SMART FARMING EVOLUTION ABNORMAL BANANA CROP DETECTION AND FINE IMAGE COLLECTION THROUGH PATH OPTIMIZATION

A PROJECT REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

Agriculture, the backbone of civilization, is evolving through technology to ensure sustainable food production, yet it faces reduced crop yields due to emerging diseases that affect banana crops. A deep learning-based methodology is proposed to automate the detection of diseases. Traditional image acquisition methods often suffer from low-value data that limits their effectiveness in disease detection. The absence of optimal path planning for fine image collection further hinders the precision and efficiency of disease identification.

This project proposes a method that employs the YOLO-FDAC target detection model to identify affected areas in banana crops from high-resolution images captured by static nodes. Coordination points are identified to accurately locate abnormal crops in affected areas, and the degree of abnormality is quantified to evaluate the severity of affected regions.The severity information is then used in the path optimization algorithm for image acquisition.

Once affected areas are detected, a robot path planning algorithm is utilized to navigate to these regions and capture fine-grained images of each banana leaf. Ant Colony Optimization (ACO) is employed to further enhance the robot's path planning by prioritizing the most critical abnormal areas for image capture, ensuring optimal path. As the robot navigates through the fields, it can adjust its path based on newly detected abnormalities, ensuring the most efficient use of resources and time.

Additionally, the integration of real-time data processing allows for dynamic decision-making and adaptability within the system. The adaptability helps optimize the disease detection process while minimizing crop damage making the system highly effective for large scale agricultural environments.

ABSTRACT TAMIL

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LIST OF ABBREVIATIONS

YOLO	You look only once
ACO	Ant Colony Optimization
ELAN-GS	Convolution module
CADI	Cooperative Autonomous Data Integration
IVAD	Intelligent Visual Attention Dynamics
IHO	Improved Heuristic Path Optimization

CHAPTER 1

INTRODUCTION

The global production of banana tree plays a vital role in agriculture with a critical source of nutrition and economic stability. In recent years, advances in image processing, deep learning, and mobile technology have opened up new avenues for disease detection. However, banana crops are highly vulnerable to various diseases, notably Banana black Sigatoka, Yellow Sigatoka, Pest disease, Bract mosaic virus, Moko disease, and Panama disease, all of which pose significant risks to both productivity and sustainability. This became challenge particularly for larger agricultural holdings due to the laborious and time-consuming nature of manual monitoring. These diseases can severely impact crop yield and quality. It essential for farmers to implement timely and effective management strategies.

Anomaly crop detection using edge intelligence and dynamic-static synergy represents a transformative approach in smart agriculture designed to identify and address abnormal crop conditions with precision and efficiency. This system combines advanced technologies to detect deviations in crop health caused by diseases, pests, or environmental stress. Static monitoring devices such as stationary cameras provide a continuous and comprehensive overview of the field capturing data on crop appearance and condition. The edge intelligence component equipped with powerful models like YOLOv7-FDAC processes these images locally to quickly identify anomalies such as discoloration unusual growth patterns or pest damage. By analyzing these indicators in real time the system ensures that abnormalities are detected at an early stage reducing the risks of widespread crop failure.

The dynamic-static synergy comes into play when the system integrates mobile devices like drones or robots with static sensors to enhance precision. Once an anomaly is detected dynamic units are dispatched to the affected areas to capture detailed data or administer localized treatments. This collaborative approach between static and mobile systems allows for both wide coverage and focused ensuring that resources are utilized efficiently. The synergy of these elements not only reduces the latency and costs associated with cloud-based solutions but also improves the overall value of agricultural data. Together these technologies enable farmers to adopt proactive crop management strategies promoting healthier yields and sustainable farming practices. Mobile robots complement the system by capturing high-resolution images of inaccessible areas, further enhancing detection accuracy.

1.1 PROBLEMS RELEVANT TO THE RESEARCH

The existing smart agriculture system struggles with capturing clear and accurate images of plants in challenging environment. These systems often generate large volumes of redundant and low-value data, overwhelming storage and processing capabilities. Stationary cameras frequently fail to provide clear images of abnormal crops in inaccessible areas meanwhile mobile robots tend to capture relevant data by neglecting critical regions of the crops. The absence of real-time detection delays crucial interventions for managing pests and diseases. Furthermore, ineffective path planning results in suboptimal robot routes leading to wasted time and resources on capturing unnecessary images of healthy crops. These issues collectively hinder efficient data acquisition and timely crop health management. Variability in environmental conditions such as lighting and weather makes it harder to capture consistent and usable data. Limited integration of advanced coordination techniques between dynamic and static imaging systems further reduces the overall data acquisition efficiency. As a result, farmers face delays in decision-making ultimately impacting crop yields and increasing the costs associated with pest and disease management.

1.2 RESEARCH OBJECTIVES

- Capture crop images using edge intelligence for real-time analysis and enhanced anomaly detection.
- Enhance image acquisition efficiency by integrating dynamic-static synergy for optimized data capture.
- Find the coordination position of the affected area in the crop to focus image acquisition on critical regions.
- Design and implement an optimized path algorithm for image acquisition robots, ensuring improved movement efficiency and accuracy.
- Find the accurate disease of each plant by analyzing captured images using advanced disease detection algorithms.
- Evaluate and refine the system based on performance metrics focusing on improving both anomaly detection and image acquisition processes.

1.3 OVERVIEW OF THE PROPOSED SYSTEM

Deep learning a powerful subset of artificial intelligence, has proven highly effective in plant disease detection. By utilizing advanced neural network architectures such as Convolutional Neural Networks (CNNs), deep learning models can automatically extract and analyze features from plant images enabling precise identification of diseases. These models are trained on large datasets of labelled plant images learning to distinguish between healthy and diseased crops with remarkable accuracy. In plant disease detection deep learning facilitates early diagnosis by processing high-resolution images to identify signs of abnormalities such as discoloration, spots, or deformities. To effectively manage these issues rapid detection and accurate assessment of disease severity are crucial. Traditionally disease severity was evaluated through manual inspections by experts. However, with the emergence of image processing technology this approach has become a more viable and efficient solution.

In this project, we employ the YOLOv7 model for image acquisition and disease detection. YOLOv7 is a state-of-the-art deep learning model designed for real-time object detection capable of processing images quickly and accurately. By utilizing static cameras or drones equipped with image capturing devices the model captures images of banana crops in various stages of health. A method that utilizes the YOLO-FDAC target detection model to detect affected areas in banana crops by analysing high-resolution images captured through static nodes. The YOLO-FDAC model is specifically designed to identify and classify abnormalities in banana crops. By processing these high quality images the system can accurately locate the areas that require attention enabling timely intervention and efficient management of crop health.

Path planning is an important part of autonomous systems especially in agriculture where robots or drones need to move efficiently through large fields. The main goal of path planning is to find the best route for the robot or drone making sure it avoids obstacles and reaches areas of interest. In this research we use Ant Colony Optimization (ACO) algorithm to guide the robot to the affected areas of banana crops. ACO is inspired by the way ants find food. Ants leave a trail of pheromones as they move and other ants follow these trails to find the quickest path.

Similarly, ACO uses virtual pheromones to direct the robot or drone to the areas with disease based on how severe the disease is affected. The algorithm updates the path as it goes ensuring the robot takes the most efficient route each time.

In summary, this project leverages YOLOv7 model for precise real-time detection of banana crop diseases through high-resolution image analysis. Ant Colony Optimization (ACO) enhances path planning guiding robots or drones efficiently to affected areas using virtual pheromones. Together, these methods enable timely intervention and improved agricultural productivity.

1.4 ORGANIZATION OF THE REPORT

This report is organized into 6 chapters, describing each part of the project with detailed illustrations and system design diagrams.

CHAPTER 2: Literature Review reviews existing research, studies, and relevant literature related Disease detection. Discusses the background, theories, and methodologies used by other researchers

CHAPTER 3: System Design describes the design of the project. Explains the architecture, components, algorithms, and any other technical details.

CHAPTER 4: Implementation provides details about how the project was implemented. Discusses the tools, technologies, programming languages, and frameworks used.

CHAPTER 5: Result and Analysis presents the results of the project. Analyzes the outcomes, compare them with expectations, and discuss any challenges faced during implementation.

CHAPTER 6: Conclusion and Future Work summarizes the findings and draws conclusions. Discusses the significance of your work and its implications.

