IMPLEMENTATION OF DIGITAL IMAGE TO DETERMINE THE QUALITY OF BALI BEEF USING A WEB-BASED CNN ALGORITHM

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ABSTRACT

Bali cattle are esteemed for their high-quality beef production; yet, the assessment of quality in practice sometimes lacks objectivity and consistency among farmers and traders. This subjectivity complicates purchasers' ability to ascertain equitable prices and heightens the danger of financial losses when the perceived quality diverges from the actual state of the meat. This paper offers an objective classification system for Bali beef quality via digital image processing via a Convolutional Neural Network (CNN) implemented with TensorFlow.js. A dataset including 600 training photos and 150 testing images was employed. Experimental results indicate that the created system attains an accuracy of 94.67% on training data and 78% on test data. The technique can classify beef quality into three categories: fresh, slightly fresh, and rotten. The results underscore the capability of web-based CNN models to deliver precise, accessible, and instantaneous evaluations of meat quality. In addition to technological performance, the deployment of this system can greatly reduce market asymmetry, facilitate transparent pricing methods, and diminish customer losses. Furthermore, it provides an economical digital solution applicable in rural or small-scale agricultural settings, thereby enhancing local agribusiness practices and fostering technological adoption in the livestock industry.

Keywords: Bali Beef Quality, Convolutional Neural Network, TensorFlow.js, Digital Image Classification

1. INTRODUCTION

Bali cattle are one of Indonesia's indigenous livestock germplasms with high economic and cultural value (Gubuku, 2024; Sapibagus, 2017) (Abadi et al., 2025; Saleh et al., 2021; Sio, 2023). Originating from the domestication of the banteng (*Bos javanicus*) since prehistoric times, this breed possesses unique genetic characteristics and has adapted exceptionally well to the tropical agro-climatic conditions of Indonesia (Jakaria et al., 2020) (Helmiah & Nasrudin, 2021). The primary advantage of Bali cattle lies in their superior meat quality compared to European beef breeds such as Hereford and Shorthorn, particularly in terms of high carcass yield and low fat content (Leestyawati, 2021) (Sabtu et al., 2022). These traits make Bali cattle a competitive and promising source of animal protein in both domestic and international markets (Tahuk et al., 2017). Furthermore, their excellent adaptability has facilitated their widespread distribution across various regions of Indonesia, including Java, Sulawesi, and Nusa Tenggara, positioning them as a strategic asset in the development of locally based national livestock production systems (Arnawa et al., 2024; Indraswari et al., 2017).

In the context of the modern livestock industry, the meat quality of Bali cattle is a key factor that influences consumer decision-making and the market competitiveness of livestock products (Mahakena & Veerman, 2019a). Meat quality is affected by several biological and managerial factors such as slaughter age, feed type and quality, fattening level, and the overall health condition of the animal. However, in practice, the assessment of meat quality is still largely performed visually and manually by farmers or traders (Marisa, 2019). This process tends to be highly subjective, relying on visual indicators such as color, fiber, and texture of the meat, which often result in inconsistent evaluations between individuals (Suada & Swacita, 2017) (Agustina, 2012). Moreover, such assessments are typically limited to meat experts with specific experience, making them unreliable and inaccessible to general buyers and sellers who lack technical knowledge in meat evaluation (Mahakena & Veerman, 2019b).

This situation creates an information gap that can disadvantage market participants, especially smallholder farmers and end consumers, when meat quality is not fairly reflected in the selling price(Arfandani, 2015). Therefore, there is a pressing need for a scientific and technology-based approach to produce a more objective, accurate, and accessible method for assessing Bali cattle meat quality (Y. Affandes & Lasniari, 2022). This new approach is expected to replace conventional methods that are prone to subjectivity and to support the digitalization of the livestock sector through data-driven systems. One promising solution is the application of digital image processing and artificial intelligence, particularly the implementation of *Convolutional Neural Network* (CNN) algorithms, which have proven effective in visual classification based on patterns and color (A. Affandes & Lasniari, 2022). This innovation not only enhances efficiency in evaluating Bali cattle meat quality but also contributes meaningfully to the sustainable digital transformation of Indonesia's livestock industry.

