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Optimization of Hijaiyah Letter Handwriting Recognition Model Based on Deep Learning

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***Abstract*—Hijaiyah handwriting recognition is a challenging research topic. There have been many works and research on character recognition from various languages, but the accuracy value is still being done to improve. Meanwhile, the dataset of handwritten characters with hijaiyah letters is still limited. This study proposes a convolution neural network to recognize and classify hijaiyah writing. The datasets used in this study were Hijja and AHCD. In enhancing the advanced model that has been done previously, we propose the addition of the Adam optimization. In addition, in this study, we have processed both Hijja and AHCD datasets with a composition of 60:20:20. This sophisticated model can improve and be better than the previous model with 91% accuracy results on the Hijja dataset and 98% accuracy on the AHCD dataset. Future work of this work can be made into an application so that the results model that has been built can be used in mobile-based applications.**

Keywords—Classification, Convolution Neural Network, Handwriting Recognition Model, Hijaiyah, Optimization

I. INTRODUCTION

Learning hijaiyah letters is the first step taken to be able to read the Quran [1]. Al-Quran is made in Arabic, and to make Arabic words, hijaiyah letters are needed [2]. Arabic is the 6th most spoken language in the world [3]. However, learning the hijaiyah letters requires an expert or special teacher to guide it. This is a different obstacle during this Covid-19 pandemic, requiring health protocols and staying at home.

Then another mechanism is needed to overcome the problem of learning hijaiyah letters, namely with the help of a system that can recognize handwriting and guide learning by automatically giving a warning if an error occurs. Optical character recognition (OCR) is essential, especially for offline handwriting recognition. The offline handwriting recognition system will differ from the online [4]. In addition, the introduction of Arabic texts has developed very slowly compared to other languages [5].

The problem in recognizing hijaiyah letters is that many characters have similar shapes but relatively different point locations. In addition, hijaiyah letters are widely used by people from various countries, including all Arab countries, besides being used in Persian, Urdu, and Pashto languages.

Along with the rapid development of technology, experts state the existence of the terms (VUCA) volatility, uncertainty, complexity, ambiguity, namely the state of the world with the nature of rapid change, lack of predictability, the absence of a causal chain, and the blurring of reality. Therefore, the challenge is how to respond creatively, and adaptive strategies must be considered to face the future [6].

Currently, the technology being developed is related to learning, namely Machine Learning (ML). ML is a branch of computer science that focuses on developing a system that can learn independently without having to be reprogrammed by humans. ML requires initial data that will be used as training data to produce a good model output. Before making the automatic learning system, a model that has a high accuracy approaching 100% is needed. One of the implementation methods of ML is Deep Learning (DL), to imitate the workings of the human brain using an Artificial Neural Network or artificial reasoning network. Deep Learning with several algorithms as "neurons" will work together in determining and digesting specific characteristics in a data set. Programs in Deep Learning usually use more complex capabilities to study, digest, and classify data. DL algorithms have taken the top place in object recognition because they can produce excellent performance improvements [7], [8].

Research in the introduction of hijaiyah letters has been carried out in several deep learning studies including in 2017, El-Sawy et al. l [9] using the Convolutional Neural Network (CNN) algorithm with the Arabic Handwritten Characters Dataset (AHCD) obtaining an accuracy value of 94.93%, 2019 by Najadat et al. obtained an accuracy of 97.2% [10]. Furthermore, Younis [7] 2017 compared two datasets with 94.7% accuracy in the AHCD dataset and 94.8% AIA9K dataset. Still, the same method was also carried out by Altwaijry et al. in 2021, with 97% accuracy results with the AHCD dataset and 88% with their Hijja dataset [11]. The CNN algorithm has the highest accuracy value when compared to others, such as Time Delay Neural Network (TDNN) [12], dan Multi-Layer Perceptron (MLP) [13], [14].

In addition to hijaiyah letters in Arabic, the development of deep learning (DL) with CNN has resulted in an excellent ability to recognize handwritten characters from various languages [15]–[17], including Chinese [18], Latin [19], Malayam [20], Devanagari [21], etc.

