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Classification of Meat Freshness using Deep Learning

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Abstrak

Daging merupakan salah satu sumber makanan berprotein yang cukup populer di kalangan masyarakat. Harga daging yang cenderung mahal menyebabkan banyak penjual daging yang mencampurkan daging segar dengan daging yang kurang segar. Daging yang kurang segar dapat mempengaruhi kesehatan orang yang mengkonsumsinya. Berdasarkan permasalahan tersebut maka diciptakanlah penelitian yang dapat membedakan kesegaran daging dengan menggunakan gambar digital. Pada penelitian ini daging yang akan dijadikan objek penelitian adalah daging sapi dan ayam. Kesegaran daging akan dibedakan berdasarkan warna dan tekstur menggunakan deep learning. Proses yang dilakukan yaitu proses preprocessing, augmentasi data, ekstraksi fitur dilakukan menggunakan fitur warna dan fitur tekstur menggunakan metode Gray Level Cooccurrence Matrix (GLCM), proses pelatihan dan proses klasifikasi menggunakan deep learning. Proses pelatihan dilakukan dengan menggunakan metode CNN, seperti arsitektur ResNet 18, ResNet 34 dan ResNet 50. Hasil pengujian menggunakan tiga jenis arsitektur ResNet diperoleh hasil terbaik menggunakan ResNet18, epoch 10 dengan akurasi 92%.

Kata kunci: *klasifikasi, citra digital, daging, GLCM, deep learning.*

Abstract

Meat is a source of food protein that is quite popular among people. The price of meat tends to be expensive, causing many meat sellers to mix fresh meat with less fresh meat. Meat that is not fresh enough can affect the health of people who consume it. Based on these problems, research was created that can differentiate the freshness of meat using digital images. In this research, the meat that will be used as research objects is beef and chicken. The freshness of meat will be differentiated based on color and texture using deep learning. The processes carried out are the preprocessing process, data augmentation, feature extraction is carried out using color features and texture features using the Gray Level Cooccurrence Matrix (GLCM) method, training process and classification process using deep learning. The training process is carried out using the CNN method, such as ResNet 18, ResNet 34 and ResNet 50 architectures. The test results using three types of ResNet architecture obtained the best results using ResNet18, epoch 10 with an accuracy of 92%.

Keywords : *classification, digital images, meat, GLCM, deep learning.*

1. Introduction

Meat is a source of food protein that is quite popular among people. Meat consumption has increased from year to year. The price of meat, which tends to be expensive, does not prevent people from consuming meat, especially before religious holidays and large ceremonies. High demand causes meat prices to increase. The high price of fresh meat causes some fraudulent traders to mix fresh meat with less fresh meat. The high price of meat causes many meat sellers to mix fresh meat with less fresh meat. Meat that is not fresh enough can affect the health of people who consume it. Currently, technological developments using computer vision can greatly help researchers and industry in increasing efficiency in recognizing food freshness. The use of image processing utilizing machine learning and deep learning models can identify food quality effectively. Based on these problems, research was carried out to determine the freshness quality of meat using digital images using the deep learning method.In this research, the meat that will be used as the research object is beef and chicken. This choice is because the majority of Indonesian people consume this meat. The freshness of this meat can be distinguished based on its color and texture.

Some related research that discusses meat freshness classification is the classification of beef freshness based on color using the VGG16 architecture and ResNet V2 inception which provides an accuracy of 98.12% [1]. Other research uses the KNN method which provides an accuracy of 86%. This research will use the CNN method with ResNet architecture for the classification process. The processes that will be carried out are the preprocessing process, data augmentation, training process and classification process using deep learning. In the preprocessing process, color contrast will be improved, then data augmentation will be carried out to increase the combination of training data, namely by rotating, mirroring, the feature extraction is carried out using color features and texture features using the Gray Level Cooccurrence Matrix (GLCM) method. The training process will be carried out using CNN method with ResNet Architecture. The model obtained will be saved and will be used during testing. In the testing process, the model obtained will be used to recognize new test data so that later the test data can be classified as fresh or non-fresh meat.

