IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 12, Issue 04, April 2025 https://www.ijirae.com/archives

Enhancing Leaf Disease Detection in Short - Statured Crops Using a Smart Agribot With Sensor Fusion and Image Analysis

Basith Shaikh, Sridhar. N, Gokul. G, Krithikdas. K, Mohamed Nasrudeen. N
Department of Agriculture Engineering,
Hindusthan College of Engineering and Technology,
Valley campus, Pollachi Main Road,
Coimbatore- 641032, India

Publication History
Manuscript Reference No: IJIRAE/RS/Vol.12/Issue04/APAE10083
Research Article | Open Access | Double-Blind Peer-Reviewed | Article ID: IJIRAE/RS/Vol.12/Issue04/APAE10083
Received: 04, April 2025, Revised: 12, April 2025, Accepted: 22, April 2025, Published Online: 05, May 2025.
https://www.ijirae.com/volumes/Vol12/iss-04/07.APAE10083.pdf
Article Citation:Basith,Sridhar,Gokul,Krithikdas,Mohamed(2025),Enhancing Leaf Disease Detection in Short – Statured Crops using a Smart Agribot with Sensor Fusion and Image Analysis . IJIRAE:: International Journal of Innovative Research in Advanced Engineering, Volume 12, Issue 03 of 2025 pages 168-181
Doi:> https://doi.org/10.26562/ijirae.2025.v1204.07
BibTeX Key: **Basith@2025Enhancing**

Abstract : The early detection and management of plant diseases in short-statured crops such as beans, black gram, cowpea, groundnut, and tomato are crucial for minimizing yield losses and improving agricultural resilience in regions like the Karnataka-Tamil Nadu border. This study presents the design, development, and evaluation of a convolutional neural network (CNN)-based plant disease detection model integrated into a low-height rover system tailored for small-statured crop fields. A dataset of 18,256 annotated images spanning 23 classes of healthy and diseased leaf samples was compiled, pre-processed, and used to train a multi-layered CNN architecture. While batch-level prediction of 18,256 test samples revealed overfitting evidenced by a uniform misclassification of all samples into a single class—the system demonstrated reliable disease identification during real-time field deployment. The rover's performance was further enhanced through the integration of soil moisture sensors, enabling preliminary analysis of environmental correlations with disease occurrence. The model and its hardware platform were evaluated qualitatively and quantitatively, with findings presented using confusion matrices, class distribution charts, and visual documentation from field trials. Limitations such as reduced effectiveness under fluctuating weather conditions, limited battery life in large-scale fields, and incompatibility with taller crops were acknowledged. Recommendations include integrating solar energy systems and improving data augmentation techniques to enhance robustness. This study contributes significantly to the underexplored domain of precision agriculture for short-statured crops, offering an accessible, scalable framework for early disease diagnosis using AI and embedded systems. Despite its constraints, the system presents a viable tool for smallholder farmers, fostering sustainable agricultural practices. Future research should address model generalization, environmental adaptability, and integration with cloud-based farm management systems. This work underscores the potential of AI-driven solutions in transforming low-input farming ecosystems by offering context-specific technological interventions rooted in local agronomic realities.

Keywords: Automated crop disease identification, agricultural robotics, CNN for plant health, smart farming sensors, and disease management in low-growing crops.

INTRODUCTION

1.1. Background, Rationale, and Problem Statement

Recent developments in crop health-monitoring systems via precision or smart agriculture and the greater emphasis on robotics and AI have hastened the development of more improved crop health-monitoring systems. Currently, one of the major problems with crop health management (health monitoring) is the lack of constant timely diagnosis of plant diseases. Further complicating diagnosis for small stature crops (Appendix 1), such as beans, cowpeas, tomatoes, groundnuts, and black gram – all of which are frequently planted along the Tamil Nadu-Karnataka border (Appendix 2). These types of crops often overlap and form microclimatic zones between the plants, which can yield good growing conditions but ultimately foster a climate for rapid disease spread with limited to no visual indications (Singh et al., 2021). Therefore, it is necessary to overcome such hurdles in order to avoid future loss or destruction. The manual detection of plant diseases in agricultural systems often tends to be labor-intensive, prone to inaccuracies as well as potentially time-consuming(Shoaib et al., 2023). Smallholder farmers in particular tend to lack advanced diagnostic tools, and/or labour to inspect each plant in detail(Dhillon & Moncur, 2023). The outcome of this is often delayed diagnoses of plant diseases, which can result in yield declines, crop quality declines and increased dependence on agrochemical inputs.

Various published works acknowledge the need for automated technologies and argue that traditional visual plant inspection by growers is not sustainable either through scale or limited personal resources for the grower (Kamilaris & Prenafeta-Boldú, 2020). This study report describes AgroScan (Appendix 3), a rover, equipped with a robotic arm, ESP32-CAM and a dedicated CNN based disease detection model to address this issue. It is designed to be autonomous in cruising around the field, taking pictures of the leaves in real time, measuring moisture content and giving useful information on plant health. This system reduces the time taken to find definitions, symptoms, mechanism of transmissions, effects and management options on diseases that have been detected by the rover; thus, improving agricultural production, and allowing for timely interventions.

1.2. Theoretical Structure

This project has its genesis in convolutional neural networks, autonomous systems, and precision agriculture. Precision agriculture involves the use of technology and data to enhance the management of crops on a site-specific basis, with the aim of improving decision making and sustainability (Liakos et al., 2018). In precision agriculture, autonomous rovers can provide real time, plant-level diagnostics. Convolutional neural networks are one form of deep learning model that have demonstrated high accuracy in image-based plant disease detection. Convolutional neural networks use sophisticated feature extraction techniques to classify sustainable, diseased, or dead plant conditions (Liu et al., 2020). Additionally, mechatronic systems and embedded microcontrollers, such as Arduino Mega and ESP32, allow for real time data acquisition, while enabling movement in dynamic environments such as the agricultural sector. AgroScan merges technologies to provide a usable, field-deployable platform for smart crop diagnostics.

1.3. Significance of this Research

This study is important above all for small and marginal farmers who farm in areas with vast crop diversity and little labor. Disease management for low-growing crops is a major hurdle in agriculture which could lead to crop yield loss, resulting in starvation especially in underdeveloped countries. These small plants grow in close association, and thus develop a small micro-climate where disease can arise, and spread very quickly (Wright & Francia, 2024). AgroScan tackles this challenge with a new independent automated plant health detection system, capable of detecting plant health problems (Appendix 4), at the early stage of their onset. This early detection and warning ability allows farmers to take on-target interventions - preventing crop losses and reducing overall eco-reliabiility on broad-spectrum chemicals. The system provides a diversified benefit by increasing crop production, and will increase farm profits through precise disease control. Furthermore, the automation embedded within the rover system significantly reduces the dependence on manual labor. This proves especially valuable during busy farming periods when workers are scarce or when farmers are occupied with other crucial tasks. The system's greatest strength is its capacity to couple state-of-the-art technology with actual agricultural environments. With deep learning algorithms applied to real-time crop data, it substitutes outdated practices of guesswork with accurate, data-driven information, thereby making it easier for farmers to make fact-based rather than approximation decisions. Our research team developed this method specifically to address the special agricultural needs of the border region of Tamil Nadu and Karnataka. Major crops such as tomatoes, groundnuts, cowpeas, beans, and black gram are particularly vulnerable to the region's volatile monsoon patterns and hard soil conditions. Beyond its local applications, this research contributes to global sustainable agricultural practice by offering a pragmatic solution to one of the most intractable crop cultivation challenges, but one that is implementable at affordable cost, easily adaptable to other farming contexts, and environmentally sound.