CNN can be used for supervised and unsupervised learning [22]. CNN is a type of neural network widely applied in various fields to solve many problems and provide efficient solutions where there are some translation invariances, such as object recognition and speech recognition applications. However, the CNN DL solution requires many sample data for training which has an impact on the computational requirements of the system, which must be high. However, technological advances, cheaper computer hardware, high-speed networks and performance, and high-performance, distributed computing encourage the use of expensive computing techniques as has been done by research [23] which uses expensive computational techniques with Graphical Processing Units (GPUs) and High-Performance Clusters (HPCs) to classify isolated characters from nine databases.

Currently, a good GPU for deep learning processes uses a popular open source code library from Google, Tensor Flow [24]. Meanwhile, one of the more straightforward frameworks and a high-level application programming interface (API) built on top of Tensor Flow is Keras [25]. Keras is more straightforward than the original Tensor Flow because it uses python programming, which makes writing programs easier.

This study will create a DL model with CNN and use several datasets, namely AHCD and Hijja, using Keras and optimize the model with the Adam Optimization Algorithm. The proposed model is expected to produce and outperform the previous research model. The contributions of this research include reviewing the latest research in the realm of identifying hijaiyah letters, proposing a new, more optimal model, and comparing several datasets to produce better accuracy.

II. Related Work

Many studies have been carried out on identifying letters, including handwritten Arabic hijaiyah letters. On the other hand, the approach taken is still tiny, which results in recognition of handwritten characters of the hijaiyah letter being less common than other letters. However, from several studies that have been carried out, the use of deep learning models using CNN gets quite good results.

Several studies using the Arabic Handwritten Characters Dataset (AHCD) dataset have been carried out, including the Younis study [7] in 2017. The model produces an accuracy value of 94.7% for the AHCD dataset. Younis also uses the AIA9K dataset with an accuracy value of 94.8 %. In addition, there is a study by El-Sawy et al. [9] who used the AHCD dataset and obtained an accuracy value of 88% with CNN, and then they improved CNN's performance with different regulations and techniques the accuracy value increased to 94.93%. On the other hand, Najadat et al. conducted the same study and only got an accuracy value of 92.2% [10].

Another study using the CNN model is the research of Altwaijry and Turaiki [11] using two datasets, AHCD and Hijja. The results of this study obtained an accuracy value of 88% with Hijja and 97% with AHCD.

Meanwhile, in this study, we try to optimize the model by applying the ADAM optimization algorithm, so the accuracy results are hoped to be better than in previous studies. This study will use two datasets, namely Hijja and AHCD.

III. Methodology

The methodology in this study is illustrated in Figure 1. Starting with preparing the dataset, then preprocessing, and then the modeling process. The last stage is to evaluate the results of the modeling process.