2. Research Method / Proposed Method

A general overview of the system for classifying meat freshness can be depicted in diagram form as Figure 1.

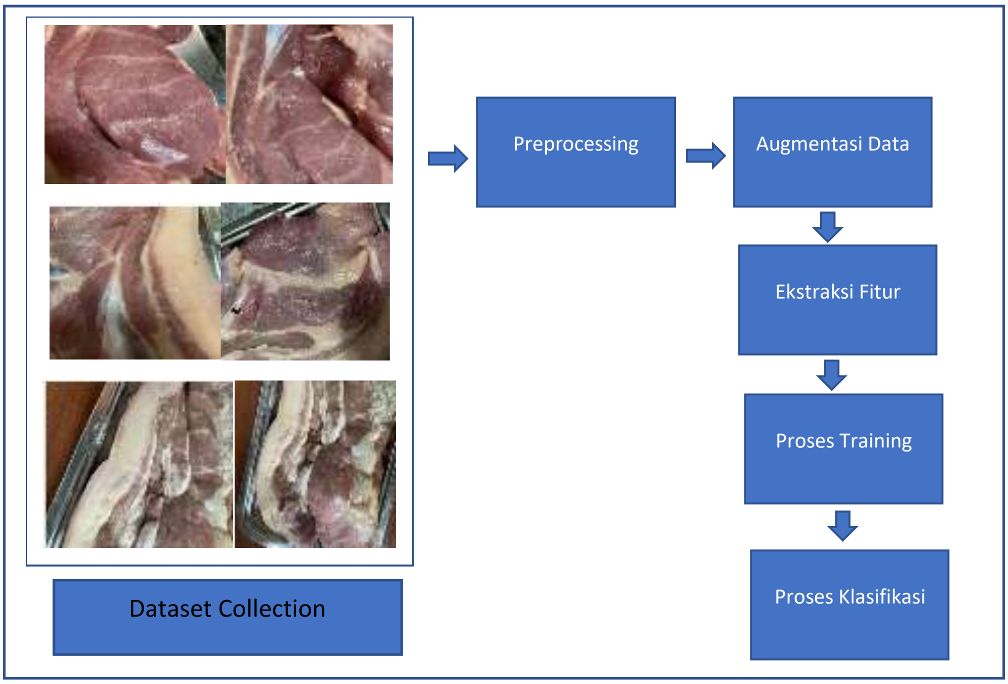

Figure 1. Overview Diagram of Meat Classification systems

The general description of the beef and chicken freshness classification system begins with collecting a training image dataset that has been labeled as fresh and less fresh meat. The image will then be pre-processed by increasing the contrast of the image. The image will then undergo a data augmentation process to increase data variations. The processes carried out in data augmentation are rotation and mirroring. The augmented image will then be subjected to feature extraction using changes to the R, G and B color channels for color characteristics and the GLCM (Gray Level Coocurence Matrix) method for texture characteristics. The characteristic matrix obtained will then be subjected to a training process using the ResCNN (Residual Convolutional Neural Network) method. The result of the training process is a class model that will be used for classification.

During the classification process, the input meat images will be processed the same as during the training process, but the difference is that the test images will be trained using a model that has been created and the classification process carried out. The final result will be in the form of a confusion matrix and F-Measurement which determines the accuracy of the model created and the success of its introduction.
The following are details of the general description above:

