Techno Nusa Mandiri: Journal of Computing and Information Technology
Vol. 19, No. 2 September 2022 | DOI https://doi.org/10.33480/techno.v19i2.3932

MEAT IMAGE CLASSIFICATION USING DEEP LEARNING WITH RESNET152V2 ARCHITECTURE

Taopik Hidayat[1]; Faruq Aziz[2]; Daniati Uki Eka Saputri[3*]

Sains Data[1]
Sistem Informasi[2,3]
Universitas Nusa Mandiri
https://nusamandiri.ac.id/
taopik.toi@nusamandiri.ac.id[1], faruq.fqs@nusamandiri.ac.id[2], daniati.due@nusamandiri.ac.id[3*]

Abstract— *Meat is a food ingredient that can be consumed by humans and consists of essential nutrients, especially protein, which is needed for various physiological functions in the human body. Beef, mutton, and pork are meats commonly used by Indonesian people as daily processed foods. A very high level of meat consumption results in a high economic value of meat consumption. However, many people do not know how to distinguish between the types of beef, mutton, and pork. This study aims to classify beef, mutton, and pork types using the ResNet152V2 algorithm. The data used are 600 images with 200 images of beef, 200 images of mutton, and 200 images of pork. The process carried out is pre-processing using 4 stages, namely image augmentation, and image sharpness process, then the image is resized to adjust the size required by the algorithm. The last pre-processing is to perform the image normalization process. After the pre-processing is done, then the data training stage is carried out using the ReNet152V2 algorithm to build a classification model, and then the model is tested against data testing to obtain the optimal results of image classification of pork, mutton, and beef by looking at the result of accuracy and loss values.*

Keywords*: Classification, ResNet152V2, Red Meat*

Intisari— Daging merupakan bahan makanan yang dapat dikonsumsi oleh manusia dan terdiri dari zat gizi esensial, terutama protein, yang diperlukan untuk berbagai fungsi fisiologis dalam tubuh manusia. Daging sapi, kambing, dan babi merupakan daging yang biasa digunakan masyarakat Indonesia sebagai makanan olahan sehari-hari. Tingkat konsumsi daging yang sangat tinggi mengakibatkan nilai ekonomi konsumsi daging juga tinggi. Namun banyak orang tidak mengetahui cara membedakan antara jenis daging sapi, kambing, dan babi. Penelitian ini bertujuan untuk mengklasifikasikan jenis daging sapi, kambing dan babi menggunakan algoritma ResNet152V2. Data yang digunakan sebanyak 600 citra dengan 200 citra adalah daging sapi, 200 citra daging kambing dan 200 citra daging babi. Proses yang dilakukan adalah pra-pemrosesan menggunakan 4 tahapan yaitu augmentasi citra, proses sharpness citra, kemudian citra dilakukan proses resize untuk menyesuaikan ukuran yang dibutuhkan algoritma. Pra-pemrosesan terakhir adalah melakukan proses normalisasi citra. Setelah pra-pemrosesan dilakukan kemudian dilakukan tahap training data menggunakan algoritma ResNet152V2 untuk membangun model klasifikasi dan kemudian model tersebut diujikan terhadap data testing untuk mendapatkan hasil klasifikasi citra daging babi, kambing dan sapi secara optimal dengan melihat hasil akurasi dan nilai loss.

Kata Kunci*:* Klasifikasi, ResNet152V2, Daging Mentah

INTRODUCTION

Meat is a food ingredient that can be consumed by humans and consists of essential nutrients, especially protein, which is needed for various physiological functions in the human body (Susanti et al., 2022). Therefore, without a doubt, meat is not only an important food for human beings but also an important part of human life. Based on data obtained from the Directorate General of Livestock and Animal

Health (Ditjen PKH) there were 4.9 million tonnes consisting of buffalo, beef, mutton, chicken, pork, and other meat consumed in 2019 (RI, 2020).

Pork, mutton, and beef are meats commonly used by Indonesian people as processed foods. Based on a survey of the Basic Needs Market Monitoring System (SP2KP), per capita meat consumption in Indonesia reaches 6.4 kg of beef, 12.2 kg of pork, and 1.7 kg of mutton per capita per year. A very high level of meat consumption results in a high economic value of meat consumption.

The beef, mutton, and pork types look like the same meat. However, the three types of meat have different characteristics and meat colors. Beef has a distinctive dark red color, is thick, and has a distinctive smell. Mutton meat has a characteristic dark red, sometimes pink and bright color and a pungent fishy odor (Maghiszha, 2020). While the physical characteristics of pork are red but rather pale, soft in texture, and have a fishy smell.

Many people do not know how to distinguish between the types of beef, mutton, and pork. This often results in fraudulent practices by mixing pork which is cheaper than beef (Delfana et al., 2020). People find it difficult to distinguish pork from other meats. The community became uneasy with this cheating, considering that pork is a food that is prohibited for consumption, especially by Muslims.

