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Image Classification of Beef and Pork Using Convolutional Neural Network Architecture EfficientNet-B1

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ABSTRACT

The increasing demand for beef has made many meat traders mix beef with pork to get more profit. Mixing beef and pork is harmful, especially for Muslims. In this study, the EfficientNet-B1 Convolutional Neural Network (CNN) approach was used to classify beef and pork. Experiments were conducted to compare accuracy using original data (without data augmentation) and with data augmentation. The data augmentation techniques used are rotation and horizontal flip. The total dataset after the data augmentation process is 3000 images. Many different settings were tested, including learning rates (0.00001, 0.0001, 0.001, 0.01, 0.1), batch size (32, 64), and optimizer (Adam, Adamax). After testing the Confusion Matrix, the highest accuracy results were obtained using data augmentation with a batch size of 32 of 98%. Meanwhile, those without data augmentation were 96%.

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1. INTRODUCTION

The increasing demand for beef [1] has prompted many meat traders to mix beef with pork to make more profits. According to [2], beef and pork had still a mixture in the Bogor City traditional market. As proof of this, it had found that up to 7.86%, or 3/33, of the beef samples that tested positive also contained pork.

Mixing beef and pork is harmful, especially to Muslims, because God forbids eating pork, as stated in Al-Qur'an Surat An-Nahl verse 115. Additionally, consuming foods prohibited in Islam (haram food) has several detrimental implications, including unanswered prayers, mental and emotional harm, and not being accepted into worship [3]. Meanwhile, the negative consequences can include a disorder of the brain, liver, spinal nerves, and lungs [4], digestive disorders, diarrhea, and anemia [5]. It is difficult to tell the difference between beef and pork, and consumers are unaware had blended. Various studies had conducted to categorize or classify beef and pork using machine learning and deep learning methods.

Research related to the classification of beef and pork using Machine Learning techniques has been conducted, among others: Eviyan, Triyogatama, and Danang implemented the Bidirectional Associative Memory (BAM) algorithm [6]. Lestari, H et al. [7] used the Probabilistic Neural Network (PNN) method. Research by Jasril and Suwanto applied the Spatial Fuzzy C-Means (SFCM) method with LVQ3 [8]. Furthermore, Lidya et al. [9] used Fuzzy Learning Vector Quantization (FLVQ). And the classification of beef and pork meat using Backpropagation, RGB color histogram value, and Gray Level Co-Occurrence Matrix (GLCM) by R A Asmara et al. [10].

Recent research on studies on unstructured data, such as image processing, has incorporated deep learning, an efficient classification method. In deep learning, artificial neural networks with a hierarchy of levels had deployed. It performs better than machine learning in classifying images [11], [12], [13] and needs less data pre-processing [14].

Convolutional Neural Networks (CNNs), a deep learning model, were used in many research to classify pork and beef. Using CNN and Hard Voting, Made Bramasta V.P., I Putu A.B., and Dewa Made S.A.

[15] achieved accuracy results of 98.88%, precision results of 98.89%, and recall results of 98.88%. Similarly, research by Sarah, L. et al. [16] employing CNN ResNet-50 produced average accuracy, recall, and precision values of 87.64%, 87.59%, and 90.90% [16]. Another study using CNN with AlexNet [17] resulted in an accuracy of 84.1%, precision of 78.6%, and recall of 79%. In addition, research by Alhafis G.Y et al. [18] implemented CNN (EfficientNet-B0) with Contrast Limited Adaptive Histogram Equalization (CLAHE) obtained results of 95.17%, precision of 92.72% and recall of 95.5%.

In this study, the EfficientNet-B1 architecture is used with the CNN method since it performs better than the EfficientNet-B0 and B2 models [19] [20]. Another justification for employing this model in research is that the EfficientNet-B1 design scales more effectively and provides high accuracy values by balancing depth, width, and resolution [21]. In addition, several studies have used the EfficientNet-B1 model [22], [23], [24].

We also used data augmentation techniques in this study to enrich the data because the amount of beef and pork data we could collect was limited. In this study, we used EfficienNet-B1 with the original and augmented data to compare the performance. In various studies, EfficienNet-B1 with data augmentation had used, and the results were more accurate than those obtained without data augmentation. Florian, T. et al. [26], Ejaz, K. et al. [27], Fadil, A., Ebnem, B., & Aybars, U. [25] are a few of the studies that fall under this category.

