INTEGRATING IOT AND MACHINE LEARNING FOR EFFICIENT PEST MANAGEMENT IN GREENHOUSES

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A thesis submitted for the Degree of Master of Computer Science

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This is the same group of farmers and agricultural practitioners who may be the biggest motivational power for this research from its very inception. It also confirmed the sustainability of the practiced farming in a case at hand that results in creative pest problem-solving.

ABSTRACT

This thesis proposes a novel design for a pest management system that increases agricultural productivity by integrating Internet of Things (IoT) technologies and Machine Learning (ML) methodologies. It describes the development of an innovative system to improve productivity in greenhouses through the use of IoT and ML. The system uses an economical and user-friendly mobile application for capturing plant images with a smartphone. These images are then processed with pre-trained TensorFlow Lite models to accurately classify pest infestations.

A custom-designed tripod, equipped with Arduino, Bluetooth module, servo motor, environmental sensors, and cameras, is used to capture images and data on humidity and temperature, enabling automated and comprehensive scanning of the plantation. The data, which include pest identifications with more than 90% confidence, are synced in real time with a Firebase Realtime Database.

Farmers can use the mobile application to select crops that require monitoring, enabling targeted pest management. A web application performs deep analytics, presenting insights through various charts on pest metrics, detection timelines, and the correlation of pest detections with environmental conditions and their impact on different crops. The system also provides custom pest control recommendations and real-time alerts, powered by Firebase Cloud Functions.

The developed system represents a significant advancement in precision agriculture, offering a scalable and efficient solution for pest management in greenhouses or home gardens, utilizing cutting-edge IoT and ML technologies.

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CHAPTER 1

INTRODUCTION

In the present world, the greenhouse plays a crucial part in feeding our everyday growing population, especially with challenges such as climate change and limited resources. To confront these issues, we are approaching innovative methods, like using technology to manage pests in greenhouses. This research explores how the Internet of Things (IoT) and Machine Learning (ML) are coming together and working together to create a revolution in pest control and make agriculture more sustainable.

This study focuses on using latest technologies to help greenhouses to prevent from pests. It uses latest in IoT with ML to not only give best pest prevention techniques but also to protect the natural environment. Most important aspect of the study is to make cost-effective solution for the greenhouse farmers who is working with limited budgets.

By integrating innovation, this research addresses ongoing challenge of pest infestations in greenhouses. It helps to prevent using heavy chemicals that can lead to environmental impacts and aims for affordable and useful solution. The goal is to make a set of applications and hardware components that uses IoT and ML to detect pests in real time. This will reduce the economic losses due to pest damages and usage of heavy chemicals.

It is relatively new in agricultural tech research on the exploration of how IoT and ML can be used in greenhouses. Most studies focus on precision and improving crop yields, not so much on pest control in greenhouses. We are in the early stages of understanding how these technologies could help manage pests in this setting.

Conventional pest management approaches in greenhouses are typically labor-intensive and time-consuming in detection and intervention. Additionally, most existing systems lack real-time capabilities.

This research stands out for combining different fields and its ambiguous goal of integrating IoT and ML research with the unique requirements of greenhouse agriculture. Therefore by customizing these technologies to address the challenges of pest management in greenhouses, this thesis offers a fresh and cost-efficient way to tackle the enduring issue in agricultural practice.

This research aims to be a transformative force in agricultural technology. It seeks to leverage IoT and ML to revolutionize pest management, offering a solution that is precise, cost-effective, and eco-friendly.

This research addresses a significant challenge in modern agriculture, considering the financial constraints faced by greenhouse operators. Uniting IoT and ML, It helps the greenhouse operators to reduce economic losses, minimize environmental impact, and make agriculture more sustainable and affordable.

Overall, this research will bring a new perception in the area of pest management through the integration of image analysis with IoT and ML. This paper presents a comprehensive guideline, having research aim, objectives, and scope of the study, along with the complete structure of the thesis, so that readers can look over this guide while consulting this document.

1.1 Motivation

The motivation for this research is the pressing need to tackle major issues in modern greenhouse farming. Pest infestations pose a formidable threat to crop yields, causing significant economic losses and environmental harm due to heavy chemical use. With the growing global demand for food, it's crucial to find better, sustainable pest management methods. This research is motivated by the idea that blending IoT and ML can help greenhouse operators and farmers adopt smarter, data-driven pest control methods, reducing losses, reducing environmental impact, and making agriculture more sustainable and affordable.

1.2 Statement of the problem

The primary focus of this research is the challenge of pest management within greenhouse environments. Present solutions or methods used are slow, high costs and have adverse environmental effects. Harmful pests can cause huge losses financially and most of the current prevention methods are rely on chemicals. This research is going to solve this problem by using IoT and ML to create an affordable solution.

Emphasizing the necessity for innovation, the research underscores the requirement for a mobile application utilizing smartphone technology, enabling greenhouse operators to identify and manage pests efficiently and sustainably.

1.3 Research Aims and Objectives

1.3.1 Aim

The objectives of this study is to create an affordable and sustainable pest management system for greenhouses using IoT and ML technology. The primary objective is to develop a functional mobile application that allows greenhouse operators to accurately recognise common pests in real time, leading to increased crop yields and a noticeable decrease in reliance on chemical treatments. With the help of proposed system, farmers can redefine pest control methods in the greenhouse industry while maintaining cost effectiveness and protecting the environment.

1.3.2 Objectives

The specific research objectives include:

- **Develop a Cost-Effective Pest Management Solution** Design and implement a system that enables farmers to manage pests in greenhouses or home gardens efficiently and cost-effectively using IoT and ML technologies.
- **Automate Pest Identification**: Utilize a mobile app and a custom-designed tripod with Arduino to automate the process of capturing and classifying plant images for pest identification. This reduces the need for manual inspection and allows for real-time monitoring.
- **Enhance Pest Detection Accuracy**: Employ a pre-trained TensorFlow Lite model to classify plant images with high accuracy. This ensures that pests are accurately identified, allowing for targeted pest control measures.
- **Incoperate Environmental Data**: Incorporate sensors to capture environmental conditions such as humidity and temperature, which are critical factors in pest development and management.
- **Provide Real-Time Data, Analytics and Notifications**: Sync captured data to a Firebase real-time database and use a web app to provide farmers with real-time analytics, pest metrics, and customized pest control recommendations.
- **Minimize Pesticide Usage and Teaching Bilogical Control**: By accurately identifying pest-infected plants, the system enables farmers to apply insecticides only where needed, reducing the overall use of pesticides and minimizing their

environmental impact. Also system will suggest the Bilogical control methods of detected pests tailord to specific crops.

- **Better Analytics and Decisions**: Analyze collected data to identify patterns, breeding seasons, and weather conditions that affect pest development. This information aids farmers in making informed decisions regarding pest management and prevention strategies.
- **Promote Automated Crop Health Monitoring**: Automate the time-consuming manual process of pest inspection, making it more accurate and cost-effective. This allows farmers to take immediate actions to maintain crop health and reduce pesticide-related hazards.

1.4 Scope

This research explores pest detection in greenhouses and home gardens, aiming to replace manual methods with automated systems using IoT and ML. This transition addresses the common inaccuracies in pest management and provide a cost effective solution.

The proposed system includes a mobile application, which captures images of the plants and employs a pre-trained Tensorflow Lite modal to identify pests with high confidence. Images along with the environmental data are then uploaded in a real time firebase database . An innovative aspect of this process is the custom-designed, Arduino-based tripod that autonomously swivels to take multiple images at designated intervals. The tripod, equipped with sensors for temperature and humidity, is controlled via Bluetooth, underscoring the IoT integration in this research.

Upon successful identification of the pests, the data that includes environmental conditions, classification, and the specific crop affected are synchronized with the cloud. Users will be able interact with the system through the mobile app, selecting crops of interest at the initial setup and specifying the crop under observation during the image capturing process.

The collected data will be analyzed via a web application, presenting insights through charts and metrics. It provides comprehensive analysis of pest activities , crop impact, environmental conditions and geographic pest distribution.The web application will also provides customized pest control recommendation and real time alert , generated by firebase cloud function based on the database information.

Initially, the concepts involved capturing pests sounds alongside the images. However, this idea was excluded due to high costs and lack of pests with detectable sounds.

By redefining the scope of this research, the thesis emphasizes its dedication to providing a comprehensive pest management solution. It focuses on pests such as caterpillars, grasshoppers, whiteflies, snails, mealybugs, aphids, and slugs, which greatly impact crop health. While the system is innovative, it also acknowledges limitations such as reduced effectiveness in low light conditions and the current exclusion of sound detection.

In summary, the thesis presents a fresh integration of technology for pest management,facilitating remote monitoring and intervention through a combination of IoT and ML, designed for widespread use by farmers in varied agricultural settings.

1.5 Structure of the Thesis

The following outline provides a coherent structure for this thesis, designed to guide the reader through the accomplished approach taken to develop a cost-effective and technologically sophisticated pest management system for greenhouses. The structure of this is not only a reflection of the logical flow of the research but also helps in understanding by highlighting how each part contributes to the whole.

- **Chapter 1: Introduction** - This chapter sets the stage for the research by outlining the significance of greenhouse agriculture and the necessity for innovative pest management solutions. It introduces the integration of IoT and ML technologies and presents the motivation, problem statement, aims, objectives, and scope of the study.
- **Chapter 2: Literature Review** - The literature review chapter delves into the existing body of work related to IoT, ML, and their application in agriculture, particularly pest management. It critically evaluates the current landscape and identifies gaps that this research aims to address.
- **Chapter 3: Methodology** - This chapter details the systematic approach taken in developing the pest management system, including design assumptions, prototype architecture, algorithmic design, and the integration of various components such as the mobile application, web application and custom-designed tripod.

- **Chapter 4: Evaluation and Results** - The evaluation chapter presents a thorough analysis of the chosen ML algorithms, providing insights into their efficiency and accuracy through real-world data. It assesses the algorithms' performance and rationalizes the selection of the most suitable one for the system.
- **Chapter 5: Conclusion and Future Work** - This chapter highlights the benefits of using a combined pest control system and suggests further research to improve the original work. It aims to be both an in-depth study and a user-friendly guide for additional work and changes.

By providing more details in each chapter, it helps readers understand what the system can achieve. The thesis outlines a straightforward approach to tackling the challenges of using IoT and ML for pest management in greenhouses, making it highly useful for anyone trying to navigate this area.

CHAPTER 2
LITERATURE REVIEW

2.1 Related Work

Recent research indicates that the integration of Internet of Things (IoT) and Machine Learning (ML) technologies holds significant potential for improving pest management in agriculture, particularly in greenhouses. By leveraging these advanced technologies, the identification and control of pests can be enhanced, leading to more effective pest management strategies. This literature review discusses several important studies and developments relevant to this project, highlighting the advancements in IoT and ML and their applications in agriculture.