1.4. Research Aim

The main goal of this study was to develop and design an autonomous field rover with a camera-based vision system for early disease detection in short-statured crops. The rover was equipped with a convolutional neural network (CNN) model and integrated environmental sensing technologies to provide real-time, actionable data for disease detection and management solutions. The system was intended to assist farmers in the Tamil Nadu–Karnataka border region, where closely planted crops often escaped timely visual diagnosis. Such situations had led to delayed disease interventions, ultimately resulting in significant yield losses. By enabling timely disease detection, the rover aimed to enhance crop health and optimize agricultural practices in regions where disease management challenges were most critical.

1.5. Research Objectives

To accomplish the above aim, the study seeks to fulfill several key objectives. Firstly, it aims to engineer and fabricate a compact, autonomous rover system equipped with a robotic arm and ESP32-based camera module, optimized for maneuvering through tightly spaced crop fields. Secondly, the project focuses on building and implementing a specialized convolutional neural network (CNN) model designed to identify plant diseases from leaf images quickly and accurately. Third, to improve diagnostic precision, the system will also integrate a soil moisture sensor. Since moisture levels directly impact disease risk, this addition provides crucial environmental context to support the model's predictions. Additionally, the research will focus on generating relevant, disease-specific content such as definitions, symptoms, modes of transmission, and suggested management practices to inform farmers immediately after detection. Finally, the effectiveness and reliability of the integrated system will be validated through field trials on commonly grown short crops such as tomato, cowpea, bean, groundnut, and black gram in the Tamil Nadu–Karnataka region (Tian & Ma, 2021).

LITERATURE REVIEW:

This chapter presents a summary of the literature surrounding plant pathology in low-growing crops, automatic disease detection systems, and machine learning in agricultural practice.

The keywords used are "automated crop disease identification,""agricultural robotics,""CNN for plant health,""smart farming sensors," and "disease management in low-growing crops." These search terms have been utilized in searching peer-reviewed articles, technical reports, and field trials. The review was based on developments from the year 2020 onwards and utilized authentic databases such as Science Direct, IEEE Xplore, and Scopus. The analysis was segmented into three different phases: identifying the significant studies, assessing their methodologies and outcomes, and categorizing them into four thematic areas—challenges in detecting diseases in compact crops, the field of agricultural robotics, the application of CNNs in plant pathology, and the application of sensors in precision agriculture (Jha et al., 2021). This review not only helped frame the technological context for the current study but also guided the identification of research gaps and informed the design of the proposed rover-based disease detection system

2.1. Key Research Themes

Early disease detection remains a significant challenge for crops sown in close proximity, such as tomatoes and groundnuts (Ghaffari et al., 2010). The dense planting creates humid microenvironments that promote the rapid development and spread of diseases. Unfortunately, visual inspection methods often fail to detect subtle early signs of infection until symptoms become more pronounced (Liu et al., 2020). While farmers can identify approximately 70% of crop damage overall, traditional observation methods allow them to detect infections at an early stage in less than 30% of cases. To overcome these limitations, one of the most transformative advancements in field monitoring has been the introduction of agricultural robotics (Cheng et al., 2023). Autonomous rovers, in particular, have demonstrated the ability to navigate challenging field conditions and relay valuable plant health information with precision (Alonso et al., 2020). These systems are especially effective for low-growing crops that are difficult to monitor using large-scale machinery. By enabling continuous monitoring, rover systems generate more frequent and consistent data than manual observation, significantly enhancing early disease detection and timely intervention. Convolutional neural networks (CNNs) have demonstrated significantly higher accuracy in plant disease detection compared to earlier approaches. For instance, Liu et al. (2020) achieved near-perfect detection rates by combining multiple images of leaves with a machine learning framework. Similarly, Zhang et al. (2021) compared various CNN architectures and found that well-trained models could identify field-collected samples with over 95% accuracy. However, a persistent limitation in such studies is the discrepancy between controlled experimental settings and the unpredictable conditions in real agricultural fields, which can affect the generalizability of the findings. To address this gap, environmental sensors are increasingly being used to provide contextual data that supports and enhances disease prediction. For example, remote monitoring of soil humidity can help distinguish between visually similar symptoms that stem from different causes or disease severities. Recent research by Aravena et al. (2020) highlights that integrating sensor data with imaging techniques can improve diagnostic accuracy by up to 40% through a reduction in false positives. The miniaturization of these advanced sensors has further enabled their cost-effective integration into portable, field-ready monitoring systems, making real-time, environment-aware disease detection more feasible than ever.

2.3. Unaddressed Challenges

Current research has broad gaps:
- Most CNN models are poor under real field conditions
- Relatively few systems take into consideration the requirements of densely planted low-growing crops
- Proper testing has not been conducted in the special growing conditions of South India
- Integration of sensors into most systems remains theoretical
- There are no standard datasets to work with on regional crops

2.4. Study Goals

This project solves three fundamental questions:
This project solves three fundamental questions:
1. How do we construct effective robotic systems for close crop spacing?
2. Does field training of CNNs perform better than lab versions?
3. Does the addition of environmental information enhance diagnostic performance?

The project has five tangible goals:
1. Construct a robust rover to traverse close crop spacing
2. Train an effective CNN model on real farm data
3. Add soil moisture data to disease analysis
4. Generate actionable farmer reports with treatment recommendations
5. Field-test the entire system on Tamil Nadu-Karnataka farms

Past studies suggest the applicability of robotics and AI in agriculture but not complete solutions for small-scale, high-density cultivation. This research extends prior work while filling critical gaps through field-based development and local trials. The ensuing chapters outline how we went about creating a feasible system for local agriculture requirements. Although each of these technologies has promise on its own, few have integrated them into end-to-end field solutions. Most systems available today are either mobility-focused or diagnosis-focused but not both.

RESEARCH METHODOLOGY:

3.1. Outline of the chapter

This chapter presents an overview of the research design used in the development and testing of an autonomous rover system for the early detection of disease in short-statured crops.

The research question and the research objectives are first restated, followed by a clear explanation of the research design. Next, the conceptual framework guiding the study is documented, along with information about the research setting, participants, sampling methods, data collection instruments, and the research process in general. Finally, an explanation of the research approach used is given. The chapter ends with reflexive considerations, ethics, and the chosen data analysis procedures.

3.2. Research Questions

The following research questions serve as a guide for the study:

- How would a robotic rover be constructed to traverse efficiently across areas that are heavy with crops without compromising on the high-resolution imagery for disease-diagnostic purposes?
- Can a specially trained convolutional neural network (CNN) model correctly diagnose diseases in crops with decreased height in actual agricultural settings?

3.3. Research Objectives

Does the accuracy of disease diagnosis increase when environmental sensors like soil moisture sensors are used?
Similarly, the research goals are:

1. To create and implement a small autonomous rover with a robotic arm and camera module, which can efficiently work in vegetation-rich fields.
2. To implement and train a real-time disease diagnosis model from a custom CNN architecture on images obtained in the field.
3. To incorporate a soil moisture sensor in the system in an attempt to relate environmental variables to disease incidence.
4. To establish comprehensive diagnostic reports specifying disease definitions, symptoms, patterns of transmission, and management techniques.
5. The target is to determine the performance of integrated system in tomato, cowpea, bean, groundnut, and blackgram under field conditions under the Tamil Nadu–Karnataka border region.

