OPTIMIZING DETECTION USING ENSEMBLE LEARNING WITH ENHANCED EFFICIENTNET AND XCEPTION ARCHITECTURE FOR BEEF QUALITY CLASSIFICATION

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Abstract

In the agriculture industry 4.0 era made of many innovative tools and machines. The aim of production in industry 4.0 is graded by progress development evert year to complete the aim of automation in all parts of the supply chain of agriculture. The automation of good precis is execution by using machine learning techniques. These techniques learn by automatic machine with self-recognizing and self-learning. Automated beef detection will help farmers, customers, traders with high quality standard. The other way it will help farmers to reduce risk of spoilage beef and help a customer to analysis which one is fresh beef. However, in agriculture industry 4.0 era, automated beef detection using machine learning techniques is crucial for maintaining high-quality meat standards. The innovation needs to creating more enhance to maintaining the accuracy for image classification. This study utilizes an ensemble model with majority voting and custom weights on the ImageNet dataset to achieve an accuracy of 99.70% in classifying beef images. This research proposes an enhanced image classification method using ensemble learning for efficient and accurate meat detection. The objective is to improve the quality control of meat products by automating the detection process. By combining multiple machines learning models and employing a majority voting strategy with custom weights, the proposed method aims to achieve high accuracy in classifying meat images. This research has the potential to contribute to the food industry by ensuring the quality and safety of meat products.

Keywords: Ensemble, Beef detection, Fresh and Spoilage.

1. INTRODUCTION

Revolution in every single field including agriculture was bringing good impact development. One of innovation that bring the agriculture revolution is the automation machine. Automation program should in processing of agriculture chains in every nation. Because, it will help farmers to reach a maximum quality and quantity to bring the economic stable and prosperous. One of source that should be good farm is beef. Beef it is very important because the body need a big protein. Beef has a lot benefit depend in used, such as to adding iron substance (risk of anaemia), increase metabolism, and adding fat (risk of autoimmune).

However, the develop of freshness and spoilage apparently a few researchers not focused on quality of beef specially about redness colour. The appearance of beef in a retail display plays a crucial role in shaping consumer choices. Shoppers tend to link the colour of beef with its quality. Bright red beef is generally seen as a sign of freshness and high quality, prompting consumers to prefer it. In contrast, beef that appears pale, discoloured, or darker is often perceived as less fresh and of lower quality by consumers, possibly nearing spoilage (Corlett, M. T, 2021).

In addition, spoilage beef gives bad impact for the healthiest such as typhus can occur due to beef contaminated by *Salmonella typhi* bacteria, digestive disorders, disorders of the nervous system caused by *Clostridium botulinum* bacteria, and the terrible disease is Anthrax. The resident of Pedukuhan Jati, Gunungkidul, Indonesia inform 73 years old died due to exposure to the anthrax virus. The Gunungkidul Livestock and Animal Health Service (DPKH) said the victim had consumed a beef of a cow that died of illness last May. The government appeals to the public to always be aware of the quality of the beef they eat and maintain self-clean and self-health. Therefore, maintaining the quality of the Beef produced is very necessary for the public to avoid diseases caused by that has been contaminated by bacteria.

To reduce the inefficiently effort it needs automation process more comprehensive. The efficient technique is automation detection using deep learning. Deep learning can be used to automate beef detection. The architecture of deep learning is made up of feed-forward networks with multiple layers. The most widely used method for image processing is deep learning. Basic image processing techniques and deep learning can be used to process beef images. The optimizing classification can be performed by enhanced their performance. For this purpose, detection with ensemble methods deliver for support the automation system and collecting the new objective for their future works.

