JOIV : Int. J. Inform. Visualization, 9(2) - March 2025 568-574

INTERNATIONAL JOURNAL ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

A Deep Learning Approach Using VGG16 to Classify Beef and Pork Images

Wildan Budiawan Zulfikar [a,*], Angelyna [a], Mohamad Irfan [a], Aldy Rialdy Atmadja [a], Jumadi [a]

[a] *Department of Informatics, UIN Sunan Gunung Djati, 105th A.H. Nasution Street, Bandung, Indonesia*
Corresponding Author: [*]*wildan.b@uinsgd.ac.id*

***Abstract*—There are 87.2% of the Muslim population in Indonesia, which makes Indonesia one of the countries with the largest Muslim population in the world. As a Muslim, it is supposed to carry out and stay away from the commands that Allah SWT commands, one of which is in QS. Al-maidah:3, one of the commands in the verse is not to consume haram food such as pork. Even so, it turns out that many traders in Indonesia still cheat to get more significant profits, namely by counterfeiting beef and pork. The lack of public knowledge supports this situation to differentiate between the two types of meat. Therefore, the classification process is used to distinguish the two kinds of meat using the convolutional neural network approach with VGG16 with several preprocessing stages. Two primary stages are used during the preprocessing stage: scaling and contrast enhancement. The VGG16 algorithm gets very good results by getting an accuracy value of 99.6% of the test results using 4,500 images for training data and 500 images for testing data. To compare the effectiveness of these techniques, it is recommended to use alternative CNN architectures, such as mobilNet, ResNet, and GoogleNet. More investigation is also required to gather more varied datasets, enabling the ultimate goal to achieve the best possible categorization, even when using cell phone cameras or with dim or fuzzy photos.**

***Keywords*—Beef; classification; deep learning; pork; vgg16.**

Manuscript received 27 Jun. 2024; revised 25 Sep. 2024; accepted 22 Oct. 2024. Date of publication 31 Mar. 2025.

I. INTRODUCTION

Indonesia is one of the countries with the largest Muslim populations in the world. A significant majority of its people are Muslim, making up a notable portion of the global Muslim population [1], [2]. This makes it essential to conduct strict supervision of food and or food ingredients by looking at their quality and halalness [3]. Beef is a commodity of high economic value in Indonesia. Since 2013-2023, the level of meat consumption in Indonesia has increased, but the production capacity has not been able to keep up with the beef consumption of the people in Indonesia. This causes a gap between production and consumption and makes beef prices relatively high [4].

According to a 2022 study on the halal status of a popular Indonesian food product made from beef, samples collected from various regions revealed that 22 out of 36 tested food samples contained pig DNA [5], [6]. The falsification is rarely realized by the public because when seen with the naked eye, beef disguised and mixed with pork looks the same, especially when seen by ordinary consumers. Of course, it makes people anxious, especially Indonesian people who are predominantly Muslim and forbidden to consume pork, so there is a need for a system that can identify pork and beef.

The purpose of this research is to build a system that can recognize and distinguish pork and beef by implementing deep learning approaches and methods. This will overcome counterfeiting caused by the public's ignorance of the difference between the two types of meat.

Currently, computer vision technology continues to experience rapid development [7], [8], [9], [10]. This positive development can create a system that recognizes and distinguishes between beef and pork images. Using Deep Learning, which has excellent capabilities in the field of computer vision, such as in the case of object classification in an image using the Deep Learning method, namely Convolutional Neural Network) [7], [10], [11]. Convolutional Neural Network (CNN) is an algorithm that has developed significantly in the case of image classification [12], [13], object detection, image segmentation, and object localization. In 2012, an architecture from the development of CNN won the ImageNet competition on image classification and detection, where there are millions of image data and dozens of classes [14], [15], [16], [17]. The victory obtained by the

AlexNet architecture was then followed by the presence of other architectures or models of CNN, one of which is Visual Geometry Group 16 (VGG16) [16], [18].

Visual Geometry Group 16 (VGG16) is a model of CNN development that uses convolutional layers with a small convolutional filter specification (3x3) [13], [19], [20]. With this convolutional filter value, the depth of the neural network can be increased with more convolutional layers. The VGG16 model has 19 layers consisting of 16 convolutional layers and 3 fully-connected layers [3], [21].

However, this research is focused on implementing a convolutional neural network approach using VGG16 with color and texture feature extraction to recognize and distinguish red meat images or images, whereas this research uses beef images and pork images. The development method used in this research is to use CRISP-DM, a standardization in the data mining process for general problem-solving strategies. CRISP-DM consists of several phases, namely, *business understanding*, *data understanding*, *data preparation*, *modeling*, *evaluation*, and *deployment*.