2.1.1 Advancements in IoT for Agriculture

The adoption of IoT has revolutionized precision agriculture, enabling more effective monitoring and management of crops. For example, Azevedo et al. (2024) developed an automatic weather station specifically for irrigation management. This IoT system is particularly beneficial as it utilizes real-time environmental data to optimize water usage, representing a significant advancement in water conservation for agriculture. Additionally, in 2024, Maity et al. introduced SmartTech-Agri, a range of IoT-based devices equipped with various sensors and tools to collect data. These devices provide a detailed overview of soil and crop health, offering farmers valuable insights to enhance their crop management strategies.

2.1.2 Deep Learning in Pest Detection

The integration of deep learning into agricultural practices, especially in pest detection, has made remarkable progress. Early work by Sladojevic et al. (2016) demonstrated the effectiveness of convolutional neural networks (CNNs) in identifying plant diseases, laying the groundwork for current pest detection systems. Kamilaris and Prenafeta-Boldú (2018) provided a comprehensive review of deep learning applications in agriculture, highlighting the potential of these technologies to address various challenges in pest management.

2.1.3 Comparative Studies in Machine Learning for Agriculture

Comparing ML techniques is essential for identifying the most effective methods for particular agricultural applications. Liakos et al. (2018) reviewed machine learning applications in agriculture, focusing on predictive analytics and decision support systems. Their findings underscore the importance of selecting the right algorithms for specific tasks, which is critical for optimizing pest management strategies.

2.1.4 Hyperspectral Imaging and Deep Learning for Crop Inspection

Combining hyperspectral imaging with deep learning techniques presents an innovative method for crop inspection. Mahlein et al. (2018) demonstrated the potential of hyperspectral imaging for plant disease detection, providing a foundation for integrating this technology with deep learning for more accurate pest and disease management.

2.1.5 IoT and Deep Learning for Crop Spraying Systems

The IoT and deep learning are also advancing in the field of crop protection. Zhang et al. (2018) explored the use of drone-based systems combined with IoT for precision spraying, highlighting the efficiency and environmental benefits of this approach.

2.1.6 Integrated Pest Management (IPM) Strategies

Integrated pest management (IPM) strategies have evolved by combining traditional farming knowledge with new technology to better detect and manage crop diseases. Bajwa and Kogan (2002) provided a comprehensive framework that modern studies, like those by Parsa et al. (2014), build upon by integrating advanced technologies such as IoT and machine learning to enhance pest management strategies.

2.2 Research Gaps

Despite the progress and promise of combining IoT and ML in agriculture, there are still several areas that need further research, which this study aims to explore:

1. Solution for Small Scale Farmers: There are various solutions can be found for pest management in greenhouses with IoT and ML. But they are very costly and not affordable for small scale farmers. Those farmers also lack technical skills to use those complex systems. This research study aims to reduce this gap by creating an affordable and easy to use system so that small farmers also can be beneficial.

2. Real-Time Data Processing and Offline Pest Identification: Many existing systems rely on cloud computing for data processing, which can introduce latency and requires a continuous internet connection. However, there is a need for systems that can process data locally, reducing reliance on constant connectivity. This is particularly crucial for remote or rural areas with limited internet access. The proposed pest management system addresses this gap by implementing local data processing, ensuring efficient operation even in areas with intermittent internet connectivity. This approach enhances the system's usability and effectiveness in diverse agricultural settings.

3. Keep Track of the Environmental Conditions: Even though modern pest management systems capable of precise pest detections, most of the systems are lack of keeping the eye on environmental conditions. Those environmental conditions can make huge impact on how the pest infestations were increased or decreased. By keeping an eye on the environmental conditions with the pest detections, proposed system will give greater details for the greenhouse owner to take accurate decisions.

4. User Friendly Design: Many agricultural technologies prioritize technical features but fall short in considering the users' perspectives, resulting in systems that may not suit the needs and abilities of the end-users. The system being developed in this research emphasizes usability to ensure that it aligns with the practical needs and skills of its target users.

5. Sustainable Pest Management Practices: There is a continuous need for research into sustainable pest management practices that reduce the reliance on chemical pesticides. This study addresses this need by presenting a system that not only detects pests but also provides integrated pest management recommendations. By doing so, it supports environmentally friendly farming practices.

6. Long-Term and Extended Crop Studies: Most of the studies in the field are conducted over short periods of time with a limited number of crops. There is a lack of long-term research project examining how effective the usage of IoT and ML systems across multiple growing seasons and variety of crops. My study aims to address this gap by testing the solution over different kind of crops and monitoring its performance over extended periods.

The proposed system in this study aims not only to address the identified gaps but also to offer a foundation for future research. By doing so, it contributes to the advancement of smart agriculture technologies that are both effective and accessible to a broader range of farmers.

CHAPTER 3
METHODOLOGY

3.1 Overview

This chapter outlines the systematic approach adopted in developing and validating the proposed pest management system. The system integrates Internet of Things (IoT) devices with Machine Learning (ML) models to create an elegant solution for smart agriculture, specifically tailored for greenhouse environments. The process flow includes design specifications, algorithm development, and the creation of a functional prototype.

3.2 Design Assumptions

The proof of concept is predicated on several design assumptions:

- **Greenhouse Environment**: The system is designed for small to medium-sized greenhouses up to 1000 square meters.
- **Crop Types**: It targets common greenhouse crops such as tomatoes, cucumbers, beans, beets, cabbage, carrots, eggplant, herbs, melons and peppers.
- **Pest Types**: The model focuses on frequently encountered pests in these environments, like aphids, whiteflies, caterpillars, grasshoppers, mealybugs, slugs and snails.
- **Environmental Parameters**: Temperature and humidity are the primary environmental factors monitored due to their influence on pest proliferation.
- **IoT Capabilities**: The IoT devices are assumed to have the capability to capture high-resolution images and accurate environmental data.

3.3 Process Flow Diagram

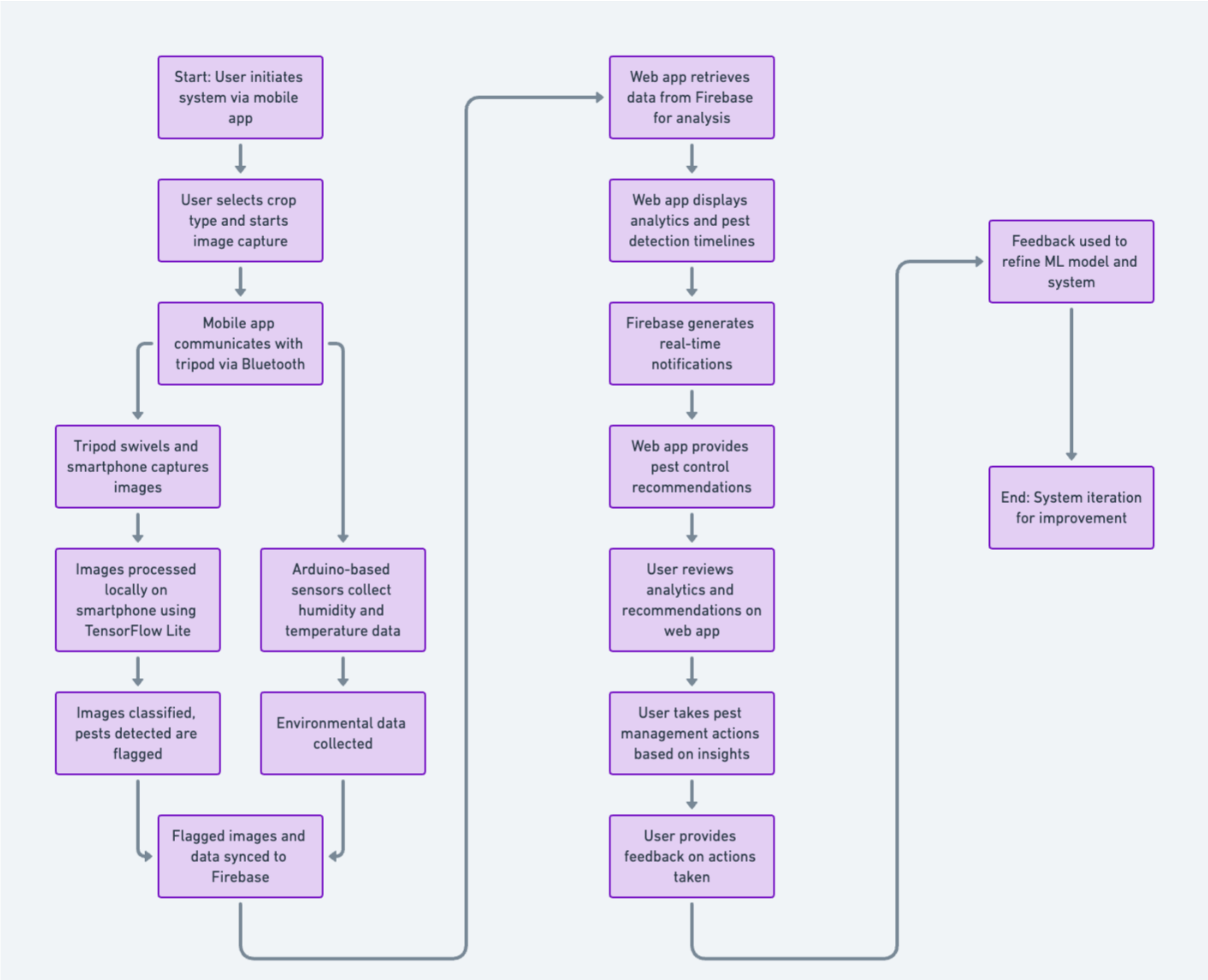


Figure 3.1 Process flow diagram

All the interconnected processes that involve with the pest management system includes in above Figure 3.1. It showcases how each process is connecting with each other.

3.4 Prototype Architecture

The prototype is structured with several interconnected components:

- **Custom-Designed Tripod**: Features a rotating mechanism controlled by Bluetooth, enabling the smartphone to capture images of the crops.
- **Sensors**: Arduino-based sensors are installed to measure temperature and humidity.
- **Mobile Application**: Provides the functionality for image capture and acts as the user interface for interacting with the system.
- **Cloud-Based Database**: Utilizes Firebase for the synchronization and storage of data in real-time.

The design of the architecture aims to facilitate smooth data flow and user-friendly operation for the end-user.

3.5 Algorithmic Design Details: Enhanced Explanation

3.5.1 Selection of Algorithms for Model Training

To develop a robust and efficient pest identification system, a range of pre-trained models were carefully selected, each offering unique advantages:

- **MobileNet**: Chosen for its compact architecture and effectiveness on mobile devices, making it suitable for real-time analysis.
- **EfficientNet**: Selected for its ability to scale and provide an optimal balance between speed and accuracy, enabling precise pest detection with minimal computational demands.
- **ResNet**: Incorporated for its deep residual learning framework, which addresses the vanishing gradient problem, allowing it to learn from large datasets without performance degradation.
- **Inception**: Chosen for its innovative convolutional architecture that enhances efficiency and reduces computational costs.
- **DenseNet**: Appreciated for its dense connectivity pattern, which improves information and gradient flow within the network, resulting in better learning and feature extraction capabilities.

