Classification of Beef and Pork with Deep Learning Approach

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Abstract—Beef is one of the most consumed meats in Indonesia. However, the high price of beef has led to rogue traders mixing pork with beef. This condition occurs due to the lack of public knowledge about the difference between the two meats. To maintain food safety in Indonesia and especially in Riau province, the Livestock Service Office of Riau province conducts market surveys. There are several methods that are usually used to check the content of beef or pork, including Rapid Test Kit and Elisa. Both methods are time consuming and costly. One other solution that can be used is the artificial intelligence method, namely deep learning. In this research, a classification approach using deep learning is used to distinguish between beef and pork in the form of a web application. This research compares Convolutional Neural Network algorithm with Inception-V3 and Inception-Resnet-V2 architecture with hyperparameter optimization. From several experiments that have been carried out, the best model is the Inception-Resnet-V2 architecture with an experimental scenario using a learning rate of 0.001, and an optimizer Adam with an accuracy of 96.50%, Precision 96.48%, Recall 96.55% and F1-Score 96.50%. By using this model, web-based applications can be developed using the flask framework well and can perform classification accurately.

Keywords—Classification, Inception-V3, Inception-Resnet-V2, Flask

I. INTRODUCTION

Food has an important role in life because food is one of the essential needs for humans [1]. Consumption of healthy food supports the growth and development of the body [2]. Meat is one of the foods that is a source of animal protein that contributes to the maintenance of organ function [3]. There are several types of meat commonly consumed in Indonesia, including beef [4].

The price of beef in Riau province tends to increase every year [5]. The high price of beef causes rogue traders to mix pork with beef. This condition occurs because the shape of pork and beef is similar and the naked eye is quite difficult to distinguish [6]. It is also influenced by the lack of public knowledge about the differences between the two meats [7]. This issue has often occurred in Indonesia. As happened in Bogor city, 7.86% of beef samples tested positive for pork [8]. Another incident was in Tangerang City. Police found 500 kg of beef mixed with pork [9].

As a country with a majority Muslim population, halal food is very important [10]. Therefore, to maintain food safety for the people in Indonesia and especially in Riau province, the Livestock Service Office of Riau province conducts market surveys to ensure the authenticity of meat. This activity is usually carried out ahead of religious holidays, such as fasting and Eid al-Fitr. There are several methods that are usually used to check the content of beef or pork, including Rapid Test Kit and Elisa (Enzyme-Linked Immunosorbent Assay) [11]. Both methods take quite a long time. In addition, the cost to test using these methods is quite expensive [12]. One other solution that can be used to distinguish beef and pork in addition to the above methods is to utilize deep learning methods.

Some related research that has been done before is the identification of beef and pork with the Resnet-50 architecture which produces a model with an average accuracy of 87.64% [13]. Further research was conducted using EfficientNet-B0 and obtained an accuracy of 95.16% [14]. The next study used the Alexnet architecture. The results of the study showed the highest accuracy of 85% [15].

The above researches are only up to algorithm modeling and not up to application development. In this research, a classification approach using deep learning is used to help distinguish between beef and pork using CNN with Inception-V3 and Inception-Resnet-V2 architectures. Then evaluation is done with Evaluation Metrics (Precision, Recall, F1 Score, Accuracy). After the best model is obtained, it is then used for web-based application development using the flask backend framework [16].

II. METHODOLOGY

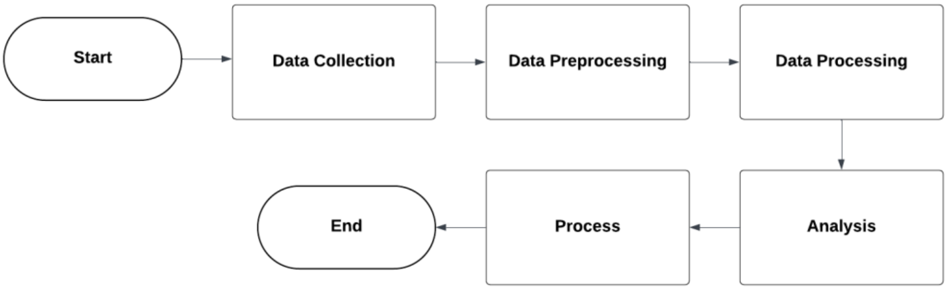

Figure 1. Research Methodology

A. Data Collection

Data was collected by purchasing beef and pork from markets in Pekanbaru. The purchased meat was then photographed. The amount of data obtained was 500 images of beef and 500 images of pork.

