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Comparison of the Accuracy of The Bahasa Isyarat Indonesia (BISINDO) Detection System Using CNN and RNN Algorithm for Implementation on Android

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Abstract

Communication is a process of exchanging information that aims to establish relationships between humans. Communication difficulties are an obstacle for people with deaf disabilities or often called Deaf Friends, where they find it difficult to interact with friends around them. Sign language is the main medium of communication used worldwide by people with disabilities i.e. deaf and speech impaired. Communication between deaf people and those around them is often an obstacle because most people do not understand sign language which is often used as a medium of communication by deaf people. In dealing with this problem, researchers want to analyze the accuracy level of the Android-Based Bahasa Isyarat Indonesia Detection System (BISINDO) using the Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) methods in order to determine which methods can be implemented to an Android device. This study shows that Convolutional Neural Network (CNN) has a greater and more stable accuracy rate compared to the Recurrent Neural Network (RNN) model where the CNN model produces an accuracy rate of 89%, and indicates that the ability to recognize images based on the division of Bahasa Isyarat Indonesia (BISINDO) alphabetic classes is good

Keyword: Sign Language, Bahasa Isyarat Indonesia (BISINDO), Convolutional Neural Netwroks (CNN), Recurrent Neural Nerwork (RNN), Image Processing

1. INTRODUCTION

Communication is a tool or process of information exchange that functions to establish relationships between humans [1]. Communication difficulties are an obstacle for people with deaf disabilities, often called Deaf Friends, because they find it difficult to interact with friends around them. One of the ways they communicate is by using sign language. Based on data quoted from Arisandi and Satya journals, the number of people with disabilities has increased over the past two years. In 2020, there were 197,582 people with disabilities, and in 2021, this figure increased to 207,604 people with disabilities, while for people with disabilities who are speech impaired and deaf, in 2022, they reached 19,392 people, which is 9.14% of the total number of people with disabilities in Indonesia [2]. Sign language is the main communication medium used worldwide by people with disabilities, namely the deaf and speech impaired [3]. Sign language uses hand gestures, hand positions, facial expressions, and body movements to convey an expressed meaning. Sign language in each country has different signs, such as American Sign Language (ASL), which has a complete visual using signs made through hand movements combined with facial expressions and body gestures [4]. The two types of sign language used in Indonesia are the Sistem Isyarat Bahasa Indonesia (SIBI) and the Bahasa Isyarat Indonesia (BISINDO). BISINDO is a natural sign language that comes from Indonesia's indigenous culture and can be easily used in everyday interactions with people who do not have sign language. [5]. The speed and practicality of BISINDO make it easy to understand and understand by the deaf, even though it does not follow the grammatical benefits of Indonesian. Hand gesture recognition has been an active area of research over the past 20 years, with a variety of approaches proposed. Hand gesture recognition is an active research area with many and varied applications, such as sign language recognition [6][7]. BISINDO and the Indonesian SIBI are two types of sign language in Indonesia.

In the era of rapidly evolving technology, the implementation of software-based sign language detection systems is becoming increasingly important to improve inclusivity and accessibility. This detection system allows users to translate hand gestures into text or voice, thus expanding the range of communication between deaf individuals and people who do not use sign language. The research entitled "Application of the

Convolutional Neural Network Method in Sign Language Classification" written by Kersen and Widhiarso, 2023, examines the creation of American sign language software using the Convolutional Neural Networks (CNN) method. This study produced a classification of American sign language using the CNN method with an accuracy rate of 52% on all letters, some letters such as B, K, U, V, and W that were tested experienced errors when classification, because they had the same letter shape[8]. The research entitled Real-Time Sign Language Alphabet Recognition Using Convolutional Neural Network and Recurrent Neural Network Methods written by Devina Yolanda, Kartika Gunadi, and Endang Setyati, discusses the creation of a real-time sign language alphabet recognition system. Where this study uses the CNN and Recurrent Neural Network (RNN) methods with input in the form of video. The CNN method is used as feature extraction in spatial features while RNN is tasked with correlating between frames extracted by CNNs in temporal features. The results of this study are in the form of text alphabet display which is the result of sign language alphabet recognition with an average accuracy level of 60.58% on all letters, while real-time testing failed because the technology used was not enough to support the architecture made by Yolanda, Gunadi and Setyati[9]. In the development of the sign language detection system, two methods are used, namely the CNN and RNN methods. The purpose of this study is to check the accuracy of BISINDO's detection system by comparing two methods, namely CNN and RNN. The implementation of this detection system is designed for the Android platform due to the popularity and accessibility of Android-based devices in the wider community. By comparing these two methods, it is hoped that the most efficient method to use in sign language detection systems can be found that can help track and identify sign language. This research uses the design science research method as an approach to analyzing the Android-based BISINDO.

