CLEANLINESS IMAGE CLASSIFICATION OF PACKAGED DRINKING WATER USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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ABSTRACT

Water is a natural resource that is very important for humans to consume in everyday life, such as Bottled Drinking Water (AMDK). The requirements for water suitable for consumption must be clean or not cloudy, odorless, tasteless and of course also meet the requirements as written in the regulations of the Indonesian Minister of Industry as criteria for quality bottled water according to SNI (Indonesian National Standard). The large number of types of water can be a problem because sometimes there are people who are not suitable for drinking bottled water with certain brands. This study aims to determine the quality level of bottled water in terms of the quality of the water turbidity values of various types of bottled water. This study uses image processing technology with the Convolutional Neural Network (CNN) method to classify AMDK based on image. The image taken only focuses on 5 types of water, namely Aqua (138 ppm), Vit (181 ppm) , Nestle pure life (175 ppm), Crystalin (142 ppm) and Le mineral (156 ppm). In this study, 500 data were used and three stages of testing were carried out on the CNN model, namely testing the epoch, testing the learning rate, and testing the optimizer. So that the best results were obtained with an accuracy of 90% at epoch 30, a learning rate of 0.01, on the RMSprop optimizer with a test time of 8 minute 58 seconds.

Keyword: Bottled Drinking Water, CNN, Epoch, Learning Rate, Optimizer

1. Introduction (10 PT)

Water is an important need for humans, and the United Nations (UN) has declared that water is an inseparable part of basic human rights [1]. Bottled drinking water (AMDK) must meet the requirements both in terms of quantity and quality. The main focus that must be met is the quality of AMDK which can contribute directly to public health [2]. The importance of air for health can be seen from the air content contained in the body's organs, for example 80% of blood is air, and losing 15% of body weight can have fatal consequences [3][4].

Air has physical and chemical properties that can have positive or negative influences on the human body and other creatures. Air quality is also influenced by environmental conditions at the air source which causes variations in the chemical content in it. To ensure that the air is safe for consumption, there are standards that regulate good water quality [5].

Bottled drinking water (AMDK) refers to water that has undergone a processing process or can be consumed directly without processing, while meeting health standards. AMDK that is considered healthy must meet the physical, microbiological, chemical and radioactive requirements set by the government in order to be considered safe drinking water and suitable for consumption [6]. According to SNI 01-3553, bottled drinking water is water that has gone through a processing process, is packaged, and is confirmed to be safe for consumption. This includes mineral water and demineralized water [7].

The parameters that must be considered in determining water quality are pH and TDS [8]. According to the health quality book standards of the Ministry of Health of the Republic of Indonesia, the pH permitted in drinking water is between 6.5 to 8.5[9]. Low corrosion properties are indicated by a pH value higher than 7, so that the higher the pH value, the lower the corrosion properties. Conversely, the lower the pH value, the higher the corrosion properties [10].

Apart from pH levels, water quality parameters are also determined from the Total Dissolved Solid (TDS) value. High TDS levels can affect taste and show a negative relationship with aquatic environmental parameters which cause toxicity to the organisms in it [11]. According to WHO, water suitable for consumption has at least a TDS value of 300 mg/L to a maximum of 500 mg/L[12].

There are many types of bottled drinking water (AMDK) in circulation that comply with existing regulations. However, sometimes there are still people who buy a brand and feel that it is not suitable and the next day they have a sore throat or cough. Therefore, the many types of AMDK brands definitely have different contents or turbidity. The image of AMDK needs to be classified because each type of AMDK has a different content or turbidity and there are more and more types of AMDK over time.

Identification of Water Turbidity Based on Image Processing using the interpolation method [13], with an accuracy of 70% has the disadvantage of using sediment to test.The classification challenge does not only come from the large number of types of AMDK, but the problem of bottles and backgrounds will affect the image, and also the quality of the camera.This research was conducted to identify types of AMDK using the Convolutional Neural Network (CNN) method. CNN is a deep learning method that represents the development of multi-layer perceptrons (MLP) [14]. CNN is one of the most popular and accurate models implemented in image classification [15]

2. Research Method (10 PT)

This research uses a research method which will be shown in the research block diagram shown in Figure 1.

