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Image Processing Computational Algorithm for Classification of Katokkon Toraja Chili Peppers Syndromes in Greenhouse Smart Farming System

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Abstract

The real-time and automatic detection and classification of various plant syndromes through the adaptation of artificial intelligence (AI) computational algorithms and image processing have significantly influenced the improvement of the quality and productivity of smart greenhouse and open field farming systems during the harvest period. Therefore, this study examines a general computational algorithm to automate the detection and classification of Toraja Katokkon chili diseases. Katokkon chili is an economically important crop in Indonesia, but its cultivation process can decrease yield and harvest quality due to pest and disease attacks. Practically, image samples of the health condition of the processed plant growth will be categorized into healthy and unhealthy ones. The dataset used in this study consists of 200 images, divided equally between healthy and unhealthy samples, which are manually labeled based on the symptoms seen. The images were first processed to a resolution of 640 x 640 pixels to meet the requirements of the developed YOLOv8 computational model. The model achieved a classification accuracy of around 81.48%, with precision and recall values showing moderate performance in distinguishing between healthy and unhealthy chilies. The results show that although the designed computational algorithm shows promise for real-time detection of agricultural diseases, increasing the size of the dataset, data augmentation, and integration of attention mechanisms are required to improve detection accuracy. These remarkable results highlight the potential of utilizing AI-based systems in smart agriculture to optimize crop management and reduce losses.

Keywords: *Image computation algorithm; disease detection and classification; Katokkon chili peppers; Smart agricultural; Real-time monitoring; Environmental surveillance.*

1. Introduction

Chili peppers are one of the high-value horticultural commodities, especially in Southeast Asia, including Indonesia [1]. In Indonesia, chili peppers play an important role not only as a staple ingredient in various dishes but also as a commodity that supports farmers' welfare and regional economies. One distinctive variety is the Katokkon chili, originating from the Toraja region in South Sulawesi [2] [3]. However, like other horticultural crops, Katokkon chili production often faces challenges due to various diseases that reduce quality and yield. Chili plant diseases can be caused by fungi, bacteria, or pest infestations, potentially leading to significant economic losses if not addressed appropriately [4][5].

The Katokkon chili, a distinctive variety from Toraja in South Sulawesi, holds significant cultural and economic value for the local community and is renowned for its unique flavor and characteristic shape. Despite its large market potential, Katokkon chili cultivation faces serious challenges in disease management, often resulting in substantial crop damage [1]. These diseases are complex for traditional farmers to detect in their early stages, frequently apparent only after they have spread extensively, and are difficult to control [6]. Conventional methods for identifying chili diseases require considerable time, labor, and specialized expertise, which local farmers often need more. As a result, Katokkon chili production is vulnerable to reductions in quality and quantity, exposing farmers to high economic risks. Therefore, a more efficient and automated solution is needed to detect and classify the health conditions of Katokkon chili plants to support sustainable production and maintain crop quality.

With advancements in precision agriculture technology, various artificial intelligence and image processing methods have been utilized to help detect plant diseases automatically [7][8]. One effective method is the You Only Look Once (YOLO) algorithm. This real-time object detection model has been successfully applied in various studies to identify and classify plant health conditions, such as tomatoes, rice, and other horticultural crops [9][10]. The YOLO algorithm is can detect objects quickly and accurately, even in diverse environmental conditions, making it particularly suitable for use in open-field farming where conditions are often uncontrolled [11][12]. Previous studies have shown that using the YOLO algorithm for classifying plant conditions enhances efficiency and accuracy in disease identification [13], reduces observation time, and facilitates early preventive actions by farmers [14][15]. Therefore, applying YOLO to Katokkon chili cultivation could serve as an innovative solution to assist farmers in early disease detection, ensuring optimal harvest quality and productivity.

