Classification of Chicken Meat Freshness using Convolutional Neural Network Algorithms

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***Abstract*—Broiler chicken meat is one of the most widely consumed meat types in Indonesia, this high level of consumption makes a lot of consumer demand in the market. However, there was a found seller who sells broiler chicken meat that are rotten. In this study, we develop chicken meat freshness identification using a convolutional neural network algorithm. This study used the image dataset of broiler chicken breasts. There are two categories of chicken meat used in the study, namely, fresh and rotten. The meat images were acquired by using a smartphone camera. For the process of cropping chicken meat images, we use thresholding with the Otsu method and conversion of RGB images to binary images to select the area of RGB images before cropping the images. The chicken meat images were cropped into three sizes and then used as a dataset in the study. The chicken meat image dataset was trained using a simple architecture that was self-made called Ayam6Net, we also used the AlexNet, VGGNet, and GoogLeNet architectures as a comparison. Ayam6Net has the highest accuracy of 92.9%. From the experiment results, we can conclude that using Ayam6Net architecture with dataset 400×400 pixels has a better accuracy result compared with other architectures and other sizes image datasets.**

***Index Terms*—chicken meat freshness, meat slice images, convolutional neural network, freshness classification**

I. Introduction

Poultry meat is one of the most consumed types of meat in Indonesia with a percentage level of 70% and almost 85% of poultry meat consumed is broiler chicken[1]. Beside of affordable prices, broiler chicken meat has a high protein content compared to pork, beef, and lamb[2]. The high level of consumption of chicken meat is accompany by a lot of consumer demand on the market. However, in several cases, such as the increasing price of chicken meat, the chicken meat in the market did not sell well, causing seller to commit fraudulent acts by selling rotten chicken meat at this time as a case that appeared in the media[3]. One of the efforts to identify rotten chicken meat is by visual based on the color and texture characteristics of the chicken meat.

Digital image processing is a method that can be used to identify the quality of chicken meat based on the color characteristics and texture characteristics of the meat. Several studies on the classification of meat-based on images have been carried out, such as classification of rotten meat based on readings from gas sensors and image processing[4], classification of red meat from hyperspectral images[5], and identification of freshness of chicken based on color and texture features[6] . In this study, the feature extraction method as well as the classification method for chicken meat images used a Convolutional Neural Network (CNN) algorithm.

II. Literature Review

In the paper[4], the classification system for the grade of meat rot consisted of the detection of gas types and image processing. In gas type detection, the sensors used are MQ-137 to detect NH3, MQ-136 to detect H2S, and TGS2602 to detect VOCs. The reading of the electric voltage from the gas sensor uses an ATMega328 microcontroller. In the image processing process, image acquisition using a webcam camera, the resulting image with a resolution of 640×480 pixels sliced into 300×300 pixels in size, and then the texture feature extraction process is carried out using the Gray Level Co-occurrence Matrix (GLCM) algorithm. The process of data collection with a gas sensor and image processing carried out every 1 hour for 12 hours. In this study also used the BH1750 digital light sensor as a measuring tool for light intensity where the reading from the sensor will determine the best level of light intensity to represent the level of rotting meat, 90 lux is the best brightness level obtained by using linear regression. The data readings come from the gas sensor and the texture features obtained using GLCM from the meat image were classified using the neural network algorithm. The neural network consists of 2 hidden layers with 4 neurons in each layer. The output of the Neural Network has 2 neurons to determine 3 levels of rotten chicken meat which are fresh, rotten, and putrid. The training step used 24 samples of meat labeled fresh, rotten, and putrid with each sample consists of different meat. At the testing step using 28 samples with the results of the classification success rate reaching up to 82%.

Al-Sarayreh et al. [5] using a sample covering 13 types of muscle from standard meat, the sample used 50 pieces of lamb, 55 pieces of beef, and 35 pieces of pork. A total of 105 samples were used as samples for training data and the rest were used for testing and validation data. The image acquisition process uses a self-developed Hyperspectral Imaging System

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with an image with dimensions of 216 x 409 x 252. Also, image retrieval is carried out in a series with a total of 600 images from the entire sample used. The hyperspectral image is then normalized and resampled into a set of representative points. Hyperspectral images are divided into classes of lamb, beef, pork, and fat. Apart from using 3D-CNN, in this study also using the PLS-DA and SVM-RBF classification methods as a comparison and the result of the greatest level of accuracy is in the use of the 3D-CNN method with an overall accuracy rate of 95.% and an average accuracy rate of 96.1 %.