2. MATERIALS AND METHOD

The design science research method is a research approach that focuses on developing new solutions to problems in research. The design science research method, which integrates the concepts, practices, and procedures required to conduct the study, is cited in the journal Andrian in 2020 as having three goals: it must be consistent with prior research, offer a nominal process model for conducting research, and offer a mental model for presenting and evaluating research. [10][11]. Design science research is used as an approach in analyzing the Android-based Bahasa Isyarat Indonesia detection system (BISINDO). This section describes the deep learning models that are used, the datasets that were gathered, and the preparatory methods for the proposed Bahasa Isyarat Indonesia recognition system [12]. This approach involves a series of stages that include identification of background and problems, formulation of specific objectives and solutions, system design and development, system demonstration, evaluation of system performance, and communication of research results. The research flow will be described in the form of a diagram, which can be seen in Figure 1 below.

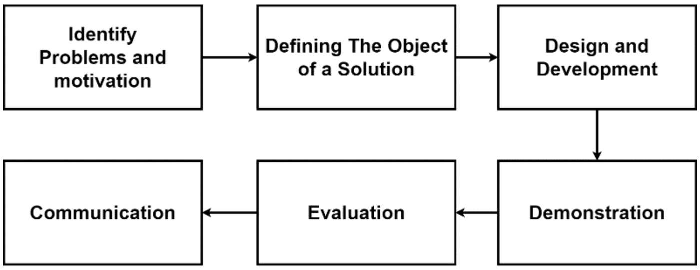

Figure 1. Metode Design Science Research

Based on Reza Andrian's journal, In accordance with the criteria and concepts of design science research that have been developed in previous research, design science research seeks to improve the creation, presentation, and evaluation of design science research [10]. The six steps of the design science research technique are problem and motivation identification, solution definition, design and development, demonstration, assessment, and communication. Each step of the design research technique is described in the sections that follow.

2.1. Identifying Problem and Motivation

Identifying problems and motivations begins with determining relevant topics, then continues with conducting in-depth literature studies to understand the existing context, conducting gap analysis based on previous research, and the last stage is identifying problems that are the main focus of research.

2.2. Defining The Object Of A Solution

The stage of defining the purpose of the solution begins with reviewing previous research in depth and identifying solutions that have been proposed and unresolved problems in the context of the research. In this stage, extracting needs is carried out to understand user needs, system goals, and limitations that will help system development later. In addition, extracting needs is also carried out to identify, interview, observe, survey, and conduct questionnaires on people involved or influential in this study.

2.3. Design and Development

Convolutional neural network (CNN) and recurrent neural network (RNN) methods were used to analyze the Android-based Bahasa Isyarat Indonesia Detection System (BISINDO) during the design and development stages. This was done in order to identify the methods that could be implemented on an Android device, based on previous research and literature studies. The determination of this method is carried out in several stages, such as data collection, pre-processing, design architecture, model training, and evaluation, which can be seen in figure 2.

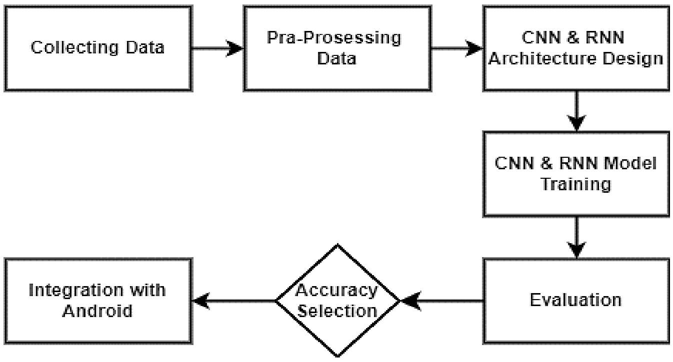

Figure 2. Machine Learning Architecture Design Flow

2.4. Convolutional Neural Networks (CNN)

Convolutional neural networks, or CNNs, are a subset of deep learning that use an at least one convolution layer in their neural network method. This model is thought to be the most effective at resolving object recognition and detection issues [13][14]. The data used in the CNN algorithm is a digital image in the form of 2-dimensional data. CNN is composed of several neurons that have bias, weight, and activation functions [15][16]. The following is an illustration of the architecture of the CNN model that can be seen in figure 3.