These models were chosen to encompass a wide range of advancements in deep learning architecture, with the goal of identifying the most effective framework for pest detection in greenhouse environments.

3.5.2 Dataset Preparation and Augmentation

The dataset for this study was obtained from respected online databases like PestID, PestNet, and IPM, featuring a varied collection of images representing different pests and environmental conditions common in greenhouse environments. Before training the model, all images were resized to ensure consistency. Data augmentation techniques, including rotation, scaling, and color adjustment, were applied to expand the diversity and size of the dataset. These enhancements improve the model's capacity to generalize and accurately identify pests in new, unseen images.

3.5.3 Training and Validation Process

A critical aspect of the methodology involved allocating 20% of the dataset for validation purposes. This separation allowed for an unbiased evaluation of each model's performance, offering a clear measure of their pest detection capabilities. During the training phase, each selected model was fine-tuned on the augmented dataset. This process involved carefully adjusting their parameters and structures to optimally address the unique pest characteristics encountered in greenhouse environments.

3.5.4 Hyperparameter Optimization and Model Evaluation

The training phase was enhanced by hyperparameter optimization, which aimed to determine the optimal settings for each algorithm. This included adjustments to learning rates, batch sizes, and the number of training epochs. This step was crucial for optimizing model accuracy and efficiency. Afterward, the performance of each model was thoroughly evaluated using the validation dataset. Evaluation metrics such as accuracy, precision, recall, and F1-score were used to measure their effectiveness in accurately detecting pests.

3.6 Android App Development

3.6.1 Overview

The Android app acts as the main interface for users to engage with the pest management system. It enables users to capture images, view results from the pest detection model, and manage and monitor data synchronized with the cloud database.

3.6.2 Design and Implementation

- **User Interface (UI):** The app boasts a user-friendly interface tailored to users of different technical backgrounds. Key features include capturing images, displaying real-time data, and analyzing historical data.
- **Image Capture Workflow:** Using the smartphone's camera, the app assists users in

capturing high-quality images of crops. The custom-designed tripod aids this process by ensuring consistent image angles and distances.

- **Data Synchronization:** The app automatically synchronizes captured images and environmental data with a Firebase real-time database. This enables immediate analysis of pest detection results and environmental conditions.
- **Notification System:** The app features a notification system to give users a reminder to monitor their plantations daily.

3.7 Custom Tripod Development

3.7.1 Overview

The custom-designed tripod is an essential hardware component of the system, enabling automated and consistent image capture across different areas of the greenhouse.

3.7.2 Design and Construction

- **Framework:** The tripod is designed with stability and mobility in mind, allowing for easy placement and adjustment in various greenhouse settings.
- **Rotating Mechanism:** The tripod features a servo motor controlled by Bluetooth, enabling it to rotate the mounted smartphone to capture images at specific intervals and angles, ensuring thorough coverage of the crops.
- **Environmental Sensors:** Arduino-based sensors integrated into the tripod setup measure temperature and humidity, providing vital data that complements the image-based pest detection.
- **Bluetooth Connectivity:** The tripod communicates with the Android app via Bluetooth, receiving commands to start image capture sequences and sending environmental data back to the app.

3.7.3 Integration with the Android App

The collaboration between the custom tripod and the Android app is crucial to the system's functionality. This integration enables smooth control over image capture and instant access to environmental data, improving the efficiency and precision of pest detection.

3.8 Web Application Development

3.8.1 Overview

The web application is a crucial component of the greenhouse pest management system. It serves as a platform for users to access and analyze data collected by the IoT devices and processed by the ML algorithms. The application provides a detailed overview of the greenhouse's pest situation and environmental conditions, along with practical recommendations for pest management.

3.8.2 Design and Implementation

- **Architecture:** The web application is developed using the modern web development framework ReactJS, ensuring a responsive and user-friendly interface. It is designed for scalability and easy maintenance, with a modular architecture that separates the front-end presentation layer from the back-end data processing and storage layer.
- **Data Visualization:** The application utilizes various charting libraries, such as Chart.js, to create interactive and informative visualizations of pest and environmental data. These visualizations help users quickly identify trends and patterns, assisting in decision-making.
- **Real-time Data Integration:** By leveraging Firebase Realtime Database and Cloud Functions, the web app ensures that the data displayed is always updated. Real-time synchronization allows users to monitor their greenhouse conditions and pest detections as they occur.
- **Notification System:** The application features a notification system that alerts users to significant events, such as high pest activity or adverse environmental conditions. These notifications are generated based on real-time data and predefined thresholds.

3.8.3 Testing and Deployment

Testing: The web application is subjected to thorough testing to verify its functionality and performance. This involves unit testing for individual components to ensure they function correctly in isolation, integration testing to check the data flow and interaction between components, and end-to-end testing to assess the overall user experience.

Deployment: The application is deployed on the cloud platform Firebase Hosting, which guarantees scalability and high availability. Continuous integration and deployment pipelines are established to automate the deployment process, ensuring that updates and fixes are seamlessly implemented.

3.9 Architectural Diagram

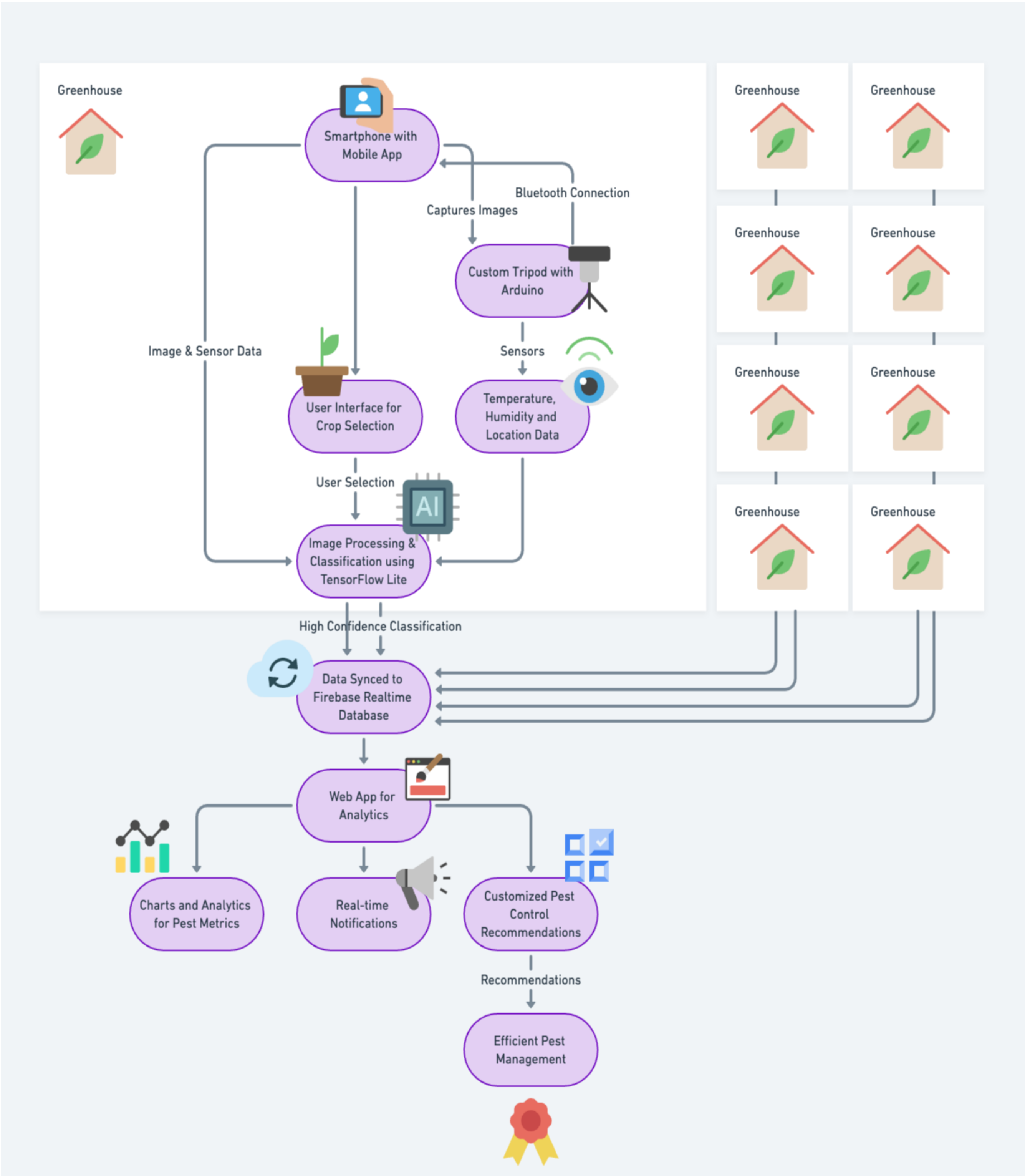


Figure 3.2 Architectural diagram

Above Figure 3.2 diagram is visualizing how structural components and relationships are connected in pest management system. It showcases holistic view of the system architecture.

CHAPTER 4

EVALUATION AND RESULTS

4.1 Algorithm Selection Rationale

When selecting the Machine Learning (ML) algorithms for image classification method in the pest management system, I had to consider several factors to shortlist the algorithms that I'm going to use. Factors such as efficiency, scalability and performance were considered and following algorithms were chosen based on their suitability for this task, real-time image classification features and ability to include with TensorFlow Lite.

- **MobileNet:**
    - **Rationale:** MobileNet is designed for mobile and embedded vision applications. It is lightweight and efficient, making it suitable for real-time pest detection in a cost-effective system. It offers a good balance between accuracy and computational efficiency.
    - **Key Features:** Uses depthwise separable convolutions to reduce the number of parameters and computational cost. Can be easily adjusted for different trade-offs between latency and accuracy.
    - **Suitability:** Highly suitable for real-time image classification due to its lightweight architecture and efficient design, which allows for quick processing of images and reduced computational requirements.
- **EfficientNet:**
    - **Rationale:** EfficientNet is known for its efficiency and scalability. It uses a compound scaling method to uniformly scale the depth, width, and resolution of the network, which leads to better performance with fewer parameters.
    - **Key Features:** Achieves higher accuracy with fewer parameters compared to other models. Can be scaled up or down to meet the requirements of the system.
    - **Suitability:** Valuable for its ability to achieve high accuracy with fewer parameters and scalability, allowing fine-tuning for a balance between speed and accuracy in real-time image classification.

