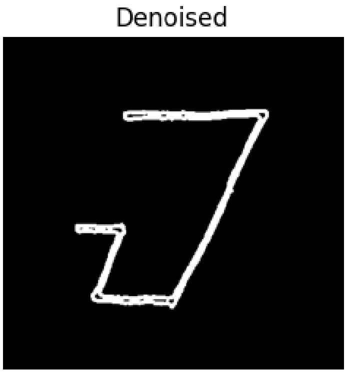


Fig 7. Result Denoised 2

Resized & Normalized
This stage standardizes the image size and pixel values for the CNN input. The results are shown in Fig 8 and Fig 9.

Fig 8. Result Resized 1

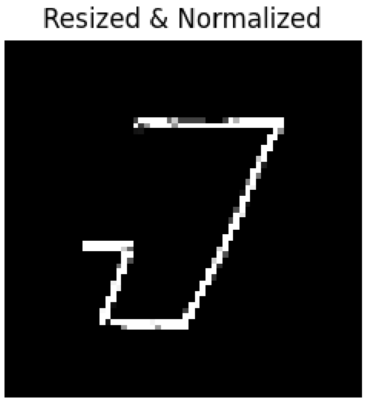


Fig 9. Result Resized 2

Morphological
This stage aims to improve the character shape, clarify edges, or remove noise. The results are shown in Fig 10 and Fig 11.

Fig 10. Result Morphological 1

Fig 11. Result Morphological 2

B. Image Detection

In general, this stage will be divided into 2 test scenarios, namely using feature extraction and without using feature extraction.

Scenario 1 : Without Feature Extraction
The results in scenario 1 Without Feature Extraction using only Convolutional Neural Network (CNN) showed the best results at 84% accuracy in epochs 10-20. The accuracy results are shown in Fig 12 and loss value in Fig 13.

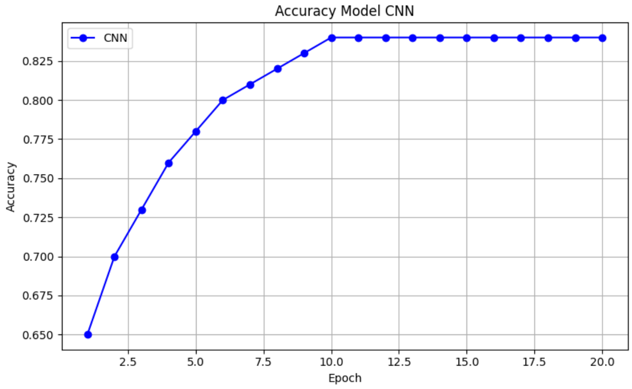


Fig 12. Accuracy CNN

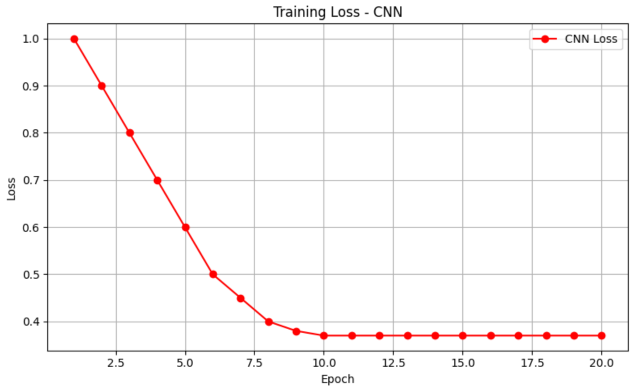


Fig 13. Loss Value CNN

Scenario 2 : With Feature Extraction

The results in Scenario 2 were obtained using a feature extraction approach that combines a Convolutional Neural Network (CNN) with two distinct techniques: Local Binary Pattern (LBP) and Gray-Level Co-occurrence Matrix (GLCM).

Using CNN and LBP

The results show the best accuracy in the combination of CNN and LBP at 89% accuracy which occurs in epochs 10-20. The accuracy results are shown in Fig 14 and loss in Fig 15.