The use of computer technology is now widely applied in various sectors of life, one of which is in the field of Artificial Intelligence (AI). AI can learn like humans by using algorithms that contain mathematical laws and is capable of doing jobs such as diagnosing diseases, predicting opportunities, and classifying objects (Maulana & Rochmawati, 2020). The scope of AI science that is capable of classifying an object/image is deep learning with image processing.

Image processing is able to classify and recognize images quickly and efficiently against large amounts of data. One of the image-processing algorithms is the Convolutional Neural Network (CNN) (Maulana & Rochmawati, 2020). CNN is an algorithm developed from the multilayer perceptron (MLP) which is designed to process two-dimensional data (Yuliani et al., 2019). Several previous studies have been carried out to differentiate meat images by utilizing the CNN algorithm with various other modifications (Ayaz et al., 2020), (Imam et al., 2021), (Yudamson et al., 2020).

Image processing for the classification of meat has been done by several researchers before. Other studies have succeeded in classifying beef, mutton, and pork. In research conducted by Alhafis (2020) using the Convolutional Neural Network method, the EfficientNet-B0 architecture for the classification of types of beef, mutton, and mixed meat. the research succeeded in classifying meat images (Alhafis et al., 2022).

However, this research cannot improve accuracy, so this research will try to use the augmentation method and several other processes so that the machine can recognize images better so as to be able to optimize the results of image classification.

Another research was conducted by Agustin (2020) and Celvin (2020) regarding the identification of chicken meat images. In Agustin's research, free-range and broiler chickens were used with the aim of classifying freshness using the GLCM method and texture extraction of the Gray Level Co-Occurance Matrix using the K-Nearest Neighbors method (Feri Agustina, 2020).

Same with Celvin's research, namely using chicken meat, to build a classification model with the K-(KNN) method (Surudin et al., 2020). Another study was conducted by Titin (2021) using the K-Nearest Neighbor (KNN) method by carrying out a feature selection process using the F-Score to select relevant features and eliminate irrelevant features in classifying the freshness level of beef (Yulianti et al., 2021). The third study used a classification technique to obtain the results of the image classification of chicken meat. So this research will try to use a more varied type of meat to classify images using the CNN method.

Based on several studies that have been carried out, this study aims to carry out a classification process for the image of red meat of several types, namely red meat consumption of local types, namely pork, mutton, and beef using the classification method. The dataset was taken using a digital camera according to the type of meat in pieces with a distance of 10 cm. The method used is a Convolutional Neural Network (CNN) using the ResNet152V2 architecture.

Image augments reproduce images so that the machine can carry out various learning processes to recognize different forms of images. After augmentation, the meat image is sharpened (sharpness) and then resized and normalized to get good classification results for beef, mutton, and pork images.

Techno Nusa Mandiri: Journal of Computing and Information Technology
Vol. 19, No. 2 September 2022 | DOI https://doi.org/10.33480/techno.v19i2.3932

MATERIALS AND METHODS

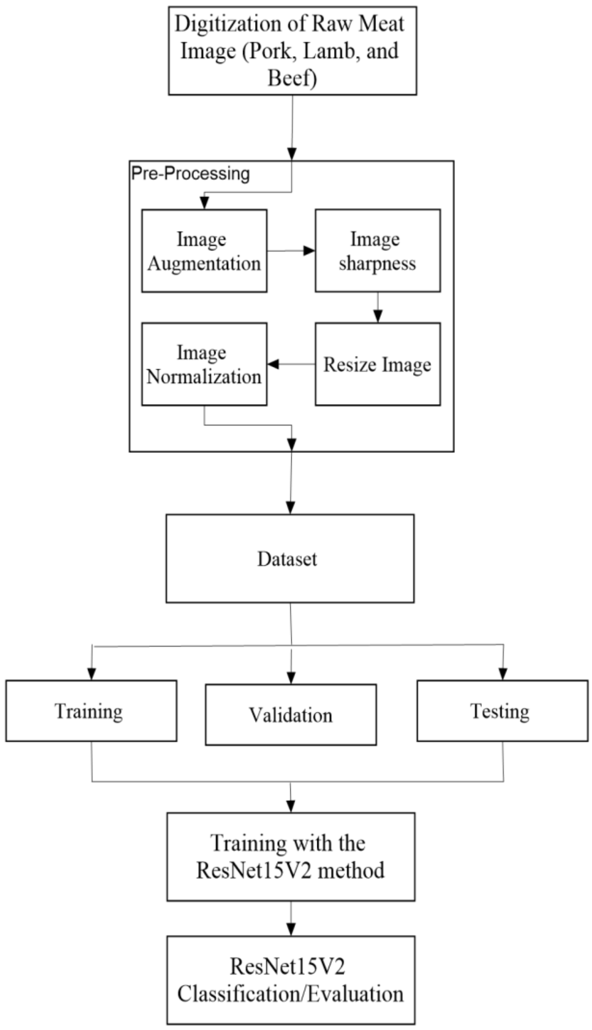


Figure 1. Research Methodology

1. Image Digitization

Image digitization is carried out by taking research objects to become dataset material by converting them into digital image forms using a digital camera. The object of this research is red meat which consists of three types, namely pork, mutton, and beef which are widely sold in local Indonesian markets.