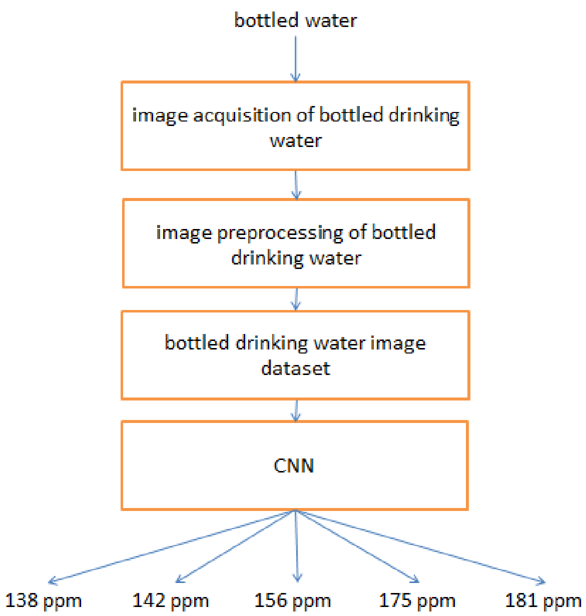

Figure 1. Research flow diagram

Based on the research block diagram above, the research will go through several stages, namely:

2.1 Bottled Water

Each type of AMDK water definitely has a different TDS level. So TDS measurements will be carried out on the types of water used in this research, namely Aqua, Crystalin, Le mineral, Nestle pure life, and Vit. The tool used to measure is the EZ-9901 waterproof temperature. The TDS measurement results will be shown in Table 1.

Table 1. TDS results for each type of water

No	Type of Bottled Drinking Water	Tds Meter
1.	Aqua	138 ppm
2.	Crystalin	142 ppm
3.	Le mineral	156 ppm
4.	Nestle pure Life	175 ppm
5.	Vit	181 ppm

2.2 Image Acquisition of Bottled Drinking Water

In this research, the data used is images of bottled drinking water which consists of five different types of AMDK, namely Le Mineral, Aqua, Vit, Nestle pure life, and Crystalin. Data was collected by purchasing from the nearest shop and taking image photos using a smartphone with 48MP wide angle camera specifications, 8MP ultrawide angle, 2MP macro camera and 2MP depth sensor. Each shot was taken at the same 4 points but played back on bottled drinking water.

2.3 Image Preprocessing of Bottled Drinking Water

Data processing (preprocessing). The preprocessing stages carried out are cropping and formatting the JPG image. Cropping is done with the aim of making the water object visible more than the background and the bottled water container in the image. Through the cropping process, researchers hope to increase the effectiveness of the analysis, because it only focuses on the desired water object rather than analyzing all objects in the image.

The cropping process proved effective because it allowed researchers to focus on water objects. If no cropping is done, the computer will analyze all objects in the image, including those that are not relevant to the research objectives, namely water. Therefore, by cropping, researchers can reduce the complexity of the analysis and get a clearer focus on the object of interest.
The cropping process was carried out manually by researchers to choose the best position where the water image was visible well. In this way, researchers can ensure that only the most relevant and high-quality images are used in the analysis, thereby increasing the accuracy and validity of research results.

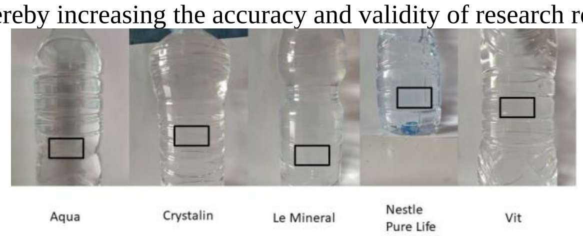

Figure 2. Example of AMDK image before preprocessing

Figure 3. Example of AMDK image after preprocessing

2.4 Convolutional Neural Network (CNN)

Determine the architecture of the CNN before processing the dataset. CNN architectural rules are generally divided into Feature Extraction and classification. The parameters that need to be included in the CNN architecture are the number of filters, kernels, number of layers and activation function used. In this study, 2 convolution layers were used. Each Convolution has a filter and kernel. Then layer reduction is carried out on the pooling layer. Next, it is flattened into a vector form. This stage is generally called a fully connected layer, and uses the softmax activation function. The CNN architecture can be seen in Figure 3.