As a solution to the issue of subjective assessment of Bali cattle meat quality, digital image processing technology with the Convolutional Neural Network (CNN) algorithm can be used to classify meat quality accurately. A study conducted by (Mellinia, 2022) Titled "Implementation of CNN Model and TensorFlow in Detecting Livestock Meat Types," the paper successfully developed a livestock meat type detection system by implementing a CNN model and TensorFlow. The system testing using 70 images of different types of livestock meat achieved the highest accuracy of 100%, with an average system accuracy of 85.71%. Thus, CNN is considered effective in recognizing patterns and allows farmers or collectors to assess meat quality quickly and efficiently through a web platform, helping to save time and resources in the field.

2. THEORY

The main factors affecting beef quality are the management practices, including feed provision such as additives (hormones, antibiotics, and minerals), genetics, gender, age, husbandry practices, and healthcare (Clinquart et al., 2022). Beef quality is also greatly influenced by environmental conditions, facilities, and infrastructure at the slaughterhouse (RPH), the condition of livestock before slaughter, slaughter procedures, carcass handling, meat transportation, sales, and processing (Sihombing et al., 2020)(Pogorzelski & Pogorzelska-Nowicka, 2021). Additionally, blood drainage during slaughter and contamination afterward also play a significant role in beef quality (Xue, 2004). According to the Indonesian National Standard (SNI), beef quality can be determined by several key characteristics: meat color, marbling (fat content), meat texture, and fat color (Devlin et al., 2017). According to E. Woods & C. Gonzalez 2008 in (Dijaya & Setiawan, 2023) A digital image is a visual representation of the real world in digital form that a computer can process. The image consists of pixels arranged in rows and columns, where each pixel has a value that represents brightness or color at a specific position. Digital images can be obtained from digital cameras, scanners, or computer simulations (Siregar et al., 2025).

A Convolutional Neural Network (CNN) is a method that is part of the Feed Forward Neural Network class, inspired by the visual cortex of the brain, and specifically designed to process data with a grid structure (Batubara et al., 2020; Batubara & Awangga, 2020; Sanjaya, 2024). CNN has several types of layers that can be used, including subsampling layers, convolutional layers, loss layers, and fully connected layers (Harjoseputro, 2018). CNN is a type of architecture in artificial neural networks specifically created to process and analyze visual data, such as images. CNN is highly effective in recognizing patterns and features within visual data, which is why it is widely used in various types of applications (Liu, 2018). In CNN, there are several key components, including: 1) Convolutional Layer: This layer is the core part of the CNN. In this process, the image undergoes convolution with a filter or kernel, which is used to generate a feature map.

This process helps detect features such as edges, textures, and other patterns (Yang & Liu, 2018). 2) Pooling Layer: The pooling layer is used to reduce the dimensions of the feature map, thereby reducing the number of parameters and computations within the network. In this stage, several operations are performed, including: Max Pooling, which extracts the highest value from a grid cell and sends it to the next stage. Average Pooling, which allows information from the entire receptive field to be considered, not just the highest value, as in max pooling (Punjabi & Katsaggelos, 2017). 3) Fully Connected Layer: After going through the previous stages, the processed data is flattened into one dimension and passed to the connected layers. Neurons in this layer are connected to all neurons in the previous layer. This stage is responsible for classification based on the features that were previously extracted (Hamid & Walia, 2021).

TensorFlow.js is a deep learning library for JavaScript that is compatible with TensorFlow, the Python deep learning framework. Compared to other libraries such as brain.js and ConvNetJS, TensorFlow.js is more widely used because it supports the entire deep learning process. In addition, TensorFlow.js is integrated with TensorFlow and Keras, making it easier to use models created in Python within the browser and allowing for easier migration across platforms (Yakip, 2021). A website is a medium that contains pages with information that can be accessed via the internet and can be enjoyed globally (worldwide). A website is essentially a series of code containing sets of instructions, which are then interpreted through a browser (R. Susilawati et al., 2020) (T. Susilawati et al., 2020).

