

Implementation of Deep Learning for Orange Variety Classification Using the Convolutional Neural Network (CNN) Method Based on Fruit Images

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Abstract

The visual similarity among several orange varieties makes manual identification difficult and prone to classification errors, particularly for individuals without specialized knowledge or experience. Therefore, this research aims to implement the Deep Learning method in classifying visually similar types of oranges using the Convolutional Neural Network (CNN) algorithm, as well as to determine the model's accuracy in recognizing orange fruit images. The study classifies four types of oranges: Keprok Brastepu, Keprok Maga, Murcott, and Siam Madu. The dataset used consists of 1,739 initial images, which increased to 2,304 images after augmentation and oversampling, with a data split ratio of 80% for training and 20% for testing. The pre-processing stages include data labeling, data organization, background removal, and image resizing to match the input requirements of the CNN model. The model employed is the InceptionV3 architecture with the Adam optimizer, categorical crossentropy as the loss function, 50 epochs, and early stopping applied at the 20th epoch when the training accuracy reached 98%. The experimental results show that the model with a learning rate of 0.0001 achieved the best performance, with a training accuracy of 0.98, validation accuracy of 0.98, precision of 0.98, recall of 0.97, and an F1-score of 0.97. Meanwhile, a higher learning rate (0.01) resulted in signs of overfitting. Based on these findings, it can be concluded that the Convolutional Neural Network method with the InceptionV3 architecture is capable of accurately classifying visually similar orange varieties, making it effective for image-based fruit identification systems.

Keywords: *Deep Learning, Convolutional Neural Network, InceptionV3, Image Classification, Orange*

1. Introduction

Indonesia is one of the world's leading agricultural countries due to its favorable tropical climate and geographical conditions. The agricultural sector significantly contributes to national economic growth, particularly through the horticultural subsector, which possesses considerable economic value and market potential [1]. Citrus fruits are among the most important horticultural commodities in Indonesia because of their high consumption rate and commercial value [2]. Various local citrus cultivars are cultivated and marketed throughout the country, particularly in North Sumatra, including Keprok Brastepu, Keprok Maga, Murcott, and Siam Madu. Although these cultivars originate from different regions, they exhibit highly similar external characteristics, especially in terms of peel color, texture, and shape, making visual identification difficult even for experienced sellers and consumers.

The inability to distinguish visually similar citrus varieties may lead to errors in product identification, affecting both commercial transactions and quality control. Conventional identification methods rely heavily on human observation, which is subjective, time-consuming, and often inconsistent [3]. Consequently, an automatic image-based classification system is required to improve classification accuracy while reducing human intervention.

Among the commonly used Deep Learning methods, the Convolutional Neural Network is a method that can potentially be applied to classify orange varieties. Compared to other classification methods, the Convolutional Neural Network demonstrates superior performance, particularly when classifying images involving a large number of classes with high accuracy [4].

Several previous studies have successfully applied machine learning and deep learning algorithms for agricultural image classification. Pawening et al. [5] classified local citrus quality using the k-Nearest Neighbor (k-NN) algorithm and achieved an accuracy of 93.33%. Amrozi et al. [6] classified banana varieties using Support Vector Machine (SVM) with an accuracy of 89.86%. Khairudin and Saputro [7] applied Gray Level Co-occurrence Matrix (GLCM) combined with k-NN to classify pomegranate quality and obtained an accuracy of 90%. Meanwhile, Iswanto and Handayani [8] implemented CNN for corn disease classification and achieved an accuracy of 97.5%, demonstrating the superiority of CNN over conventional machine learning algorithms in image classification tasks.

Therefore, this study proposes a CNN-based citrus classification model using the InceptionV3 transfer learning architecture with an additional Undefined Class to recognize non-citrus objects. The model is evaluated using Accuracy, Precision, Recall, F1-score, and Confusion Matrix. The proposed approach is expected to improve classification performance for visually similar citrus varieties while reducing misclassification of out-of-distribution objects.

The main contribution of this study is the development of a CNN-based citrus classification model capable of distinguishing visually similar citrus varieties while simultaneously recognizing objects outside the predefined classes through the incorporation of an Undefined Class. The proposed approach is expected to improve the reliability and practical applicability of automatic fruit classification systems in real-world environments.