For instance, in another researcher was shown classifying an image into various groups according to the kinds of fish that are present in it. For these kinds of image detection issues, there are distinct practical obstacles: The articles, first and foremost, are tiny when contrasted with the foundation. Standard CNN based techniques like ResNet and Faster R-CNN might get familiar with the component of the boats (background) but not the fishes (objects). As a result, when images of new boats are shown, it will fail. Second, imbalanced data sets are prevalent in the real world and have made classification tasks extremely difficult. Consequently, CNN models may have difficulty categorizing classes with few training samples because they may be biased toward majority classes with large training samples. Thirdly, obtaining data is costly and labour-intensive in real-world applications. For instance, ground truth must be labelled and verified by multiple experts in the field. In both academia and industry, achieving high performance from a small training dataset remains a significant obstacle (YANG, Xulei., 2018).

In the other subject, several researchers start to develop CNN architecture and expand it by enhanced customizing performance. The subset method for enhancing model performance is ensemble learning. Ensemble learning was giving good development for enhancement. The improvement of developing ensemble has a significant impact on classification for enhance performance to adapt some method by merging many predictions (Abouelmagd, L. M., 2022).

This work suggested demonstrates how detection can give better results from ensemble learning with optimizing detection of beef quality on ensemble method. The set of data are organizing with image detection and set on the trainer model using ensemble method. The result shows an improving accuracy and predicting percent level of combining Xception and EfficientNet for enhance ensemble. Furthermore, this paper brings a benefit to researcher for future analyses of using ensemble on automation machine detection.

2. METHODOLOGY

In this section containing a process of ensemble workflow with agile and then combining Xception and EfficientNet architecture model to getting prediction result. Agile methodology development is a methodology that characterized by iterative cycles of development and delivery, prioritizing adaptability, stakeholder involvement, and the frequent release of functional increments (Whiting, E., 2021) (Rajan, E. R., 2021). Improving with agile method was getting good impact for discipline, the ability of response changes, and flexibility (Merelo-Guervós, J. J., 2021). The methodology includes data collection, pre-processing, data augmentation, ensemble learning, data training, and assessing performance/evaluating are featured by Figure 1.

