Jurnal Serambi Engineering
Volume XI, No.3, Juli 2026 Hal 20456 - 20466
p-ISSN : 2528-3561
e-ISSN : 2541-1934

Learning Rate Tuning of Transfer Learning Models for Fresh and Spoiled Beef Image Classification

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Received: June 27, 2026 Approved: July 15, 2026

Abstract
Beef freshness assessment is a critical aspect of the food industry, where conventional methods relying on visual inspection and olfaction are subjective and prone to human error. This study aims to develop an automated beef freshness classification system utilizing deep learning to enhance the accuracy and objectivity of quality assessments. A total of 2.800 beef images were sourced from an open research data repository, divided equally into fresh and spoiled classes. Three Convolutional Neural Networks (CNN) architectures with transfer learning VGG16, ResNet50-V2, and Inception-V3 were evaluated. The models were systematically tested using learning rate tuning at 0.01, 0.001, and 0.0001 to optimize training convergence. Evaluation results showed that VGG16 outperformed other models in classifying beef freshness. VGG16 achieved a peak testing accuracy of 99.46% at a learning rate of 0.001. The main contribution of this study is the systematic evaluation of transfer learning architectures to establish an optimal baseline for beef quality assessment. By deploying the best performing model into a web based application, this approach offers a practical, objective, and accessible alternative to conventional manual inspection, enabling rapid early detection of beef freshness to improve food safety.
Keywords: *beef quality, convolutional neural networks, deep learning, VGG16, learning rate*

Abstrak
Penilaian kesegaran daging sapi merupakan aspek krusial dalam industri pangan, mengingat metode konvensional yang mengandalkan inspeksi visual dan penciuman bersifat subjektif serta rentan terhadap kesalahan manusia. Penelitian ini bertujuan untuk mengembangkan sistem klasifikasi kesegaran daging sapi otomatis menggunakan *deep learning* guna meningkatkan akurasi dan objektivitas penilaian kualitas. Sebanyak 2.800 citra daging sapi diperoleh dari repositori data penelitian terbuka dan dibagi secara merata ke dalam kategori daging segar serta daging busuk. Tiga arsitektur *Convolutional Neural Networks* (CNN) yang menggunakan teknik transfer learning yaitu VGG16, ResNet50-V2, dan Inception-V3 dievaluasi dalam penelitian ini. Model-model tersebut diuji secara berkala dengan variasi *learning rate* sebesar 0,01, 0,001, dan 0,0001 untuk mengoptimalkan konvergensi pelatihan. Hasil evaluasi menunjukkan bahwa VGG16 mengungguli model lainnya dalam mengklasifikasikan kesegaran daging sapi, dengan mencapai akurasi pengujian tertinggi sebesar 99,46% pada learning rate 0,001. Kontribusi utama penelitian ini adalah evaluasi sistematis terhadap arsitektur transfer learning untuk menetapkan tolok ukur optimal bagi penilaian kualitas daging sapi. Dengan mengimplementasikan model berkinerja terbaik ke dalam aplikasi berbasis web, pendekatan ini menawarkan alternatif yang praktis, objektif, dan mudah diakses dibandingkan inspeksi manual konvensional, sehingga memungkinkan deteksi dini kesegaran daging sapi secara cepat demi meningkatkan keamanan pangan.
Kata Kunci: *kualitas daging sapi, convolutional neural networks, deep learning, VGG16, learning rate*

1. Introduction

Beef is a widely consumed food ingredient and plays an important role in fulfilling human requirements for animal protein. This is because beef is considered an ideal food source that provides a wide range of complete essential nutrients needed by the body, such as high-quality protein, healthy fats, and essential minerals like iron. In addition, its rich nutritional content supports muscle growth, energy production, and overall metabolic function, making beef a commonly consumed food in many countries [1]

According to the Central Statistics Agency (BPS), Indonesia's beef production in 2025 will amount to 499,149.96 tons, indicating a positive growth trend in the livestock sector [2]. Although beef consumption typically peaks during religious holidays and special events, demand remains relatively stable throughout the year due to culinary needs [3]. However, despite increasing demand, beef is highly perishable and susceptible to microbial contamination if improperly stored, leading to serious food safety issues. Freshness of meat is one of the most important factors in evaluating the quality and safety of meat. Fresh beef can be identified by its bright red color, not pale, its dense texture, not soft, its dry surface, not sticky, and the absence of a bad smell. In contrast, spoiled beef often exhibits discoloration to a darker tone, sticky or slimy texture, and a bad odor caused by bacterial growth and spoilage [4].