In research [6] using a dataset of 150 images of broiler chicken meat divided into 66% training data and 34% test data. Image acquisition using a smartphone camera, webcam, and a digital microscope. The image of chicken meat is divided into 3 classes, namely fresh, fresh- medium, and not fresh. Extraction of chicken meat image features based on color features using RGB and HSV and texture features using the Gray Level Co-Occurrence Matrix (GLCM) method, the Histogram of Oriented Gradients (HOG) method, and the Gabor method. The classification method used is Support Vector Machine (SVM), Naive Bayes, and Decision Tree with the biggest classification accuracy obtained from webcam images using the SVM method, which is 98%.

III. Research Methodology

In this paper, the method used for image classification of chicken meat consists of 3 main steps. There are image acquisition, image preprocessing, and image classification using CNN. At the image acquisition step, samples of chicken meat are photographed using a smartphone camera. In the second step, image preprocessing aims to increase the features of the chicken meat image to be processed on CNN. The last step is the process of classifying the image of chicken meat.

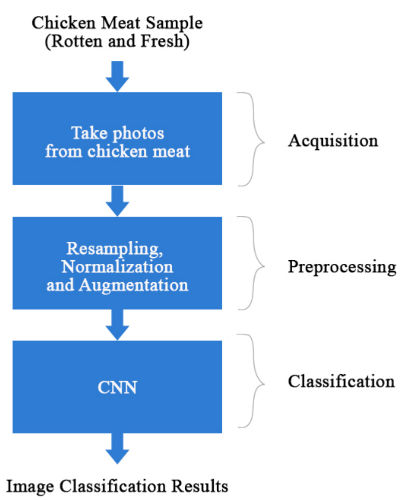

Fig. 1. Research Methodology

A. Image Acquisition

The chicken meat image data used is a sample of chicken breast image. The chicken breast is cut to various lengths and widths but with almost uniform thickness, which approximately 0.5 cm. The process of capturing chicken meat image data used Vivo Y51L smartphone camera with 8 MP resolution and the distance between the chicken meat and the camera as far as 10 cm. The chicken meat image with a fresh category is taken 6-8 hours after slaughtered the chicken, then the chicken meat is stored in the room and covered by a container that leaves several gaps in and out of the air, this chicken is stored for approximately 21-23 hours to take the image of the chicken with the rotten category. The process of taking the image of chicken meat is carried out in an open area which is illuminated by the natural sunlight.

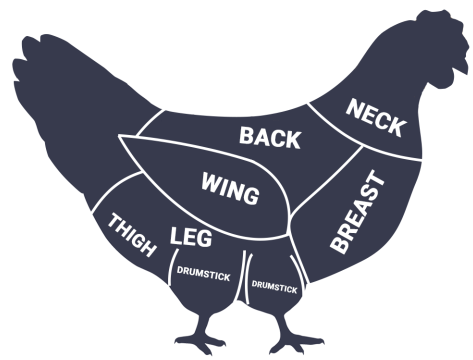

Fig. 2. Illustration of parts of chicken meat [7]

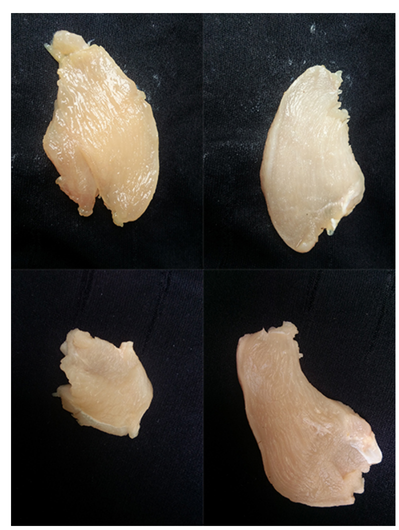

Fig. 3. Samples of chicken meat image

B. Preprocessing

After the process of taking the chicken meat image data, a certain part of the chicken meat image object would be cropped. The RGB image of chicken meat is converted into a grayscale image using the equation shown (1)[8].

