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A DEEP LEARNING-BASED SMART MOBILE APPLICATION FOR AUTOMATED CITRUS FRUIT QUALITY CLASSIFICATION

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Abstract

This study aims to develop a digital image-based citrus fruit quality detection system using the Convolutional Neural Network (CNN) method with the MobilenetV2 architecture and implement it into a cross-platform mobile application. The dataset used is a combination of public datasets and local citrus fruit datasets with five quality classes, namely fresh, half-ripe, black spots, damaged, and rotten. The total data is 5001 data, with 80% as training data and 20% as testing data. The CNN model was trained for 10 epochs and evaluated using accuracy, precision, recall, and F1 score metrics. The test results show that the CNN model is able to classify citrus fruit quality with high and consistent performance, indicated by precision, recall, and F1 score values in the range of 0.96-0.97. The trained model is integrated into a Flutter-based mobile application through the Flask backend, enabling real-time citrus fruit quality detection through a smartphone camera. The results of the study prove that the integration of CNN and cross-platform mobile applications can be an effective and objective solution in automatically detecting citrus fruit quality.

Keywords: *Convolutional Neural Network, image classification, orange fruit, mobile application, Flutter.*

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1. INTRODUCTION

Citrus fruit is an agricultural commodity that has high economic value in Indonesia. However, the process of assessing the quality of orange fruit at the farmer level is still being carried out manually through visual observation, so the results are subjective and not consistent. This method is not able to detect internal damage such as unripe fruit perfectly ripe or has a less sweet taste. This condition can be detrimental consumers and reduce the competitiveness of orange products in the market[2].

With advances in artificial intelligence technology, espcially in the field of computer vision, the process of assessing fruit quality can now be done automatically and objectively[3]. The Convolutional Neural Network (CNN) method was chosen because of its ability to extract complex features from images such as color, texture and shape that are difficult for humans to detect consistent[4]. Different from conventional methods such as Support Vector Machine (SVM) or K-Nearest Neighbor (KNN), CNN is able to learn directly from visual data and produce high accuracy[5]. The image of citrus fruit has complex visual characteristics, such as variations in skin color, fine texture, and non-uniform shape. This challenge makes Conventional difficult methods achieve consistent results[6]. Therefore, a CNN model is needed which is specially drilled to recognize these visual patterns, so it is capable of distinguish the level of fruit quality more accurately[7]. In addition, the CNN development model locally it is very important so that the system can adapt to lighting conditions, environment, as well as the specific characteristics of citrus fruit in Indonesia[8]. A CNN model needs to be built and drilled from the start because each type of fruit has different visual characteristics[1].General models drilled on overseas datasets may not be able to recognize color patterns, texture and shape of local citrus fruit accurately[9]. Apart from that, lighting conditions and background The environment in Indonesia also influences image results, so the training model with Local datasets are important so that the system can adapt to real conditions in the field [10].

The CNN model differentiates the quality of citrus fruits based on visual patterns learned from training image data. Through convolution layers, CNN is able to extract important features such as the brightness of skin color, spot patterns, smoothness of texture, and overall fruit shape[11]. These features are then analyzed by subsequent layers to recognize the differences between fresh fruit and damaged fruit . For example, good quality citrus fruit usually has an even orange color on the smooth surface of the skin, while damaged fruit shows dark areas, spots, or an asymmetrical shape[12]. With this capability, CNN can classify fruit quality more objectively and consistently compared to manual observation[13] .

Various previous studies have tried to classify fruit using various methods. Conventional approaches generally utilize the extraction of color, texture and shape features which are then classified using algorithms such as Support Vector Machine (SVM) or K-Nearest Neighbor (KNN)[14]. However, this method has limitations because the features used are statistical in nature and are unable to capture complex visual variations in citrus fruit [15]. With the development of deep learning, several studies have begun to use Convolutional Neural Networks (CNN) and obtain more accurate results, but most still use foreign datasets and do not consider lighting conditions or local fruit characteristics. This shows the need to develop a CNN model that is drilled using local citrus datasets so that the system is able to recognize fruit quality more accurately in real conditions[16].