Accurately distinguishing between fresh and spoiled beef requires careful evaluation, as it is not always easy to differentiate them based on visual inspection alone. Beef quality assessment can be conducted using subjective or objective methods, each with its own advantages and limitations[5] , [6]. Objective detection methods such as chemical analysis, microbiological testing, or advanced imaging technologies are often needed to ensure accurate evaluation; however, they require equipment and facilities that are difficult for the general public to access and are often limited in availability [7]. Subjective methods rely on human expertise, such as sensory evaluation by trained inspectors [5].

Literature Review

Deep learning continues to improve in performance, particularly in image classification within image recognition. Various studies have shown that Convolutional Neural Networks (CNNs), in particular, have become the most relevant method for recognizing complex image patterns. Architectural efficiency, higher accuracy, and techniques such as transfer learning are key factors that influence model generalization and computational trade-offs [8], [9].

One study that applied CNNs to beef image classification achieved 93% accuracy by implementing a CNN architecture that utilized the Gray Level Co-occurrence Matrix (GLCM) feature extraction method [10]. Previous studies have confirmed that CNN architectures can capture and recognize complex image patterns from datasets. However, most of these studies have focused more on detection accuracy within specific architectures rather than conducting controlled cross-architecture comparisons under identical experimental conditions.

In the assessment of beef quality, several studies have proposed meat classification frameworks. Classification models for determining the quality of fresh and spoiled beef have shown promising performance, particularly when using pre-trained networks. Improvements in architecture and optimization strategies have also been introduced to enhance residual-based networks. However, most of these studies focus on pre-trained classification frameworks, dataset enhancements, and configuration adjustments to improve the models.

Related Work

To address these limitations, a recent study explored the use of Deep Learning (DL) and Machine Learning (ML) techniques for meat quality assessment [11]. These methods utilize image processing and pattern recognition to classify meat freshness with high accuracy, offering a faster and more scalable alternative compared to traditional approaches. For example, Convolutional Neural Networks (CNNs) have been successfully applied to analyze images of meat and detect its quality. **Table 1** list relevant studies that have been proposed to address issues related to beef quality.

Table 1. Summary of Related Works

Study	Object	Model	Accuracy	Limitation
[10]	Fresh and Spoiled Meat	Random Forest and Decision Tree (GLCM)	93%	The number of initial primary data samples used is still limited 50 initial images before augmentation.
[12]	Fresh, Half-Fresh and Spoiled Meat	Transfer Learning Xception	86.92%	This study is still limited in terms of the dataset used and requires further development by incorporating additional data variations
[13]	Beef and Pork meat	VGG16	99.6%	No studies have yet compared the effectiveness of the performance results with other alternative CNN architectures

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Volume XI, No.3, Juli 2026 Hal 20456 - 20466
p-ISSN : 2528-3561
e-ISSN : 2541-1934

Study	Object	Model	Accuracy	Limitation
[14]	beef, pork, and lamb	Ensemble Learning (Hard Voting Classifier)	98,88%	Limited Dataset Size Total dataset

Although previous studies have used various pre-trained methods and architectural models for beef freshness classification, these approaches have limitations; a recent study explores the use of Deep Learning (DL) and Machine Learning (ML) techniques for meat quality assessment. Building on prior research, this study focuses on developing a beef quality classification model using smartphone image data. The dataset is designed for a fast and affordable quality assessment method utilizing transfer learning and learning rate analysis configurations. The model is then integrated into a user-friendly web-based application, capable of delivering direct benefits to the public.

2. Material and Methods

Below is the research workflow for hyperparameter tuning of a Pretrained-CNN-based algorithm for meat classification, along with a diagram illustrating each step of the process.