2. Image Pre-processing

After the red meat image digitization process is carried out, then proceed with the image pre-processing process, the process is carried out in 4 stages, namely the image augmentation process or multiplying the image, followed by the sharpness process so that the image has better image quality, then the image is resized according to the process. with the size required by the algorithm and the last is to perform the image normalization process.

3. Dataset

A total of 600 images were successfully collected from the image digitization process using a camera, the images were taken at a distance of 10 cm. Image consists of types of pork, mutton, and beef. 200 images of beef were taken, 200 images of mutton, and 200 images of pork. The entire image will be processed to the next stage and divided into training data, validation data, and testing data.

4. Training Process

This study implements the deep learning method with the ResNet152V2 classification algorithm for red meat images. After the four pre-processing stages have been completed, then the red meat image is divided into training data/training data, validation data, and test data/testing data. The images used for the training process are 585 images that have been augmented. The augmented training data is then taken as much as 30% to become validation data. Furthermore, as many as 15 original images of meat were used for data testing, where the 15 images consisted of 5 images of pork, 5 images of mutton, and 5 images of beef.

5. Classification/Evaluation Process

The image classification process was carried out using the ResNet152V2 algorithm for three types of red meat to obtain the optimal classification accuracy value. After the training phase is completed, then a testing process is carried out to find out the results of the accuracy of the model built, whether it can carry out image classification properly, and find out how accurate the prediction of the type of red meat.

RESULTS AND DISCUSSION

1. Digitizing the Image of Red Meat

The first stage in the image digitization process is to carry out the initial acquisition process, namely, image digitization or taking digital versions of objects in image format using a 20.1 megapixel Canon PowerShot G7X Mark II digital camera with a distance of 10 cm. Objects are placed on a pedestal for the shooting process to be carried out based on their respective types. This determination is made to facilitate image processing because the image taken is in accordance with what is desired.

Each image can be seen in Figure 2 below.

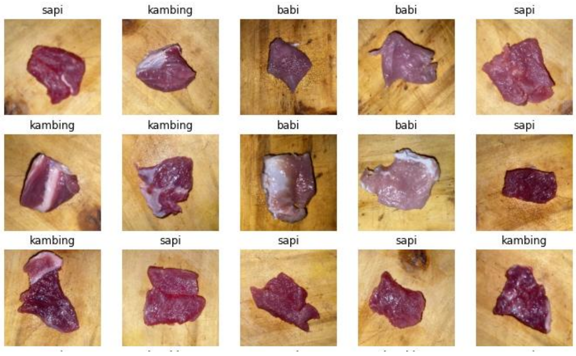


Figure 2. Red Meat Image Dataset

Figure 2 is an example of red meat images consisting of types of pork, mutton, and beef where the three have several differences in color and texture when taken with the same size and lighting. Pork has a paler color when compared to beef and mutton.

2. Image Augmentation

In the image augmentation process, it was used to multiply the images which were then used for training data, as many as 585 consisting of 195 pork images, 195 mutton images, and 195 beef images were augmented and produced 1746 images.

The augmentation process is carried out using the Flip technique (horizontal and vertical), Rotation of 90°, and exposure of the image by giving the light to make it brighter and reducing the light to make it darker where the brightness and darkness are 10%. The augmentation process is carried out so that the machine can carry out more of the learning process, namely recognizing various different forms of images from different sides.

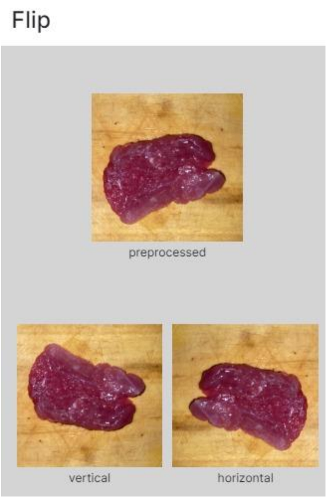


Figure 3. Image Augmentation Results with the Flip Technique

Figure 3 shows meat image processing using the flip technique, the flip process increases the number of images by rotating the image position vertically and horizontally so that different versions of the image are obtained.

