# Non-destructive rapid prediction of raw salted duck egg quality using optimized convolutional neural network

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**Abstract:** A system to determine the quality of salted duck eggs is necessary to increase egg production and prevent consumption of bad-salted duck eggs. Egg images were captured by a camera with a Light Emitting Diode (LED) light, and a box with a black interior was utilized. A proposed optimized Convolutional Neural Network (opti-CNN) model using a small number of parameters (6.5 million) and convolutional layers was developed to recognize the key elements of the salted duck egg image utilizing pooling, activation, fully connected layers, and a sigmoid layer to enhance the performance of the CNN model. VGG-16, AlexNet, Inception-V3, and MobileNet were used for comparison. The findings revealed that all the models had accuracy levels above 90%. The MobileNet model exhibited 100% accuracy, which was the highest, and the opti-CNN exhibited 97% accuracy. However, the opti-CNN showed a computation time of only 50 ms, whereas the other models showed a computation time above 500 ms. These findings show that determining the quality of salted duck eggs using the proposed opti-CNN yields outstanding results and can be applied in large-scale sorting procedures.

**Keywords:** convolutional neural network, duck salted egg, food industry, computation time.

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## 1 Introduction

Eggs are a healthy staple food that is widely consumed. Increased egg production is directly proportional to consumption requirements. Salted duck eggs are widely consumed in Asia. Duck eggs contain high levels of protein, which is beneficial to the human body (Quan and Benjakul, 2019). In addition to being consumed directly, duck eggs can be processed into various derivative products to attract consumer interest (Huang and Lin, 2011). Salted duck eggs are duck eggs that are processed using a special technique without opening the eggshell to produce duck eggs that taste salty. The quality of salted eggs is largely determined by their condition before they turn into salted eggs (Quan and Benjakul, 2019; Xu et al., 2017). A nice raw salted egg features a colorless or transparent egg white

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and a vivid orange or son yolk. Additionally, salted eggs do not smell unpleasant (Ariviani et al., 2018).

A good-quality salted egg gives a better taste and provides greater health benefits (Ema et al., 2018). Therefore, numerous studies have examined various aspects of the production process of salted duck eggs in an effort to improve their quality, such as reducing fat and salt content (Suretno et al., 2021), ultrasonic assisted cooking (Wang et al., 2021), changes in egg yolk structure (Lai et al., 2010) and oil concentration (Wang et al., 2017b). Nevertheless, it is impossible to completely prevent bacteria from entering the salted egg from the outside, thus causing damage to the egg. The same is true for the egg's own degradation caused by spoilage bacteria (Yang et al., 2021).

In general, the salted duck egg processing industry still uses minimal technology to increase the amount of production. While the number of needs for salted eggs continues to increase (Sumekar et al., 2018). Salted duck eggs however should be maintained for their quality. Salted duck egg producers conduct manual evaluations of the quality to maintain the quality of salted duck egg products (Li et al., 2022). They evaluate the salted duck eggs by looking at them directly with their eyes with the help of a bulb. As a result, a lot of effort and personnel are needed. This is due to the fact that everyone has a unique perspective on how quality standards are applied in the workplace (Hasdar and Windyasmara, 2022). A number of studies have been carried out on the non-destructive evaluation of egg quality using images such hyperspectral images (Suktanarak and Teerachaichayut, 2017; Yao et al., 2022), image processing (Chen et al., 2011), machine vision (Wang et al., 2017a), computer vision (Ma et al., 2017; Nasir et al., 2018), and Artificial Neural Network (ANN) (Soltani et al., 2015) as shown in Table 1. These previous studies, however, neglected to consider how rapidly the quality of eggs can be assessed using computing. In contrast, the food industry's checking procedure proceeds swiftly.