2. Literature Review

Oranges (*Citrus sinensis*) are one of the fruit varieties that provide numerous health benefits. In addition, oranges have strong development potential and high economic value in Indonesia due to their broad market demand [5]. Oranges are horticultural crops that can be cultivated in almost all regions of Indonesia. In North Sumatra, various orange varieties are commonly found and widely sold in local markets.

Deep Learning is a subfield of machine learning that utilizes multi-layer artificial neural networks to automatically learn feature representations from large datasets. Compared with conventional machine learning methods, deep learning can extract hierarchical features directly from raw data without manual feature engineering, making it highly effective for image classification tasks [9][10]. Deep learning techniques involve various interconnected artificial neural networks. Some deep learning algorithms include: Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short Term Memory Network (LSTM), and Self Organizing Maps (SOM).

One of the methods that can be used to classify orange varieties is the Convolutional Neural Network (CNN). CNN is specifically designed to process two-dimensional data, such as digital images. Compared with other classification methods, CNN has demonstrated superior performance, particularly in image classification tasks involving a large number of classes [4]. In multiclass classification, a dedicated category such as an Undefined Class can be introduced to identify data that do not belong to any of the target classes defined in the study. This approach helps reduce misclassification of data that fall outside the distribution of the training dataset.

Convolutional Neural Network (CNN) is one of the most widely used deep learning architectures for image recognition and classification. CNN consists of convolution, pooling, and fully connected layers that automatically learn discriminative visual features from images [11]. This architecture has demonstrated superior performance in various computer vision applications due to its ability to capture spatial information and reduce the need for handcrafted feature extraction [12]. CNN is also designed to recognize complex patterns in images through data-driven learning, enabling it to perform well on a variety of object and texture recognition tasks [13].

To improve classification efficiency and accuracy, this study employs the InceptionV3 transfer learning architecture. Transfer learning enables the model to utilize feature representations learned from large-scale datasets, thereby reducing training time while maintaining high classification performance, especially when the available dataset is limited.

Model performance was evaluated using a confusion matrix, which provides comprehensive performance measurements through Accuracy, Precision, Recall, and F1-score. Unlike accuracy alone, these evaluation metrics offer a more reliable assessment of classification performance by considering both correctly and incorrectly classified samples [14].

Several previous studies have demonstrated the effectiveness of image classification techniques in agriculture. Pawening et al. classified local citrus quality using the k-Nearest Neighbor (k-NN) algorithm and achieved an accuracy of 93.33% [5]. Classification of Onion Varieties Using the K-Nearest Neighbor Method Based on Shape and Texture Feature Extraction, Achieving an Accuracy of 84% [15]. Ahmad et al. implemented CNN for tomato classification with an accuracy of 93.3% [16]. Furthermore, Iswantoro and Handayani applied CNN for corn disease classification and reported an accuracy of 97.5% [8]. Although these studies achieved promising results, they generally focused on objects with distinct visual characteristics and assumed that all testing samples belonged to predefined classes. In contrast, this study addresses the classification of visually similar citrus varieties by incorporating an additional Undefined Class to identify non-target objects, thereby improving the robustness of the classification model.

3. Methodology

3.1. Research Procedure

This study proposes a Deep Learning-based citrus classification system using the Convolutional Neural Network (CNN) method with the InceptionV3 transfer learning architecture. The research workflow consists of six stages: data acquisition, image preprocessing, data augmentation, dataset splitting, CNN model implementation, and model evaluation. The overall research framework is illustrated in Figure 1.

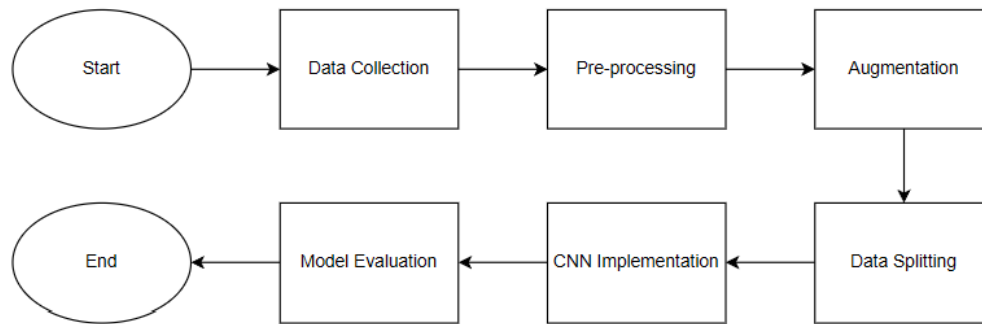


Fig. 1: Research Procedure

3.2. Dataset Acquisition

The primary dataset was collected through direct observation at Suka Ramai Market, Medan, Indonesia, using a Canon EOS 550D DSLR camera. Four citrus varieties were selected as classification targets, namely Keprok Brastepu, Keprok Maga, Murcott, and Siam Madu. Additionally, an Undefined Class containing non-citrus objects was incorporated to improve the model's ability to recognize images outside the predefined categories. Sample images from each citrus variety are presented in Figure 2.

