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BANANA AND ORANGE CLASSIFICATION DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract

Fruits play a crucial role in human health, with an average consumption of 81.14 grams per capita per day in Indonesia, where bananas and oranges are the most consumed fruits. Inconsistent fruit quality, typically evaluated manually by farmers, can influence consumer decisions. Artificial intelligence (AI) and computer vision can enhance efficiency and consistency in analyzing fruit quality. Convolutional Neural Networks (CNN) are particularly effective in image recognition. This research uses CNN to classify the quality of bananas and oranges from a dataset of 4000 images, divided into 10% test data, 80% training data, and 10% validation data. Among three models tested, Model 2 performed best with an accuracy of 96.75% and balanced high F1-scores across all categories. The results demonstrate that the CNN model is capable of classifying the quality of bananas and oranges with high accuracy and good evaluation results.

Keywords : Artificial Intelligence, Convolutional Neural Network, Fruits, Fruits Quality, Machine Learning

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INTRODUCTION

Fruits are a healthy dietary choice as they are part of plants that can be eaten, providing positive effects, maintaining health, and giving a feeling of fullness. Numerous health benefits can be gained from consuming fruits, making it highly recommended to include them in daily diets[1]. According to BPS data from 2021, the average daily per capita consumption of fruit in Indonesia is 81.14 grams. Among the fruits consumed, bananas rank highest with an average consumption of 24.71 grams per capita per day, followed by oranges with 12.57 grams, papayas with 11.71 grams, and watermelons with 8.57 grams per capita per day [2]. The quality of fruit significantly influences consumers' purchasing decisions [3] [4]. Consumers prefer higher quality fruits that meet their needs and desires [5]. For example, in peaches and nectarines, red skin indicates superior exterior quality, whereas light yellow or greenish hues indicate immaturity [6].

In representing an understanding of the human brain, images are the most basic method for classifying the physical quality of food and agricultural products. Factors affecting fruit quality can be visually measured based on color [7]; however, this process is time-consuming, costly, and subject to physical factors like inconsistent evaluations and subjective results [9]. Fruit farmers still manually inspect quality by feeling and looking, which is highly inconsistent, variable in results, and often differs among trained fruit inspectors. In agriculture, fruit analysis based on various criteria is a continuous task, making machine vision very suitable for conventional analysis and quality assurance. In agriculture, computer vision and image processing are rapidly growing research areas and are significant analytical techniques for monitoring crops from pre-harvest to post-harvest [8].

AI is divided into three categories: narrow artificial intelligence, general artificial intelligence, and super artificial intelligence [9]. AI components include Conventional Machine Learning (CML), Scheduling, Deep Learning, Computer Vision, Robotics, Reasoning, General Intelligence, Expert System, Automated Learning, Natural Language Processing, and Machine Learning [10]. Deep Learning is a class of algorithms in Machine Learning that uses multiple layers of nonlinear processing units stacked in a hierarchy to perform feature extraction and transformation. Each layer uses the output from the previous layer as input [11] [12][13]. Currently, the most prominent deep learning method in image recognition is the Convolutional Neural Network (CNN). CNN mimics the image identification system in the

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human brain, enabling highly effective image information processing [14]. A CNN consists of several layers arranged sequentially. The basic structure includes an input layer, followed by several convolutional layers, pooling layers, and finally, a fully connected layer [15][16][17]. Convolutional layers extract features from input data through the application of filters. Pooling layers help reduce the spatial dimensions of feature maps, lowering computational complexity. Fully connected layers connect extracted features to the output layer, allowing the network to make predictions or classifications based on learned features [18][19].

Previous types of research related to the current research is using CNN for cabbage quality classification [20]. This research targets the CNN method so that it can be used to classify cabbage quality. The final result of this research is that the CNN model can classify the quality of cabbage with 80% accuracy on the test data. Then, previous research that has been carried out also with the title Classification of Fresh and Rotten Orange Fruit Based on RGB and HSV Using the KNN Method gets the final result in the form of an accuracy of 88.95% [21].