The research dataset will be collected from two main sources, namely a public dataset from the Kaggle platform and a local dataset taken directly in Karo Regency, Jalan Barusjulu, Kec. Barusjahe, North Sumatra 22171 especially North Sumatra province. Each fruit image will be taken in various lighting conditions, backgrounds, and fruit ripeness levels to ensure representative data variations[17]. Image data is saved in JPG format with a resolution of 224x224 pixels and categorized into five classes, namely: fresh, half cooked, black spots, damaged, rotten. The labeling process is carried out manually by horticulture experts to ensure the accuracy of ground truth[18]. The dataset will be divided into three parts: 70% for training, 20% for validation, and 10% for testing. This approach ensures that the CNN model can learn optimally and avoids overfitting. With a combination of public and local datasets, the model is expected to be able to recognize the visual characteristics of citrus fruit more adaptively to real conditions in the field[19].

Although this research does not directly focus on integration with Internet of Things (IoT) systems, the development of cross-platform mobile applications was chosen because it is easier to access and use by farmers and agricultural businesses without requiring special additional equipment[20] . This application allows users to detect the quality of citrus fruit directly via their cellphone camera by utilizing a trained CNN model. This approach is the first step towards implementing artificial intelligence technology in digital agriculture that is practical, portable and adaptive to devices. Apart from that, the results of this research also form the basis for further development towards IoT systems in the future. [21]Thus, the main contribution of this research is the development of a CNN model that is integrated into a cross-platform mobile application to detect the quality of citrus fruit automatically and accurately, as well as providing innovative solutions for improving production quality in Indonesia.

2. RESEARCH METHOD

This research is quantitative research with the type of experimental research (experimental research). Quantitative research was chosen because the entire process focuses on numerical data analysis, including aruation models, loss values, precision, recall, F1-score, as well as other performance metrics derived from orange fruit image processing. Explain that quantitative research is research based on the philosophy of positivism, which emphasizes objective measurement of the phenomena being studied.

2.1 Data Collection

This research carried out data collection from images of orange fruit by combining local datasets and public datasets, where local orange fruit was taken directly from the Karo Regency area, Jalan Barusjulu,

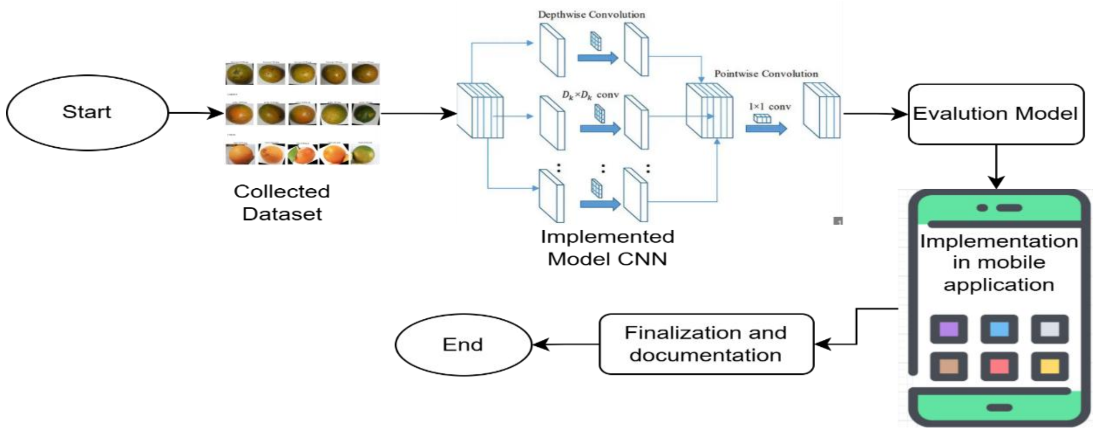

Figure 1. Research Work Procedures

Kec. Barusjahe, North Sumatra 22171 using a camera or smartphone with various lighting conditions, shooting angles and backgrounds. Image capture is carried out to represent five classes of fruit quality, namely: fresh, half ripe, black spots, damaged, rotten, so that the model can learn to recognize real visual variations in the field. Public datasets are obtained from the Kaggle platform to increase the variety and number of images per class, so that the model is not only limited to local ones. All images are saved in jpg format 224x224 pixels and classified by quality class. The dataset is then divided into training (70%), validation (20%), and testing (10%), so that the CNN model can be drilled optimally, validated during the training process, and tested using representative data. This approach aims to make the model able to recognize visual patterns of orange fruit adaptively to various real conditions, increase classification accuracy and minimize detection errors.