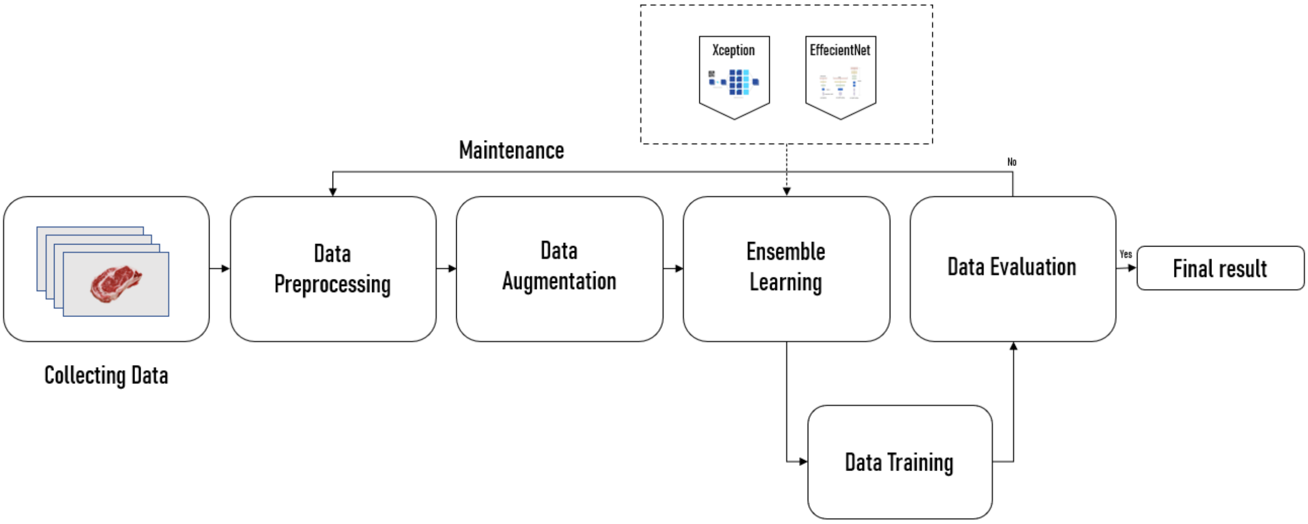

Figure 1. Ensemble methodology with agile workflow

2.1 Dataset

Dataset used are provided on Table 1 by Vinayak Shanawad on Kaggle (Shanawad, V., 2022) contains a set of 2266 photos, which classified by condition: Fresh (853), Half-fresh (789), Spoiled (624). The set of data are divided into 1586 for training, 453 for validation, and 226 for testing.

Table 1. Dataset distribution

Class	Data Training	Data Validation	Data Total
Fresh	675	178	853
Half-fresh	630	159	789
Spoiled	510	114	624

2.2 Data Preprocessing

The procedure to be carried out in the preprocessing stage is to divide the process into three parts: 70% training and 20% validation 10% testing (Alhussein, M., 2020). The division ensures that in the amount of data each label must be overlaid by fulfilling all subsets that have been divided consequently (Anggoro, D. A., 2023).

Data preprocessing is a primary procedure for preparation data that involves applying various techniques and operations to raw data prior to model training. It is a crucial step in the machine learning process as it enhances data quality, resolves inconsistencies, and optimizes data for effective utilization by learning algorithms. For enhance preprocessing, data image was modified on Kaggle dataset by resize of dimension into 416 x 416 and including auto-orientation of pixel data (with EXIF-orientation stripping). The auto-orientation refers to feature the automation orientation of image based on EXIF metadata which mean an automatically rotating or flipping of image based on EXIF original orientation tag and striping the orientation refers to remove original EXIF metadata after the auto-orientation process (Karantoumanis, E., 2022).

2.3 Data Augmentation

Data augmentation is method for deep neural network training to enhance model capacity for generalization such as rotation, flipping, cropping, scaling, shear, zoom, feature wise, shifting, and fill mode (Walawalkar, D., 2020). The data augmentation working for assisting deep learning on allocated models to avoid underfitting and overfitting (Shorten, C., 2019). Underfitting arises when a model is too simplistic and misses the underlying patterns and overfitting happens when a model grows too complex or extremely skilled and fits the noise in the training data (Gavrilov, A. D., 2019). This research involved several augmentation techniques include:

2.3.1 Flip

The operation of flipping provides horizontal or vertical opposites on original image. This technique was commonly to use for reduce overfitting or underfitting and has potential to enhance performance. This process used to improve dissimilarity of training dataset. Researcher suggesting the potential of flipping able for enhance performance by presenting additional training examples with similarity (Anggoro, D. A., 2023). The sample data result before flipping (Figure 2a) and after flipping horizontally (Figure 2b) are creating for testing the ability of data training to decrease similarity to the data training.

Figure 2a. Original picture

Figure 2b. Horizontal flip picture

2.3.2 Rotation

The fundamental manipulation method suffers from the padding effect is on rotation concept. That mean is certain portions of the photos will be lost or relocated outside of the boundaries following the process. Terminology rotation is technique of computation that involves rotating an image along the horizontal line or x-axis by predetermined angle (Anggoro, D. A., 2023). The researcher implement rotation by 30 degrees to the left is shown on Figure 3.

Figure 3. Rotated with 30 degree to the left

2.4 Architecture Classification

Convolutional Neural Networks (CNNs) are a sort of deep, feed-forward artificial neural network that is mostly used in the field of machine learning for the analysis of visual data. CNNs are made to use many layers of perceptron and reduce the amount of preprocessing that is required. Because of its shared-weights architecture and translation invariance, they are frequently referred to as Shift Invariant or Space Invariant Artificial Neural Networks (SIANN). Convolutional networks are inspired by biological processes, specifically how animals' visual cortex is organized. Receptive fields are regions of the visual field that neurons in the visual cortex respond to when activated. The entire visual area is covered by the partial overlap of these distinct neuron's receptive fields. CNNs require comparatively less preprocessing than other image classification techniques. This implies that the filters or features that were previously created by hand in traditional algorithms are learned by the network. CNNs have a major benefit in that their feature design is not dependent on human labour or prior knowledge. CNNs are useful in many other fields besides visual imaging analysis, including recommender systems, natural language processing, and image and video recognition. (Alkahlout, M. A., 2021), (O'shea, K., 2015).