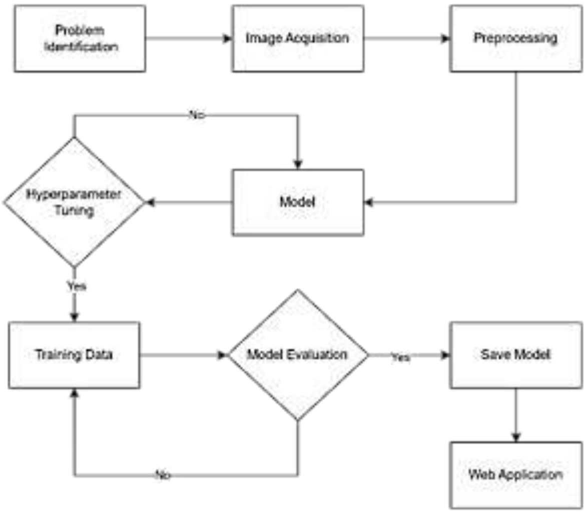

Fig. 1. Model Design Stages

Figure 1 shows the system design for beef quality classification. The process stages include problem identification, beef image acquisition, preprocessing, transfer learning–based CNN model design, and subsequent training and testing phases, which together produce a CNN model with optimal accuracy that is further validated through application-level trials. Accurate early detection is crucial to prevent food poisoning. This study aims to optimize CNN hyperparameters to improve the accuracy and precision of the beef image classification model, thereby enhancing the detection performance for beef freshness classification [15]. This study includes literature review, system requirements identification, classification system design, system testing, and data analysis. During the system testing phase, if the system does not provide satisfactory performance, the test will be repeated with different configurations to achieve the optimal level of accuracy.

Dataset

This dataset available from the Mendeley dataset, to see the configuration used can be seen in Mendeley public data access [16]. Images were categorized into two classes fresh and rotten. The image acquisition dataset was selected for training and testing. The dataset was divided using a ratio of 80% training data (2,240 images) and 20% testing data (560 images). In the Preprocessing and Augmentation Pipeline stage, several stages were carried out, such as resizing, Rescale 1/255, and adding dataset augmentation to manipulate the dataset, such as 40-degree image rotation (rotation_range = 40), 20-degree horizontal image enlargement (width_shift_range = 0.2), 20-degree vertical image enlargement (height_shift_range = 0.2), counterclockwise image enlargement (shear_range = 0.2), 20% image enlargement or zoom (zoom_range = 0.2) in **Table 3**.

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Table 1. Image Dataset

Image Label	Image		
Fresh			
Rotten			

Table 3. Preprocessing and Augmentation Pipeline

Stage	Process	Description
Resize	224 × 224 pixels	Required input size for pretrained
Normalization	Rescale 1/255	Stabilizes network training
Augmentation	Rotation, width/height shift, shear, zoom	Applied exclusively to the training dataset to prevent overfitting

CNN Model and Configuration

In its development, new models such as transfer learning have been introduced to enhance the performance of CNN-based models. This approach uses models that have been previously trained, often referred to as pre-trained models. Pre-trained models are typically trained on large benchmark datasets such as MNIST, CIFAR-10, and ImageNet. The purpose of pre-trained is to increase time efficiency by utilizing pre-trained data that is already available for application to CNN architecture [17]. The architecture of the pre-trained CNN modification model in this study can be seen in **Figure 2**.