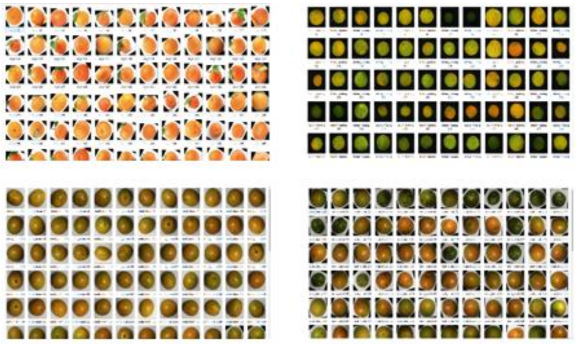

Figure 2 Data Collection

2.2 Data Processing

After the dataset is collected, the next step is to process the data so that it is ready to be used for training the CNN model. Data processing stages include:

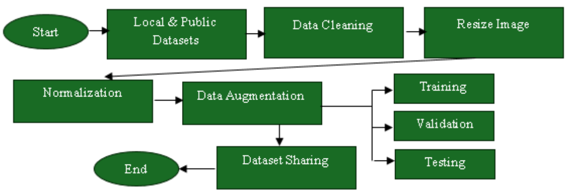

Figure 3 Data Processing

2.3 Modelling

In this research, the Convolutional Neural Network (CNN) algorithm approach is used to model the classification of orange fruit quality based on visual images. CNN was chosen because of its ability to extract complex features from images, such as color, texture and fruit shape, as well as its higher performance compared to conventional methods such as Support Vector Machine (SVM) or K-Nearest Neighbor (KNN).

Convolutional Neural Network (CNN) is a deep learning algorithm based on artificial neural networks that utilizes convolution layers to extract features from input images. Each convolution layer is followed by a pooling layer to reduce the dimensionality of the data while preserving important information. The result of the pooling layer is to reduce data dimensions while retaining important information. The results of the convolution layer are then flattened into a 1D vector before entering Fully Connected Layers (Dense Layers), and the output layer uses softmax activation to produce probability predictions of five orange fruit quality classes: fresh, half-ripe, black spot, damaged, and rotten. The advantage of CNN lies in its ability to recognize complex and non-linear visual patterns automatically, so that the model can adapt to variations in lighting conditions, backgrounds and local fruit characteristics.

The choice of CNN as the research model was based on the characteristics of the dataset in the form of images with high visual variation, as well as the need to produce a classification model that is accurate and can be implemented in real-time in mobile applications. The trained CNN model is then converted to flask format to be compatible with cross-platform mobile applications, allowing users to detect the quality of citrus fruit directly via the cellphone camera.

2.4 Model Testing and Evaluation

The CNN model is tested using a testing dataset that has not been seen during training. Each orange fruit image is predicted into five quality classes: fresh, half-ripe, black spots, damaged, and rotten, then compared with the original label (ground truth).

Evaluation Metrics: accuracy, precision, recall, F1-score, and loss function (categorical crossentropy). Confusion matrix is used to see prediction errors between classes. After testing the dataset, the model is integrated into a mobile application and tested in the field to assess prediction speed, detection accuracy, and user friendliness.

3. RESULT AND DISCUSSION

Convolutional Neural Network (CNN) model training was carried out using a dataset of orange fruit images that had gone through the pre-processing stage, using 5 classes (fresh, half-ripe, black spots, damaged, rotten). The dataset is divided into 70% train, 20% valid, and 10% test, to ensure the model can learn well. The training process was carried out for 10 epochs.

Figures 4 and 5 are graphs of the accuracy and loss process.