- **ResNet:**
    - **Rationale:** ResNet introduces residual connections to alleviate the vanishing gradient problem, allowing for deeper networks that can learn more complex features. This can be beneficial for accurately classifying a wide variety of pests.
    - **Key Features:** Utilizes skip connections to enable the training of very deep networks. Has shown excellent performance in image classification tasks.
    - **Suitability:** Well-suited for real-time image processing due to its ability to train deeper networks without a significant increase in computational complexity, ensuring accuracy and speed.

- **Inception:**
    - **Rationale:** Inception (or GoogLeNet) uses a combination of different-sized convolutional filters within the same layer, allowing it to capture features at various scales. This can be useful for detecting pests of different sizes and shapes.
    - **Key Features:** Incorporates multiple filter sizes in each layer to capture various feature representations. Efficient in terms of computational cost and parameters.
    - **Suitability:** Suitable for real-time image classification due to its ability to capture features at various scales and efficient use of computational resources.
- **DenseNet:**
    - **Rationale:** DenseNet connects each layer to every other layer in a feed-forward fashion, which leads to better feature propagation and reuse. This can enhance the model's ability to learn detailed features of pests.
    - **Key Features:** Features dense connections between layers, leading to improved information flow and reduced number of parameters. Known for its efficiency and effectiveness in image classification.
    - **Suitability:** Strong candidate for real-time image classification in a cost-effective system due to its efficient feature reuse, reduced parameter count, and ability to learn detailed features with limited computational resources.

4.2 Algorithm Evaluation

To determine the most suitable algorithm for the pest management system, the performance of each algorithm was evaluated using a set of predefined metrics. Each algorithm was trained using TensorFlow Lite with the same dataset and compared based on accuracy, precision, recall, F1 score, and average inference time.

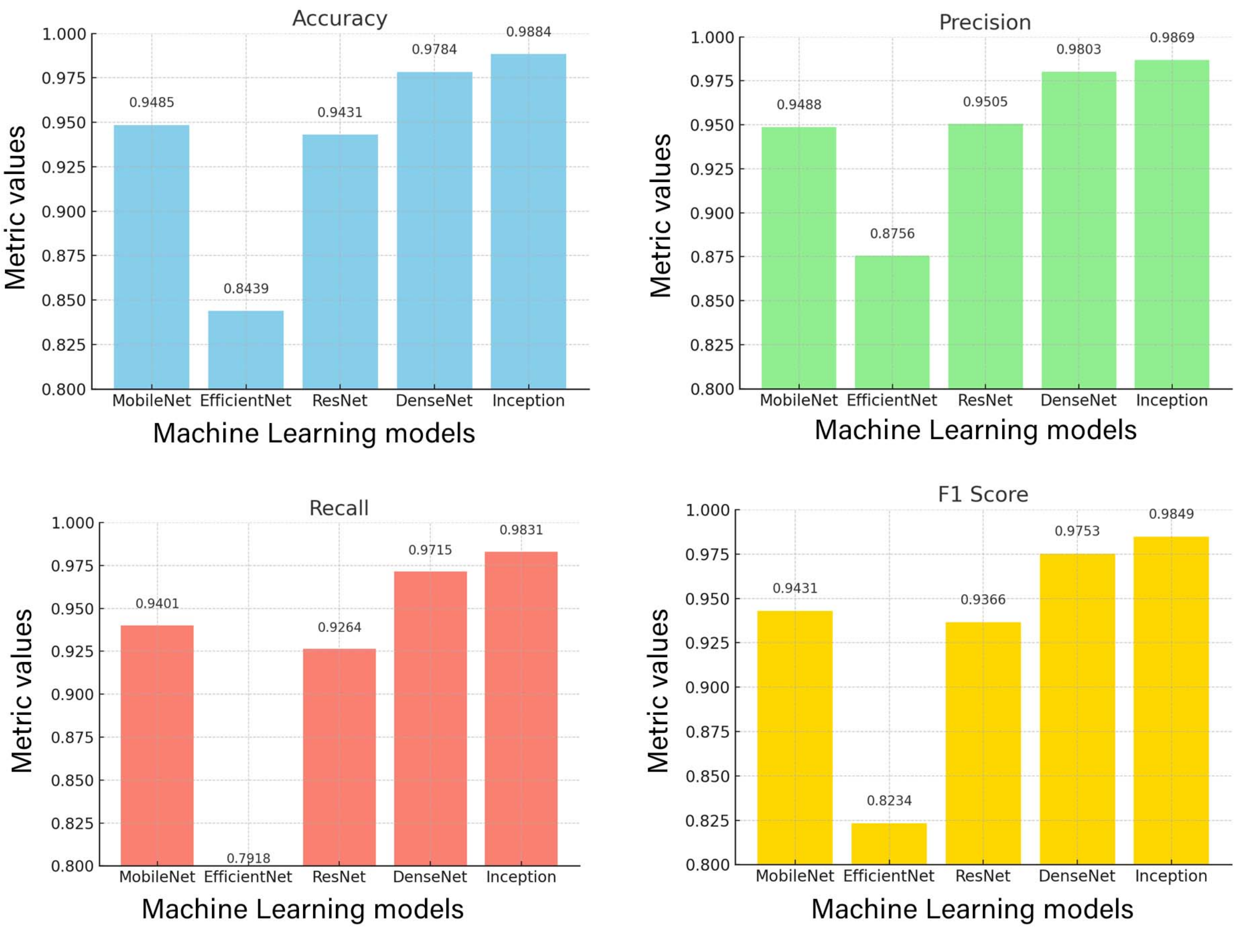


Figure 4.1 Comparison of Machine Learning algorithms for pest management system

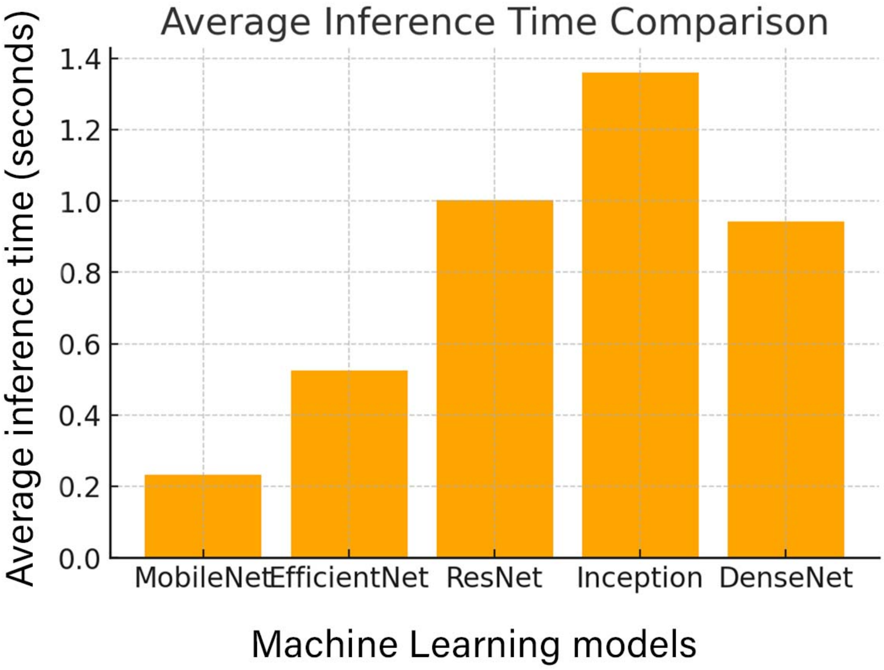


Figure 4.2 Average inference time comparison

With the results of the evaluation showed in Figure 4.1, **Inception** outperformed the other algorithms in terms of accuracy, precision, recall, and F1 score, with an accuracy of 98.84%, precision of 98.69%, recall of 98.31%, and F1 score of 98.49%. However as you can see in the Figure 4.2, it had the longest average inference time of 1.3611 seconds. **DenseNet** also performed well, with high accuracy and a relatively shorter inference time.

Considering the balance between performance and computational efficiency, **DenseNet** must be the best algorithm for the pest management system due to its high accuracy, efficiency, and ability to learn detailed features with limited computational resources.

4.3 Real World Data

To validate the effectiveness of the selected ML algorithms in a real-world setting, a comprehensive evaluation was conducted using actual pest images collected from various greenhouses. A total of 7 distinct pests were imaged, and each was classified by the following algorithms: MobileNet, EfficientNet, ResNet, Inception, and DenseNet. The classification confidence levels, the true classifications, and the algorithm-identified classes were recorded for each instance.

4.3.1 Data Collection Methodology

The images were captured with the combination of mobile application and custom developed tripod setup. Each pest image was classified by the algorithms I've used and following data is recorded.

- **Real Class of the Pest**: The actual pest identified by an expert or the known class label from the dataset.
- **Algorithm Identified Class**: The pest classification as identified by the algorithm.
- **Confidence Level**: The probability assigned by the algorithm to its classification, indicating how certain it is of its decision.

4.3.1.1 Aphids vs Algorithms Performance

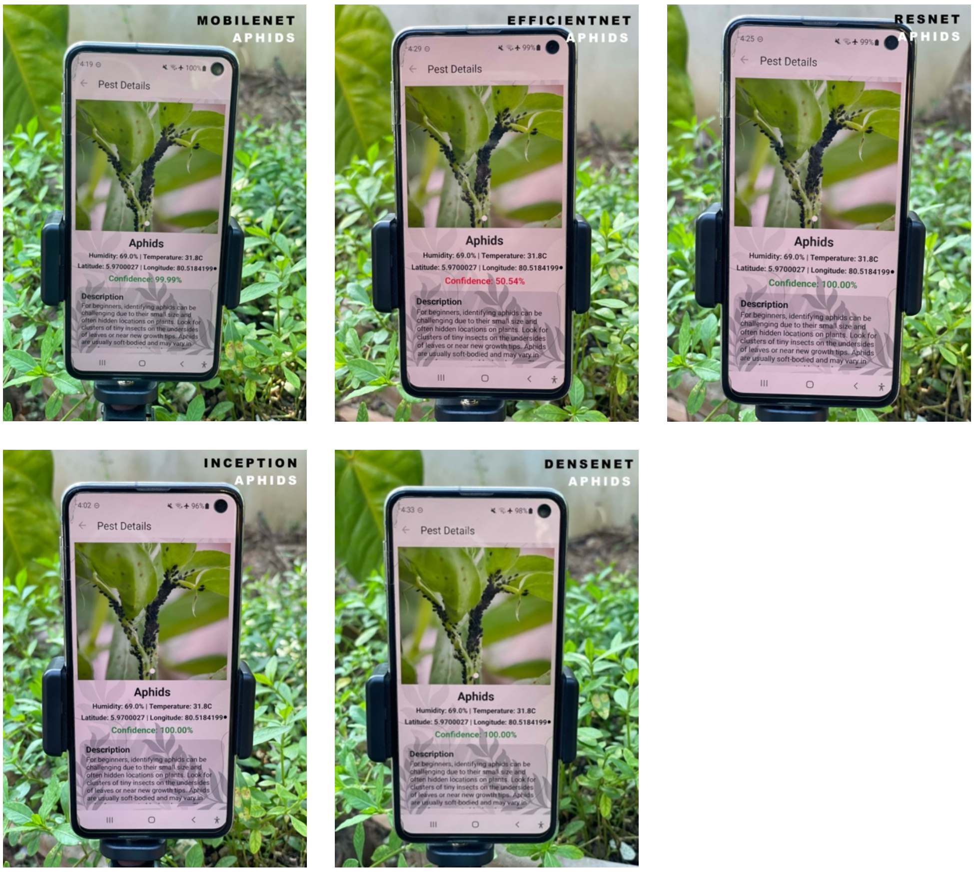


Figure 4.3 Aphids vs algorithms performance

Figure 4.3 presents a detailed analysis of the performance of various algorithms in detecting aphids from images captured in real-world greenhouse environments. The algorithms included MobileNet, EfficientNet, ResNet, Inception, and DenseNet, with a particular focus on their ability to classify aphid images accurately. Results showed exceptional performance by DenseNet and Inception, both achieving 100% confidence levels in identifying aphids, underlining their suitability for real-time pest detection. This high accuracy and precision suggest that these algorithms are highly effective in recognizing aphid-specific features such as shape, color, and texture from the captured images.