Applying the YOLO algorithm for automatic classification in Katokkon chili offers several advantages over conventional methods. First, YOLO enables real-time detection and classification, allowing for rapid and efficient identification of chili diseases without requiring expensive hardware. Second, YOLO's ability to detect objects accurately under various lighting and environmental conditions makes it well-suited for open-field agriculture, where environmental factors are difficult to control. Third, this algorithm offers flexibility in its implementation, as it can be integrated with mobile devices or drone systems, making it easier for farmers to conduct regular field monitoring. Consequently, YOLO reduces the time and labor needed for disease identification and allows for earlier preventive action, minimizing potential crop losses due to disease. These advantages highlight YOLO as a viable and efficient solution to enhance the resilience and productivity of Katokkon chili sustainably.

This research aims to develop a YOLO-based system that automatically classifies Katokkon chili as healthy or diseased. This system aims to improve efficiency and accuracy in early disease detection, thereby assisting farmers in preventing wider disease spread and reducing potential economic losses caused by plant diseases. Some limitations of this research include environmental factors, such as lighting and weather conditions, which may affect the algorithm's detection outcomes. For data collection, this study will use images of Katokkon chili in various disease states and healthy conditions gathered directly from agricultural fields in Toraja. These data will serve as the basis for training the YOLO model to recognize visual differences between healthy and diseased chilies. The anticipated benefits of this research are enhancing the productivity and quality of Katokkon chili harvests and providing a technological solution that could be applied to other horticultural crops.

The subsequent sections of this paper will consist of several main parts. The Methods section will detail the data collection process, data processing techniques, and YOLO model training parameters. Next, the Results and Discussion section will present and analyze the evaluation results of the YOLO system in processing chili images. Finally, the Conclusion section will summarize the key findings of this study and provide recommendations for further development in the application of automated detection technology for other horticultural crops.

2. Materials and Methods

2.1 Smart Agriculture

Smart agriculture, often synonymous with precision farming, leverages cutting-edge technologies to enhance crop productivity and sustainability [16]. This approach integrates various technologies, such as IoT, AI, drones, and remote sensing, to optimize farming practices, reduce resource waste, and improve crop yields [17][18]. Applying these technologies in agriculture has transformed traditional farming into a more efficient, data-driven industry.

The introduction of smart agriculture is driven by the need to meet the increasing global food demands while addressing the challenges of climate change and limited agricultural land. As described by Rakhra and Singh (2021), smart agriculture utilizes data from IoT devices and advanced analytics to improve decision-making processes in farming, which can lead to increased productivity and sustainability [19][20].

Shaikh et al. (2022) highlight the use of AI and machine learning algorithms in various domains of agriculture, including soil management, plant growth monitoring, and pest and disease prediction. These technologies enable farmers to predict crop yields, optimize irrigation schedules, and detect plant diseases early, significantly improving agricultural operations' overall efficiency [21].

One of the primary challenges is integrating and standardizing data from diverse IoT devices [22][23]. Different sensors often produce data in various formats, making combining and analyzing it effectively tricky. According to Cavaliere et al. (2020), a multitier architecture incorporating an ontology-based data integration process is essential to address this issue. This architecture can

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enhance data acquisition from various IoT devices, facilitating more comprehensive crop monitoring and decision-making processes [24].

Many existing IoT-based precision agriculture systems focus on real-time monitoring of environmental conditions such as soil moisture, temperature, and humidity [18]. However, early detection of plant diseases remains a challenge[25]. Abu et al. (2022) emphasize that while IoT devices can significantly enhance the monitoring of crop health and environmental conditions, there is still a need for more advanced systems that can detect diseases at a pre-symptomatic stage, which would allow for more timely interventions [26].

2.2 GAP Analysis

Goals, Actual and Performance (GAP) analysis is a strategic tool used to identify discrepancies between the current state and desired outcomes in various domains such as business processes, project management, and organizational performance. It involves assessing the difference between where an organization or process currently stands and the objectives or standards it aims to achieve. This method provides actionable insights by pinpointing areas of inefficiency, underperformance, or unmet goals, facilitating targeted strategies to bridge these gaps [27]. In project management, for instance, gap analysis is utilized to evaluate the alignment between resource allocation and project goals, ensuring optimal performance [28]. Additionally, in digital transformation initiatives, gap analysis serves as a critical mechanism to transition organizations from their current state to their optimal digitalized future [29].

