Classification of Cia-cia Letters Using MobileNetV2 and CNN Methods

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***Abstract*— The Cia-cia script, one of Indonesia's threatened cultural heritages, was chosen as the object of study due to the lack of research and documentation on the script. This study aims to create an automated system for classifying Cia-cia letters by utilizing the MobileNetV2 architecture and Convolutional Neural Networks (CNN). By applying deep learning techniques, the developed system achieves high accuracy, reaching 98.35% after 100 epochs. The research involved collecting 1823 handwriting samples covering 23 Cia-cia alphabets, processed through a series of augmentation and normalization techniques to improve model performance. The results show that artificial intelligence-based technology is effective in documenting and preserving traditional scripts, while providing a foundation for the development of educational applications that can reintroduce Cia-cia alphabets to the younger generation. This research contributes to cultural preservation by integrating modern technology to ensure the continued use of the Cia-cia script in the digital era.**

Keywords*— *cia-cia, MobileNetV2, CNN, deep learning

I. Introduction

In this era of advanced globalization, the dominance of technology and global languages is increasing, putting many regional languages worldwide at risk of extinction [1]. Language and script are an important part of a society's cultural heritage, as they not only serve as a means of communication, but also reflect the identity, values and history of that society [2]. Unfortunately, according to UNESCO on January 5, 2022, nearly half of the world's approximately 7000 languages are currently threatened with extinction, largely due to cultural shifts and a lack of attention to preserving these languages. For example, many indigenous languages in different regions of the world, such as the Navajo language in North America or the Maori language in New Zealand, are experiencing a drastic decline in the number of speakers and are on the verge of losing relevance in their home communities [3],[4],[5].

In Indonesia, a country with tremendous linguistic diversity, a similar situation exists. Although Indonesia has more than 700 regional languages [6],[7], many of them are being abandoned by the younger generation, including the Cia-cia language and script from Buton, Southeast Sulawesi. The Cia-cia script, which has been used by the local community for many years [8],[9], is now rarely recognized, even by the locals themselves. The influence of modernization, globalization, and the dominance of national and international languages have led to the diminishing use of the Cia-cia script in everyday life [10].

The lack of research and documentation on the Cia-cia script exacerbates this situation. This lack of knowledge about the script not only threatens its existence but also hinders efforts to preserve it. To overcome this problem, an innovative approach is needed that can help recognize and preserve the Cia-cia script more effectively. One potential solution is the application of deep learning- based pattern recognition technology, specifically the MobileNetV2 architecture with Convolutional Neural Networks (CNN). MobileNetV2 is an efficient, lightweight architecture crafted for various applications on resource-constrained devices while [11] CNNs have proven highly reliable in identifying patterns and characteristics within images [12]. Utilizing MobileNetV2 for image classification enhances letter recognition accuracy while maintaining low computational demands, making it ideal for diverse applications [13],[14].

The application of MobileNetV2 architecture and CNN in image classification tasks has demonstrated effectiveness, as evidenced by various studies, as shown in several studies. B. J. Bipin Nair successfully classified medicinal flowers with an accuracy reaching 98.23% [15]. Neda Pirzad Mashak classified prostate cancer with accuracy ranging from 87% to 95% [16]. Meanwhile, Abhay M. Pamadi successfully classified Diabetic Retinopathy (DR) disease with 78% accuracy for multinomial classification and up to 97% for binary classification [17].

This research aims to design and apply an automated classification system for Cia-cia alphabets using the MobileNetV2 architecture and CNN. By utilizing deep learning technology, this research aims to achieve high accuracy in letter recognition, as well as provide a practical solution that can be accessed and used to digitize this script.

After this research is completed, it is expected to provide a deeper understanding of the Cia-cia script and improve its classification accuracy. Furthermore, this research is expected to increase public awareness about the importance of preserving the script as a significant part of cultural heritage, thus encouraging collaborative efforts in the preservation and development of the Cia-cia script. This research is also expected to inspire future generations to appreciate and learn their cultural heritage.

II. Methods

This research utilizes a systematic approach to process and analyze data pertaining to the Cia-cia alphabet. The steps start from dataset collection, data splitting, data augmentation, image resizing and scaling, application of MobileNetV2

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model for feature extraction and training, and evaluation of model performance using an evaluation matrix. The spesific phases within each step are illustrated in Fig 1.