Given the background, the research problem is identified as follows: How effective is the Convolutional Neural Network model in classifying the quality of bananas and oranges? To address the identified problem, this research proposes the application of CNN to classify two fruits frequently consumed by the Indonesian population, namely bananas and oranges, based on their quality (good and bad). The purpose of this research is to classify the quality of bananas and oranges using CNN and to measure the performance of the CNN model in classifying the quality of bananas and oranges, with the output being the classification accuracy of fruit quality.

METHOD

The materials used in this research consist of a dataset obtained from a website. The dataset includes images of two types of fruits that are commonly consumed in Indonesia according to BPS data from 2021: bananas and oranges. There are two quality classes for both bananas and oranges: good and bad, with a total after proper data sorting is carried out is 4000 images sourced from Kaggle [22]. The quality-classified banana fruit (good and bad) is the Cavendish variety and the quality-classified citrus fruit (good and bad) is the Citrus Nobilis variety.

One of the most prominent features of the Cavendish banana is its distinctive appearance and taste. The fruit is recognized for its bright yellow skin and soft, sweet flesh, which has a delicate fiber texture[23]. The fruit of Citrus nobilis is typically characterized by its vibrant color, which can range from a bright orange to a yellowish hue, depending on the specific cultivar and ripeness stage. Citrus nobilis fruits are usually spherical to slightly flattened, with a diameter that can vary significantly among different cultivars[24]. Eating bananas with (Cavendish) and oranges (Citrus Nobilis) together provides significant health benefits as both are rich in essential nutrients. Bananas, with their soft texture and sweet flavour, provide a good source of energy through carbohydrates and contain potassium, which is important for heart and muscle health[7]. In addition, bananas' high natural sugar content helps maintain energy levels[25]. Oranges, on the other hand, are rich in vitamin C which is a powerful antioxidant, helps boost the immune system, and repairs and maintains body tissues[26]. The combination of these two fruits offers a balance between the instant energy of bananas and the long-term health protection of oranges, making it an ideal choice for everyday diets.

This dataset is processed through a series of steps illustrated in Figure 1. The steps include data preprocessing, model training, and evaluation, utilizing Convolutional Neural Networks (CNN) to classify the fruit quality.

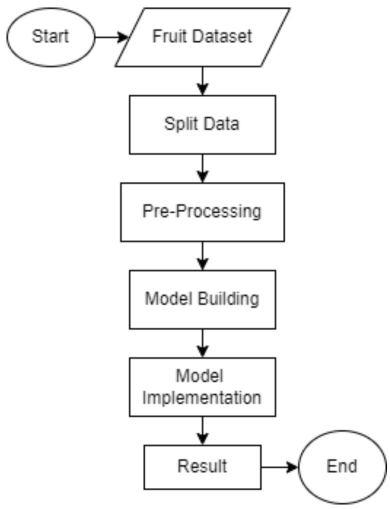

Figure 1. Research Method

In this stage, the dataset is divided to separate the images used for training the model from those used for testing it with images the model has not encountered before. The data is split into 80% for training, 10% for validation, and 10% for testing.

The next step is preprocessing the divided images. This includes data augmentation and normalization. Data augmentation is performed using TensorFlow's ImageDataGenerator. TensorFlow provides tools for data augmentation

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through the ImageDataGenerator class, allowing researchers to easily configure various augmentation techniques. Some parameters include: rotation range (defining the rotation range of images to help the model better recognize objects from different angles), shift range (controlling the range of horizontal and vertical shifts to help the model recognize objects in different positions), shear range (setting the image shear range to introduce variation in object shapes), zoom range (defining the zoom range to help the model recognize objects at different scales), horizontal flip (allowing or disallowing horizontal flipping to create additional variation in object orientation), and fill mode (specifying how to fill pixels that may appear after augmentation). The model is built with the goal of classifying oranges and bananas into good and bad quality categories. The research employs layers including input layers, convolutional layers, max-pooling layers, flatteninglayers, fully connected layers, and output layers. The parameters, kernel, and filter of each layer are configured based on the model training results.