1. The dataset collection process is the process of collecting data from data sources. The dataset taken is a dataset of fresh and less fresh beef classes, as well as fresh and less fresh chicken meat. The dataset is sourced from Kaggle and data collection is direct with the amount of meat_fresh data: 853, meat_spoiled: 1413, poultry_fresh: 1560 and poultry_spoiled: 1637 data.
2. The Image Augmentation process uses Roboflow tools and augments or reproduces the data from the original data by adding settings such as flip, rotation and brightness. Preprocessing is done by converting RGB color images to Grayscale. The amount of data obtained after augmentation was meat_fresh: 2089, meat_spoiled: 3323, poultry_fresh: 3710, poultry_spoiled: 3951 data.
3. Extract features using the GLCM method by looking for neighborhood values with a distance of 1 pixel and 4 directions, namely 00, 450, 900, and 1350. The GLCM matrix is then normalized using four features, namely: energy, contrast, homogeneity and correlation.
4. The modeling process uses the ResNet18 architecture for GLCM also tried uses ResNet50. ResNet34 uses for colors with the best training results which will be saved which will later be used in the classification process.
5. In the Classification process, the test image will be processed using the model that has been saved, then the results will be displayed for the class of the image entered, including fresh beef meat, less fresh beef, fresh chicken meat and less fresh chicken meat.

3. Literature Study

3.1 State of The Art

Research related to the object of this research is research conducted by Habib Muhammad Al-Jabbar who classified the freshness of beef using Naïve Bayes [2]. In this research the author created a tool using a Raspberry Pi as a mini computer and a camera as a tool for taking pictures. The results of beef grouping are based on color level, where from 40 training data and 20 test data an accuracy of 95% was obtained. In the next research, 3 types of meat were classified, namely beef, goat and chicken and the method used was Linear Discriminant Analysis to differentiate meat based on its texture. The accuracy results obtained for the classification of this type of meat were 90% using the combination of HSI and Invariant Moment features [3].

Another research is research that classifies chicken meat images using HSV and KNN. The 160 images were divided into 80% training images and 20% test images. The test results from this research were accuracy of 96.88%, precision of 100%, and recall of 93.75% at a value of K=1 [4].

Another research related to meat freshness is the classification of pork freshness using near-infrared spectroscopy (NIRS) and ResNet techniques. The accuracy results obtained were 93.72 [5]. Beef freshness classification was also carried out by Titin Yulianti using GLCM feature extraction and KNN classification. The accuracy obtained was 77% [6]. Another research using IoT to detect the freshness of chicken meat is Praklik Wahyu Nastiti. In this research, meat will be classified based on quality during gas formation during meat storage. Gas is detected using a set of equipment consisting of a Raspberry Pi gas sensor and Metal Oxide-Semiconductor (MOS). The data obtained was then analyzed using Principle Component Analysis (PCA) for meat quality classification [7].

The next research uses Gray Level Cocurrent Matrix (GLCM) for feature extraction and Deep Neural Network for classification which is used to determine the freshness of beef. The accuracy obtained from this method is 93.46% [8]. Research using the GLCM method for feature extraction and KNN for classification was carried out by Ade Prabowo. The classification was carried out to detect the freshness of beef with an accuracy of 82% [9]

3.2 Deep Learning

Deep learning is an artificial intelligence (AI) feature that imitates the way the human brain processes data and creates models for decision making. Deep learning is a subset of machine learning in artificial intelligence with networks capable of enabling unsupervised learning from unstructured or unlabeled data, known as deep neural networks. The difference between deep learning and machine learning can be seen in Figure 2 [10] [11][12].