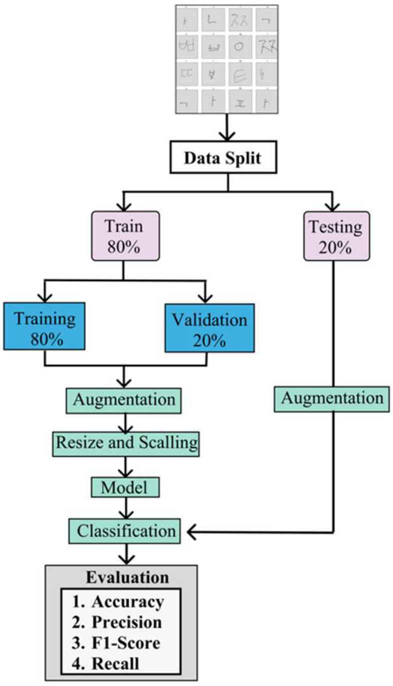


Fig. 1. Research design

A. Data collection

The information for this study was gathered from 1823 distinct samples of handwritten Cia-cia letters. Each sample was categorized into 23 classes representing each letter. The primary source of data was the Cia-cia alphabet letter references available on Wikipedia. To ensure broader representation, additional samples were obtained from volunteer participants, consisting of males and females between 20 and 22 years old.

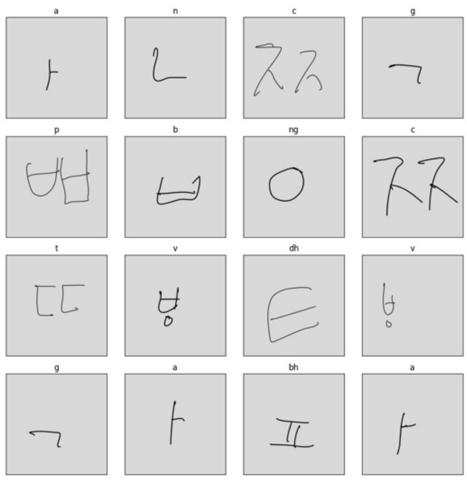


Fig. 2. Sample cia-cia letters

All the samples were collected in a controlled environment using a digital device with a standard handwriting format. During this process, participants were asked to write each letter of the Cia-cia alphabet, which varied in number to cover variations in writing style. All images had a consistent size of 500×500 pixels. The main challenge during data collection was to ensure the clarity of each letter's writing, especially for letters with similar shapes, to avoid bias in classification. Visual examples of letters can be seen in Fig 2.

B. Preprocessing

Data preprocessing serves as a fundamental phase in data mining. Before entering the main processing phase, raw data is first subjected to an initial processing step. This preprocessing of data is typically performed by eliminating inappropriate data. Furthermore, during this process, the data will be transformed into a format that the system can comprehend more effectively.

In this research, preprocessing is performed because the image data collected varies in size, necessitating resizing and normalization to ensure uniform pixel scaling, which can enhance the performance of the algorithm.

The dataset is separated into two primary subsets: 80% allocated for training and 20% for testing. The training subset is used to develop the model, while the testing subset evaluates the model's effectiveness after training is complete. Additionally, the training data is further divided into 80% for actual training and 20% for validation, enabling performance monitoring during training and helping to mitigate overfitting. This data split aims to help the model learn effectively from the training dataset while retaining its ability to generalize well when tested on unseen data.

TABLE I. IMAGE AUGMENTATION TECHNIQUES FOR TRAIN AND VALIDATION

Transformations	**Setting**
Normalization	Range From -1 to 1
Validation Split	0.2
Rotation Range	30
Shear Range	0.2
Zoom Range	0.2
Width Shift Range	0.2
Height Shift Range	0.2
Fill Mode	Nearest

TABLE II. IMAGE AUGMENTATION TECHNIQUES FOR TEST

Transformations	**Setting**
Normalization	Range From -1 to 1

To improve the model's performance and strengthen its generalization capability [18], image augmentation techniques with Image Data Generator are used, which include image normalization in the range of -1 to 1, random rotation transformation up to 30 degrees, shear of 0.2, and horizontal and vertical shifts in the range of 0.2, and nearby. With this approach, the dataset is not only enriched, but also prepares the model to face challenges and variability in the real world, making it more robust and adaptive. A short overview of the augmentation process can be seen in Table I and Table II.