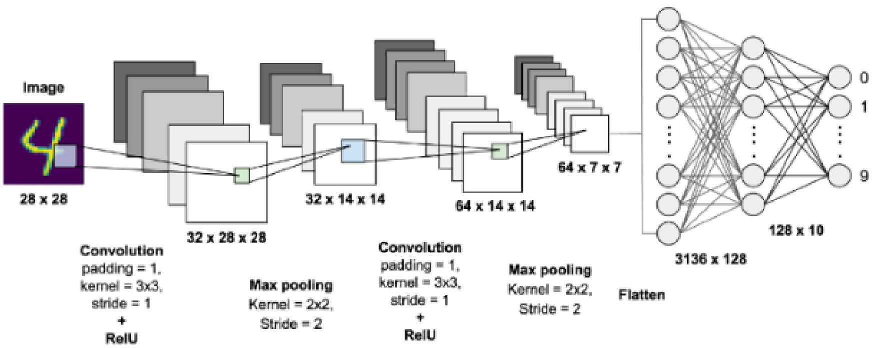

Figure 3. CNN Architecture

2.5. Recurrent Neural Network (RNN)

A more advanced class of neural networks called recurrent neural networks (RNNs) are best suited for simulating intricate relationships in time-series data. RNNs are capable of extracting temporal features from multivariate sequence data, processing it as input, and producing multivariate (predictive) outputs [17]. The "memory" of an RNN retains all the data related to the calculations that have been made. Unlike other neural networks, RNN reduces parameter complexity by performing the same task on all inputs or hidden layers, therefore it utilizes the same parameters for each input [9]. One drawback of RNN is that, in practice, RNNs are not able to learn long-term dependencies [18][19].

2.6. Demonstration

Simulations are carried out for system testing, where the system will be tested both in terms of accuracy and the process of running the system. In addition, system testing is also carried out with people who understand

BISINDO to find out the correctness of hand movements or gestures given with the results obtained by the system. If there is an error in the hand gesture with the results obtained, the researcher will repeat it at the design and development stage to satisfy the dataset inputted with the results obtained being the same or accurate.

2.7. Evaluation

The confusion matrix is a method of evaluation that computes F-score values, recall, specificity, accuracy, and precision in order to compare and analyze the performance of digital picture categorization. There are four elements in this matrix: False Positive (FP), True Negative (TN), False Positive (TP), and False Negative (FN). The numbers that represent successfully anticipated positive data (TP), mistakenly predicted positive data (FN), correctly predicted negative data (TN), and incorrectly predicted negative data (FP) are as follows: Table 1 is an example of the confusion matrix [20].

Table 1. Confusion Matrix

	Predicted Label : Yes	Predicted Label : No
True Label : Yes	TP	FN
True Label : No	FP	TN

1. Accuracy measures the degree to which a classification model can correctly predict positive and negative classes. Here is the formula for accuracy, which can be seen in the formula below.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

2. The degree to which a classification model can accurately predict a positive class out of all predictions that are classified as positive is measured by precision. This is the precision formula, which is displayed in the formula below.

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

3. The recall of the classification model quantifies its ability to accurately recognize all positive data. This is the recall formula, which is displayed in the formula below.

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

4. The degree to which a classification model can accurately identify all negative data is measured by its specificity. The formula below shows the corresponding specificity formula.

$$Specificity = \frac{TN}{TN+FP} \quad (4)$$

5. The F1-Score is a metric that evaluates the relative weights of recall and precision to produce a single score. This is the F1-Score formula, which is shown in the formula below.

$$F1 - Score \ = 2\frac{Precision \ . \ Recall}{Precision + Recall} \quad (5)$$

3. RESULTS AND DISCUSSION

3.1. Identifying Problem and Motivation

Researchers compared trends over the previous five years in image recognition, RNN, CNN, BISINDO, SIBI, sign language, and other fields using Google Trends. Additionally, Publish or Perish is used by scholars to establish mapping based on previously published research publications. Vos viewer is used to ascertain how research and journals that have been previously published or expired relate to one another. Based on the research that has been done, researchers are able to compare and analyze the methods of CNN and RNN to determine which is more accurate and which can be implemented on an Android device. These results are presented in the form of problems.