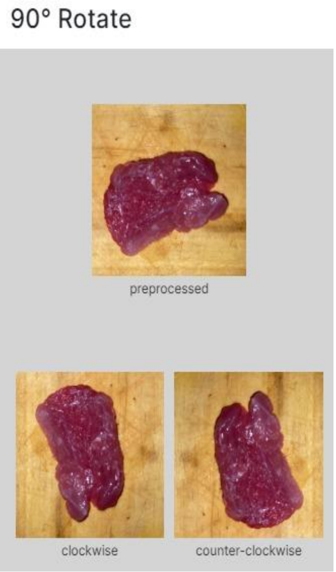


Figure 4. Image Augmentation Results with Rotation Techniques

Figure 4 is the result of meat image processing with a 90 degree rotation technique. By rotating it 90 degrees, the image has different display versions.

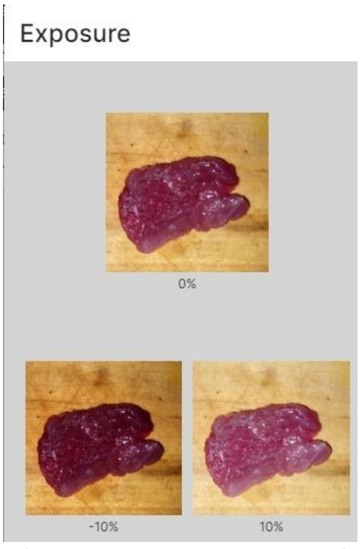


Figure 5. Image Augmentation Results with Exposure Techniques

Figure 5 is the result of meat image processing with an exposure technique of 10%. The exposure results show that the image appears brighter toward a positive number and appears darker toward a negative number. With this process, increasing the number of images used for the training process.

Techno Nusa Mandiri: Journal of Computing and Information Technology
Vol. 19, No. 2 September 2022 | DOI https://doi.org/10.33480/techno.v19i2.3932

3. Image Sharpness

After the image augmentation process is carried out, the next step is to carry out the image sharpening process with the sharpness technique where the original images of beef, mutton, and pork that have noise or are blurry are sharpened so that the image looks clearer.

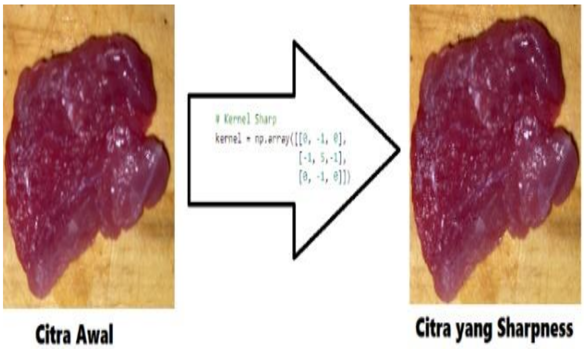


Figure 6. Meat Image Sharpness Results

Figure 6 is the image of the meat before and after the sharpness process. It can be seen that the image on the right has a sharper color after the sharpness process.

4. Resize Image

The resize process is used to reduce or enlarge the size of an image according to the desired size, it is intended that during the machine learning process it occurs faster and reduces memory usage so that image processing becomes more optimal (Asmara et al., 2017) (Yudamson et al., 2020).

The image resizing process is carried out using the Photoshop application by making the pixel size the same between images. The resizing process is carried out because the original size of the image is too large, so it is necessary to make the image size have the same dimensions, namely 224x224 pixels with a density of 72 dpi to match the method to be used.

Figure 7. Meat image resizing process

Figure 7 is the flow of the resizing process, where the left image is the original image of red meat which is then converted into a new image with new dimensions of 224x224 pixels with a density of 72 dpi.

5. Image Normalization

Images that have been resized will produce a certain size with the dimensions of each image fixed and the same. The normalization process here is used so that the resolution of the resized image can be reduced so that during the machine learning process it is better and the resulting accuracy is optimal.

6. Dataset

The collection of images resulting from image digitization that can be used in the classification process is divided into 3 types, namely training data, validation data and testing data.

A. Training Data
A total of 1746 augmentation images were taken by 70% used for training data, the number of training images was 1222.

B. Validation Data
Validation data is data used as comparison data with training data (training data). The function of data validation is as the accuracy of the model obtained from training data (training data) (Breck et al., 2019). The validation data consists of 524 images or 30% of the total augmented images. The set of images from the validation data is different from the training data.
The image on the validation data is used to validate the built training model. After the training data and validation data carry out the training process and produce accuracy, then the model is stored in a file that stores the results of the machine learning.

C. Testing Data
A total of 15 images are stored in the test data set. The image contained in the testing data is different from the image contained in the training data and data validation. The testing image used is the original image without any processing. Images in data testing also have different representations.