$$Y = (0.299 * R) + (0.587 * G) + (0.114 * B) \tag{1}$$

Then the grayscale image is converted into a binary image with a thresholding process using the Otsu method. The Otsu method calculates the threshold value T automatically based on the input image. The threshold value sought is expressed in k, the value of k ranges from 1 to L, where $L = 255$. The probability for a pixel i is given by:

$$P_i = \frac{n_i}{N} \tag{2}$$

Where n_i represents the number of pixels with a gray level I and N denotes the number of pixels in the image. The values for the zero cumulative moment, the first cumulative moment, and the mean values, respectively, can be stated as follows.

$$\omega(k) = \sum_{i=1}^{k} P_i \tag{3}$$

$$\mu(k) = \sum_{i=1}^{k} i \cdot P_i \tag{4}$$

$$\mu_T = \sum_{i=1}^{L} i \cdot P_i \tag{5}$$

The threshold value of k can be determined by maximizing the equation:

$$\sigma_B^2(k^*) = max_{1 \leq k < L}(\sigma_B^2(k)) \tag{6}$$

where:

$$\sigma_B^2(k) = \frac{[\mu_T \omega(k) - \mu(k)]^2}{\omega(k)[1 - \omega(k)]} \tag{7}$$

The value of k chosen is the value of k that maximizes the equation (7) [9]. The binary image used only to find coordinate points that have a pixel value area with a value of 255, then from the obtained coordinates, the RGB image was cropped and saved to be used as a dataset in this study. After the cropping step, before being included in the CNN learning model, a normalization process is carried out on the chicken meat image dataset so that each chicken meat image has a pixel value with a value range of 0 to 1, the purpose of this normalization process is to obtain a stable dynamic value range. After the normalization step, the augmentation process is then carried out by rotating the chicken meat image in the dataset by 30°.

C. Convolutional Neural Network (CNN)

In this study, there are 4 CNN architectures used for training the chicken meat image dataset which are AlexNet, VGGNet, GoogLeNet and Ayam6Net.

1) AlexNet: AlexNet architecture published in [10], The AlexNet architecture is the winner of neural network architecture in the ILSVRC-2012 competition, AlexNet architecture has 8 layers consisting of 5 convolutional layers and 3 fully connected layers, with a total parameter of 60 million. This architecture was made by Alex Krizhevsky, it shows significant results on the test data with a test error percentage of 15.31%.

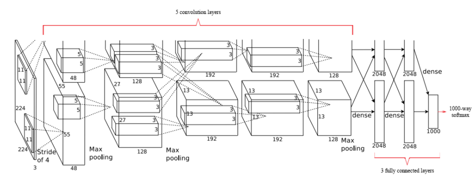

Fig. 4. AlexNet architecture [10]

2) VGGNet: The VGGNet architecture introduced in [11]. The VGGNet architecture was the second winner of the ILSVRC image classification competition in 2014. There are several layer structures were tested on the VGGNet architecture, including VGG-11, VGG-11 (LRN), VGG-13, VGG-16 (Conv1), VGG-16, and VGG-19. The smallest error rate is found in the VGG-16 architecture with an error rate of 8.8% and then followed by VGG-19 with an error rate of 9.0%.

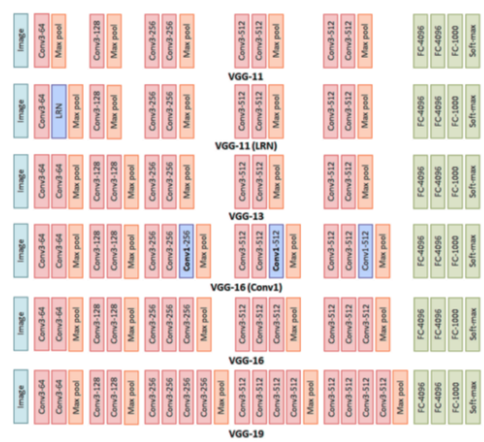

Fig. 5. VGGNet architecture [11]

3) GoogLeNet: GoogLeNet architecture proposed in [12] by Google researchers. GoogLeNet architecture was the winner of the ILSVRC image classification competition in 2014 with an error rate lower than the VGGNet architecture which is 6.67%. GoogLeNet is also sometimes called Inception-v1 because there are newer v2, v3, and v4. The GoogLeNet architecture introduces a new module called inception which combines filters of various sizes, which can be seen in figure 7. The filter size consists of 3×3, 5×5, 1×1 filters and then all filters are combined.