3.2. Defining The Object of A Solution

This system comparison is done to determine which method has an adequate level of accuracy so that it can be implemented into Android. Additionally, by developing more advanced sign language recognition technology, this project aims to enhance communication abilities between deaf and non-deaf individuals in

Indonesian culture. Excavation of needs was done, including recognizing datasets from BISINDO, comprehending sign language, and integrating or processing sign language into the system using CNN and RNN techniques to achieve high accuracy.

3.3. Defining The Object of A Solution

At this stage, a flow mapping of system creation or often known as a flowchart is carried out as seen in figure 2. The following is a description of the results of system creation based on the system flow diagram as shown in figure 2.

3.3.1. Data collection

Dataset used is a collection of BISINDO sign language images taken from Kaggle, which is open to the to the public. Data science and machine learning can be found on the website Kaggle. Developers can freely use a variety of open datasets available on the website. [21]. The dataset obtained is a collection of photos of hand gestures and body language that includes the alphabet from letters A to Z. Each dataset folder from letters A to Z has 12 photos, and the total number of datasets amounts to 312 images.

3.3.2. Pre-Processing

In the pre-processing stage, it is carried out to adjust the image resolution, normalize the image by changing the pixels in the image so that it has a uniform scale, and reduce noise to improve system performance. The open-source framework's numerous capabilities have been utilized to accomplish all required dataset preprocessing approaches. [12]. At this stage, a division is carried out to carry out the training and testing process. The number of shares in the training process is 80% of the total dataset, and the number of shares in the number of shares in the testing process is 20% of the total dataset. After the division was carried out, the image was resized to 64x64 pixels to get the best accuracy between the CNN model and the RNN model based on the tests carried out.

3.3.3. CNN and RNN Architectural Design

This stage is carried out the implementation of the architecture in each method. Here's the filter layer format used on each model as seen in table 2.

Table 2. Layer filter param

Layer (Type)	Output Shape	Param #
Conv2d (Conv2D)	(None, 62, 62, 32)	896
Max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0
Conv2d_1 (Conv2D)	(None, 29, 29, 64)	18496
Max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 64)	0
Conv2d_2 (Conv2D)	(None, 12, 12, 128)	73856
Max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
Flatten	(None, 4608)	0
Dense	(None, 128)	589952
Dense_1	(None, 26)	3354

3.4. Demonstration

At this stage, the model is trained for as many as 20 epochs; this aims to get the best accuracy in each model. The epoch also serves to provide an understanding of how well the model learns from the data. By performing multiple epochs, the model has the opportunity to look at the data repeatedly and update its parameters in hopes of improving performance on previously unseen data (validation data or test data). Here are the results of the epoch that has been done on each model, which can be seen in table 3 and 4.

Table 3. Epoch with CNN Model

Epoch	Accuracy	Loss	Val_Accuracy	Val_Loss
1/20	0.0297	3.2851	0.0638	3.2572
2/20	0.0199	3.2571	0.0426	3.2556
3/20	0.0620	3.2471	0.1277	3.2341
4/20	0.2017	3.2153	0.2128	3.1529
5/20	0.2514	3.0563	0.2979	2.8759
6/20	0.2942	2.6866	0.3404	2.3610
7/20	0.4324	2.0308	0.4043	1.7845
8/20	0.5764	1.5275	0.4681	1.5562
9/20	0.6112	1.1902	0.5745	1.4341
10/20	0.7391	0.8877	0.5957	1.4524

Epoch	Accuracy	Loss	Val_Accuracy	Val_Loss
11/20	0.7423	0.7876	0.6809	1.2102
12/20	0.8068	0.6200	0.7021	1.1152
13/20	0.8944	0.3992	0.7234	1.0415
14/20	0.8651	0.3627	0.7447	0.9942
15/20	0.8809	0.3266	0.7872	0.9436
16/20	0.9384	0.2714	0.7660	0.9951
17/20	0.9295	0.2158	0.7872	0.9574
18/20	0.9429	0.1990	0.7872	1.0544
19/20	0.9449	0.2048	0.7660	1.0830
20/20	0.9130	0.3003	0.7447	1.0125