CHAPTER 2

LITERATURE SURVEY

The detection and management of crop diseases require significant advancements in data handling, image processing, and model collaboration. Effective solutions are needed to overcome challenges such as the scarcity of labeled data, image distortions during processing, and the need for scalable training datasets. Additionally, achieving high-quality disease classification and timely detection remains a critical issue. Optimizing image acquisition methods and improving path planning for data collection robots are crucial for enhancing the efficiency and effectiveness of crop disease monitoring. Addressing these challenges is essential for the development of robust systems that can support real-time decision-making and improve agricultural productivity. A method is proposed that captures entire field images using static acquisition nodes to identify the most affected regions based on severity. A mobile robot is then deployed to these regions to capture fine images of each affected plant, which are analyzed to diagnose specific diseases. The following research addresses these issues and provides detailed insights into the methodology.

2.1 DATA HANDLING FOR ABNORMAL CROP

The IOT-based image acquisition system integrates edge intelligence and motion-static collaboration to enhance the quality of agricultural images. By deploying the YOLO-FDAC model and severity quantification, it guides a mobile robot along optimized paths using [1] ant colony algorithms. Experimental results demonstrate improved efficiency and data value, providing a reliable approach for addressing abnormal crops. The path to successful detection and management of crop disease starts with solving problems in data handling as well on-ground plant disease prediction and model collaboration. The detection results of various models are compared and analyzed, as shown in figure2.1, highlighting the best performing model.

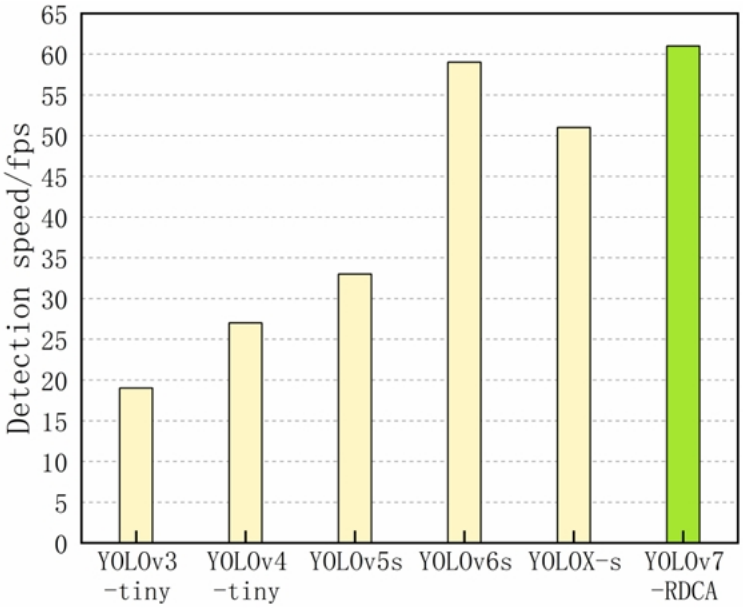

Figure 2.1: Execution speed comparison of YOLOv7-FDAC with other models

In order to solve the problem of lack of labeled data [2], a robot with depth sensors that collected images of segmented objects and created new collection by copy-pasting creation filters on different backgrounds. This enabled the training datasets to scale much faster than before requiring less manual labeling and a broader base for model permutation on images specific to agriculture. The lack of public datasets for crop/weed discrimination and plant phenotypic analysis in precision agriculture hinders progress. By providing annotated images and evaluation methods it enables comparative research and advances in computer vision for agriculture[3]. This in turn fosters the development of more accurate and efficient tools for crop management and pest control.

2.2 IMAGE ACQUISTION OF BANANA PLANTS

A crucial issue in image processing revealed that YOLO's image resizing to 416x416 pixels caused distortions when aspect ratios varied. This insight emphasized the need for methods that retain image integrity, enabling more accurate detection across agricultural datasets. Agriculture is an important pillar of world development, and smart agriculture is an emerging paradigm in current practices. RGB Images contain rich information and play an increasingly important role in various scenes of smart agriculture. Image sensing, transmission and other key aspects rely on agricultural Internet of Things infrastructure[4] image-based agricultural Internet of Things applications are discussed. The system generates synthetic images for object detection by following a four-step process. The Image Picker selects a random object class retrieves an image and crops the annotated region. The Scale Modifier resizes cropped objects to fit the target detection size. The Image Maker places these scaled objects onto base images with matching backgrounds and dimensions at random locations. Finally the Annotation[5] Creator calculates and adds annotations for object positions and sizes ensuring the dataset is ready for training models. Data labeling is performed by manually annotating the locations of blueberry bushes in orchard images to train object detection models. This annotated dataset supports the task of[6] blueberry bush detection, filling a gap in existing datasets. Therefore it resolved a persistent issue in image processing providing the final key for deploying robust and scalable detection models across all stages of crop disease monitoring and management.

2.3 BANANA DISEASE CLASSIFICATION

Expanding the efficient abnormality detection, federated learning with CNN and decision trees was first introduced [7], by which disease classification became a collaborative effort without centralization. Through experiments, we demonstrated that this model can classify banana leaf diseases safely across six clients without sacrificing any classification accuracy or leaking data privacy. While these disease classification systems evolved [8], a methodology to monitor the banana crops during its growth period until harvest stage.Batch Normalization makes training deep neural networks faster and easier by normalizing inputs to each layer, allowing higher learning rates and better stability. It can reduce the need for [9] Dropout and improves model performance. The model was also able to segment localities into areas experiencing health or disease status like Panama-infested and uninfected zones for farmers' perception of the dynamics between different infection statuses over time. The ensemble-based Convolutional Neural Network (E-CNN) model effectively diagnoses micro-nutrient deficiencies in banana crops using leaf images. By combining the top-performing pre-trained models, the InceptionV3+Dense169 model achieved a validation accuracy of 98.62 and an F1 score of 93 [10]. This demonstrates its potential for accurate and efficient identification of nutrient deficiencies in banana crops and contributes to better crop management and yield.

2.4 THRESHOLD BASED ALGORITHM FOR DISEASE MANAGEMENT

Following that lays emphasis on one disease and comes up with an economic threshold algorithm for banana streak virus [11]. It is supported by economically driven decision-making to inform on-farm disease affects and its potential mapped spread across the region with an additional benefit of offering cost-effective control solutions to farmers, helping them prevent further economic losses. A comparison of transfer learning models included AlexNet, GoogleNet, VGGnet-18, SqueezeNet, LSTM, RNN, and SVM to identify Sigatoka leaf spot from its initial stage. This assessment provided a proactive tool for preventing outbreaks, an important aspect of [12] economic threshold model, and enabled intervention at the earliest possible stage. The image processing using CNN is shown in figure 2.2.

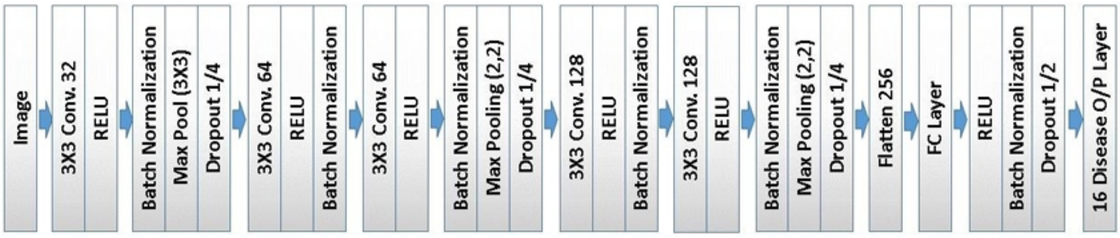

Figure 2.2: Multilayer CNN architecture

Later, developed NexGen Agricare for a completely dedicated crop health management platform. Combining the diagnosis of diseases and environmental detection based on IoMT, this system provided a comprehensive tool for growers to monitor crop health in addition to their external environment. By integrating disease detection, weather tracking, and soil analysis into a single solution based on the Plant Village dataset, these systems built up upon recent works [13].

2.5 YOLO MODEL AND PRECISION FEATURE EXTRACTION

GCN-YOLO model, which enhances the feature extraction ability as well by merging graph convolutional networks with YOLO and incorporating Convolutional Block Attention Module. It was further able to improve detection of crop abnormalities by modeling nonlinear relationships between features [14]. These advances in Precision Agriculture using a machine vision sensor unit gathered information about grain heights [15]. Consequently, this application of PV for precision crop monitoring completes the loop with practical data-driven insights to complement feature extraction. The DS-YOLO model's techniques can be applied to identify crop abnormalities or diseases. The use of Diverse Branch Block (DBB) and SlimNeck reduces complexity while improving detection, especially for small anomalies. Normalized Gaussian Wasserstein distance enhances accuracy making it effective for detecting early-stage crop issues[16]. GDRS-YOLO for remote sensing images by addressing challenges such as scale variations, tightly arranged objects and indistinguishable feature boundaries. The method aims to improve feature extraction[17], reduce information loss and enhance detection performance, particularly for small objects, using a multi scale feature aggregation network and the normalized Wasserstein distance for hybrid loss training.