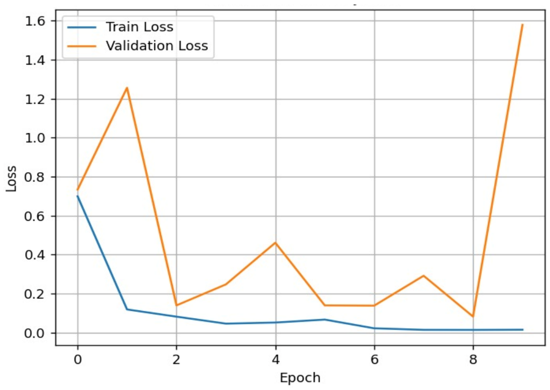

Figure 4. Graphic loss 10 epochs

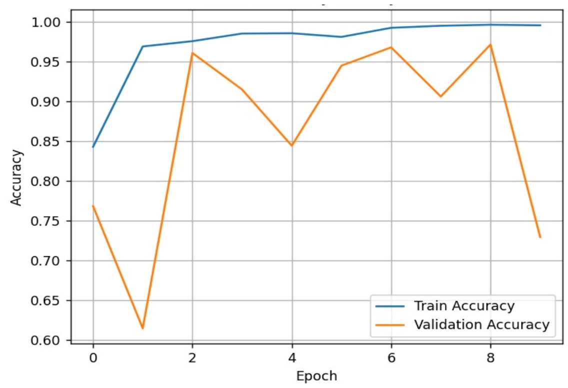

Figure 5. Graphic accuracy 10 Epochs

Based on the experimental results shown in Figures 4 and 5, it shows that the model has achieved the highest accuracy during initialization of epoch 10. Thus, this model will be saved for the classification process. The classification results are shown in Figure 6.

Classification Report:

	precision	recall	f1-score	support
bintik_hitam	1.00	1.00	1.00	200
busuk	0.81	1.00	0.90	200
rusak	0.99	1.00	0.99	201
segar	1.00	0.76	0.86	200
setengah_matang	0.99	0.99	0.99	200
accuracy			0.95	1001
macro avg	0.96	0.95	0.95	1001
weighted avg	0.96	0.95	0.95	1001

Figure 6. Classification report

3.1 Classification Report

Based on the results of the classification report, the CNN model developed to detect the quality of citrus fruit produces very good performance. Divided into 5 classes (fresh(segar), half-cooked(setengah-matang), black spots(bintik-hitam), damaged(rusak), rotten(busuk)), however, the precision, recall and F1-score values are in the range of 0.96 to 0.97, reflecting that the model works consistently across all classes.

3.2 Confusion Matrix

Confusion Matrix, is used to evaluate model performance by comparing the original labels and the predicted results. Based on these results, it can be seen that most of the values are on the main diagonal with a value of 5, which shows that the model succeeded in classifying the test data very accurately. As shown in Figure 7.

However, there was one classification error, namely one data with damaged original labels which was predicted as black spots. This error is likely caused by the visual similarity between the damage characteristics and the presence of spots on the surface of the oranges, so that the model has difficulty distinguishing between the two classes. However, the other classes were successfully classified with an accuracy rate of 100%, so that overall the model performance can be categorized as very good.

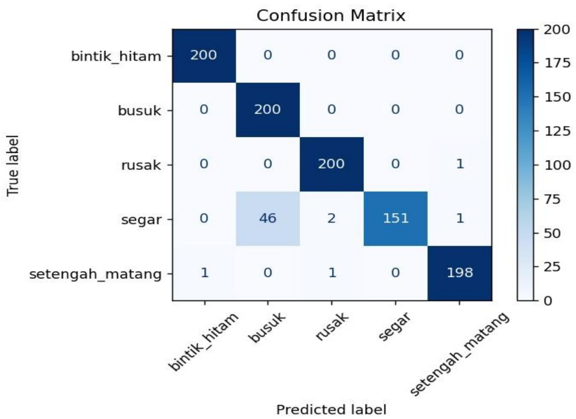

Figure 7. Result of confussion matrix.