**Table 1 Articles summary of identifying egg quality using different techniques**

| Technique | Input Ultrasonic | Input Images | Freshness | Yolk | Eggshell | Shape |
|---|---|---|---|---|---|---|
| Hyperspectral Images | | (Suktanarak and Teerachaichayut, 2017; Yao et al., 2022) | (Suktanarak and Teerachaichayut, 2017; Yao et al., 2022) | (Yao et al., 2022) | (Yao et al., 2022) | |
| Image processing | | (Chen et al., 2011) | | | (Chen et al., 2011) | |
| Machine vision | | (Wang et al., 2017a) | | | (Wang et al., 2017a) | |
| Computer vision | | (Ma et al., 2017; Nasir et al., 2018) | | (Ma et al., 2017) | | (Nasir et al., 2018) |
| ANN | (Soltani et al., 2015) | (Soltani et al., 2015) | | (Soltani et al., 2015) | | |

Convolutional Neural Network (CNN) has been used by many researchers because of their ability to accurately detect objects. This is evident in the widespread use of CNN in various fields. In the food sector, CNN are used to identify banana species from fruit groups. A CNN with five layers was used to extract the feature values for each type of banana (Vijayalakshmi and Peter, 2021). In facial recognition, a CNN can be used to determine the facial expressions (Rusia and Singh, 2021). Furthermore, in the field of agricultural diseases, CNN have been used to classify rice plant types. In this study, a CNN was used to classify three types of plant diseases (Upadhyay and Kumar, 2022).

To increase the output parameters from the CNN, several parameters can be changed, which is often called hyper parameter tuning. Changes to these parameters aim to streamline the CNN process so that it can produce the best model with the best performance and short processing time or inference time. Some of these parameters include the number of layers, filters, and neurons. This is similar to several previous studies that made improvised changes to the CNN architecture (Menaka and Vaidyanathan, 2022) and also made efficiency by performing quantization (Garifulla et al., 2022).

The primary objective of this study was to evaluate the salted duck egg quality using the CNN as a result of the reduced computational time of the CNN, which can detect the egg quality required for the food industry. Therefore, various CNN models have been applied to examine salted duck eggs for comparison with opti-CNN. There are two salted egg states, excellent and rotting, which can be distinguished depending on the status of the egg yolk. This study proposes a system using an opti-CNN to identify the quality of raw salted duck eggs, which is important for consumers and the food processing industry.

## 2 Material and method

This investigation was conducted in different stages. The gathering of salted duck eggs, which was the major component, was the initial stage. Next, egg images were captured, followed by image pre-processing and identification with a CNN. The procedure used to evaluate the quality of the CNN model is illustrated in Figure 1.


**Figure 1** The diagram of salted duck egg quality detection process

### 2.1 Material

Raw salted eggs were obtained from local breeders of the alabio duck (*Anas platyrhynchos Borneo*) in the area around Makassar city, Indonesia. Raw salted duck eggs were prepared using the rubbing ash technique and soaked for 14 days to obtain good-salted eggs. In this study, 80 raw salted duck eggs were used for data collection. 40 raw salted duck eggs were collected and left outside for 14 days to obtain data on rotting raw salted duck eggs. Furthermore, 40 raw salted duck eggs were collected one day before image acquisition. Images were obtained after 14 days for both types of treatment.

### 2.2 Image acquisition system

Images were taken using a camera with a resolution of 13 MP, f/2.2, which was placed approximately 25 cm from the top of the egg holder, as shown in Figure 2. The egg was placed on top of a holder inside a box that had been painted black to reduce light reflection with a size of 40 × 40 × 60 cm (width × length × height). A light bulb with an LED of 220V, 5 W, and 3000 K was mounted on the bottom to provide lighting on the eggs. Eggs were laid horizontally at the time of image acquisition. Furthermore, the image recordings were saved using the PNG format.

### 2.3 Image preprocessing

The Data Augmentation technique (Shorten and Khoshgoftaar, 2019) was used to obtain a sufficient amount of data, namely, by rotating the image slightly to obtain new data so that the amount of image data was as high as 400. The 400 image samples were collected and classified into two classes, 218 images of "good" salted egg and 182 image of "rotten" salted egg. In addition, the dataset resolution from the camera was 590×1280, and then resized into images with a resolution of 224 × 224 to fit the size of the CNN input layer proposed in this work. Moreover, all the datasets were also selected randomly and split into the training, validation, and testing section with the ratio of 60:10:30.