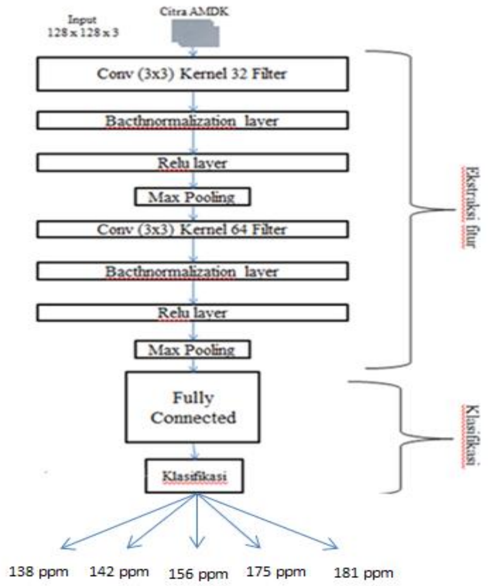

Figure 4. CNN Model Architecture

This research, as in the picture above, uses a CNN architecture where the research carries out 2 stages of layer convolution with a size of 3x3 and filter kernels of 32 and 64 filters. Convolutional Layer is the main stage that is the basis of the Convolutional Neural Network (CNN) method. In the Convolutional Layer, the convolution operation is carried out on the output of the previous layer and produces a feature map. The convolution operation involves using filters over the entire input area. Each filter position is applied to the input, and the element-by-element multiplication between the filter field and the input is summed to produce a single value in the feature map. The result is a feature representation that can visualize local responses to specific features in the input. Through training, the filters in the Convolutional Layer are automatically adjusted to learn relevant feature patterns in the data.

The next stage is to do the Pooling Layer. The Pooling Layer functions to take a feature map as input and perform statistical operations on the closest pixel values. At this stage, the feature map produced from the Convolutional Layer will undergo a downsampling process.

The purpose of Pooling Layer is to encapsulate the information contained in map features and reduce their dimensions. By downsampling, the resulting image is more concise but still contains important information. In this research, the Maxpooling method is used, where the downsampling process is carried out by selecting the largest value for each pixel in the pooling area.

By using Maxpooling, only the largest value will be taken in each pooling area. This helps highlight the most significant features in each part of the feature map, resulting in a more concise representation while retaining important information needed for further classification processes.

The next step is Fully Connected Layer. Fully Connected Layer is a layer in a neural network where each activated neuron is connected to all neurons in the next layer. At this stage, each neuron in the convolution layer must be converted into one-dimensional data so that it can enter the Fully Connected Layer. Fully Connected Layer produces output values that will be used in the object classification process. This output can be considered as the final representation of the data that has passed through the previous layers in the neural network. In a Fully Connected Layer, each neuron contributes to the final output with appropriate weights. These results will then be used to classify objects based on the research objectives or tasks carried out. In the final stage of this research, the softmax method is used to classify the results. Softmax is a variation of the Logistic Regression algorithm which is used specifically to classify output into more than two classes. Softmax is applied to the last layer of the neural network. The advantage of the softmax method is that it produces output probabilities that are in the range between 0 and 1. This allows a clear interpretation of the probabilities associated with the possible classes. Additionally, the total probability of all classes in one output object will always be 1, so softmax ensures that there is a valid probability distribution for each class prediction.

2.5 CNN Testing

In this research, tests were carried out to evaluate and analyze the results of image processing using the CNN method. The way to find out the performance of the CNN algorithm uses a reference from the Confusion Matrix which is shown in Figure 5. In this research, the parameter used to test system performance is accuracy. Accuracy describes the comparison between correct predictions across data. Accuracy measures the extent to which the model can classify correctly, following accuracy equation 1.