2.6 OPTIMAL SOLUTION TO ROBOT PATH PLANNING

There are Various path planning algorithms, including Dijkstra, A*, RRT, and RRT*, were tested for smart farm applications in environments with [18] static and dynamic obstacles. The performance of these algorithms was evaluated through field tests and statistical analysis. Tasks such as harvesting and spraying were used as scenarios for testing. The findings provide useful insights for selecting the most appropriate algorithm for specific smart farm tasks. To enhance the effectiveness of path planning for agricultural information-gathering robots, a model combining [19] the Ant Colony Algorithm and Particle Swarm Optimization is proposed.

The approach begins by applying the Simulated Annealing algorithm to optimize global path planning, camera capturing images of the farmland environment, which are processed in the Farmland Environment. This information is sent to the Information Collection Module, where environmental data is gathered and analyzed by the Processing Information Module. Simultaneously, the Operation Execution Module uses algorithms to make decisions based on the analyzed data. These decisions are transmitted to an agricultural robot, which executes specific tasks such as navigation and action within the farmland. Finally, the robot completes path planning tasks to ensure precise and efficient operations based on the processed data. SA is a probabilistic global optimization technique that prevents the algorithm from getting trapped in local optima by allowing random searches and accepting suboptimal solutions under certain conditions. A machine-vision-based [20] height measurement system for autonomous cultivation robots was developed using a stereo camera configuration. The system accurately calculated crop heights through disparity maps and region segmentation

2.7 CHALLENGES AND RESEARCH GAP

The challenges in crop disease detection and management are multifaceted with significant issues arising from limited labeled data, image processing inaccuracies, data privacy concerns, inefficient path planning for robotic systems and the inadequate integration of edge intelligence with IoT technologies. The scarcity of labeled data hampers the training of accurate disease detection models and the distortion caused by resizing images such as those processed by YOLO reduces detection accuracy.

Meanwhile federated learning offers a decentralized approach to classification, it raises concerns regarding data privacy and security. Path planning for image acquisition robots remains inefficient which limits their ability to gather data from the most affected areas. Furthermore, the insufficient integration of edge intelligence with IoT impedes real-time decision-making and data processing affecting the overall effectiveness of disease monitoring systems.

To address these challenges, future work should focus on enhancing data augmentation and labeling techniques to build larger, more accurate training datasets, reducing the reliance on manual labeling. Improved image processing algorithms such as adaptive resizing or image stitching are necessary to preserve image quality and enhance model accuracy. Privacy and security mechanisms in federated learning need to be strengthened to ensure data protection while maintaining model performance.

Additionally, advancing path optimization algorithms possibly incorporating machine learning and real-time sensor feedback could improve robotic systems for more efficient crop monitoring. Lastly, better integration of IoT with edge computing is essential for enabling real-time data processing which will ensure timely and effective responses to crop disease outbreaks further improving crop health management systems.

2.8 SUMMARY

The successful identification and control of crop diseases face several challenges, including the scarcity of labeled data, image processing distortions, and the need for scalable training datasets. Overcoming these challenges is crucial for improving disease classification accuracy and timely detection. Optimizing image acquisition methods and enhancing path planning for data collection robots are key to increasing the efficiency of crop disease monitoring. Addressing these issues is essential for developing robust systems that can enable real-time decision-making and boost agricultural productivity. The integration of advanced technologies such as edge intelligence and federated learning can help improve the performance of disease detection models while preserving data privacy. Continuous improvements in image processing algorithms and machine learning techniques will also contribute to more accurate and efficient disease management systems. By addressing these obstacles, agriculture can benefit from more reliable, automated solutions to detect and manage crop diseases, ultimately ensuring higher yields and crops.

CHAPTER 3

SYSTEM DESIGN

This chapter discuss the development of an integrated system for real-time detection and monitoring of abnormal banana plants. The system identifies issues like diseases, pests, and growth abnormalities, enabling prompt responses from farmers. YOLO-FDAC processes high-resolution images to detect and quantify abnormalities. ACO-enhanced robot path planning ensures optimized navigation and efficient image capture. The Figure 3.1illustrates the system's framework for image acquisition and path planning in banana crop monitoring.

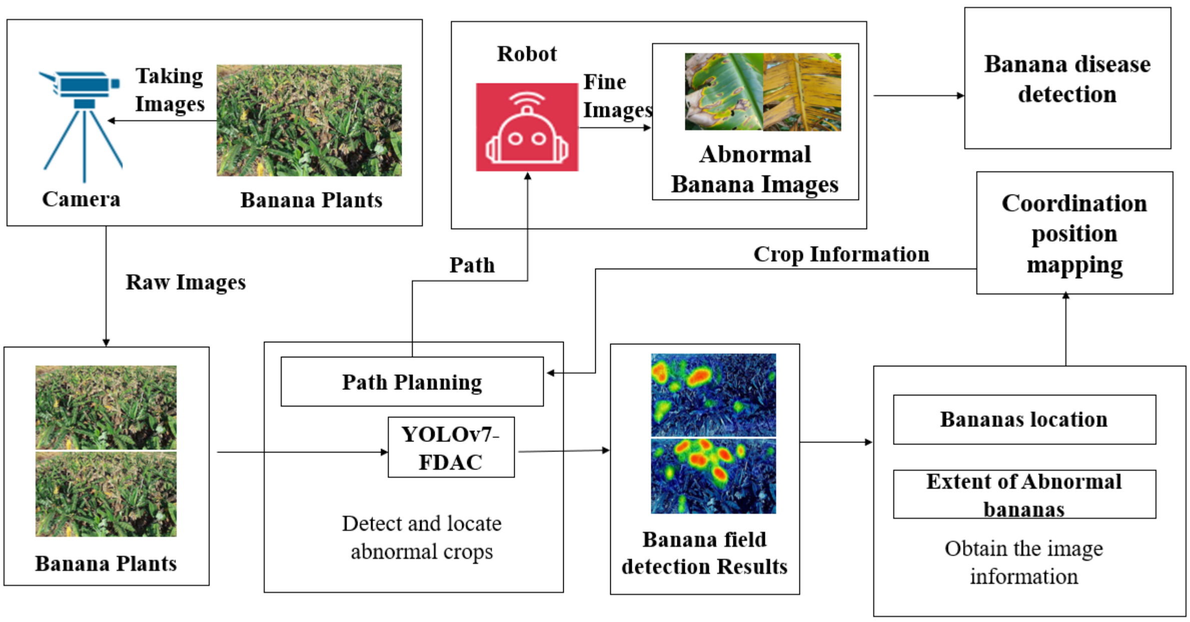

Figure 3.1: High-quality image data acquisition model for abnormal crops based on edge intelligence and motion dynamic– static synergy

3.1 VISUAL DATA COLLECTION IN BANANA FIELDS

Image acquisition serves as the critical factor, the first step in detecting abnormalities in banana crops focusing on capturing high-resolution images of entire banana fields rather than individual plants. Advanced imaging systems such as those mounted on drones, robots, or stationary camera nodes, are utilized to efficiently cover extensive areas. These systems ensure the capture of detailed visuals encompassing all parts of the to provide a comprehensive dataset. The primary aim is to identify specific areas within the field exhibiting abnormalities such as discoloration, deformities, or pest infestations, which may indicate the presence of crop diseases. Given the irregular distribution of these abnormality, it is imperative to capture high-quality images that enable precise differentiation between healthy and affected regions. The figure 3.2 shows the detection of affected area in the field.

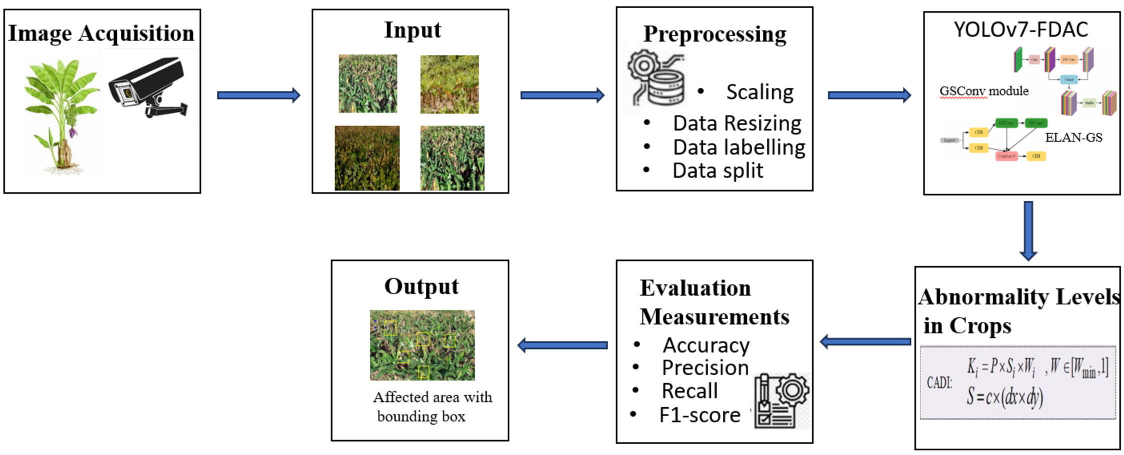

Figure 3.2: Affected area of crops

To achieve this image are acquired under various climatic and lighting conditions to account for factors variations. By capturing entire field images this methodology allows for the prioritization of affected regions optimizing subsequent analysis and intervention processes. The method enhances resource allocation by focusing on areas most in need of attention.