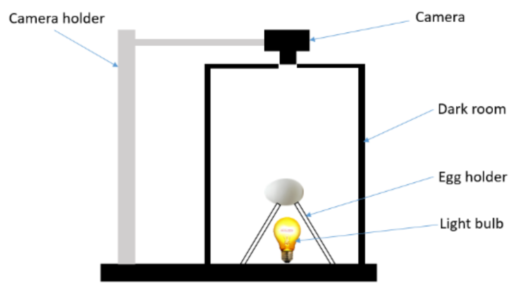


Figure 2 The system for taking the raw salted egg images

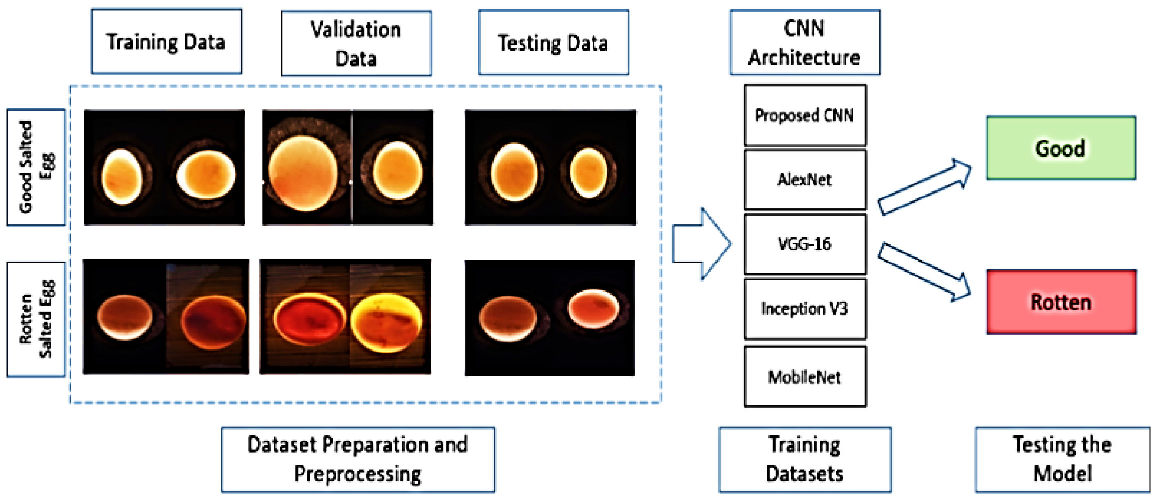


Figure 3 Method of the proposed work

## 2.4 Convolutional neural network (CNN)

After preparing the datasets, training the image data on the various CNN models was performed. In this study, an opti-CNN model and also 4 pre-trained CNN models such as VGG-16, AlexNet, Inception-V3, and MobileNet were evaluated. All the pre-trained models (all the models except the proposed CNN model) were previously trained on the ImageNet dataset, then trained again with salted duck egg datasets. The method of this work is shown in Figure 3. Training the datasets using several CNN models for the classifying the quality of salted egg were performed. Furthermore, testing and comparing the models based on various CNN architectures were evaluated.

### 2.4.1 Opti-CNN model

The architecture of the proposed CNN was constructed by tuning several hyper parameters such as the number of interconnected layers, convolutional layers, pooling locations, stride, sizes, kernel, and number of neurons in the interconnected layers. Furthermore, the computation of relevant parameters was chosen manually by trial and error. The proposed network architecture is depicted in Figure 4.

Four convolutional layers, three max-pooling layers, three activation layers, two interconnected layers, and a sigmoid layer compose the design. The purpose of these layers is to increase the performance of the model by decreasing the data dimensionality, extracting useful features, and generating nonlinear properties (Zeiler and Fergus, 2014). Convolutional layers were implemented to enhance the spatial invariance property in blocks, which assists in recognizing important features in the salted egg images. For learning, the CNN model is dependent on the spatial or sequential properties of the data. When the input data are extremely sparse, the ability of the CNN model to learn is significantly reduced. This problem was resolved and reported in Luo et al. (2020). Nevertheless, we used

Adam optimizer (Kingma and Ba, 2015) to accommodate sparse data input, the suggested system includes an adaptable learning rate, because it performs well in optimization as the gradients become sparser.