The images were captured from multiple viewpoints (front, back, left, right, top-front, and top-back) and at three acquisition distances (10 cm, 20 cm, and 30 cm) to increase dataset diversity. The initial dataset consisted of 2,315 images, including the Undefined Class.

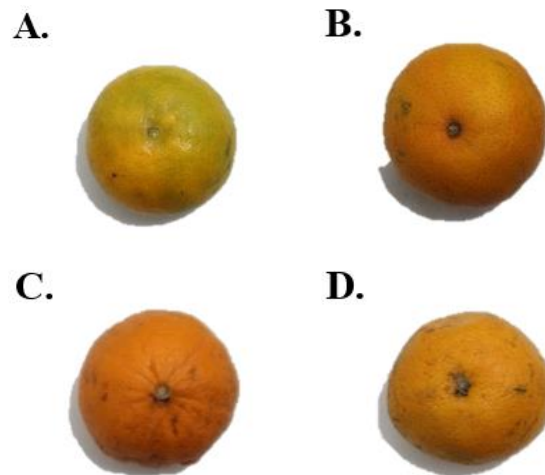


Fig. 2: Sample Images of Orange Varieties, (A) Keprok Brastepu Sample, (B) Keprok Maga Sample, (C) Murcott Sample, (D) Siam Madu Sample

3.3. RGB Characteristic Analysis

Before training the CNN model, an RGB channel analysis was conducted to investigate the color characteristics of each citrus class. The analysis revealed that the Red channel exhibited the highest standard deviation, while the Green and Blue channels remained relatively stable across all classes. Furthermore, Keprok Brastepu and Keprok Maga showed greater color variation than Murcott and Siam Madu, indicating that these two varieties are more difficult to distinguish visually. These findings demonstrate that although the citrus varieties appear similar to the human eye, they possess distinctive RGB distribution patterns that can be effectively learned by CNN for image classification. And here are some graphs showing the RGB channel values for each class.