II. Materials and Method

A. Related Works

Convolutional Neural Networks (CNNs) have been investigated in a number of recent studies as a means of accurately classifying images of beef and pork. These techniques use a variety of CNN architectures, including Keras-based custom models, EfficientNet-B1, and MobileNetV2, to train deep learning models on meat images. To improve performance, the studies also used strategies like data augmentation and regularization. CNNs have the potential to be useful tools for automated meat classification, especially in the context of halal verification and food fraud detection, as evidenced by reported accuracy levels ranging from 92% to 98% [22], [23], [24].

As for research using the VGG16 architecture, which uses X-ray images to detect weld defects, traditionally, checking for defects must be done by skilled technicians, which takes much time and is greatly influenced by many factors. In this study, the data used is 3,000 x-ray image data of welding defects, which get a fairly high accuracy of 97.6% [25]. Moreover, a Deep Convolutional Neural Network is used for beef and port image classification. It is evaluated with a variety of training and testing data and different epoch values; the highest accuracy is 95.2% [26].

B. Meat Image in the Perspective of Image Processing

Meat is composed of very small fibers of animal muscle; connective tissue unites these fibers, which are elongated cells, and then forms bundles of bonds, which in most meats are visible fat blood vessels and veins. Whereas texture in meat is a function of the size of the bundles and into which the perimysial septa of the connective weave divide the veins in the meat longitudinally, such as large *diatere* which are veins in meat arranged in a rough pattern, have a large degree of postnatal growth, as well as small fibers that have small growth [27], [28], [29].

Digital image processing (PCD) is a discipline in which it studies techniques for processing an image. The image in question is a still image (photo) or video obtained from a webcam. What is meant by digital is image processing on images that are done digitally by utilizing the use of computers [30]. Some digital image processing methods used in the preprocessing stage in this study are contrast enhancement and image resizing.

Contrast Enhancement is a method to improve image quality by increasing the contrast value contained in the mind so that the noise contained in the image is not excessive and makes the image appear clearer. Resizing is a method of changing the resolution or horizontal and vertical size of an image. Several types of algorithms are used for the resizing process, one of which is Lanczos interpolation. This method uses the 8 nearest pixels and assigns new pixels by taking the average of their weight values.

C. Convolutional Neural Network and VGG16

Convolutional Neural Network (CNN) is a type of neural network that consists of several layers, namely, *convolutional layer*, *pooling layer,* and *connected layer*. Convolution will produce a linear transformation of the input data according to the spatial information in the data. The *weights* in the layer specify the convolution kernel used, allowing the *convolution* kernel to be trained based on the *input* to the CNN [31], [32], [33].

Visual Geometry Group 16 (VGG16) uses convolutional layers with a filter value. Because it uses convolutional layers of this size, the depth of the neural network can be added with more convolutional layers. The addition of these layers makes this model more accurate than previous CNN models [20], [31], [34], [35], [36]. VGG16 has 13 convolutional layers and 3 fully connected. The architecture of VGG16 can be seen in the Figure below [37]:

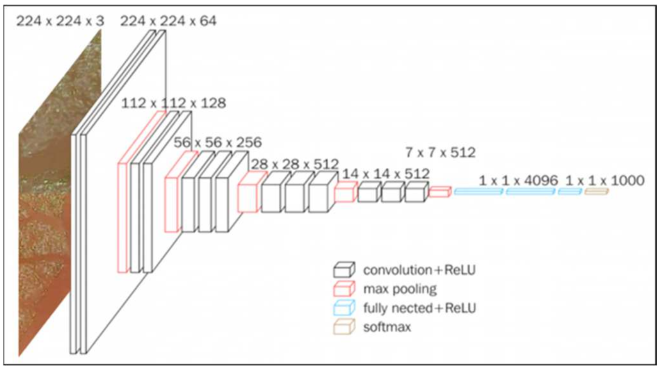


Fig. 1 Architecture of VGG16

D. Confusion Matrix

Confusion Matrix is a method used to perform calculations to obtain accurate results on data mining concepts. Confusion Matrix is also used to assess how the performance of a model has been made. The four terms above are also very important to provide information from the classification results because the classification results cannot be seen with just one number.

E. Proposed Method

Problem analysis is used to solve or get the best solution. To solve the problem in this study, the solution that can be used is to use the VGG16 algorithm to classify beef and pork images. This image classification process can provide information to users to distinguish beef and pork that have been classified into two meat labels, namely beef and pork. Color and texture are used to distinguish the two types of meat.