7. Training Data with the ResNet152V2 Method

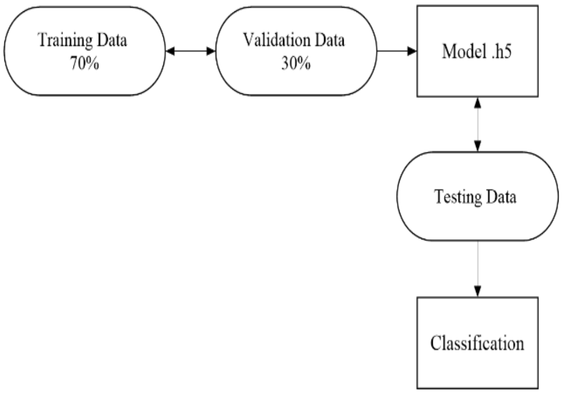


Figure 8. Illustration of the image training process

Figure 8 is an illustration of the meat image classification process. Starting with the training process on 70% of the data from a total of 1222 images of augmented meat at the pre-processing stage. The training process is carried out using the ResNet152V2 algorithm. Validation data is used to validate or ensure whether the model is appropriate and able to prevent overfitting, the number of images used for validation is 524 images, or 30% of the total training data. Then the training and validation results are stored in the .h5 model, where the file is a machine-learning model that will be used during the testing process. The testing process produces a red meat image classification model.

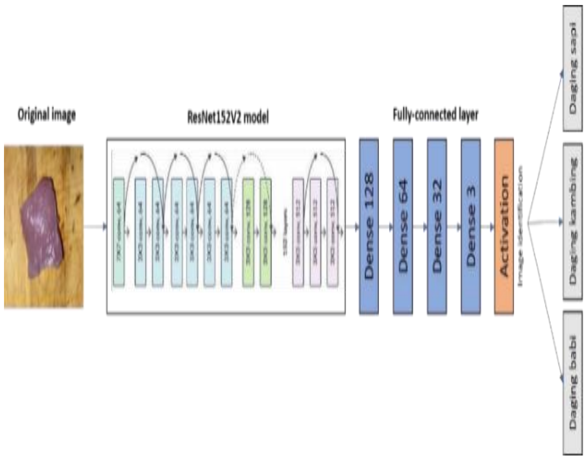


Figure 9. Illustration of the ResNet152V2 Architecture

Figure 9 is an illustration of the architecture built on by the ResNet152V2 algorithm. The model describes the stages performed by the algorithm, starting from image input, then the model performs a machine learning process based on the input provided. The algorithm uses a CNN network consisting of a pooling/subsampling layer, a fully-connected layer, and a convolution layer (Ložnjak et al., 2020). Illustration of the ResNet152V2 architecture begins with the process of determining the hidden layer using trial and error with 3 hidden layers. Then it is continued by producing 128, 64, and 32 neurons. By using 2 types of activation functions to obtain output from each layer.

After determining the activation function then select the optimizer to determine the weight. The optimizer used in this study is the adam optimizer with a learning rate of 0.01, a batch size of 128, and an epoch of 100. This model accelerates the machine training process, where the input image will be processed and inserted into the convolution layer. In the next stage, the image will be labeled, namely the type of beef with label 2, mutton with label 1 and pork with label 0.

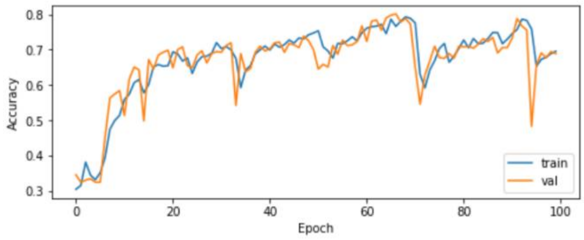


Figure 10. ResNet152V2 Architecture Training Accuracy Graph

Figure 10 is an accuracy graph generated during the training process with the ResNet152V2 architecture. It can be seen that the accuracy results increase when using high epochs. The training accuracy value shows the number 0.6956 and the accuracy value in the validation data is 0.6889. It can be seen that the graph of the accuracy value of the training data with the blue line and the validation data with the orange line shows comparable results increasing upwards, meaning that the accuracy of the training data is quite good for the image classification process.

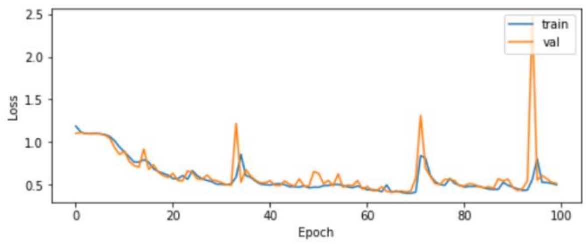


Figure 11. ResNet152V2 Architecture Loss Training Graph

Figure 11 is the result of loss or error in the image classification process produced during the

Techno Nusa Mandiri: Journal of Computing and Information Technology
Vol. 19, No. 2 September 2022 | DOI https://doi.org/10.33480/techno.v19i2.3932

training process with the ResNet152V2 architecture. The loss value generated from the training data is 0.4974 and the loss value in the validation data is 0.5118. It can be seen that the loss value gets smaller when the epoch is higher, and the loss value from the training data with the blue line and the validation data with the orange line is directly proportional when it decreases.