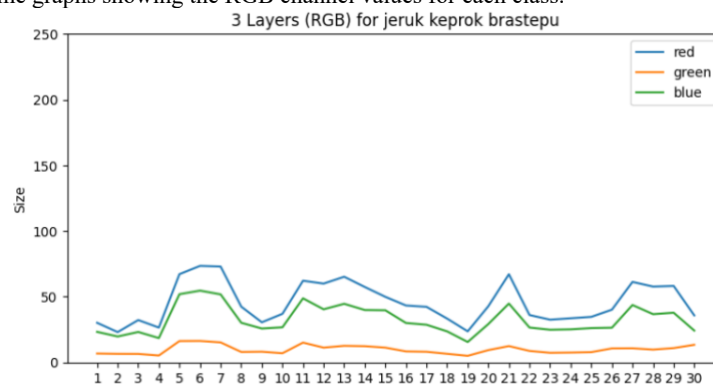


Fig. 3: Graph of RGB Channel Value for Keprok Brastepu Class

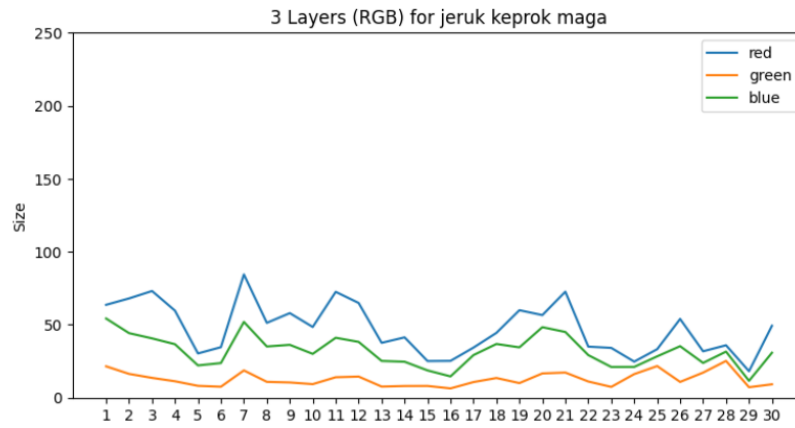


Fig. 4: Graph of RGB Channel Value for Keprok Maga Class

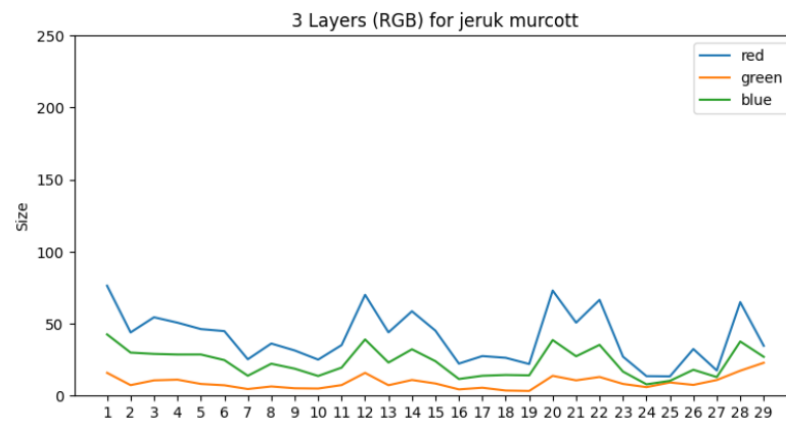


Fig. 5: Graph of RGB Channel Value for Murcott Class

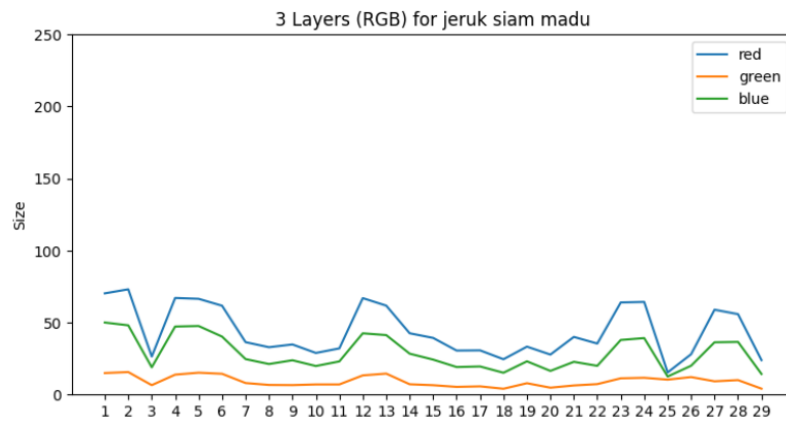


Fig. 6: Graph of RGB Channel Value for Siam Madu Class

3.4. Image Preprocessing

Image preprocessing was performed to ensure compatibility with the CNN architecture. The preprocessing pipeline consisted of four stages:

1. Image labeling according to citrus class,
2. Dataset organization,
3. Background removal to isolate the fruit object,
4. Image resizing to 299×299 pixels, matching the input size required by the InceptionV3 architecture.

These preprocessing steps improve data consistency and reduce the influence of irrelevant background information during feature extraction.

3.5. Data Augmentation and Dataset Splitting

To increase dataset diversity and reduce overfitting, data augmentation was applied using brightness adjustment and zoom transformation. After augmentation and oversampling, the dataset consisted of 2,304 images.

The dataset was then divided into 80% training data (1,840 images) and 20% testing data (464 images) following the supervised learning paradigm.

3.6. CNN Implementation

The classification model was implemented in Python using the TensorFlow framework. This study employed the InceptionV3 architecture with transfer learning, utilizing pretrained weights from the ImageNet dataset. Transfer learning enables the model to leverage previously learned visual representations such as edges, textures, colors, and object shapes, thereby improving classification performance while reducing computational cost. The model was trained using the Adam optimizer, Categorical Crossentropy loss function, and 50 training epochs. To determine the optimal learning configuration, three learning rates (0.01, 0.001, and 0.0001) were evaluated.

3.7. Model Evaluation

The trained model was evaluated using an independent testing dataset. Classification performance was assessed through the Confusion Matrix, from which four evaluation metrics were calculated: Accuracy, Precision, Recall, and F1-score. These metrics provide a comprehensive assessment of the model by measuring overall accuracy as well as its capability to correctly identify each citrus class.