These two parameters were chosen because this research uses a way to visually distinguish meat by looking at color and texture. As for the difference between the color and texture of the two types of meat, as quoted on the CNN Indonesia web page, beef has a color that tends to be pale when compared to meat. Besides, when viewed in terms of texture, beef has a texture that is more on and stiff, in contrast to pork, which has a soft texture and is easily stretched. The architecture of this research can be seen in the Figure below:

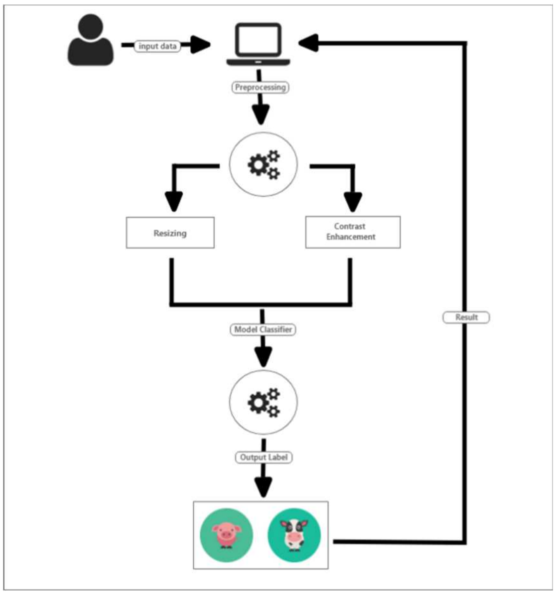


Fig. 2 The architecture of Proposed System

The Figure above is an overview of the architecture design of the system, it can be explained that after the data is inputted, the first stage is that the data is entered into the pre-processing process before being entered into the classification process. Pre-processing consists of two stages; the first is resizing using the Lanczos interpolation method available in the Python image library. This process is used to meet the needs of a system that only accepts input with a size of 224x224 pixels. After the data is resized, it enters the second stage, namely contrast enhancement. This stage is used to add contrast to the image data so that it makes the image look clearer. After the data passes the preprocessing stage, then the data enters the Classification stage. In this stage, the VGG16 algorithm is used to classify data into two predetermined labels; the 2 labels are pork and beef labels. Then, the last stage of the system will produce output in the form of classification results from the VGG16 algorithm, which will be in the form of a beef or pork label.

The total number of images was 5,000, with two labels, beef, and pork, which amounted to 2,500 images each. The beef parts taken were tenderloin, sirloin, and chuck. Meanwhile, the pork that was taken was pork thigh meat. In addition, it was obtained using a digital microscope with a magnification of about 20x to 200x captured with a 2MP camera, as illustrated in Figure 3.

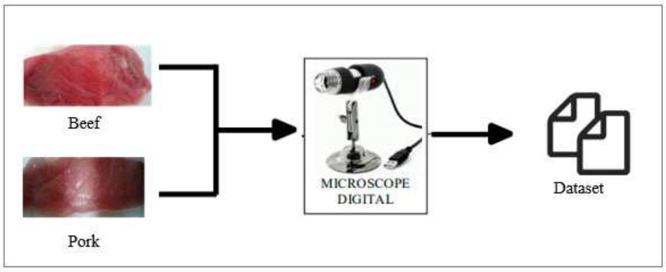
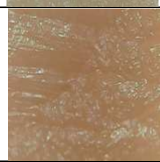
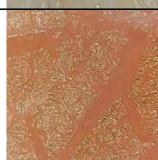
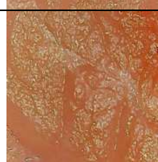


Fig. 3 Dataset collection process

Based on the process in Fig. 3, the datasets involved in this study were obtained. Some of them are presented in Table 1 below:

TABLE I
INVOLVED DATA

No.	Images	Class
1		Pork
2		Pork
3		Pork
4		Pork
5		Pork
6		Beef
7		Beef
8		Beef

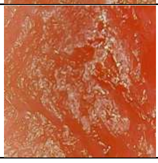
No.	Images	Class
9		Beef
10		Beef

Image preprocessing is one of the stages used to improve the image for processing in the next stage. The preprocessing that will be carried out in this study consists of 2 stages, namely resizing and contrast enhancement. The first stage carried out in preprocessing is resizing, which changes an image's resolution or horizontal and vertical size. This process meets the system's needs because the algorithm used in this study accepts input images with a size of 224x224 pixels.

This process is carried out using Lanczos interpolation, which uses the 8 closest pixels and assigns new pixels by taking the average of their weight values. The resizing process is represented in the Figure below.

