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Meat Freshness Classification Using Convolutional Neural Network (CNN) Method

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Abstract

This study aims to develop a digital image-based meat freshness classification model. This model uses a Convolutional Neural Network (CNN) method to distinguish between fresh and spoiled meat automatically and objectively. The CNN was built from scratch using a Sequential architecture with three convolution blocks with 32, 64, and 128 3×3 filters, without using any pretrained architecture. The dataset used is the Meat Freshness Image Dataset, which is publicly available on the Kaggle platform. After validating the image quality, the dataset used consisted of 2,266 images; 1,815 training data images and 451 validation data images. All images went through a preprocessing stage that included resizing to 128×128 pixels, converting the color space from BGR to RGB, and normalizing pixel values to the range 0–1. The model was trained for 20 epochs with a batch size of 32. The optimizer used was Adam, with a learning rate of 0.001 and a binary crossentropy loss function. Evaluation results on validation data show that the model achieved 95.34% accuracy, 95.32% precision, 97.07% recall, 96.19% F1-score, and an Area Under the Curve (AUC) of 0.9785. These results demonstrate that a simple CNN architecture, trained without transfer learning, is capable of classifying meat freshness with excellent performance. This makes it an efficient alternative for image classification systems with relatively low computational resource requirements.

1. Introduction

Digital image processing and artificial intelligence technologies are developing rapidly and have been applied in various fields, including the food sector. One such application is the automatic identification of food freshness using deep learning methods. Meat freshness detection is crucial because meat quality directly impacts food safety and consumer health. Manual freshness inspections, which still involve observing color, aroma, and texture, tend to be subjective and influenced by observer experience and environmental conditions. Therefore, a more objective digital image-based approach is needed.[1],[2]

The Convolutional Neural Network (CNN) method is a deep learning algorithm that is highly capable of recognizing visual patterns in images. CNNs have been widely used in various food quality classification studies due to their ability to automatically extract features and achieve high levels of accuracy.[3],[4],[5].

Several previous studies have demonstrated the success of CNN applications in classifying meat images. Ardianto et al.'s study used the EfficientNet-B2 architecture to classify beef and pork images with an accuracy of 98.22%.[3], while Paisal et al. applied the EfficientNet-B4 architecture to a similar classification case.[6]. Sulistia et al.'s research applied the ResNet-50 architecture to classify chicken

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meat images.[4], and research by Yuda Alhafis et al. combined feature extraction with CNN for the same problem[7]. Lasniari et al.'s research also applied ResNet-50 with image augmentation for pork and beef classification.[8]In addition to meat type classification, Sahera et al.'s research optimized the CNN algorithm for beef freshness classification and achieved an accuracy of up to 98.50%.[5], while Ekamila et al. applied deep learning to mobile application-based beef freshness classification so that the identification process can be carried out practically.[9]. Mujiono et al. proposed a hybrid CNN-SVM model to classify the freshness condition of chicken meat.[10].

The use of CNN has also been widely applied to mobile devices, for example in the study by Asmoro and Solichin who created an Android application to classify beef quality.[11], as well as research by Winardi and Setyati which proves that visual features of images can be used to automatically identify types of meat[2]. In addition, research on detecting the freshness of chicken meat continues to develop. Zuhdi and his colleagues used CNN with ROC and AUC analysis to determine the freshness level of chicken meat.[12], Naturizal and his colleagues developed an Android-based chicken meat freshness classification system with CNN[13], while Pasya and Fachrie utilized the YOLO architecture to classify the freshness of chicken meat through digital images.[14]Another approach was taken by Sutarman and his team by combining RGB color features and Support Vector Machine (SVM) to identify the freshness level of chicken meat.[15].