From the results in Figure 7, it shows that the model is very good in classifying the classes "black spots, rotten, damaged, and half-cooked" while the system still has difficulty in classifying the "fresh" class, where the recall value obtained is only 76% or 49 data are wrong in classifying. The reason is because the fresh class has similarities with other classes such as rotten.

3.3 Cross-Platform Mobile Application

The trained Convolutional Neural Network (CNN) model is saved in the file model_jeruk.h5 and implemented on the backend using the Python programming language with the Flask framework. The backend functions as an image classification service that receives input images of orange fruit from the mobile application, processes them using a CNN model, and produces predictions of orange quality. The mobile application was developed cross-platform using the Flutter framework as the frontend which is tasked with taking images, sending data to the backend via HTTP request, and displaying prediction results to users. This client–server architecture separates the computing process and user interface so that applications are lighter, more flexible and easier to manage and develop systems.

In the image below, real-time detection of orange fruit quality, where users can directly take pictures of oranges via their smartphone camera. The image is then processed by a Convolutional Neural Network (CNN) model to determine the quality category of orange fruit automatically

Apart from that, the application also displays classification results and the level of confidence of the model. This information helps users understand how accurate the prediction results are, thereby increasing transparency and trust in the citrus fruit detection system being developed. The display of orange quality detection using a smartphone is shown in Figure 8.

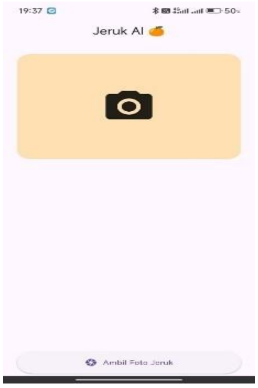

Figure 8. Real time display of orange Fruit Quality

4. DISCUSSION

Based on the results of testing and system implementation, the Convolutional Neural Network (CNN) model developed is able to detect the quality of orange fruit with a high level of accuracy and consistent performance in each class. This is indicated by the high precision, recall and F1-score values as well as the dominant prediction distribution on the main diagonal of the confusion matrix. These results indicate that the CNN model is able to extract visual features of orange fruit effectively, even though there are similarities in characteristics between certain classes.

The integration of CNN models into Flutter-based mobile applications via the Flask backend allows the system to run efficiently, flexibly, and structured. This client–server architectural approach separates the model computing process from the user interface, so that the processing load is not borne by the mobile device. Additionally, the separation of the backend and frontend makes it easier to manage the model, allowing for future updates or development of the CNN model without requiring significant changes to the mobile application.

With the real-time citrus fruit quality detection feature and the presentation of classification results along with the model's confidence level, this system not only provides prediction results, but also increases the transparency and reliability of the system from the user's perspective. Overall, the system developed has the potential to be applied as a supporting solution in the digital image-based citrus fruit quality identification process.

5. CONCLUSION

Based on the results of the research that has been carried out, it can be concluded that the Convolutional Neural Network (CNN) method can be used effectively to detect and classify the quality of citrus fruit based on visual images. The CNN model drilled using a combination of local orange datasets and public datasets succeeded in classifying orange fruit into five quality categories, namely fresh, half-ripe, black spots, damaged, and rotten, with a high level of accuracy and consistent performance in each class. The results of model evaluation using precision, recall, F1-score and confusion matrix metrics show that the CNN model is able to extract important visual features such as color, texture and surface patterns of orange fruit optimally. Although there are slight classification errors due to visual similarities between certain classes, overall the model shows very good generalization abilities to the test data.

The implementation of the CNN model into a cross-platform mobile application using the Flutter framework with a Flask backend was successful. The

Figure 9. Classifcation results and confidence Levels

Client–server architecture implemented allows the model computing process to be run on the backend, so that mobile applications become lighter and easier to use on various devices. Apart from that, the real-time citrus fruit quality detection feature and the presentation of classification results along with the model's confidence level provide convenience and transparency for users in understanding the detection results. Thus, this research proves that the integration of CNN and cross-platform mobile applications can be an effective, practical and applicable solution in supporting the process of automatically identifying the quality of citrus fruit based on digital images.

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