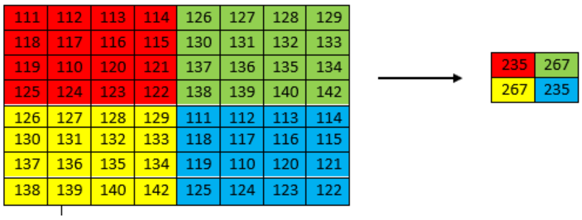


Fig.4 Illustration of resizing an image of 8x8 pixels to 2x2 pixels

Fig. 4 above is the process of resizing the image from 8x8 pixels to 2x2 pixels, and taking the average value of the 8 nearest pixels, the value of each new pixel is obtained as follows:

$$\begin{aligned} \text{P1} &= (111 + 112 + 113 + 114 + 118 + 117 + 116 \\ &\quad + 115 + 119 + 110 + 120 + 121 + 125 \\ &\quad + 124 + 123 + 122)/8 \ = 235 \\ \text{P2} &= (126 + 127 + 128 + 129 + 130 + 131 + 132 \\ &\quad + 133 + 137 + 136 + 135 + 134 + 138 \\ &\quad + 139 + 140 + 142)/8 \ = 267 \\ \text{P3} &= (126 + 127 + 128 + 129 + 130 + 131 + 132 \\ &\quad + 133 + 137 + 136 + 135 + 134 + 138 \\ &\quad + 139 + 140 + 142)/8 \ = 267 \\ \text{P1} &= (111 + 112 + 113 + 114 + 118 + 117 + 116 \\ &\quad + 115 + 119 + 110 + 120 + 121 + 125 \\ &\quad + 124 + 123 + 122)/8 \ = 235 \end{aligned}$$

The next stage is the contrast enhancement process using PIL (Python Image Library), which aims to make the colors and textures in the image data clearer and make the noise in the image not excessive. The value (C) in this process is set at 2.0. the calculation process in this process uses (1) below:

$$F = \frac{259\,(c+255)}{255\,(259-c)} \tag{1}$$

The implementation of (1) results in the value of the contrast correction factor (F), which is detailed in the calculation results below:

$$F = \frac{259\,(c+255)}{255\,(259-c)}$$

$$F = \frac{259\,(2+255)}{255\,(259-2)}$$

$$F = \frac{66563}{65535}$$

$$F = 1.016$$

The value of F is stored in float data type so the algorithm can work properly. After the F value is obtained, contrast enhancement is performed on the red, green, and blue layers. The following equation shows how to set contrast enhancement.

$$R' = F\,(\,R - 128) + 128 \tag{2}$$

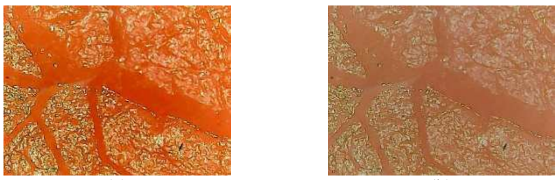
$$R' = F\,(\,G - 128) + 128 \tag{3}$$

$$R' = F\,(\,B - 128) + 128 \tag{4}$$

The contrast enhancement calculation process is represented by pixels that have RGB values (140,130,130), using the equation above, the results obtained are as follows:

$$\begin{aligned} R' &= \text{F}\,(\text{R} - 128) + 128 \\ R' &= 1.016\,(140 - 128) + 128 \\ R' &= 1.016\,(12) + 128 \\ R' &= 141 \\ G' &= \text{F}\,(\text{G} - 128) + 128 \\ G' &= 1.016\,(130 - 128) + 128 \\ G' &= 1.016\,(2) + 128 \\ G' &= 131 \\ B' &= \text{F}\,(\text{B} - 128) + 128 \\ B' &= 1.016\,(130 - 128) + 128 \\ B' &= 1.016\,(2) + 128 \\ B' &= 131 \end{aligned}$$

Then, the result of the RGB value after the contrast enhancement process from the original RGB (140,130,130) becomes RGB (141,131,131). This calculation is also done for images that have been previously resized to 250 x 250 pixels. Figure 4 below shows a beef image that has passed the image enhancement process.



(a) (b)

Fig. 5 (a) Image before the contrast enhancement process (b) image after contrast enhancement process

This research uses the VGG16 (Visual Geometry Group 16) algorithm to create a model that can recognize and classify an image. VGG16 is an algorithm that can recognize and classify a 2-dimensional object in the form of an image into a label that has been previously determined; in this study, the labels used are beef and pork labels. By using convolutional layers (3x3) stacked to increase the network, the Vgg16 architecture comprises 13 convolutional layers, 3 fully connected layers, and 4 pooling layers. This research uses SoftMax as the activation function and then uses the RMSprop optimizer with the conditions (lr=0.001, rho= 0.9, momentum=0.0, epsilon=le-07), and the batch size value used is the default value of 32.

III. Result and Discussion

The testing process was run using 10 scenarios consisting of two main parts: epoch value variants and data variants. In testing the epoch value variant, 5 scenarios are used by giving different epoch values, namely 10, 20, 30, 40, and 50, by using a data ratio of 60% or as many as 3,000 images for training data and 40% or 2,000 images for testing data. The results of testing using epoch values can be seen in Table 2 below:

TABLE II
Precision and Recall Results from Variant Epoch Testing

Epoch	Precision		Avg	Recall		Avg
	Beef	Pork		Beef	Pork	
10	0.974	0.977	0.975	0.974	0.977	0.975
20	0.993	0.949	0.971	0.947	0.994	0.970
30	0.980	0.980	0.980	0.980	0.981	0.980
40	0.978	0.984	0.981	0.985	0.978	0.981
50	0.987	0.978	0.979	0.978	0.988	0.983

Based on Table 2, the average precision value at each epoch is stable, with a value above 0.900, as well as the average recall value, which is obtained with an average value above 0.970 for each class. Other elements, namely accuracy and f1-score, are described in Table 3.