During model implementation, training and testing are conducted. Training involves feeding the divided images into the input layer. Testing aims to determine if the model can predict previously unseen images. The images used are those that the model has not encountered before, and they are fed into the input layer of the trained. testing data are evaluated using a confusion matrix, precision, recall, and F1-score. This analysis is used to evaluate the model's performance. The results of this research are derived from the model's application, which should address the research questions and problem statements. The overall process is illustrated in Figure 1.

RESULT AND DISCUSSION

This research utilizes secondary data obtained from the website Kaggle. The dataset includes two quality classes for each type of fruit: good quality and bad quality. In total, there are 4000 images representing various conditions of bananas and oranges within these categories. Table 1 provides an illustration of images per class.

During the data splitting stage, the collected dataset of 4000 images is divided into 80% for training data, 10% for validation data, and 10% for testing data. The distribution of the data is shown in Table 2.

Table 1. Illustrations Per Class

Fruit	Good	Poor
Banana		
Orange		

Table 2. Split Data

Category	Data Train	Data Validation	Data Test
Poor Quality Banana	800	100	100
Good Quality Banana	800	100	100
Poor Quality Orange	800	100	100
Good Quality Orange	800	100	100

The training data for the poor quality banana class includes a total of 800 images, with the validation data comprising 100 images, and the testing data also consisting of 100 images. For the good quality banana class, the training data has 800 images, the validation data includes 100 images, and the testing data has 100 images. Similarly, the training data for the poor quality orange class contains 800 images, with 100 images each for validation and testing. For the good quality orange class, the training data includes 800 images, and both the validation and testing data consist of 100 images each.

After collecting the dataset used in this research, the next step is preprocessing. Preprocessing involves using the augmentation process provided by ImageDataGenerator, which will be applied to the dataset. The results of the augmented training data images can be seen in Figure 2.

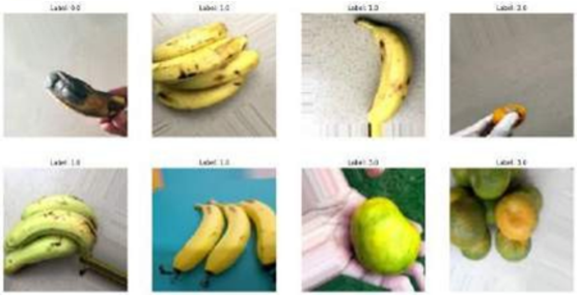

Figure 2. Samples of the augmented training images

Augmentation is performed using various settings to enhance the diversity of the training data without increasing the overall dataset size. The augmentation configurations used include rescaling each image for normalization by 1/255, rotating images up to 40 degrees, shifting the width and height of images by up to 20%, applying shear and zoom transformations within a 20% range, and horizontally flipping the images. Additionally, the fill mode is set to 'nearest' to fill in missing pixels after transformations. The results of the augmented training images can be seen in Figure 2, demonstrating the various transformations applied to the training data to improve diversity and generalize the model. The validation and test datasets are only normalized by rescaling each image by a factor of 1/255.

Model development is carried out in Visual Studio Code. The aim of model development is to achieve image classification results. Three models are constructed with variations in architecture, serving as benchmarks to measure the performance of CNN in classifying fruits and their classes. For model 1, its details are provided in Table 3, while model 2's specifications can be found in Table 4, and model 3's configurations are presented in Table 5.