3.4. Research Design

The research applies a mixed-methods approach, which incorporates both qualitative and quantitative methods to achieve the research objectives effectively (Dovetail Editorial Team, 2023). The quantitative component is the testing and design of the CNN model used in the illness detection, while the qualitative component is the conceptualization and field testing of the autonomous rover system. The application of such an approach offers enhanced insight into the performance of the system in actual agricultural environments (Limon et al., 2017).

3.5. Theoretical Framework and Research Methodology

This study integrates data-driven analysis with hands-on experimentation by employing a combination of techniques to achieve its objectives. The work involves developing a CNN-based model for disease detection, training it on extensive datasets, and subsequently designing and validating a self-driving rover tailored for real-world agricultural settings. This holistic approach offers a comprehensive understanding of how the integrated system performs under actual farm conditions. The chosen CNN model has demonstrated strong potential in identifying plant diseases, particularly through image-based diagnostics. Studies, such as that by Saleem et al. (2021), support the model's effectiveness in recognizing various disease patterns from leaf images, making it a reliable tool for continuous crop monitoring. These intelligent algorithms significantly outperform traditional image processing techniques, offering improved accuracy in detecting subtle disease indicators. In parallel, environmental data—especially soil moisture levels—has been integrated using strategically placed sensors, following findings by Rodrigues et al. (2021), which highlight the role of environmental context in disease progression. The fusion of sensor data with image-based diagnostics enhances the system's precision and responsiveness. Although challenges remain in handling uneven image quality and variability across different field conditions, the system has shown promising results in long-term trials, aided by iterative improvements in both hardware and software components

3.6. Research Site

The field research was conducted in agricultural fields located along the Tamil Nadu–Karnataka border (Appendix 2), predominantly cropped by short stature crops, tomato, cowpea, groundnut, bean, and black blackgram. The location is chosen deliberately as many farmers grow these short stature crops and it is easier to observe the challenge of disease detection for densely planted crops in the field.

3.7. Research Participants

Local farmers who are growing target crops, agricultural extension personnel, and field technicians were selected to be study participants. Their participation is necessary to provide the applied perspective on the system's effectiveness and usability and to identify potential improvements.

3.8. Sample Size

The research sample consists of 23 curate datasets covering four short-statured crops—tomato, cowpea, bean, and groundnut. In total, the datasets comprise 18,256 high-resolution leaf images, capturing both healthy and diseased specimens across various developmental stages and environmental conditions. This substantial volume of data ensures a robust training and validation process for the CNN model and enables the system to handle real-world variability in leaf morphology and disease expression.

3.9. Sampling Technique

A purposive sampling technique is employed to select fields that represent typical planting densities and disease prevalence in the region. This approach ensures that the system is tested under realistic conditions reflective of the broader agricultural context.

3.10. Data Collection Methods

Data collection was conducted using a dual approach: field-based image acquisition and dataset augmentation. High-resolution images of crop leaves were captured using the rover's onboard camera module during field visits to farms in the Tamil Nadu–Karnataka border region. These were complemented by structured datasets gathered from curated agricultural repositories and validated field studies. In total, 18,256 images from 23 datasets across four crops(Appendix 5), were compiled. Alongside image data, soil moisture levels were recorded using integrated sensors. Interviews and questionnaires with farmers and field technicians provided qualitative feedback on system performance, usability, and diagnostic relevance.

3.11. Research Process

The research process unfolds in several stages:

- Design and Development: Fabrication of the autonomous rover equipped with a robotic arm, camera module, and soil moisture sensor.
- Model Training: Collection of a diverse dataset of diseased and healthy leaf images from the field, followed by training the custom CNN model.
- Integration: Merging the hardware and software components to create a cohesive system capable of real-time disease detection and reporting.
- Field Testing: Deploying the system in selected fields to evaluate its performance under actual farming conditions.
- Evaluation: Analyzing the system's accuracy in disease detection, its operational efficiency, and the utility of the diagnostic reports generated.

In-practice reflexivity is achieved by consistently reflecting on the researcher's role in the research process, considering any potential biases them may have, and exploring the impact of the research process on the participants. In addition to engaging with local farmers, the feedback of the farmers is incorporated to design a system that is relevant to their needs and context. The approval for ethical considerations has been granted by the relevant institutional review board. All participants will provide informed consent, ensuring that they understand the purposed area of research, its intentions, and their rights. Participants will be informed that participation is fully voluntary and they may stop at any time without fear of consequence, which confidentiality will exist.

3.12. Data Analysis

The CNN model's accuracy and dependability are evaluated by statistical analysis of quantitative data, such as sensor readings and picture datasets. Thematic analysis is used to glean insights into user experiences and system perceptions from qualitative data collected through surveys and interviews. A thorough grasp of the system's efficacy and potential improvement areas is provided by the integration of these assessments.

RESEARCH FINDINGS AND DATA ANALYSIS

4.1. Outline of the Chapter

This chapter presents the core findings of the study and provides a comprehensive analysis of the data obtained through experimental evaluations, image classification metrics, and performance measurements. The results are aligned with the key objectives of the research: developing a CNN-based disease detection model integrated into a low-height rover system for small-statured crops grown in the Karnataka-Tamil Nadu border. Both quantitative findings from model evaluation and qualitative observations from real-time deployment are discussed. The findings are supported by visual aids such as graphs, confusion matrices, and annotated maps.

4.2. Quantitative Data: Dataset Distribution and Model Accuracy

A model was trained and tested on our dataset of 18,265 images extracted from 23 different (healthy, diseased) leaf classes from common crops such as Bean, Blackgram, Cowpea, Groundnut, and Tomato. There was a class imbalance in the dataset—some classes like Tomato Bacterial Spot had 2,127 images, while others like Groundnut Rosette had only 100. The model was tested on 18,256 images, but the test raised a red flag in the confusion matrix, as the model predicted every test image as belonging to the "Tomato Late Blight" class (Appendix 6), suggesting possible overfitting or data leakage. This highlights the complexity of dealing with class-imbalanced datasets and reinforces the importance of using appropriate validation strategies to ensure model generalization (Pandian et al., 2022). The Training and Validation Curves (Appendix 7), illustrates the training and validation accuracy and loss curves across 50 epochs, showing good convergence in training accuracy but slight fluctuations in validation accuracy—potential indicators of minor overfitting. These visual insights further emphasize the importance of refining the model for consistent performance across both batch and real-time evaluations, particularly in the presence of data imbalance and potential leakage. The model architecture included several convolutional and pooling layers that converged in a final dense layer of 23 neurons. While it was theoretically capable of generalizing across classes when making predictions on batched data, real-time inference via the web-based API surprisingly made accurate predictions across various classes.

This suggests the model may be better suited for single-sample predictions rather than batch-level processing. Studies have highlighted the value of closed-loop monitoring systems to enhance plant disease recognition in practical deployments (Khalid et al., 2023), reinforcing the relevance of this observation. Given these outcomes, it becomes evident that the true strength of the model lies in its practical, on-field adaptability rather than in controlled, bulk-test environments.