This method is intended to align the scale of the test data with that of the training data, enabling the model to make consistent and precise predictions when faced with new, unseen data. Fig 3 illustrates an example of the results obtained from the applied augmentation. In the data preparation stage, images of 500×500 pixels were resized to 300×300 pixels to achieve a balance between visual details and processing efficiency, and to ensure uniform image dimensions. A scaling technique with a factor of 1./255 was also applied to normalize the pixel values from 0-255 to 0-1, with the aim of speeding up training, improving model performance, and coping with intensity variations more effectively.

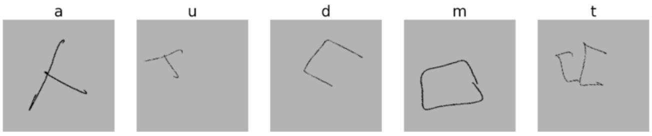


Fig. 3. Sample augmentation for train

By using this method, the training data quality is enhanced for model development, enabling the model to learn more efficiently and produce accurate predictions on unfamiliar data.

This research uses MobileNetV2 as the main feature extractor due to its computational efficiency as well as its ability to perform optimally on limited hardware without sacrificing performance [19]. MobileNetV2 adopts depthwise separable convolutions, which separate spatial and channel convolutions to significantly reduce the number of parameters. The main advantage of this architecture is its feature reuse capability through inverted residuals and linear bottlenecks, which enables better feature representation for large-dimensional image data [20],[21]. In this study, MobileNetV2 is initialized without a classification layer (include_top=False) to focus on feature extraction from 300×300×3 dimensional input images, resulting in a feature map that includes important patterns and objects. The selection of MobileNetV2 is based on its more efficient and accurate performance compared to other models such as ResNet or VGG [22],[23]. Fig 4 provides a depiction of the MobileNetV2 architecture.

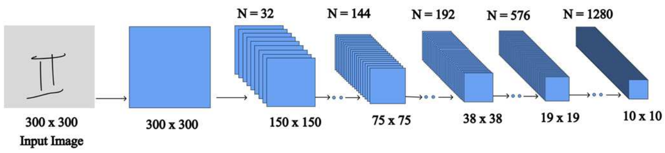


Fig. 4. MobileNetV2 architecture for feature extraction

C. Classification Process

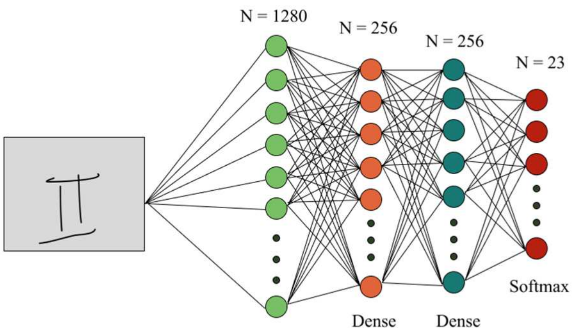


Fig. 5. CNN architecture for classification

This research uses CNN for the classification of Cia-cia alphabets. This model, initialized using pre-training parameters from ImageNet, has proven to be efficient in feature extraction on image data [24],[25]. The fully connected part of MobileNetV2 was modified to support the classification task of 23 classes, corresponding to the number of letters of the Cia-cia alphabet. Two dense layers with 256 neurons and ReLU activation function were added, each followed by 20% dropout to prevent overfitting. The output layer used a softmax activation function to generate class probabilities [26],[27].

The model was trained using Adam's optimizer with a learning rate of 0.0001 and a categorical crossentropy loss function for 100 epochs. Training and validation data were divided into fixed-sized batches, with training parameters chosen based on initial experiments for best results. This architecture was designed to maximize the classification performance of Cia-cia alphabets. The architecture of this CNN can be seen in Fig 5.