Current machine learning models, including deep learning approaches, often need help with high accuracy when applied to diverse agricultural environments outside of controlled experimental settings. Dwivedi et al. (2021) noted that while various disease classification methodologies show promise, there is a significant variation in performance across different crops and disease types, indicating a gap in the generalization capabilities of these models [30].

The early detection of plant diseases is critical for effective management and control. However, many existing machine learning techniques are only effective at recognizing diseases once visible symptoms appear [31]. Pandey et al. (2023) discuss the need for models to detect diseases at a pre-symptomatic stage to prevent spread and reduce crop losses [32].

The scalability of machine learning models in diverse agricultural settings remains challenging [33]. Most models are developed and validated in small-scale studies or specific regions, and they often need to perform better when scaled up to national or global levels. Chaschatzis et al. (2021) highlight the challenges associated with deploying these models in different agricultural contexts, where variations in climate, crop types, and farming practices can affect model performance [34]. There is also a gap in integrating machine-learning technologies with current farming practices [35]. Many farmers need more technical expertise to implement sophisticated machine-learning solutions. This disconnect between technological advancements and practical, on-the-ground applications must be addressed to make smart agriculture tools more accessible and beneficial to the broader farming community.

Our research aims to address these challenges by introducing an advanced machine learning model based on the YOLOv8 algorithm, specifically designed to enhance accuracy and generalization in identifying Katokkon chili peppers. This model enables the early detection of fruit diseases, even before visible symptoms appear, paving the way for faster and more effective management.

2.3 Data Processing and Model Training

At the data collection stage, images of Katokkon chili peppers were gathered from various chili cultivation farms. This data includes chili peppers in various conditions, such as ripe, semi-ripe, young, with black spots, and without spots. This data serves as the foundation for training the model. Once the samples have been collected, a selection process is conducted to choose high-quality and relevant images for the training process. The selected images must be of adequate quality so that the model can recognize the features of the chili peppers more accurately, such as good lighting. In Fig. 1 below, an example sample image of Katokkon chili is shown.

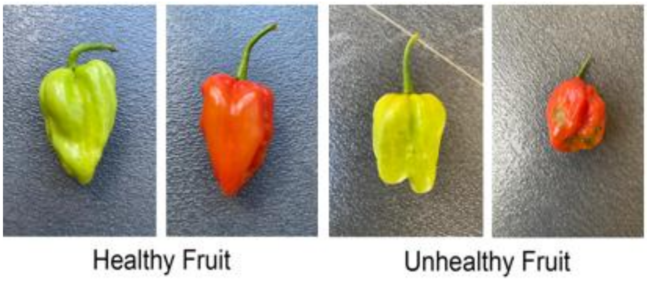

Figure 1 Chili pepper samples

The data processing and model training process in this study involves several essential stages, starting from data collection to model evaluation shown in Fig.2. The following flowchart illustrates the steps taken to prepare and train the deep learning model for classifying the health status of Katokkon chili peppers. These stages include image selection, data splitting, image annotation, as well as model training and testing.