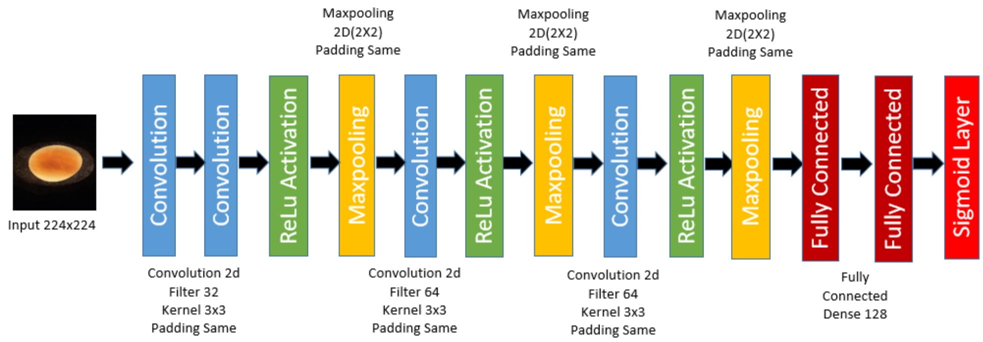


Figure 4 Architecture of the proposed CNN model

2.4.2 AlexNet

AlexNet is similar to the CNN model, which was first created using the LeNet-5 architecture. However, it is only much larger and deeper, and is the first to stack convolutional layers directly on top of each other (Krizhevsky et al., 2012). Figure 5 shows the AlexNet architecture. Furthermore, AlexNet is quite similar to the CNN model we propose, but it has many more parameters than the customized model. To reduce overfitting, the AlexNet model used two regularization techniques. First, dropout (with a 50% dropout rate) was applied during training to the outputs of the interconnected connected layer. Second, AlexNet also applies normalization after the ReLU step in the first and third convolutional layers, which is called local response normalization.

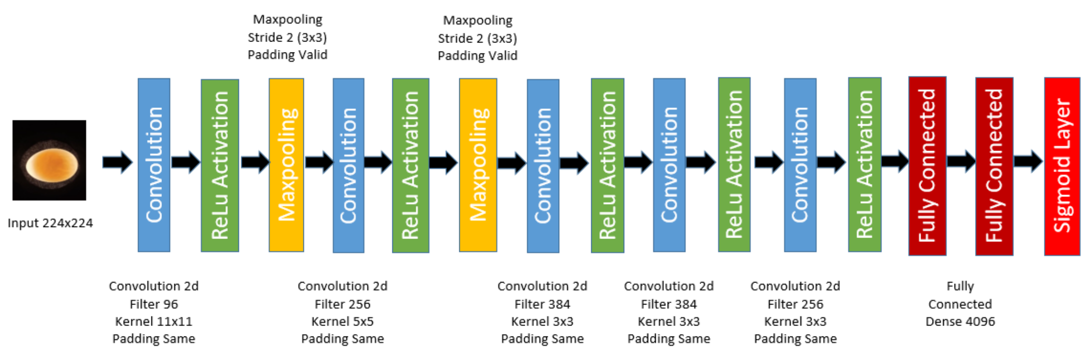


Figure 5 Architecture of AlexNet

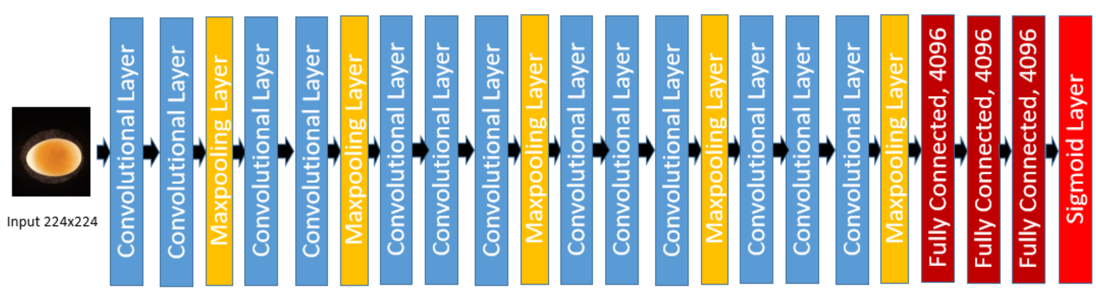


Figure 6 Architecture of VGG-16

2.4.3 Vgg-16

The VGG-16 architecture is shown in Figure 6. It consists of 13 convolutional layers and three interconnected layers with a kernel size of 3 × 3 (Simonyan and Zisserman, 2014). The convolution operation was divided into five layers, followed in each group by a max-pooling layer. The input image to the VGG-16 model has a resolution of 224×224×3, and it goes through a series of convolutional and max-pooling layers. Furthermore, the output of this layer is flattened to be the input to the three interconnected layers. Finally, the output of the interconnected layers was passed into the sigmoid layer for binary classification.