D. Evaluation

The evaluation process uses a confusion matrix that produces accuracy, precision, recall, and F1 score values. Accuracy indicates the ratio of correct predictions to total predictions, offering a comprehensive measure of the model's performance. Precision indicates how accurately the model identifies positive instances, i.e. out of all the positive predictions generated, how many are positive. Recall evaluates how effectively the model identifies all positive cases, indicating the percentage of true positives accurately detected. The F1-Score integrates both precision and recall, offering a balanced metric that combines these two aspects. The formula can be seen in equation (1-4) [28],[29].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + TN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

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

$$F1 - Score = \frac{2 \times \frac{TP}{TP + FP} \times \frac{TP}{TP + FP}}{(\frac{TP}{TP + FP} + \frac{TP}{TP + FN})} \tag{4}$$

The evaluation process uses a confusion matrix. Here, TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, consecutively.

III. Result And Discussion

All experimental results are displayed in table format, facilitating a straightforward comparison of the performance metrics averaged across each conducted epoch. The evaluation results for each experiment are presented in Table III.

Table III highlights a significant improvement in the CNN model's performance during the early training epochs. At 20 to 40 epochs, the Accuracy increases from 92.60% to 95.34%, accompanied by consistent improvements in Recall, F1-Score, and Precision. Computation time also increased as epochs increased, from 17 minutes to 32 minutes. At 60 to 100 epochs, the model reached optimal Between 60 and 100 epochs, the model attained its peak performance, achieving an accuracy of 98.35%, indicating that it continued to enhance its learning, even though the enhancement in performance diminished after 60 epochs. After 100 epochs, the performance of the model began to degrade, with accuracy dropping slightly to 97.53% at 200 epochs, indicating overfitting. Although the metrics remained high, adding epochs above 100 did not provide any significant improvement, while the training time continued to grow to almost 167 minutes at 200 epochs. This suggests that 100 epochs is the optimal point in terms of efficiency and performance.

It was found that the use of MobileNetV2 in the classification of Cia-cia letters shows good performance. In the initial stage, with 20 epochs, the Accuracy reached 92.60%, and continued to increase to 98.35% at 100 epochs. In addition, metrics such as Recall, F1-Score, and Precision also reached the best value at 100 epochs, indicating that the model can recognize all classes well and provide accurate and balanced classification results.

TABLE III. RESULTS

Epoch Count	Accuracy (%)	Recall (%)	F1- Score (%)	Precision (%)	Time
20	92.60	92.60	92.67	92.16	17m 0.6s
40	95.34	96.34	95.52	96.23	32m 23.0s
60	97.26	97.26	97.28	97.45	48m 28.1s
80	97.26	97.26	97.25	97.54	64m 20.5s
100	**98.35**	**98.35**	**98.35**	**98.51**	**80m 18.8s**
120	97.80	97.80	97.81	97.94	94m 50.4s
140	97.53	97.53	97.53	97.73	110m 24.4s
160	98.35	98.35	98.35	98.44	126m 28.8s
180	98.08	98.08	98.09	98.24	146m 9.1s
200	97.53	97.53	97.54	97.70	166m 50.3s

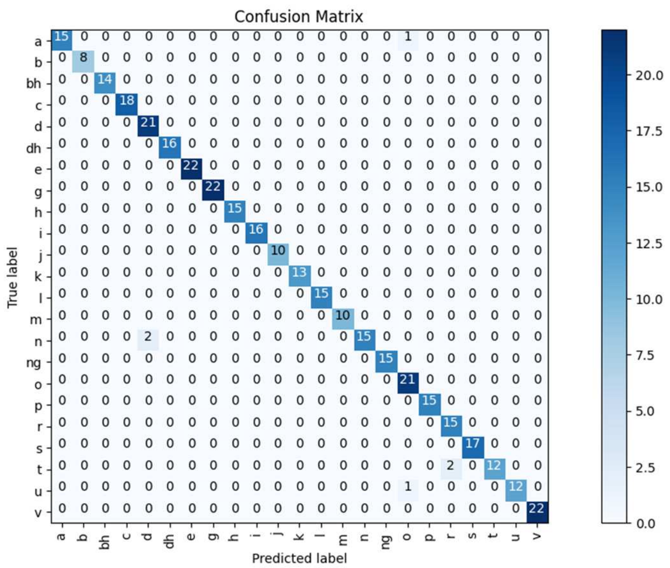
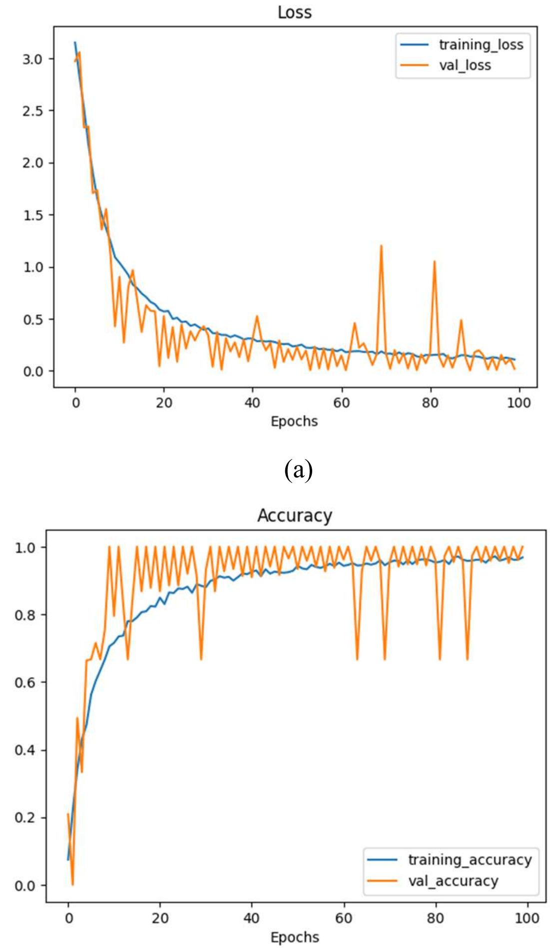