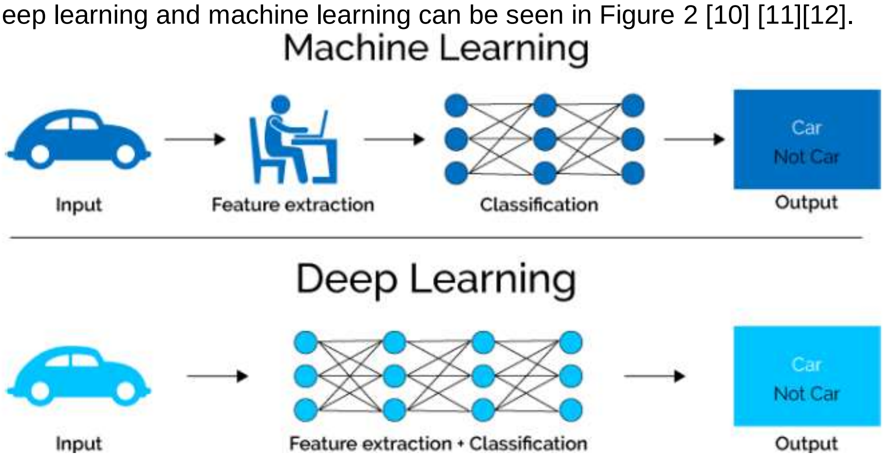

Figure 2. Deep Learning method

3.3 Convolutional Neural Network

Convolutional Neural Network (CNN) is a development of Multilayer Perceptron (MLP) which is designed to process two-dimensional data [13] [14] [15]. CNN is included in the Deep Neural Network type because the network depth is high and is widely applied to image data. Technically, CNN is an architecture that can be trained and consists of several stages. The input and output of each stage consists of several arrays which are usually called feature maps. Each stage consists of three layers, namely convolution, activation function layer and pooling layer. The following is a Convolutional Neural Network architecture network.

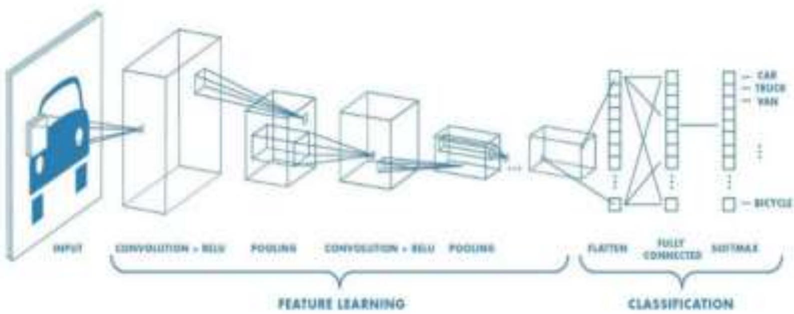

Figure 3. CNN Architecture

Figure 3 is the architecture of CNN. The first stage in the CNN architecture is the convolution stage. This stage is carried out using a kernel of a certain size. The calculation of the number of kernels used depends on the number of features produced. Then proceed to the activation function, usually using the ReLU (Rectifier Linear Unit) activation function. Then, after exiting the activation function process, it goes through the pooling process. This process is repeated several times until a sufficient feature map is obtained to proceed to the fully connected neural network, and from the fully connected network is the output class.

3.4 ResNet Architecture

This research use ResNet architecture, ResNet is a classic neural network. This model was the winner of the ImageNet challenge in 2015 [16][17]. The fundamental breakthrough with ResNet was that it was possible to train very deep neural networks with 150+ layers. Before ResNet training, deep neural networks were very difficult due to the gradient vanishing problem.

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The Resnet architecture shows that this neural network is easier to optimize, and can obtain much increased accuracy from greater depths [18] [19] [20]. ResNet is a solution for deep neural networks, the deeper the training, the more complicated it is and depth is very important for training so that parameters or neurons can remember or store optimal training values. So that training is not saturated and avoids quite high errors, there is a resnet function, namely adding layer identities as shown in the image below:

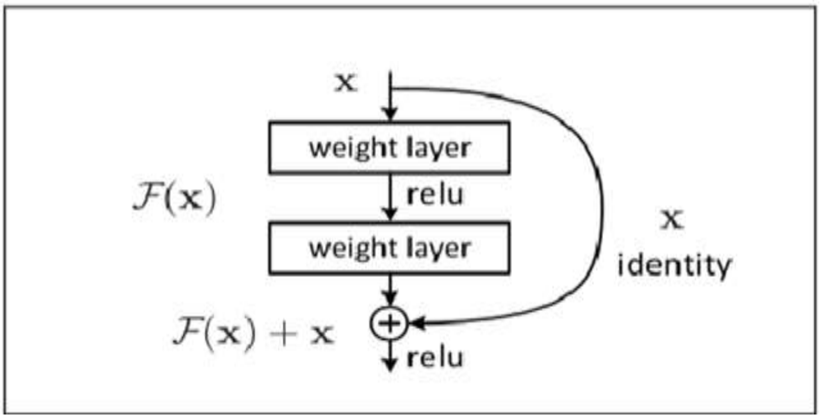

Figure 4. Identity Block ResNet

ResNet18 has a layer network of 18 layers while ResNet34 has a layer network of 34 layers while ResNet50 has a layer network of 50 layers. Bellow shown the architecture of ResNet18, ResNet34 and ResNet50 [21].

Layer Name	Output Size	18-Layer	34-Layer	50-Layer
cov1	112×112	7×7, 64, stride 2		
cov2_x	56×56	3×3 max pool, stride 2		
		$\begin{bmatrix} 3 \times 3, & 64 \\ 3 \times 3, & 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, & 64 \\ 3 \times 3, & 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, & 64 \\ 3 \times 3, & 64 \\ 1 \times 1, & 256 \end{bmatrix} \times 3$
cov3_x	28×28	$\begin{bmatrix} 3 \times 3, & 128 \\ 3 \times 3, & 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, & 128 \\ 3 \times 3, & 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, & 128 \\ 3 \times 3, & 128 \\ 1 \times 1, & 512 \end{bmatrix} \times 4$
cov4_x	14×14	$\begin{bmatrix} 3 \times 3, & 256 \\ 3 \times 3, & 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, & 256 \\ 3 \times 3, & 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, & 256 \\ 3 \times 3, & 256 \\ 1 \times 1, & 1028 \end{bmatrix} \times 6$
cov5_x	7×7	$\begin{bmatrix} 3 \times 3, & 512 \\ 3 \times 3, & 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, & 512 \\ 3 \times 3, & 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, & 512 \\ 3 \times 3, & 512 \\ 1 \times 1, & 2048 \end{bmatrix} \times 3$
	1×1	average pool, 1000-d fc, softmax		
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9

Figure 5. ResNet Architecture

3.5 Confussion Matrix

Confusion matrix is an error matrix which is said to be a source of information comparing the prediction results made by the system with the actual prediction results. There are variable cases, namely TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) [22] [23]. These four variables can be a source for finding precision and recall. Precision or precision explains the calculation which aims to calculate the ratio of true positive predictions compared to the overall positive predicted results, the formula is:

$$Precission = \frac{TP}{(TP + FP)} \tag{1}$$

The precision value is obtained from calculating the division between the number of correct class x data and the amount of data predicted as x. Recall is a calculation that aims to

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calculate the ratio of true positive predictions compared to the total true positive data. The formula is:

$$Recall = \frac{TP}{(TP + FN)} \tag{2}$$

The recall value is obtained from the number of correct predictions of data x with the actual amount of data x.

4. Result and Discussion

4.1 Data Collection

The dataset collection process is the process of collecting data from data sources. The dataset was sourced from Kaggle and took pictures of chicken and beef directly from market traders using a smartphone camera. The total data for fresh beef is 853, spoiled beef is 1413, fresh chicken is 1560 and spoiled chicken is 1637. The distribution of the dataset for training is 75% and 25% for testing data. Training data is used to create characteristic data models, while testing data is used to test model performance.

4.2 Preprocessing

In the initial stage, image data measuring 412x412 will be augmented to increase image variations. The augmentation processes carried out include flip and rotation. The amount of data obtained after augmentation was meat_fresh: 2089, meat_spoiled: 3323, poultry_fresh: 3710, poultry_spoiled: 3951 data.