4) Ayam6Net: The architecture of Ayam6Net is self-made architecture. The Ayam6Net architecture consists of three Convolutional layers, a pooling process with max pooling. There

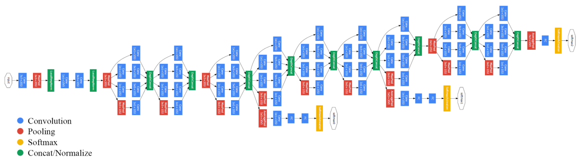

Fig. 6. GoogLeNet architecture

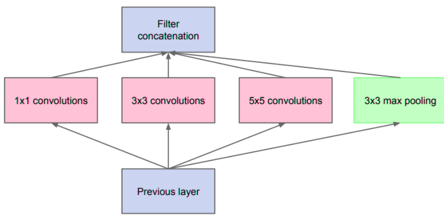

Fig. 7. Illustration of GoogLeNet Inception module

are three fully connected layers and ReLU activation function after the max pooling process and after fully connected layer. At the end of the layer, Sigmoid function is used for binary class classification.

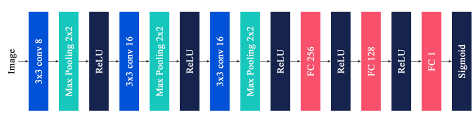

Fig. 8. Ayam6Net architecture

IV. Result and Discussion

A. Dataset

From the image acquisition process, there are 50 chicken meat images with the rotten category and 50 chicken meat images with the fresh category. Then the pixel area in the image acquisition process was selected using the OpenCV library for converting RGB image to grayscale image and the thresholding process using the Otsu method. Then the selected area cropped and used as a dataset in the CNN learning model.

The cropping process for each image has been done three times and it resulted three different sizes of images, that are 200×200 pixels, 300×300 pixels, and 400×400 pixels. The 200×200 pixels fetches $3,197$ of images consisting of $1,637$ of rotten labeled images and $1,560$ of fresh labeled images. The 300×300 pixels yields $1,068$ images consisting of 542 of images with rotten labels and 526 of images with fresh labels. 400×400 pixels fetches 433 of images consisting of 218 of images with rotten labels and 215 of images with fresh labels. Then each label from the chicken meat image dataset was divided into 80% for training data, 10% for validation data, and 10% for testing data. Figure 9 shows examples of images from the chicken meat dataset used in this study.

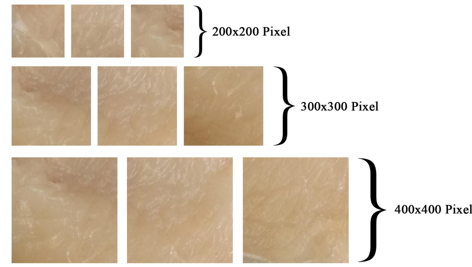

Fig. 9. Samples of Chicken meat image dataset

B. Analysis Test Results

The training, validation, and testing processes are carried out on the Google Colaboratory platform, using Tensorflow and Keras. The four CNN architectures used in the study are Ayam6Net, Alexnet, VGGNet, and GoogLeNet. These architectures were trained as much as 100 epochs and then from each epoch, the weight was chosen which produces the best performance.

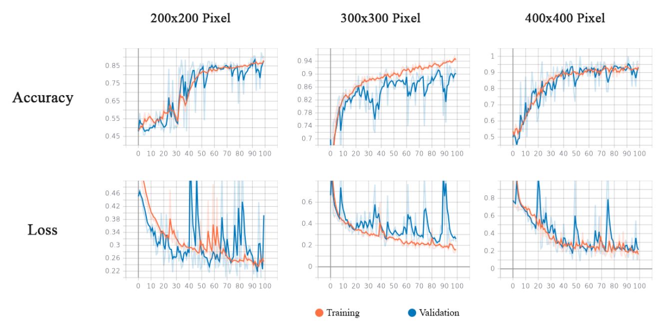

Fig. 10. Plot of Ayam6Net training and validation accuracy and Ayam6Net training and validation loss