For instance, the development of CNN architecture has provided many innovations including architecture. In this case, researcher implementation two architectures for margin on ensemble method on as:

2.4.1 EfficientNet

EfficientNet is enhancement method by employing a scaling compound. The development EfficientNet shown improvement for adjust and scale the depth, width, and resolution of the network by using consistently on coefficient high accuracy and efficiency (Desiani, A., 2024). Transfer learning was frequently uses for EfficientNet to computation and time efficiency. The researcher conducted assessment to make comprehensive in ensemble method. Table 2 shows EfficientNet configuration model architecture.

Table 2. EfficientNet model configuration

Layer	**Parameter**

Batch Normalization	Axis: -1 Momentum: 0.99 Epsilon: 0.001
Dense	128
Dropout	Rate: 0.5
Dense	64
Dropout	Rate: 0.3
Dense(num)	Softmax

This configuration purpose to preventing overfitting and extraction feature of EfficientNet models. Figure 4 show model performance of EfficientNet with the configuration.

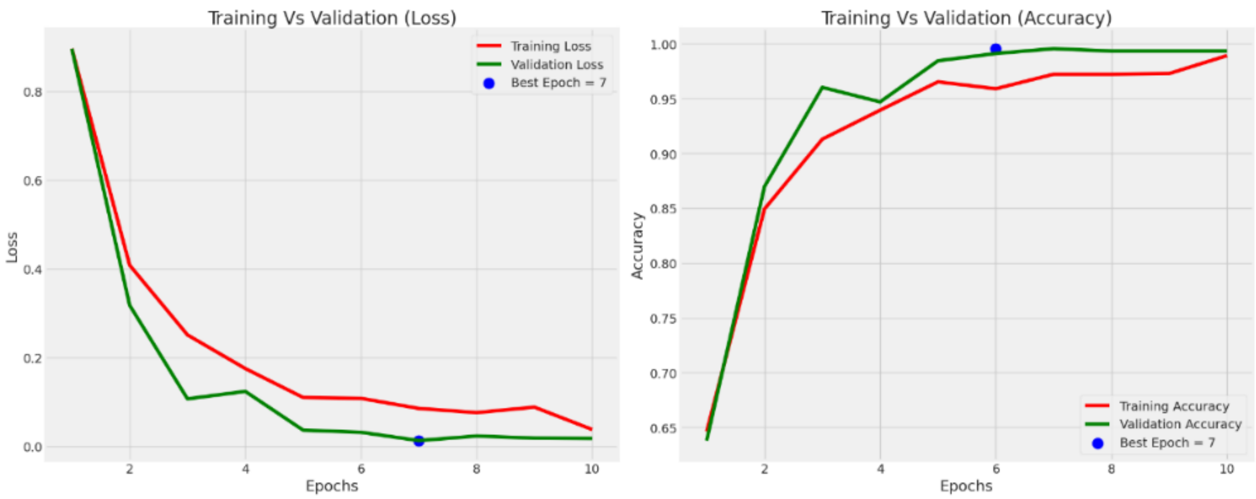

Figure 4. EfficientNet model performance

2.4.2 Xception

Xception or “Extreme Inception” is improvement extension of the inception architecture to get highly performance efficiency computation. In actuality, transfer learning frequently uses the Xception model as a foundational paradigm. Purposed it was pre-trained on massive datasets such as ImageNet, it already has some image processing skills (Li, S., 2024). The researcher conducted assessment to make comprehensive in ensemble method. Table 3 shows Xception configuration model architecture.