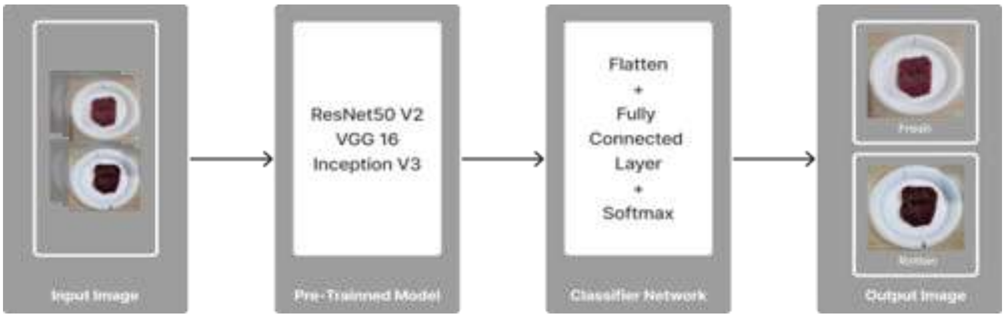

Fig. 2. Workflow (Pipeline) Of Image Classification System Architecture

In the pre-trained CNN model, it is done the same as before, but there are some additions such as adding dataset augmentation to manipulate the dataset such as image rotation 40 degrees (rotation_range= 40), image zooming horizontally 20 degrees (width_shift_range= 0.2), image zooming vertically 20 degrees (height_shift_range= 0.2), image zooming counterclockwise (shear_range = 0.2), image zooming or zooming 20% (zoom_range= 0.2). Next, a flatten, dense-layer layer with 128, 64, and 32 neurons was added to the final layer and hyperparameter learning rate experiments were carried out at 0.01, 0.001, and 0.0001 to control the weight speed. Hyperparameter configuration on the pre-trained CNN modification model. Hyperparameters were then configured using a trial-and-error approach, as shown in **Table 4**. The Pretrained-CNN models were trained on the beef image dataset. The training process was executed using Python 3 with the TensorFlow/Keras framework, running on the Google Colab platform.

Table 4. Model and Training Configuration

Parameter	Value
Model	VGG16, ReistNet50_V2 , Inception V3
Image Size	224 × 224 x 3 (RGB)
Dataset Split	2,240 Train, 560 Test
Epoch	100
Batch Size	32
Dense Layer	Flatten Layer, Dense Layer + ReLu 128

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Volume XI, No.3, Juli 2026 Hal 20456 - 20466
p-ISSN : 2528-3561
e-ISSN : 2541-1934

Parameter	Value
	Dense Layer + ReLu 64 Dense Layr + ReLu 32 Dense Layer 2, Softmax
Optimizer	Adam (Default: beta-1=0.9, beta-2=0.999)
Learning Rate	0.01, 0.001, 0.0001

This study contains three architectures due to their different advantages, the VGG16 model was chosen because of its simple and stable architecture, providing a strong foundation for visual classification, the ResNet50-V2 model utilizes residual connections, allowing for deeper network training without vanishing gradients and the Inception-V3 model due to its multi-scale feature extraction capabilities.

Learning Rate (LR)

One of the problems that arise when conducting data training is determining the Learning Rate (LR) value. Determining LR as a hyperparameter allows the model to generalize during the data training process[18]. Therefore, in this study, hyperparameter tuning is performed to find the best learning rate in order to obtain the highest possible accuracy. LR tuning is used to determine the optimal learning rate for training, with the goal of ensuring fast and efficient convergence without causing divergence or degraded performance. The process begins by configuring the model to undergo training with a range of different learning rates. During training, the learning rate is varied exponentially at each iteration, and the loss is recorded for every learning rate value. This technique helps identify learning rates that can improve training speed and model accuracy [19]. The training model and configuration can be seen in **Table 4**.

Model Evaluation

Model evaluation is carried out using a confusion matrix to assess the performance of the classifier. The confusion matrix combines the prediction results with the true label values after the classification process. From this matrix, accuracy, precision, recall, and F1-score are calculated[20]. The formulas used to compute these confusion-matrix-based performance metrics are shown in Equations (1), (2), (3), and (4).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$f1\text{-}Score = 2x\,\frac{Recall\ x\ Precision}{Recall\ +Precision} \tag{4}$$

Application Development

This web application is built using Gradio and Hugging Face Spaces from the training results of the best performing models stored in .h5 format. This web application is built using Gradio and Hugging Face Spaces from the training results of the best performing models stored in .h5 format

3. Results and Discussion

This study conducts a hyperparameter analysis to optimize the performance of pretrained Convolutional Neural Network (CNN) models for classifying images of fresh and spoiled beef. The results of each stage and the impact of different hyperparameters on model performance are described below.

