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YOLOv11-based detection and classification of diseases in Siamese orange fruit using digital images

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ABSTRACT

Diseases in Siamese orange fruit are one of the factors that can reduce the quality and yield of agricultural production. Manual disease identification requires considerable time and depends heavily on human observation skills; therefore, an automated system capable of detecting diseases quickly and accurately is needed. This study aims to implement the YOLOv11 model for detecting and classifying diseases in Siamese orange fruit based on digital images. The dataset used consisted of four classes, namely anthracnose, citrus canker, scab, and healthy, with a total of 627 images divided into training, validation, and testing datasets. The study utilized 20 variations of data augmentation, and DataV18 produced the best performance. The training process was conducted using the YOLOv11s architecture with 200 epochs and various data augmentation techniques. Based on the testing results, the model achieved a precision of 70.5%, recall of 61.2%, F1-score of 65.5%, mAP@0.5 of 61.8%, and mAP@0.5:0.95 of 44.8%. The results indicate that the YOLOv11 model has a fairly good capability in detecting diseases in Siamese orange fruit based on digital images and has the potential to be applied in the development of artificial intelligence-based plant disease detection systems.

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1. INTRODUCTION

The Siamese orange/citrus (*Citrus nobilis var. deliciosa*) is one of Indonesia's leading horticultural commodities, possessing high economic value and playing a crucial role in meeting domestic and export market demand [1, 2]. West Sumatra is one of the national tangerine production centers, with production levels increasing annually [3]. However, the productivity and quality of Siamese orange often decline due to plant diseases that affect the fruit's physical condition, particularly during the post-harvest stage. The main diseases commonly found in Siamese orange include anthracnose, citrus canker, and scab, which can cause visual damage, quality degradation, and even economic losses for farmers [4-6].

The disease identification process in Siamese orange is currently dominated by manual visual inspections carried out by farmers and field supervisors [4]. This conventional method has various limitations, such as subjectivity in assessment, reliance on operator experience, and low consistency in detecting early symptoms of disease. Furthermore, the manual inspection process is also less efficient when applied to large harvests in a short period of time. Therefore, an Artificial Intelligence (AI)-based automatic detection system is needed to assist in the process of identifying orange fruit diseases more quickly, objectively, and accurately [7, 8].

The development of Artificial Intelligence technology, particularly Computer Vision and Deep Learning, has shown great potential in automating digital image analysis in agriculture [7-9]. Convolutional Neural Network (CNN) architectures are capable of automatically learning complex visual patterns such as texture, color, and shape of disease lesions from digital images [8, 9]. Several previous studies have applied YOLO-based approaches to plant disease detection and fruit quality classification. Research by Prasetya et al. used YOLOv8 for quality classification of tangerines and demonstrated good performance in the computer vision-based classification process [10]. Another study by Sowmya and Guruprasad implemented Inception V4 and YOLOv8 for deep learning-based tomato plant disease detection [11]. In addition, several studies have developed lightweight YOLO-based models to support fruit disease detection on devices with limited computing [12, 13]. The development of a orange fruit disease detection system based on edge computing and the Internet of Things (IoT) has also been carried out to support real-time agricultural monitoring [14].

As object detection technology advances, the YOLO architecture has continuously improved in performance from YOLOv1 to YOLOv11 [15, 16]. YOLOv11, as the latest generation, offers improvements in multi-scale feature extraction mechanisms, feature fusion, and a decoupled head, making it more effective in detecting objects with high visual complexity [17-19]. Several recent studies have shown that YOLOv11 can improve the accuracy and efficiency of object detection compared to previous generations, especially for small objects and complex visual conditions [18, 20, 21]. However, the implementation of YOLOv11 in agriculture is still relatively limited, and most studies focus on leaf diseases rather than diseases on the fruit surface. Furthermore, the use of original datasets from local Indonesian production centers for orange fruit disease detection is still very limited in the literature.

Based on these problems, this study proposes the application of the YOLOv11 model to detect and classify diseases in tangerine fruit based on digital images end-to-end. The research dataset was collected directly from Siamese orange plantations in Agam Regency, West Sumatra, consisting of healthy fruit and fruit infected with Anthracnose, Citrus Canker, and Scab. The model training process was carried out using the YOLOv11s architecture with various data augmentation techniques to improve the model's generalization ability. The novelty of this study lies in the application of the YOLOv11 model to detect diseases on the surface of Siamese orange fruit using original datasets from local Indonesian production centers. This research is expected to produce an accurate and efficient disease detection model and contribute to the development of computer vision technology to support smart agricultural systems in Indonesia.