2. RESEARCH METHODOLOGY

The research methodology is carried out in several stages. The following are the stages of image classification in this research. Figure 1 shows the classification process without data augmentation and Figure 2 with augmentation.

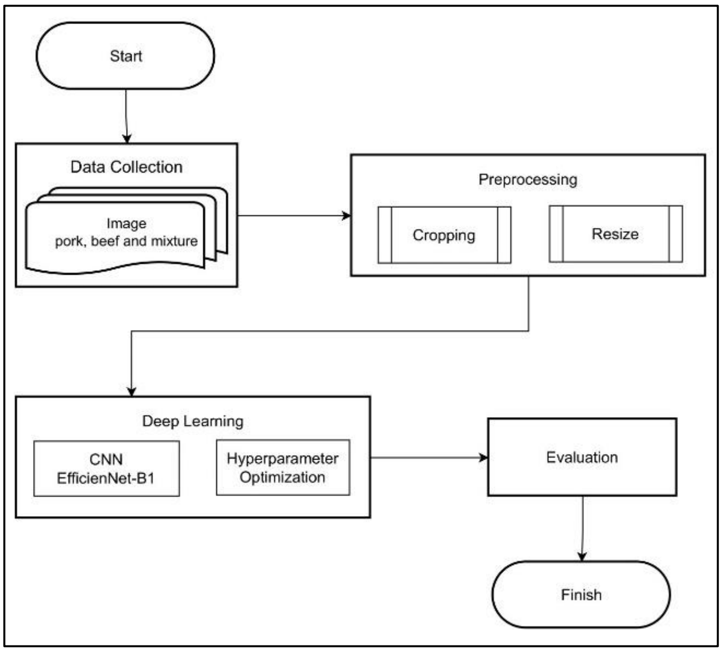

Figure 1. Research stages without augmentation

2.1 Data Collection

Data gathered through the direct collection (primary data) comes from various traditional markets (*Pasar Bawah and Pasar Dupa*) in Pekanbaru, Riau. Image capture of beef and pork using a 44MP front camera and a 64MP camera for the Vivo V20 smartphone. The distance used is between 8 to 15 cm. The capture of lighting adjusts to the surroundings. Pork, beef, and mixed are the three classes. There were 600 total images acquired, each with 200 images

2.2 Preprocessing

Preprocessing is done after data collection, including cropping and scaling. While scaling produces identical sized images, cropping removes areas that do not represent part of the image. In this paper, a cropped photo with a resolution of 1000 x 1000 pixels was used. The following is an illustration of the image used in this study. Below is an illustration of the images used in this study. Figure 3a shows an image that has not been cropped, while Figure 3b has been cropped. Meanwhile, Figure 4 shows the results of the resize. The image was resized to 240X240 pixels.