Subsection of result

At a learning rate of 0.01, the VGG16 model achieved the best results with a validation accuracy of 98.67% and a validation loss of 2.65%. However, at epochs 12, 26, 90, and 91, there was a fluctuation/change of 14-19% in the validation loss value. Furthermore, the ResNet50_V2 model achieved a validation accuracy of 98.37% and a validation loss of 2.75%, but there was significant fluctuation in both accuracy and loss values from epochs 50 to 100, particularly epochs 54 and 55. Meanwhile, the Inception V3 model achieved a validation accuracy of 98.23% and a validation loss of 4.05%, with a decrease from epochs 60 to 80, where the loss reached 1125.56% at epoch 67.

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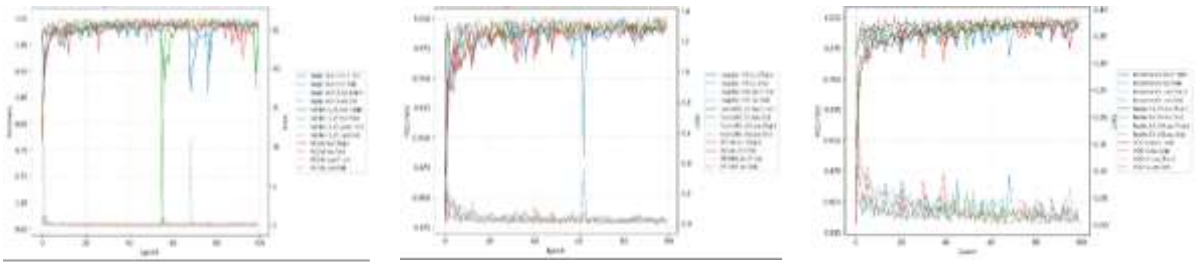
Volume XI, No.3, Juli 2026 Hal 20456 - 20466
p-ISSN : 2528-3561
e-ISSN : 2541-1934

At a learning rate of 0.001, the ResNet50_V2 model achieved the best results, with a validation accuracy of 99.13% and a validation loss of 2.15%. Furthermore, the VGG16 model achieved a validation accuracy of 98.95% and a validation loss of 2.04%. Meanwhile, the Inception V3 model achieved a. validation accuracy of 98.62% and a validation loss of 2.66%. Although there was a slight dip in the 61st epoch, where the validation loss reached 36.23%, it then returned to normal

At LR=0.0001, the VGG16 model achieved the best results, with a validation accuracy of 99.27% and a validation loss of 1.64%. Furthermore, the ResNet50_V2 model achieved a validation accuracy of 99.23% and a validation loss of 1.66%. Meanwhile, Inception V3 achieved a validation accuracy of 99.04% and a validation loss of 2.09%. The training and validation results can be seen in **Figure 3**. The accuracy value of this pre-trained CNN modified model is VGG16 at LR=0.0001 with a validation accuracy value of 99.27% and a validation loss value of 1.64%.



(a) (b) (c)

Fig. 3. Training Data Results (a) Lr=0,01 (b) lr=0,001 (c)lr=0,0001

The results of this test are used to test the model's performance with new data or test data. Several parameters were used in testing the model's performance during training. The test data consisted of 560 beef images, divided into 280 fresh beef images and 280 rotten beef images. At a learning rate (LR) of 0.01, Inception V3 achieved the highest accuracy at LR 97.14%, a fairly good performance across all metrics. ResNet50_V2 was slightly below Inception V3 with an accuracy of 96.96%. VGG16 showed the second-highest accuracy of 97.86% and a very high sensitivity of 99.64%. This indicates that VGG16 tends not to miss positive cases.

At LR=0.001, Inception V3 achieved a slightly lower accuracy compared to LR 0.01, which was 96.79%, but its sensitivity was very high at 99.64%, and its precision was relatively low at 94.26%, indicating that this model had more False Positives in this LR. ResNet50_V2 experienced a significant performance decrease in this LR, especially at 95.36% accuracy, 90.71% specificity, and 91.50% precision. However, its sensitivity reached 100.00%, meaning that this model never missed a positive case or had no False Negatives. This could be an indication of overfitting to the positive class or that the model tends to always predict positives. VGG16 achieved the best overall performance, with the highest accuracy of 99.46%. In addition, its specificity, sensitivity, precision, and F1 Score were also very high at above 99%, indicating that this model was very balanced and accurate in classifying both classes.