TABLE I
Test Result of Ayam6Net Architecture

	Ayam6Net					
	200×200 **Pixels**		300×300 **Pixels**		400×400 **Pixels**	
	Rotten	**Fresh**	**Rotten**	**Fresh**	**Rotten**	**Fresh**
Precision	75.5%	97.2%	90.7%	90.4%	95.0%	90.9%
Recall	98.2%	66.7%	90.7%	90.4%	90.5%	95.2%
F1-score	85.3%	79.1%	90.7%	90.4%	92.7%	93.0%
Accuracy	82.8%		90.6%		92.9%	

1) Ayam6Net: The results shown in Ayam6Net architecture is moderately good. The best result is placed at a dataset with a pixel area of 400×400 where the figure above shown that dataset with a pixel area of 400×400 produces a good fit model and has high training and validation accuracy comparing to other dataset. For the test results, the table above shown on the image dataset with a pixel area of 400×400 results the highest percentage of accuracy, which is 92.9%. Other results such as precision, recall, and f1-score also yield good percentages with a dataset 400×400 pixel. This shows that chicken meat is successfully classified according to its freshness.

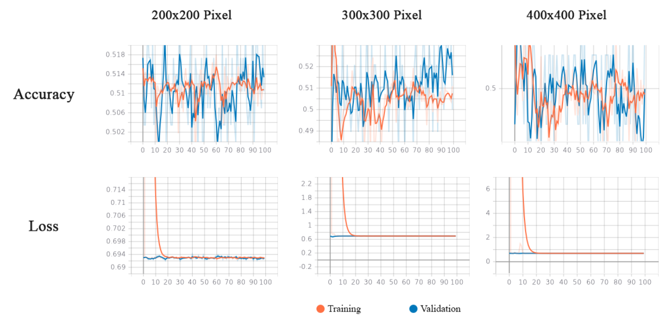

Fig. 11. Plot of AlexNet training and validation accuracy and AlexNet training and validation loss

TABLE II
TEST RESULT OF ALEXNET ARCHITECTURE

	AlexNet					
	200×200 **Pixels**		300×300 **Pixels**		400×400 **Pixels**	
	Rotten	**Fresh**	**Rotten**	**Fresh**	**Rotten**	**Fresh**
Precision	51.1%	0%	50.9%	0%	50.0%	0%
Recall	100%	0%	100%	0%	100%	0%
F1-score	67.6%	0%	67.5%	0%	66.7%	0%
Accuracy	51.1%		50.9%		50.0%	

2) AlexNet: The figure above shows that all dataset trains on AlexNet architecture result underfitting model where the training and validation accuracy are poor. For the test result from the table above, the accuracy of dataset 200×200 pixels, 300×300 pixels, and 400×400 pixels are 51.1%, 50.0% and, 50.0% respectively. AlexNet architecture fails to predict fresh chicken meat images.

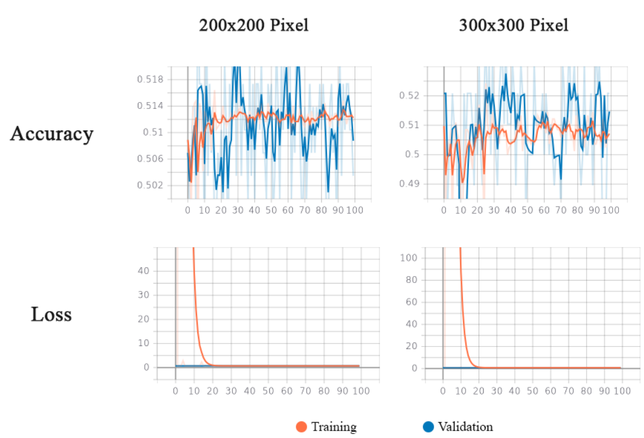

Fig. 12. Plot of VGGNet training and validation accuracy and VGGNet training and validation loss

TABLE III
TEST RESULT OF VGG ARCHITECTURE

	VGGNet			
	200×200 **Pixels**		300×300 **Pixels**	
	Rotten	**Fresh**	**Rotten**	**Fresh**
Precision	51,1%	0%	50,9%	0%
Recall	100%	0%	100%	0%
F1-score	67,6%	0%	67,5%	0%
Accuracy	51,1%		50,9%	

3) VGGNet: In the VGGNet architecture, the architecture used is VGG-19 and has only been tested on a 200×200 pixels and 300×300 pixels image dataset. The test results of VGGNet are similiar with the test results of AlexNet architecture. It fails to predict fresh chicken meat images. This probably happens cause AlexNet and VGGNet are suitable for complex and numerous image datasets, but not for simple and few image datasets.