Although many studies confirm that deep learning techniques are capable of achieving high classification accuracy, the majority still rely on pre-trained models such as EfficientNet-B2, EfficientNet-B4, or ResNet-50.[3]-[8], as well as other fairly complex architecture[14]These models generally require more computational resources, both during the training phase and during implementation. Furthermore, most previous research has focused on identifying meat types (beef, pork, or chicken) rather than assessing overall freshness. Research on freshness classification has been conducted.[5],[9],[10]-[15], but the majority still use transfer learning, hybrid models, or complex architectures; so the potential of simple CNN networks designed and trained from scratch is still rarely explored.

Based on the research that has been conducted, this study provides an innovation in the form of creating a special CNN architecture consisting of three convolutional layers with 32, 64, and 128 filters, which are trained entirely from scratch (not using pretrained models or transfer learning). The architectural design is optimized to have a lighter computational load compared to pretrained models, while still being able to produce competitive classification performance. Model evaluation is carried out comprehensively with metrics of accuracy, precision, recall, F1 score, confusion matrix, and ROC-AUC, to assess the model's ability to distinguish fresh meat images from rotten meat.

Based on this explanation, this study aims to create a digital image-based meat freshness classification model using a specially designed Convolutional Neural Network (CNN) architecture trained from scratch without relying on transfer learning. The resulting model is expected to be a lighter, more efficient, and easier-to-implement alternative without compromising classification accuracy, making it applicable to various computing devices and artificial intelligence-based meat freshness identification systems.

2. Research Methodology

This study applies the Convolutional Neural Network (CNN) method to classify meat freshness levels based on digital images into two classes: fresh meat and spoiled meat. The research stages include dataset collection, image preprocessing, CNN architecture design, model training, and performance evaluation using several classification metrics. CNN was chosen because it is capable of automatic feature extraction, making it widely used in image classification research in the food sector and has proven to provide good performance.

The research stages consist of five main processes, namely (1) dataset collection, (2) image preprocessing, (3) CNN architecture design, (4) model training, and (5) model performance evaluation. The entire process is carried out using a cloud-based computing environment on Kaggle Notebook so that all stages can be reproduced consistently.

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2.1 Research Tools

This research was conducted using the Kaggle Notebook computing environment as a cloud platform for model development and training. The data used was sourced from the Meat Freshness Image Dataset, which is publicly accessible through Kaggle. The software used in this study includes:

1. Python 3 as the primary programming language.
2. TensorFlow/Keras version 2.20.0 to build and train CNN models.
3. NumPy version 2.0.2 and Pandas version 2.3.3 for data manipulation.
4. OpenCV version 4.13.0 for image preprocessing.
5. Scikit-Learn to calculate evaluation metrics such as accuracy, precision, recall, F1-score, confusion matrix, classification report, and ROC-AUC.
6. Matplotlib for visualization of the training process and model evaluation results.

2.2 Data collection

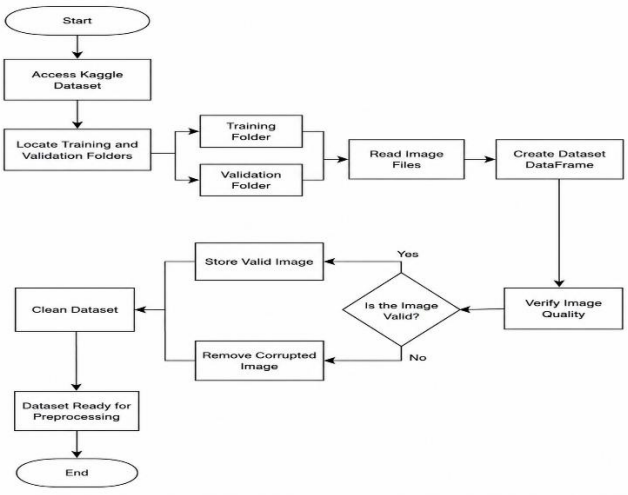


Figure 1. Data collection flowchart

The dataset used in this study is the Meat Freshness Image Dataset, taken from Kaggle. The dataset is divided into two image groups: Fresh Meat for fresh meat and Spoiled Meat for spoiled meat.