3. METHOD

This research was performed in Mr. Juning's Bali cattle farm in Tri-tiro village, Bontotiro sub-district, Bulukumba district. The data gathering process entailed direct observation of Bali cow meat, followed by the acquisition of pictures of samples classified into three quality categories: fresh, slightly fresh, and rotten. The meat samples were sectioned into smaller pieces and captured from a distance of around 30 cm using a smartphone camera in JPG format (Tupan et al., 2025) assert that image acquisition and preprocessing are essential in digital image processing, as they directly affect the feature extraction and classification phases. Alongside image gathering, interviews with farmers and collectors were performed to corroborate traditional assessment methods and discern primary problems in meat quality evaluation. The qualitative results confirmed that the built system met genuine user needs, as advocated in participatory technology design (Zorzetti et al., 2022).

The system was constructed utilizing the Convolutional Neural Network (CNN), a deep learning framework adept at image classification tasks owing to its capacity for autonomous spatial feature extraction(Archana & Jeevaraj, 2024). Model training was conducted using TensorFlow.js, a JavaScript-based deep learning framework that facilitates deployment across various platforms, including web browsers, without requiring specific hardware (Goh et al., 2023). The model training procedure adhered to the workflow depicted in Figure 1.

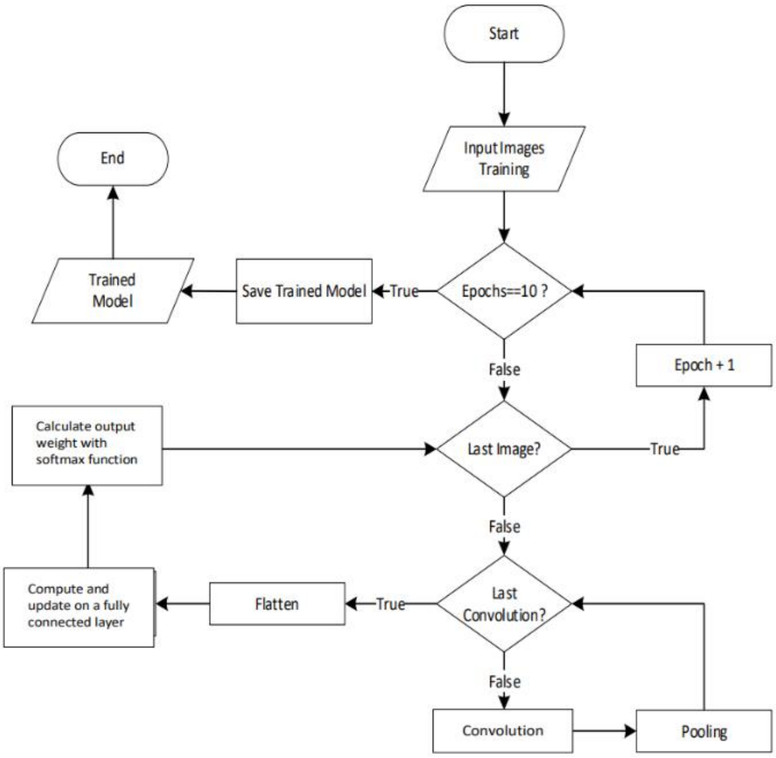

Figure 1. Flowchart of CNN Algorithm Model Training

The training dataset comprised 200 photos for each category of Bali meat quality: fresh, slightly fresh, and spoiled. Before training, all photos were resized to a consistent dimension of 128 × 128 pixels to standardize the input for the network and enhance computational performance (Sarwar et al., 2024). The CNN architecture was established using multiple convolutional layers with a kernel size of 3 × 3 and a stride of 1, succeeded by the use of the Rectified Linear

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Unit (ReLU) activation function to incorporate non-linearity into the model. A max pooling layer utilizing a 2 × 2 kernel and a stride of 2 was implemented to diminish the spatial dimensions while preserving essential features. The last step had completely connected layers that executed the classification into the three predetermined groups. This architecture was chosen due to the established efficacy of CNNs in picture classification tasks, especially in evaluating food quality, such as assessing the freshness of fish and fruits (Singh et al., 2025).