This comprehensive and systematic approach ensures the collection of relevant high-value data laying a strong foundation for accurate disease detection and efficient crop health management.

3.2 DATA PREPARATION AND PROCESSING

The preprocessing phase is vital for preparing input images to ensure effective analysis by the model. This involves scaling all images to a standard size of 416x416 pixels to maintain uniformity during both training and inference, with the model architectural requirements. Data labelling is a critical step, where images are annotated with their respective disease categories to help the model associate specific features with particular diseases. In this project the affected areas in banana crops are precisely marked using bounding boxes created with the YOLO model highlighting abnormal regions for targeted training. These bounding boxes enable the model to focus on relevant areas improving its detection accuracy.

Further the dataset is systematically divided into subsets to ensure comprehensive evaluation and reduce the risk of overfitting as shown is figure**??**. Together these preprocessing steps establish a robust foundation for accurate disease detection and severity analysis. The edge server determines the coordinates of abnormal crops and formulates the robot's movement path enabling the robot to capture images of affected crops along the designated route. During the path planning process, it is assumed that X represents the set of crops the robot must monitor expressed as X = X1, X2, ..., Xi, ..., Xn figure 3.1. To ensure that crops with higher levels of severity are prioritized for observation a heuristic optimization algorithm is introduced. This algorithm based on the severity of the abnormal crops identifies an optimal route for image collection enhancing the efficiency and accuracy of the data acquisition process.

3.3 YOLOV7-FDAC

These are modules such as GSConv a spatial convolution optimization technique that enhances the detection process by accelerating computations and reducing latency. This improvement enables faster and more efficient identification of objects in images. Another key module ELAN-GS significantly boosts feature extraction capabilities by merging multiple feature maps from different network stages ensuring a more comprehensive understanding of image data as shown in figure **??**. This combination allows the model to effectively detect and classify diseases such as Panama and Moko disease in crops by identifying visual patterns and abnormalities associated with these conditions. Additionally, the YOLOv7-FDAC model is fine-tuned to handle high-resolution images with exceptional speed and accuracy making it ideal for agricultural applications where real-time decision making is crucial. Its ability to process large datasets with minimal computational resources ensures timely interventions and enhances precision in disease monitoring and management ultimately contributing to improved crop health and yield.

3.4 ABNORMALITY LEVELS IN CROPS

Once the YOLOv7-FDAC model detects anomalies within the input images then comes quantifying the abnormality levels that occur in crops. The abnormality index is carried out by computing a formula involving all the factors with respect to size color deviation and texture changes. Such a CADI then captures how these features are combined in producing a score or level of severity. This score quantifies the damage or disease level in each image to place them into different categories of disease. Specifically, if an image contains abnormal banana trees, the expression 3.1 finds the abnormality level in crops, and i represents one of the banana trees, its CADI expression is

$$K_i = P \times S_i \times W, \quad W \in [W_{\min}, 1] \tag{3.1}$$

where W denotes the confidence level of the target detectionresult. Wmin is the confidence threshold, the crops with confidence lower than the threshold are considered normal, and the default confidence threshold in this paper is Wmin = 0.3. P denotes the accuracy of the target detection model

S represents the area covered by the abnormal crop in the image, calculated by the pixel length (dx) and width (dy) of the image along with the number of pixels occupied by the crop. The total number of pixels is found using the expression 3.2 denoted as c, is determined as follows:

$$S = c \times (dx \times dy) \tag{3.2}$$

Objects that appear within grid cells are detected by the corresponding grid cell. Subsequently the model predicts bounding box coordinates with respect to their cell coordinates and at the same time it also predicts the class probability of the object that is present in the cell.

3.5 COORDINATION POSITION OF ABNORMAL CROPS

Coordinate positioning in abnormal crop localization focuses on accurately determining the position of crops within a field using image-based sensing systems. To efficiently plan robot paths and ensure precise image acquisition, it is crucial to identify the exact location of abnormal crops. This is achieved by integrating camera imaging principles with coordinate system transformations. First, a coordinate system is established for the orchard and a reference point is set. The camera then captures the direction and distance of abnormal crops relative to this reference. By utilizing fixed camera parameters such as focal length and pixel size, the 3D position of the abnormal crops can be calculated from 2D image data. The camera model maps 3D spatial points onto a 2D image plane using the principle of small-hole imaging, allowing the conversion of 2D pixel coordinates to image coordinates. These image coordinates are then used to determine the 3D spatial coordinates of the abnormal crops. This approach enables accurate mapping of crop positions usng expression 3.3, which can be applied for robot path planning or further analysis, enhancing crop monitoring and detection in smart agricultural systems.

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} dx & 0 \\ 0 & dy \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} + \begin{bmatrix} -u_0 dx \\ -v_0 dx \end{bmatrix} \tag{3.3}$$

Each camera has a fixed image size for pixels, each pixel size length and width are dx and dy. Assuming that the pixel corresponding to the origin o of the image coordinate system is (uo,vo), its specific coordinates in the image coordinate system can be computed by the expression 3.4 given specific pixel coordinates (u,v).

$$\begin{aligned} X_I &= X_P - \frac{Z_P(x_p - x_i)}{f} \\ Y_I &= Y_P - \frac{Z_P(y_p - y_i)}{f} \\ Z_I &= \frac{X_I f}{x_i} \end{aligned} \tag{3.4}$$

Assuming that point P and point are the positions of the reference and the anomalous crop in 3-D space respectively, point p and point I are the positions of both mapped in the image. p(xp,yp) and i(xi,yi) can be calculated by P(Xp,Yp,Zp) are the known coordinates of the reference relative to the cam-era, and f is the focal length of the camera.

3.6 PATH PLANNING TO AFFECTED CROPS

Path planning is essential for mobile robots to efficiently execute image acquisition tasks determining the optimal route for the robot to navigate while avoiding obstacles. Ant Colony Optimization (ACO) inspired by the foraging behavior of ants is widely used in multi-objective path planning due to its adaptability and robustness. However ACO faces challenges such as poor convergence where the algorithm may take too long to find the optimal path and a tendency to fall into local optima where it gets stuck in suboptimal solutions. These issues arise from the exploitation of paths with high pheromone concentration making it difficult for the algorithm to explore better routes. Solutions such as pheromone evaporation and combining ACO with other optimization techniques can help improve performance by accelerating convergence and preventing local optima. Furthermore dynamic updates in pheromone concentration based on real-time environmental feedback can enhance its adaptability. The process of Ant colony optimization in shown in figure3.3