The data collection process begins with an automated search of the training and validation data directories in the Kaggle Notebook environment. All image file paths are then stored in a DataFrame structure to simplify data management. Next, a labeling process is performed based on file names. Images with the prefix "FRESH" are labeled 0, representing the fresh meat class, while images without this prefix are labeled 1, representing the spoiled meat class.

The initial dataset consisted of 1,816 training images and 452 validation images. After image quality verification, one image file was found to be corrupted and could not be processed. Therefore, the final dataset used in this study consisted of 1,815 training images and 451 validation images, for a total of 2,266 images. The verification process was carried out to ensure that all images used had the correct labels and could be processed during model training.



Figure 2. Example of fresh meat and rotten meat images
on the research dataset.

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Figure 2 shows sample images from each class. Fresh meat images generally have a bright red color with a firm texture, while spoiled meat images show a paler or grayish color change accompanied by changes in the surface texture.

2.3 CNN Model Design

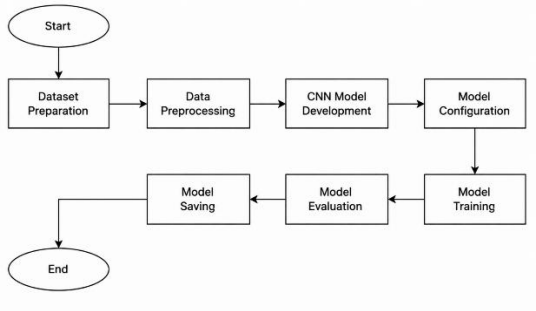


Figure 3. Flowchart of CNN model design

The first step in model design is image preprocessing. First, all images are verified to ensure no files are corrupted. After that, the images are resized to 128 × 128 pixels to ensure all images have a consistent input size. Next, the images are converted from BGR to RGB color space using OpenCV. The next step is to normalize the pixel values to the 0–1 range by dividing each pixel by 255, thus ensuring more stable training. Finally, all preprocessed images are converted into NumPy arrays to be used as input to the CNN model.

The CNN model was built using a Sequential architecture developed from scratch (train from scratch) without utilizing pre-trained models or transfer learning techniques. The architecture consists of three convolution blocks, each using 32, 64, and 128 filters with a 3 × 3 kernel and a ReLU activation function. Each convolution layer follows a 2 × 2 MaxPooling2D layer, which aims to reduce the dimensionality of the features while preserving the important information extracted.

After the feature extraction process, the results are converted into one-dimensional vectors through a Flatten layer, then processed by a Dense layer that has 128 neurons with ReLU activation. To reduce the risk of overfitting, a Dropout layer with a value of 0.5 is added. In the output layer, only one neuron with Sigmoid activation is used so that the model can produce binary classification probabilities between fresh and rotten meat. Details of the CNN architecture configuration used in this study can be seen in Table 1.

2.4 Model Training

The preprocessed dataset was used to train a CNN model in the Kaggle Notebook environment. The model was compiled using the Adam optimizer with a learning rate of 0.001, a loss function (binary crossentropy), and an accuracy evaluation metric.

The Adam optimizer was chosen because it provides faster and more stable convergence in neural network training than conventional optimizers. Binary crossentropy was used because this research is a binary classification problem, while a learning rate of 0.001 was chosen because it is frequently used in CNN training and balances convergence speed with learning stability.

Model training lasted for 20 epochs with a batch size of 32. This batch size was chosen to balance memory requirements and the stability of the optimization process. During training, training accuracy, validation accuracy, training loss, and validation loss were monitored to assess the model's ability to learn image characteristics and identify potential overfitting.[3],[5],[11].