Table 3. Model 1

Type	Result	Num
conv2d	(None, 148, 148, 16)	448
max_pooling2d	(None, 74, 74, 16)	0
conv2d_1	(None, 72, 72, 8)	1160
max_pooling2d_1	(None, 36, 36, 8)	0
flatten	(None, 4)	0
dense	(None, 4)	41476
Total parameters: 43,084		
Trainable parameters: 43,084		
Non-trainable parameters: 0		

Table 4. Model 2

Type	Result	Num
conv2d	(None, 148, 148, 64)	1792
max_pooling2d	(None, 74, 74, 64)	0
conv2d_1	(None, 72, 72, 32)	18464
max_pooling2d_1	(None, 36, 36, 32)	0
flatten	(None, 41472)	0
dropout	(None, 41472)	0
dense	(None, 128)	5308544
dense_1	(None, 64)	32896
dense_2	(None, 4)	260
Total parameters: 5,337,316		
Trainable parameters: 5,337,316		
Non-trainable parameters: 0		

Table 5. Model 3

Type	Result	Num
conv2d	(None, 148, 148, 150)	4200
max_pooling2d	(None, 74, 74, 150)	0
conv2d_1	(None, 72, 72, 75)	101325
max_pooling2d_1	(None, 36, 36, 75)	0
flatten	(None, 97200)	0
dropout	(None, 97200)	0
dense	(None, 256)	24883456
dense_1	(None, 128)	32896
dense_2	(None,64)	8256
dense_3	(None, 4)	260
Total parameters: 25,030,393		
Trainable parameters: 25,030,393		
Non-trainable parameters: 0		

The model is implemented by compiling the prepared architecture with the ADAM optimizer, Sparse Categorical Crossentropy for the loss function, and accuracy as metrics to measure how often the model predicts results correctly. Subsequently, the model implementation continues with the fitting method for training. The illustration can be seen in Figure 3.

```
model.compile(optimizer=tf.optimizers.Adam(),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Figure 3. Configuration of the model

The fit method is used to train the model. The results of this method are stored in the variable 'history', which contains information about the training such as loss and metrics at each epoch. The model training employs 20 epochs with a batch size of 32. Data used to evaluate the model's performance at each epoch are obtained from the 'validation_generator', which includes images unseen by the model during training. The illustration can be seen in Figure 4.