Table 4. Epoch with RNN Model

Epoch	Accuracy	Loss	Val Accuracy	Val_Loss
1/20	0.7009	0.9874	0.5769	1.2226
2/20	0.7607	0.7815	0.5385	1.4574
3/20	0.7863	0.7519	0.6538	1.3030
4/20	0.7735	0.7181	0.6154	1.3273
5/20	0.7650	0.7174	0.6538	1.0892
6/20	0.7991	0.6518	0.6923	0.9812
7/20	0.8248	0.5486	0.5769	1.1937
8/20	0.8590	0.4640	0.6538	1.1932
9/20	0.8077	0.5169	0.6154	1.2480
10/20	0.8333	0.5396	0.6923	1.1249
11/20	0.8718	0.4503	0.6538	0.9029
12/20	0.8291	0.5481	0.6923	0.9359
13/20	0.8718	0.4276	0.6538	1.3189
14/20	0.8034	0.5714	0.6923	0.9749
15/20	0.8803	0.4430	0.6538	0.8817
16/20	0.8675	0.4519	0.7308	0.8758
17/20	0.8803	0.4099	0.7308	0.7902
18/20	0.8974	0.3282	0.6923	0.8696
19/20	0.8803	0.3450	0.8462	0.7380
20/20	0.9103	0.3030	0.7308	0.8503

3.5. Evaluation

The CNN test findings revealed an accuracy score of 89%, indicating a good ability to recognize images based on the alphabetic classes division of BISINDO. In the meantime, the accuracy of the RNN model was 88.46%. The CNN model performs better at identifying photos from the BISINDO dataset, as evidenced by both outcomes. Figures 5 and 6 below provide a graphic representation of training and validation accuracy and loss.

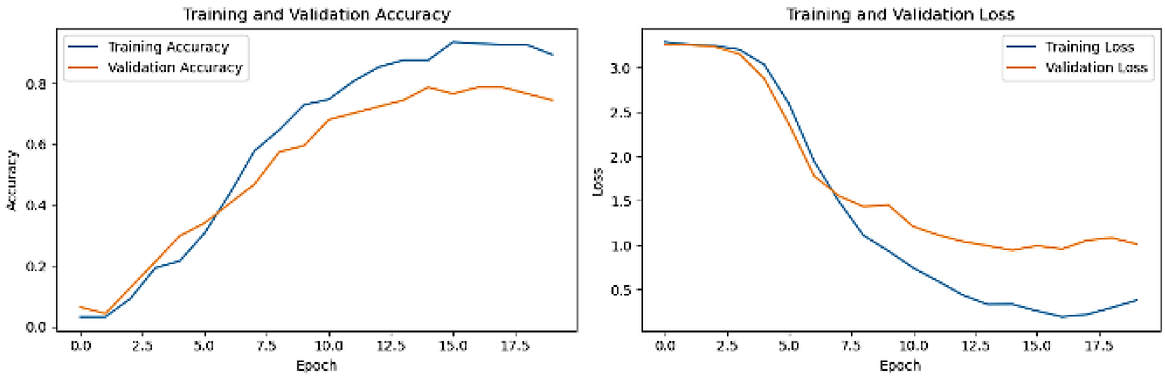

Figure 4. CNN Drain and Loss Charts

Figures 5 and 6 demonstrate how the accuracy of the CNN model is more consistent than that of the RNN model. Figures 7 and 8 display the confusion matrix findings for each model, which show how many BISINDO classifications the model accurately performed.