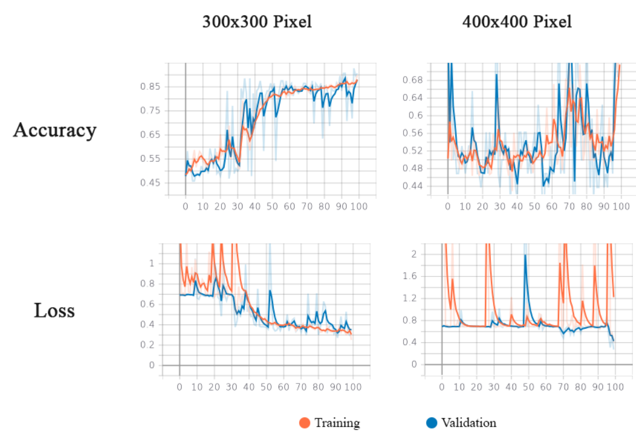

Fig. 13. Plot of GoogLeNet training and validation accuracy and GoogLeNet training and validation loss

TABLE IV
TEST RESULT OF GOOGLENET ARCHITECTURE

	GoogLeNet			
	300×300 **Pixels**		400×400 **Pixels**	
	Rotten	**Fresh**	**Rotten**	**Fresh**
Precision	100%	85.2%	77.8%	100%
Recall	83.3%	100%	100%	71.4%
F1-score	90.9%	92.0%	87.5%	83.3%
Accuracy	91.5%		85.7%	

4) GoogLeNet: In the GoogLeNet architecture, the datasets tested were only 300×300 pixels and 400×400 pixels. The two tested datasets produce an equitably good level of accuracy and the 300×300 pixels dataset produces a high accuracy rate with a value of 91.5 %. From the figure above shown GoogLeNet architecture with dataset 300×300 pixels produces a good fit model with a low loss training and validation and high accuracy on the training and validation, despite the test results of GoogLeNet with dataset 400×400 pixels shown a good result, but in the training and validation phase show that the model is an underfitting model.

C. Comparison

Beside of precision, recall, f1-score and accuracy, we also collect data on total parameters, training time and weight size of the CNN models that used in this study as a comparison. From the table of comparison based on total parameters shows the least number of parameters is in the Ayam6Net architercure with a 200×200 pixel dataset. In the table of comparison based on training time shows the fastest training time is in the Ayam6Net architecture with a 400×400 pixel dataset. In the table of comparison based on weight size shows the smallest weight size is in the Ayam6Net architecture with 200×200 pixel dataset.

TABLE V
COMPARISON BASED ON TOTAL PARAMETERS

	Total Parameters		
	200×200 **Pixels**	300×300 **Pixels**	400×400 **Pixels**
AlexNet	29,973,889	105,471,361	256,466,305
VGGNet	112,311,361	206,683,201	-
GoogLeNet	-	5,989,937	6,023,729
Ayam6Net	4,372,881	10,074,513	18,913,681

TABLE VI
COMPARISON BASED ON TRAINING TIME

	Training Time(hh:mm:ss)		
	200×200 **Pixels**	300×300 **Pixels**	400×400 **Pixels**
AlexNet	00:58:17	00:35:50	00:23:35
VGGNet	01:27:41	00:49:25	-
GoogLeNet	-	00:37:36	00:23:44
Ayam6Net	01:03:22	00:33:23	00:21:39

TABLE VII
COMPARISON BASED ON WEIGHT SIZE

	Weight Size		
	200x200 Pixels	**300x300 Pixels**	**400x400 Pixels**
AlexNet	114 MB	402 MB	978 MB
VGGNet	428 MB	788 MB	-
GoogLeNet	-	23 MB	23 MB
Ayam6Net	17 MB	38 MB	72 MB

V. CONCLUSION

In this study, we proposed an identification of chicken meat freshness using a Convolutional Neural Network algorithm. The freshness level of chicken meat is divide into two categories, fresh (6-8 hours after slaughtered) and rotten (21-23 hours after slaughtered). In this experiment, we use a smartphone camera for the acquisition process of chicken meat images. From the experiment results, we can conclude that the best result achieved using Ayam6Net architecture with the dataset 400×400 pixel where the training and validation accuracy has over a 95% and the test result accuracy has a 92.9%.

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