```
history = model.fit(train_generator,
                    epochs=20,
                    batch_size=32,
                    validation_data=validation_generator
                    )
✓ 4m 9.7s
```

Figure 4. Training configuration of the model

Following that, the model will be tested with the test data containing images unseen by the model during training and validation. Then, the model's predictions on the test data will be evaluated with a confusion matrix, precision, recall, and F1-score.

For training model 1, the results can be seen in Table 6, which demonstrates that over the course of 20 epochs of training, both the loss and accuracy values significantly improved. Initially, the loss started at 0.8535 with an accuracy of 0.6288, and the validation loss was 0.4392 with a validation accuracy of 0.8375. As the epochs progressed, there was an increase in accuracy, reaching 0.9388 by epoch 18, while the validation accuracy reached 0.9525 by epoch 19. Despite some fluctuations in certain epochs, overall, the model displayed optimal performance escalation, with the validation loss and accuracy indicating that the model has a good capability of identifying characteristics based on what it has learned from previously unseen data. The graphical illustration can be seen in figure 5 and figure 6.

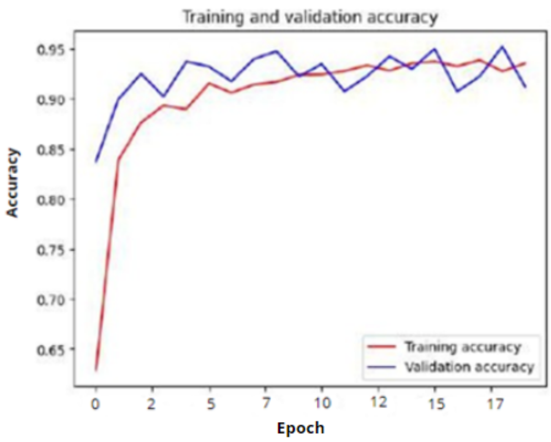

Figure 5. Accuracy Graph of Model 1

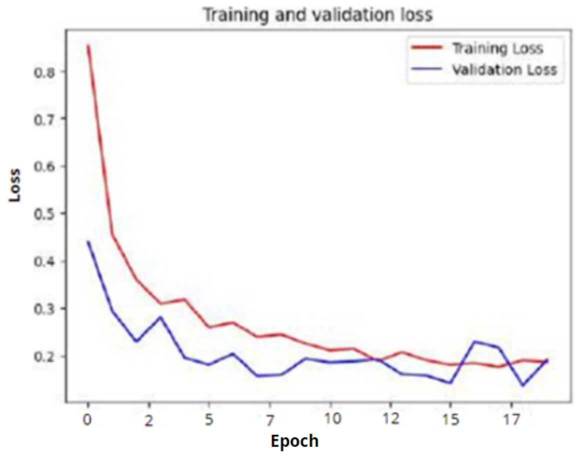

Figure 6. Loss Graph of Model 1

For training model 2, the results can be seen in Table 7, indicating that over the course of 20 epochs of training, both the loss and accuracy values experienced significant improvement. Initially, the loss started at 0.7897 with an accuracy of 0.6647, and the validation loss was 0.3244 with a validation accuracy of 0.8925. As the epochs progressed, the accuracy continued to increase, reaching 0.9422 by epoch 17, while the validation accuracy peaked at 0.9675 by epoch 20. Despite some fluctuations in certain epochs, such as performance declines in epochs 6 and 19, overall, the model demonstrated consistent performance improvement. The good validation loss and accuracy indicate that the model is capable of generalizing previously unseen data quite well, with the lowest validation loss reaching 0.0926 and the highest validation accuracy reaching 0.9675. Graphical illustrations can be seen in figure 7 and figure 8.

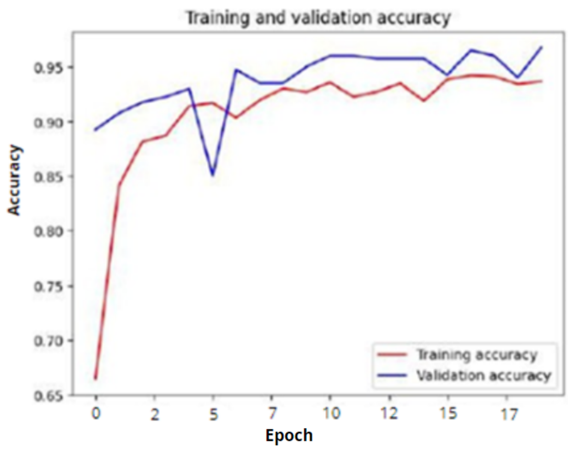

Figure 7. Accuracy Graph of Model 2

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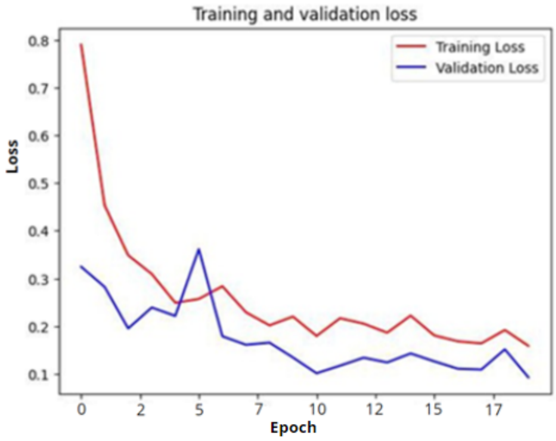

Figure 8. Loss Graph of Model 2

For training model 3, the results can be seen in Table 8, indicating that over the course of 20 epochs of training, both the loss and accuracy values experienced significant improvement. Initially, the loss started at 1.3216 with an accuracy of 0.3400, and the validation loss was 1.0266 with a validation accuracy of 0.5325. As the epochs progressed, the accuracy continued to increase, reaching 0.9459 by epoch 19, while the validation accuracy peaked at 0.9675 