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

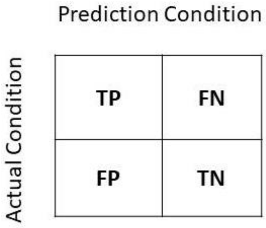

Figure 5. Confusion Matrix

Information :
TP (True Positive) is the number of positive data that is classified correctly by the system.
TN (True Negative) is the amount of negative data that is classified correctly by the system.
FP (False Positive) is the number of positive data but classified incorrectly by the system.
FN (False Negative) is the amount of negative data but is classified incorrectly by the system.

3. Result and Analysis

This research uses a dataset that is divided into 5 categories of Bottled Drinking Water with the names of folders for Tds measurement results, namely, 138 ppm, 142 ppm, 156 ppm, 175 ppm, and 181 ppm. The number of datasets used is 500 images. With the number of image data in each category being 100. The dataset will be divided into 70% training data and 30% testing data
Next, testing will be carried out on the existing dataset by testing the SGDM, ADAM, and RMSprop optimizers

3.1. SGDM Optimizer Testing

The first test was carried out with the SGDM optimizer using an epoch 30 configuration, learning rate 0.01, and deep layer 8. Obtained results with an accuracy of 82% and a testing time of 5 minutes 42 seconds. The test results are shown in Figure 6.

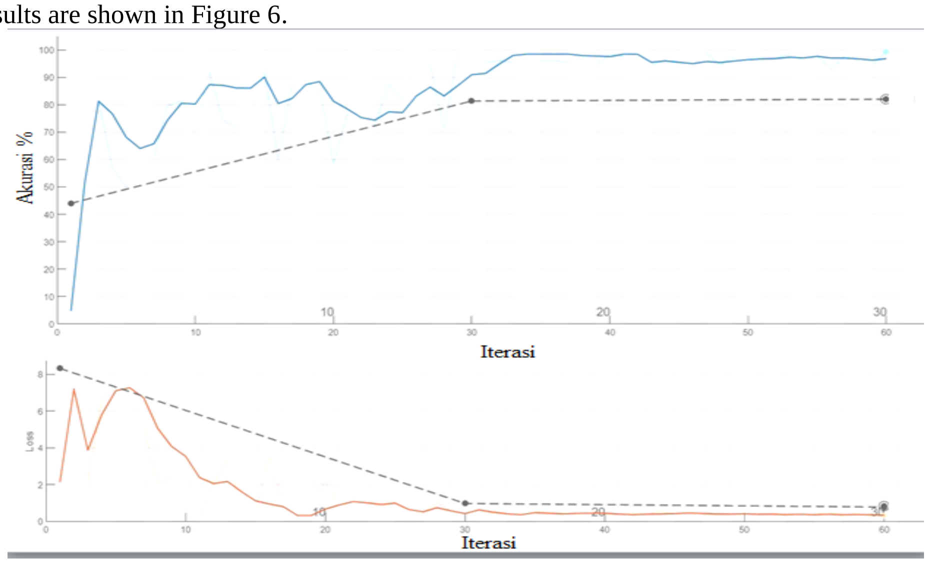

Figure 6. SGDM Depth 8 Optimizer Testing

3.2. ADAM Optimizer Testing

The second test was carried out with the ADAM optimizer using an epoch 30 configuration, learning rate 0.01, and deep layer 8. Obtained results with an accuracy of 79.33% and a testing time of 5 minutes 57 seconds. The test results are shown in Figure 7.