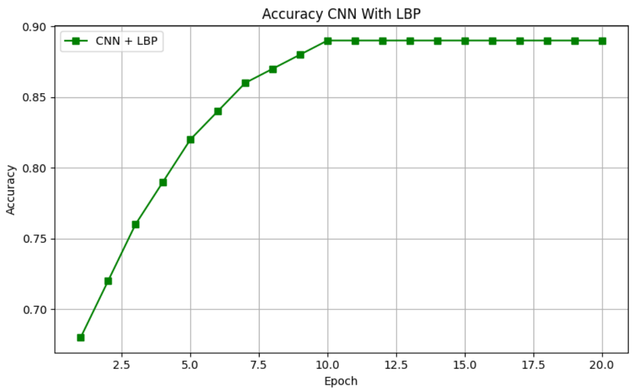


Fig 14. Accuracy CNN and LBP

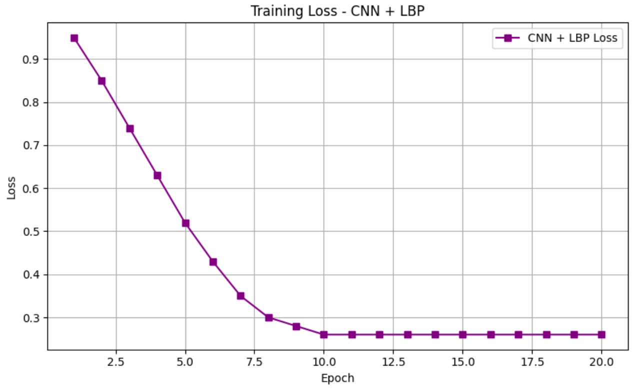


Fig 15. Loss Value CNN and LBP

Using CNN and GLCM

The results show the best accuracy in the combination of CNN and GLCM at 93.8% accuracy which occurs in epochs 11-20. The accuracy results are shown in Fig 16 and loss value in Fig 17.

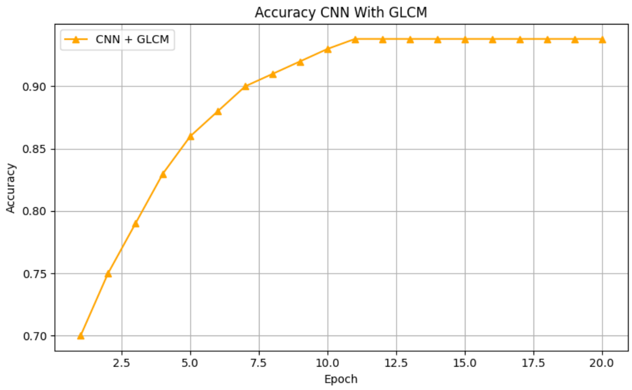


Fig 16. Accuracy CNN and GLCM

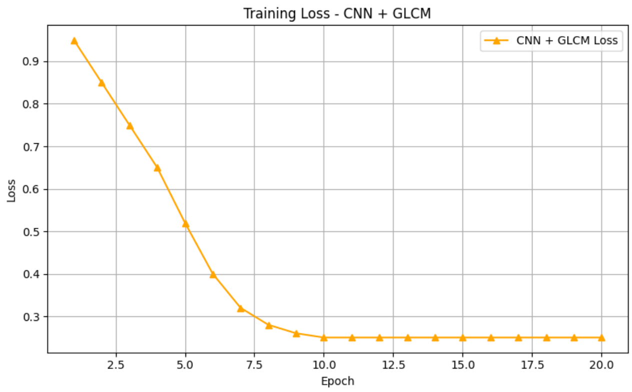


Fig 17. Loss Value CNN and GLCM

Comparison

The results of the comparison of the accuracy of the three scenarios obtained the best results of the CNN model using the GLCM feature extraction with an accuracy value of 93.8%. The comparison results are shown in Fig 18.