2.4.4 Inception-v3

The Inception-V3 model consisted of approximately 22 million parameters. This model architecture consists of asymmetrical blocks and symmetrical. Each block is made up of a number of average, dropout, convolutional, max pooling, concatenation, and interconnected layers (Szegedy et al., 2016). Moreover, batch normalization is commonly applied to the activation layer input into the Inception V3 architecture. Finally, classification was performed using a sigmoid layer to classify the quality of the salted eggs. The architecture of the Inception-V3 model is shown in Figure 7.

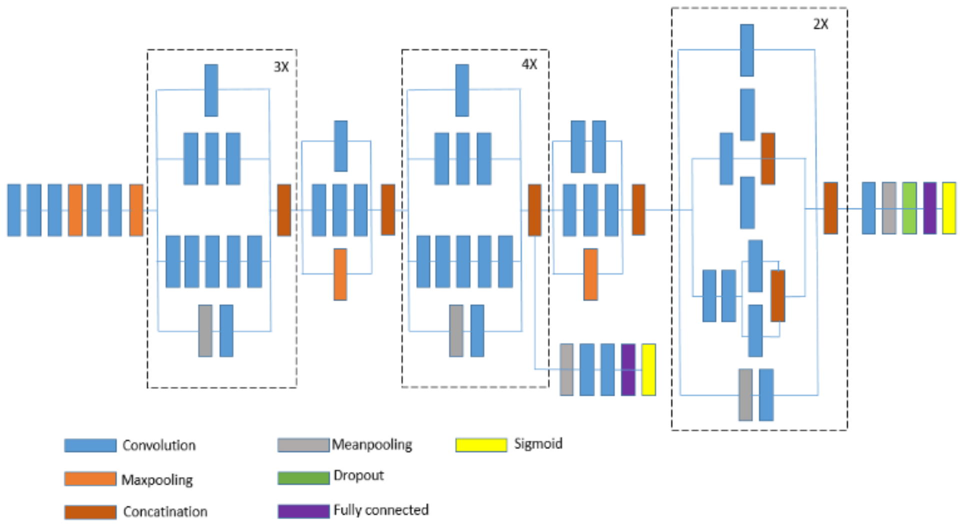


Figure 7 Architecture of Inception-v3

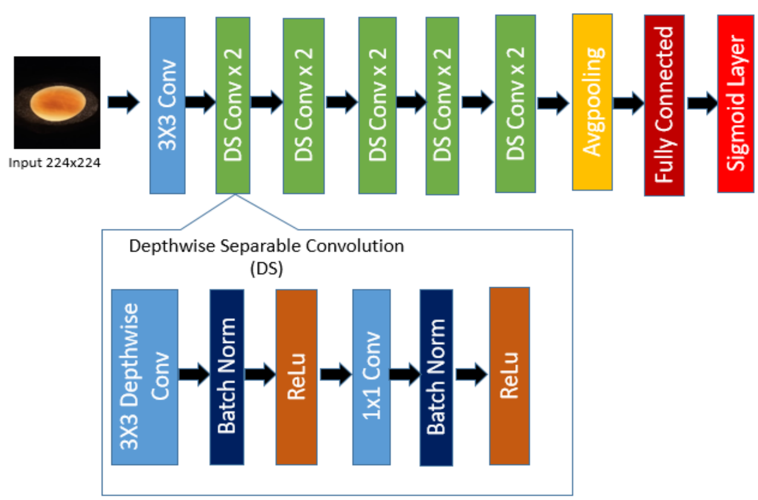


Figure 8 Architecture of MobileNet

2.4.5 MobileNet

MobileNet architecture is designed to be applied in mobile applications, and is the first model of mobile computer vision. This model uses depthwise separable convolutions because it significantly decreases the quantity of parameters when compared to the network with regular convolutions with the same depth (Howard et al., 2017). Depthwise separable convolution is made from two operations, which are depthwise convolution and pointwise convolution. The architecture of

MobileNet model is shown in Figure 8.

### 2.5 Testing of CNN models

After training the CNN model, we test how well the model performs against 120 new images that have been prepared. Before testing the model, we set the evaluation metrics to measure the result of the testing. In this work, we use accuracy to measure the performance. As illustrated in the equation below, accuracy can be defined as the ratio of 'good' and 'rotten' salted eggs to the total number of inputs.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

where *TP* (True Positive) and *TN* (True Negative) indicate properly identified "good" and "rotten" salted eggs, respectively, and *FP* (False Positive) and *FN* (False Negative) indicate wrongly identified "good" and "rotten" salted eggs.