2. RESEARCH METHODS

This research methodology uses an experimental method combined with a machine learning workflow to develop a orange fruit disease detection system based on the YOLOv11 architecture. The experimental method was chosen because the research focuses on testing the effect of model configurations such as learning rate, batch size, and number of epochs on disease detection performance. In general, the research stages begin with a literature review and problem identification, orange fruit image dataset collection, data preprocessing, YOLOv11 model design and training, and model performance testing and evaluation. All stages are systematically structured to ensure a structured research process and produce a model capable of detecting orange fruit diseases accurately and efficiently. The overall flow of the research methodology is shown in the following Figure 1.

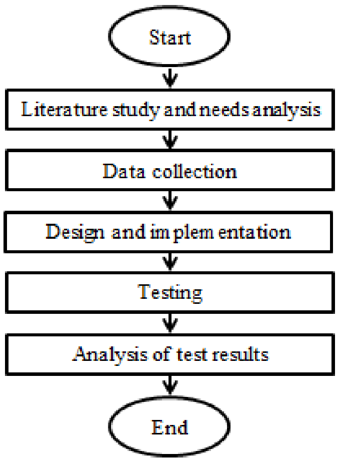

Figure 1. Research methodology flowchart.

The research phase began with a literature review to review previous research related to orange fruit diseases, computer vision, deep learning, and the development of YOLO through YOLOv11. This phase aims to understand the characteristics of diseases such as citrus canker, anthracnose, and scab, and to identify research gaps. Next, primary data was collected in the form of orange fruit images using a smartphone camera with varying angles, distances, and white and black backgrounds. All images were then manually labeled according to disease type. The obtained data then underwent a preprocessing stage, including resizing to 640x640 pixels, data augmentation (rotation, flipping, lighting changes, and geometric transformations), and dividing the dataset into training, validation, and testing datasets. The YOLOv11 model was then trained using pre-trained weights to accelerate convergence. The model learned through backpropagation and loss function optimization to produce the best weights (best.pt). The final stage was testing and evaluation using test data with Precision, Recall, F1-Score, and Mean Average Precision (mAP) metrics based on Intersection over Union (IoU) to assess the model's ability to accurately and efficiently detect and classify orange fruit diseases.

2.1. Model Design

The model design in this study uses a Deep Learning architecture based on YOLOv11 (You Only Look Once version 11), chosen for its real-time object detection capabilities with improved parameter efficiency and accuracy compared to previous generations. YOLOv11 maintains a single-stage detector and end-to-end approach, enabling simultaneous object localization and disease classification in a single inference process. This architecture is considered suitable for detecting citrus fruit diseases such as Citrus Canker, Anthracnose, and Scab because it can more effectively recognize variations in texture, color, and lesion patterns on the fruit's surface. The system designed in this study is image-upload-based, where users manually upload orange fruit images, which are then processed by the YOLOv11 model to detect and classify diseases.

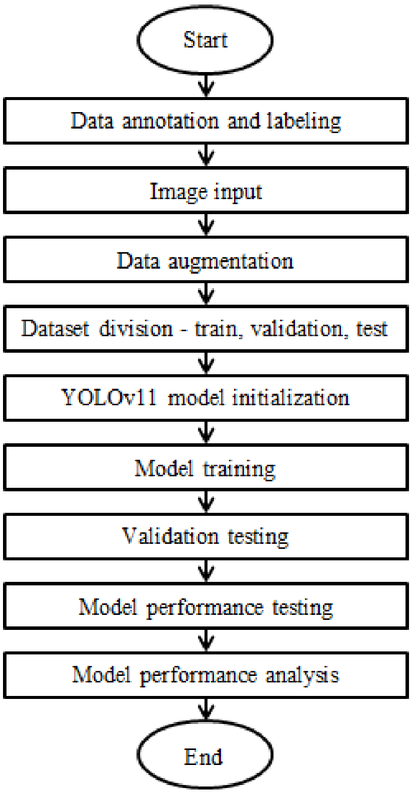

Figure 2. YOLOv11 model design.

Based on the Figure 2 above, the model design flow begins with the data annotation and labeling stage, which is the process of labeling orange fruit images according to the type of disease detected. This is followed by the image input stage, where orange fruit images are entered into the system as the primary research data. The next stage is preprocessing, which involves resizing the images to 640×640 pixels and reducing noise to improve data quality before being processed by the model. Data augmentation is then performed using techniques such as rotation, flipping, lighting changes, and geometric transformations to increase the variety of training data and improve the model's generalization ability. The processed dataset is then divided into training, validation, and testing data to ensure a structured and objective model training and evaluation process.