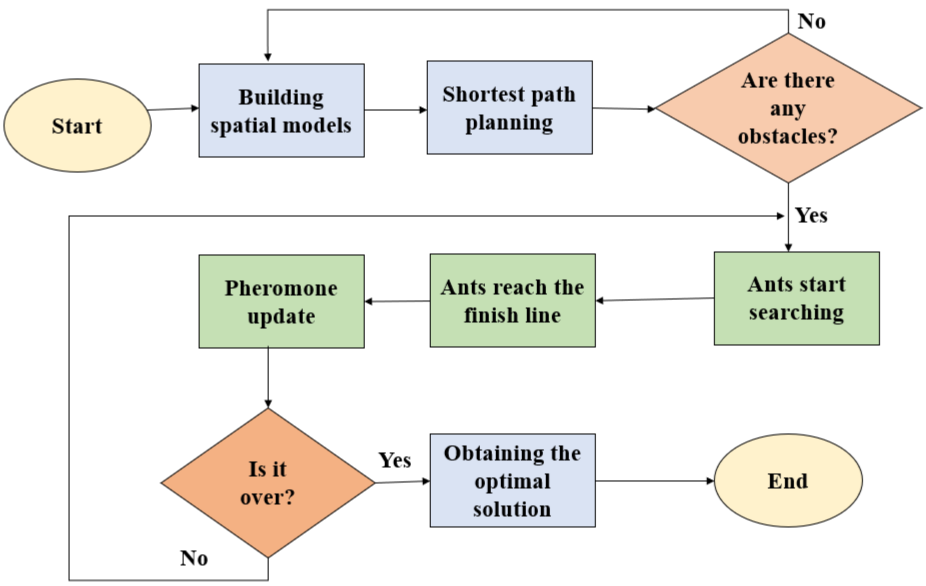

Figure 3.3: Ant colony optimization process

Initially, a colony of artificial ants is initialized each starting from a given position in the environment with pheromone levels set on the paths. The ants then move based on a probability influenced by pheromone concentrations and heuristic information exploring the environment while introducing randomness to avoid premature convergence on suboptimal paths. During exploration the ants avoid obstacles and prioritize efficient routes leveraging both local and global heuristic factors. Once the ants reach their destinations the paths are evaluated based on objectives like length, cost, or energy efficiency. Pheromone levels on the paths are updated through evaporation and reinforcement with successful paths receiving higher pheromone levels to guide future iterations. The algorithm repeats through multiple cycles where ants continuously explore and refine paths allowing the system to adapt dynamically to environmental changes. The process continues until a termination condition such as reaching a satisfactory solution achieving desired performance metrics or completing a predefined number of iterations is met. Finally, the best path discovered is selected for the robot to follow ensuring optimal navigation and efficient image acquisition. This iterative approach balances exploration and exploitation improving the system's robustness and adaptability in real-world scenarios.

3.7 DATA ACQUISITION FOR EFFICIENT CROP MONITORING

An innovative hybrid data acquisition approach combines static monitoring nodes with mobile robots to enhance precision in crop field analysis. The static nodes strategically positioned across the field provide a comprehensive broad view of the entire crop area continuously monitoring for potential anomalies such as diseases, pest infestations, or growth irregularities. These nodes act as an early-warning system detecting potential issues in real-time and relaying information to a central control system.Once abnormalities are identified, mobile robots equipped with advanced imaging systems, YOLOv7 for anomaly detection, and path optimization via Ant Colony Optimization (ACO) are deployed to the affected regions. These robots efficiently navigate through the field prioritizing the most critical areas based on the severity of the detected anomalies and capture high-resolution detailed images of the abnormal crops to facilitate further analysis. The integration of ACO ensures that the robots follow optimized paths minimizing redundant movements and eliminating repetitive data collection processes. This not only reduces energy consumption and operational costs but also significantly improves the quality and reliability of the data gathered. By seamlessly coordinating static monitoring nodes with mobile robots the system achieves a dynamic-static synergy that conserves valuable resources while enabling real-time accurate monitoring of the crop field. This approach enhances the overall efficiency of crop management by providing actionable insights and supporting better decision-making processes.

3.8 SUMMARY

As a result, an advanced framework detects abnormalities in banana crops using high-resolution imaging, efficient preprocessing and YOLOv7-FDAC enhanced with GSConv and ELAN-GS modules for accurate fast detection. Severity is quantified and 2D imaging with 3D mapping aids robot path planning via Ant Colony Optimization (ACO). This hybrid system ensures real-time monitoring optimizing crop health and productivity. The model's ability to adapt to new data ensures its robustness across various growth stages and environmental conditions. By leveraging advanced algorithms the system provides actionable insights for timely interventions and decision-making. Furthermore it enables automated responses to evolving crop health issues enhancing efficiency and reducing manual labor.

CHAPTER 4

HIGH-RESOLUTION CROP ANOMALY DETECTION WITH MOBILE ROBOT ASSISTANCE

This chapter discuss the implementation of the system. As previously outlined, the core modules of the system are fundamental to the process, and now we focus on their practical implementation to achieve the desired results. The first key objective is the precise detection of abnormal crops and the accurate extraction of their location information. The second objective involves optimizing the image acquisition path for the ground robot starting from the image data itself. This section presents the detailed methodology for achieving these goals. It begins by discussing the development of a fast detection model built on a lightweight neural network followed by an explanation of the crop position mapping process which incorporates both image data and coordinate system transformations. Finally the section concludes with an exploration of the heuristic path optimization algorithm which adjusts the robot's trajectory based on the severity of crop abnormalities.

4.1 DETECTION OF AFFECTED AREA USING YOLOv7-FDAC

YOLOv7-FDAC is designed to detect and localize affected areas in agricultural fields by efficiently identifying abnormal crops or diseased plants in real-time using a lightweight object detection framework. The model processes the input image through feature extraction using the ShuffleNet v1 backbone, applies grouped and depth-wise separable convolutions to reduce computation, and fuses multi-scale features in the neck with GSConv and improved ELAN-GS modules. It employs the WIoUv3 loss function for accurate localization of bounding boxes, particularly in complex scenarios with occlusion, and uses Mish activation functions to improve gradient flow and model convergence. Postprocessing involves non-maximum suppression to filter low-confidence predictions, resulting in bounding boxes, confidence scores, and class labels that identify affected areas for effective agricultural management.

The optimization of IVAD can be achieved through two main aspects. First it involves accurately detecting the abnormal crop and obtaining its positional information. Second starting with the value of the image the path for image acquisition by the ground robot is optimized. This section outlines the specific implementation methods beginning with the development of a fast detection model using a lightweight neural network followed by the explanation of the crop position mapping technique based on image and coordinate system transformation and concluding with the presentation of a heuristic path optimization algorithm based on the severity of crop abnormalities.

4.1.1 COORDINATION POSITION MAPPING

Accurately determining the position of abnormal crops is essential for planning the robot path and ensuring successful image acquisition operations. The ability to perceive the environment effectively relies on vision sensing systems equipped with cameras, which enable the acquisition of spatial information. To achieve 3D perception for crop localization, two primary approaches are widely used: binocular vision systems and RGB-D cameras. Binocular vision systems utilize optical geometry principles and triangulation to calculate the 3D position of a target, further refined using traditional optimization algorithms. However, these systems require complex calibration processes, and stereo matching consumes significant computational resources, which can hinder real-time performance. Despite their efficiency,

Algorithm 4.1 Detection of Abnormal Crops and Solution of Their Severity and Coordinates

Input: Image A acquired by static node
Output: CADI and location coordinates of abnormal banana tree X_i
Procedure:

Information extraction(A)
YOLO-FDAC detects abnormal banana trees $X_1, X_2, \ldots, X_i, \ldots, X_n$ and confidence $W_1, W_2, \ldots, W_i, \ldots, W_n$
for $i = 1$ to n do
    if $W_i \geq 0.3$ then
        $S_i \leftarrow c_i \times (dx \times dy)$
        Calculate the anomalous area S_i by Equation
        $K_i \leftarrow P \times S_i \times W_i$
        Calculate the anomaly index K_i of crop X_i by Equation using W_i and S_i
        Read the camera's internal reference and reference P coordinates $P(X_P, Y_P, Z_P)$
        Get coordinates $x(x_i, y_i)$ and $p(x_p, y_p)$ by (16)
        Calculate the coordinates of crop X_i and reference P in the image according to Equation
        $X_i \leftarrow X_P - \frac{Z_P}{f}(x_p - x_i)$
        $Y_i \leftarrow Y_P - \frac{Z_P}{f}(y_p - y_i)$
        $Z_i \leftarrow \frac{X_i}{f} \times x_i$
        Calculate the position coordinates of crop X_i relative to the camera by Equation
    else
        break
    end if
end for
$K \leftarrow \{K_1, K_2, \ldots, K_i, \ldots, K_n\}$
K is the anomaly index of all banana trees
$X \leftarrow \{X_1(X_1, Y_1, Z_1), X_2(X_2, Y_2, Z_2), \ldots, X_i(X_i, Y_i, Z_i), \ldots, X_n(X_n, Y_n, Z_n)\}$
X is the set of coordinates of all abnormal banana trees
return K, X

RGB-D cameras are sensitive to strong or uneven lighting conditions, which can introduce errors in depth measurements. Selecting an appropriate vision sensing system based on environmental conditions and computational requirements is crucial for accurate localization of abnormal crops and facilitating efficient robot navigation and data collection. Additionally, integrating machine learning techniques with these vision systems can help reduce the impact of environmental factors, improving depth accuracy and robustness in varying conditions.

This combination of technologies ensures a more reliable and efficient system for detecting and localizing abnormal crops in diverse agricultural environments. The algorithm focuses on detecting and localizing abnormal banana trees using YOLO-FDAC and calculating their anomaly index. The process begins by acquiring an image (A) from a static node, followed by information extraction. YOLO-FDAC detects abnormal banana trees (X1, X2, ..., Xi, ..., Xn) and their corresponding confidence scores (W1, W2, ..., Wi, ..., Wn). For each detected tree, if the confidence score (Wi) is greater than or equal to 0.3, the anomalous area (Si) is calculated based on the image dimensions (dx × dy), and the anomaly index (Ki) is computed by multiplying the area and confidence score.