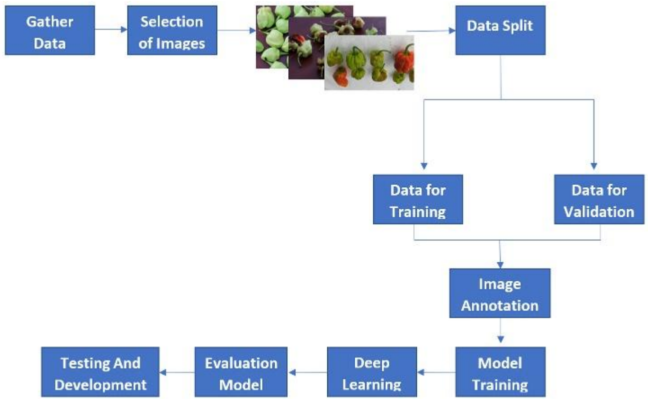

Figure 2 Stages of model training and validation process

After the data is collected, it is divided into several subsets, usually for training and validation. This division aims to allow the model to be tested on data that is different from the training data, enabling a more objective assessment of the model's performance. This subset of data is specifically prepared for model validation. Validation helps evaluate the model's ability to recognize patterns on new data that were not used during training, providing a more realistic view of the model's capabilities. During the training phase, the model is trained using the prepared data to recognize patterns

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relevant to classification, such as the presence of spots indicating that the chili is in an unhealthy condition.

Next, each image is labeled or annotated as 'healthy' and 'unhealthy' to ensure the model has the necessary contextual information. This annotation is essential for improving the model's accuracy in classifying chili images. The training data is the most significant subset used for training the model. Through the training data, the model learns to recognize patterns and key characteristics of chili more optimally. In the deep learning phase, algorithms are applied to learn complex features from the data. Deep learning enables the model to capture more intricate patterns that are not easily recognized by simpler algorithms. After training, the model is evaluated using validation data to measure its performance.

2.4 Dataset Description

The dataset used in this research were manually captured in the field using a high-resolution camera to document both healthy and diseased fruits. The dataset consists of 200 images of Katokkon chilies, with 100 images of healthy fruits and 100 images of fruits infected with fruit rot disease caused by fruit flies. Each image is categorized based on its health status for the labelling process.

The collected images have an original resolution of 1920x1080 pixels and are stored in JPEG format. For the YOLOv8 model processing, these images were resized to 640x640 pixels. Each image in the dataset was manually labelled based on visual observation. The images were classified as 'healthy' or 'diseased' with specific markers such as dark spots indicating fruit discoloration same as Fig. 3.

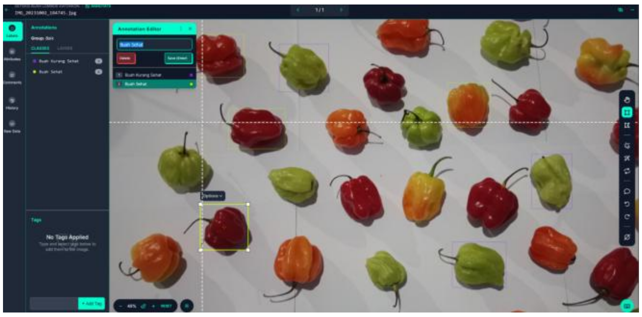

Figure 3 Labelled images

The dataset was divided into two parts, with 80% of the images used for training the YOLOv8 model, while the remaining 20% was used for testing and validation. This split was done randomly to ensure an even distribution between healthy and diseased fruits. To increase data variation and avoid overfitting, data augmentation was applied to the training dataset. Augmentation techniques included image rotation up to 90 degrees, horizontal flipping, and lighting adjustments to simulate different field conditions.

One of the main challenges in this dataset is the variation in lighting conditions in the field, which can affect image quality, as well as some images taken from a distance where disease details are not clearly visible.

2.5 YOLO Algorithm

The YOLO algorithm is a state-of-the-art machine learning model for object detection that is both fast and accurate [15][36][37]. It has been widely adopted in various applications, from computer vision to real-time object tracking due to its ability to process images in real-time with high accuracy.

YOLO frames object detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities. This unique approach allows it to predict multiple bounding boxes and class probabilities for those boxes simultaneously. This makes YOLO exceptionally fast, as it only requires a single forward pass through the neural network to make predictions, unlike other detection systems where a separate network is run on each image region [38][39].