Table 3. Xception model configuration

Layer	**Parameter**
Batch Normalization	Axis: -1 Momentum: 0.99 Epsilon: 0.001

Dropout	Rate: 0.3
Dense	128
Dense(num)	Softmax

This configuration purpose to preventing overfitting and extraction feature of Xception models. Figure 5 show model performance of Xception with the configuration.

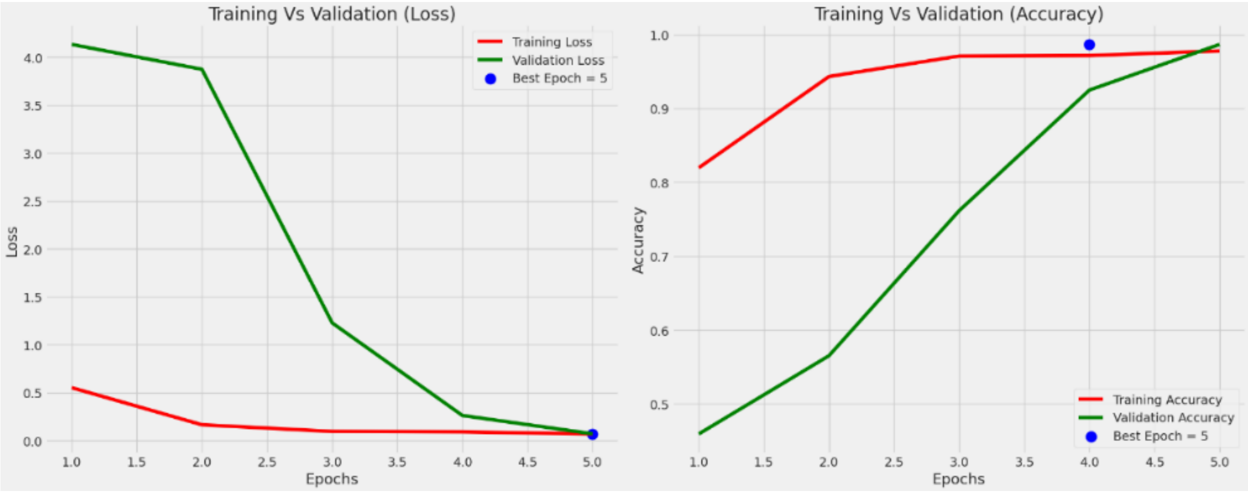

Figure 5. Xception model performance

2.5 Ensemble Learning

Ensemble Learning is feature of classification method by merge the prediction as a result of decision to get better on predictive performance. To ensure ensemble performance, researcher using majority voting with custom weight to perform high prediction. In this stage, research provide a process of training data on ensemble method between Xception and EfficientNet. The ensemble process workflow shown in Figure 6.