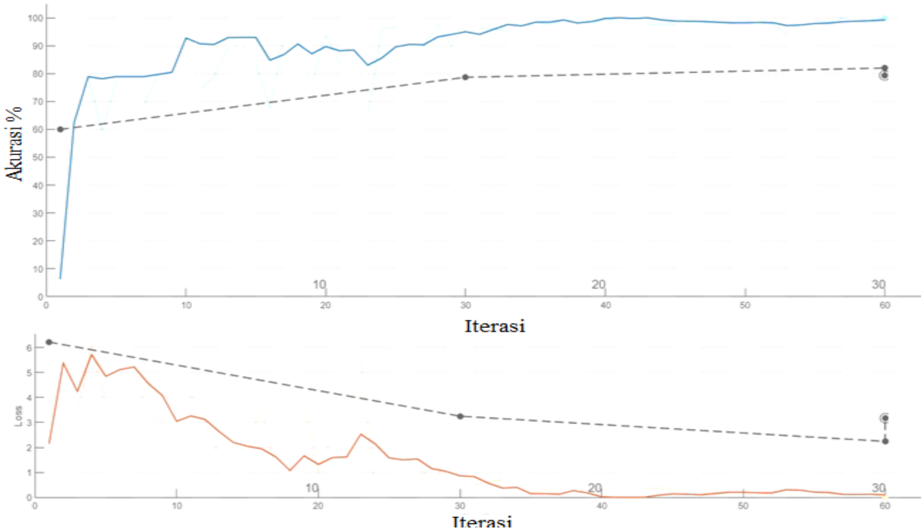

Figure 7. ADAM Depth 8 Optimizer Testing

3.3. RMSprop Optimizer Testing

The third test was carried out with the RMSprop optimizer using an epoch 30 configuration, learning rate 0.01, and deep layer 8. Obtained results with 80% accuracy and a testing time of 5 minutes 33 seconds. The test results are shown in Figure 8.

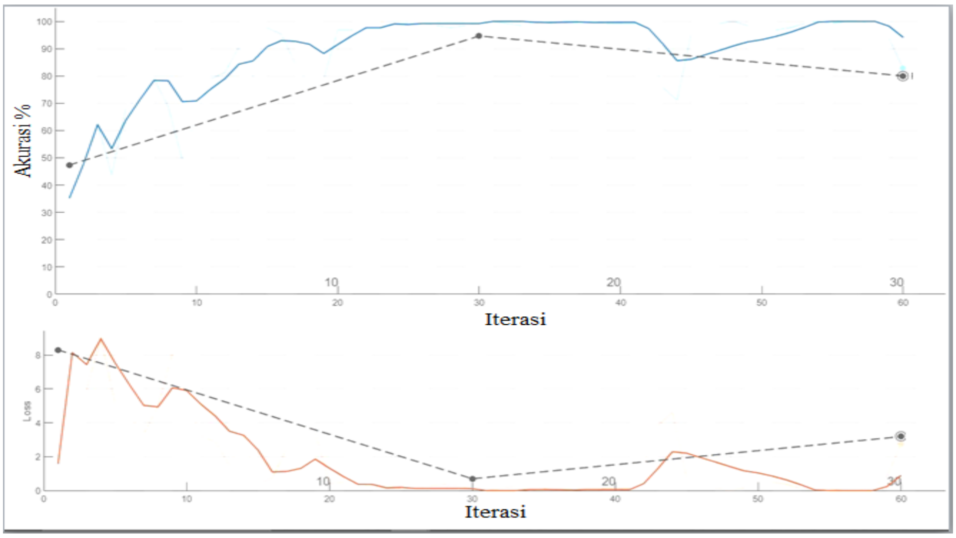

Figure 8 . RMSprop Depth 8 Optimizer Testing

3.4. SGDM Optimizer Testing

The fourth test used the SGDM optimizer with an epoch configuration of 30, learning rate 0.01, and deep layer 12. Obtained results with an accuracy of 84% and a testing time of 8 minutes 44 seconds. The test results are shown in Figure 9.