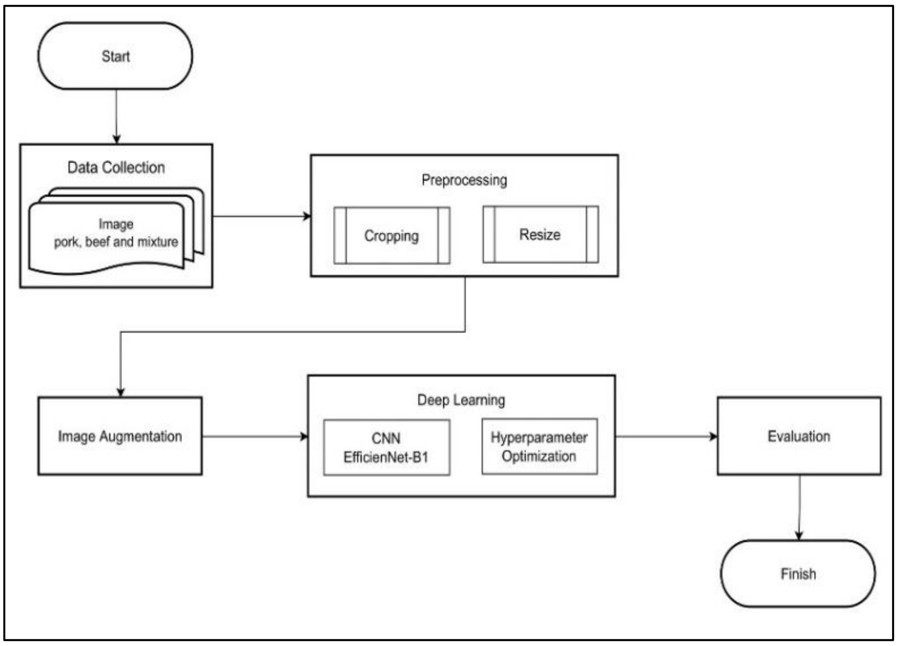

Figure 2. *R*esearch stages with Augmentation

Figure 3. (a) Original Image, (b) Image of Cropped

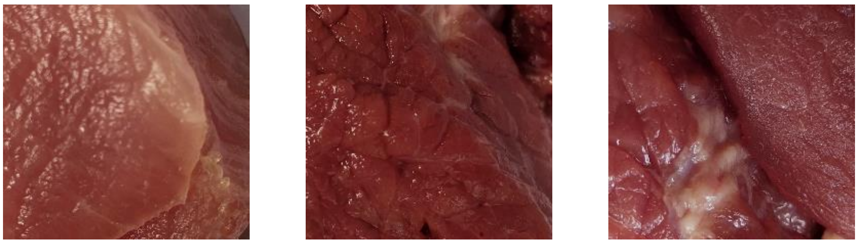

Figure 4. The results of the resize

2.3 Data Augmentation

After preprocessing, the next step is data augmentation to increase the size of the training data by converting existing data into new data. This augmentation process is necessary because CNN requires a lot of labeled data for training. In this study the data augmentation technique used was the horizontal flip technique and the rotation technique with random degrees between 0 and 10. The total data generated from this augmentation process is 3000 images.

2.4 Deep Learning

The following process is the classification process using EfficientNet-B1. The first step is to divide the dataset into training data (80%) and testing data (20%). Furthermore, the training data is to split into new training data (80%) and validation data (20%). The distribution of training and testing data can be seen in table 1 (without data augmentation). While table 2 shows the distribution of data using data augmentation.

Table 1. Dataset Beef, Pork, Mixed without Augmentation

Class	Training Data (80%)		Testing Data (20%)
	New Training Data (80%)	Validation Data (20%)	
Beef	128	32	40
Pork	128	32	40
Mixed meat	128	32	40

Table 2. Dataset Beef, Pork, Mixed with Augmentation

Class	Training data (80%)		Testing Data (20%)
	New Training Data (80%)	Validation Data (20%)	
Beef	640	160	200
Pork	640	160	200
Mixed meat	640	160	200

2.5 Convolutional Neural Network

CNN performs image classification based on similarity and is capable of recognition. CNN describes a variety of multilayer perceptrons that can operate on two-dimensional data like existing neurological systems in humans. CNN has a convolution layer which is formed from several combinations of convolution layers, polling layers, and fully connected layers[20].

1. EfficientNet-B1
   EffiienNet-B1 is the classification architecture used in this research. EfficientNet has the advantage of being able to increase the accuracy and increase effectiveness of the model. EfficientNet leverages a scaling method that combines all network dimensions at resolution, width, and depth. The following figure 5 is an architectural stage EfficientNet-B1 in this research.