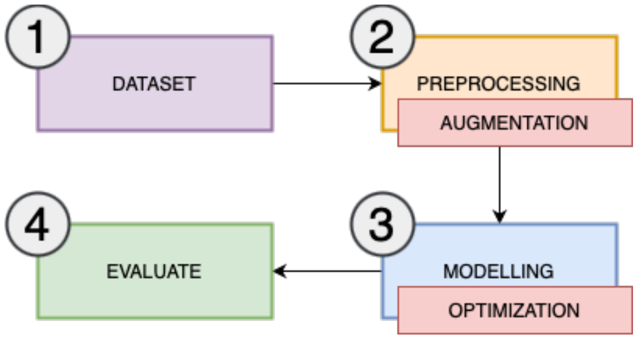

Fig. 1. Methodology

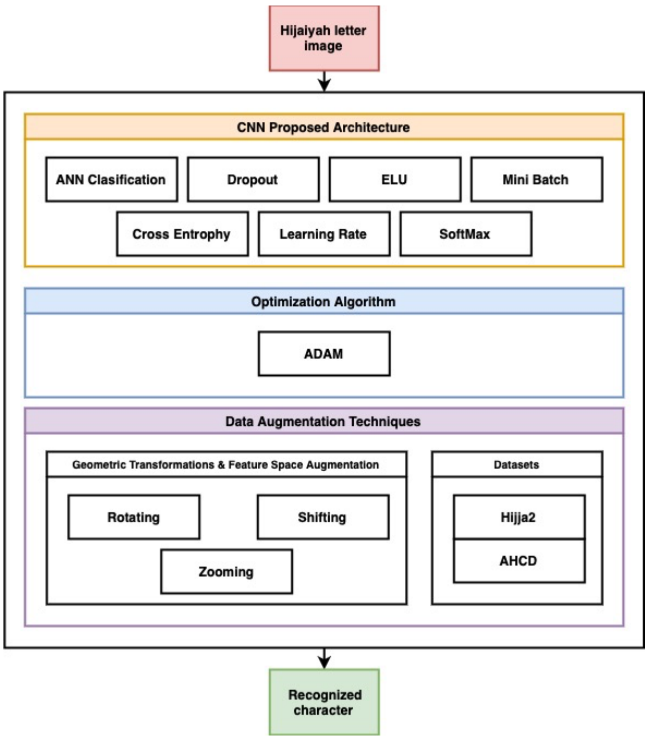

Fig. 2. The proposed hijaiyah letter recognition scheme

While the proposed hijaiyah letter recognition scheme can be seen in Figure 2, each dataset of Hijaiyah letters Hijja and AHCD is then processed with CNN architecture, a popular deep learning method [26], [27]. The novelty of this research is using the ADAM optimization algorithm. After that, three data augmentation techniques were used in this study.

In CNN, several architectures are well known among researchers because of their uniqueness and ability to obtain high accuracy. Among them is LeNet-5 made by LeCun et al.

[28], AlexNet created by Krizhevsky et al. [29], Network In Network (NN) created by Lin et al. [30], VGG-16 prepared by Simonyan et al. [31], Inception by Szegedy et al. [32], and ResNet by He et al. [33]. Of course, each CNN architecture above is unique. However, almost all of these architectures have something in common, namely the deeper an architecture is, the smaller the H×*W* dimension and the C more large.

A. Dataset

This study uses two open source datasets of handwritten hijaiyah letters, namely Hijja2 and AHCD, with dimensions of 32 x 32 x 1 pixel. Another advantage of this study is that the dataset has been divided by validation, with a weight of 60:20:20, training data 60%, validation 20%, and testing 20%.

The first dataset used is the open source Hijja dataset with the url https://github.com/israksu/Hijja2 with a total of 47,434 characters [34]. This data set of hijaiyah letters was written by 591 Arabic-speaking school children aged seven to twelve years which was collected from January to April 2019 in Riyadh, Saudi Arabia.

CSV.zip contains four files, with letters in alphabetical order:

1. X_train.csv: training set, with 37933 rows
2. y_train.csv: training set label, with 37933 rows
3. X_test.csv: training set, with 9501 lines
4. y_test.csv: training set label, with 9501 lines

Contributors include: Najwa Altwaijry, Monera Al-Megren, Haya Al-Shumisi, Lamya Al-Arwan, and Isra Al-Turaiki. The *.png format dataset consists of 29 classes, namely alif, ba, ta, tha, game, ha, kha, dal, thal, ra, zay, sin, shin, sad, dad, da, za, ayn, gayn, fa, qaf, kaf, lam, mim, non, ha, waw, ya, and hamza.

The second dataset is the Arabic Handwritten Characters Dataset (AHCD) at the url https://www.kaggle.com/datasets/mloey1/ahcd1 totaling 16,800 [35]. Sixty people between 19 and 40 wrote this dataset. The dataset consists of 28 classes and is divided into a training set of 14,440 characters and a test of 3,360 characters.

B. Preprocess and Augmentation

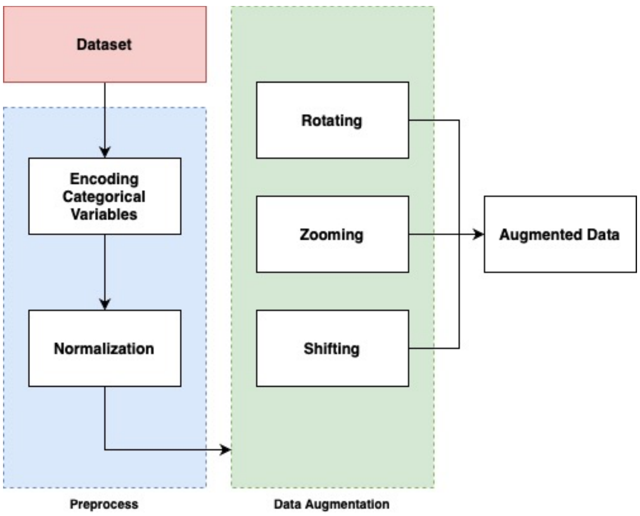

Fig. 3. Preprocessing and Data Augmentation

The preprocessing and augmentation stages are illustrated in Figure 3. The data is firstly performed by encoding categorical variables by taking one of a limited number of possible values and assigning other observation units to specific groups.