YOLO has undergone several iterations, each improving upon the previous. YOLOv3 and YOLOv4 have been particularly noted for their balance of speed and accuracy, incorporating features like multi-scale predictions, which allow them to detect objects at different sizes more effectively[40][8]. YOLOv5, the latest version, has continued this trend, offering further optimizations and speed improvements while reducing the complexity and size of the model, making it even more efficient for real-time applications [10] [41].

Recent adaptations have focused on improving YOLO's accuracy and speed further. Modifications include integrating attention mechanisms and better feature extraction techniques, such as the use of convolutional block attention modules (CBAM) to enhance the model's focus on relevant features of an image. These improvements help in reducing false positives and increasing the precision of the detection [33] [42].

YOLO's capability to perform real-time object detection makes it ideal for applications requiring rapid and accurate object detection such as in autonomous vehicles, surveillance systems, and various forms of automated monitoring and inspection systems. Its efficiency and speed have made it a popular choice in scenarios where computational resources are limited but high performance is required [43] [44].

YOLO is an advanced machine learning algorithm for object detection, designed for high speed and accuracy [45][46]. YOLO treats object detection as a single regression problem, predicting bounding box coordinates and class probabilities directly from the image [47]. Unlike traditional approaches that divide the image into several parts, YOLO processes the entire image at once in a single pass through the neural network, making it much faster and more efficient[9]. YOLO simultaneously generates bounding boxes and class predictions, enabling rapid object detection.

This study uses YOLOv8, the latest version of the algorithm. YOLOv8 includes several improvements, such as multi-scale prediction and a more efficient model size, making it highly suitable for real-time object detection applications with limited computing resources. The YOLO algorithm was chosen for its ability to perform real-time object detection with high accuracy, along with computational efficiency that allows it to be deployed on hardware with limited resources. Features like attention mechanisms in YOLOv8 also enhance detection accuracy[12].

In the context of agriculture, YOLO is highly suitable for automatically detecting and classifying healthy and diseased chilies. This algorithm can process plant images in real-time, providing quick detection results so interventions can be made immediately to prevent disease spread.

Although YOLO has exceptional speed, the algorithm sometimes struggles to detect very small objects. However, features like multi-scale prediction in YOLOv8 have helped reduce this issue.

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3. Results and Discussion

The objective of this study was to apply the YOLOv8 algorithm for the detection and classification of Katokkon Toraja chili peppers into two categories: healthy fruit and unhealthy fruit. The dataset consisted of 200 images, equally divided between the two classes. The images were preprocessed to a resolution of 640x640 pixels to align with the YOLOv8 model's input specifications.

3.1 Model Performance

The training process was conducted over 50 epochs using a batch size of 16. The model summary indicated that YOLOv8 achieved moderate performance with an overall classification accuracy of approximately 70%. The confusion matrix analysis shown in Fig. 4 revealed that the model struggled to distinguish between the two categories, especially in cases where the visual symptoms of unhealthy chilies were not pronounced. The confusion matrix shows 22 true positives for “healthy fruit", 2 misclassifications where "healthy fruit" was predicted as "unhealthy fruit", 2 misclassifications where "unhealthy fruit" was predicted as "healthy fruit."

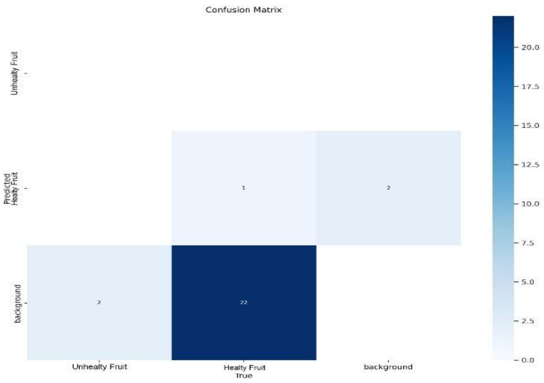

Figure 4 Confusion matrix

3.2 Precision and Recall

As shown in the precision-confidence curve (Fig. 5), the model's precision fluctuated significantly across various confidence thresholds, reaching a maximum precision of 39.9% at specific levels. Despite this achievement, the precision remained inconsistent, highlighting challenges in accurately detecting unhealthy chilies. These issues may stem from overlapping features between classes, insufficient training data, or suboptimal feature extraction techniques used during the classification process. Addressing these limitations could improve the model's precision, stability, and overall classification performance.