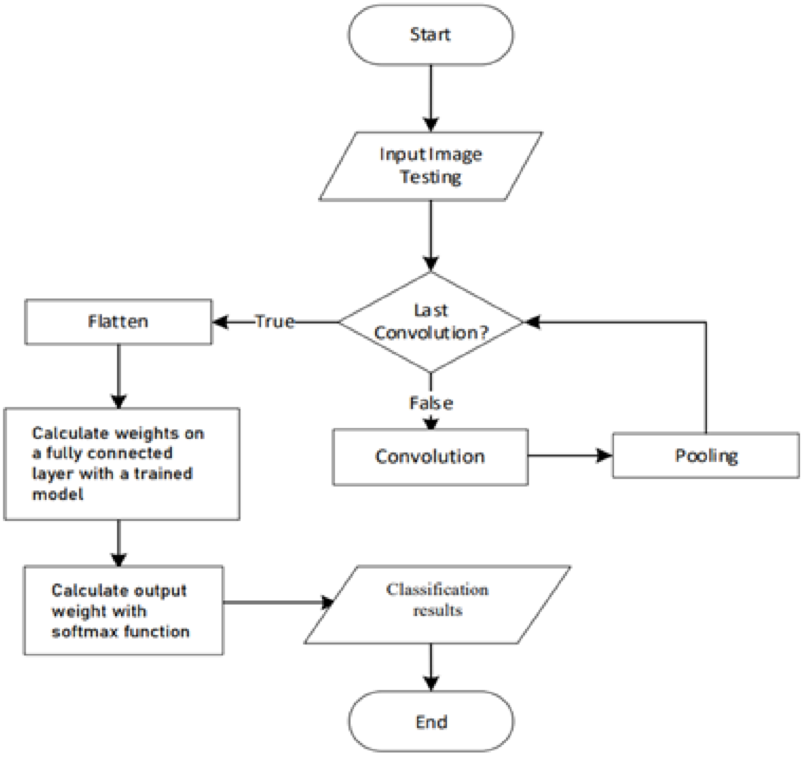

Figure 2. Flowchart of CNN Classification Algorithm

In Figure 2, the classification process involves inputting an image of Bali beef slices. The system then uses TensorFlow.js to classify the quality of the Bali beef using the previously trained model. The result of the classification will then be displayed. The system will be built using TensorFlow.js and Node.js as a cross-platform runtime environment, allowing users to access the system through various devices. The system is equipped with a web-based user interface built using Node.js. The user interface includes an interface for training data and an interface for users, such as meat collectors, to perform the classification.

4. RESULTS AND DISCUSSION

4.1 Flowchart of the Model Training Procedure

The model training process, depicted in Figure 3, commences with the input of a dataset comprising 200 photos for each quality category of Bali beef: fresh, slightly fresh, and rotten. All images were scaled to 128 × 128 pixels to maintain consistent input dimensions before training. Preprocessing techniques, including cropping, were employed as needed to enhance data quality. This activity aligns with the suggestion of (Pei et al., 2023), who highlighted that image normalization markedly improves feature extraction and classification efficacy. After preprocessing, the CNN model was established utilizing convolutional layers, activation functions, and pooling layers, followed by fully connected layers for classification.