4.3.1.2 Caterpillar vs Algorithms Performance

Figure 4.4 Caterpillar vs algorithms performance

The caterpillar detection performance analysis in the Figure 4.4 reveals a challenging scenario for the algorithms tested. Despite the high efficiency of DenseNet and Inception in other pest detections, caterpillar identification proved difficult, with significantly lower confidence levels across all algorithms. The best performance was noted from MobileNet, which identified caterpillars with a 79.24% confidence, albeit mistakenly classifying some as whiteflies. This indicates a need for further model refinement or data augmentation to improve caterpillar detection accuracy.

4.3.1.3 Grasshopper vs Algorithms Performance

Figure 4.5 Grasshopper vs algorithms performance

In the case of grasshopper detection, as you can see in the Figure 4.5, the Inception algorithm is the only model identified the image accurately, demonstrating a 95.94% confidence level. All the other models were identified the image incorrectly. They all are identified it as aphids with variety of confidence levels. It looks like they all are struggled with the background of where the grasshopper is. This superior performance of the Inception highlights its capability of identifying pests accurately even in the complex backgrounds. Inception showcases its robustness in feature extraction and categorization under varying situations.

4.3.1.4 Mealybug vs Algorithms Performance

Figure 4.6 Mealybug vs algorithms performance

Figure 4.6 showcases the analysis of algorithm performance for mealybug detection, the challenge was notable due to the mealybugs' small size and the complexity involved in their identification. Despite these challenges, the analysis showed that some algorithms, particularly DenseNet and Inception, were able to achieve significant confidence levels in identifying mealybugs. Inception, with a confidence level of 95.41%, demonstrated a strong capability in accurately classifying mealybugs from the captured images. This indicates that, while challenging, the detection of mealybugs is within the reach of current ML models, suggesting a path forward for refining these models to improve detection accuracy.

4.3.1.5 Slug vs Algorithms Performance

Figure 4.7 Slug vs algorithms performance

Figure 4.7 showing how each algorithm identified slug. With the above results we can see that Inception and ResNet showcases high accuracy. The Inception algorithm achieved a confidence score of 99.99% and ResNet scored 99.53% with accurately identifying the slug. The results highlight the effectiveness of these algorithms in identifying slugs bringing their ability to correctly identify slugs accurately from other pests and elements in the images. The high confidence levels accomplished by Inception and ResNet indicate these two models are highly reliable to identify slugs, offering valuable tools for pest management systems aiming to accurately identify pest with high confidence.

EfficientNet also identified the image as a slug, but with lower confidence level. DenseNet identfied the image as aphids, making it the least accurate model.

4.3.1.6 Snail vs Algorithms Performance

Figure 4.8 Snail vs algorithms performance

The performance analysis for snail detection as showcasing in the Figure 4.8, echoed the high accuracy seen in slug identification, with all algorithms achieving near perfect or perfect scores. This uniform success across the board highlights the distinct visual features of snails that make them easier to identify by ML algorithms, affirming the potential of technology in enhancing pest detection and management strategies.

4.3.1.7 Whitefly vs Algorithms Performance

Figure 4.9 Whitefly vs algorithms performance

Figure 4.9 re-examines the algorithms' capabilities in detecting whiteflies, highlighting the continued challenges faced in accurately identifying this pest. Despite previous efforts, all algorithms, particularly Inception and DenseNet, struggled with high accuracy rates. DenseNet, however, demonstrated a notable ability to classify whiteflies with relatively higher confidence levels compared to others. This underscores the need for further optimization and targeted improvements in algorithmic strategies for better whitefly detection in pest management systems.

4.3.2 Evaluation Metrics

The performance of each algorithm was assessed using the following metrics:

- **Accuracy**: The proportion of true results among the total number of cases examined.
- **Precision**: The proportion of true positive identifications over all positive identifications made.
- **Recall**: The proportion of true positive identifications over all pests that were actually present.
- **F1 Score**: A measure of an algorithm's accuracy that considers both the precision and the recall.

4.3.3 Results Summary

Table 4.1 summarizing the evaluation results for each pest across all algorithms is presented below. This Table 4.1 showcases the performance of each algorithm in classifying the pests with a high level of confidence.

Actual Pest Class	DenseNet (Class, Confidence)	EfficientNet (Class, Confidence)	Inception (Class, Confidence)	MobileNet (Class, Confidence)	ResNet (Class, Confidence)
Aphids	(Aphids, 100%)	(Aphids, 50.54%)	(Aphids, 100%)	(Aphids, 99.99%)	(Aphids, 100%)
Caterpillar	(Caterpillar, 40.32%)	(Aphids, 70.54%)	(Aphids, 72.14%)	(Whitefly, 79.24%)	(Whitefly, 60.62%)
Grasshopper	(Aphids, 55.57%)	(Aphids, 86.25%)	(Grasshopper, 95.94%)	(Aphids, 99.39%)	(Aphids, 78.21%)
Mealybug	(Whitefly, 97.85%)	(Aphids, 68.72%)	(Whitelfy, 95.41%)	(Whitefly, 55.16%)	(Whitefly, 99.74%)
Slug	(Aphids, 71.56%)	(Slug, 74.63%)	(Slug, 99.99%)	(Slug, 93.36%)	(Slug, 99.53%)
Snail	(Snail, 100%)	(Snail, 91.95%)	(Snail, 99.94%)	(Snail, 100%)	(Snail, 97.86%)
Whitefly	(Aphids, 98.79%)	(Aphids, 85.77%)	(Whitefly, 81.28%)	(Aphids, 89.21%)	(Aphids, 93.18%)

Table 4.1 Real world test results

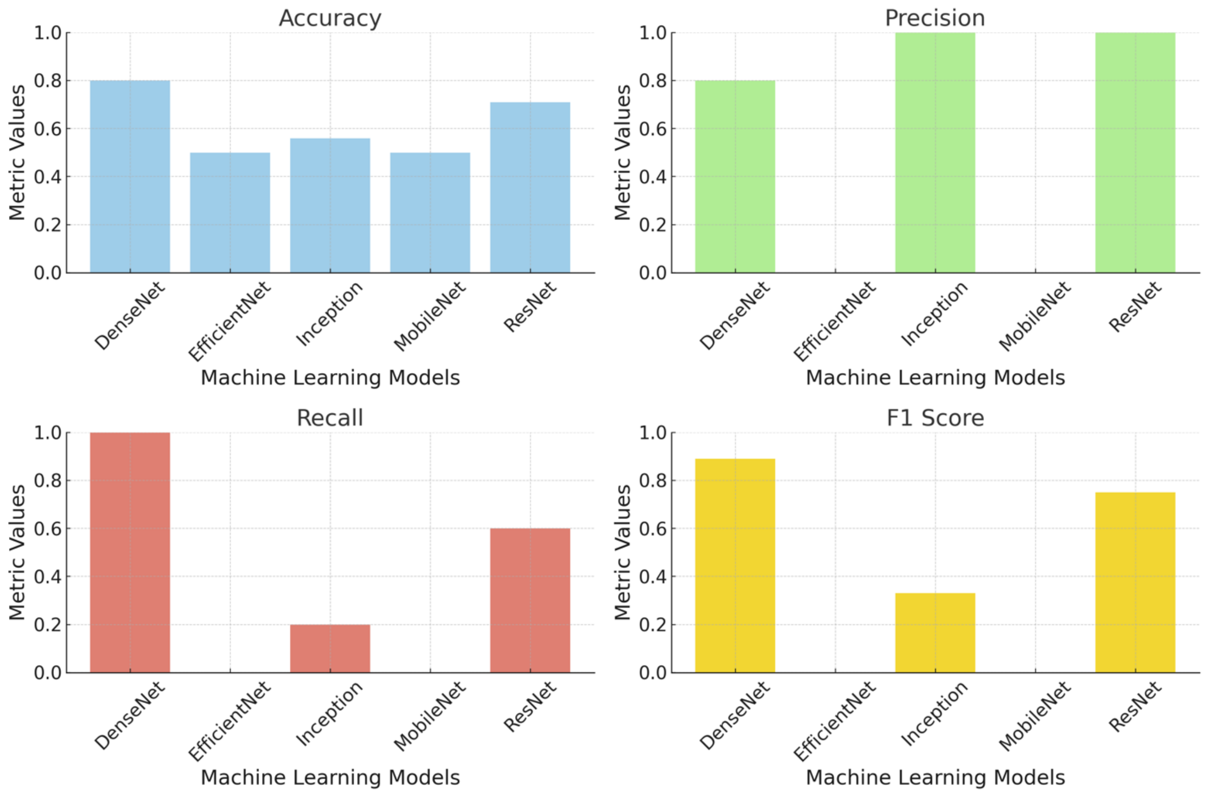


Figure 4.10 Comparison of Machine Learning algorithms for pest management system with real world data

4.3.4 Discussion

As you can see in the Figure 4.10 data, it indicates that **DenseNet** demonstrated a high degree of accuracy with a confidence level above the 90% threshold for most pests. This suggests that the algorithm is highly reliable for real-time pest identification in greenhouse environments. This real world conclution matches with the above test dataset conclusion. Detailed observations for each pest and algorithm performance are as follows:

- **Aphids:** DenseNet, Inception, MobileNet, and ResNet achieved high accuracy and precision, indicating their effectiveness in identifying aphids with high confidence.
- **Caterpillar:** None of the algorithms performed well in identifying caterpillars, with all metrics indicating poor performance. This suggests that further tuning or alternative approaches may be needed for caterpillar identification.
- **Grasshopper:** Inception showed the highest accuracy and F1 score for grasshopper identification, although the recall rate was still relatively low. This

indicates that while Inception can identify grasshoppers accurately, it may miss some instances.