Next, perform normalization to bring all data into a range between 0 and 1. In neural networks, it is best to normalize and also scale them. Meanwhile, several techniques are used at the data augmentation stage, including rotation, zooming, and shifting.

C. Modeling and Optimization

The deep learning model consists of the layers in Figure 4. In this model, it is composed of Conv2D, Flatten, Dense, and Dropout layers. To prevent overfitting, a Dropout layer is used by removing neurons in the form of hidden and visible layers in the network.

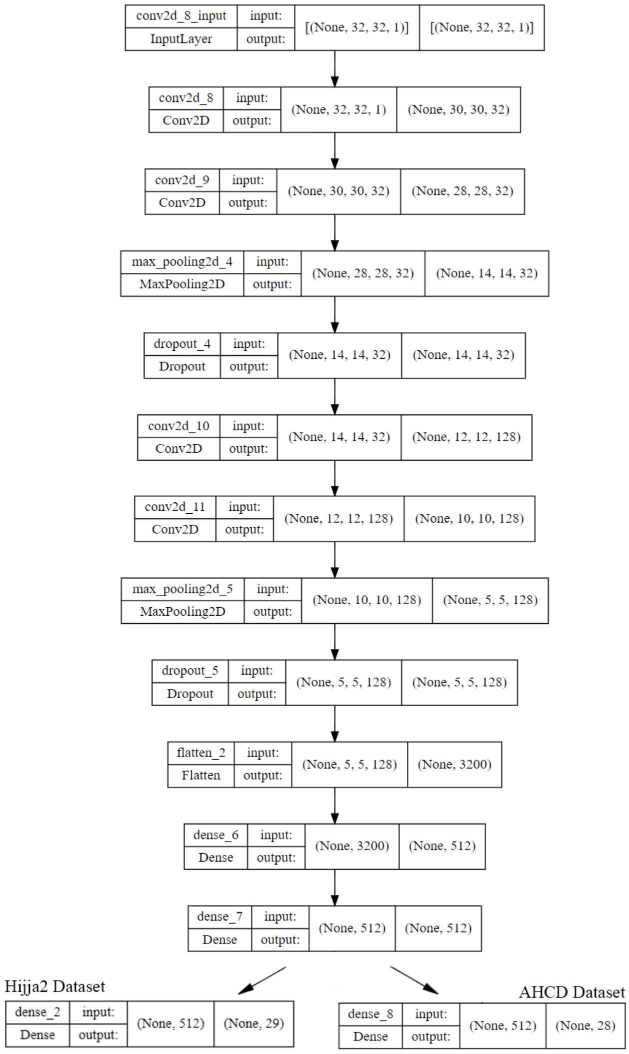

Fig. 4. Deep Learning Layer Model

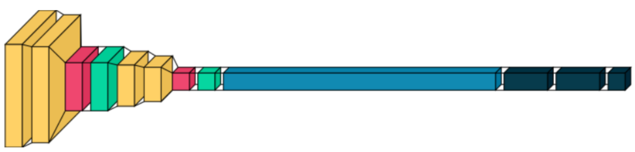

Fig. 5. Deep Learning Model Visualization

Figure 5 shows the visualization of the designed deep learning model. It can be seen that the layer described as yellow is the Conv2D layer; red color, which is the MaxPooling2D layer; green color, namely the Dropout layer; light blue color, namely Flatten layer; and dark blue color, namely the Dense layer. In the last layer, there are differences in units because, in the Hijja2 dataset, there are 29 classes available, but in the AHDC dataset, there are 28 classes. The AHDC dataset does not have a class labeled 'Hamza.'

The loss function used is categorical entropy. This is because the label has been encoded at the preprocessing stage. The optimization used is Adam. Adam is an optimization algorithm that replaces the classic stochastic gradient descent (SGD) procedure for iteratively updating the network weights based on the training data.

D. Evaluate

The deep learning model that has been built is evaluated using a classification report. A classification report is a performance evaluation in machine learning that shows precision, recall, F1 Score, and support of a classification model.