The camera's internal reference coordinates (XP, YP, ZP) are used to calculate the spatial coordinates (Xi, Yi, Zi) of each abnormal tree relative to the camera, based on the image's reference points and the camera's parameters. If the confidence score falls below 0.3, the process halts. After processing all detected abnormal trees, the algorithm returns the anomaly index set (K) and the set of coordinates (X) of all abnormal banana trees, providing both the severity of the anomalies and their spatial locations. This allows for efficient mapping and targeted intervention strategies to address crop health issues.

4.1.2 IMPROVED HEURISTIC PATH OPTIMIZATION BASED ON ABNORMAL CROP SEVERITY

This project introduces an integrated approach that combines YOLO-FDAC object detection with an optimized IHO (Improved Heuristic Optimization) path-planning algorithm to enhance crop monitoring within banana plantations. YOLO-FDAC is an adaptation of the YOLO model designed specifically to detect abnormal banana trees, assess their severity levels and calculate an anomaly index in a single image pass. This model is highly efficient, rapidly identifying crop abnormalities while providing a confidence score which ensures high accuracy and real time performance key attributes for agricultural applications where timely detection is essential. The grid representation of with obstacles of the entire field is shown in figure4.1

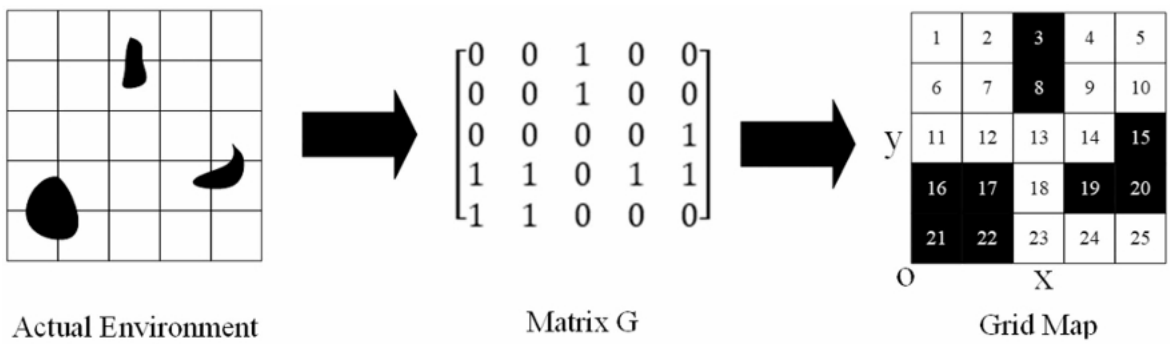

Figure 4.1: Grid environment

Once YOLO-FDAC detects abnormalities, the IHO algorithm comes into play, optimizing the robot's inspection route. It prioritizes paths based on the severity of detected abnormalities using the CADI (Crop Abnormality Detection Index) score derived from YOLO's outputs. This score acts as the initial pheromone levels in an Ant Colony Optimization (ACO) model which directs the robot to areas with the most severe crop issues. By adjusting pheromone levels according to severity, the robot is more likely to follow paths that lead to crops with significant abnormalities.

4.2 ANT COLONY OPTIMIZATION IN PATH PLANNING

The Ant Colony Optimization (ACO) algorithm is inspired by the foraging behavior of ants where natural ants lay down pheromones to guide others toward food sources. In ACO artificial ants mimic this by exploring a problem space represented as a grid or network with probabilistic choices informed by pheromone levels and a heuristic factor such as path distance. Successful paths accumulate more pheromones making them more attractive to other ants. ACO continuously updates pheromone levels both locally within each iteration and globally across the best-performing paths while pheromone evaporation on less-used paths prevents premature convergence on suboptimal solutions. By setting CADI values as initial pheromone weights this crop monitoring application adapts ACO to guide robots toward areas with higher crop abnormality optimizing real-time data-driven agricultural monitoring.

The pheromone intensity influences the robot's path decision encouraging it to revisit high-priority regions for further inspection. Over successive iterations, the algorithm fine-tunes the path choices ensuring that the robot efficiently covers the plantation while focusing on the most critical areas. This adaptability allows for dynamic response to varying crop conditions and enhances monitoring precision. Furthermore, by incorporating ACO, the system minimizes time spent on low-priority areas significantly improving operational efficiency. The dynamic nature of the ACO-based path planning enables the robot to continuously adjust its trajectory as new abnormalities are detected or existing conditions change, ensuring that the most important regions are always addressed first. This results in a more thorough inspection process and a higher likelihood of identifying early-stage crop abnormalities. Additionally, the algorithm reduces travel time by finding the shortest and most effective routes between detection points, optimizing energy consumption and extending operational hours. The robot is thus able to maintain high productivity levels over extended periods making it an effective tool for large-scale agricultural monitoring.

Algorithm 4.2 Robot Path Planning for Fine Image Data Collection

Input: The value K of CADI and position coordinate X of all abnormal banana trees
Output: Ground robot working path
Procedure:

while receives K, X do
    procedure PATH PLANNING(K, X)
    Initialize the robot working environment, converting map coordinate X to grid coordinates
    for $i = 1$ to n do
        Calculate the initial pheromone concentration of abnormal banana tree i
        Calculate the heuristics of abnormal banana tree i
    end for
    for $e = 1$ to b do
        b is the total number of ant colony iterations
        for $i = 1$ to n do
            Calculate the transition probability P_i of banana tree$i$
        end for
    $P \leftarrow \{P_1, P_2, \ldots, P_i, \ldots, P_n\}$
    Plan the robot acquisition path R_e according to P
    Update the pheromone by
    end for
    From $\{R_1, R_2, \ldots, R_e, \ldots, R_b\}$ choose an optimal path as the final path R
  end procedure
  end while

The algorithm focuses on robot path planning for fine image data collection, utilizing the CADI values and position coordinates of abnormal banana trees. The process begins by receiving the CADI (K) values and position coordinates (X) of the detected abnormal banana trees. The map coordinates are then converted into grid coordinates to initialize the robot's working environment. For each abnormal banana tree, the algorithm calculates its initial pheromone concentration and heuristic values. The algorithm iterates through a set number of ant colony iterations (b), during which the transition probability (Pi) for each tree is calculated, determining the likelihood of selecting each tree for robot path planning. Based on these probabilities, the robot's acquisition path is planned and the pheromone values are updated. After completing the iterations, the optimal path (R) is selected from the multiple paths generated during the process, guiding the robot to efficiently collect data from the most significant abnormal banana trees.

4.3 DISEASES IN BANANA PLANTS

The optimal path is utilized to take fine images of individual banana leaves ensuring that every part of the plant is thoroughly captured for accurate disease detection. Once the images of individual leaves are acquired they are processed using a deep learning model such as YOLOv7 which is trained specifically for detecting banana plant diseases. YOLO is a real-time object detection algorithm that efficiently detects and classifies objects in images by dividing the image into grids and assigning bounding boxes to the detected objects. In the context of banana leaf disease detection YOLOv7 is particularly suited due to its speed and accuracy making it ideal for real-time analysis.

Each individual leaf image is fed into the trained YOLOv7 model which identifies potential disease symptoms such as spots discoloration or unusual patterns indicative of diseases like Black Sigatoka Panama Disease or Yellow Sigatoka. The model processes the image and returns a set of bounding boxes each containing a disease label and a confidence score that reflects the likelihood of the detected condition. The detection model is capable of distinguishing between healthy and diseased leaves with high precision even under varying environmental conditions. After detecting the diseases the severity of the infection is quantified by analyzing the size and distribution of the affected areas on the leaf. This enables the system to generate actionable insights such as the specific regions requiring intervention treatment or further observation.

4.4 CROP MONITORING WITH REAL-TIME OBJECT DETECTION

Integrating YOLO-FDAC object detection capability with ACO-based path planning brings a new level of precision to agricultural monitoring by enabling real-time data-driven decision-making. YOLO- FDAC model design ensures fast processing with minimal computational overhead, allowing it to run effectively on edge devices. This is particularly valuable in agricultural settings where quick detection and response to crop abnormalities, such as disease outbreaks or pest infestations, are crucial to minimize damage. By focusing on high-confidence detections of abnormal crops, the system reduces false positives, allowing for more targeted interventions. Moreover, combining YOLO-FDAC with IHO's ACO-based path optimization enables robotic systems to carry out efficient, targeted surveys across expansive plantations. As these robots navigate, the real- time feedback from YOLO-FDAC allows them to refine their inspection strategies dynamically, responding to crop conditions as they detect them. This adaptability helps farmers save time and resources.