- **Mealybug:** Similar to caterpillars, none of the algorithms performed well in identifying mealybugs, with all metrics indicating poor performance. Further refinement or alternative methods may be necessary for mealybug identification.
- **Slug:** Inception, MobileNet, and ResNet achieved high accuracy and precision for slug identification, with DenseNet also performing well. This suggests that these algorithms are suitable for accurate slug identification in greenhouse environments.
- **Snail:** All algorithms achieved perfect accuracy and precision for snail identification, indicating their high reliability for this pest.
- **Whitefly:** Similar to caterpillars and mealybugs, whitefly identification proved challenging for all algorithms, with low accuracy, precision, and recall rates. Further optimization or alternative approaches may be required for whitefly identification.

4.3.5 Implications for System Deployment

The real-world data support the selection of DenseNet for the pest management system, balancing computational efficiency with high classification performance. The results also guide future improvements, such as algorithm tuning for specific pests that may have shown lower confidence levels.

4.4 Web Application Evaluation

The web application serves as a crucial component of the greenhouse pest management system, providing users with an intuitive interface for accessing real-time data, analytics, and recommendations. This section evaluates the web application's functionality, user interface, and overall integration with the pest management system.

4.4.1 User Interface and Functionality

The web application is designed with a user-friendly interface that allows greenhouse operators to easily navigate through different sections and access various features. Key functionalities of the web app include:

- **Dashboard:**

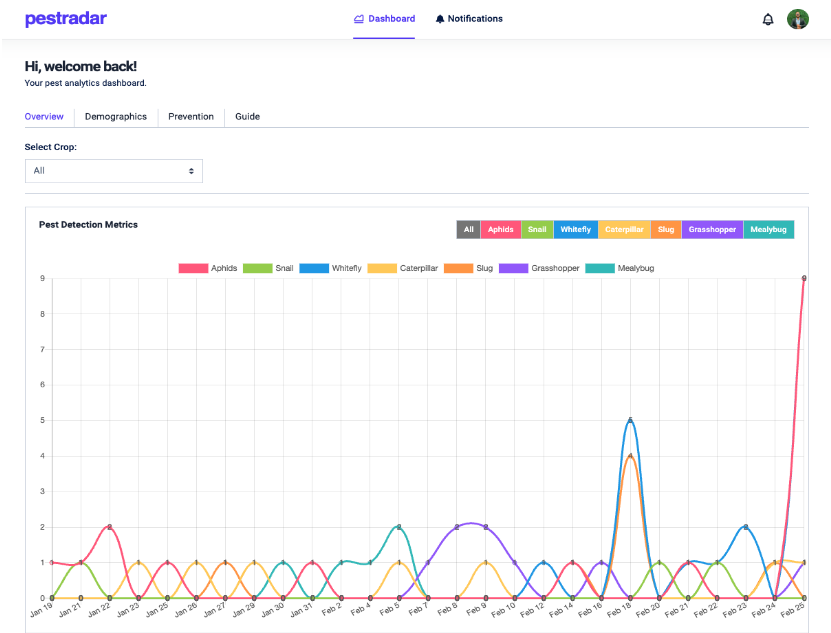


Figure 4.11 Screenshot of the web app - dashboard

The Figure 4.11 showcases how main dashboard provides an overview of the greenhouse's current status, including recent pest detections, environmental conditions, and critical alerts.

- **Pest Metrics:**

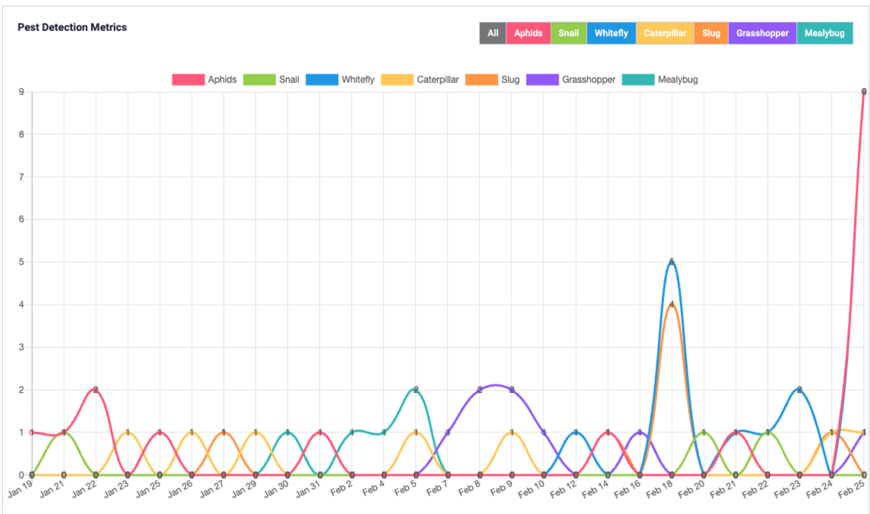


Figure 4.12 Screenshot of the web app - pest metrics chart

As you can observe in the Figure 4.12 this section displays detailed analytics on pest detections over time, allowing users to identify trends and patterns in pest activity. Users can filter data based on specific pests, crops, or time periods.

- **Environmental Analysis:**

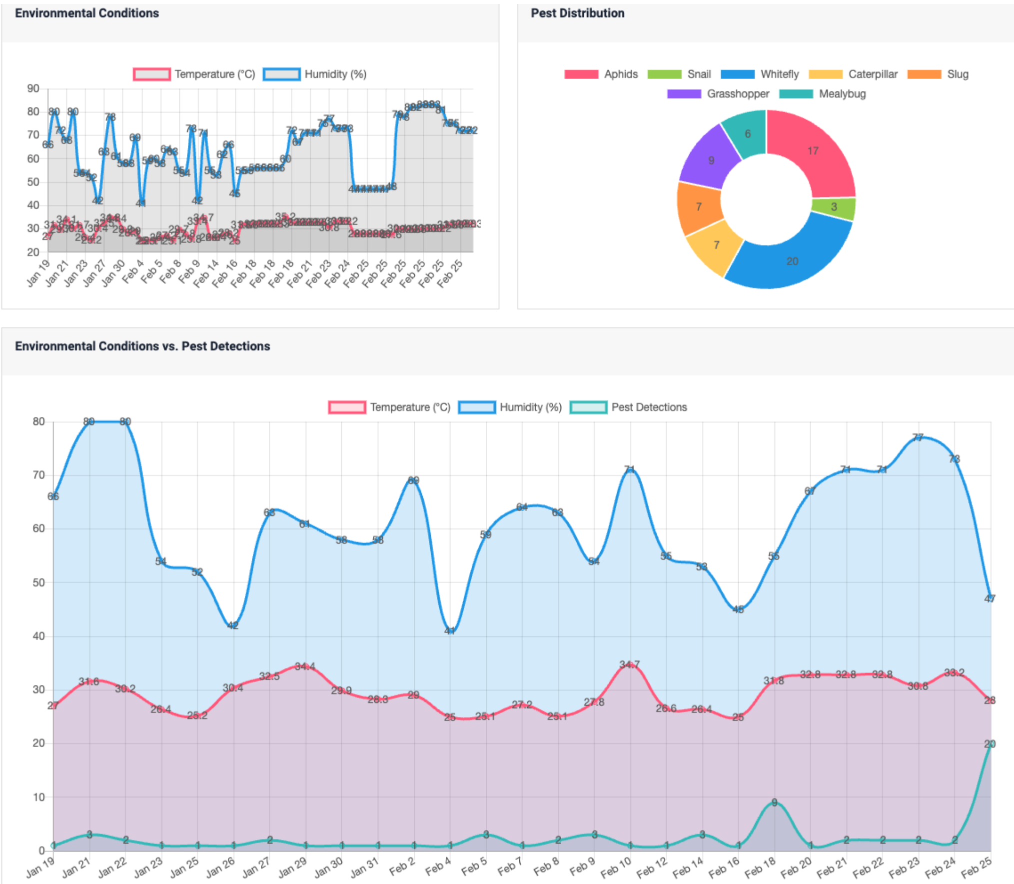


Figure 4.13 Screenshot of the web app - environmental analysis

The Figure 4.13 depict how the web app correlates pest detections with environmental conditions, such as temperature and humidity, helping users understand the factors influencing pest prevalence.

- **Recommendations:**

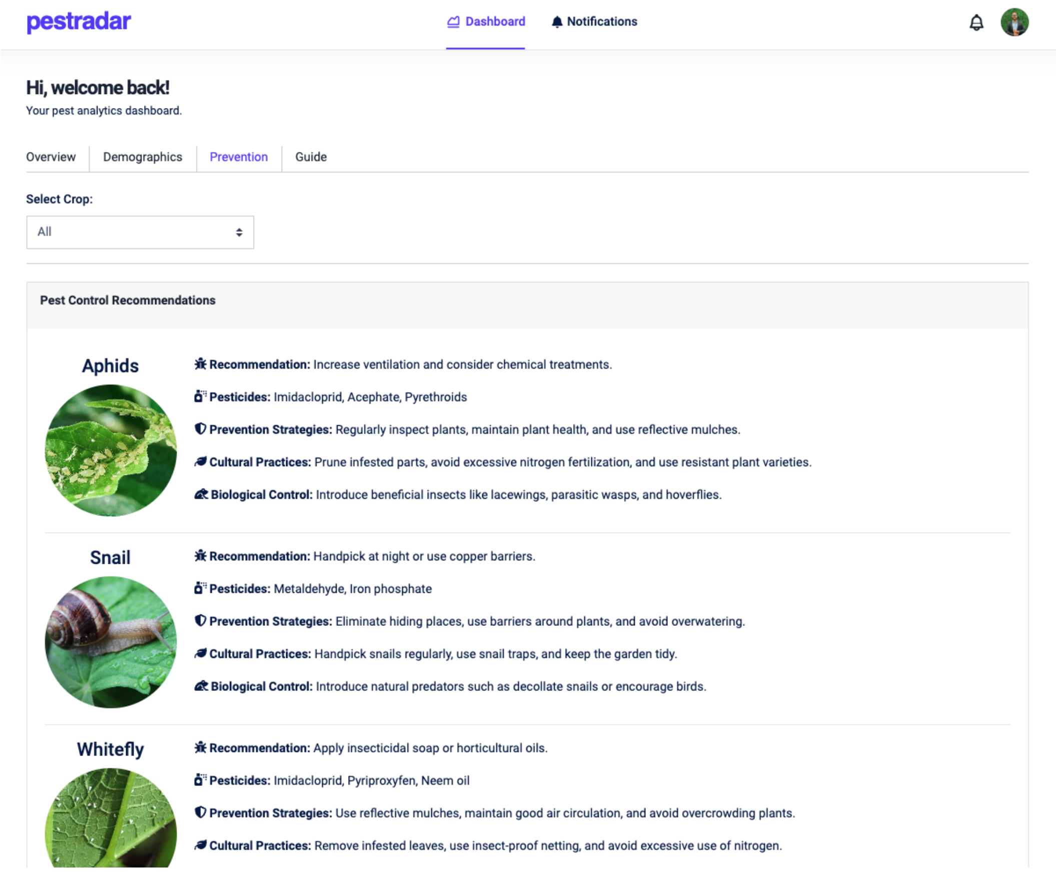


Figure 4.14 Screenshot of the web app - recommendations

Based on the analysis, the web app provides customized pest control recommendations for each crop, including suggested pesticides and preventive measures. You can find the screenshot of pest recommendation tab in the Figure 4.14.