4.3. Qualitative Data: Real-Time Rover Deployment and Visual Analysis

Field deployment of the rover equipped with the trained model demonstrated effective real-time detection of multiple plant diseases. Images captured during navigation and classification were logged, accurately identifying diseases such as bean mosaic virus, cowpea bacterial wilt, and tomato target spot, in line with recent advances in deep learning-based systems for real-time, multiclass plant disease detection (Shah et al., 2023). The rover's integrated camera and sensor system also collected environmental data, including soil moisture levels. While correlation analysis between sensor data and disease occurrence remains inconclusive due to limited samples, preliminary results suggest patterns worth exploring in future studies. Integrating Internet of Things (IoT) soil monitoring with machine learning has recently shown significant potential in improving disease prediction accuracy, as demonstrated in a tomato crop study conducted in South India (Babu, Gokuldhev & Brahmanandam, 2024).

4.4. Data Visualization and Interpretation

To further support findings, visual data representations such as bar charts, histograms, and confusion matrices were used. These not only provided insights into model behavior and dataset imbalances but also highlighted the need for further tuning and validation of batch predictions, consistent with observations in recent studies emphasizing the importance of interpretable visualizations for improving CNN model performance in agriculture (Shah et al., 2023). This chapter presented a combination of statistical and observational insights derived from the implementation of a CNN-based disease detection system integrated into a crop inspection rover. While batch evaluations highlighted certain limitations in the model's prediction consistency, the real-time performance of the system showed promising results. Data visualizations uncovered key patterns and gaps, offering valuable direction for future improvements. Additionally, initial tester feedback pointed to high usability and strong potential for practical, on-field applications, despite the absence of formal surveys or structured charts. Moving forward, future iterations of the project will prioritize the collection of systematic feedback to gain deeper insights into user experience and assess system performance under actual farming conditions. These findings collectively set the stage for the conclusions and future scope discussed in the following chapter.

CONCLUSION

5.1. Summary of the Research

This study set out to develop a low-height autonomous rover equipped with a convolutional neural network (CNN)-based plant disease detection model tailored specifically for short-statured crops grown along the Karnataka-Tamil Nadu border. By combining computer vision, environmental sensing, and mobility, the aim was to provide a cost-effective and efficient disease monitoring tool for smallholder farmers. The project followed a systematic methodology, from dataset compilation and model development to integration with sensor systems and real-time field deployment. Data-driven analysis was performed to evaluate the model's effectiveness and operational viability.

5.2. Field Testing and Preliminary Results

A rover prototype was subjected to field-testing (Appendix 8) in a groundnut growing space to perform a real-time field test of the plant disease detection model in natural environmental conditions. The field-test showed that the visual model was able to classify groundnut healthy leaves with confidence levels of 86.07% and 76.49% (Appendix 9) respectively, while being able to locate groundnut rust at a lower confidence level of 40% (Appendix 10). The results of the testing are nearly congruent with the performance measures of the model when trained and validated utilizing the dataset because healthy groundnut leaves were classified most reliably when looking at unanimous representation of uniform features (e.g., healthy groundnut leaves) in the dataset. Meanwhile, the lower confidence rating for detection and classification of groundnut rust means there was probably a misalignment between the training of the model's image dataset and the nonlinear variables of real field symptoms (e.g. severity of rust symptoms from the groundnut plant, lighting, or occlusions from leaves in field images). The physical images in the field of rust-infected leaves showed more natural noise and environmental detail than the images comparing to the dataset that were captured under controlled or ideal lighting. This means an essential next step for increasing robustness is to have more images for the dataset that have a more natural variable detail captured in field condition. If we take into account the variation in the environment, being able to navigate the crop row and provide disease inference in real-time with the rover is a significant move toward practical use in precision agriculture.

5.3. Reiteration of Key Findings and Analysis

Key findings from the study revealed a significant disparity between batch prediction and real-time performance. The CNN model, though trained on a robust dataset of 18,256 annotated images across 23 disease classes, exhibited overfitting when evaluated in bulk—misclassifying all test samples into a single category. However, in real-time scenarios, the same model produced accurate and relevant predictions, particularly when tested on isolated samples captured during rover navigation. The sensor systems recorded soil moisture levels, laying the groundwork for future correlation studies between environmental factors and disease prevalence. Visual representations, including confusion matrices and classified image outputs, reinforced the practical utility of the integrated system.

5.4. Contributions to Knowledge

This research contributes a novel integration of AI and robotics to the relatively underexplored area of disease detection in short-statured crops. Unlike existing approaches focused on drone surveillance or manual inspections, this work introduces a ground-based inspection model that can traverse between narrow rows and function autonomously. It addresses challenges specific to small-statured crops and provides a working prototype that merges machine learning, embedded systems, and field engineering. Recent efforts have emphasized ground-level robotic platforms for improved crop monitoring and real-time diagnosis in smallholder farming systems (Ravi et al., 2022), supporting the direction of this study. Ultimately, the interdisciplinary framework proposed here offers a practical step toward scalable innovations in sustainable and precision agriculture.

5.5. Recommendations

Future implementations of the rover should prioritize sustainable power sources, such as solar panels, to extend field operation time and reduce dependency on limited battery life. Improving the CNN's robustness through advanced data augmentation techniques and adaptive learning models can reduce overfitting and improve generalization, a need also emphasized in recent studies focusing on practical field deployment of deep learning models in agriculture (Shah et al., 2023). Adding capabilities such as cloud-based data logging, remote model updates, and automated path planning will make the system more scalable and farmer-friendly. Moreover, integration with weather APIs and mobile notifications can enhance its practical relevance on the ground.

5.6. Limitations of the Present Study

Several constraints affected the outcomes of this research. Firstly, the rover system and disease detection model are not suited for operation under unpredictable or extreme weather conditions, limiting its deployment to fair weather periods. Secondly, the hardware was constrained by battery limitations, reducing its applicability to small or medium-sized farms. Thirdly, the current system was designed exclusively for low-height crops and does not accommodate taller crops such as maize or sugarcane, which require alternative sensor positioning and mechanical design. An additional critical limitation was the computational challenge faced during the model training phase. The researcher encountered significant obstacles due to hardware limitations—particularly the repeated crashing of the development laptop during model training. This not only delayed progress but also restricted the possibility of experimenting with deeper networks or conducting extensive hyperparameter tuning. With access to higher-end GPUs or cloud-based platforms, the model could have been trained more efficiently, potentially avoiding the overfitting issue and improving its generalizability, as highlighted by recent studies emphasizing infrastructure constraints in deep learning for agriculture (Nyalala et al., 2021).

5.7. Future Scope of the Study

This research opens new avenues for the application of AI in short-statured crop monitoring, an area with minimal prior exploration. Expanding the rover's capabilities to support multi-spectral imaging, real-time weather analytics, and multi-crop support can revolutionize disease management at the grassroots level. Future studies should aim to scale the solution for commercial viability and integrate it within broader agricultural ecosystems. Additionally, incorporating feedback systems from farmers can refine the interface and optimize the model's decision-making algorithms for real-world scenarios, as highlighted by recent advancements in AI-integrated smart farming solutions (Ahmad et al., 2021).I believe that by bridging the gap between technological innovation and farmer engagement, this research can lay the foundation for more inclusive, adaptive, and sustainable agricultural practices in regions that need it most.