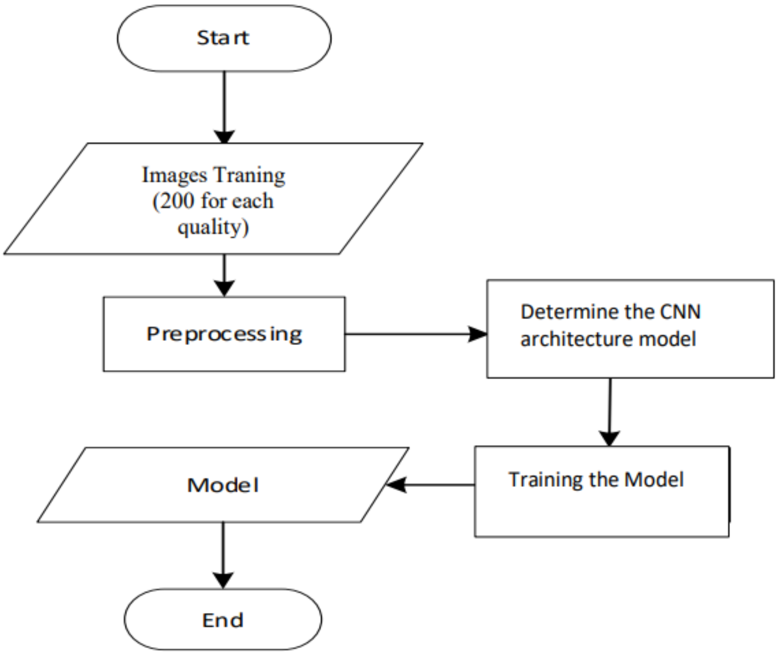

Figure 3. Model Training Flowchart

4.2 Flowchart of Meat Quality Prediction

Figure 4 illustrates that the classification method uses TensorFlow.js to forecast meat quality. The input photos are initially scaled to 128 × 128 pixels to ensure compatibility with the model. The trained CNN model is subsequently loaded, and predictions are produced in real time. The categorization outcomes are shown on the web-based interface, allowing end-users, like farmers and collectors, to readily access predictions. This method corresponds with the results of (Goh et al., 2023), who demonstrated that TensorFlow.js enables effective machine learning implementation in browser-based apps without requiring specialized hardware.

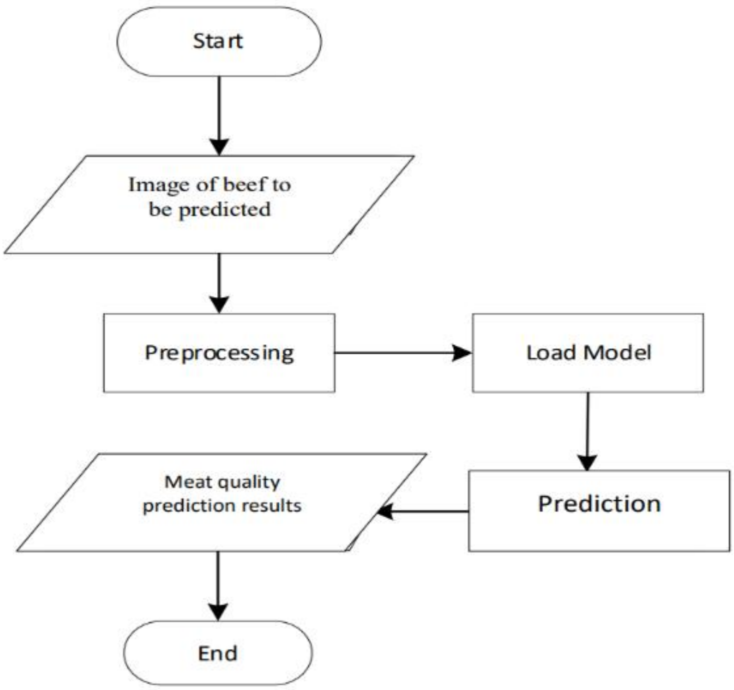

Figure 4. Meat Quality Prediction Flowchart

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4.3 Dataset Preparation Steps

The dataset comprised 600 training photos, evenly allocated among three classes (Table 1), along with 150 testing images (50 each class). Photographs were taken using a smartphone camera situated roughly 30 cm above the meat samples. Prior research has underscored the efficacy of smartphone-based image capturing for agricultural quality evaluation, owing to its cost-effectiveness and accessibility (Amani et al., 2022). Figures 5, 6, and 7 exemplify each category. A balanced dataset design, as recommended by (Zhu & Salimi, 2024), was implemented to mitigate bias and enhance classification reliability.

Table 1. Training Data Distribution

Class	Amount
Fresh Meat	200
Less Fresh Meat	200
Rotten Meat	200
Total	600

Below are examples of Bali beef images for each class.