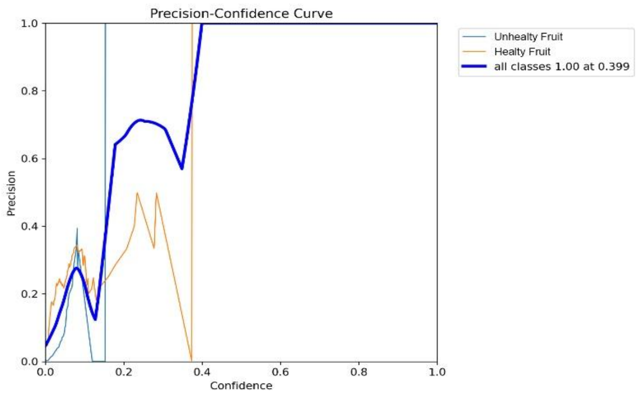

Figure 5 Precision and confidence curve

The F1-confidence curve (Fig.6) shows the model's potential in classifying the "Healthy Fruit" and "Unhealthy Fruit" categories at lower confidence levels. With an F1-score reaching 0.35 at a confidence of 0.075, the model still demonstrates positive results in capturing consistent prediction patterns. The model's performance appears more stable at confidence levels below 0.1, indicating a solid foundation that can be further improved. Enhancing the data or model parameters has significant potential to improve accuracy, consistency, and overall performance.

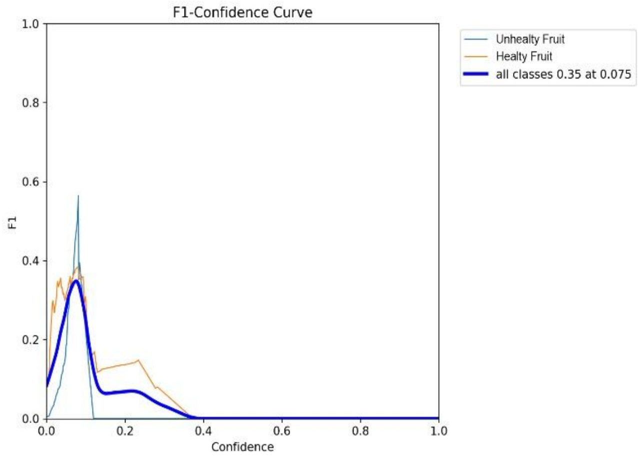

Figure 6 F1-Confidence curve

3.3 Training and Validation Loss

The training loss curves (Fig. 7) show that the model's classification loss and box regression loss steadily decreased throughout the training process, indicating that the model was effectively learning the patterns in the training data. However, the relatively high validation loss suggests potential overfitting, meaning the model struggled to generalize to unseen data. This underscores the importance of adopting strategies such as data augmentation, regularization techniques, or expanding the dataset to improve the model's robustness, accuracy, and overall performance across diverse and real scenarios.

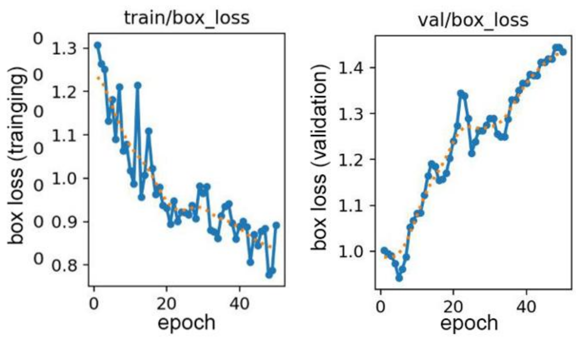

Figure 7 Training and validation loss

3.4 Performance Evaluation

The evaluation metrics (Fig. 8) showed that the mean Average Precision at an Intersection over Union (IoU) threshold of 50% (mAP50) was around 0.28, while the mAP50-95 was significantly lower, averaging 0.15.