5.8. Conclusion

That journey of creating an integrated system helped to expose both the vast opportunity space and technical challenges in agricultural AI. Though its performance in live mode seemed impressive but limitations with training set explaining the crux that academic research landscape needs more tunable and powerful computing infrastructure, as can be seen from the model. As Nyalala et al. (2021) computational efficiency and the provision of high-performance hardware if necessary are key factors for the successful implementation of precision agriculture technologies that allow faster model training, accurate predictions and reliable in-time predictions for complex field dynamics. This, in the challenges faced during this study – hardware limitations and model overfitting – emphasize the need for careful system design, preprocessing of data and algorithms enhancement in order to conquer technical obstacles. Yes, through this project it shows developing low cost and impactful innovations out of small setups with dedication and systematic approach as per requirements. In turn, this research underpins a significant body of information emerging in digital agriculture and signals that there must be more done to provide the support and infrastructure needed for student-led discoveries in nascent agri-tech areas. Moreover, the research advocates for the need of multi-stakeholder collaboration (academia, industry and governmental) in deploying the required infrastructure and resources to ensure innovation preparedness which are particularly crucial for innovations coming from resource-constrained environments.

ACKNOWLEDGEMENT

First and foremost, praises and thanks to the God, the Almighty, for His showers of mercy and blessings throughout my research work to complete the research successfully. I would like to express my deep and sincere gratitude to my research supervisor, Dr. N Sridhar, Associate Professor and Head, Department of Agriculture Engineering, Hindusthan College of Engineering and Technology, for giving me the opportunity to do research and providing invaluable guidance throughout this research. His dynamism, vision, sincerity and motivation have deeply inspired me. He has taught me the methodology to carry out the research works as clearly as possible. It was a great privilege and honor to work and study under his guidance. I would also like to thank him for his friendship, empathy, and great sense of humor.

I am very much thankful to Class Tutor Dr. V Dhayalan and the rest of the faculty of the Agriculture Engineering department for their endless support and encouragement. I am extremely grateful to my parents for their love, prayers along with continuous support in this research writing. My special thanks go to my friends Sufiyan, Sajid and Ashwaque who helped during my research with their extensive knowledge which helped me to complete this thesis.

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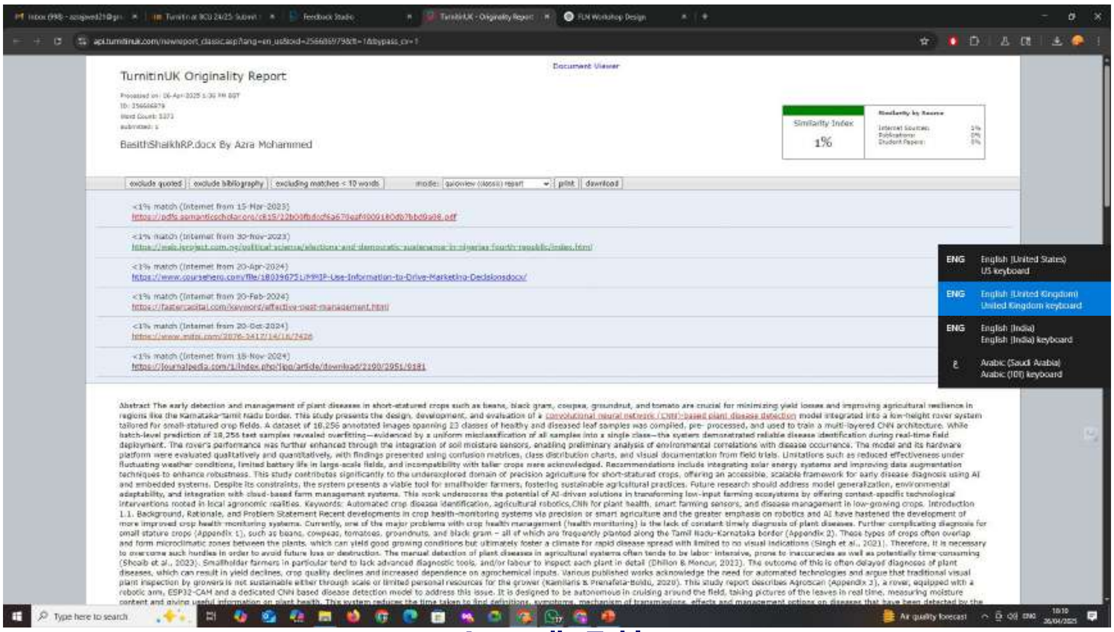
PLAGIARISM REPORT:



Appendix Table

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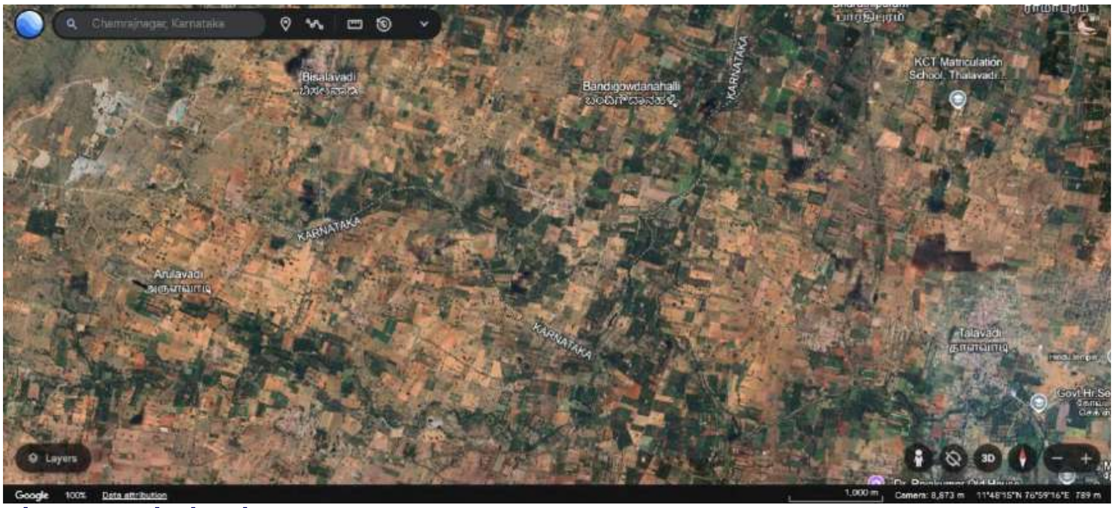
Appendix 1:

Short stature crops:

Short stature crops are defined as crops that grow shorter than conventional agricultural components (generally less than 1 m tall). They are well suited to close planting, require less water, and manageability is easier, making more applicable when space or water for growing are limited. This picture was taken from https://www.mdpi.com/2073-4395/12/1/141

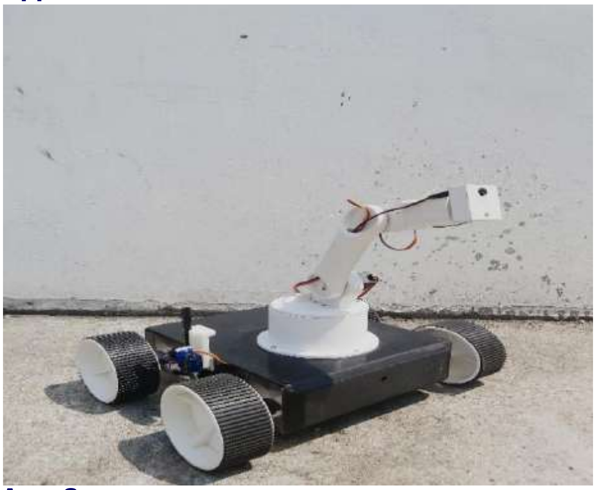
Appendix 2:

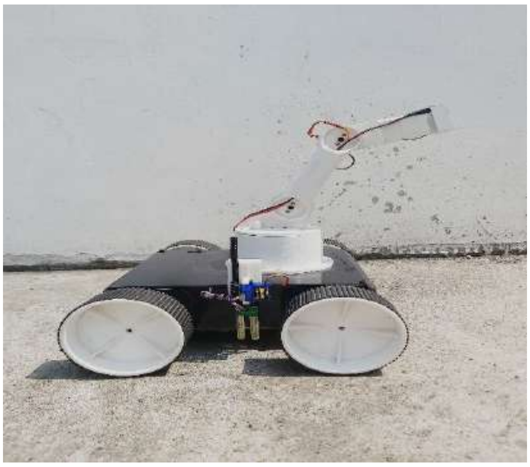


Tamil Nadu-Karnataka border:

The dataset predominantly covers the Tamil Nadu–Karnataka border region, a diverse agro-climatic zone known for its varied topography and small-scale farming practices. This area was selected due to its rich agricultural activity and cross-regional cultivation patterns, offering a representative sample for analysis. A screenshot from Google Maps of the region has been included to visually support this geographical context.

Appendix 3:

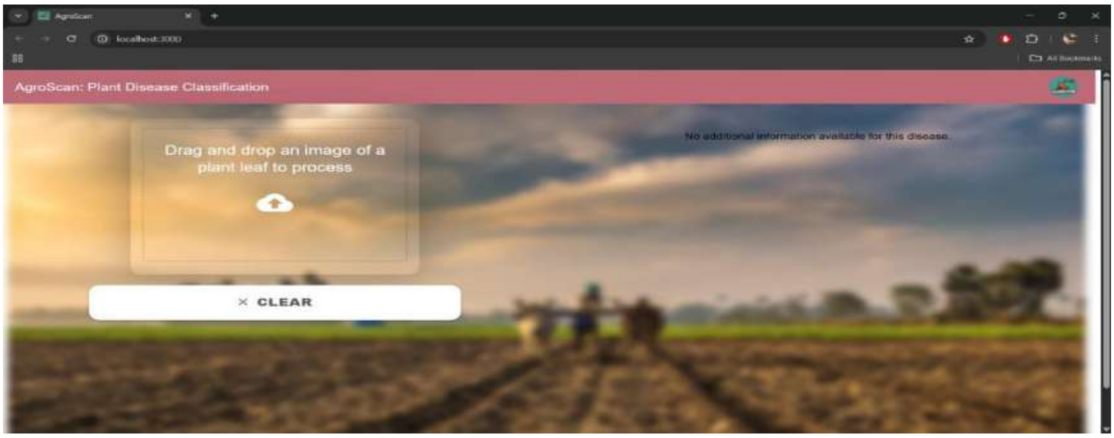


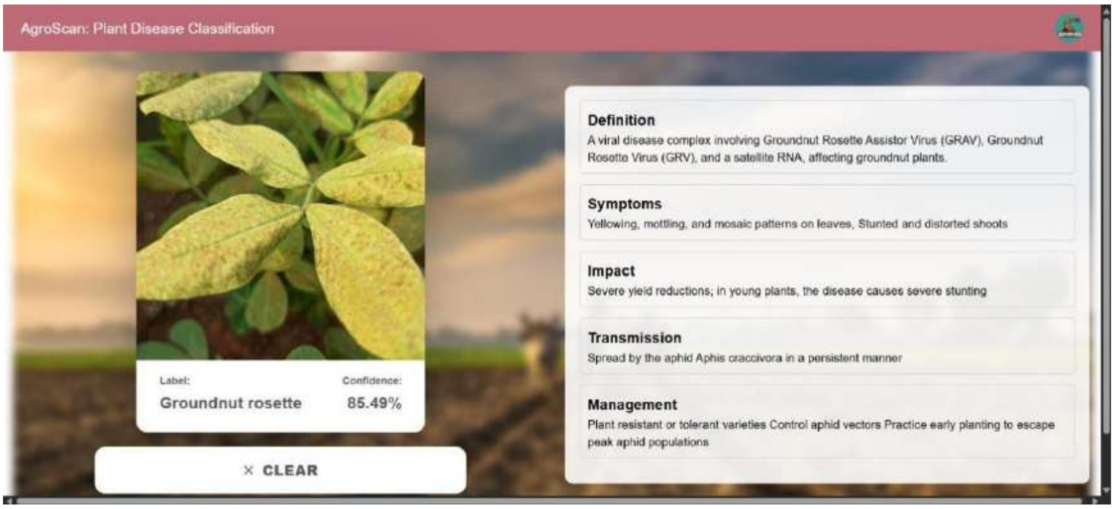


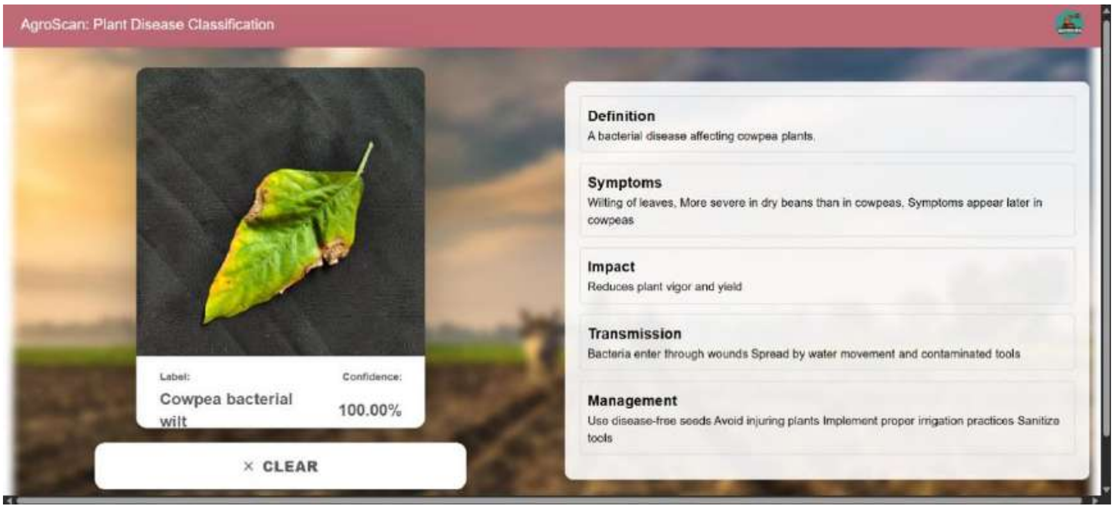
AgroScan:

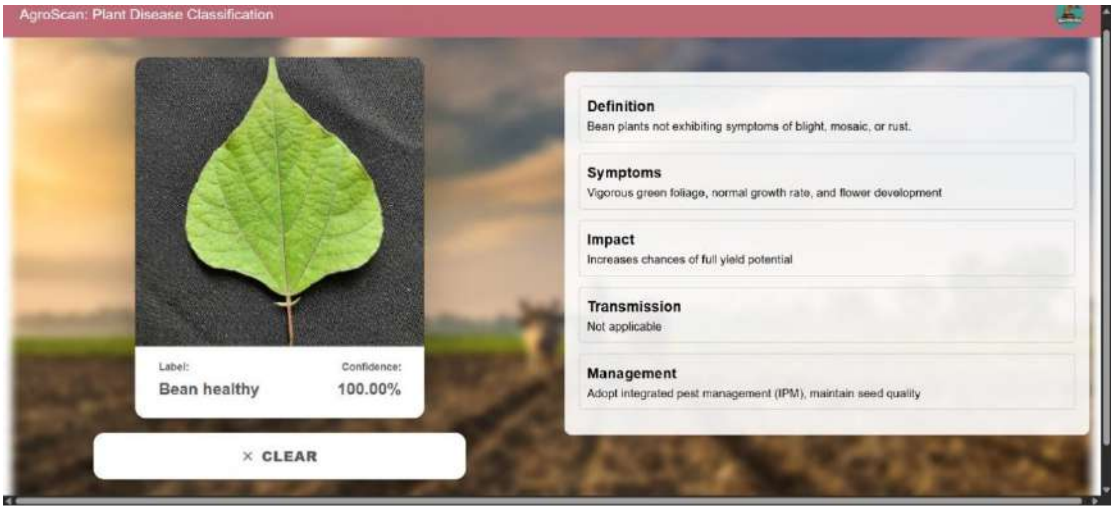
AgroScan is a rover that was developed by the team utilizing open-source materials and built to spec. We have also improved the scan's generation by integrating a soil moisture sensor so it can capture and measure visual and environmental data for agricultural analysis.

Appendix 4:









Automated plant health detection system:

The Automated Plant Health Detection System is a web-based platform where users can upload an image of a plant leaf to identify potential diseases. The system uses machine learning to detect the disease and displays the result along with a confidence percentage. Additionally, it provides informative messages on the side, including the disease's definition, symptoms, impact, transmission methods, and recommended management practices.

Appendix 5:

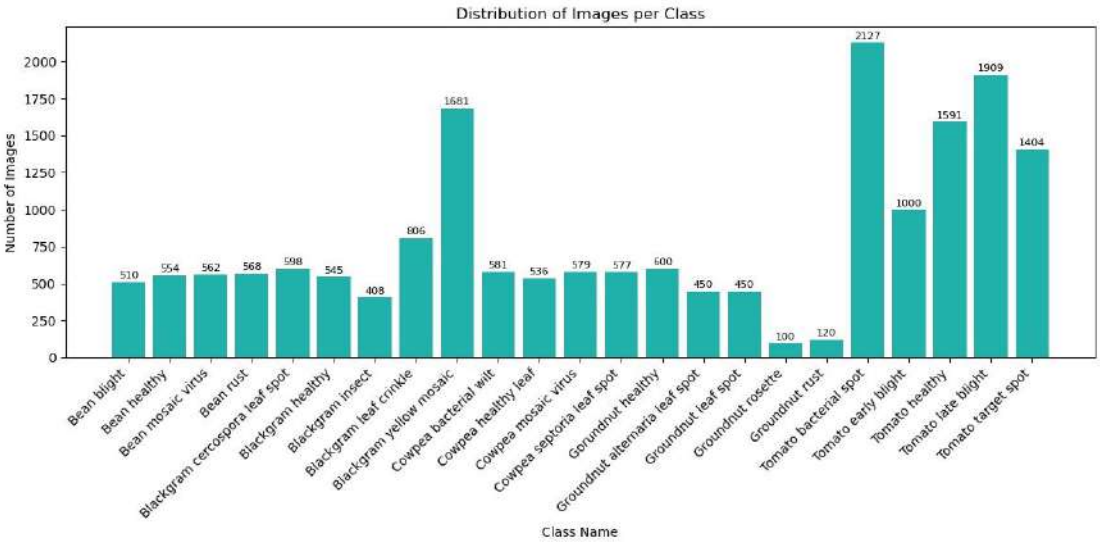
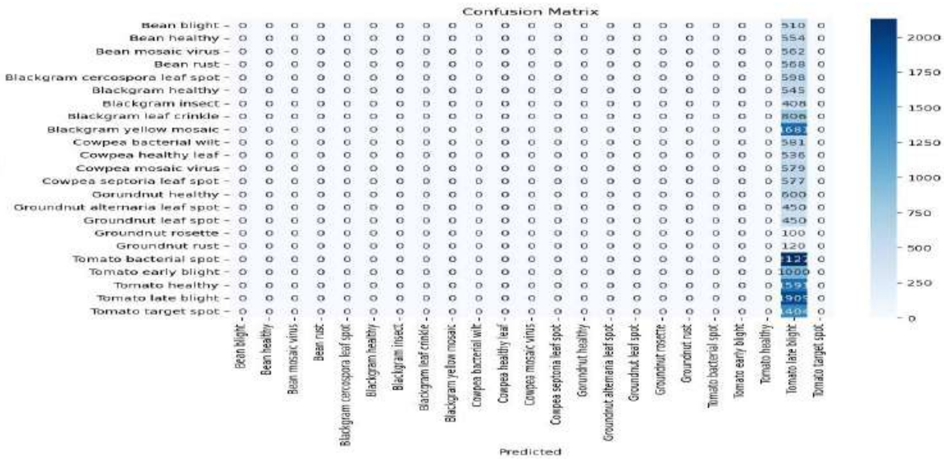


Image Dataset Summary – Crops, and Distribution:

In total, during the model training and analysis phase of plant health detection, we used 18,256 images from 23 datasets comprising all four major crops—tomato, cowpea, groundnut, and beans. These contributed toward the accurate model development methodology for plant health detection.

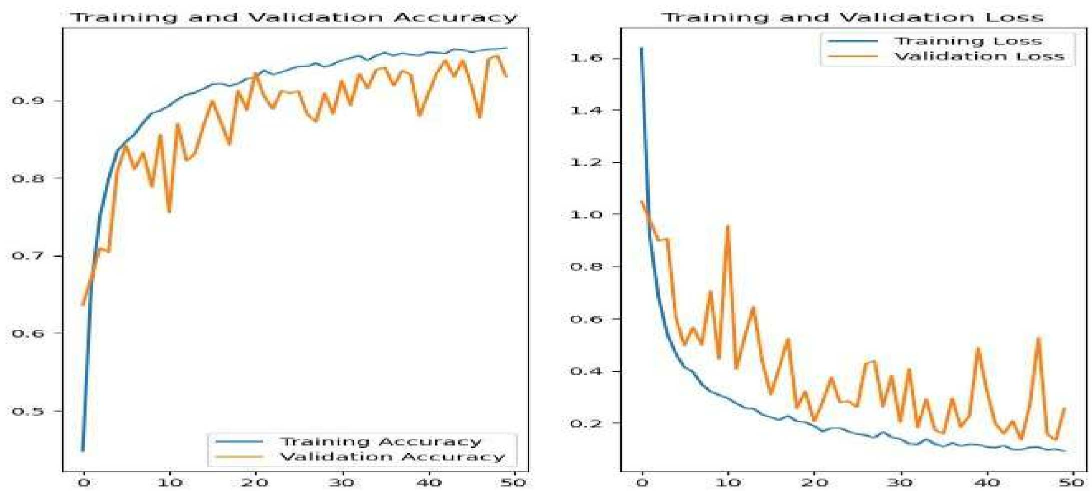
Appendix 6:



Confusion matrix:

The confusion matrix demonstrated that the model trained on a class imbalanced dataset had predicted every test image as "Tomato Late Blight". This could indicate the model overfitting or a potential data leakage. This highlights the challenges of class imbalances and the importance of good validation strategies to ensure model robustness.