4.3 Feature Extraction Result

In the feature extraction stage, two stages are carried out, namely taking color features and texture features to characterize the freshness of the meat. Color features are used to differentiate the color of fresh meat and not by taking RGB color channels, while texture features are differentiated using the GLCM (Graylevel Coocurent Matrix) texture feature. The image to be processed for GLCM feature extraction is first converted into a grayscale image. The GLCM feature extraction results are resized to 256x256 so they can be used as input when creating the CNN model. Figure 6 Below are the results of extracting RGB color features.

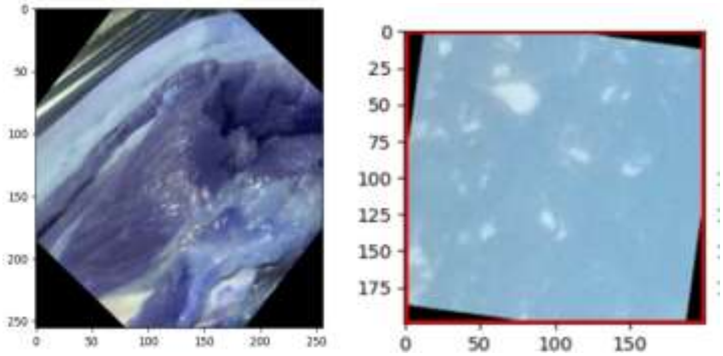

Figure 6. Color Extraction for Meat and Poultry

Images with color features are further processed using ResNet18, ResNet34 and ResNet50 architectures. Figure 6 is the result of converting images of beef and chicken into grayscale images and Figure 7 is feature extraction using GLCM of damaged beef and chicken which has been converted to a size of 256x256. This 256x256 image will be converted back to 32x32 as input image for model training data.

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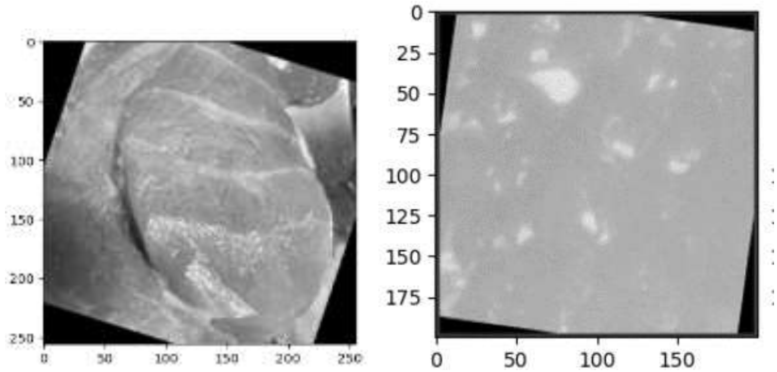

Figure 7. Grayscale Image

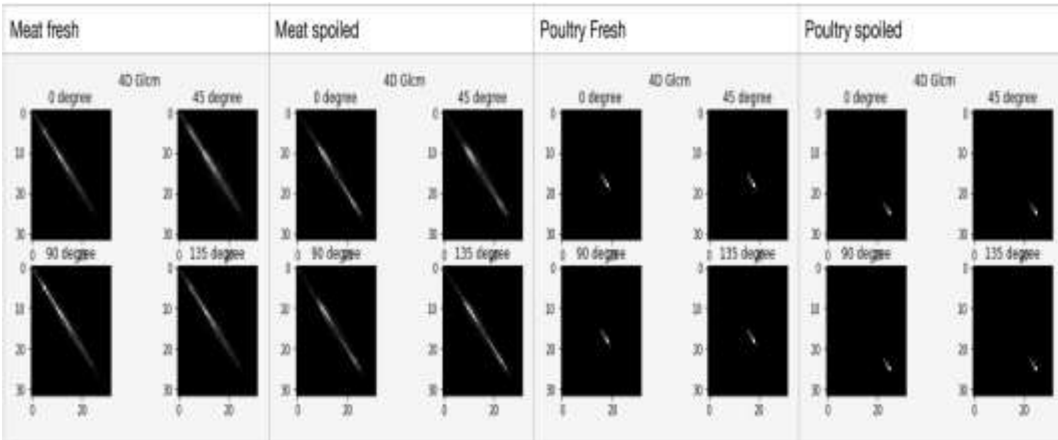

Figure 8. GLCM Feature

The results of GLCM feature extraction will also be input for the ResNet18, ResNet34 and ResNet50 architectures. The following is a function used for GLCM using the Python programming language.

