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Detection of Diseases and Dry Leaves in Corn Plants Using YOLOv8

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Abstract

Corn plants can grow well in areas with hot or tropical climates, as long as there is adequate rainfall and a sufficient irrigation system. Corn is a strategic agricultural commodity that plays an important role in the economy, both on a national and global scale. This crop is widely used as a primary food source, animal feed, and raw material for various industrial purposes[1]. According to data from the official website satudata.pertanian.go.id, the projected corn production in Indonesia from 2020 to 2024 is expected to experience a steady annual increase, ranging from 0.94% to 0.97% [1]. However, throughout its life cycle from seed to seed, each part of the corn plant is vulnerable to various diseases, which can reduce both the quantity and quality of the yield. Therefore, disease problems are one of the key factors hindering production and seed quality. This study implements YOLOv8 technology to identify types of diseases and pests in corn plants as a form of innovation in the application of artificial intelligence in the agricultural sector, particularly in efforts to improve the efficiency of corn plant health monitoring. The dataset used in this study consists of four classes of corn leaf images: leaf blight, downy mildew, rust, and healthy plants, with a total of 1,162 images. The dataset was collected at the same time using a POVA Pro5 smartphone. The training and evaluation results of the model show that the use of YOLOv8 with a Spatial Pyramid Pooling architecture provides fairly good performance in detecting diseases and pests in corn plants. Using a batch size of 32 and 64 epochs, the model achieved a precision of 0.67, a recall of 0.78, an F1-score of 0.67, a mAP@0.5 of 0.701, and a mAP@0.5:0.95 of 0.295. Meanwhile, increasing the batch size to 64 and the number of epochs to 100 resulted in improved model performance, with a precision of 0.75, recall of 0.79, F1-score of 0.75, mAP@0.5 of 0.792, and mAP@0.5:0.95 of 0.343. The findings of this study indicate that the implementation of YOLOv8 technology has the potential to make a significant contribution to the development of smart farming systems, particularly in the early detection of disturbances in corn plants in an automated and efficient manner. The availability of accurate information regarding the types of diseases and pests affecting corn plants enables farmer groups to respond quickly and appropriately, for instance, by selecting more targeted pesticides or applying organic control methods that are suitable for field conditions.

Keywords: Detection, Corn Plant, Color Feature Extraction, Texture Feature Extraction, YOLOV8.

1. INTRODUCTION

Corn holds a strategic position as one of the main food commodities in Indonesia, alongside rice and wheat. This commodity is multifunctional, serving as a food source, industrial raw material, and a key component in livestock feed formulation[1]. Given its significant contribution to national food security, the government has consistently implemented various policy interventions to encourage the expansion of corn cultivation areas and increase productivity at the national level.

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Corn plants can grow well in hot or tropical climates, as long as there is adequate rainfall and a sufficient irrigation system. According to data from the official website satudata.pertanian.go.id, the projected corn production in Indonesia from 2020 to 2024 is expected to experience a steady annual increase, ranging from 0.94% to 0.97%. However, throughout its life cycle from seed to seed, each part of the corn plant is vulnerable to various diseases, which can reduce both the quantity and quality of the yield. Disease-related problems are therefore a major constraint in achieving optimal production and seed quality.

This study implements YOLOv8 technology to identify types of diseases and pests in corn plants as a form of innovation in the application of artificial intelligence in agriculture, particularly in enhancing the efficiency of crop health monitoring. The dataset used consists of four classes of corn leaf images: leaf blight, downy mildew, rust, and healthy plants, totaling 1,162 images. All images were collected simultaneously using a POVA Pro5 smartphone.

Model training and evaluation were conducted using YOLOv8 with a Spatial Pyramid Pooling architecture. The initial training configuration used a batch size of 32 and 64 epochs, yielding a precision of 0.67, recall of 0.78, F1-score of 0.67, mAP@0.5 of 0.701, and mAP@0.5:0.95 of 0.295. Subsequently, the batch size was increased to 64 and epochs to 100, resulting in improved performance: a precision of 0.75, recall of 0.79, F1-score of 0.75, mAP@0.5 of 0.792, and mAP@0.5:0.95 of 0.343.