TABLE III
Accuracy and F1-Score Results from Variant Epoch Testing

Epoch	Accuracy		Avg	F1-Score		Avg
	Beef	Pork		Beef	Pork	
10	0.974	0.977	0.975	0.974	0.975	0.974
20	0.947	0.994	0.970	0.969	0.970	0.969
30	0.980	0.981	0.980	0.980	0.98	0.980
40	0.985	0.978	0.981	0.981	0.980	0.980
50	0.978	0.988	0.983	0.982	0.983	0.982

On the other elements, namely accuracy and f1-score, the 5 different epochs show that the average epoch value for both classes is above 0.900, as described in Table 3.

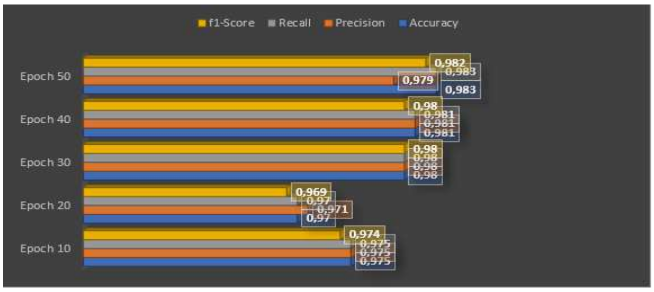


Fig. 6 Graph of the results of the accuracy value in each experiment variant epoch value

Based on Tables 2 and 3, represented in Figure 6, it can be seen that the accuracy value generated from the VGG16 algorithm by testing 5 times using different epoch values obtained the highest accuracy with a value of 98.3% on the trial epoch value of 50 By using different epoch variants, the model has not been able to increase the accuracy value significantly. The results of testing 5 times with different epoch values could only increase accuracy by 0.8%. So another experiment is needed to determine other factors affecting the accuracy value.

Other tests were carried out, using 5 scenarios with different data variants between training and testing data with an epoch value of 50, while the data comparison used is 90:10 (training data 4,500, data testing 500), 80:20 (training data 4,000, data testing 1,000), 70:30 (training data 3,500, data testing 1,500), 60:40 (training data 3,000, data testing 2,000), 50:50 (training data 2,500, data testing 2,500). The results of the precision and recall elements are described in the Table below.

TABLE IV
Precision and Recall Results from Variant Epoch Testing

Training & Testing Composition	Precision		Avg	Recall		Avg
	Beef	Pork		Beef	Pork	
90:10	1.000	0.992	0.996	0.992	1.000	0.994
80:20	0.997	0.990	0.993	0.990	0.998	0.994
70:30	0.981	0.981	0.981	0.981	0.981	0.981
60:40	0.987	0.978	0.979	0.978	0.988	0.983
50:50	0.986	0.979	0.982	0.979	0.986	0.982

In the Table above, it is explained that epoch 50 results in average precision and recall values for both classes are only slightly different from 90:10 to 50:50. The accuracy and f1-score elements are explained in the Table below:

TABLE V
Accuracy Results and F1-Score by Variant Epoch Testing

Training & Testing Composition	Accuracy		Avg	F1-Score		Avg
	Beef	Pork		Beef	Pork	
90:10	0.992	1.000	0.996	0.993	0.993	0.993
80:20	0.990	0.998	0.994	0.993	0.994	0.993
70:30	0.981	0.981	0.981	0.981	0.981	0.981
60:40	0.974	0.977	0.975	0.981	0.983	0.982
50:50	0.979	0.986	0.982	0.982	0.983	0.982

Table 5 explains the accuracy and f1-score values for each variation of training data and testing data. The average accuracy and f1-score value for each class is slightly different in each scenario.