At LR=0.0001, Inception V3 consistently achieved the same accuracy as LR=0.01, at 97.14%. ResNet50_V2 achieved an improved accuracy of 97.86%, with significant improvements across all three models in this LR. ResNet50_V2's accuracy is comparable to VGG16 at LR=0.01. At this LR,VGG16 got a slightly decreased performance from LR=0.001, but the accuracy remained very good at 98.75% and the sensitivity reached 100.00%.

Overall, the best model based on Table 4 is VGG16 at LR=0.001, achieving a peak accuracy of 99.46% and a very balanced performance across other metrics at 99.29% precision, 99.64% sensitivity, and 99.47% F1 Score. VGG16 consistently performs very competitively and often outperforms other models. The Inception V3 model also performs consistently, although slightly below VGG16. The ResNet50_V2 model exhibits greater variability with respect to learning rate, with a significant decrease at LR=0.001 but an increase at LR=0.0001. Learning rate has been shown to have a significant impact on model performance. Selecting the right LR is crucial for deep learning model optimization. VGG16 demonstrates very strong and consistent performance across all tested LRs, achieving its highest accuracy at LR=0.001.

Although VGG16 at LR=0.0001 achieved the highest accuracy on the training data split, it failed to surpass its performance when generalized to the testing data split. In contrast, VGG16 with a learning rate of 0.001 achieved the highest testing accuracy of 99.46% and a very balanced F1 score of 99.47%. This indicates that LR=0.001 helps the VGG16 layer build robust features that do not overfit at the validation boundary.

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p-ISSN : 2528-3561
e-ISSN : 2541-1934

Table 4. Test Result

Model	Learnig Rate	Accuracy	Specificity	Sensitivity	Preision	F1 Score
Inception V3	0,01	97.14%	98.21%	96.07%	98.18%	97.11%
ResNet50_V2		96.96%	95.71%	98.21%	95.82%	97.00%
VGG16		97.86%	96.07%	99.64%	96.21%	97.89%
Inception V3	0,001	96.79%	93.93%	99.64%	94.26%	96.88%
ResNet50_V2		95.36%	90.71%	100.00%	91.50%	95.56%
VGG16		**99.46%**	99.29%	99.64%	99.29%	99.47%
Inception V3	0,0001	97.14%	95.71%	98.57%	95.83%	97.18%
ResNet50_V2		97.86%	96.79%	98.93%	96.85%	97.88%
VGG16		98.75%	97.50%	100.00%	97.56%	98.77%

Figure 4 shows the accuracy graphs of the three models Inception V3, ResNet50_V2, and VGG16 at three different LR 0.01, 0.001, and 0.0001. The highest graph is obtained by the VGG16 model at LR 0.001.