2.5 Model Evaluation

The trained model was evaluated using 451 validation data images not included in the training process. The evaluation used several metrics to obtain a comprehensive overview of the model's performance. The metrics used included accuracy, precision, recall, and F1-score to measure the model's

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classification accuracy. Additionally, a confusion matrix and classification report were generated to determine the number of correct and incorrect predictions for each class.

The model's ability to differentiate between the two classes was tested using the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) value. The AUC value was used to assess the model's discriminatory power between fresh and spoiled meat images at various threshold values. This multi-metric evaluation approach was chosen because it provides a more comprehensive picture of model performance than accuracy alone and has been widely applied in previous meat image classification research.[5],[9],[10].

3. Results and Discussion

This study evaluates the use of a Convolutional Neural Network method to classify meat freshness based on digital images into two classes: fresh meat and spoiled meat. The results include the model design process, training results, evaluation results, and comparisons with previous research.

3.1 CNN Model Design

Table 1. CNN Model Design

Layer (type)	Output shape	Parameter
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_2 (Conv2D)	(None, 28, 28, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 128)	0
flatten	(None, 25088)	0
dense	(None, 128)	3,211,392
dropout	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

The table above shows the Convolutional Neural Network (CNN) design applied to categorize meat freshness levels into two types: Fresh Meat and Stale Meat. This model was built with a Sequential architecture (built from scratch) without using a pre-trained model, so each weight in the network was learned directly from the dataset used in this study. This approach was chosen to create a more straightforward model with lower computational requirements than transfer learning methods such as EfficientNet or ResNet.

In the initial stage, the model receives a pre-processed image with a size of 128 × 128 pixels containing three color channels (RGB). The image is then processed through three convolution blocks that function to extract visual features in stages. The first block consists of a Conv2D layer with 32 filters measuring 3 × 3 using the ReLU activation function, followed by a MaxPooling2D layer measuring 2 × 2 that reduces the dimensionality of the features while retaining important information. The second block uses 64 filters, while the third block applies 128 filters, with the same kernel configuration, activation function, and pooling as the first block. The increasing number of filters in each block is intended to enable the model to understand increasingly complex visual patterns, from edges to texture and surface characteristics of meat related to its freshness.

The feature extraction results from the convolution layer are then converted into one-dimensional vectors through a Flatten layer before being continued to a Dense layer that has 128 neurons with a ReLU activation function. To reduce the possibility of overfitting, a Dropout layer of 0.5 is added that randomly deactivates some neurons during the training process, allowing the model to have better generalization capabilities to data that has not been encountered before. In the output layer, 1 neuron is used with a

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Sigmoid activation function to generate a binary classification probability, namely fresh meat or spoiled meat.

The design implemented in this study is relatively simpler compared to several previous studies that used pretrained models such as EfficientNet-B2, EfficientNet-B4, and ResNet-50. Despite its lower complexity, the developed CNN model can still effectively understand the visual characteristics of meat images and demonstrates high classification performance on validation data. This indicates that a simple CNN architecture can still be considered as an option in developing meat freshness classification systems, especially in environments with limited computing resources.

3.2 Training Model

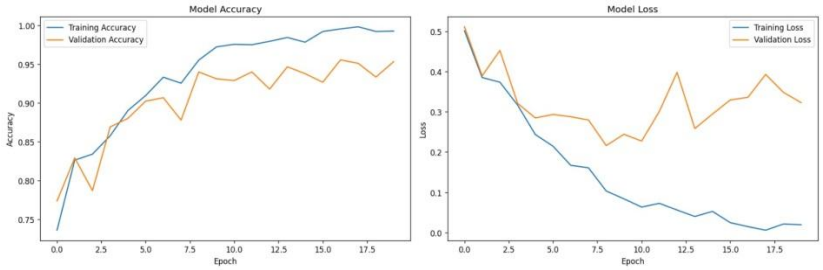


Figure 4. Training model

The model training process was carried out using 1,815 training data sets and 451 validation data sets over 20 epochs with a batch size of 32. The model was compiled using the Adam optimizer, a learning rate of 0.001, and a binary crossentropy loss function. During the training process, the accuracy and loss values of both training and validation data were monitored to determine the model's ability to learn image characteristics and detect the possibility of overfitting.[3],[5],[11].