The results show that YOLOv8 demonstrates promising performance in detecting diseases and pests in corn plants. The improvements seen with larger batch sizes and more training epochs suggest that the model benefits from extended learning and data exposure. This supports the feasibility of applying YOLOv8 in practical agricultural scenarios, particularly in areas with limited access to expert plant pathologists.

The availability of accurate and timely information on the types of diseases and pests attacking corn plants enables farmers to take prompt and appropriate actions. This could include the targeted selection of pesticides or the adoption of suitable organic control methods, improving the responsiveness and sustainability of agricultural practices.

The findings of this study indicate that the implementation of YOLOv8 has significant potential in supporting the development of smart farming systems in Indonesia. Its ability to automatically and efficiently detect plant health issues can help improve productivity and reduce crop losses. Future research could focus on expanding the dataset and exploring real-time deployment in the field to further validate and enhance system performance.

Corn is an agricultural commodity that arguably holds the most strategic role in supporting food security and the economy, both globally and nationally. Di Indonesia, jagung menempati posisi penting setelah padi, karena tidak hanya dimanfaatkan sebagai bahan pangan pokok, tetapi juga sebagai bahan utama untuk pakan ternak dan bahan baku dalam berbagai industri, seperti makanan, minuman, dan bioenergi. The demand for corn continues to rise along with population growth, the development of . processing industries, and the needs of the livestock sector. Therefore, the development of the corn subsector has become a key focus in national agricultural policies to enhance food security and economic stability[2]. According to data from the Satu Data Pertanian website (satu-data.pertanian.go.id), the projected corn production in Indonesia from 2020 to 2024 is expected to experience a steady annual increase, ranging from 0.94% to 0.97%. This projection reflects a positive trend in the development of the corn commodity and indicates the potential for continued productivity improvements through policy interventions, technological innovations, and the expansion of cultivated areas[1].

The increasing demand for corn consumption each year presents both opportunities and challenges for the agricultural sector to meet this demand sustainably. In this context, the quality of corn plant growth becomes a key factor influencing the volume of production that can be achieved. Optimal plant growth directly contributes to increased productivity and harvest quality, making it an important indicator in efforts to improve the efficiency and effectiveness of corn cultivation[3]. If the growth of corn plants does not reach optimal conditions, there is a high likelihood that the resulting production will decrease significantly, and there is even a risk of crop failure. This indicates that the quality of plant growth plays a crucial role in ensuring the overall success of corn production.

Monitoring corn plant growth can be conducted through the identification of pests and diseases, which forms the basis for taking preventive measures to minimize the risk of reduced harvest yields or crop failure. This identification can be carried out by utilizing pattern recognition techniques on images that represent the symptoms of pests and diseases on corn plants. In recent years, various technologies have been developed to support the automatic monitoring of plant growth, one of which is Computer Vision technology that integrates the YOLOv8 (You Only Look Once) method based on Supervised Learning with a Spatial Pyramid Pooling (SPP) architecture to efficiently and accurately detect and classify objects.

YOLOv8 (You Only Look Once version 8) is one of the latest object detection models developed by Ultralytics and released in January 2023. This model is an improvement over previous versions of YOLO, with various enhancements in efficiency, accuracy, and ease of integration into various image processing systems. YOLOv8 features an anchor-free architecture, meaning it no longer relies on anchor boxes like previous versions, thus speeding up the training and inference processes. In general, the YOLOv8 architecture consists of three main components, namely:

1. Backbone

This component is responsible for extracting features from the input image. YOLOv8 uses an optimized CSPDarknet architecture, combined with an SPP (Spatial Pyramid Pooling) module, which functions to capture spatial information from objects at various scales. SPP allows the network to combine features from different receptive field sizes, thereby enhancing the model's ability to detect objects with varying sizes.

2. Neck

The Neck component is responsible for merging features from various depth levels through Feature Pyramid Networks (FPN) or Path Aggregation Networks (PaNet), enabling multi-scale detection. This is particularly important in the context of agriculture, where symptoms of diseases or pests can appear in a variety of sizes and shapes.

3. Head

The Head component of YOLOv8 is responsible for making the final predictions, including generating bounding boxes, confidence scores, and object classifications. The anchor-free architecture simplifies and speeds up the prediction process, eliminating the need for anchor matching calculations as in previous versions.