B. Data Preprocessing

Resize image is done to change the size of the data to have the same size and remove noise [17]. Then data augmentation is done to enrich the variety of data owned and prevent overfitting [18]. Meanwhile, data division uses the Holdout Method.

C. Data Processing

1) Implementation of Deep Learning Algorithm

The process of implementing deep learning algorithms using CNN with Inception-V3 and Inception-Resnet-V2 architectures by testing various hyperparameters to find the best model for image classification.

2) Metrics Evaluation

Accuracy can be misleading in cases where there is a large class imbalance, hence the need for another evaluation matrix that can measure the performance of the classification model created. The evaluation is done by creating a confusion matrix consisting of accuracy, precision, recall, and f1score [19]

D. Analysis

After the data processing stage, the next step is the analysis stage. What is done at this stage is to analyze the model that has been trained to see the best model.

E. Application Deployment

The application built is a web-based application using the flask framework. Flask is used because it is lightweight and fast. Flask was created with the idea of simplifying the core framework to a minimum [20]. Flask can help create applications very quickly even with a simple library [21].

III. RESULTS AND DISCUSSION

A. Data Collection

The types of meat used were Lampung beef and local pork.. These types of beef and pork were chosen because they are the most widely sold types in Pekanbaru.

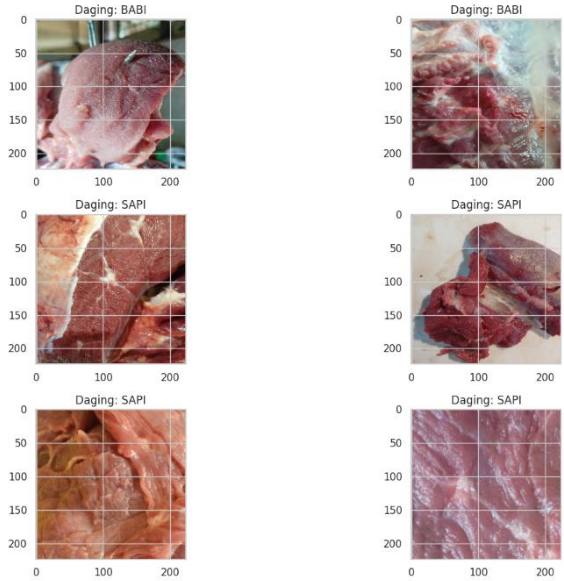

Figure 2. Beef and Pork Dataset

B. Data Preprocessing

1) Resize Image

all images are resized to the same size. In this study using an image with a size of 224 x 224 pixels.

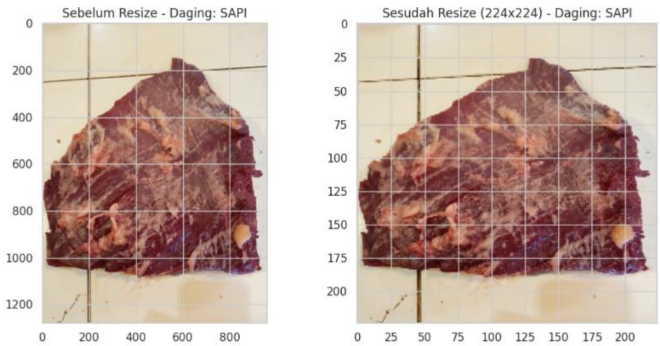

Figure 3. Resize Image Result Example

2) Data Augmentation

Data augmentation is performed using the library from hard tensorflow, ImageDataGenerator. There are 5 data augmentations performed, namely rotation_range, zoom_range, width_shift_range, height_shift_range, and horizontal_flip.