Based on Figure 4, the training accuracy and validation accuracy values increased gradually, while the training loss and validation loss values decreased during the training process. These results indicate that the model is able to learn image patterns well and has a fairly good generalization ability to the validation data. After the training process was completed, the model produced an evaluation performance with an accuracy of 95.34%, indicating that the CNN architecture used was able to effectively perform the learning process on the meat freshness dataset.

3.3 Model Evaluation

```
========================================
Model Evaluation
========================================
Accuracy  : 0.9534
Precision : 0.9532
Recall    : 0.9707
F1-Score  : 0.9619
```

Figure 5. Model evaluation

After the training phase was completed, the model was evaluated using 451 images from the validation data not used during training. The evaluation used accuracy, precision, recall, and F1-score metrics to assess the model's overall freshness classification.[5],[9],[10].

The evaluation results shown in Figure 5 show that the model achieved an accuracy of 95.34%, a precision of 95.32%, a recall of 97.07%, and an F1-score of 96.19%. These figures indicate that the model successfully classified fresh and spoiled meat images with excellent accuracy. The balance between precision, recall, and F1-score values also indicates that the model performs well in making consistent predictions, making it suitable for use as a meat freshness classification model.

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3.4 Model Storage

After obtaining good evaluation results, the model is saved in HDF5 format (.h5) with the name cnn_meat_freshness.h5. Saving the model allows the entire network architecture and training weights to be reused without having to repeat the training process from scratch.

The saved model can then be used to predict new meat images or implemented in a computer-based classification system. This stage is crucial in system development because it saves computation time and simplifies implementation in future research.

3.5 Confusion Matrix and Classification Report

After the CNN model was evaluated using validation data, a more in-depth analysis was performed using a confusion matrix, Receiver Operating Characteristic (ROC) curves, and classification reports. These three test results provided deeper insights into the model's performance in categorizing fresh and spoiled meat images, not only based on overall accuracy but also on performance in each category.

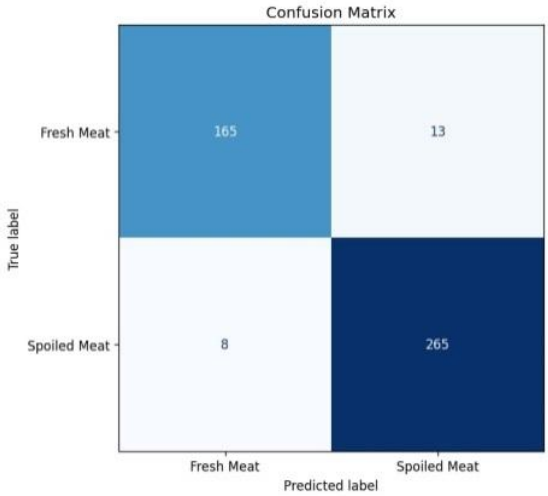


Figure 6. Matrix

Based on the confusion matrix shown in Figure 6, the majority of images from both categories were correctly categorized. Values on the main diagonal represent the number of predictions that matched the actual class (true positives and true negatives), while values outside the diagonal represent categorization errors (false positives and false negatives). The relatively low number of prediction errors indicates that the model is able to understand the visual characteristics of both categories well. However, there are still a number of images that share similar visual characteristics, resulting in a small number of categorization errors, especially in images with colors and textures that are close to the border between fresh and rotten meat.