There are several categories of possible cases [36]:

- True Positive (TP): the case where the hijaiyah letters are predicted according to the (Positive) class and match the (True) class.
- True Negative (TN): a case where the hijaiyah letter is predicted to be inappropriate (Negative) for its class and does not match (True) its class.
- False Positive (FP): a case where the hijaiyah letters are predicted to match the (Positive) class, and it turns out to be an inappropriate (False) class.
- False Negative (FN): a case where the hijaiyah letter is predicted to be incompatible (Negative) for its class, and it turns out to be true (True) for its class.

Precision (P) is the ratio of the correct prediction to the overall positive predicted result. Precision explained, "What percentage of hijaiyah letters are by their class of the total predicted hijaiyah letters according to their class ."Precision uses the function in equation (1).

$$Precision\ (P) = \frac{True\ Positive\ (TP)}{(True\ Positive\ (TP) + False\ Positive\ (FP)} \dots (1)$$

Recall (R) is the correct prediction ratio to the total number of correct data. Recall explained, "What percentage of hijaiyah letters are predicted according to their class compared to all hijaiyah letters by their class ."Recall using the function in equation (2).

$$Recall\ (R) = \frac{True\ Positive\ (TP)}{(True\ Positive\ (TP) + False\ Negative\ (FN)} \dots (2)$$

F1 Score is a weighted ratio of the average precision and recall. F1 Score uses the function in equation (3).

$$F1\ Score = \frac{2X\ (Recall\ (R) x\ Precission(P))}{(Recall\ (R) + Precission\ (P)} \dots (3)$$

Accuracy (A) is the ratio of the correct predictions of the actual data. For example, accuracy explains, "What percentage of hijaiyah letters are predicted according to their class from the total data ."Accuracy uses the function in equation (4).

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + FP + FN + TN} \dots (4)$$

IV. Result and Analysis

The experimental environment was using a laptop with a 64-bit Windows 11 operating system, 16 GB RAM with an AMD Ryzen 9 processor running in Google Collaboratory using a GPU from Google Collaboratory. Some of the results obtained include:

a. Hijja2 Dataset

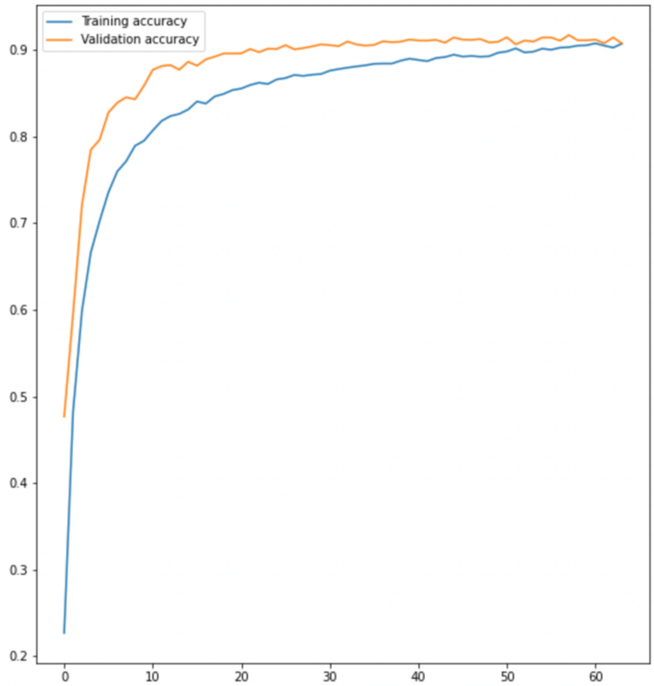

Fig. 6. Accuracy Metrix

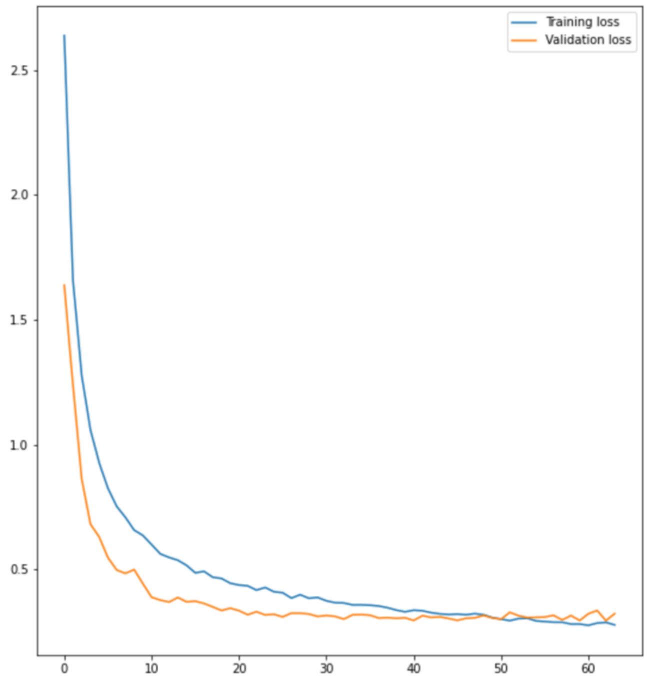

Fig. 7. Loss Metrix

Using the model created, the training and validation accuracy results are found for the Hijja2 dataset in Figures 6 and 7.

The results of this deep learning modeling, then evaluated by a classification report using test data, can be seen in table 1.

The training accuracy and validation accuracy obtained in the last epoch was 90.7% and 90.72%, the highest training accuracy could reach 90.73%, and the highest validation accuracy could reach 91.69%.

b. AHCD Dataset

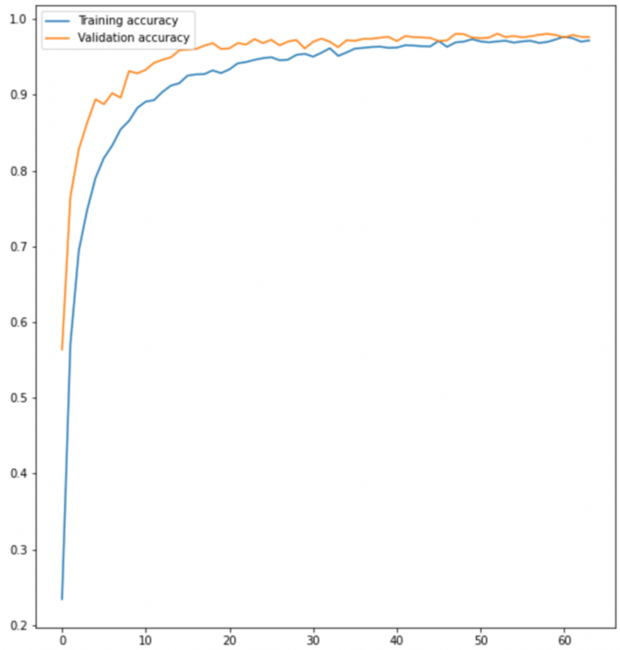

Fig. 8. Accuracy Metrix

The results of training and validation accuracy for the AHCD dataset were found using the same model, which can be seen in Figures 8 and 9.