- **Notifications:**

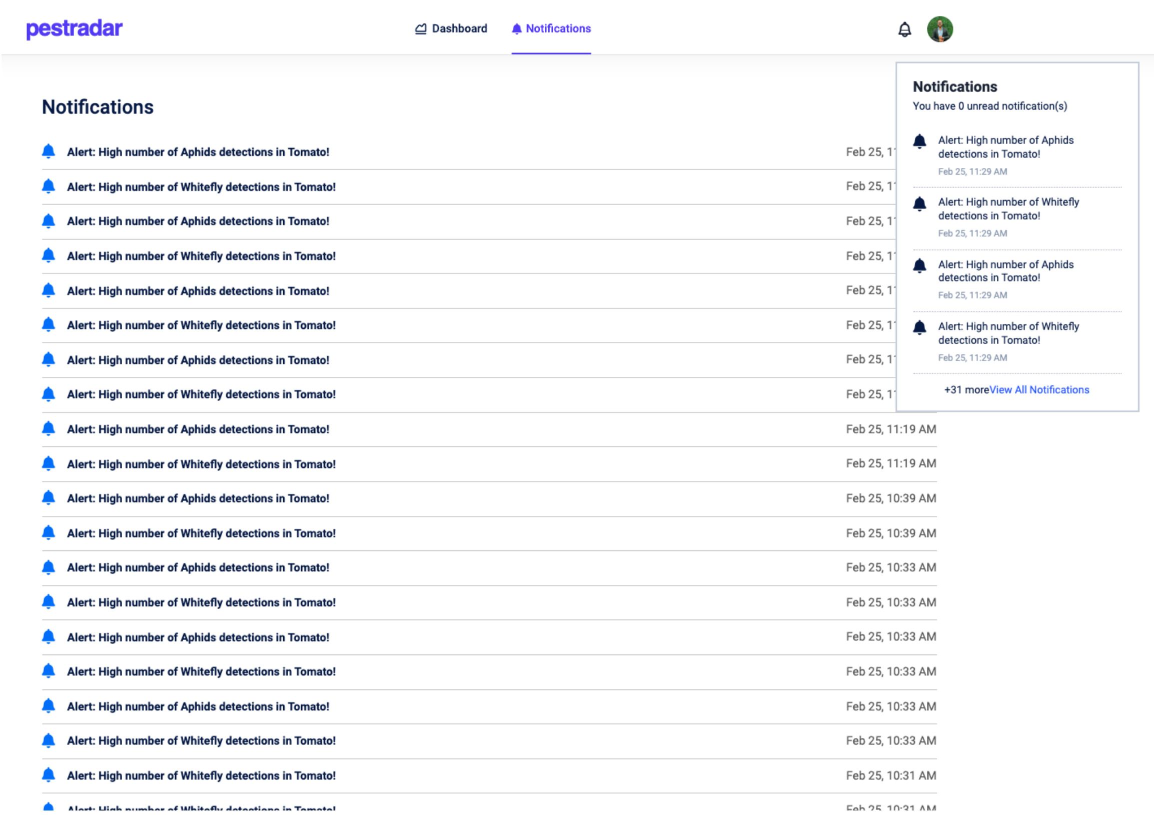


Figure 4.15 Screenshot of the web app - notifications

Figure 4.15 displayed and screenshot of the web app notifications page where Real-time notifications alert users how critical the issue is, such as high pest activity or unfavorable environmental conditions, enabling prompt action.

4.4.2 Integration with the Pest Management System

The web application seamlessly integrates with the overall pest management system, receiving real-time data from the Firebase database. This ensures that the information displayed on the web app is up-to-date and accurate. The integration facilitates:

- **Automatic Data Synchronization:** As soon as the mobile app detects pests or captures environmental data, it is synchronized with the Firebase database and reflected in the web app's analytics.
- **Cloud Functions for Notifications:** Firebase Cloud Functions are utilized to generate real-time notifications based on predefined criteria, enhancing the responsiveness of the pest management system.

4.4.3 Evaluation of Web Application Performance

The web application performance is evaluated based on it's responsiveness across various mobile devices, accuracy of the displayed data, user satisfaction and feedback of the greenhouse operators. With the received feedbacks from greenhouse operators, it indicates high satisfaction with ease of use, valuable analytics data and recommendations provided. Specially the real time notifications appreciated because of it enables quick interventions.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

This research was conducted to include Internet of Things (IoT) and Machine Learning (ML) teachnologies to revolutionize pest management in greenhouses or home gardens. Aim of this research to develop a cost-effective and sustainable pest management system that that uses these advanced technologies to enable real-time , data-driven, accurate pest identification and pest management.

Looking back at the start of this research study, it's clear that the research has not only met the the objectives, but also exceeds the expectations in different aspects.

1. **Identify Pest in Planatations:** With the use of mobile application integrated with pre-trained image classification model, the system showcased remarkable accuracy in identifying the pests in the plantation in real-time. This addresses the objective of helping the farmers to monitor their cultivations more efficiently by reducing the time and labor for inspect the plantations manually for pest identification.

2. **Cost Effective Solution:** The research successfully achieved the cost effectiveness by using Android smartphone for use with the custom-developed tripod to detect the pests efficiently. This saved the requirement of separate camera devices and internet access capable devices.

3. **Analystics and Decision Making:** With all the collected data in the greenhouse field, mobile app will sync the records to the cloud database. With recorded environmental data, pest identifications, locations and crops, analytics were shown in the web application for easily identify the pest patterns and insights, enabling decision-making and predicting pest infestations can be easily achieved by farmers.

4. **Automated Crop Health Monitoring:** By automating the process of pest detection and significantly reducing the reliance on chemical pesticides, the system has made strides towards the objective of promoting healthier crop cultivation practices. The precision in pest management facilitated by the system not only minimizes environmental impact but also enhances crop health monitoring.

The evaluation of ML algorithms, particularly the superior performance of DenseNet, underscores the feasibility and effectiveness of the proposed system in a real-world setting. The system's architecture, encompassing a custom-designed tripod and a user-friendly mobile app, embodies the innovative spirit of this research, offering a cost-effective, efficient, and sustainable solution to a longstanding challenge in greenhouse agriculture.

5.2 Future Work

The foundation laid by this research paves the way for several avenues of future investigation:

Enhanced Pest Identification Accuracy: With the evaluation of image classification models I have found that pests like caterpillars and whiteflies are difficult to accurately identified by the machine learning algorithms. It means more accurate image classification algorithms should be developed that can identify the small feature and behaviors of the pests.

Pest Sounds Integration: Since I wanted to make more cost effective solution, capturing pest sounds to identify pests were not included. Somehow I should find a cost effective way to integrate the pest sound integration since it can help to gain the accuracy of identified pest.

Long-Term Studies: Long-term study needs to be conducted to really found how efficient is the pest management system is. How it identified pests in different growing seasons.

Extending Pest and Crop Range: System should be expanded to identify larger number pests and give the recommendations for larger number of crops, Which can improve the system usefulness for several type greenhouses or home gardens.

User Experience Optimization: User interface and user experience in both mobile application and web application should be monitord and continously increased. So that farmers with different technical knowledge can be still use the system for increase the production of their plantations

Pest Management Suggestions: Should be updated the pest management recommendations in web app by investigating different kinds of eco-friendly pest management solutions so that I can help the world transition to sustainable agriculture.

Data Synchronization: Should be looked in to find the ways to store the recorded data when there is no internet connection, so that when the internet connection is resumed saved data can be synced to the cloud database.

Integration with Existing Agricultural Systems: Investigating the possibility of integrating current agricultural management systems with them in order to give farmers and greenhouse operators a full range of capabilities.

Future developments could greatly advance the overall objective of attaining sustainable and effective global food production in addition to improving pest management strategies by building on this research.

APPENDICES

Appendix A: User Manual for Greenhouse Pest Management System

User Manual for Greenhouse Pest Management System

Pestradar

Prepared By: Shan Nirmala

Date: 2024-03-03

Introduction

Welcome to the Greenhouse Pest Management System, a comprehensive solution designed to revolutionize pest management in your greenhouse. This system integrates a mobile application with a custom-designed tripod to provide real-time, accurate pest detection and environmental monitoring, enabling efficient and sustainable pest management.

System Requirements

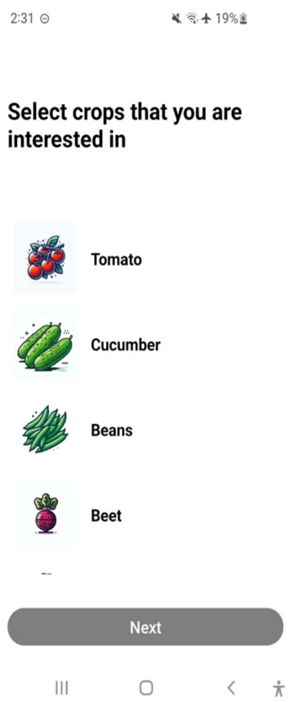
- **Mobile App**:
    - Compatible with Android smartphones.
    - Requires Android version 8.0 or higher.
- **Tripod Setup**:
    - Bluetooth-enabled smartphone for tripod connectivity.
    - Stable internet connection for data synchronization with Firebase.