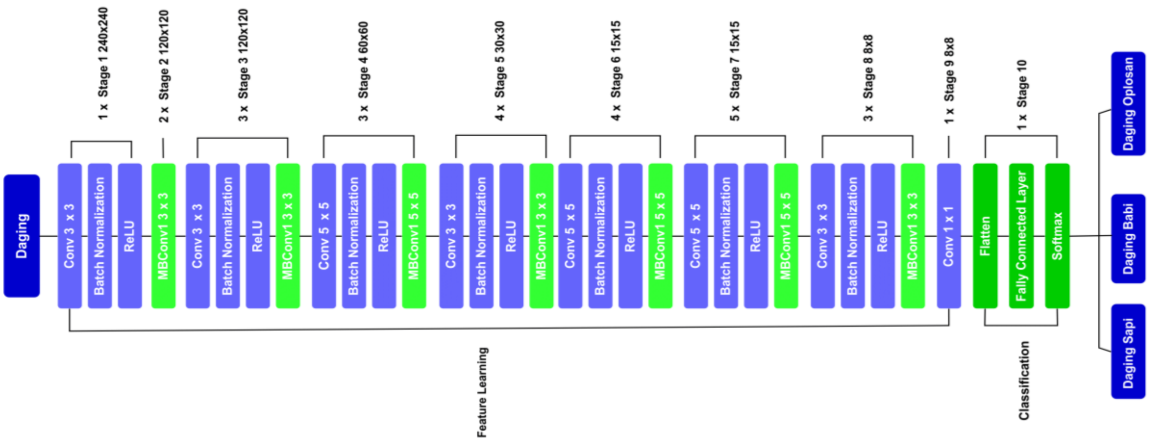

Figure 5. EfficientNet-B1 Architecture

2. Hyperparameter Optimization
   Hyperparameter Optimization is proposed to optimize media image processing on the CNN Model formed. This study uses optimization hyperparameters including epoch, batch size, learning rate, adam and adamax optimizer.

2.6 Evalution

Evaluation of beef and pork classification results is measured using the Confusion matrix. There are 4 components used, namely (TP) True Positive, namely data that is positive and correctly predicted, (FP) False Positive, namely data that is negative but predicted as positive, (FN) False Negative, namely data that is positive but predicted as negative, (TN) True Negative the negative amount of data and correctly predicted. The following is the formula for calculating the evaluation model with the confusion matrix.

$$\text{Accuracy}(\%) = \frac{TP + TN}{TP + FP + FN + TN} \quad (1)$$

$$\text{Precision (\%)} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Recall (\%)} = \frac{TP}{TP + FN} \quad (3)$$

$$\text{F1-Score (\%)} = 2x\,\frac{Recall \times Precision}{Recall + \; Precision} \quad (4)$$

3. RESULTS AND DISCUSSION

As indicated in Table 3, numerous variables had used in the test scenario, including batch size, epoch, learning rates, and optimizer. Based on the parameters are used, the experiment carried out 40 times, where 20 experiments used data augmentation and 20 without it.

Table 3. Hyperparameter are used in the experiment

Class	Batch Size	Epoch	Learning Rate	Optimizer
Pork	32		0.1	Adam
			0.01	
Beef		50	0.001	
	64		0.0001	Adamax
Mixed meat			0.00001	

The results had obtained using Google Colab tools with the Python programming language within various libraries such as Tensor Flow and Keras. The values of the accuracy, recall, precision, and f1 score for each scenario run had displayed in Table 4.

Table 4. Experimental results without augmentation and with augmentation

Batch Size	Learning Rate	Optimizer	Evaluasi							
			Without Augmentation				With Augmentation			
			Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score
32	0.1	Adam	93%	93%	93%	92%	**98%**	**98%**	**98%**	**98%**
		Adamax	89%	91%	89%	89%	97%	97%	97%	97%
	0.01	Adam	93%	94%	93%	93%	96%	96%	96%	96%
		Adamax	90%	91%	90%	90%	**98%**	**98%**	**98%**	**98%**
	0.001	Adam	**96%**	**96%**	**96%**	**96%**	96%	96%	96%	96%
		Adamax	88%	91%	88%	89%	96%	96%	96%	96%
	0.0001	Adam	92%	93%	92%	92%	97%	97%	97%	97%
		Adamax	93%	94%	93%	93%	97%	97%	97%	97%
	0.00001	Adam	85%	88%	85%	85%	95%	96%	96%	96%
		Adamax	85%	85%	85%	85%	94%	94%	94%	94%
64	0.1	Adam	91%	92%	91%	91%	97%	97%	97%	97%
		Adamax	94%	94%	94%	94%	96%	96%	96%	96%
	0.01	Adam	95%	95%	95%	95%	97%	97%	97%	97%
		Adamax	78%	86%	78%	77%	97%	97%	97%	97%
	0.001	Adam	95%	95%	95%	95%	96%	96%	96%	96%
		Adamax	82%	87%	82%	81%	96%	96%	96%	96%
	0.0001	Adam	86%	89%	86%	86%	96%	96%	96%	96%
		Adamax	91%	92%	91%	91%	96%	96%	96%	96%
	0.00001	Adam	82%	86%	82%	82%	95%	95%	95%	95%
		Adamax	88%	90%	88%	80%	94%	94%	94%	94%