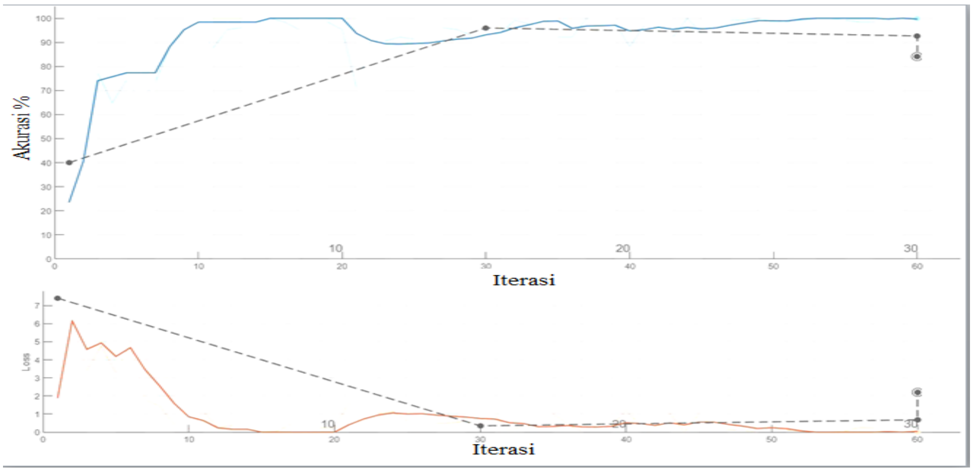

Figure 9. . SGDM Depth 12 Optimizer Testing

3.5. ADAM Optimizer Testing

The fifth test was carried out with the ADAM optimizer using an epoch 30 configuration, learning rate 0.01, and deep 12. Obtained results with 80% accuracy and a testing time of 8 minutes 48 seconds. The test results are shown in Figure 10.

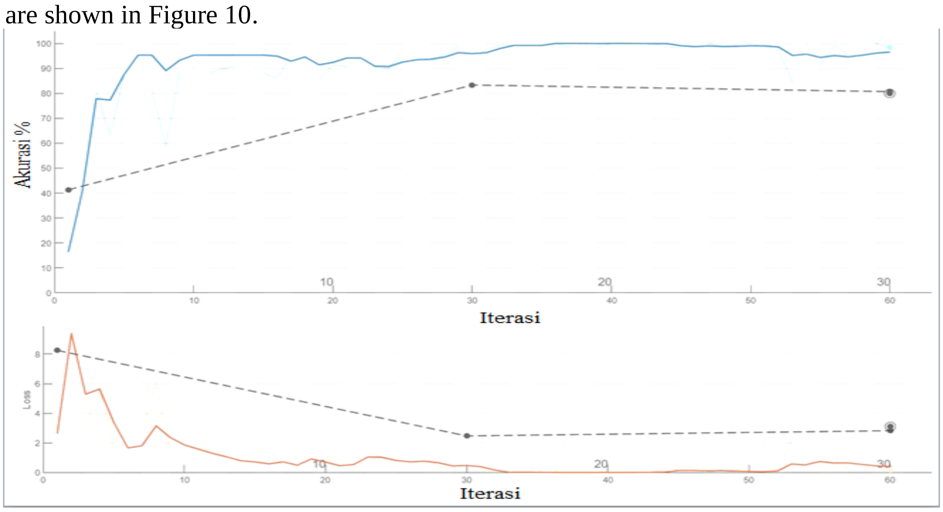

Figure 10. . ADAM Depth 12 Optimizer Testing

3.6. RMSprop Optimizer Testing

The final test was carried out with the RMSprop optimizer using an epoch 30 configuration, learning rate 0.01, and deep layer 12. Obtained results with 90% accuracy and a testing time of 8 minutes 58 seconds. The test results are shown in Figure 11.