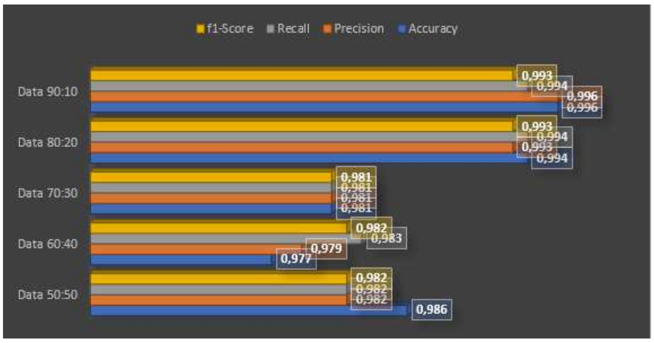


Fig. 7 Graph of accuracy value results on each data variant experiment

As presented in Tables 4 and 5, several experiments using variants on different training and testing data, namely with a ratio of 90:10, 80:20, 70:30, 60:40, 50:50, the results of this experiment get a fairly high accuracy rate of 0.996 or 99.6% obtained from the results of data experiments with a ratio of 90:10 (90% or as many as 4,500 images for training data and 10% or as many as 500 images as testing data). The accuracy generated from this test is high enough for using the VGG16 algorithm. This test proves that the amount of training and testing data influences accuracy. It finds that the higher the composition of training data to test data, the higher the accuracy value. Moreover, the VGG16 algorithm recognizes and classifies beef and pork images well.

IV. CONCLUSION

This study uses a development method approach from CNN, namely the Visual Geometry Group 16 (VGG16) method. The proposed method can recognize and distinguish beef and pork images very well, with the highest accuracy value of 99.6% obtained from the results of a 90:10 data ratio or as many as 4,500 images used for training data and 500 images used for testing data with an epoch value of 50. The factors that influence the results of this test are the large amount of train data, besides the balanced distribution of data between cattle and pork labels. The irregular distribution of train and test data will result in unbalanced data distribution for the two labels so that the model can learn the data well; besides that, it is known that many or few epoch values do not affect the accuracy value in the training process. For further work, we suggest using other CNN architectures to compare the performance of these methods, such as mobilNet, ResNet and GoogleNet. In addition, further research is needed to obtain more diverse datasets so that the final target can perform optimal classification, even using cell phone cameras or with faint or blurry images.

REFERENCES

[1] F. Aidulsyah, "The rise of urban Salafism in Indonesia: The social-media and pop culture of new Indonesian Islamic youth," *Asian J Soc Sci*, vol. 51, no. 4, pp. 252–259, Dec. 2023, doi:10.1016/J.AJSS.2023.07.003.

[2] M. Mujahidin, Zainuddin, N. Rahmadani, and Q. A. R. Putri, "Analysis of the Influence of Religiosity Values In Reducing Consumptive Behavior in Indonesian Muslim Consumers," *Amwaluna: Jurnal Ekonomi dan Keuangan Syariah*, vol. 8, no. 2, pp. 253–274, Jul. 2024, doi: 10.29313/amwaluna.V8I2.3785.

[3] P. S. Muttaqin, E. B. Setyawan, and N. Novitasari, "Factors Influencing Readiness towards Halal Logistics among Food and Beverages Industry in the Era of E-Commerce in Indonesia," *JOIV : International Journal on Informatics Visualization*, vol. 7, no. 3, pp. 781–787, Sep. 2023, doi: 10.30630/joiv.7.3.2055.

[4] BPS, *Distribusi Perdagangan Komoditas Daging Sapi di Indonesia 2018*. 2018.

[5] H. N. Siswara, Y. Erwanto, and E. Suryanto, "Study of Meat Species Adulteration in Indonesian Commercial Beef Meatballs Related to Halal Law Implementation," *Front Sustain Food Syst*, vol. 6, p. 882031, Jul. 2022, doi: 10.3389/fsufs.2022.882031.

[6] A. Windarsih, F. D. O. Riswanto, N. K. A. Bakar, N. D. Yuliana, Dachriyanus, and A. Rohman, "Detection of Pork in Beef Meatballs Using LC-HRMS Based Untargeted Metabolomics and Chemometrics for Halal Authentication," *Molecules*, vol. 27, no. 23, p. 8325, Dec. 2022, doi: 10.3390/molecules27238325/S1.

[7] W. Fan, J. Fang, and G. Huang, "An improved image texture synthesis based on algorithm convolution neural network," *Physical Communication*, vol. 66, p. 102395, Oct. 2024, doi:10.1016/J.phycom.2024.102395.

[8] A. Setiawan, R. Sigit, and R. Rokhana, "Face Recognition Using Convolution Neural Network Method with Discrete Cosine Transform Image for Login System," *JOIV : International Journal on Informatics Visualization*, vol. 7, no. 2, pp. 502–510, May 2023, doi:10.30630/joiv.7.2.1546.

[9] S. U. Masruroh, M. F. Syahid, F. Munthaha, A. T. Muharram, and R. A. Putri, "Deep Convolutional Neural Networks Transfer Learning Comparison on Arabic Handwriting Recognition System," *JOIV : International Journal on Informatics Visualization*, vol. 7, no. 2, pp. 330–337, May 2023, doi: 10.30630/joiv.7.2.1605.