The evaluation metrics are defined as follows:

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

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

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

$$F1-Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

4. Results and Discussion

4.1. Dataset Collection

The dataset used in this study was collected through direct observation at Suka Ramai Market, Medan, Indonesia. Image acquisition was performed using a Canon EOS 550D DSLR camera under controlled lighting conditions with a white background to minimize background interference. Four citrus varieties were selected as the target classes, namely Keprok Brastepu, Keprok Maga, Murcott, and Siam Madu. In addition, an Undefined Class consisting of non-citrus objects was introduced to improve the model's ability to recognize objects outside the predefined categories.

To increase dataset diversity, each fruit was photographed from multiple viewpoints, including the front, back, left, right, top-front, and top-back, at distances of 10 cm, 20 cm, and 30 cm. The final dataset contained 2,304 images, which were divided into 1,840 training images (80%) and 464 testing images (20%).

4.2. Dataset Collection

Prior to model training, all images underwent several preprocessing stages to improve data quality and ensure compatibility with the CNN architecture. The preprocessing pipeline included image labeling, dataset organization, background removal, image resizing to 299×299 pixels, and data augmentation. Brightness adjustment and zoom transformation were applied during augmentation to increase dataset diversity and reduce the risk of overfitting. In this research, augmentation is also used for the oversampling process. Since the initial dataset is imbalanced as shown in Figure 7, an oversampling technique is employed.

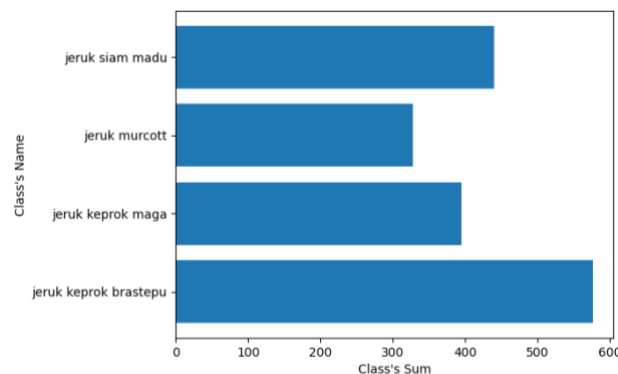


Fig. 7: Dataset before Augmentation

The augmentation techniques used are `brightness_range`, and `zoom_range`. They are applied to every class with fewer than 576 data samples.

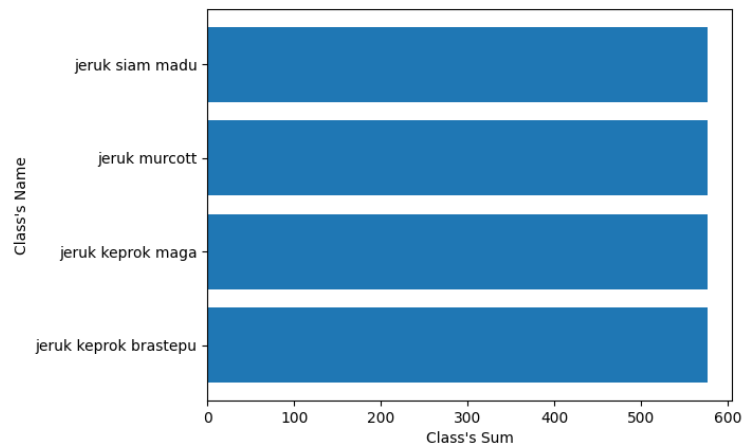


Fig. 8: Dataset After Augmentation

Then, dataset was split into training and testing sets using an 80:20 ratio. A total of 1,840 data points were used for training to build and train the models, while 464 data points served as the test set for the 32 models. The total dataset comprised 2,304 data points following augmentation and oversampling.

4.3. Training Performance

This section presents the results of training the model using three different learning rates (10^{-2} , 10^{-3} , and 10^{-4}). Based on the experimental results, the model with a learning rate of 10^{-4} delivered the best performance, with a training accuracy of 98%, a validation accuracy of 98%, a training loss of 0.063, and a validation loss of 0.062.