In addition, YOLOv8 supports export to various model formats (ONNX, TensorRT, CoreML, and others), making it easy to integrate into edge devices or IoT-based systems for field implementation[5]. Computer Vision is a branch of Artificial Intelligence (AI) technology that focuses on the analysis of digital images through image processing and object recognition in images. One of the algorithms widely used in this field is YOLOv8 (You Only Look Once version 8), which is capable of performing real-time object detection with high efficiency. This algorithm is typically trained using a Supervised Learning approach, a machine learning method that relies on labeled input data to build a model capable of producing appropriate output when faced with new, unlabeled data. In the process, the algorithm learns patterns and relationships between variables based on examples of data that have been previously labeled by humans[6]. The labeled data can be used to train machine learning models to detect and classify specific objects, such as types of pests and diseases affecting corn plants.

The application of Computer Vision technology using the YOLOv8 algorithm has been widely implemented across various sectors, including agriculture. One example is in plant disease detection systems through leaf analysis, where YOLOv8 successfully classified up to 15 types of diseases with an accuracy rate of 97.36%. This achievement demonstrates the great potential of this technology in supporting early identification and efficient management of plant diseases. The second study, which detected rice types with 12 samples, achieved an accuracy of 100%[7]. The next study using object detection technology was conducted to identify the presence of weeds by collecting a dataset of 374 RGB images, with four training datasets. The results of this study showed a relatively high accuracy, with an average precision (AP) score of 91.48% and 86.13% at an Intersection over Union (IoU) threshold of 25% (AP@0.25), and 63.37% and 45.13% at an IoU threshold of 50% (AP@0.5). Meanwhile, another study implementing YOLOv8 version 5 Plus to detect pork in the context of artificial intelligence development in the livestock sector achieved an accuracy of 0.989, with a recall value of 0.996, MAP@0.50 of 0.994, and MAP@0.50:0.95 of 0.796. The detection process in this study also demonstrated good time efficiency with an inference time of 24.1 milliseconds per image[8].

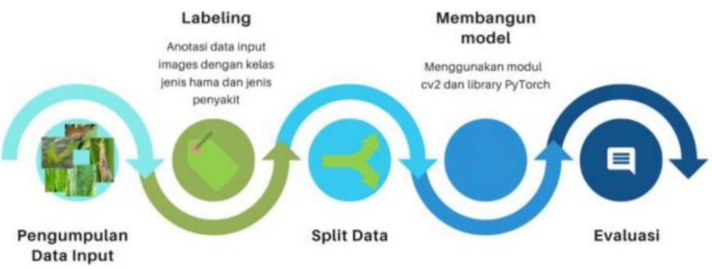
This study examines the application of YOLOv8 technology to detect pests and diseases in corn plants as part of artificial intelligence innovation in agriculture. YOLOv8 is an object detection algorithm that has undergone continuous development from its previous versions since it was first introduced in 2016, with significant improvements in performance, efficiency, and accuracy. In the context of this study, the implementation of YOLOv8 is aimed at supporting a more effective disease detection system and monitoring the growth of corn plants. The main goal is to improve efficiency and productivity in the corn cultivation process, as well as provide innovative technological solutions to better understand plant growth dynamics and develop more accurate maintenance strategies. Thus, the use of YOLOv8 in this detection system holds great potential to optimize production yields, reduce operational costs, and minimize reliance on manual monitoring.

Based on previous research results, this study develops a disease detection system for corn plants using the YOLOv8 algorithm. The classification process in this system is carried out using a corn leaf image dataset obtained directly from the BUMDes Randurejo Corn Farm. The dataset is categorized into four classes: leaf spots, leaf blight, leaf rust, and healthy leaves, each representing the health condition of the corn plants.

The automatic detection system developed in this study is expected to support the increase of productivity in the agricultural sector. Through accurate early detection, farmers can promptly take preventive or corrective measures, thus enhancing the potential for higher crop yields and better corn quality. The application of the YOLOv8 algorithm model in detecting diseases and dry leaf symptoms in corn plants demonstrates significant potential in addressing various challenges in the agricultural sector. The development of this artificial intelligence-based detection system can also be regarded as an effective, efficient, and accessible solution, especially for farmers in dealing with the risks of disease outbreaks and plant conditions that could potentially lead to crop failure[9].