4.4 Modelling

The modeling process was created using the CNN architecture, namely Resnet18, ResNet 34 and ResNet 50.

```
class Resnet18_Gray_3FineTune(BaseModel3):
def __init__(self):
    super().__init__()
    self.model = models.resnet18()
    self.model.conv1 = nn.Conv2d(1, 64, kernel_size=7,
    stride=2, padding=3, bias=False)
    self.model.fc = nn.Linear(in_features=512,
    out_features=4, bias=True) def forward(self, x):
    return self.model(x
```

Code 1. Program code for the ResNet18 function

```
    self.model = resnet34()
    self.model.conv1  =  nn.Conv2d(3,  64,  kernel_size=7,
    stride=2, padding=3, bias=False)
    self.model.fc       =       nn.Linear(in_features=512,
out_features=4, bias=True)
```

Code 2. Program code for the ResNet34 function

```
    class Net(nn.Module):
     def __init__(self):
     super().__init__()
     self.model = resnet50()
     self.model.conv1 = nn.Conv2d(3, 64, kernel_size=7,
stride=2, padding=3, bias=False)
     self.model.fc = nn.Linear(in_features=2048,
out_features=4, bias=True)
```

Code 3. Program code for the ResNet50 function

The program code above shows several architectures used in this research. A Convolution Neural Network is used to find unique features from the image, then several Fully Connected Layers are used to draw conclusions and obtain a class from the image. The Resnet architecture is trained using transfer learning techniques, by changing the first layer according to the input image, and the last layer according to the number of classes is 4.

4.5 Accuration Result

The following is a confusion matrix from the results of testing a dataset with a total of 4088 data using a combination of color channels, the ResNet34 architecture obtained system accuracy of 92%, fresh meat classification accuracy of 89.1%, spoiled meat accuracy of 94.4%, fresh poultry accuracy of 94.6%, accuracy for spoiled poultry it is 91.4%, where class 0 indicates fresh meat, class 1 indicates spoiled meat, class 2 indicates fresh poultry and class 3 indicates spoiled poultry.

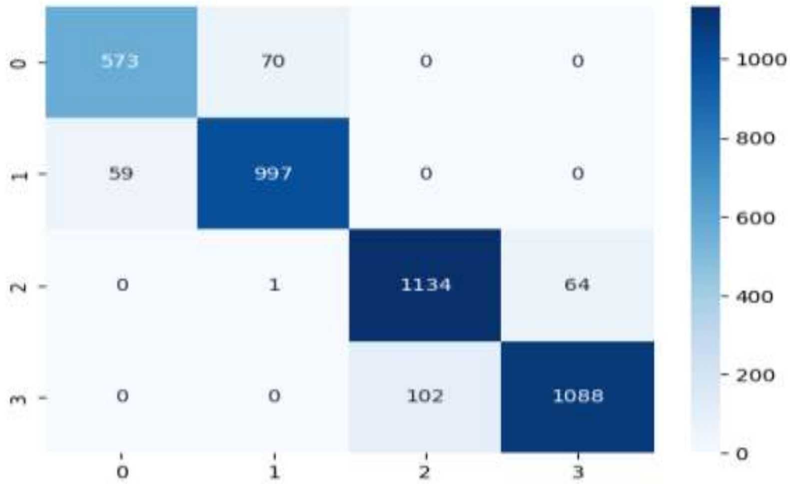

Figure 9. ResNet34 confusion matrix

The following is a confusion matrix from the results of testing a dataset with a total of 4088 data using a combination of color and texture, ResNet18 obtained system accuracy of 88%, fresh meat classification accuracy of 70.2%, spoiled meat accuracy of 97.2%, fresh poultry accuracy of 87.2%, accuracy for spoiled poultry it is 91.1%, where class 0 indicates fresh meat, class 1 indicates spoiled meat, class 2 indicates fresh poultry and class 3 indicates spoiled poultry.