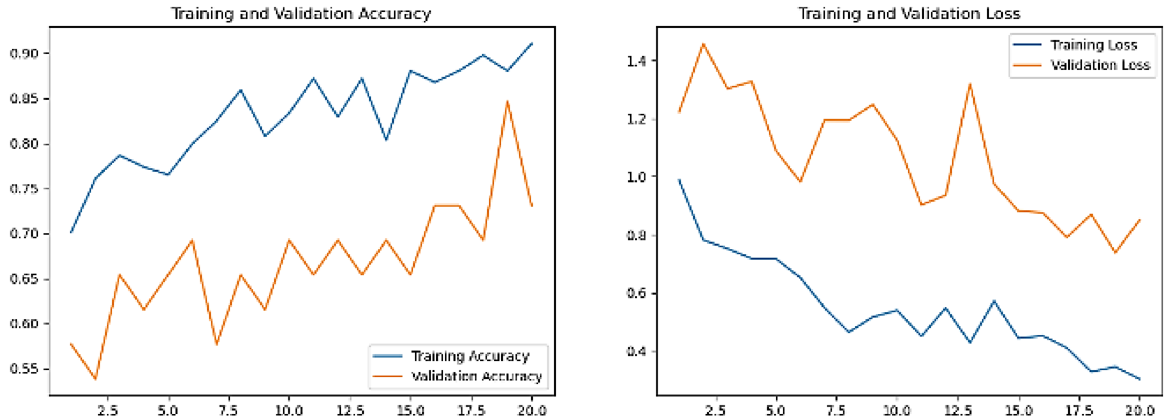

Figure 5. RNN Drain and Loss Charts

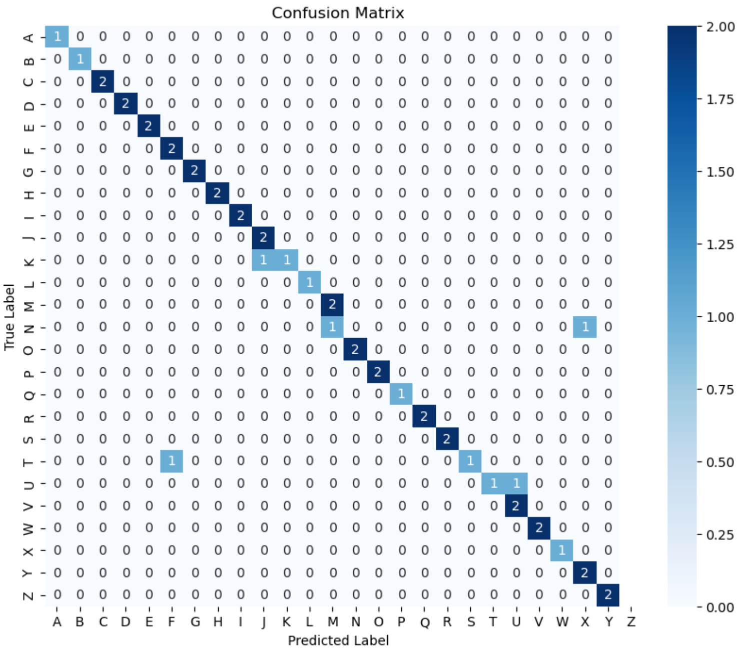

Figure 6. Confusion Matrix Results Using CNN

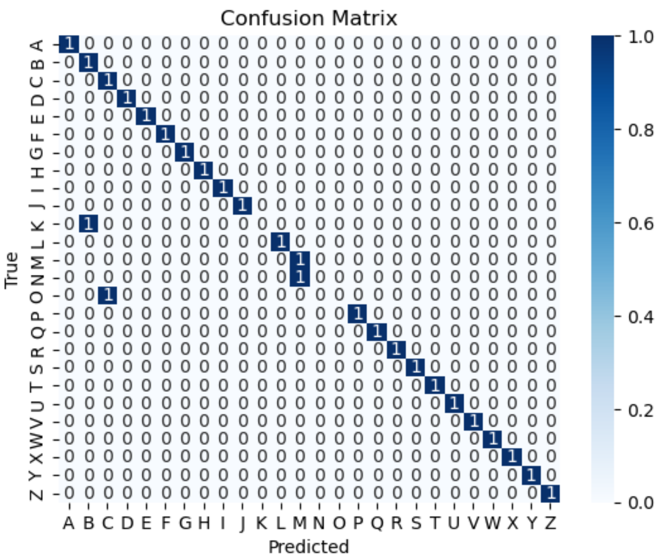

Figure 7. Confusion Matrix Results Using RNN

4. CONCLUSION

This study shows that the CNN has a greater and more stable accuracy rate compared to the RNN model, where the CNN model produces an accuracy rate of 89%, and indicates that the ability to recognize images based on the division of BISINDO alphabetic classes is good. Meanwhile, the RNN model showed an accuracy of 88.46%. Both results show that the CNN model is superior in classifying BISINDO dataset images. This makes the CNN model feasible to use or implement on Android because it has advantages both in terms of accuracy and stability in classifying images based on the BISINDO dataset. However, this research needs further research and more in-depth evaluation to determine the advantages and weaknesses of each model in a broader applicable context.

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