## 3 Results and analysis

The efficacy of five CNN models for predicting salted egg quality was reviewed based on the accuracy. Python programming was used on Google Collaborator Environment. Table 2 shows the number of parameters and convolutional layer for each model.

**Table 2 Number of convolutional layer and parameters in five CNN models**

| Architecture | Number of Convolutional Layer | Number of Parameter (Millions) |
|---|---|---|
| Opti-CNN | 4 | 6.5 |
| AlexNet | 5 | 61 |
| Inception V3 | 48 | 22 |
| VGG-16 | 16 | 135 |
| MobileNet | 22 | 13 |

According to Table 2, the suggested CNN model has the fewest variables and convolutional layers. The architecture of AlexNet has the second lowest number of convolutional layers with only five layers, but it has the second highest number of parameters with 61 million parameters. In addition, the VGG-16 architecture has the highest number of parameters, approximately 135 million, and is four times deeper than the proposed CNN modeling terms of the quantity of the convolutional layer. The architecture of MobileNet also has a deep network with 22 layers of convolution, which is deeper than the VGG-16 model, but has a lower number of parameters compared with VGG-16, with only 13 million parameters. Moreover, the depth of the Inception-v3 model is the highest among all the architectures, but has approximately 11 times fewer parameters compared to the VGG-16 architecture.

The results of these experiments were compared using the proposed CNN, AlexNet, VGG-16, Inception V3, and MobileNet architectures. All the models were trained in 20 epochs. The performance of the trained models was measured based on their accuracy and tested by providing them with a new set of data images, as shown in Table 3.

**Table 3 Validation and testing accuracy of the CNN models**

| Architecture | Validation Accuracy | Testing Accuracy |
|---|---|---|
| Opti-CNN | 0.9714 | 0.9683 |
| AlexNet | 1.0000 | 0.9841 |
| Inception V3 | 0.9143 | 0.9424 |
| VGG-16 | 0.9429 | 0.9683 |
| MobileNet | 1.0000 | 1.0000 |

From all trained models, the results demonstrated that the performance of all models was greater than 90 percent. The best scores are obtained when using MobileNet architecture with 100 percent accuracy (both validation and testing accuracy), followed by AlexNet model with testing accuracy about 98 percent. Moreover, the testing accuracy of both proposed CNN and VGG-16 architecture achieve 96.83 percent. However, Inception V3 have the accuracy below 95 percent, which is 94.24 percent.

**Table 4 Size of CNN models and its inference time**

| Architecture | Computation Time (millisecond) | Model Size |
|---|---|---|
| Opti-CNN | 50 | 6.8 MB |
| AlexNet | 633 | 233 MB |
| Inception V3 | 761 | 92 MB |
| VGG-16 | 597 | 528 MB |
| MobileNet | 555 | 16 MB |

The computational times expected to go through the test images for each model are listed in Table 4. The proposed CNN model performed the fastest in terms of testing time, requiring 50 ms to classify a 224 × 224 input imageThe amount of time it takes the MobileNet model to categorize a single image was 555 ms, which was almost 11 times longer than the improved CNN model. The VGG-16 model obtained 555 ms for single-image classification, which is comparable to the VGG-16 model. Furthermore, the AlexNet model's inference time for a single dataset was 633 ms, which was greater than the VGG-16, MobileNet, and suggested CNN models but less than Inception V3, which had the longest inference time of 761 ms. When compared to the other approaches, the opti-CNN architecture produced the shortest inference time for classifying the quality of salted eggs. As a result, this system can be improved by using many cameras in tandem for the salted egg selection process on a large scale.

## 4 Conclusions

This study aimed to evaluate the quality of salted duck eggs using CNN and the opti-CNN. The results demonstrate that this identification may be performed with an accuracy above 90% using the CNN approach. Additionally, the opti-CNN that was used, with an accuracy of 97.14% and a computation time of 50 ms, displayed promising results for implementation in this application. Therefore, the system under development has the potential to be applied to large-scale sorting systems, which require fast time in the sorting process because it has the shortest computational time, model parameters, and finest detail among all models.

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