8. ResNet152V2 Classification/Evaluation

The model generated from the machine learning process on pork, mutton, and beef training data is used to evaluate the results of meat image classification. The evaluation results can be used to find out how optimal the ResNet152V2 algorithm is in classifying red meat images.

The machine learning model resulting from the training process is then tested at this stage. The .h5 model was tested and produced accuracy and loss values. The test is carried out by adding a batch size parameter of 64.

The confusion matrix resulting from the learning model testing process is shown in Figure 12. The confusion matrix shows the results of measuring classification performance with results in the form of two or more classes where there are 4 terms, namely true positive (TP), true negative (TN), false positive (FP), and false negatives (FN) (Sarang Narkhede, 2018) (Mohajon, 2020). It can be seen that the y-axis is the predictive label of the model and the x-axis is the actual label of the red meat image.

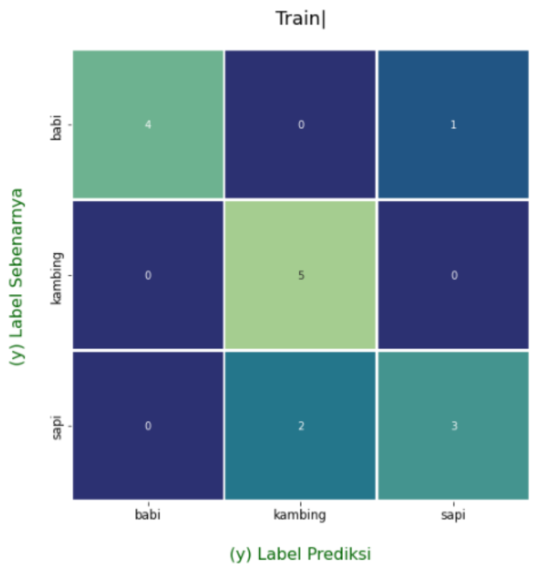


Figure 12. Image Classification Confusion Matrix

Based on Figure 12 it is known that each class has 5 images as test data. The results of the test based on the label can be concluded that 12 images were successfully identified and 3 images failed to be identified with the following information:

A. Prediction of pork images according to the class as many as 4 images and 1 image failed to be identified. Based on the results of the classification report, it can be concluded that a recall value of 0.80 means that 80% of the pork image is identified.
B. Prediction of 5 images of mutton meat according to the class. Based on the results of the classification report, it can be concluded that a recall value of 1.00 means that the image of pork is 100% identified.
C. Prediction of beef images according to the class as many as 3 images and 2 images failed to be identified. Based on the results of the classification report, it can be concluded that a recall value of 0.60 means that 60% of the pork image is identified.

Precision=

$$\frac{\text{The image of meat A is correctly identified}}{\textit{The image of meat A is correctly identified + the image of meat X is identified as A}} \quad (1)$$

1. $\textit{Precision}\ \text{Pork} = \frac{4}{4+0+0} = \frac{4}{4} = 1 \quad (2)$
2. $\textit{Precision}\ \text{Mutton} = \frac{5}{0+5+2} = \frac{5}{7} = 0{,}71 \quad (3)$
3. $\textit{Precision}\ \text{Beef} = \frac{3}{1+0+3} = \frac{3}{4} = 0{,}75 \quad (4)$

From the precision calculations performed for each class, it can be concluded that the model obtained can identify well with the accuracy level of the model obtained to identify pork 1 images, the accuracy level for mutton image identification is 0.71, and the accuracy level for image identification beef 0.75. The model obtained can be concluded as a good model because it has a good precision value. If it is concluded again from the three comparisons above, it will produce an average precision value of 0.82.

$$\textit{F1-score} = 2\text{x}\ \frac{\textit{Precision value x recall value}}{\textit{precision value + recall value}}$$
(5)

1. $\textit{F1-score}\ \text{Pork} = 2(\frac{1\ x\ 0{,}80}{1+0{,}80}) = 2(\frac{0{,}80}{1{,}80}) = 0{,}89$
(6)
2. $\textit{F1-score}\ \text{Mutton} = 2(\frac{0{,}71\ x\ 1}{0{,}71+1}) = 2(\frac{0{,}71}{1{,}71}) = 0{,}83$
(7)
3. $\textit{F1-score}\ \text{Beef} = 2(\frac{0{,}75\ x\ 0{,}60}{0{,}75+0{,}60}) = 2(\frac{0{,}45}{1{,}35}) = 0{,}67$
(8)

From the f1-score calculations performed for each class, it can be concluded that the model obtained has an average ratio of precision and recall of 0.89 for pork images, and an average comparison of precision and recall of 0.83 for mutton images. and the average comparison of precision and recall is 0.67 for beef images. If it is concluded again from the three comparisons above, it will produce an average comparison value of 0.80.