The next stage is initializing the YOLOv11 model by preparing the architecture structure and initial parameters using pre-trained weights. The model is then trained using the training data through an iterative, epoch-based process to learn the visual patterns of orange fruit diseases end-to-end, encompassing simultaneous object localization and disease classification. During the training process, validation tests are conducted using the validation data to monitor model performance and prevent overfitting. After the training process is complete, the model is tested using the testing data to measure disease detection and classification performance based on evaluation metrics such as Precision, Recall, F1-Score, and Mean Average Precision (mAP). The final stage is the analysis of model performance to evaluate the level of effectiveness of YOLOv11 in detecting orange fruit diseases and identifying The strengths and limitations of the developed model.

2.2. Research Data

Research data is a crucial component in developing a deep learning system because data quality significantly impacts the model's ability to recognize patterns and generalize to new data. In this study, the primary data used were digital images of oranges obtained directly by the researcher through a smartphone camera. The images were captured indoors using a white and black background to reduce visual distractions from the surrounding environment and to clarify the oranges being observed. Furthermore, the image capture process varied camera angles, positions, and distances to enhance visual diversity and better represent the actual condition of the objects. The use of a controlled environment was chosen because it provides more stable lighting quality, allowing for clearer visibility of the texture, color, and disease symptoms on the surface of the oranges.

The dataset in this study consists of four main classes: Fresh (healthy), Anthracnose, Cancer, and Scab. The Fresh class served as a negative control, representing healthy oranges without disease symptoms. Meanwhile, the Citrus Canker class is characterized by rough, corky spots on the surface of the fruit's skin. The Anthracnose class is characterized by small black spots that can spread across the skin's surface. The Scab class is characterized by a rough, uneven skin surface due to disease infection. All obtained images then undergo a selection process to ensure good image quality and are free from blur, excessive noise, or file corruption. After the selection process is complete, the data is standardized into image file formats such as .jpg and .png to ensure compatibility with image processing and YOLOv11 model training.

The next stage is data labeling based on the type of disease visible on the surface of the orange fruit. Labeling is done manually, referring to the visual characteristics of each disease, so that each image has an appropriate class label. This labeling process is crucial because the labels assigned will serve as a reference for the model in learning the relationship between the visual features of the image and the detected disease class. In addition to labeling, a data cleaning process is also carried out to remove irrelevant data, duplicates, or images of poor quality. This stage aims to improve dataset consistency so that the model training process can run more optimally and stably.

To ensure the quality of the data used, a validation and reliability verification process was conducted through a visual inspection of all images and labels. This inspection aimed to ensure that each image accurately represented the disease condition according to agricultural literature references. The dataset was then organized by class and divided using a stratified sampling method into training, validation, and testing data to maintain a balanced distribution of data within each class. Training data was used for the model learning process, validation data was used to monitor model performance during training and detect potential overfitting, while testing data was used to objectively evaluate the model's final performance using previously unseen data. The number of data sets for each research class is shown in the following Table 1.

Table 1. Distribution of images per class.

Class name	Image	Total
Anthracnose		101
Cancer		84
Scabies		267
Healthy		175

3. RESULTS AND DISCUSSIONS

This chapter discusses the results of the YOLOv11 model implementation in detecting and classifying diseases in Siamese orange based on digital images. Furthermore, the model's performance is analyzed based on training and testing results using several object detection evaluation metrics.