Figure 4. Example of Data Augmentation Result

3) Data Splitting

The dataset of beef and pork images totaling 500 of each class will be divided using the Train-Test split (Holdout Method). The division of training data and test data is made with a percentage of 80% for training data and 20% for testing data. This dataset division is done using train_test_split from the scikit learn library.

C. Modeling

1) Model Designing

There were several experiments conducted to find the best parameters. The experiments conducted were a total of 24

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inception_v3 (Functional)   (None, 5, 5, 2048)        21802784

 global_average_pooling2d_1  (None, 2048)              0
  (GlobalAveragePooling2D)

 flatten_1 (Flatten)         (None, 2048)              0

 dense_2 (Dense)             (None, 256)               524544

 dropout_1 (Dropout)         (None, 256)               0

 dense_3 (Dense)             (None, 1)                 257

=================================================================
Total params: 22327585 (85.17 MB)
Trainable params: 524801 (2.00 MB)
Non-trainable params: 21802784 (83.17 MB)
_________________________________________________________________
```

Figure 5. Inception-V3 Model summary

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inception_resnet_v2 (Funct  (None, 5, 5, 1536)        54336736
 ional)

 global_average_pooling2d (  (None, 1536)              0
 GlobalAveragePooling2D)

 flatten (Flatten)           (None, 1536)              0

 dense (Dense)               (None, 256)               393472

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 1)                 257

=================================================================
Total params: 54730465 (208.78 MB)
Trainable params: 393729 (1.50 MB)
Non-trainable params: 54336736 (207.28 MB)
_________________________________________________________________
```

Figure 6. Inception-Resnet-V2 Model summary

In the model, the convolutional layer is frozen to maintain the parameters of the pre-trained imagenet weight. Then 1 dense layer with 256 neurons is added. Then added a dropout method of 0.5 to improve the performance of the model and prevent overfitting. In the last layer, 1 dense output layer with sigmoid activation is added. Sigmoid activation was chosen because the classification consists of only 2 classes, namely beef and pork classes.

Furthermore, the model is compiled with a binary-crossentropy loss function. Binary-crossentropy is used because in this study only uses 2 classes or what is often called binary classification. In one example of the model used is using the Adam optimizer and with a learning_rate of 0.001..

```
model.compile(optimizer=Adam(learning_rate=0.001),loss='binary_crossentropy',metrics=['accuracy'])
```

Figure 7. Model Compile

2) Model Training

The model is trained with 50 training epochs with a batch size of 16. Each model will get the same treatment for fair comparison.

D. Model Evaluation

After the model has been trained, an evaluation of the model is performed. The following is one of the evaluation results of Inception-V3 model training using Adam's optimizer and learning rate 0.001

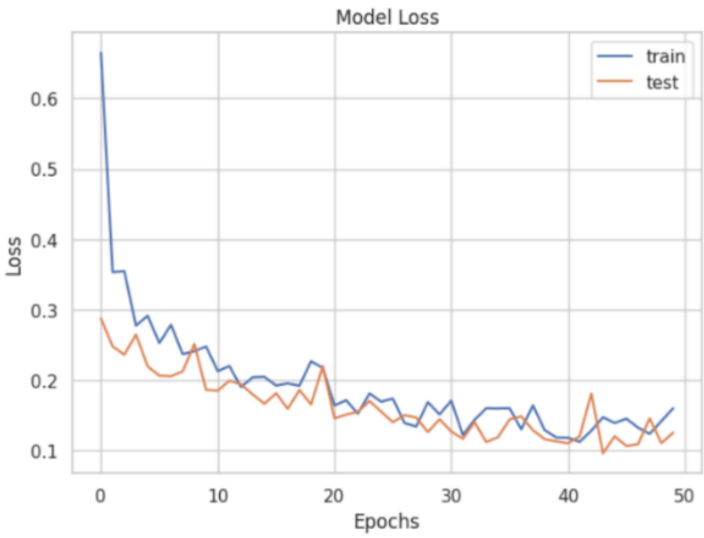

Figure 8. Inception-V3 Model Loss

Figure 9. Inception-V3 Model Accuracy

The following is one of the evaluation results of training the Inception-Resnet-V2 model using the Adam optimizer with a learning rate of 0.001