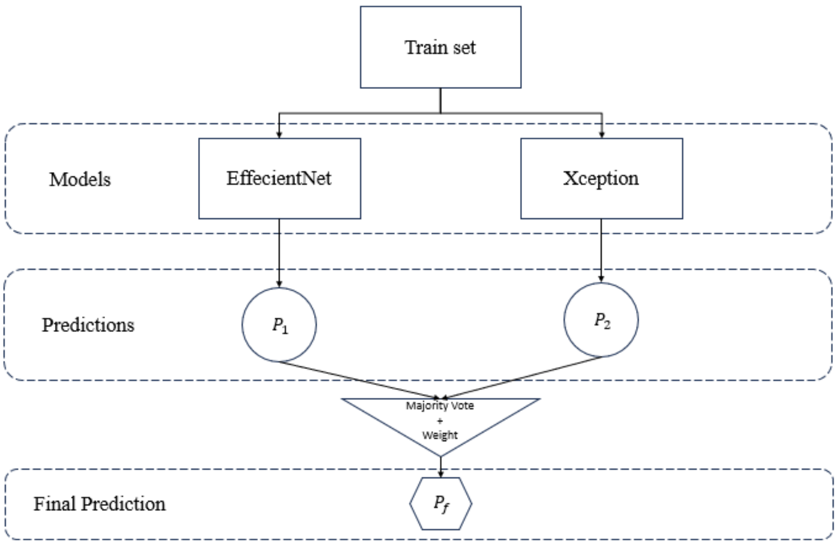

Figure 6. Illustrate ensemble workflow

2.6 Model Evaluation

To evaluate the performance of a classification model, several metrics such as accuracy, precision, recall, and F1-score are commonly used. These metrics can be calculated using a confusion matrix, which summarizes the outcomes of the classification process (Putri, A. 2022). Table 4 shows the confusion matrix formula.

Table 4. Confusion matrix

Confusion Matrix		***Predicted Class***	
		Positive	**Negative**
Actual class	**Positive**	TP (True Positive)	FP (False Positive)
	Negative	FN (False Negative)	TN (True Negative)

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN} \qquad F1\text{-}score = 2\ x\ \frac{(Recall\ x\ Precision)}{(Recall+Precission)} \tag{1}$$

The accuracy provides an overall measure of correctness, precision focuses on the correctness of positive predictions, recall focuses on the completeness of positive predictions, and the F1-score balances precision and recall (Putri, A. 2022). Inconsistency performs on model made prediction inaccurate because of uncalculated similarities between predicted output and the true output. Therefore, the model need calculating by loss testing parameter for determine models from inconsistency which data not detected during the training process. In this case, the optimal loss model for enhance ensemble image classification is cross-entropy. The formula as follows.

$$L(\theta) = -\sum_{i=1}^{k} y_1 \log \hat{y}_1 \tag{2}$$

$L(\theta)$ as loss; y_1 as the quantity of data that were accurately detected; and $\hat{y}_1$ as number of detected data (Anggoro, D. A., 2023). The purposed of this equation is to improve model performance and accurate prediction by minimizing cross-entropy loss.

When a machine learning model exhibits signs of overfitting or underfitting, indicated by poor performance on a validation set, it requires retraining. Retraining involves adjusting the model's parameters or architecture to improve its ability to generalize to unseen data.

3. RESULT AND DISCUSSION

The experiment was conducted on Google Colab environment with Tensor Flow and Keras library. The dataset using from Kaggle published by Vinayak Shanawad (Shanawad, V., 2022). This research concludes an ensemble learning concept with integration between EffecientNet and Xception. Given the myriad challenges surrounding deep learning analysis, researchers have devised algorithms aimed at enhancing the precision of predictive outcomes.

Table 5. Compiler configuration

Parameter	**Score**
metrics	accuracy
loss	categorical_crossentropy
learning rate	0.001

This optimizer utilized a learning rate of 0.001 as control the model in response to estimated error each time. Categorical cross-entropy as a loss function utilized for addressing multi-class and metrics are focus on accuracy. The accuracy score of models is implemented in Table 6.

Table 6. Early stopping

Parameter	**Score**
monitor	accuracy
patience	5
mode	auto
verbose	1

This callback stops the training process when a specified metric. The demonstrate improving over a set number of epochs (with a patience of 5). By continuously assessing model performance, it helps prevent overfitting. The installation of observes on Early Stopping would be deliver in Table 7.

Table 7. ReduceLROnPlateu

Parameter	**Score**
monitor	accuracy
patience	5
mode	auto
factor	0.3
min_delta	0.001

In Auto Mode, the learning rate will be reduced by a factor of 0.3 if the validation accuracy does not increase by at least 0.001 over two consecutive epochs. The model that achieves the highest validation accuracy will be saved for evaluation. This approach enhances the model's generalization ability and helps avoid overfitting, ensuring it converges to an acceptable solution (Anggoro, D. A., 2023). To optimize the process more wisely, majority vote with custom weight is presented to enhance ensemble more comprehensive. This experimental research delivered by 2 scenarios.