by epoch 19. Despite some fluctuations in certain epochs, such as performance declines in epochs 13 and 20, overall, the model demonstrated consistent performance improvement. The good validation loss and accuracy indicate that the model is capable of generalizing previously unseen data quite well, with the lowest validation loss reaching 0.1098 and the highest validation accuracy reaching 0.9675. Graphical illustrations can be seen in figure 9 and figure 10.

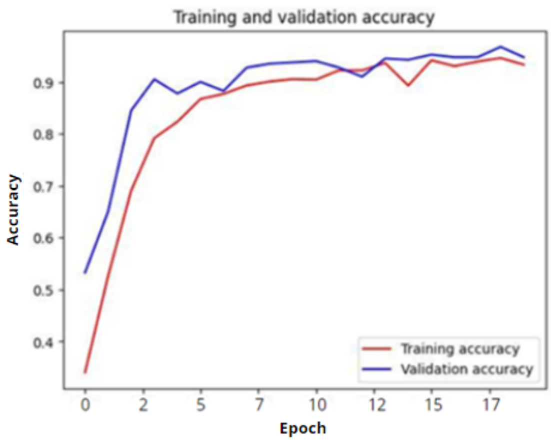

Figure 9. Accuracy Graph of Model 3

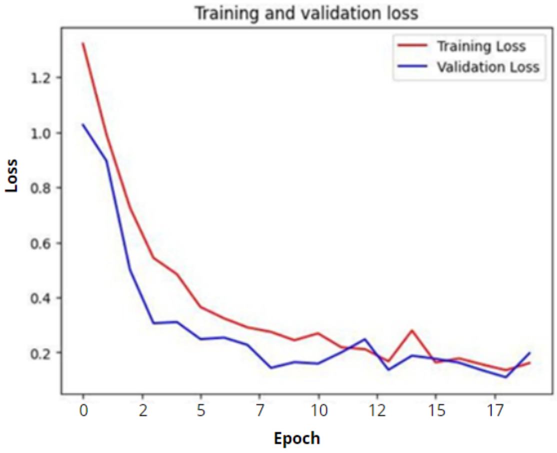

Figure 10. Loss Graph of Model 3

Further testing is conducted using image datasets that were not utilized during the training process. The evaluation results of model 1 using precision, recall, and F1-score can be observed in Table 6.

Table 6. Testing Model 1

Category	Precision	Recall	F1-Score
Poor Quality Banana	0.94	0.98	0.96
Good Quality Banana	0.96	0.94	0.95
Poor Quality Orange	0.81	0.97	0.88
Good Quality Orange	0.97	0.76	0.85

From the CNN model evaluation results, the "Poor quality banana" category exhibited the best performance with precision of 0.94, recall of 0.98, and F1-Score of 0.96, indicating the model's ability to detect poor quality bananas with high accuracy and minimal errors. The "Good quality banana" category also showed promising results with precision of 0.96, recall of 0.94, and F1-Score of 0.95. Meanwhile, "Poor quality orange" had a high recall of 0.97 but lower precision at 0.81, suggesting that the model is highly sensitive but tends to make more false positive predictions. "Good quality orange" exhibited high precision at 0.97 but lower recall at 0.76, indicating the model's accuracy in positive predictions but less sensitivity in detecting all good quality oranges. Overall, the model demonstrated strong performance with some areas for improvement in recall for certain categories. Subsequently, the evaluation results of model 1 using the confusion matrix can be observed in Figure 11.

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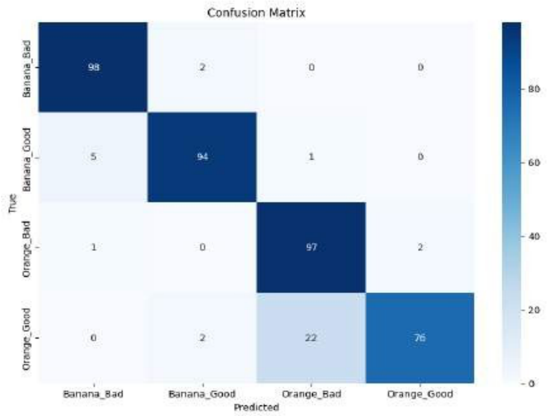

Figure 11. Confusion Matrix Model 1

From Figure 11, it can be observed that the CNN model performed exceptionally well in classifying "Poor quality banana" and "Poor quality orange" with accuracies of 98% and 97% correctly classified samples, respectively. However, there were some errors in the "Good quality orange" category, where 22 samples were misclassified as "Poor quality orange." Overall, the model demonstrated strong capability in classifying categories with high accuracy in most classes.

The evaluation results of model 2 using precision, recall, and F1-score can be seen in Table 7.

Table 7. Testing Model 2

Category	Precision	Recall	F1-Score
Poor Quality Banana	0.98	0.99	0.99
Good Quality Banana	0.99	0.98	0.98
Poor Quality Orange	0.97	0.93	0.95
Good Quality Orange	0.93	0.97	0.95