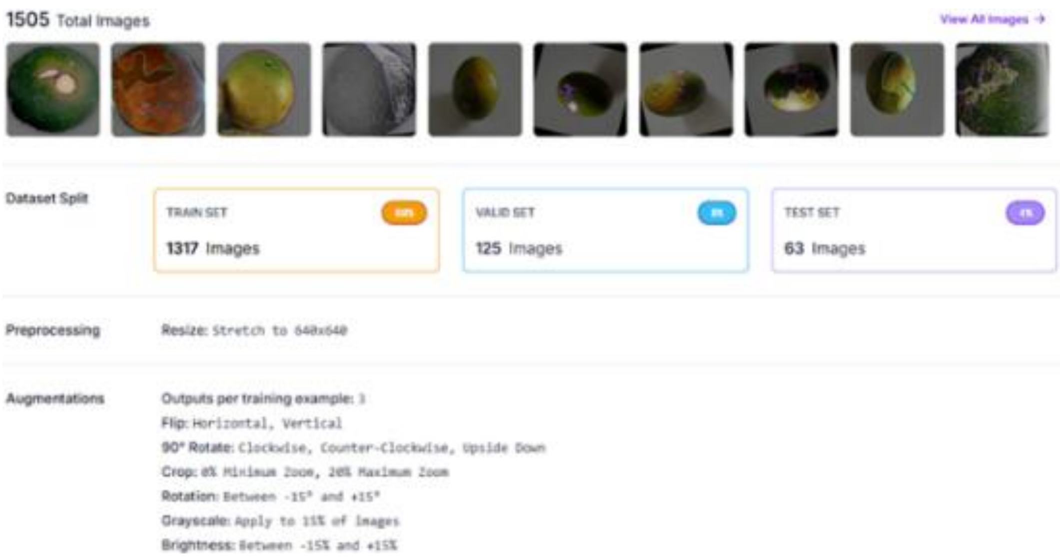

Figure 3. Data preprocessing and augmentation results in Roboflow.

3.1. Preprocessing and Data Augmentation Results

Based on the dataset processing results using the Roboflow platform (see Figure 3), a total of 1,505 images underwent preprocessing and data augmentation. The dataset was divided into 1,317 images (88%) for training data, 125 images (8%) for validation data, and 63 images (4%) for testing data. In the preprocessing stage, all images were resized to 640 × 640 pixels using the stretch method to match the input size of the YOLOv11 model. This process aimed to standardize the image dimensions so that model training could run more consistently without losing important information about the orange disease objects.

During the data augmentation stage, several techniques were applied, such as horizontal flip, cropping, random rotation, brightness adjustment, and exposure adjustment to increase the variety of the training data. Furthermore, during the training process in Google Colab, additional augmentations were applied, such as mosaic augmentation, copy-paste, scaling, object translation, and HSV-based color changes. The augmentation results showed an increase in visual image variation in terms of object position, orientation, and lighting, thus helping to improve the generalization ability of the YOLOv11 model in detecting orange fruit diseases under various image conditions.

3.2. YOLOv11 Model Training Results

The YOLOv11 model training process was conducted using a orange fruit disease image dataset that had undergone preprocessing and data augmentation stages. In this study, 20 variations of the augmented dataset were tested to determine the effect of augmentation on the model's performance in detecting orange fruit diseases. Based on the test results, the DataV18 dataset performed best compared to the other datasets and was therefore selected as the primary dataset for the model training and evaluation stages. Training was conducted using the YOLOv11s architecture with pretrained yolo11s.pt weights, an input size of 640 × 640 pixels, a batch size of 16, and the AdamW optimizer. Throughout the training process, the model demonstrated a steady decrease in loss values, enabling it to effectively learn visual disease patterns without experiencing significant overfitting.

Table 2 YOLOv11 model training configuration.

Parameter	Value
Model	YOLOv11s
Pre-trained Weights	yolo11s.pt
Epoch	200
Batch size	16
Input size	640 × 640
Optimizer	AdamW
Initial learning rate (lr0)	0.001
Final learning rate (lrf)	0.01
Warmup Epoch	3
Patience	30
Cosine learning rate	True
HSV-H	0.015
HSV-S	0.5
HSV-V	0.3
Rotation (degrees)	8.0
Translation	0.05
Scaling	0.3
Horizontal fip (fliplr)	0.5
Mosaic	0.8
MixUp	0.05
Copy-paste	0.15
Close Mosaic	10
Dropout	0.1

Based on this configuration (see Table 2), the model was trained using several optimization techniques such as a cosine learning rate scheduler, warmup epoch, label smoothing, and online augmentations such as flipping, rotation, scaling, mosaic augmentation, and copy-paste augmentation.

This combination of techniques aims to improve the model's generalization ability to various citrus fruit image conditions. Model performance evaluation was performed using Precision, Recall, F1-Score, mAP@0.5, and mAP@0.5:0.95 metrics to measure the model's overall ability to classify and localize diseased objects.

Table 3. YOLOv11 model evaluation results.

Evaluation metrics	Result
Precision	70.5%
Recall	61.2%
F1-score	65.5%
mAP@0.5	61.8%
mAP@0.5:0,95	44.8%

Based on the evaluation results in the Table 3 above, the YOLOv11 model performed quite well in detecting orange fruit diseases. The precision value indicates that the model is capable of providing fairly accurate predictions, while the recall value indicates the model's ability to detect the majority of disease-related objects in the image. In addition to the overall evaluation, evaluations were also conducted for each disease class to determine the model's performance in more detail for each object category.