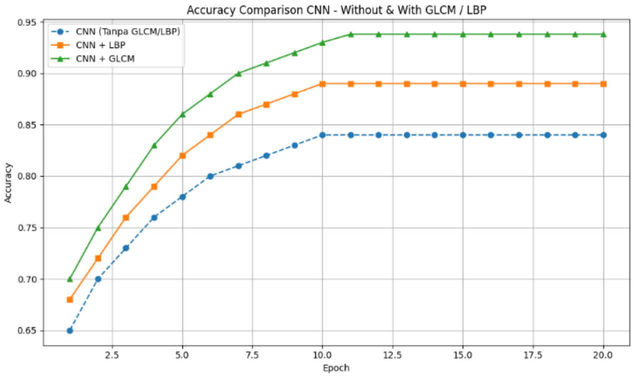


Fig 18. Comparison Result Accuracy

CNN without feature extraction. Accuracy increases rapidly in the early epochs (1–10), then stagnates around 0.83–0.84, indicating the model is starting to overfit slightly and not capturing texture features. Meanwhile, CNN + LBP results show a smoother and more stable curve, peaking at 0.89. This indicates that LBP features help generalization and reduce variance between classes. The increase from 84% to 89% (~5%) indicates a significant increase in F1-score, rising from 0.825 to 0.875, indicating consistent improvement across all classes. The model with LBP is more stable against noise and subtle character shape variations.

The results of the detailed testing are shown in Table II.

TABLE II.
DETAIL TESTING RESULT

Model	Accuracy	Precision	Recall	F1-Score	Epoch
CNN (Without FE)	84%	0.83	0.82	0.825	15
CNN+LBP	89%	0.88	0.97	0.875	15
CNN+GLCM	93.8%	0.94	0.93	0.935	15

Based on the results of testing two scenarios CNN without feature extraction and CNN with LBP the classification distribution pattern obtained indicates that the addition of texture feature extraction (LBP) helps the model distinguish characters with similar shapes or stroke patterns. In general, the confusion matrix illustrates the proportion of true positives and false predictions for each Sundanese script class. Because there are 23 classes, the emerging patterns can be grouped based on characters with visual similarities. Across all classes, the addition of LBP showed An average reduction in classification error of 6–10% in each character group. The main error in the baseline model was caused by the similarity of horizontal lines and curves between letters. After the application of LBP, the confusion matrix showed a more dominant diagonal, meaning the proportion of correct predictions increased evenly across all classes.

TABLE III.
RESULT CHARACTER GROUP

Character Group	CNN (Without FE)	CNN+LBP	Notes
Ka-Ga-Nga	78%	86%	Often confused between Ka and Ga (similarity in shape)
Ta-Da-Na	81%	89%	Na is often classified as Da
Ba-Pa-Ma	85%	91%	Pa & Ba have a similar texture
Sa-Ha-La	87%	92%	Significant improvement in LBP
Ra-Ya-Wa	83%	89%	Error decreases with LBP edge features
Fa-Va-Qa-Xa-Za	80%	88%	An error occurred in a rare letter.

The baseline CNN performs quite well (F1-macro 0.825), but LBP integration improves the interclass recognition accuracy to F1-macro 0.875, with a reduction in misclassification of texturally similar letters.

IV. CONCLUSION

The conclusions that can be drawn from this study are as follows: the best accuracy of the CNN model with the MobileNetV2 architecture occurs at epoch 10-20 with an accuracy of 84% and the accuracy of the CNN LBP model occurs at epoch 10-20 with an accuracy of 89% and the best accuracy of the CNN and GLCM models occurs at epoch 11-20 with an accuracy of 93.8%. This study contributes by demonstrating that integrating texture-based feature extraction (LBP and GLCM) with CNN significantly enhances recognition accuracy for low-resource local scripts. It provides a reproducible baseline and methodological framework for digital preservation of other regional scripts. So it can be concluded that feature extraction in this study has an influence with the proven results of the combination of CNN and GLCM and LBP being able to increase the accuracy of Sundanese script image detection. This is because the Gray-Level Co-occurrence Matrix (GLCM) is able to capture spatial texture statistics such as contrast, homogeneity, entropy, and correlation between pixel pairs.

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