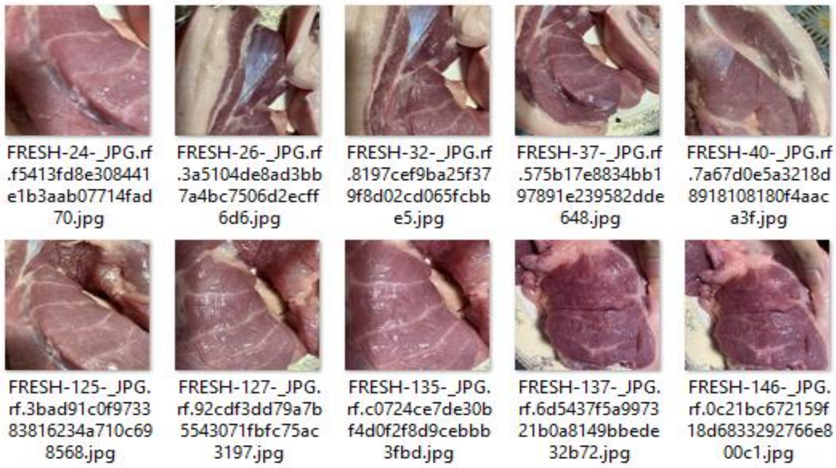


Figure 5. Fresh meat class

Figure 6. Less Fresh Meat Class

Figure 7. Rotten Meat Class

4.4 Interface Design Implementation

In the implementation of the interface design, this application consists of two pages: the prediction page and the CNN model training page. The Prediction (Classification) page is used to predict the quality of Bali beef.

Figure 8. Prediction Page

Figure 8 is the prediction page that provides an output in the form of meat quality predictions (fresh, less fresh, or spoiled). To make a prediction, select (choose file) the image of beef to be predicted. After selecting the image, it will be displayed. Then, click the prediction button. The application will perform the prediction and display the result, with the highest value prediction being the final result.

Figure 9. Model Training Page (Loading)

Figure 9: This is the model training page (CNN Model) used to train (create) the CNN model using TensorFlow.js, or the model training page during the loading stage (when the model is being trained). Training the model takes some time, depending on several factors, including the amount of training data, the number of convolutions, the number of filters used, and the specifications of the computer's CPU, as this research uses a CPU-based TensorFlow.

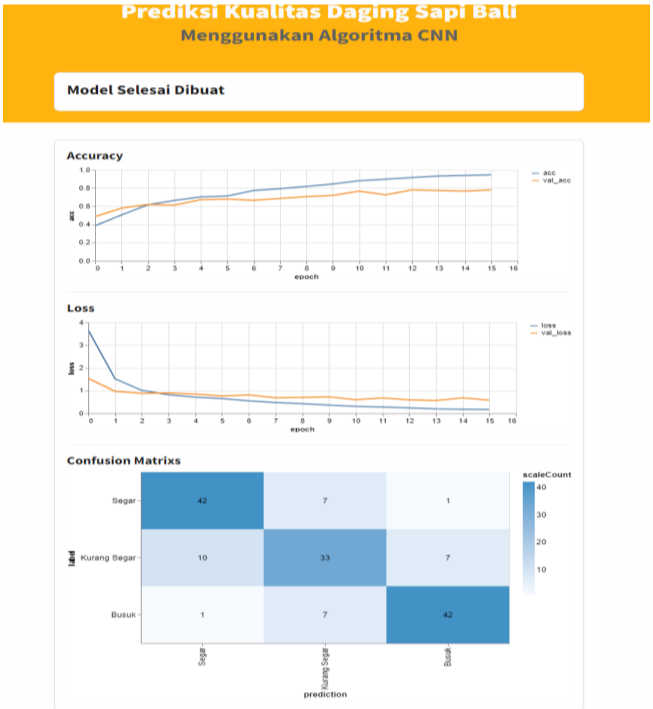


Figure 10. Model Training Page (Completed)

Figure 10 is the model training page displayed once the model training is completed. It shows information that the model has been successfully created, along with accuracy graphs, loss graphs, and the confusion matrix. The resulting model can be used for the prediction process and is saved in a format compatible with TensorFlow.js, consisting of two files: model.json and weights.bin.