Additionally, the early stopping mechanism halted the training process at the 20th epoch because the model had reached optimal performance, thereby reducing the risk of overfitting and saving computation time. The following are the results of training the model with three different learning rates for the four types of oranges:

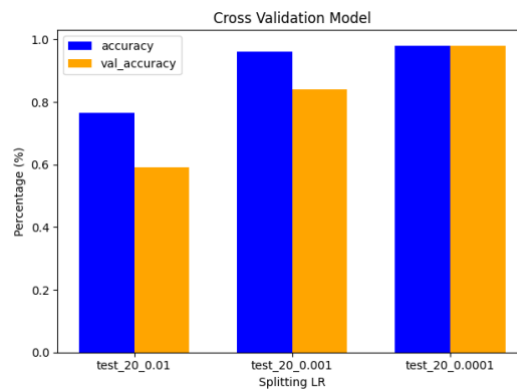


Fig. 9: Bar Chart of Accuracy and Validation Accuracy

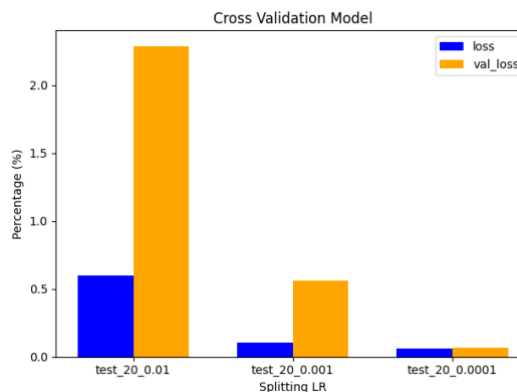


Fig. 10: Bar Chart of Loss and Validation Loss Values

For simplicity and clarity, the test results are presented in Table 1.

Table 1: Training Performance of the Proposed Model

Learning Rate	Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
10^{-2}	50/50	0,764	0,598	0,590	2,286
10^{-3}	50/50	0,959	0,104	0,840	0,563
10^{-4}	20/50	0,980	0,063	0,980	0,062

4.4. Model Evaluation

The trained models were evaluated using Accuracy, Precision, Recall, and F1-score. As shown in Table 2, the model trained with a learning rate of 10^{-4} consistently outperformed the other configurations, achieving an accuracy of 98%, precision of 98%, recall of 97%, and F1-score of 97%. These results indicate that the selected hyperparameter configuration provides the best balance between learning capability and generalization performance.

Table 2: Performance Comparison of Different Learning Rate

Learning Rate	Ratio Dataset	Accuracy	Precision	Recall	F1-score
10^{-2}	80:20	0.59	0.67	0.59	0.54
10^{-3}		0.84	0.90	0.84	0.84
10^{-4}		0.98	0.98	0.97	0.97

The confusion matrix presented in Figure 10 further confirms the effectiveness of the proposed model. Most testing images were correctly classified into their respective citrus classes, with only a few misclassifications observed between visually similar varieties. These results demonstrate that the InceptionV3 model successfully learned discriminative visual features despite the high similarity among citrus varieties.

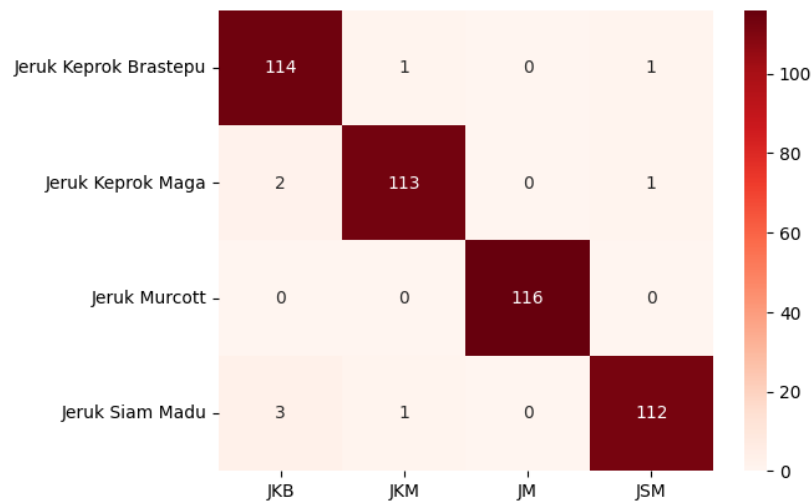


Fig. 11: Confusion Matrix of the Best Model (Learning Rate = 10^{-4})

The following is the classification report evaluating the metrics of precision, recall, F1-score, and accuracy based on the confusion matrix shown in Table 3, calculated using the standard confusion matrix formulas, where “Support” is the amount of data per class. Among the four citrus classes, Murcott achieved perfect classification performance, indicating that its visual characteristics were more distinguishable than those of the other classes. In contrast, minor classification errors occurred between Keprok Brastepu, Keprok Maga, and Siam Madu due to their similar peel color and texture. Nevertheless, the overall results confirm that the proposed CNN model provides reliable multiclass classification performance.