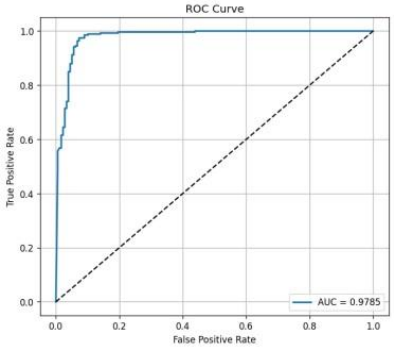


Figure 7. ROC curve

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The ROC curve shown in Figure 7 shows the interaction between the True Positive Rate (TPR) and False Positive Rate (FPR) at various threshold values. The closer the curve is to the upper left corner, the better the model can distinguish between the two categories. The test results show that the model achieved an Area Under the Curve (AUC) of 0.9785, which is considered excellent. This figure indicates that the model has a high ability to distinguish fresh meat images from spoiled meat at various threshold decisions, so the classification results are not solely dependent on a single threshold value.

Classification Report

	precision	recall	f1-score	support
Fresh Meat	0.95	0.93	0.94	178
Spoiled Meat	0.95	0.97	0.96	273
accuracy			0.95	451
macro avg	0.95	0.95	0.95	451
weighted avg	0.95	0.95	0.95	451

Figure 8. Calcification report

The classification report results shown in Figure 8 show the model's performance for each category. For the Fresh Meat category, the model recorded a precision of 0.96, a recall of 0.88, and an F1-score of 0.92 from 178 test datasets. These figures indicate that the model was able to identify most fresh meat images well, although some images were misclassified as spoiled meat due to similarities in visual characteristics.

In the Spoiled Meat category, the model achieved a precision of 0.93, a recall of 0.97, and an F1-score of 0.95 using 273 test data sets. The high recall indicates that the model is highly effective in detecting spoiled meat, thus reducing misclassification of unfit products.

Overall, the CNN model achieved 95.34% accuracy, 95.32% precision, 97.07% recall, 96.19% F1-score, and 0.9785 AUC. These results demonstrate the model's excellent classification capabilities, enabling a CNN architecture built from scratch to deliver competitive performance without the use of pre-trained models.

3.6 Comparison with Previous Research

This study produced a meat freshness classification model using a Convolutional Neural Network (CNN) method built from scratch. Based on testing results on 451 validation data sets, the model achieved an accuracy of 95.34%, a precision of 95.32%, a recall of 97.07%, an F1-score of 96.19%, and an AUC of 0.9785. These results indicate that the model is capable of classifying meat freshness levels with high performance.

Compared with research by Ardianto et al.[3], Paisal et al.[6], and Sulistia et al.[4]While using pretrained architectures like EfficientNet and ResNet, this study employed a simpler CNN architecture, requiring less computational resources. Although the accuracy obtained differed slightly from previous studies, the evaluation results showed that the proposed model still has good classification capabilities and has the potential to be implemented as an alternative digital image-based meat freshness identification system.

4. Conclusion

This study successfully created a model to classify the freshness level of meat by applying the Convolutional Neural Network (CNN) method that was built from scratch to distinguish two categories, namely Fresh Meat and Rotten Meat. This model was trained using 1,815 images for training and 451 images for validation after undergoing a preprocessing process, which included resizing, color

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conversion, and image normalization. The implemented CNN design consists of three convolutional layers with the number of filters respectively 32, 64, and 128, as well as Dense and Dropout layers to improve the model's generalization ability.

Based on the evaluation conducted, this model achieved an accuracy rate of 95.34%, precision at 95.32%, recall at 97.07%, F1-score at 96.19%, and AUC value at 0.9785. These findings indicate that the model can classify images of fresh meat and spoiled meat with high precision. Therefore, the main objective of this study has been achieved, namely creating an efficient CNN model for meat freshness classification and has the potential to be further developed as a meat freshness identification system based on digital images.

For future research, model performance can be improved by utilizing larger datasets, applying data augmentation techniques, performing parameter optimization, or by comparing the developed CNN architecture with transfer learning methods such as EfficientNet or ResNet to obtain models with better performance.

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