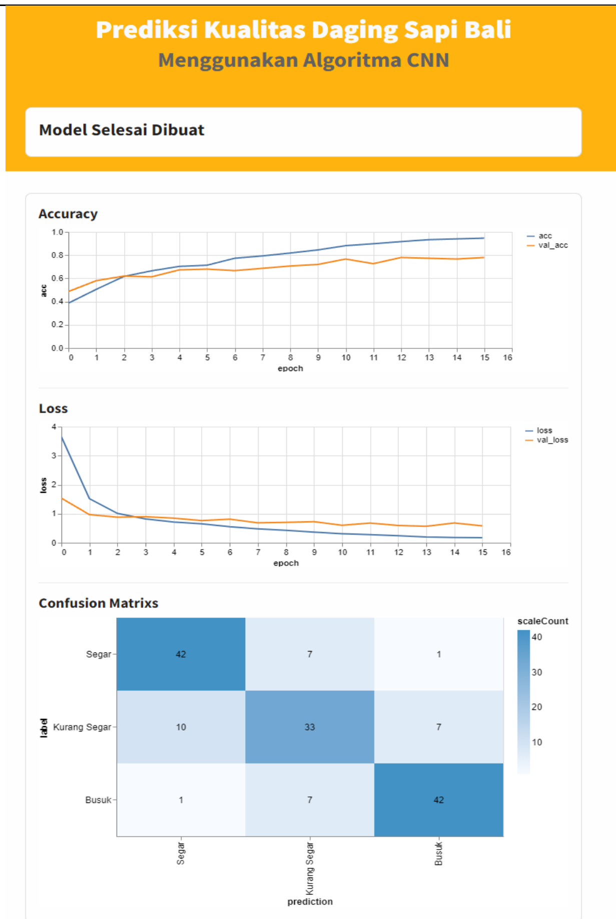
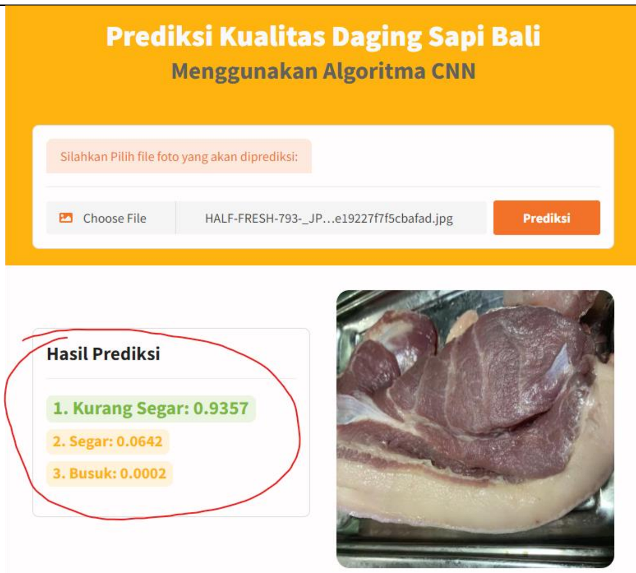
4.5 System Testing

Black-box testing was used for system validation, and the results showed that the training and prediction features worked as intended (Table 2). The confusion matrix produced from the 150 test images used is displayed in Figure 11. Table 4 summarizes performance measures such as recall, accuracy, and precision. Overall, the system's accuracy on test data was 78%, but on training data, it was 94.67%. The precision values were lower for slightly fresh meat (0.66), but higher for fresh and rotting beef (0.84). Similarly, the recall for fresh was 0.79, for slightly fresh it was 0.70, and for rotting it was 0.84.

These findings imply that the model performs exceptionally well at differentiating between fresh and ruined meat, but it has trouble correctly detecting intermediate categories (somewhat fresh). This problem aligns with research on food quality evaluation. According to (Gomaa & Saad, 2025), transitional classes frequently exhibit overlapping visual characteristics that make classification more difficult. The discrepancy between testing and training accuracy also suggests that CNN models with relatively limited datasets may be overfitting (Asiri et al., 2024).

The accuracy attained, however, is comparable to prior research that uses CNN to classify food quality. CNN was found to be effective in fruit ripeness detection tasks by (Wang et al., 2022), whereas (Yasin et al., 2023) reached about 80% accuracy in fish freshness classification. These similarities make the present findings more credible and show that CNN models can produce accurate classification results even when used in lightweight frameworks like TensorFlow.js.

Table 2. Blackbox Testing Results

No.	Testing	Expected Results	Test Results	Description
1.	Model Training	Can generate model output and display accuracy results		Valid
2.	Beef Quality Prediction	Can display prediction results		Valid

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A test was conducted with 150 test data divided into three classes: 50 fresh, 50 slightly fresh, and 50 rotten. The resulting confusion matrix is shown in the image below.