2. RESEARCH METHODOLOGY

The research steps begin with the data collection phase, which includes several types of diseases and pests affecting corn plants. The next step is the data labeling process through annotation, followed by the division of data for training, testing, and validation, model development, model training, and data detection. The research steps are carried out as shown in Picture 1.



Gambar 1. Metode Penelitian

Corn (Zea mays L.) is an annual plant that completes its life cycle within a period of 80 to 150 days, depending on the variety and the environmental conditions where it grows[15]. The life cycle of corn plants is divided into two main phases: the vegetative phase in the first half and the generative phase in the second half. During the vegetative phase, the plant experiences the growth of organs such as leaves, stems, and roots, while the generative phase is marked by the formation of flowers and seed development. The height of corn plants varies greatly, depending on the variety used, environmental conditions, and the cultivation techniques applied[16]. Although the height of corn plants generally ranges from 1 to 3 meters, there are certain varieties that can grow up to a height of 6 meters.

The measurement of corn plant height is typically taken from the soil surface to the highest node located just below the male flower (tassel)[18]. Although certain varieties are capable of producing tillers, corn plants, in general, do not

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have the ability to form tillers like some other plant species[19]. A variety of corn varieties are known and cultivated in Indonesia, including Abimanyu, Arjuna, Bromo, Bastar Kuning, Bima, Genjah Kertas, Harapan, Harapan Baru, Hybrid C1 (Cargill Hybrid 1), Hybrid IPB 4, Kalingga, Kania Putih, Malin, Metro, Nakula, Pandu, Parikesit, Permadi, Sadewa, Wiyasa, and Bogor Composite-2. Each variety has specific characteristics tailored to certain agroecosystem conditions and cultivation purposes, whether for consumption, livestock feed, or industrial needs[20].

Diseases in corn plants result from a complex interaction between three main components: pathogens, the host (the corn plant itself), and the environment. The occurrence of disease epidemics, characterized by an increase in intensity and widespread disease spread, largely depends on the contribution of each of these components. When these three factors support each other, the risk of an epidemic increases, ultimately leading to a significant decrease in production yields[21].

This study will focus on four categories of corn plant leaf conditions: leaf spots (leaf blight), leaf blight, leaf rust, and healthy leaves as a comparison. These four categories were chosen because they represent common types of leaf diseases found in corn cultivation and have a significant impact on plant productivity.

2.1 Data Collection Process

The data used in this study consists of corn leaf images with types of pests or diseases affecting corn plants, with a total of 1162 image data in JPG format. These images were obtained directly using a Techno Pova 5 Pro smartphone under consistent lighting conditions and at the same time. The dataset consists of 1162 images with four classes of corn leaf images: leaf spots, leaf blight, leaf rust, and healthy plants. This dataset was created for the purpose of identifying the types of diseases present in corn plants, in line with the goals of this study. Samples of healthy and infected corn leaf images can be seen in Picture 2.

Gambar 2. Contoh daun jagung sehat dan daun jagung terinfeksi

2.2 Labeling Process

The data labeling process in this study was conducted using the Roboflow platform, by annotating objects in the images according to the predefined classes. Roboflow is a framework in the field of Computer Vision that functions to manage datasets systematically, including the collection of high-quality data before entering the preprocessing and model training stages. This platform supports efficiency in creating accurate and standardized labeled datasets, thereby improving the performance of the developed detection model[10].

The class labels in the dataset represent the categories of corn plant leaf conditions, which include leaf spots, leaf blight, leaf rust, and healthy condition. The annotation process resulted in 1,162 label files in JSON format. Each annotation file contains the coordinates of the corner points of a rectangular bounding box that indicates the location of the object according to the class assigned to each image.

2.3 Data Splitting Proces

The data splitting process is the stage of dividing the input data into several subsets for the purpose of model training and evaluation. In this study, the dataset was divided into three parts: 70% for training data, 20% for validation data, and 10% for testing data. The data splitting was performed using the train_test_split function. Before being input into the model, the images were converted into numerical representations in the form of arrays to be processed by the machine learning algorithm. Next, a normalization process was applied to the images by scaling the pixel values to a range between 0 and 1. This step aims to enhance processing efficiency, accelerate convergence during model training, and aid in more stable feature learning[11].