3.3. Model Performance Analysis

Performance analysis was conducted to determine the YOLOv11 model's ability to detect and classify orange diseases using precision, recall, F1-score, mAP@0.5, and mAP@0.5:0.95 metrics. Based on the evaluation results, the model achieved a precision of 70.5%, recall of 61.2%, F1-score of 65.5%, mAP@0.5 of 61.8%, and mAP@0.5:0.95 of 44.8%. The precision value A higher precision than recall indicates that the model is quite good at producing correct predictions and reducing false positives. However, the low recall value indicates that some disease objects have not been optimally detected.

Table 4. Evaluation results for each disease class.

Class	Precision	Recall	F1-score	mAP@0.5	mAP@0.5:0.95
All	70.5%	61.2%	65.5%	61.8%	44.8%
Anthracnose	77.7%	61.6%	68.7%	71.4%	38.1%
Cancer	53.4%	29.0%	37.6%	24.0%	12.9%
Healthy	89.3%	98.6%	93.7%	97.1%	94.6%
Scabies	61.6%	55.7%	58.5%	54.8%	33.4%

Based on the evaluation per class (see Table 4), the Fresh class performed best with a precision of 89.3%, a recall of 98.6%, and a mAP@0.5 of 97.1% due to its more consistent and easily recognizable visual characteristics. The Anthracnose class also performed quite well, while the Scab class still experienced some detection errors. Furthermore, the amount of data for the Citrus Canker class was relatively small compared to the other classes because the research dataset was obtained directly from field conditions in a Siamese orange plantation. The availability of fruit infected with a particular disease depends on the actual conditions at the time of data collection, so the data distribution between classes is not entirely balanced. Nevertheless, the use of primary datasets from the field provides a better representation of real-world conditions than datasets obtained from controlled environments, so the resulting model is expected to have more relevant generalization capabilities for real-world implementation.

Based on the F1-Score graph (see Figure 4), the Fresh class has the highest F1-Score compared to the other classes. This indicates that the model has a good balance between precision and recall in the Fresh class. Meanwhile, the Canker class has a lower F1-Score than the other classes because the model still has difficulty consistently recognizing diseased objects.

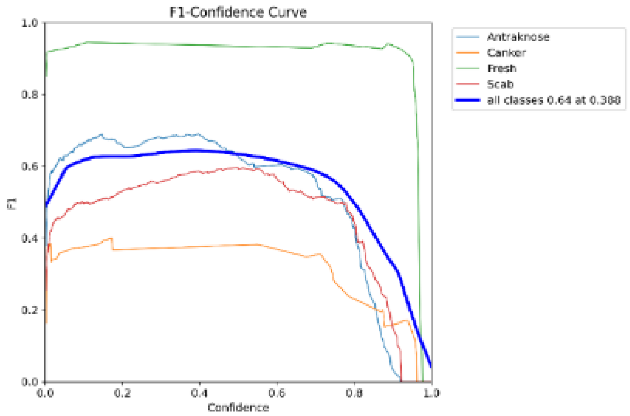

Figure 4. F1-score graph of the YOLOv11 model.

The precision graph (see Figure 5) shows the model's accuracy in predicting orange fruit disease objects. Based on the graph, the Fresh class has the most stable precision value compared to the other classes. Meanwhile, the Canker class shows a lower precision value due to the smaller amount of data and the similarity of visual patterns to other disease classes.

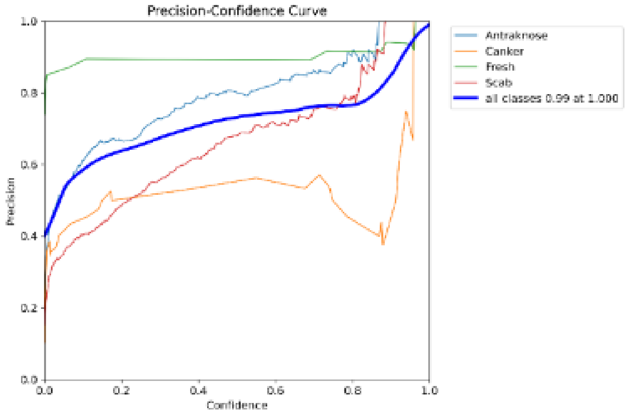

Figure 5. Precision graph of the YOLOv11 model.