According to Table 4, the best accuracy value of 98% had achieved during testing using data augmentation with batch sizes of 32, learning rates of 0.1 with the Adam optimizer, and learning rates of 0.01 with the Adamax optimizer. Meanwhile, testing without data augmentation using batch size 32 and learning rates 0.001 with Adam optimizer has the highest accuracy value of 96%.

Using the data from Table 4, Figure 6 displays a graph of the training results without data augmentation. With batch sizes of 32 and 64, and learning rates of 0.1, 0.01, 0.001, and 0.00001, this training employs the Adam and Adamax Optimizer with epoch settings of 50. An accuracy value of 96%, a precision of 96%, a recall of 96%, and an F1 score of 96% had obtained using batch size 32, a learning rate of 0.001, and Adam Optimizer for the highest accuracy. Figure 7 displays a graph of the training results with data augmentation. This training utilizes the parameters of Epoch 50, batch sizes of 32 and 64, learning rates of 0.1, 0.01, 0.001, and 0.0001, and Adam and Adamax Optimizers. The best results of 98% accuracy, 98% precision, 98% recall, and 98% f1 score were obtained, with batch sizes of 32, Adam and Adamax optimizers, and learning rates of 0.1 and 0.01, respectively. We can infer that using data augmentation resulted in a 2% increase in accuracy.