2.4 Pembangunan Model

The model development in this study utilizes the YOLOv8 architecture, which is equipped with the Spatial Pyramid Pooling (SPP) component. The use of SPP aims to enhance feature extraction capabilities at multiple scales, thereby supporting more accurate object detection performance. YOLOv8 itself is the latest version of the YOLO (You Only Look Once) algorithm series, officially released on January 10, 2023, with various improvements in efficiency, inference speed, and accuracy compared to its previous versions[12]. In the YOLOv8 architecture, the backbone network is equipped with a Spatial Pyramid Pooling (SPP) module, which functions to extract and aggregate features from images at various convolutional layer levels. SPP enables the model to capture spatial information at multiple scales, which is crucial in detecting objects of varying sizes.

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The development of the disease and pest detection model for corn plants in this study was carried out using the Python programming language. To support image processing and model training for object detection, several libraries and modules were used, including OpenCV (cv2) as a computer vision library, as well as PyTorch and utils as machine learning frameworks.

The entire model training and testing process was carried out in the Google Colaboratory environment. The use of a Graphics Processing Unit (GPU)-based runtime was chosen to accelerate computational processes, particularly in training the YOLOv8 network, which requires high processing power. The use of a GPU also enables training to be conducted more efficiently, both in terms of time and modeling performance.

2.5 Proses Pengujian Dan Evaluasi

The model's performance evaluation was conducted using several key testing metrics, namely precision, recall, F1-score, and mean Average Precision (mAP), which serve as primary indicators for assessing the accuracy and effectiveness of the detection model. Additionally, loss and accuracy values were also calculated to monitor the model training process and identify the level of prediction error. The combination of these metrics provides a comprehensive overview of the model's performance in accurately detecting and classifying objects[13]. The loss value is used to measure how well the model learns during the training process, with the goal of minimizing prediction errors to maximize the performance of the algorithm's architecture. Meanwhile, the accuracy metric is used to evaluate the precision of the model's predictions on the test data. This evaluation was conducted on the performance of the model built using the OpenCV library and YOLOv8 technology in detecting and classifying objects in images[14].

After the model is trained, the prediction stage is carried out using YOLOv8 technology. During the detection process, YOLOv8 divides the input image into an S × S grid. Each grid cell is responsible for predicting B bounding boxes along with a confidence score indicating the likelihood of an object being present in the box, as well as C conditional class probabilities for each object category. The loss function in YOLOv8 calculates the difference between the predicted and actual values based on errors in position, width, height, and confidence of the bounding box, using the mean square error (MSE) method as a measure of total error [21]. The model evaluation equations are as follows:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$recall = \frac{TP}{TP + FP} \tag{2}$$

$$F1\ score = 2x\frac{PxR}{P + R} \tag{3}$$

$$\frac{confidence = \Pr(class_i|object)x\Pr(object)xIOU\frac{truth}{pred}}{\Pr(object)€\{0,1\}} \tag{4}$$

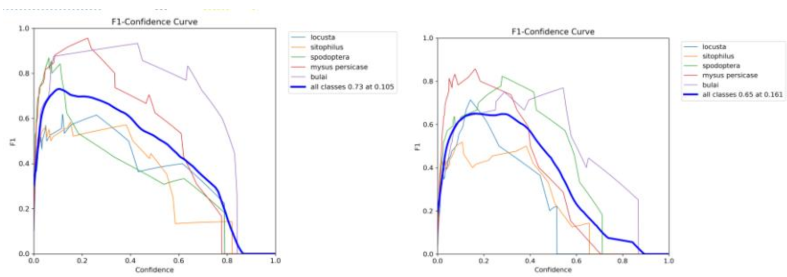
3. RESULT AND DISCUSSION

The input dataset consists of image data trained using an object detection model through the Google Colaboratory platform. This training process involves the model recognizing patterns from the input data, with data division based on specific batch size and epoch parameters. The training results from each model configuration are presented in Table 1, which shows the performance of the YOLOv8 model in detecting types of diseases and pests in corn plants.