Scenario 1: This experiment containing architecture model for image classification case; EfficientNet and Xception with cross validation to enhance and evaluate prediction. Figure 7 shows confusion matrix result. Table 8 provide a confusion matrix class label. Table 9 shows classification label from experimental result for each model classifier.

(a) (b)

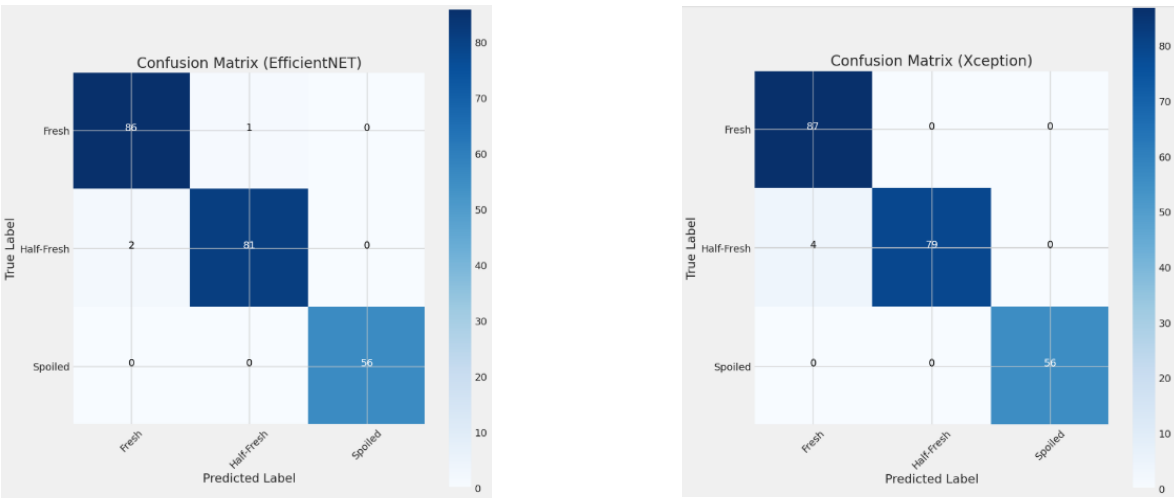

Figure 7. Confusion matrixes (a) EfficientNet and (b) Xception

The model EfficientNet accurately categorized 86 of 87 fresh samples implement the prediction miss recognize with true label and 81 of 83 half-fresh samples implement the prediction miss calculate with true label, this demonstrating exceptional performance in recognizing these categories. While slightly less perfect, the model still correctly identified 56 of 56 spoiled samples, indicating solid accuracy in detecting spoiled produce. The model Xception accurately categorized 87 of 87 fresh samples show perfectly indicates and 79 of 83 half-fresh samples was not better for good on indicates cause the prediction miss calculate with true label and the model still correctly identified for 56 of 56 spoiled samples.

Table 8. Confusion matrix class label

Label	EfficientNet				Xception			
Class	**True Positive (TP)**	**True Negative (TN)**	**False Positive (FP)**	**False Negative (FN)**	**True Positive (TP)**	**True Negative (TN)**	**False Positive (FP)**	**False Negative (FN)**
Fresh	86	137	2	1	87	135	4	0

Half-fresh	81	142	1	2	79	143	0	4
Spoiled	56	167	0	0	56	166	0	0

Table 9. Classification report using different classifier

Evaluation \ Classifier	EfficientNet	Xception	Average
Precision	98.80	98.50	98.70
Recall	98.80	98.40	98.60
F1 Score	98.80	98.40	98.60
Accuracy	99.11	98.81	98.96

The result using classification classifier shows the different average of percent evaluation between EfficientNet and Xception. This case EfficientNet providing better average percent than Xception.