4.5 SUMMARY

This system efficiently detect banana leaf diseases using a combination of optimized path planning and advanced image processing. The robot follows a pre-defined path to capture high-resolution images of individual banana leaves ensuring each leaf is thoroughly examined. The images are processed using YOLOv7 an object detection algorithm capable of identifying and classifying disease symptoms such as discoloration. By evaluating the size and extent of the affected areas the system calculates the severity of the disease and offers insights for targeted interventions improving overall crop management and monitoring efficiency.

CHAPTER 5

RESULTS AND ANALYSIS

This Chapter explores the prerequisites and results of the experiments. It begins by evaluating the effectiveness of each improvement and compares its performance with other advanced models. Next, the position mapping method based on RGB images is verified for its impact on accuracy. The image-efficient acquisition strategy is then compared with conventional methods. Finally, the performance of the proposed approach in abnormal crop detection is highlighted.

5.1 EXPERIMENTAL CONDITIONS OF BANANA FIELD

The YOLOv7-FDAC model was trained on an Ubuntu 20.04 system with an Intel Xeon Gold 5218 CPU. The training parameters were carefully selected to ensure optimal performance while considering real-world deployment constraints. Performance evaluations of the model were conducted on a CPU-based system to simulate real-world application scenarios and analyze the model's performance under CPU-only conditions. This approach allows for assessing the model's efficiency and accuracy in situations where high-performance hardware like GPUs is unavailable. The entire field dataset used for training and testing consists of 1300 images of abnormal banana trees collected from field surveys under varying environmental conditions.

These images represent a range of growth stages and disease types, ensuring that the model is exposed to diverse scenarios. The dataset was divided into training, validation, and test sets using a 70:15:15 ratio, resulting in 910 images for training, 195 images for validation, and 195 images for testing. This split helps ensure the model's generalization capabilities while maintaining a balanced representation of the dataset across all phases of training. The images were collected over several months, incorporating different weather conditions and lighting to provide a comprehensive dataset for training and testing the model.

Parameter	**Value**
Speed	0.5 m/s
Learning Rate	0.01
Batch Size	16
Image Size	640x640
Epochs	600
Weight Decay	5×10^{-4}

Table 5.1: Experiment Parameters

The table presents the key parameters used in the experiment for abnormal banana tree detection. The speed at which the robot moves to acquire images is set to 0.5 m/s. The learning rate for training the model is 0.01, with a batch size of 16 and an image size of 640x640 pixels. The model is trained for 600 epochs, and a weight decay value of is used to help prevent overfitting during training. These parameters were carefully selected to optimize the model's performance and simulate real-world image acquisition conditions. The experiment uses a field dataset consisting of 700 images of abnormal banana trees. These settings are designed to balance computational efficiency with model accuracy in abnormal crop detection.

The figure5.1 shows the result of the input image being divided into a grid (e.g., 10x10 or 25x25), where each grid cell is responsible for detecting objects whose center falls within that cell. Each grid cell predicts a fixed number of bounding boxes and for each box the model provides the coordinates (center x, center y), width, and height which are normalized relative to the image size. Additionally, each grid cell also predicts the confidence score for the presence of an object, indicating how confident the model is in the predicted bounding.

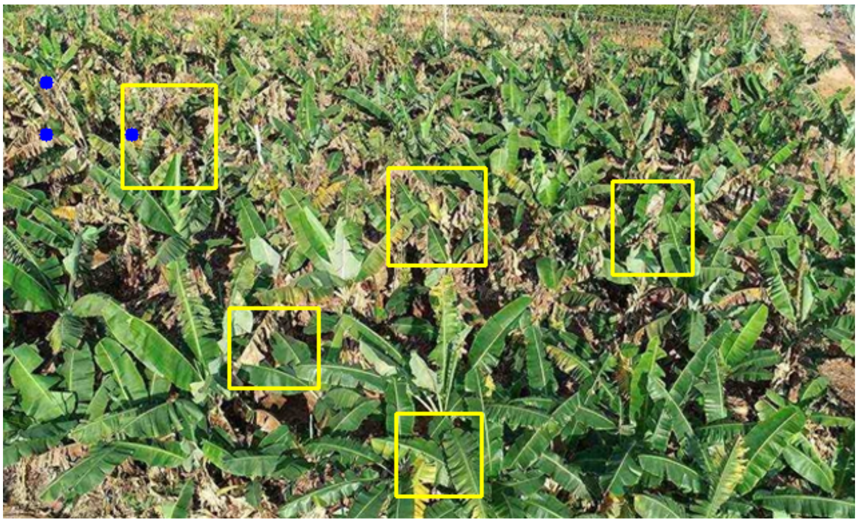

Figure 5.1: Affected area with bounding box

The class probabilities are also predicted for each bounding box, which helps in identifying the type of object within the bounding box. This approach ensures efficient and precise detection by leveraging the spatial structure of the image.

The coordination position of abnormal crops is determined using a camera-based imaging system that maps 3D points in space to 2D image coordinates and vice versa. First, a coordinate system for the orchard is established with a known reference point. The camera captures images of the environment and pixel coordinates of the crops are extracted. These pixel coordinates are converted into the image coordinate system considering parameters like pixel size, image center, and camera focal length. Using the spatial depth information and principles of geometry, particularly the properties of similar triangles, the 3D coordinates of the abnormal crops are calculated relative to the reference point. The result of the coordination position is shown in the figure5.2. This precise localization allows accurate mapping of abnormal crop positions, which is essential for robot path planning and targeted image acquisition.

```
Path Planning Grid with Affected Areas (marked by region i
[[0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0]
 [0 5 5 0 0 0 0 0 4 4]
 [0 5 5 0 0 0 0 0 4 4]
 [0 5 5 0 0 0 0 0 4 4]
 [0 0 0 0 0 0 0 3 3 3]
 [2 2 2 1 1 0 0 3 3 3]
 [2 2 2 1 1 0 0 0 0 0]]
```

Figure 5.2: Coordination position with grid representation

5.2 PATH PLANNING RESULTS

The robot path planning, after determining the coordinates of the abnormal banana trees, path planning executed using the grid-based approach and Ant Colony Optimization (ACO) algorithm. The robot efficiently navigated through the environment, optimizing its path to ensure comprehensive coverage of all abnormal tree locations.

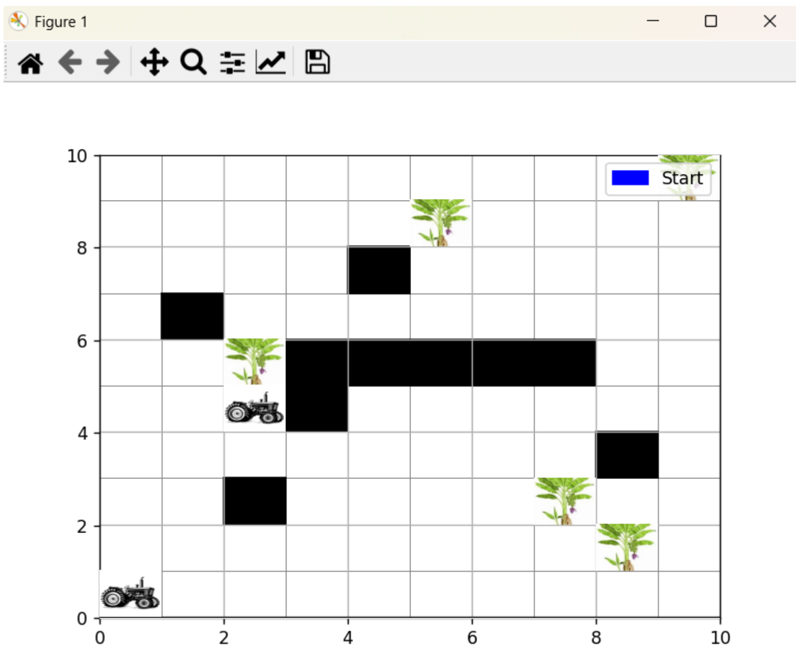

Figure 5.3: Ant colony optimization

Multiple iterations of the ACO algorithm led to the identification of the most efficient routes, balancing factors such as distance and obstacles. The final planned path was optimized for minimal travel time while ensuring accurate data collection. This process demonstrated the effectiveness of ACO in enhancing path planning for precise image acquisition in agricultural environments. This figure 5.3 represents a 10x10 grid of a banana field, where black cells indicate obstacles, banana plant icons mark diseased or affected areas, and the tractor represents the starting point of a robot or autonomous vehicle. The goal is to navigate the field efficiently using the Ant Colony Optimization (ACO) algorithm

5.3 VALIDATION OF INDIVIDUAL BANANA LEAF

This research comprises a total of 2,856 images collected from various sources including agricultural research databases, field surveys, and online repositories. These images are categorized into seven classes representing different diseases affecting banana plants is.