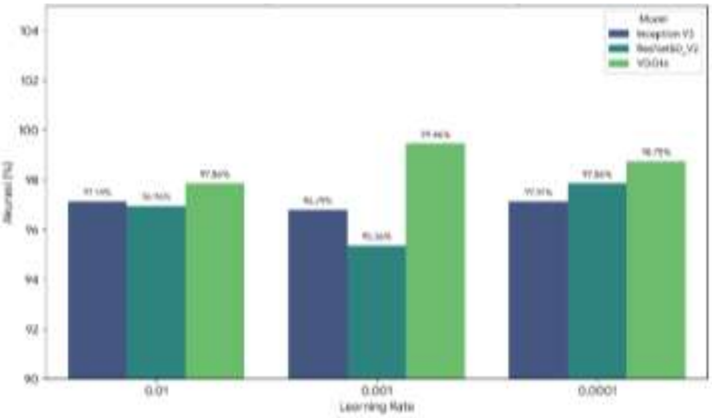

Fig 4. Hyperparameter LR Model Comparison Test Result

Training execution with exponential learning rate tuning yields varying behavior across architectures LR = 0.01 proved too aggressive for stable convergence. The VGG16 model achieved a high validation accuracy of 98.67% but experienced sharp fluctuations in validation loss of 14-19% at some stages of epochs 12, 26, 90, 91. Inception-V3 showed dramatic divergence, with its validation loss increasing to 1125.56% at epoch 67 due to the massive gradient step. LR = 0.0001 indicates a very smooth and controlled optimization path. VGG16 achieved the highest peak validation dataset accuracy of 99.27% and a low validation loss of 1.64%. LR = 0.001 achieved a balance between training speedup and generalization stability. ResNet50-V2 peaked here during training with a validation accuracy of 99.13%, while VGG16 achieved a validation accuracy of 98.95%.

Confusion Matrix

Based on the confusion matrix generated from testing the model on 560 image samples, equally composed of 280 fresh and 280 spoiled meat samples, the model demonstrated very strong visual classification performance. In the true positive performance evaluation, the model correctly predicted 278 fresh meat images out of a total of 280 samples as true fresh. This demonstrates the model's excellent ability to recognize meat in optimal condition. The model also successfully identified 279 images of spoiled meat out of a total of 280 spoiled meat samples. The model is highly sensitive to visual degradation patterns in meat that is no longer fit for consumption.

In contrast, the analysis of prediction error rates shows very promising results for real-world implementation. Two fresh meat samples were incorrectly predicted by the model as spoiled, or false positives. In the food industry context, this is a safe or low-risk error. The fatal error, predicting spoiled meat as fresh, or false negative, occurred in only one test sample. This is significant, considering that the probability of failing to detect spoiled meat was successfully reduced to a minimum of one in 280 negative test samples.

Overall, the model successfully predicted 557 of the 560 test data points correctly, resulting in a peak accuracy rate of 99.46%. From a food safety perspective, the system's ability to reduce the freshness prediction error rate to nearly zero significantly minimizes the risk of food poisoning for consumers.

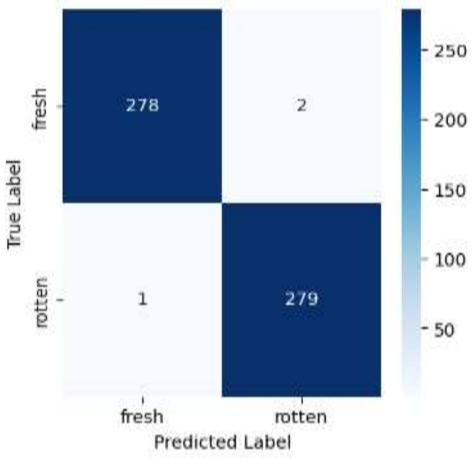

Fig 5. *Confusion Matrix model VGG16*

Web Application

Beef quality prediction testing was conducted by uploading beef images to a web application. The web application was built using Gradio and Huggingface, using the best .h5 model previously developed. During the application testing, all images came from external datasets; fresh beef images were taken directly from vendors, while spoiled beef images were obtained online. This introduced potential inaccuracies, as the lighting, background, and camera parameters in the online images differed from those in the main dataset. Despite this, the model demonstrated high confidence scores, ranging from 87% to 100%, in its predictions.

Table 5. Application Test

Image Label	Image Input	Predict	Result
Fresh			100 %
Fresh			99 %
Fresh			100 %

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Image Label	Image Input	Predict	Result
Fresh			100 %
Fresh			93 %
Rotten			100%
Rotten			99%
Rotten			100%
Rotten			93%
Rotten			87%

4. Conclusion

This study successfully developed and evaluated an automated beef freshness classification model. Through systematic hyperparameter tuning, VGG16 trained with a learning rate of 0.001 emerged as the optimal architecture, achieving an outstanding testing accuracy of 99.46% and an F1 score of 99.47%. The model was successfully implemented as a web application for practical use. An acknowledged limitation of this study is the use of images from external, less validated sources. Future work should expand the dataset using standardized sensory and chemical validation and test the model's robustness across various environmental lighting conditions.

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