Table 3: Classification Report

Class	Precision	Recall	F1-score	Support
Keprok Brastepu	0.95	0.98	0.97	116
Keprok Maga	0.98	0.97	0.97	116
Murcott	1.00	1.00	1.00	116
Siam Madu	0.98	0.96	0.97	116
Accuracy			0.98	116

4.5. Classification Testing

The best-performing model (learning rate = 10^{-4}) was subsequently used for inference on unseen citrus images. During testing, each input image underwent the same preprocessing pipeline before being classified by the trained InceptionV3 model. The system generated the predicted class together with the confidence score and inference time. An example of the prediction result is shown in Figure 12 and 13.

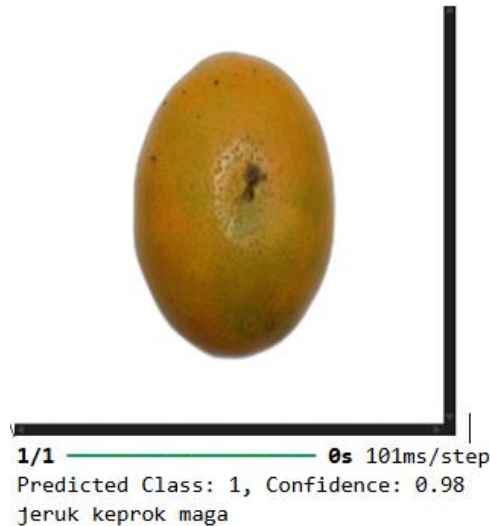


Fig. 12: Example of Model Prediction

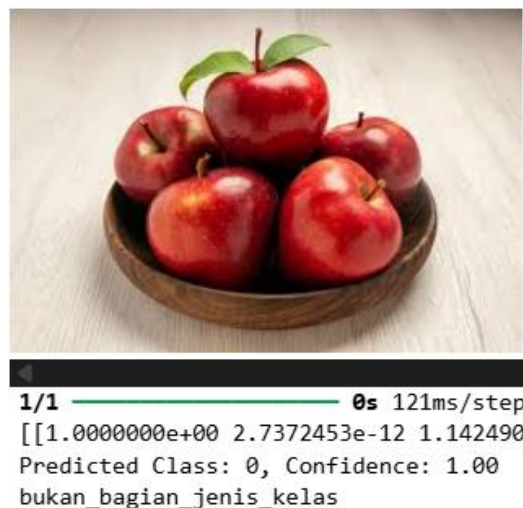


Fig. 13: Example of Model Prediction for An Undefined Class

The prediction output includes the predicted citrus class, confidence score, and processing time. In the presented example, the model correctly classified the input image with a confidence value of approximately 98%, while the inference process required only around 101/ms per step. These findings demonstrate that the proposed model is capable of providing accurate and efficient citrus classification, making it suitable for practical image-based fruit identification systems.

5. Conclusion

This study successfully implemented a Deep Learning-based citrus classification system using the Convolutional Neural Network (CNN) method with the InceptionV3 transfer learning architecture. The proposed model was trained to classify four visually similar citrus varieties, namely Keprok Brastepu, Keprok Maga, Murcott, and Siam Madu, while incorporating an additional Undefined Class to recognize objects outside the predefined categories. The inclusion of the Undefined Class enhances the model's robustness by reducing the likelihood of misclassifying non-citrus objects into one of the target classes.

Experimental results demonstrated that the learning rate significantly affected the classification performance. Among the evaluated configurations, a learning rate of 0.0001 produced the best performance, achieving 98% training accuracy, 98% validation accuracy, 98% precision, 97% recall, and 97% F1-score, with training and validation loss values of 0.063 and 0.062, respectively. These results indicate that the proposed model is capable of accurately distinguishing citrus varieties with highly similar visual characteristics while maintaining stable convergence during the training process.

Overall, the proposed approach demonstrates that combining transfer learning with the InceptionV3 architecture and an additional Undefined Class provides an effective solution for automatic citrus classification based on fruit images. The developed model has the

potential to support fruit identification in agricultural production, quality control, and commercial distribution, where fast and accurate classification is required.

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