[10] W. Chen, H. Sang, J. Wang, and Z. Zhao, "DSTCNN: Deformable spatial-temporal convolutional neural network for pedestrian trajectory prediction," *Inf Sci (N Y)*, vol. 666, p. 120455, May 2024, doi: 10.1016/J.INS.2024.120455.

[11] M. Yasin, M. Sarıgül, and M. Avci, "Logarithmic Learning Differential Convolutional Neural Network," *Neural Networks*, vol. 172, p. 106114, Apr. 2024, doi: 10.1016/j.neunet.2024.106114.

[12] A. S. Kasman, A. A. Zikri, Fariduzzaman, and W. Srigutomo, "Convolutional Neural Networks-Based For Predicting Aerodynamic Coefficient Of Airfoils At Ultra-Low Reynolds Number," *JOIV : International Journal on Informatics Visualization*, vol. 8, no. 1, pp. 309–317, Mar. 2024, doi: 10.62527/joiv.8.1.2197.

[13] A. E. Minarno, B. Y. Sasongko, Y. Munarko, H. A. Nugroho, and Z. Ibrahim, "Convolutional Neural Network featuring VGG-16 Model for Glioma Classification," *JOIV : International Journal on Informatics Visualization*, vol. 6, no. 3, pp. 660–666, Sep. 2022, doi:10.30630/joiv.6.3.1230.

[14] B. Sahithi and S. Vigneshwari, "Exploring the Performance of VGG16 and Efficient Net Models for Plant Disease Classification: A Comparative Approach," *Proceedings of the 2023 1st International Conference on Cyber Physical Systems, Power Electronics and Electric Vehicles, ICPEEV 2023*, 2023, doi:10.1109/icpeev58650.2023.10391936.

[15] A. Kaur, V. Kukreja, M. Kumar, A. Choudhary, and R. Sharma, "A Fine-tuned Deep Learning-based VGG16 Model for Cotton Leaf Disease Classification," *2024 5th International Conference for Emerging Technology, INCET 2024*, 2024, doi:10.1109/incet61516.2024.10593164.

[16] A. Ben Slama, H. Sahli, Y. Amri, and S. Labidi, "V-NET-VGG16: Hybrid deep learning architecture for optimal segmentation and classification of multi-differentiated liver tumors," *Intell Based Med*, vol. 11, p. 100210, Jan. 2025, doi: 10.1016/j.ibmed.2025.100210.

[17] C. H. Praharsha and A. Poulose, "CBAM VGG16: An efficient driver distraction classification using CBAM embedded VGG16 architecture," *Comput Biol Med*, vol. 180, p. 108945, Sep. 2024, doi:10.1016/j.compbiomed.2024.108945.

[18] A. S. Arnob, A. K. Kausik, Z. Islam, R. Khan, and A. Bin Rashid, "Comparative result analysis of cauliflower disease classification based on deep learning approach VGG16, inception v3, ResNet, and a custom CNN model," *Hybrid Advances*, vol. 10, p. 100440, Sep. 2025, doi: 10.1016/j.hybadv.2025.100440.

[19] H.-C. Tey, L. Y. Chong, and S.-C. Chong, "Comparative Analysis of VGG-16 and ResNet-50 for Occluded Ear Recognition," *JOIV : International Journal on Informatics Visualization*, vol. 7, no. 4, pp. 2247–2254, Dec. 2023, doi: 10.30630/joiv.7.4.02276.

[20] M. S. M. Yazed, M. A. M. Yunus, E. F. A. Shaubari, N. A. A. Hamid, A. Amzah, and Z. M. Ali, "Corrugation and Squat Classification and Detection with VGG16 and YOLOv5 Neural Network Models," *JOIV : International Journal on Informatics Visualization*, vol. 8, no. 2, pp. 916–922, May 2024, doi:10.62527/joiv.8.2.2756.

[21] Y. Chen, Y. Chen, S. Fu, W. Yin, K. Liu, and S. Qian, "VGG16-based intelligent image analysis in the pathological diagnosis of IgA nephropathy," *J Radiat Res Appl Sci*, vol. 16, no. 3, p. 100626, Sep. 2023, doi: 10.1016/j.jrras.2023.100626.

[22] N. S. Fauzi, I. Salamah, and I. Hadi, "Image Identification System for Beef and Pork Using a Convolutional Neural Network," *PIKSEL : Penelitian Ilmu Komputer Sistem Embedded and Logic*, vol. 12, no. 2, pp. 343–354, Sep. 2024, doi: 10.33558/piksel.v12i2.9831.

[23] I. M. Ramadhan, J.- Jasril, S. Sanjaya, F. Yanto, and F. Syafria, "Image Classification of Beef and Pork Using Convolutional Neural Network Architecture EfficienNet-B1," *Indonesian Journal of Artificial Intelligence and Data Mining*, vol. 6, no. 1, pp. 54–62, Jun. 2023, doi:10.24014/ijaidm.V6I1.21843.