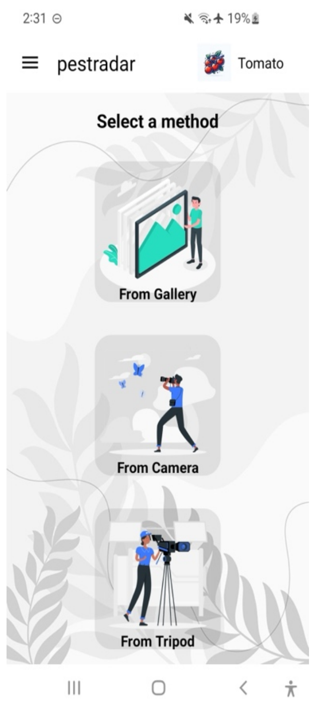
Installation and Setup

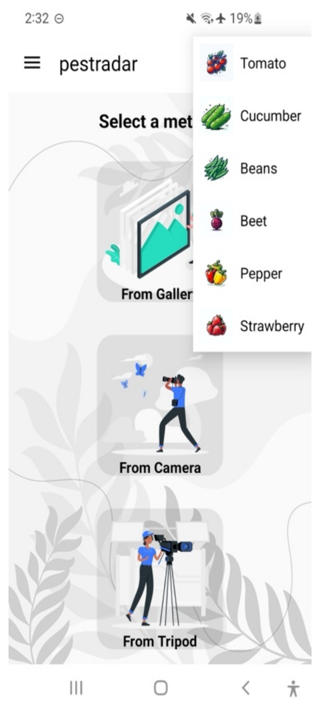
- **Mobile App**:
    - Download the app from the Google Play Store.
    - Open the app and select the crops that you are interested in and navigate to home screen.
- **Tripod Setup**:
    - Power up the tripod by using a power bank or external battery pack.
    - Enable Bluetooth on your smartphone and pair it with the tripod through the app.
        - App will automatically connected to the tripod if the tripod is powered on and placed near the smartphone. If not it will show the relevant information on the screen.

Usage Instructions

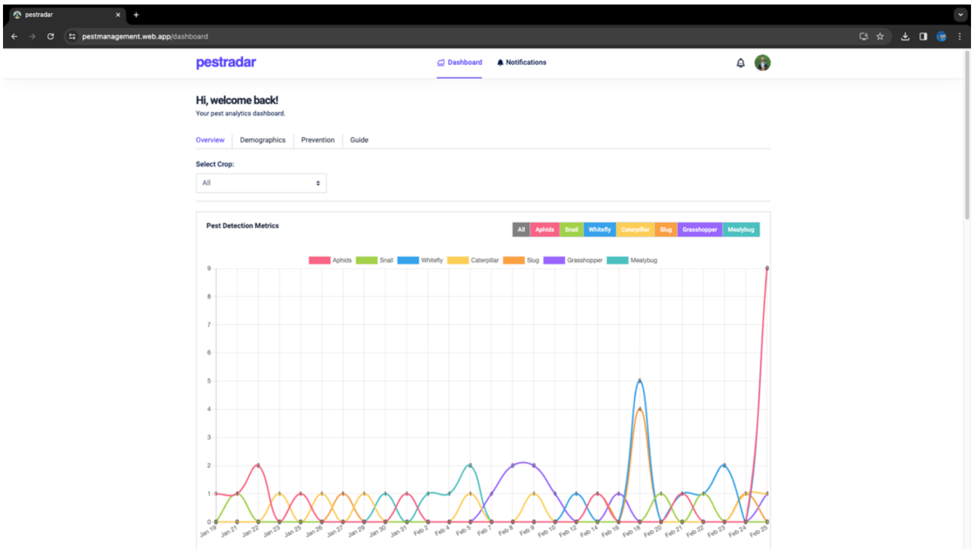
- **Selecting Crops**:
    - In the app, select the crop selection drop down to choose the crops you are monitoring before start the image capturing process.
- **Capturing Images**:
    - Attach the smartphone securely to the tripod mount.
    - In the app, select the "From Tripod" option to start the automated image capture process.
    - Position the tripod at various points around your greenhouse to ensure comprehensive coverage.
    - You can also use the “From Gallery” and “From Camera” options to get the pest details by selecting an image from gallery or capturing an image using camera.
- **Viewing and Interpreting Data**:
    - Access the url https://pestmanagement.web.app/dashboard to access the web app to view pest detection results and environmental data.
    - Use the web app for more detailed analytics, including pest metrics, detection timelines, and recommendations.
- **Mobile app setup**

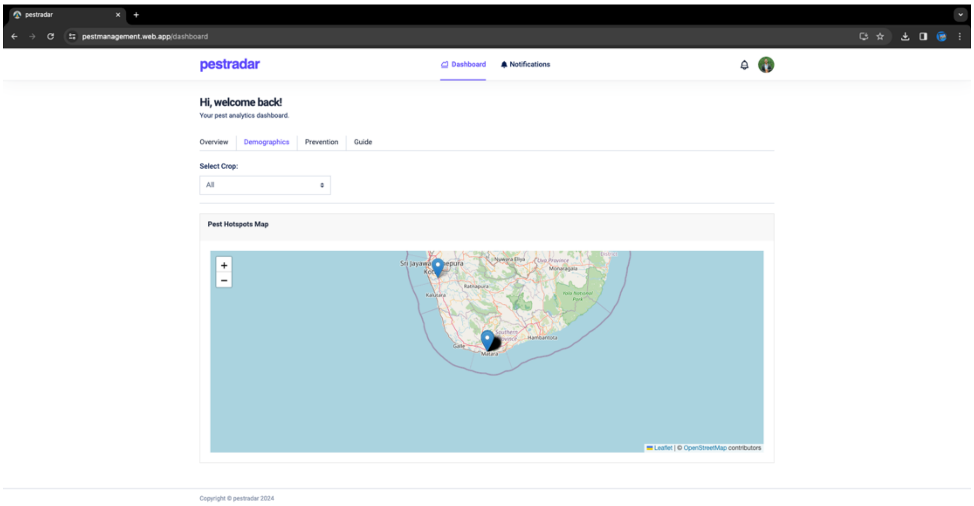


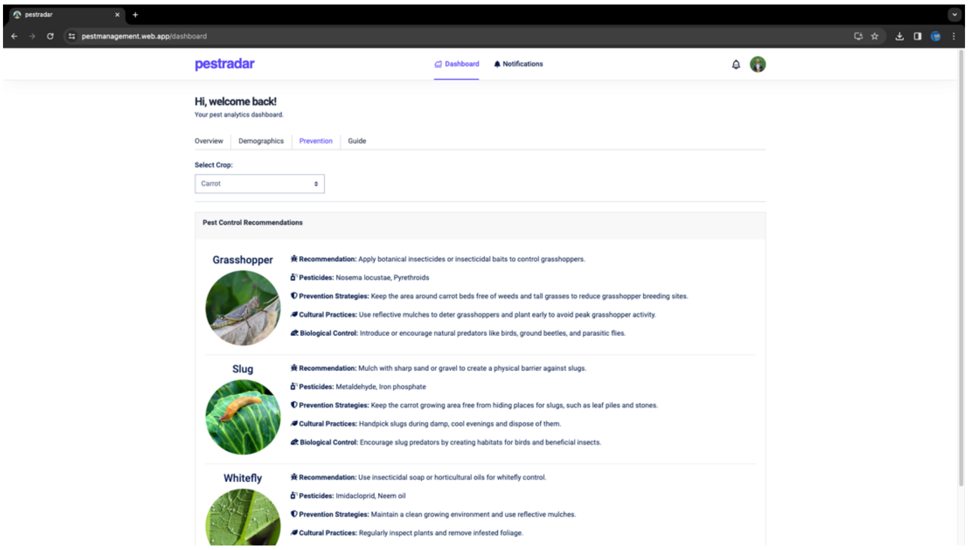




- **Web app dashboard**







Maintenance and Troubleshooting

- **Maintenance**:
    - Regularly clean the tripod and sensors to ensure accurate data collection.
    - Check for firmware updates in the app to keep the system up-to-date.
- **Troubleshooting**:
    - If the tripod fails to connect, ensure Bluetooth is enabled and try reconnecting.
    - For issues with image capture, ensure the smartphone camera is not obstructed and has sufficient battery.

Safety Precautions

- Do not expose the tripod and sensors to extreme weather conditions.
- Handle the equipment gently to avoid damage.
- Keep the tripod stable to prevent accidents.

Contact Information

For technical support or further assistance, please contact our customer service at shannirmala01@gmail.com

FAQs

Q: How often should I capture images in my greenhouse?

A: For optimal monitoring, it's recommended to capture images at least once a day.

Q: What should I do if the app shows a high pest detection alert?

A: Review the recommended pest control measures in the app and take appropriate action to manage the infestation.

Q: Can I use the system for multiple greenhouses?

A: Yes, the app allows you to monitor multiple greenhouses. App will automatically record the greenhouse location and crop that pests were identified and those data can be viewed from web app.

REFERENCES

[1] Maity, T., Paul, S., Samanta, J. and Saha, P., 2024. Design and Development of IoT-Based SmartTech-Agri Devices for Smart Agriculture Crop Field. *Journal of The Institution of Engineers (India): Series B*. Springer.

[2] Azevedo, A.T., Coelho, R.D., Carnervisk, E. and Maciel, A., 2024. Development of a complete automatic weather station for irrigation management via IoT. *Research Square*. Available at: www.researchsquare.com/article/rs-3976074 [Accessed 26 February 2024].

[3] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., and Stefanovic, D., 2016. Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification. Computational Intelligence and Neuroscience. Hindawi.

[4] Kamilaris, A. and Prenafeta-Boldú, F.X., 2018. Deep learning in agriculture: A survey. Computers and Electronics in Agriculture. Elsevier.

[5] Liakos, K.G., Busato, P., Moshou, D., Pearson, S., and Bochtis, D., 2018. Machine learning in agriculture: A review. Sensors. MDPI.

[6] Mahlein, A.-K., Rumpf, T., Welke, P., Dehne, H.-W., Plümer, L., Steiner, U., and Oerke, E.-C., 2018. Development of spectral indices for detecting and identifying plant diseases. Remote Sensing of Environment. Elsevier.

[7] Zhang, C., Walter, M.T., and Niyogi, D., 2018. Drones in agriculture: How big data and advanced analytics will impact the sector. IEEE Technology and Society Magazine.

[8] Bajwa, W.I. and Kogan, M., 2002. Compendium of IPM Definitions (CID)—What is IPM and how is it defined in the Worldwide Literature? Integrated Plant Protection Center (IPPC).

[9] Parsa, S., Morse, S., Bonifacio, A., Chancellor, T.C., Condori, B., Crespo-Pérez, V., Hobbs, S.L.A., Kroschel, J., Ba, M.N., Rebaudo, F., Sherwood, S.G., Vanek, S.J., Faye, E., Herrera, M.A., and Dangles, O., 2014. Obstacles to integrated pest management adoption in developing countries. Proceedings of the National Academy of Sciences.

[10] Google. (2022). TensorFlow (Version 2.8.0). Google.

[11] TensorFlow Lite | ML for mobile and edge devices (2023).

[12] A Complete Guide for IoT Based Pest Detection with its Benefits (no date). https://www.biz4intellia.com/blog/a-complete-guide-for-iot-based-pest-detection-with-its-benefits/.