The CNN model demonstrates excellent performance in classifying fruit categories. "Poor quality banana" and "Good quality banana" each have F1-Scores of 0.99 and 0.98, indicating nearly perfect balance between precision and recall. "Poor quality orange" and "Good quality orange" also exhibit strong performance with F1-Scores of 0.95 each, although there is a slight difference between precision and recall. Overall, the model successfully classifies all categories with high accuracy and consistent performance.

Subsequently, the evaluation results of model 2 using the confusion matrix can be observed in Figure 12.

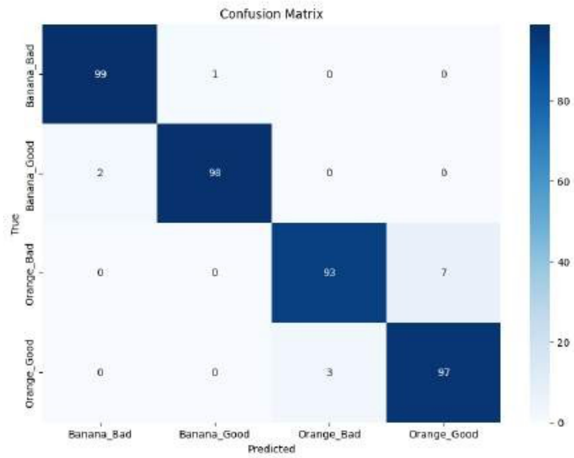

Figure 12. Confusion Matrix Model 2

From the Confusion Matrix, it is evident that the CNN model performs exceptionally well in classifying "Poor quality banana" and "Good quality banana" with 99% and 98% correctly classified samples, respectively. However, there are some errors in "Poor quality orange," where 7 samples are misclassified as "Good quality orange," and in "Good quality orange" with 3 samples misclassified as "Poor quality orange." Overall, the model demonstrates strong capability in recognizing most categories with high precision. The evaluation results of model 3 using precision, recall, and F1-score can be observed in Table 8.

Table 8. Testing Model 3

Category	Precision	Recall	F1-Score
Poor Quality Banana	0.96	0.99	0.98
Good Quality Banana	0.94	0.98	0.96
Poor Quality Orange	0.98	0.86	0.91
Good Quality Orange	0.92	0.97	0.94

The CNN model demonstrates excellent performance in classifying fruit categories. "Poor quality banana" exhibits a precision of 0.96, recall of 0.99, and F1-Score of 0.98, indicating high accuracy in detection. Similarly, "Good quality banana" also performs strongly with precision of 0.94, recall of 0.97, and F1- Score of 0.96.

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However, "Poor quality orange" shows a precision of 0.98 but a lower recall of 0.86, resulting in an F1-Score of 0.91, indicating difficulty in detecting all poor quality oranges. On the other hand, "Good quality orange" has a precision of 0.92 and recall of 0.97, with an F1- Score of 0.94, highlighting a good balance between accuracy and sensitivity. Overall, the model demonstrates strong classification ability with high precision and recall in most categories. Subsequently, the evaluation results of model 3 using the confusion matrix can be observed in Figure 13.

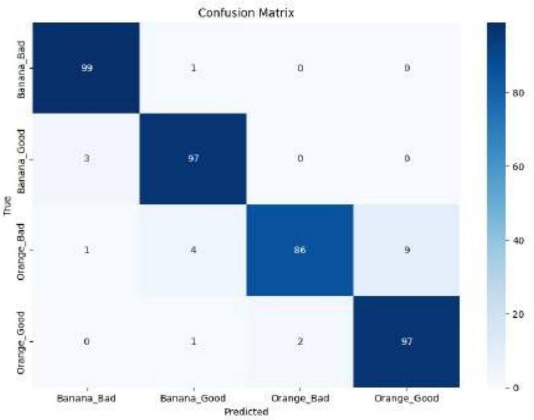

Figure 13. Confusion Matrix Model 3

From the Confusion Matrix, it is evident that the CNN model shows excellent performance in classifying "Poor quality banana" and "Good quality banana," with 99% and 97% of samples correctly classified, respectively. However, there are some errors in "Poor quality orange," with 9 samples misclassified as "Good quality orange," and in "Good quality orange," with 2 samples misclassified as "Poor quality orange." Overall, the model demonstrates strong classification ability with high precision in most categories, but there are still some errors in the orange class.