[24] S. bila, A. Fitrianto, and B. Sartono, "Image Classification of Beef and Pork Using Convolutional Neural Network in Keras Framework," *International Journal of Science, Engineering and Information Technology*, vol. 5, no. 02, pp. 245–248, Jul. 2021, doi:10.21107/ijseit.V5I02.9864.G5810.

[25] B. Liu, X. Zhang, Z. Gao, and L. Chen, "Weld defect images classification with VGG16-based neural network," *Communications in Computer and Information Science*, vol. 815, pp. 215–223, 2018, doi: 10.1007/978-981-10-8108-8_20.

[26] P. Chanasupaprakit, N. Khusita, C. Chootong, J. Charoensuk, W. K. Tharanga Gunarathne, and S. Ruengittinun, "Fake Beef Detection with Machine Learning Technique," *Proceedings of the 2022 5th IEEE International Conference on Knowledge Innovation and Invention, ICKII 2022*, pp. 124–127, 2022, doi:10.1109/ickii55100.2022.9983559.

[27] A. Arsalane, A. Klilou, N. El Barbri, and A. Tabyaoui, “Artificial vision and embedded systems as alternative tools for evaluating beef meat freshness,” *6th International Conference on Optimization and Applications, ICOA 2020 - Proceedings*, Apr. 2020, doi:10.1109/icoa49421.2020.9094503.

[28] S. Verdú *et al.*, “Multivariate image analysis for assessment of textural attributes in transglutaminase-reconstituted meat,” *Chemometrics and Intelligent Laboratory Systems*, vol. 256, p. 105280, Jan. 2025, doi:10.1016/j.chemolab.2024.105280.

[29] S. Ayu Aisah, A. Hanifa Setyaningrum, L. Kesuma Wardhani, and R. Bahaweres, “Identifying Pork Raw-Meat Based on Color and Texture Extraction Using Support Vector Machine,” *2020 8th International Conference on Cyber and IT Service Management, CITSM 2020*, Oct. 2020, doi: 10.1109/citsm50537.2020.9268892.

[30] O. N. Shpakov and G. V. Bogomolov, “Technogenic activity of man and local sources of environmental pollution,” *Studies in Environmental Science*, vol. 17, no. C, pp. 329–332, 1981, doi:10.1016/S0166-1116(08)71924-1.

[31] F. Zhao, B. Zhang, Z. Zhang, X. Zhang, and C. Wei, “Classification and detection method of Blood lancet based on VGG16 network,” *2021 IEEE International Conference on Mechatronics and Automation, ICMA 2021*, pp. 849–853, Aug. 2021, doi:10.1109/icma52036.2021.9512686.

[32] Z. Bao, Y. Wu, G. Pan, Y. Liu, J. Hu, and Y. Liu, “VGG16 Fire Image Fast Detection Based on Multi-layer Features Fusion,” *2022 IEEE 5th International Conference on Electronics Technology, ICET 2022*, pp. 1158–1162, 2022, doi: 10.1109/icet55676.2022.9824459.

[33] N. L. Tun, A. Gavrilov, N. M. Tun, D. M. Trieu, and H. Aung, “Remote Sensing Data Classification Using A Hybrid Pre-Trained VGG16 CNN-SVM Classifier,” *Proceedings of the 2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering, ElConRus 2021*, pp. 2171–2175, Jan. 2021, doi:10.1109/elconrus51938.2021.9396706.

[34] D. I. Swasono, H. Tjandrasa, and C. Fathicah, “Classification of tobacco leaf pests using VGG16 transfer learning,” *Proceedings of 2019 International Conference on Information and Communication Technology and Systems, ICTS 2019*, pp. 176–181, Jul. 2019, doi:10.1109/icts.2019.8850946.

[35] H. Wang, “Garbage recognition and classification system based on convolutional neural network vgg16,” *Proceedings - 2020 3rd International Conference on Advanced Electronic Materials, Computers and Software Engineering, AEMCSE 2020*, pp. 252–255, Apr. 2020, doi: 10.1109/aemcse50948.2020.00061.

[36] H. Aung, A. V. Bobkov, and N. L. Tun, “Face detection in real time live video using yolo algorithm based on VGG16 convolutional neural network,” *Proceedings - 2021 International Conference on Industrial Engineering, Applications and Manufacturing, ICIEAM 2021*, pp. 697–702, 2021, doi: 10.1109/icieam51226.2021.9446291.

[37] D. I. Swasono, H. Tjandrasa, and C. Fathicah, “Classification of tobacco leaf pests using VGG16 transfer learning,” *Proceedings of 2019 International Conference on Information and Communication Technology and Systems, ICTS 2019*, pp. 176–181, 2019, doi:10.1109/icts.2019.8850946.