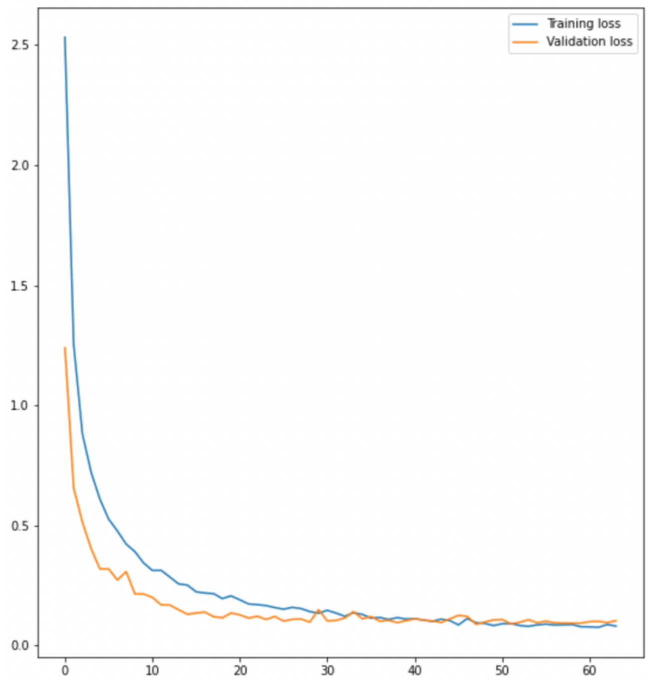

Fig. 9. Loss Metrix

TABLE I. EXPERIMENTAL RESULTS ON THE HIJJA DATASETS

No	Characters	Precision	Recall	F1-Score
1	Alif	1.00	0.98	0.99
2	Ba	0.95	0.94	0.95
3	Ta	0.89	0.93	0.91
4	Tha	0.94	0.93	0.94
5	Gim	0.92	0.96	0.94
6	Ha	0.90	0.86	0.88
7	Kha	0.93	0.85	0.89
8	Dal	0.80	0.74	0.77
9	Thal	0.76	0.80	0.78
10	Ra	0.90	0.93	0.91
11	Zay	0.93	0.88	0.91
12	Sin	0.97	0.95	0.96
13	Shin	0.94	0.99	0.96
14	Sad	0.87	0.91	0.89
15	Dad	0.90	0.92	0.91
16	Da	0.94	0.95	0.94
17	Za	0.97	0.94	0.95
18	Ayn	0.91	0.80	0.85
19	Gayn	0.94	0.85	0.89
20	Fa	0.88	0.81	0.84
21	Qaf	0.86	0.96	0.91
22	Kaf	0.86	0.96	0.91
23	Lam	0.91	0.93	0.92
24	Mim	0.91	0.95	0.93
25	Non	0.82	0.87	0.84
26	Ha	0.94	0.92	0.93
27	Waw	0.95	0.96	0.96
28	Ya	0.91	0.97	0.94
29	Hamza	0.92	0.83	0.87
	Accuracy			0.91
	Macro Avg	0.91	0.91	0.91
	Ighted Avg	0.91	0.91	0.91

The results of this deep learning modeling, then evaluated by a classification report using test data, are in table 2.

TABLE II. EXPERIMENTAL RESULTS ON THE AHCD DATASETS

No	Characters	Precision	Recall	F1-Score
1	Alif	0.99	0.98	0.99
2	Ba	1.00	0.99	1.00
3	Ta	0.92	0.99	0.96
4	Tha	0.99	0.98	0.99
5	Gim	0.99	1.00	1.00
6	Ha	0.99	0.97	9.88
7	Kha	0.94	0.99	0.97
8	Dal	0.95	0.98	0.97
9	Thal	0.98	0.95	0.97
10	Ra	0.96	0.97	0.97
11	Zay	0.97	0.96	0.97
12	Sin	0.99	1.00	1.00
13	Shin	0.99	0.99	0.99
14	Sad	0.98	0.99	0.98
15	Dad	1.00	0.97	0.99
16	Da	0.98	0.91	0.94
17	Za	0.91	0.98	0.95
18	Ayn	0.98	0.95	0.97
19	Gayn	0.97	0.98	0.98
20	Fa	0.97	0.96	0.97
21	Qaf	0.96	0.97	0.96
22	Kaf	0.98	1.00	0.99
23	Lam	1.00	1.00	1.00
24	Mim	0.98	0.99	0.99
25	Non	0.99	0.93	0.96
26	Ha	0.98	0.98	0.98
27	Waw	0.98	0.97	0.98
28	Ya	1.00	0.99	1.00
	Accuracy			0.98
	Macro Avg	0.98	0.98	0.98
	Ighted Avg	0.98	0.98	0.98

The training accuracy and validation accuracy obtained in the last epoch is 97.16% and 97.62%, the highest training accuracy can reach 97.67%, and the highest validation accuracy can reach 98.07%.

V. Conclusions

This paper proposes optimizing the recognition model for classifying hijaiyah written characters using the Hijja character dataset and the Arabic Handwritten Characters Dataset (AHCD) using the Convolutional Neural Network (CNN).

In improving the model from several previous research results, we have implemented the ADAM optimization algorithm and different data augmentation techniques, and the dataset has been divided by validation, with a weight of 60:20:20, training data 60%, validation 20%, and testing 20%. As a result, the model that has been built can solve the classification problem well, with an accuracy of 91% on the Hijja2 dataset and 98% accuracy on the AHCD dataset.

An interesting future work direction is dataset optimization and dataset combination experiment. Meanwhile, the resulting model can be developed into a mobile-based application to make it easier to identify the type and quality of hijaiyah writing.

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