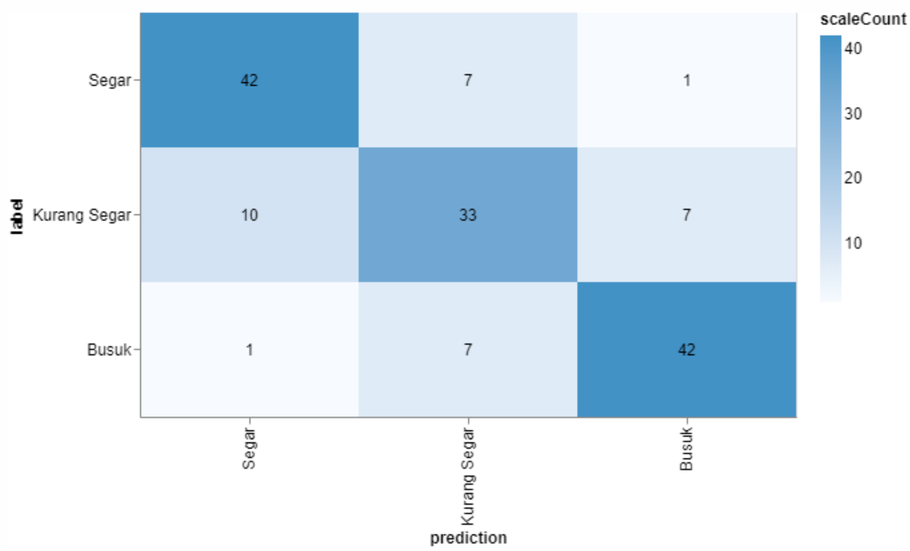

Figure 11. Confusion Matrix

In Figure 11, the values of TP, TN, FP, and FN are as follows:

Table 3. The values of TP, FP, and FN

	Fresh	Slightly Fresh	Rotten
TP	42	33	42
FP	8	17	8
FN	11	14	8

From the values of TP, FP, and FN, the accuracy, precision, and recall can be calculated and are as follows:

Table 4. The values of Accuracy, Precision, and Recall.

Formula	**Performance Vector**				Final Result
		Fresh	Slightly Fresh	Rotten	
TP/Data Quantity	Accuracy				78%
TP/(TP+FP)	Precision	0,84	0,66	0,84	78%
TP/(TP+FN)	Recall	0,7924528	0,70212766	0,84	78%

According to the findings, using CNN-based digital image processing has several advantages for assessing the quality of beef. First, the methodology reduces the subjectivity involved in conventional assessments made by farmers and collectors by offering a consistent and objective classification procedure. Secondly, the web-based implementation facilitates instantaneous accessibility, bolstering openness and equity in commercial dealings. In conclusion, the strategy contributes to the larger objectives of smart farming and digital agriculture by providing an inexpensive digital innovation that may be implemented in rural farming contexts (Karunathilake et al., 2023). To improve classification performance, future research can focus on expanding the dataset, employing data augmentation strategies, and evaluating cutting-edge designs such as ResNet or EfficientNet, which have demonstrated exceptional accuracy in image recognition tasks (Mahesh et al., 2025).

5. CONCLUSIONS AND SUGGESTIONS

This study effectively created a web-based digital image processing system that uses TensorFlow.js and Convolutional Neural Networks (CNN) to categorize Bali beef into three groups: bad, slightly fresh, and fresh. The algorithm performed poorly for slightly fresh meat but had a comparatively high precision and recall for fresh and rotten classes, with an accuracy of 94.67% on training data and 78% on testing data. The findings show that CNN can efficiently enable food quality categorization even when used on lightweight systems.

This study's practical significance stems from its capacity to offer farmers, merchants, and consumers a dispassionate and easily comprehensible instrument for assessing the quality of beef. This helps to minimize customer losses, increase openness in the beef market, and lessen subjectivity. Additionally, the system is a low-cost digital innovation that can help Indonesia's shift to smart farming and improve smallholder farming methods. It is recommended that the dataset be enlarged for subsequent research by adding more varied meat samples from various lighting and environmental settings. Classification performance may also be enhanced by utilizing sophisticated deep learning architectures like ResNet, EfficientNet, or hybrid CNN-LSTM models. Including support for mobile applications could also improve user accessibility and enable real-time use in field settings.

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