After all the testing, model 1 achieves an accuracy of 91.25%. This model demonstrates strong performance in terms of precision and recall for the "Poor Quality Banana" category, with an F1-score of 0.96. However, it struggles with the "Good Quality Orange" category, where it achieves a lower recall of 0.76, indicating that while it can identify poor quality bananas effectively, it has difficulty detecting all instances of good quality oranges, resulting in some misclassifications.

Model 2 stands out with the highest accuracy of 96.75%. It balances precision and recall effectively across all categories, achieving near-perfect F1-scores for "Poor Quality Banana" (0.99) and "Good Quality Banana" (0.98). For the orange categories, it maintains strong performance with F1-scores of 0.95 for both "Poor Quality Orange" and "Good Quality Orange." This model's strength lies in its consistent high accuracy and balanced performance, making it the best among the three. Its primary weakness is minor misclassifications between poor and good quality oranges, though these are minimal.

Model 3 achieves an accuracy of 94.75%, showing excellent performance for "Poor Quality Banana" (F1-score of 0.98) and "Good Quality Banana" (F1-score of 0.96). It also performs well for "Good Quality Orange" with an F1-score of 0.94. However, it has a noticeable weakness in the "Poor Quality Orange" category, where it has a lower recall of 0.86. This indicates that while it is good at identifying the majority of poor quality oranges, it misses some, resulting in a lower F1-score of 0.91 for this category.

CONCLUSION

Based on the results and discussions conducted, the following conclusions can be drawn:

a. The three CNN architectures developed for performance measurement in this study successfully classified the quality of bananas and oranges. These CNN architectures consist of input layers, convolutional layers, max-pooling layers, flatten layers, fully connected layers, and output layers that use softmax activation to predict the fruit class based on the given images.
b. All three CNN models developed in this study are effective in classifying the quality of bananas and oranges, with varying degrees of success. Model 2 is identified as the best-performing algorithm with an accuracy of 96.75% and balanced high F1-scores across all categories. Its minor weakness is in misclassifying a few instances of orange quality. Models 1 and 3, while also effective, have specific weaknesses, particularly in recall for certain categories, which slightly reduce their overall performance compared to Model 2.

Future research can enhance the model by using advanced data augmentation, ensuring balanced datasets, and exploring deeper CNN architectures like ResNet. Utilizing transfer learning, optimizing hyperparameters, and combining image data with additional features can improve accuracy. Applying regularization techniques, early stopping, and conducting detailed error analysis will prevent overfitting and provide insights for further adjustments, leading to more reliable fruit quality classification.

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