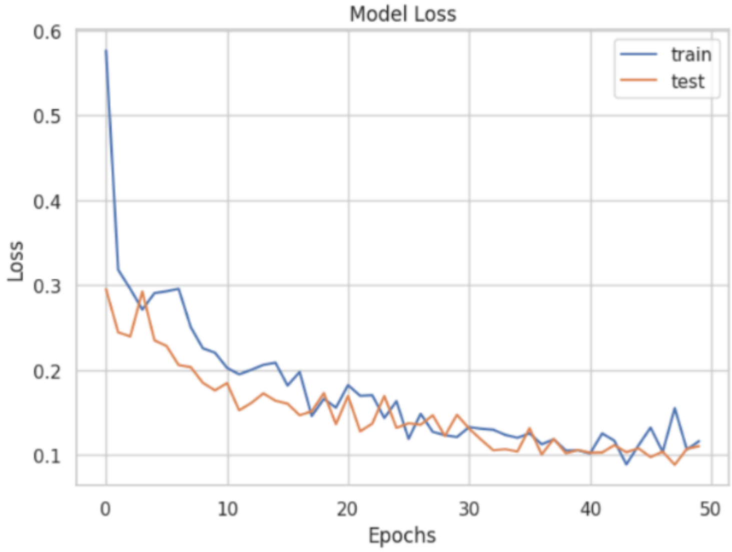

Figure 10. Inception-Resnet-V3 Model Loss

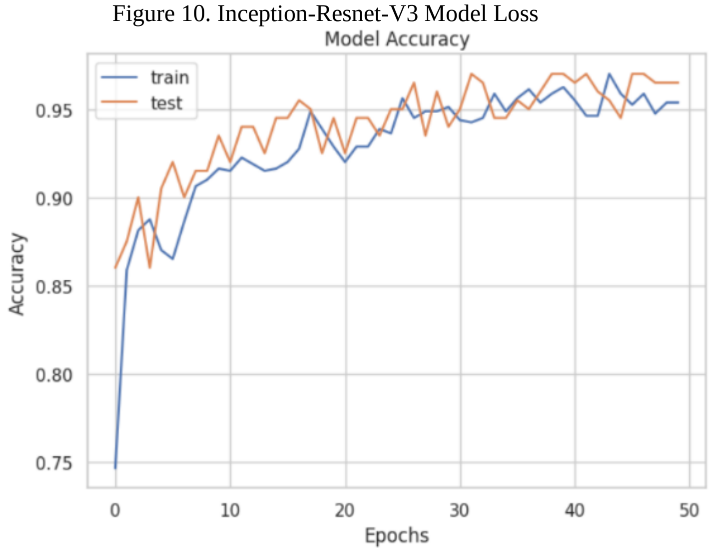

Figure 11. Inception-Resnet-V3 Model Accuracy

E. Analysis

After evaluating the two models, Inception-V3 and Inception-Resnet-V2 with various experiments, the next step is to compare the models.

Table 1.
Experiment Results

No	Model	Learning Rate	Optimizer	Running Time	Accuracy	Precision	Recall	F-1 Score
1	Inception-V3	0.1	RMSprop	10 Minutes 38 Seconds	48.00%	24.00%	50.00%	32.43%
2		0.01	RMSprop	11 Minutes 03 Seconds	94.00%	94.04%	93.05%	93.98%
3		0.001	RMSprop	09 Minutes 50 Seconds	94.50%	94.58%	94.43%	94.48%
4		0.0001	RMSprop	10 Minutes 25 Seconds	92.50%	92.48%	92.55%	92.50%