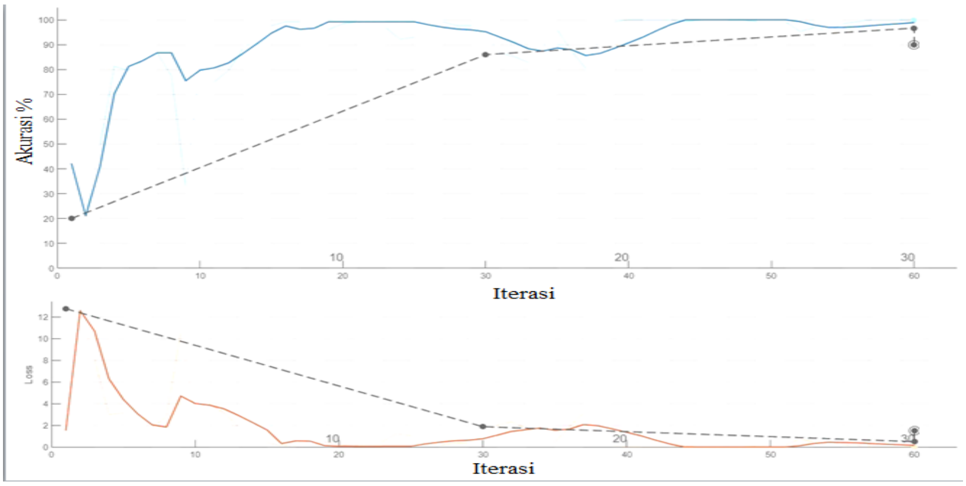

Figure 11. . RMSprop Deep 12 Optimizer Testing

3.6. Test Result

After carrying out several tests, the results will be shown in Table 2.

Table 2.Test Result

Optimizer	Epoch	Depth	Time	Accuracy
Sgdm	10	8	5 minute 42 second	82%
Adam	10	8	5 minute 57 second	79,33%
RMSprop	10	8	5 minute 33 second	80%
Sgdm	10	12	8 minute 44 second	84%
Adam	10	12	8 minute 48 second	80%
RMSprop	10	12	8 minute 58 second	90%

From Table 2, several tests have been carried out using the SGDM, ADAM, and RMSprop optimizers. Get the best results in the RMSprop test with epoch 30 configuration, learning rate 0.01, and depth 12 with 90% accuracy and a time of 8 minutes 58 seconds. RMSprop is a type of optimization algorithm that adapts the learning rate for each parameter in the model based on gradient calculations accumulated from previous iterations. The goal is to optimize the learning rate for each parameter so that the learning process becomes more efficient and convergent. The results of the confusion matrix in testing the RMSprop optimizer with epoch 30, learning rate 0.01 and depth 12 can be seen in Figure 12.

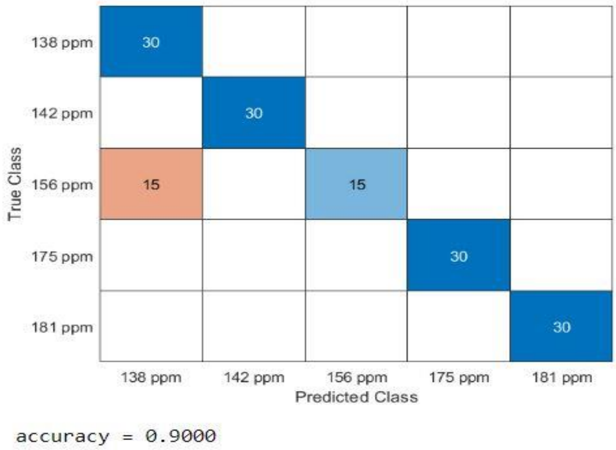

Figure 12. Confusion Matrix optimizer RMSprop epoch 30. Learning rate 0,01 And Depth 12

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Based on Figure 12. There are 15 images of 156 ppm minerals that are clarified as 138 ppm images and the rest have been clarified correctly, meaning that the CNN method can classify AMDK images based on different turbidities.

4. Conclusion (10 PT)

Based on research and tests that have been carried out to classify 5 types of AMDK on a ppm scale, namely 138 ppm (Aqua), 181 ppm (Vit), 175 ppm (Nestle pure life), 142 ppm (Crystalin) and 156 ppm (Le mineral). Getting the best results is at epoch 30, learning rate 0.01, and RMSprop optimizer with 90% accuracy. After going through this process, it can be concluded that the CNN method is able to image AMDK with a high level of accuracy.

Acknowledgements

The author must thank informatic friends who have helped in completing this research.

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