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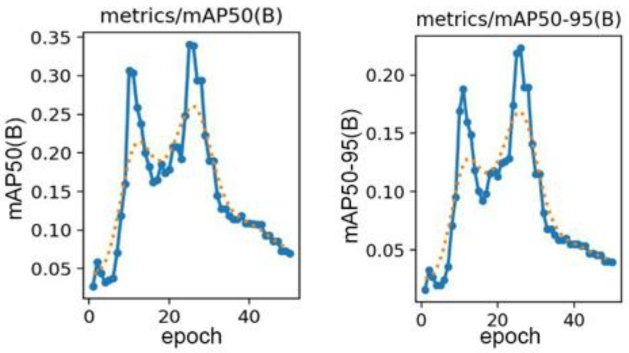

Figure 8 Performance evaluation

These results indicate that the model's ability to generalize across different IoU thresholds remains limited.

The research results indicate that the YOLOv8 algorithm has the potential for real-time detection of the health status of Katokkon Toraja chili peppers. This local chili variety from the Toraja region has been rarely studied, particularly in terms of image processing for its fruits. Although the current implementation has not achieved a high accuracy level (around 81.48%), this result significantly outperforms previous studies. For example, a study by M. Abdul Aziz et al. [48] achieved an accuracy of 80% using Artificial Neural Networks (ANN) for chili sorting, while another study by Song Zhang and Mingshan Xie [49] using an improved YOLOv5s model for clustered chili recognition reported an accuracy of 80.18%. This demonstrates that the YOLOv8 algorithm not only shows better accuracy than these earlier implementations but also provides enhanced potential for future optimization and real-time applications, particularly for this under-researched chili variety. The model's performance can be improved in future studies research in the following ways.

1. **Enhancing Dataset Quality:** Utilizing a larger and more diverse dataset can significantly improve the model's accuracy and generalization capabilities. Data that includes variations in lighting, angles, and other visual conditions will help the model classify more reliably. Data augmentation techniques such as rotation, scaling, and color adjustments can also increase dataset diversity [50].
2. **Incorporating Attention Mechanisms:** Integrating attention mechanisms into the network can help the model focus on key areas in the images, improving its ability to detect finer details. This has been demonstrated to enhance detection precision in YOLO applications, particularly for agricultural environments [51].
3. **Optimizing Model Architecture:** Modifying YOLOv8 to include lightweight and efficient modules such as DenseNet or SE-CSPGhostnet can improve feature extraction and small object detection. These adjustments have shown significant accuracy improvements in agricultural detection tasks [52].
4. **Using More Optimal Loss Functions:** Adopting loss functions like Generalized Intersection Over Union (GIoU) or Scylla IoU has proven to enhance detection accuracy and bounding box quality. These functions improve YOLO performance in various object detection tasks by refining bounding box regression methods [53].
5. **Implementing Edge Computing Technology:** Edge computing can optimize real-time image processing for detection tasks in agriculture. Devices like Raspberry Pi combined with lightweight models, as demonstrated in smart farming applications, can lower computational demands and costs [54].

4. Conclusion

This study explored the application of the YOLOv8 algorithm for detecting and classifying Katokkon Toraja chili peppers' health status. Despite the challenges posed by limited dataset size and varying field conditions, the results demonstrate that YOLOv8 has the potential to automate disease detection with moderate accuracy. The model achieved an overall classification accuracy of approximately 81.48%, with notable difficulties in distinguishing between healthy and diseased chilies, particularly under conditions with complex visual variations.

The findings of this study underline the importance of leveraging AI-based solutions in smart agriculture, particularly for crops with significant economic value, like Katokkon chili. By improving early disease detection, such systems could help farmers reduce crop losses and ensure sustainable agricultural productivity.

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