Table 1. Model Using YOLOv8.

batch size	epoch	MAP 0,5:0,95	MAP 0,5	F1-score	recall	presisi
32	60	0,295	0,701	0,67	0,78	0,67
64	100	0,343	0,792	0,75	0,79	0,75

Based on Table 1, the F1-score values for the batch size configurations of 32 and 64 reached 0.67 and 0.75, respectively. The visualization of the prediction results for both configurations can be seen in Picture 3.



(a) (b)

Picture 3. Result Values

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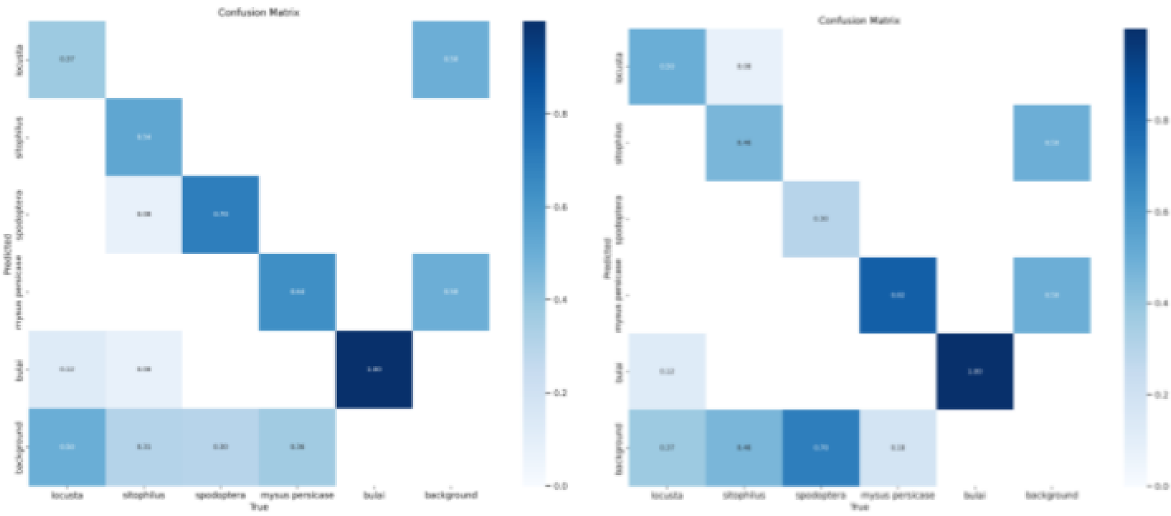
Based on Table 1, the model was trained using 167 images as training data. In the first configuration, the model was trained with a batch size of 32 and 60 epochs, resulting in an accuracy of 72%. Meanwhile, in the second configuration with a batch size of 64 and 100 epochs, the accuracy increased to 79%. The visualization of the model's prediction results for the batch size configurations of 32 and 64 is presented in Figure 4 to provide a comparative overview of the detection performance between the two parameter settings.

Picture 4. Model Using YOLOv8

Based on the model predictions shown in Figure 3, the model's performance evaluation is presented using a confusion matrix. In the first row of the evaluation table, the model trained with a batch size of 32 and 60 epochs shows the prediction results as seen in Figure 3(a), where several images were not accurately predicted by the model. Meanwhile, in the configuration with a batch size of 64 and 100 epochs, as shown in Figure 3(b), the model demonstrated better performance in classifying images according to the predefined labels. The true predictions and false predictions were obtained through analysis of the confusion matrix, as illustrated in Picture 5.



Picture 5. Confusion Matrix Results

4. CONCLUSION

The training and evaluation results indicate that the implementation of YOLOv8 technology, supported by the Spatial Pyramid Pooling architecture, has significant potential to improve productivity and harvest success. This is demonstrated by its ability to accurately identify symptoms of diseases and pests in corn plants, thereby enabling faster and more targeted control actions. The predictions generated by the YOLOv8-based model not only contribute to accurate detection but also support the implementation of smart agriculture.The information provided by this system enables farmers to respond quickly and accurately, such as by applying the appropriate pesticides and using relevant organic control methods. Furthermore, early detection of diseases and pest attacks allows farmers to take preventive actions, thereby minimizing crop loss and overall improving agricultural productivity.

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