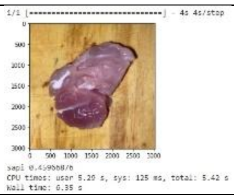
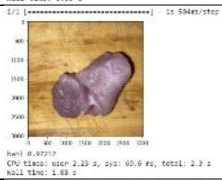
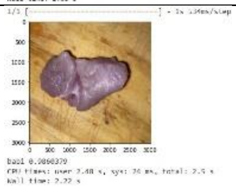
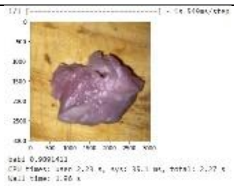
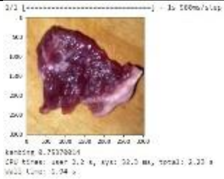
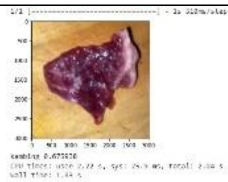
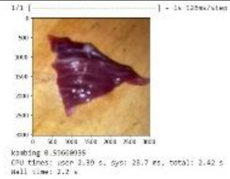
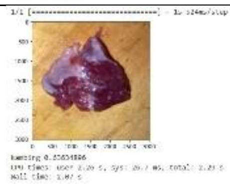
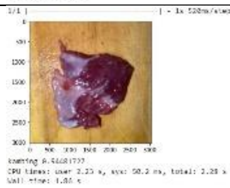
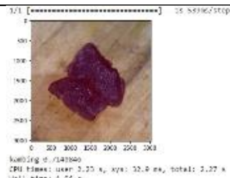
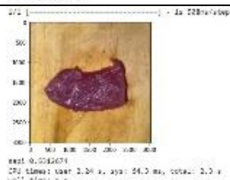
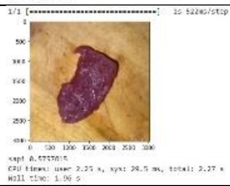
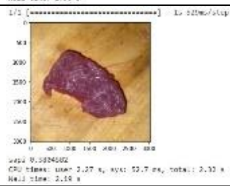
The results of testing or testing with the ResNet152V2 model on 15 images produce good accuracy values and loss values with the following calculations:

$$\text{Accuracy} = \frac{12}{15} = 0{,}8 = 80\% \quad (9)$$

$$Loss = \frac{6}{15} = 0{,}4 \quad (10)$$

From the calculation above, the resulting accuracy and loss is equal to 80% and a loss of 0.4. Classification results based on the results above, the ResNet152V2 classification model that has been built in the training process is then tested against the testing image. The following shows the results of image testing in table 1.

Table 1. Image test results

No	Image	Real Image	Prediction
1		Pork	Beef (0,46)
2		Pork	Pork (0,97)
3		Pork	Pork (0,98)
4		Pork	Pork (0,98)
5		Pork	Pork (0,99)
6		Mutton	Mutton (0,75)
7		Mutton	Mutton (0,67)
8		Mutton	Mutton (0,59)
9		Mutton	Mutton (0,63)
10		Mutton	Mutton (0,54)
11		Beef	Mutton (0,70)
12		Beef	Beef (0,53)
13		Beef	Beef (0,57)
14		Beef	Beef (0,58)

Vol. 19, No. 2 September 2022 | DOI https://doi.org/10.33480/techno.v19i2.3932

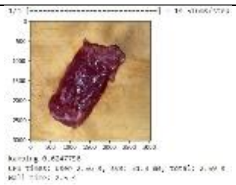
15		Beef	Mutton (0,62)

Table 1 is the result of testing the image of the model that was built during the training process. Table 1 shows that there are 4 columns where the second column is the original image used for testing as many as 15 images. In the third column are the actual image names, pork, mutton, and beef. In the fourth column is the predicted value given by the machine resulting from the classification process of the ResNet152V2 method. The predicted value is very influential in determining the results of the classification of meat images.

In the 5 pork images, it can be seen that 1 image is predicted as beef with an accuracy value of 0.46. In the mutton image, it can be seen that all images are predicted as mutton images, in other words, 100% of mutton images are correctly predicted. Then in the beef image, it can be seen that as many as 2 images are predicted as mutton images.

CONCLUSION

Based on the results of the above research, the red meat image classification process using the ResNet152V2 method was carried out by making a machine learning classification model for 585 images resulting in a classification accuracy value of 80% with an error value of 0.51. The accuracy value increases after several trials by increasing the epoch value and several pre-processing processes such as image augmentation, image sharpness, image resizing, and image normalization processes. Image testing with the model that has been built is able to classify images of pork, mutton, and beef according to the labels given. The classification results are greatly influenced by the color of the meat image and this study still uses three types of red meat, namely pork, mutton, and beef, so that in future research it can be developed again by adding the number of other red meat classes. In addition, in terms of methods, you can try other algorithms to compare better accuracy values and need to experiment with several other pre-processing so that the images are really good for machine processing to produce optimal accuracy values.