5		0.1	SGD	10 Minutes 14 Seconds	94.50%	94.52%	94.59%	94.50%
6		0.01	SGD	10 Minutes 08 Seconds	91.50%	91.50%	91.47%	91.47%
7		0.001	SGD	10 Minutes 01 Seconds	88.00%	87.98%	88.02%	87.99%
8		0.0001	SGD	10 Minutes 07 Seconds	79.50%	79.52%	79.57	79.50%
9		0.1	Adam	09 Minutes 52 Seconds	48.00%	24.00%	50.00%	34.43%
10		0.01	Adam	10 Minutes 32 Seconds	92.50%	92.48%	92,51%	92.49%
11		0.001	Adam	11 Minutes 53 Seconds	95.00%	95.06%	95.11%	95.00%
12		0.0001	Adam	10 Minutes 40 Seconds	93.50%	93.52%	93.59%	93.50%
13	Inception-Resnet-V3	0.1	RMSprop	11 Minutes 25 Seconds	50.50%	74.62%	52.40%	37.58%
14		0.01	RMSprop	11 Minutes 26 Seconds	93.50%	93.52%	93.59	93.50%
15		0.001	RMSprop	11 Minutes 31 Seconds	96.00%	96.00%	96.07%	96.00%
16		0.0001	RMSprop	10 Minutes 39 Seconds	94.50%	94.52%	94.59%	94.50
17		0.1	SGD	11 Minutes 11 Seconds	95.50%	95.51%	95.47%	95.49%
18		0.01	SGD	11 Minutes 23 Seconds	94.00%	94.15%	94.15%	94.00%
19		0.001	SGD	11 Minutes 50 Seconds	92.00%	92.22%	91.87%	91.96%
20		0.0001	SGD	11 Minutes 31 Seconds	84.00%	84.14%	83.85	83.92%
21		0.1	Adam	10 Minutes 29 Seconds	48.00%	24.00%	50.00%	32.43%
22		0.01	Adam	12 Minutes 01 Seconds	96.00%	95.99%	95.99%	95.99%
23		0.001	Adam	11 Minutes 26 Seconds	96.50%	96.48%	96.55%	96.50%
24		0.0001	Adam	11 Minutes 43 Seconds	93.50%	93.71%	93.67%	93.50%

In the Inception-V3 architecture, the highest accuracy was obtained at 95.00%. While in the Inception-Resnet-V2 architecture, the highest accuracy is 96.50%. From the 24 experiments above, it is obtained that each of the best models uses the Adam optimizer with a learning rate of 0.001. Based on the model training time required, the Inception-V3 model architecture obtained the fastest training time, which is 9 Minutes 50 Seconds. On the Inception-Resnet-V2 architecture itself, the fastest time is 10 Minutes 29 Seconds.

F. Deployment

After the best model is saved in h5 format, a web-based application is developed using the Flask framework. The appearance of the application that has been developed is as follows:

1) Home Menu

The home menu is the first menu when the website is opened. This menu provides brief information about the application. This application is named Meatify or stands for Meat Identify.

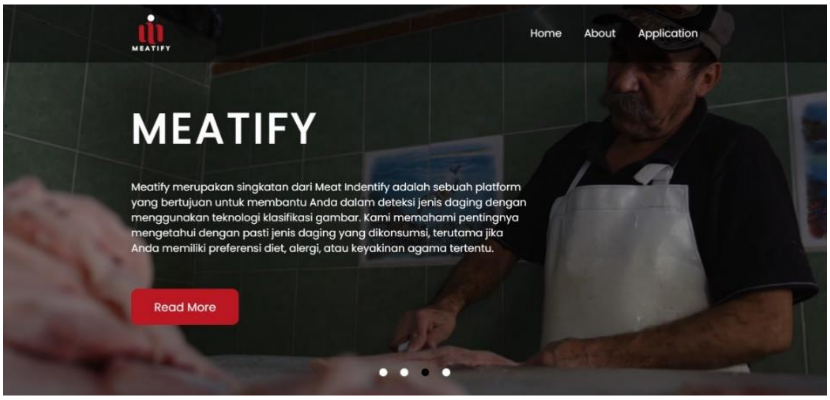

Figure 12. Menu Home

2) About Menu

After the Home menu, there is the About menu. This menu will briefly explain the characteristics of beef and pork.