The precision-recall graph (see Figure 6) shows the relationship between precision and recall values in the object detection process. Based on the graph, model performance decreases as recall increases for several disease classes. This indicates that the model still has difficulty optimally detecting all diseased objects under some image conditions.

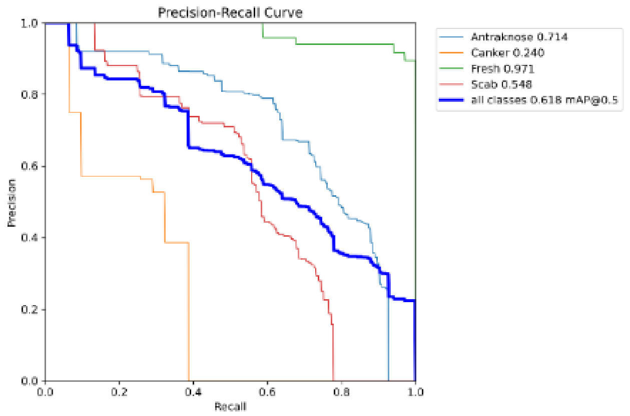

Figure 6. Precision-recall graph of the YOLOv11 model.

The recall graph (see Figure 7) shows the model's ability to identify all disease objects in the test image. Based on the graph, the Fresh class has the highest recall value compared to other classes. This indicates that the model is capable of detecting almost all objects in the Fresh class effectively.

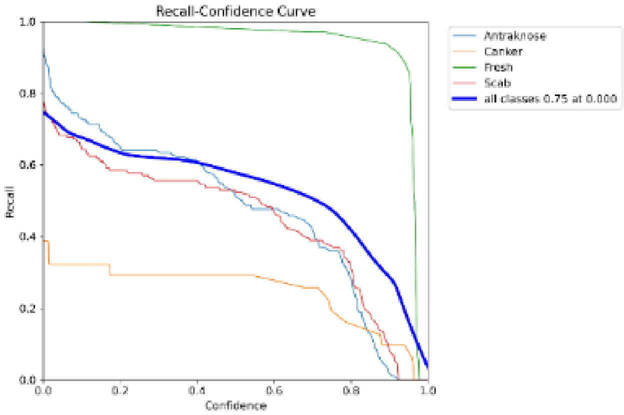

Figure 7. YOLOv11 model recall graph.

The confusion matrix (see Figure 8) shows the proportion of successful classifications for each disease class. Based on these results, the Fresh class has the highest classification accuracy compared to other classes. Meanwhile, the Canker class has a higher classification error rate due to the smaller amount of data compared to other classes.

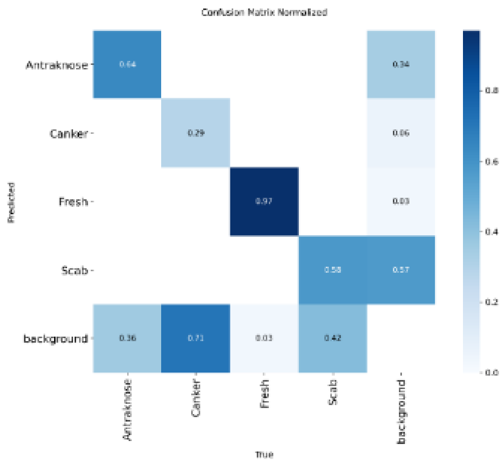

Figure 8. YOLOv11 model confusion matrix.

4. CONCLUSION

Based on the implementation and testing results, this study successfully applied the YOLOv11 model to detect and classify diseases in tangerines based on digital images. The conclusions drawn from this study are as follows:

- The YOLOv11 model was successfully implemented to detect and classify diseases in tangerines, namely anthracnose, canker, scab, and fresh fruit, using an annotated digital image dataset.
- The use of 20 variations of data augmentation, specifically the DataV18 variant, improved the model's ability to recognize objects in various image conditions through techniques such as flipping, rotation, mosaic augmentation, and copy-paste augmentation.
- The evaluation results showed that the model achieved overall performance with a precision of 70.5%, recall of 61.2%, F1-score of 65.5%, mAP@0.5 of 61.8%, and mAP@0.5:0.95 of 44.8%.
- Based on the per-class evaluation, the Fresh class performed best, while the Canker class performed lowest due to the smaller dataset and the similarity of visual characteristics to other diseases.

- Overall, the YOLOv11 model is capable of automatic disease detection and localization by displaying bounding boxes, class labels, and confidence scores. It has an average inference time of 6.5 ms per image, making it potentially applicable to real-time artificial intelligence-based fruit disease detection systems.

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