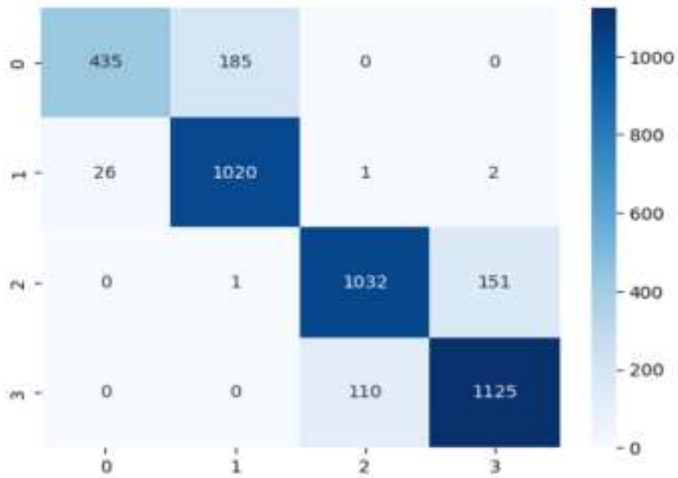

Figure 10. ResNet18 confusion matrix

The following is a confusion matrix from the results of testing a dataset with a total of 4088 data using a combination of textures, ResNet50 obtained system accuracy of 81%, fresh meat classification accuracy of 71.5%, spoiled meat accuracy of 81.5%, fresh poultry accuracy of 86.3, accuracy for spoiled poultry amounting to 81.3%, where class 0 indicates fresh meat, class 1 indicates spoiled meat, class 2 indicates fresh poultry and class 3 indicates spoiled poultry.

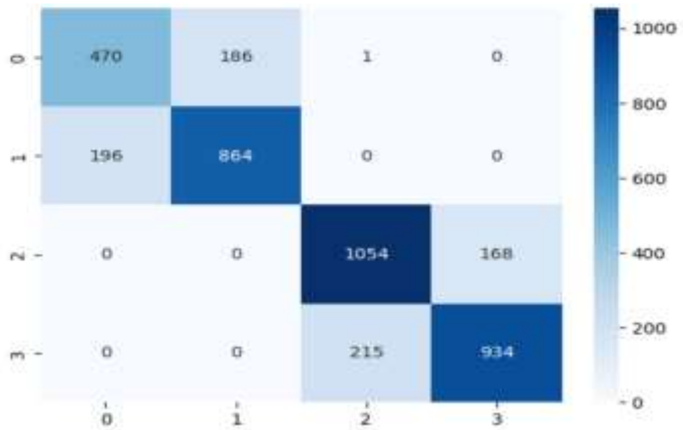

Figure 11. ResNet50 confusion matrix

5. Conclusion

The conclusions that can be drawn from this research on Meat Freshness Classification using Deep Learning are as follows: The process stages carried out in this research are carrying out an augmentation process, a feature extraction process based on color by dividing R, G and B color channels, while texture feature extraction uses GLCM (Gray Level Cooccurrence Matrix). The process of creating the Deep Learning model used in this research uses the CNN architecture ResNet18, ResNet34 and ResNet50 and the classification used is ArgMax. Based on the three CNN models that were tried, it was found that the ResNet34 architecture provided the highest accuracy using a combination of color and test features with an accuracy value of 92%. Suggestions that can be given for the development of this research are as follows: Combination of classification application development on mobile and on the server.

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