Disease Class	**Number of Images**
Banana Black Sigatoka	469
Banana Bract Mosaic Virus	350
Banana Insect Pest Disease	602
Banana Moko Disease	385
Banana Healthy Leaf	602
Banana Panama Disease	287
Banana Yellow Sigatoka Disease	161
Total	**2,856**

Table 5.2: Dataset Distribution for Banana Disease Classes

Standardizing the image size to 640x640 pixels ensures consistency input for the YOLO model which enhances the model's ability to learn and generalize across different classes effectively leading to improved disease detection accuracy. Input image are shown in figure5.4

Figure 5.4: Banana leaf disease

The figure 5.5 represents the results of running a YOLO model on an image during inference. The image was resized to 224x224 pixels before processing. The model's pipeline involved three stages: preprocessing the image, which took 13.4 milliseconds, performing inference (object detection) that required 55.2 milliseconds, and post-processing the results, which took 0.0 milliseconds. The processed image had a shape of (1, 3, 224, 224), representing a single RGB image with dimensions of 224x224. The detected classes included Banana Black Sigatoka Disease with a confidence of 1.00.

The detection outputs were stored in a Results object from the Ultralytics YOLO engine containing attributes like bounding boxes, class labels, and confidence scores for further analysis or visualization. This inference highlights the efficiency of the YOLO model in processing images with high precision and low latency, demonstrating its capability to detect objects within milliseconds which is critical for real-time applications. The structured Results object simplifies the integration of detection outputs into downstream processes such as visualization, statistical analysis, or automation workflows. The rapid inference time ensures that the system can handle large volumes of data without significant delays. The model's ability to detect multiple classes simultaneously

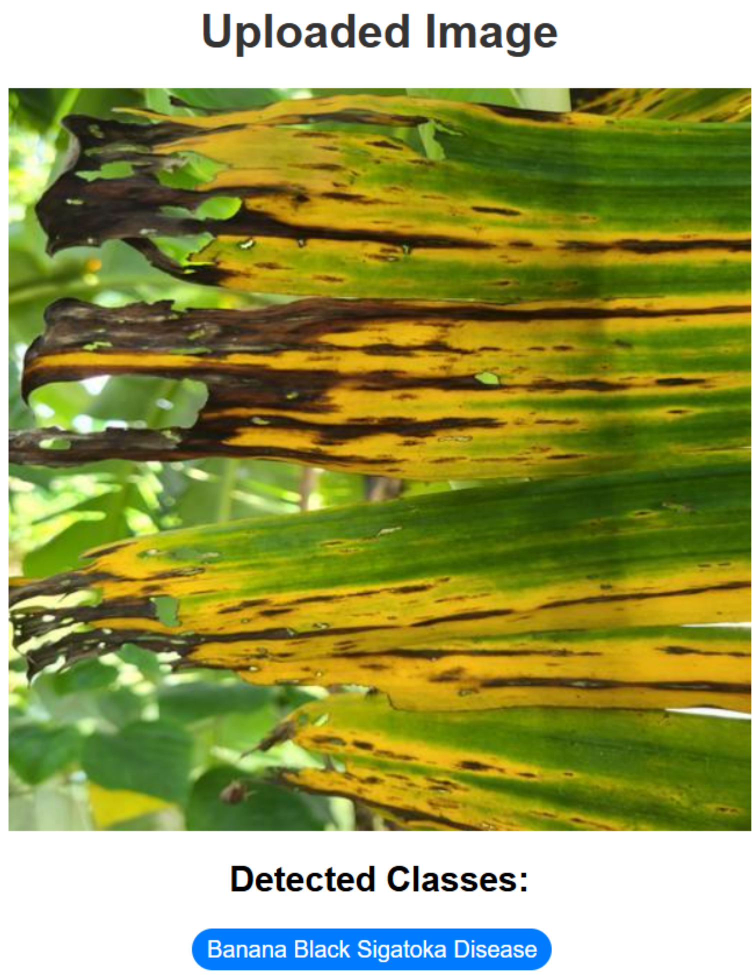

Figure 5.5: Detection result using YOLOv7

enhances its utility in complex environments. The confidence scores provide a quantifiable measure of detection accuracy, enabling the system to prioritize more reliable predictions. This approach demonstrates the potential of YOLO in industrial applications where timely and accurate object detection is essential. YOLO's efficiency in both speed and accuracy makes it highly suitable for applications requiring fast decision-making such as real-time disease detection. Its low latency and high precision contribute to the optimization of workflows in automated systems. By enabling seamless integration of results into further analysis YOLO represents a critical tool for advancing precision agriculture and similar industries.

5.4 ANALYSIS

The issue of abnormal banana crop detection in the model suggests that there may be challenges with its ability to accurately identify and classify abnormal crops in diverse conditions. This problem could arise from factors such as insufficient training data which limits the model's exposure to various crop abnormalities or a lack of proper dataset augmentation to simulate different environmental conditions. As a result the model may struggle to generalize across different situations leading to lower accuracy or miscommunications. To address these issues additional data collection and augmentation techniques are necessary to expand the variety of conditions and abnormalities the model encounters, improving its robustness and generalization capabilities.

Disease	**Precision**	**Recall**	**F1-Score**
Banana Black Sigatoka	0.720	0.680	0.700
Banana Bract Mosaic Virus	0.850	0.760	0.800
Banana Insect Pest Disease	0.680	0.610	0.640
Banana Moko Disease	0.720	0.750	0.830
Banana Healthy Leaf	-	-	-
Banana Panama Disease	0.750	0.680	0.710
Banana Yellow Sigatoka Disease	0.710	0.800	0.750

Table 5.3: Evaluation metrics for banana disease detection

Furthermore, evaluation metrics must go beyond basic accuracy to provide a more assessment of the model performance in real-world scenarios. Metrics such as precision, recall, and F1 score will give a clear picture of how well the model identifies abnormal crops as shown in table5.3 while minimizing false positives and negatives. The model's ability to adapt to unseen data and generalize across a range of environments should also be assessed. A thorough analysis of the model's predictions including the detection of abnormal crops under varying environmental conditions will help pinpoint areas for improvement and guide further optimization of the system to enhance its effectiveness in practical agricultural applications.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

This project presents an intelligent framework for abnormal crop image data acquisition in smart agriculture leveraging edge intelligence and dynamic-static synergy. It integrates the YOLOv7-FDAC model for detecting abnormal crops and Ant Colony Optimization (ACO) for efficient robot path planning ensuring precise and timely image collection. By overcoming the limitations of traditional method such as low-value data acquisition and inefficient path optimization the framework offers a scalable and effective solution for modern agricultural environments.

The dataset begins with the collection of entire field images that capture the agricultural environment comprehensively. These images are analyzed to identify areas affected by various crop diseases with coordinate position mapping used to assess the severity of crop health issues. This enables real-time predictions with high precision. The model accuracy varies across different diseases with some showing higher precision and recall than others. By focusing on high-severity areas the system ensures timely intervention reducing crop losses and optimizing yields.

In terms of practical applications, this system enhances the efficiency and adaptability of agricultural processes. The integration of edge intelligence reduces redundancy in data and optimizes resource usage for real-world deployment. By offering a robust and scalable solution for monitoring and managing crop health, the project advances precision agriculture, contributing to more sustainable and productive farming practices.

6.2 FUTURE WORK

The future expansion of this work holds promising avenues for enhancing the robustness and applicability of the research. One key area for development is scaling the system to manage larger agricultural fields and a wider variety of crops. Expanding the dataset to include additional crops, diseases and environmental conditions will improve the model's ability to generalize and handle diverse agricultural scenarios. This expansion will also help create a more comprehensive system capable of addressing the complexities of global food production challenges.

Another avenue for improvement involves incorporating IoT sensors for real-time environmental monitoring can significantly enhance the system's functionality. Sensors capable of measuring parameters such as soil moisture, temperature, humidity and nutrient levels can provide valuable context to the crop health data. Integrating this information with weather forecasts and field-specific conditions allows for dynamic adjustments to the detection algorithms improving accuracy and responsiveness. This holistic approach ensures that both crop health and environmental factors are considered in decision-making offering a comprehensive solution for modern agriculture.

Furthermore, developing a cloud-based platform for centralized data storage and analysis can enhance collaboration among stakeholders in agriculture. By uploading and processing data in the cloud farmers researchers and agronomists can access insights and recommendations in real time. This platform can also facilitate large-scale benchmarking of crop health trends across regions enabling a more unified approach to addressing agricultural challenges globally. Such a system can support predictive analytics, enabling early interventions to prevent crop losses and improve yields.

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