Fig. 6. Confusion matrix of the MobileNetV2 model

After 100 epochs, the performance of the model began to decline, with indications of overfitting. Accuracy decreased slightly at 200 epochs, while computation time increased significantly. Therefore, 100 epochs is considered to be the optimal number in terms of performance and time efficiency, providing the best results without taking too much time.

The results of the Cia-cia letter classification regarding the preservation of Cia-cia letters indicate that the MobileNetV2 machine learning model can achieve remarkably high levels of accuracy, recall, precision, and F1-score, with the peak value reaching 98.35% after training for 100 epochs. These results represent that artificial intelligence-based technology can be an effective tool in recognizing and classifying Cia- cia letters very accurately.



(a)

(b)

Fig. 7. (a) loss graph, and (b) accuracy graph of the proposed model

TABLE IV. PERFORMANCE EVALUATION OF MOBILENETV2 ON VARIOUS DATASETS

Research	Dataset	Accuracy
Metin Akay [30]	Sclerosis	97.20%
Rarasmaya Indraswari [31]	Melanoma	85.00%
Tej Bahadur Shahi [32]	Fruit	96.74%
Our proposed method	**Cia-cia letters**	**98.35%**

Based on Table IV, MobileNetV2 used indicated excellent performance on various datasets. Previous research by Metin Akay and Tej Bahadur Shahi recorded high accuracy on Sclerosis (97.2%) and Fruit (96.74%) datasets. This research with the Cia-cia alphabet dataset showed even higher accuracy, reaching 98.35%. In contrast, the Melanoma dataset studied by Rarasmaya Indraswari had a lower accuracy (85%), possibly due to the complexity of the dataset. Overall, the algorithm still provides competitive performance and serves as a viable alternative for image classification.

Table IV shows that the proposed method has competitive performance on various image datasets, despite their different characteristics. This comparison is relevant because each data set reflects unique challenges, and comparison of similar data sets can strengthen claims. This comparison table also highlights the relative performance of the algorithm as well as their broad potential.

IV. CONCLUSION

The analysis indicates that utilizing the MobileNetV2 machine learning method for classifying Cia-cia letters demonstrates outstanding performance, with accuracy reaching 98.35% after being trained with 100 epochs. This result confirms that artificial intelligence-based technologies are not only effective in recognizing and classifying Cia-cia letters. As such, this research provides a solid foundation for further development in the documentation and digitization of Cia-cia alphabets, ensuring that this cultural heritage remains relevant in the modern era.

Suggestions for future researchers are to explore other models or optimize training parameters to improve accuracy and other evaluation matrices. Further research could also include testing the model on more diverse and complex datasets to ensure the effectiveness of the model in recognizing Cia-cia letters in various contexts and situations. In addition, researchers can consider developing more interactive and educational applications that utilize this character recognition technology, such as learning software or mobile applications that can help the younger generation understand and use Cia-cia letters in everyday life.

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