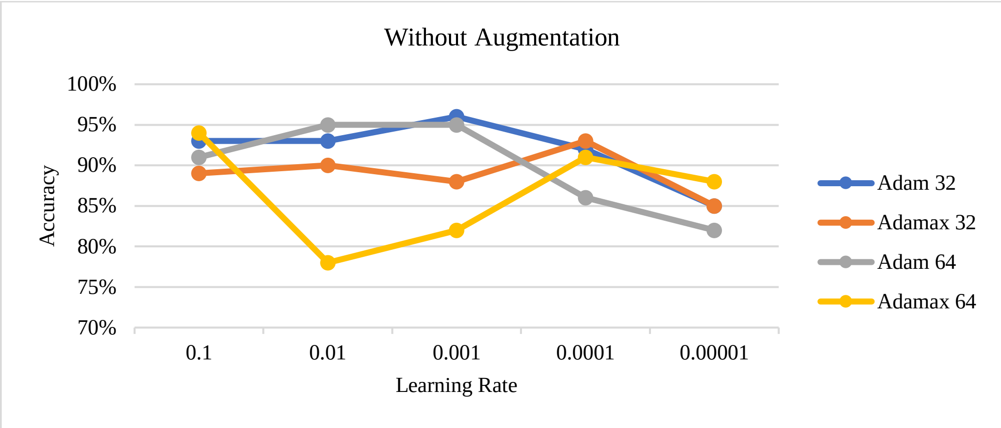

Figure 6. Graph of training results withaout Augmentation

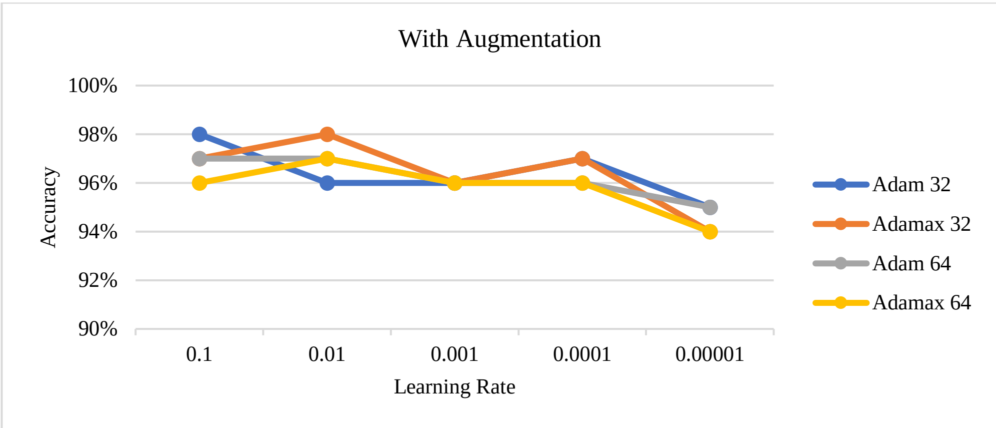

Figure 7. Graph of training results with Augmentation

A further analysis followed utilizing the confusion matrix graph based on the best results. Figures 8 and 9 illustrate the confusion matrix graphs deploying the Adam and Adamax optimizers. Based on Figure 8, out of a total of 200 pork samples analyzed, one (1) sample was identified as beef, while the other two (2) samples had classified as mixed meat. Meanwhile, from the 200 mixed meat samples analyzed, two (2) and four (4) were identified as beef and pork, respectively. Figure 9, which applies the Adamax optimizer, demonstrates that of the 200 porks that had analyzed, only one (1) has classified as mixed meat and none as beef. Of the 200 blend types of meat tested, three (3) beef and six (6) pork had founded.

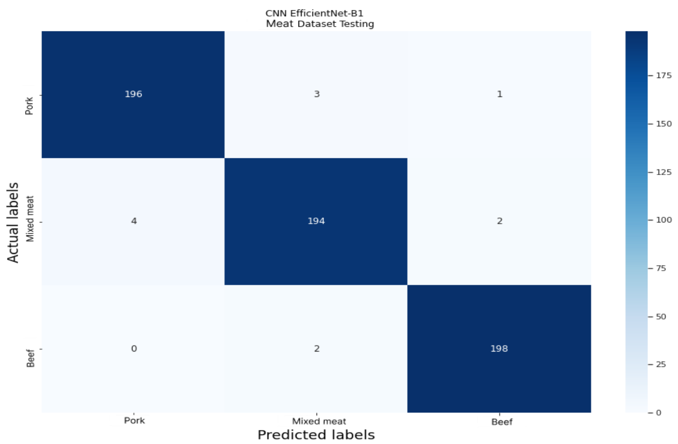

Figure 8. Confusion matrix with Augmentation using parameter batch size 32, learning rates 0.1 and Adam Optimizer

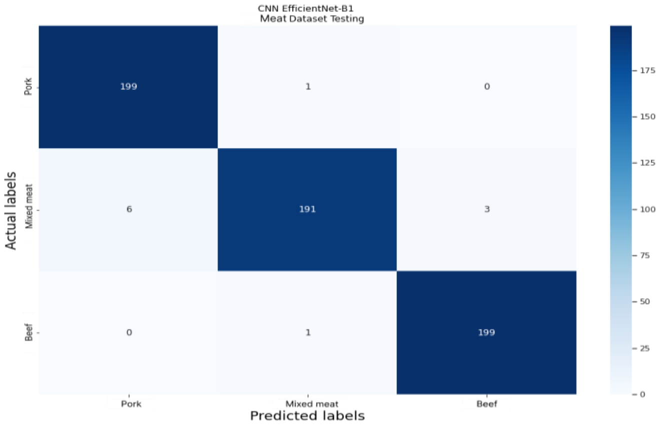

Figure 9. Confusion matrix with Augmentation using parameter batch size 32, learning rates 0.01 and Adamax Optimizer

4. CONCLUSION

Based on the experiments conducted, using data augmentation with parameters including batch sizes of 32, learning rates of 0.1 and 0.01, and optimizing Adam and adamax, the highest accuracy rate was 98%. However, when the settings batch size 32, learning rates 0.001, and Adam optimizer had used, the highest accuracy value without data augmentation was 96%. Based on these results, there is an increase in accuracy using data augmentation. However, there is still a misclassification where pork or mixed meat is still known as beef. It is better to misidentify beef as pork or blend types of meat than to mistakenly identify pork or a mixture as beef.

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