REFERENCE

Alhafis, G. Y., Sanjaya, S., Syafria, F., Budianita, E., & Optimizer, A. (2022). Klasifikasi Citra Daging Sapi dan Daging Babi Menggunakan Ekstraksi Ciri dan Convolutional Neural Network. *JURIKOM (Jurnal Riset Komputer)*, *9*(3), 653–660.

Asmara, R. A., Puspitasri, D., Romlah, S., H, Q., & Romario, R. (2017). Identifikasi Kesegaran Daging Sapi Berdasarkan Citranya Dengan Ekstraksi Fitur Warna dan Teksturnya Menggunakan Metode Gray Level Co-Occurrence Matrix. *Prosiding SENTIA*, *9*(1), 89–94.

Ayaz, H., Ahmad, M., Mazzara, M., & Sohaib, A. (2020). Hyperspectral imaging for minced meat classification using nonlinear deep features. *Applied Sciences (Switzerland)*, *10*(21), 1–13. https://doi.org/10.3390/app10217783

Breck, E., Polyzotis, N., Roy, S., Whang, S. E., & Zinkevich, M. (2019). Data Validation for Machine Learning. *Proceedings Ofthe 2nd SysML Conference*, 334–347.

Delfana, U., Jurusan, R., Informasi, T., Negeri, P., Malang, M., Teknologi, J., Politeknik, I., Malang, N. M., Unggul, Y., & Jurusan, A. (2020). Klasifikasi Citra Daging Berdasarkan Fitur Warna dan Tekstur Berbasis Android Putra Prima Arhandi. *Seminar Informatika Aplikatif Polinema*, 223–226.

Feri Agustina, Z. A. A. (2020). Identifikasi Citra Daging Ayam Kampung dan Broiler Menggunakan Metode GLCM dan Klasifikasi-NN. *Jurnal Infokam*, *XVI*(1), 25–36.

Imam, C., Hidayat, E. W., & Kurniati, N. I. (2021). Classification Of Meat Imagery Using Artificial Neural Network Method And Texture Feature Extraction By Gray Level Co- Occurrence Matrix Method. *Jurnal Teknik Informatika*, *2*(1), 1–8.

Prošnjak, S., Kramberger, T., Cesar2, I., & Kramberger, R. (2020). Automobile Classification Using Transfer Learning on ResNet Neural Network Architecture. *Polytechnic & Design*, *8*(1). https://doi.org/10.19279/TVZ.PD.2020-8-1-18

Maghiszha, D. F. (2020). *Mengenal Daging Kambing: Jenis, Karakteristik, Komposisi, Manfaat, dan Risiko Kesehatan*. Tribunnewswiki.

Maulana, F. F., & Rochmawati, N. (2020). Klasifikasi Citra Buah Menggunakan Convolutional Neural Network. *Journal of*

Informatics and Computer Science (JINACS), *1*(02), 104–108. https://doi.org/10.26740/jinacs.v1n02.p104-108

Mohajon, J. (2020). *Confusion Matrix for Your Multi-Class Machine Learning Model*.

RI, K. P. (2020). *Statistik Peternakan Dan Kesehatan Hewan/Livestock and Health Statistics 2020*.

Sarang Narkhede. (2018). *understanding confusion matrix*.

Surudin, C. H. M., Widiastiwi, Y., & Chamidah, N. (2020). Penerapan Algoritma K-Nearest NeighborPada Klasifikasi Kesegaran Citra Ayam Broiler Berdasarkan Warna Daging Dada Ayam. *Seminar Nasional Mahasiswa Ilmu Komputer Dan Aplikasinya (SENAMIKA)*.

Susanti, S., Isnawati, I., & Muhaimin, F. I. (2022). Pengurangan Konsumsi Daging Merah Berlebih untuk Menghambat Penuaan. *Muhammadiyah Journal of Geriatric*, *3*(1), 17. https://doi.org/10.24853/mujg.3.1.17-22

Yudamson, A., Sulistiyanti, S. R., Alam, S., Setyawan, F. A., & Yulianti, T. (2020). Substraksi RGB untuk Identifikasi Jenis Daging Konsumsi Berbasis Pengolahan Citra. *Electrician*, *14*(2), 52–55. https://doi.org/10.23960/elc.v14n2.2148

Yuliani, E., Aini, A. N., & Khasanah, C. U. (2019). Perbandingan Jumlah Epoch Dan Steps Per Epoch Pada Convolutional Neural Network Untuk Meningkatkan Akurasi Dalam Klasifikasi Gambar. *Jurnal INFORMA Politeknik Indonusa Surakarta*, *5*(3), 23–27.

Yulianti, T., Telaumbanua, M., Septama, H. D., & Fitriawan, H. (2021). The Effect Of Image Feature Selection On The Local Beef. *Jurnal Teknik Pertanian Lampung*, *10*(1), 85–95.