Scenario 2: Experiment with ensemble classification model. This built uses various classification which crossing entire a model. The algorithm model of EfficientNet and Xception merge with ensemble method. The training set all in single run implemented each model. The ensemble work on combining all of output into single prediction. The prediction is completed by getting majority vote with custom weight between the model and cross-validation uses to evaluate the prediction properly. This purpose of strategy is to increasing classifier between model and evaluate the model by combining entire the model. The hyperparameters of ensemble learning classifiers were; voting='hard', and n_jobs=-1. The custom weight assigned to each prediction for 0.7 weight of EfficientNet and 0.3 weight of Xception. Figure 8 shows confusion matrix result. Table 10 provide a confusion matrix class label. Table 11 shows classification label from experimental result for each model classifier.

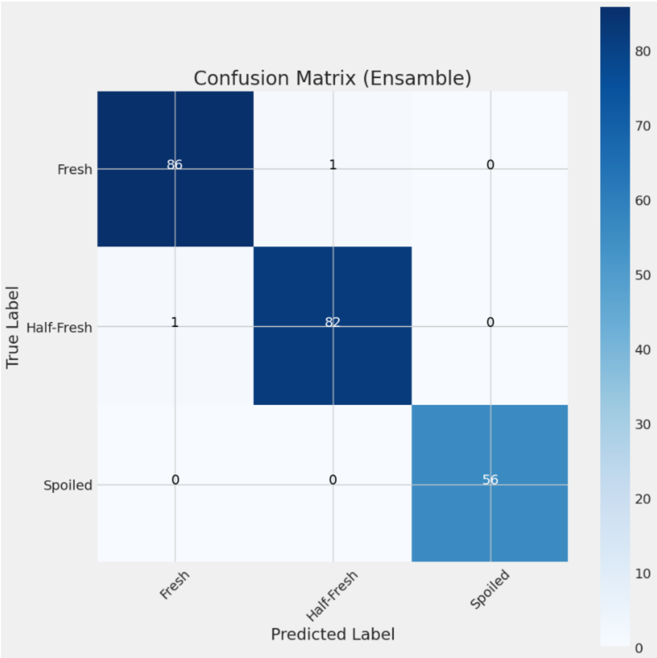

Figure 8. Ensemble learning confusion matrix

The confusion matrix shows of greatly categorizing on ensemble, which is 86 of 87 fresh samples implement the prediction miss recognize with true label and 82 of 83 half-fresh implement the prediction miss calculate. Then for spoiled categorized show 56 of 56 samples was perfectly recognizing and calculating.

Table 10. Confusion matrix class label

Label	Ensemble			
Class	**True Positive (TP)**	**True Negative (TN)**	**False Positive (FP)**	**False Negative (FN)**
Fresh	86	138	0	1
Half-fresh	82	142	1	0
Spoiled	56	168	0	0

Table 11. Ensemble learning report result

Classifier / Evaluation	Majority voting with custom weight Ensemble classifier

Precision score	99.60
Recall score	99.60
F1 Score	99.60
Accuracy	99.70

The result using majority vote with custom weight on ensemble learning algorithm show the accuracy was 99.70% is better than average individual classifier performance. Therefore, ensemble is a methods combine multiple models to make more accurate predictions. This diversity reduces the risk of errors from any single model, leading to better overall performance.

4. CONCLUSION

Maintaining the quality of meat is necessary to balance the nutritional needs produced by the meat consumed. This is a concern for the government to meet the needs of its people by paying attention to the quality of meat either sold or consumed. In this case, detecting meat by classifying images is a means to maintain efficient and good meat quality. To improve image classification, ensemble learning is needed to improve the performance of the meat detection machine by majority vote and setting the custom weight so that the classification of the model touches high accuracy. In order to implement this research, it is necessary to develop an enhanced method utilizing computer vision for real-time meat interaction. Alternatively, it is required to enhance it through collaboration with an external scanning provider to further develop this research.

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