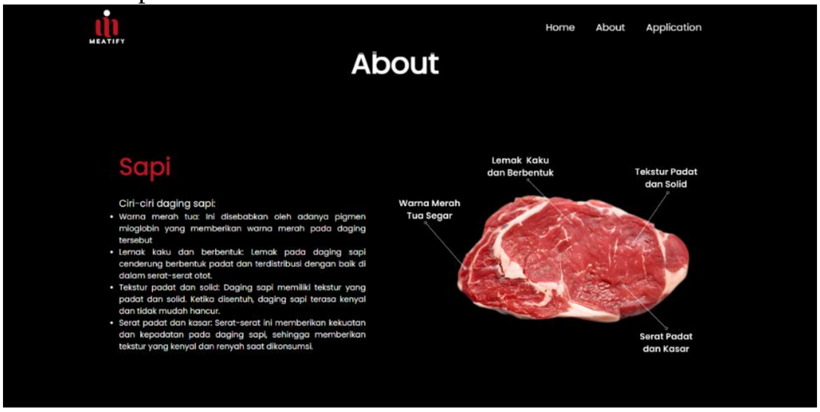

Figure 13. About Beef Menu

3) Application Menu

The main menu of this application is on the Application menu. The way it works is that the user uploads a photo of meat to the application. Then the application will classify the meat image based on the machine learning model that has been trained.

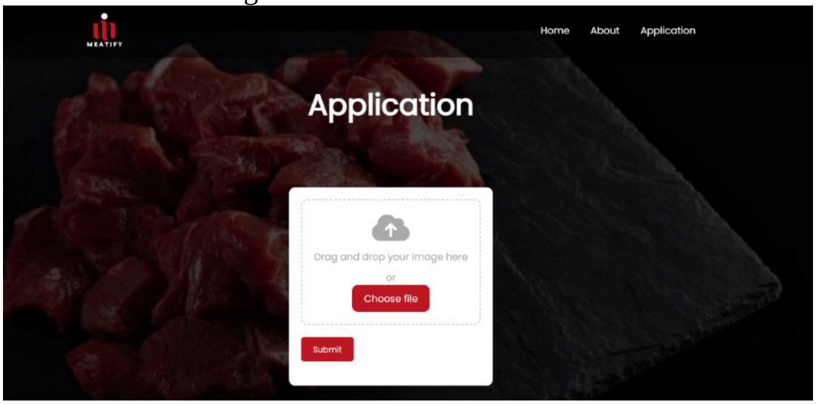

Figure 15. Application Menu

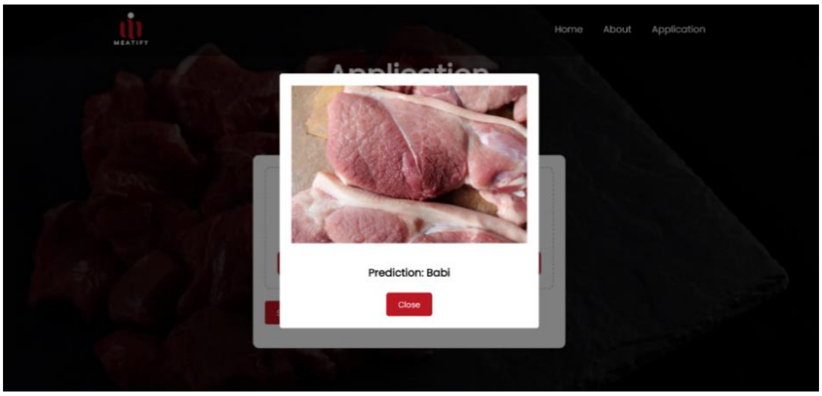

Figure 16. Prediction Result

The image above is one example of the results of the prediction performed by the application. From 20 trials using new data, the application was able to carry out classification correctly and accurately.

IV. CONCLUSION

Based on the results and analysis that has been done, it can be concluded that the Inception-V3 and Inception-ResnetV2 models produce very good accuracy. From several experiments that have been carried out, the best model is using the Inception-Resnet-V2 architecture with an experimental scenario using a Learning rate of 0.001, and an optimizer Adam with an accuracy of 96.50%, Precision 96.48%, Recall 96.55%, and F1-Score 96.50%. The application can be developed properly using the Inception-Resnet-V2 model and the application can perform classification correctly.

This research can certainly be developed even better. Future research can develop machine learning models into other forms of applications such as in the form of android applications. The selection of learning rate and optimizer has a significant influence on the accuracy of the model so it is highly recommended for future research to pay attention to the learning rate and optimizer used.

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