Appendix 7:



Training and Validation Curves:

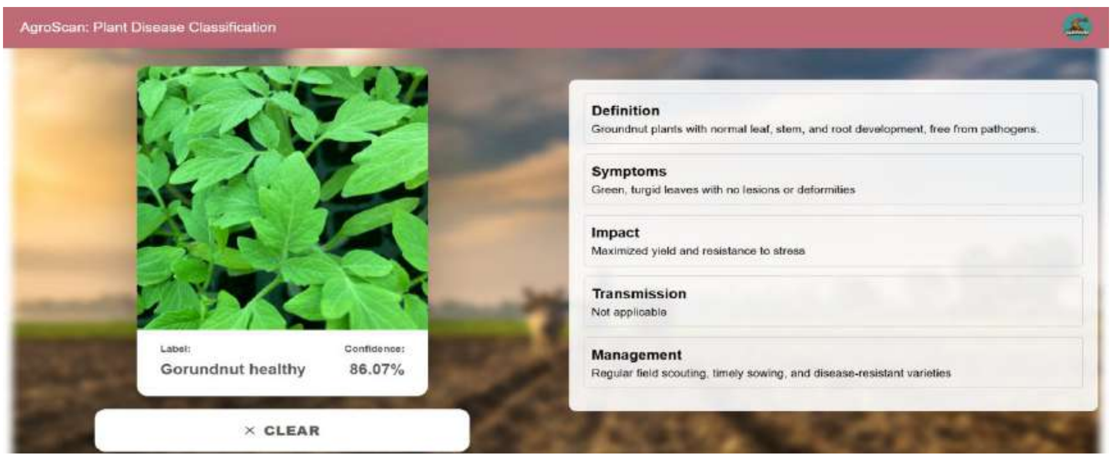
The training and validation curves show a satisfactory convergence of training accuracy with small fluctuations in the validation accuracy, indicating some overfitting. This indicates a need to further refine the model and make it more consistent, particularly with respect to potential data imbalance and data leakage issues.

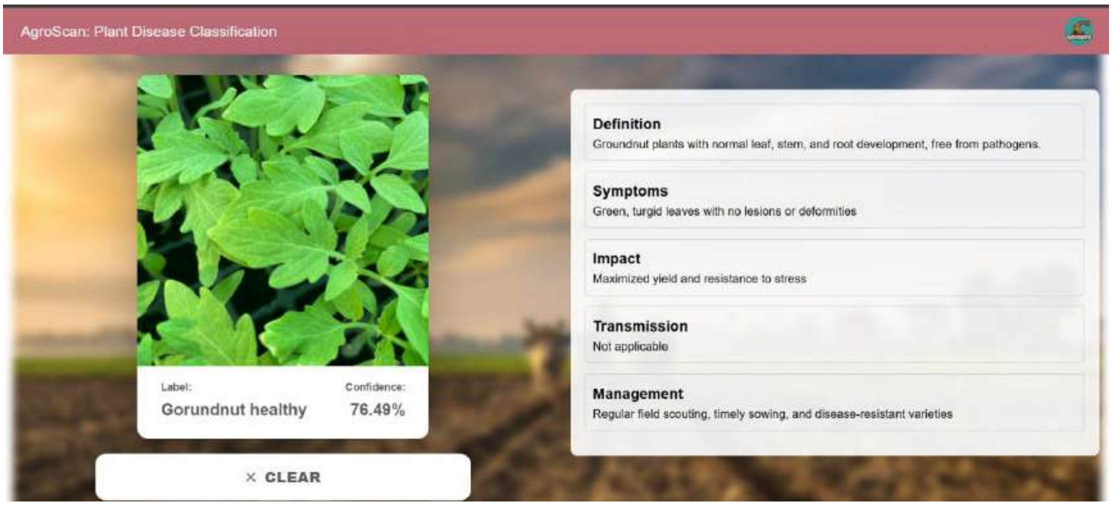
Appendix 8:

Field-testing:

Field experiments were conducted in a groundnut field to assess the real-time disease detection capabilities of the rover. The model classified groundnut healthy leaves with high confidence and identified groundnut rust with moderate accuracy. The results from the field were compared with the predictions from the dataset in order to evaluate the model's performance in real-world situations.

Appendix 9:

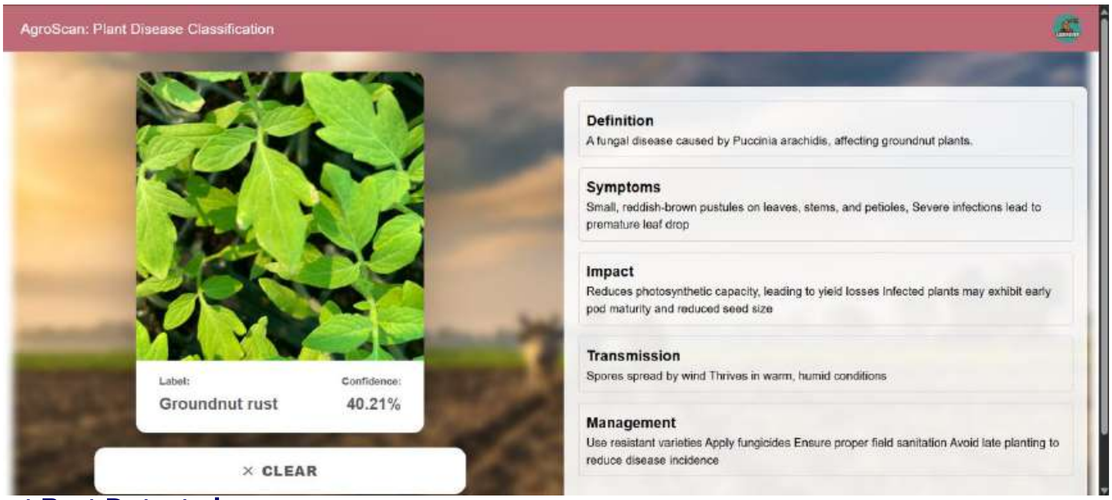




Groundnut Healthy Leaves Detected

In the field testing phase, the disease detection model accurately classified groundnut healthy leaves on two occasions with confidence levels of 86.07% and 76.49%. The high prediction confidence indicated the reliability of the model to accurately classify healthy groundnut leaves given the environmental field conditions that varied (light, leaf orientation, and background noise). In comparison, consistency was observed between the field and dataset results achieved in the controlled testing phase for healthy leaves, demonstrating the disease detection model's reliability to perform outside of a laboratory conditions for generalization.

Appendix 10:



Groundnut Rust Detected:

The model showed a 40% confidence level for groundnut rust during field tests. In contrast to the dataset performance, the field accuracy was lower, indicating difficulty in recognizing disease symptoms in the field. This could be due to things like differences in rust severity, variation in lighting, and/or environmental noise that added challenges to the model's efforts to accurately classify the rust-infected leaves. This emphasizes the need to supplement the dataset with more diverse and field-acquired images in order to increase the model's sensitivity to complex disease symptoms.