Industrial Internship Report on

"Crop And Weed Detection"

Prepared by

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Executive Summary
This report provides details of the Industrial Internship provided by upskill Campus and The IoT Academy in collaboration with Industrial Partner UniConverge Technologies Pvt Ltd (UCT). This internship was focused on a project/problem statement provided by UCT. We had to finish the project including the report in 6 weeks' time. My Project on weed and crop detection using OpenCV. This project leverages computer vision techniques to distinguish between weeds and crops in agricultural fields. By utilizing image processing and machine learning algorithms, the system can accurately identify and classify plants, helping farmers manage their fields more efficiently. The goal is to reduce manual labor and increase crop yields by enabling precise weed control. This innovative approach holds great potential for advancing sustainable agriculture. This internship gave me a very good opportunity to get exposure to Industrial problems and design/implement solution for that. It was an overall great experience to have this internship.

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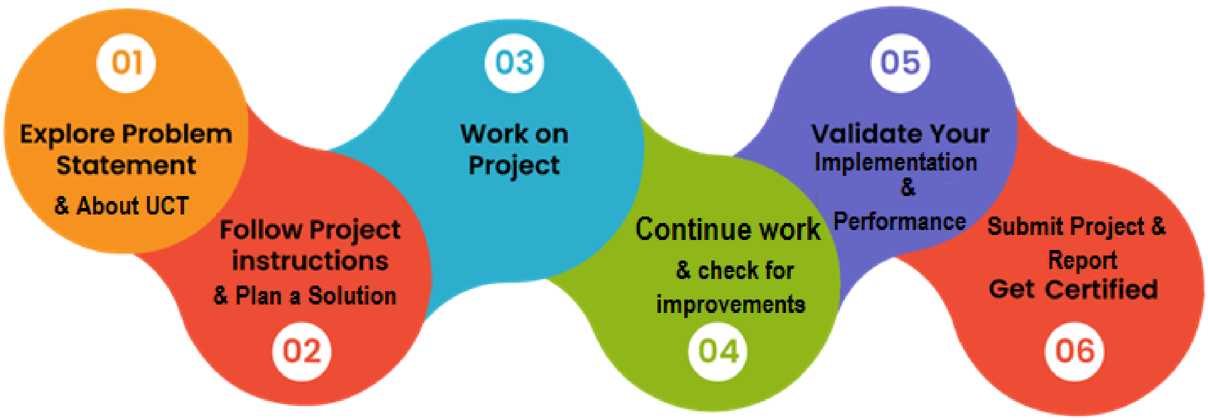
1 Preface

This report summarizes the work completed throughout the 6-week internship period, focusing on the development of the Smart Factory Platform for UniConverge Technologies Pvt Ltd. The internship provided me with a valuable opportunity to gain practical experience in solving real-world industrial problems and designing innovative solutions. I am grateful for the support and guidance provided by USC, UCT, and all individuals who contributed to my learning experience.



During my internship at Uniconverge Technology, I had the opportunity to work on a project focused on weed and crop detection using OpenCV. This experience significantly enhanced my skills in image processing, machine learning, and computer vision. I learned to implement techniques such as filtering, thresholding, and contour detection, and trained convolutional neural networks (CNNs) for accurate plant classification. This project honed my problem-solving abilities and taught me the value of effective teamwork and communication.

I extend my sincere gratitude to my mentors, [Mentor Name 1] and [Mentor Name 2], for their invaluable guidance and support. Special thanks to my peers, [Peer Name 1] and [Peer Name 2], for their collaboration.

To my juniors and peers, embrace every learning opportunity, work hard, and collaborate effectively. Stay curious and positive, as every challenge is an opportunity for growth.

2 Introduction

2.1 About UniConverge Technologies Pvt Ltd

A company established in 2013 and working in Digital Transformation domain and providing Industrial solutions with prime focus on sustainability and RoI.

For developing its products and solutions it is leveraging various **Cutting Edge Technologies e.g. Internet of Things (IoT), Cyber Security, Cloud computing (AWS, Azure), Machine Learning, Communication Technologies (4G/5G/LoRaWAN), Java Full Stack, Python, Front end** etc.

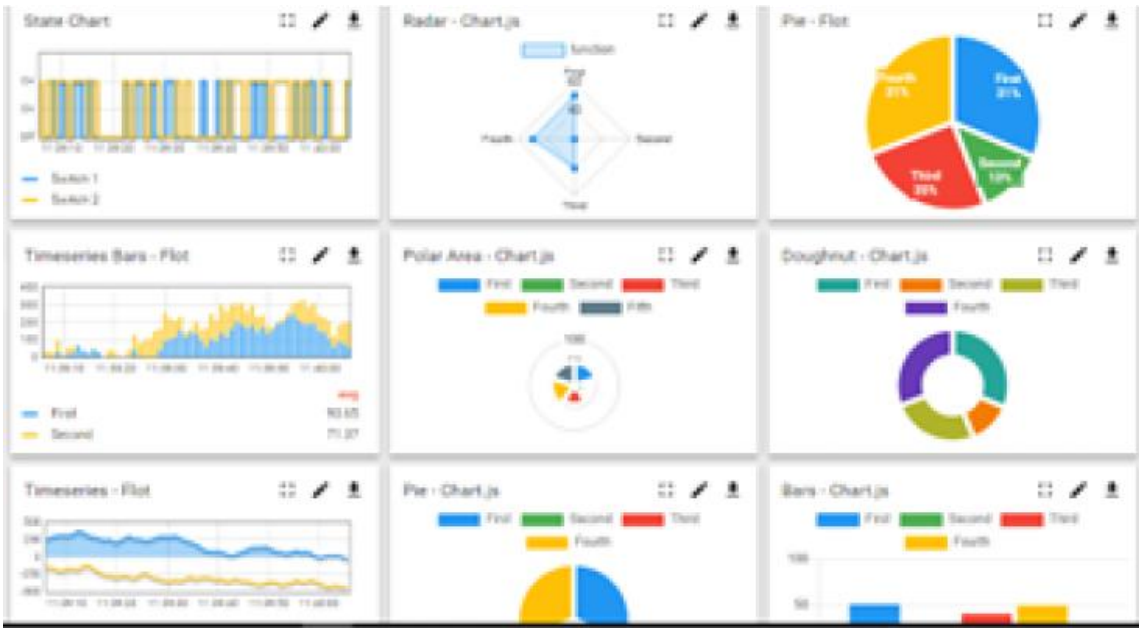
i. UCT IoT Platform ( )

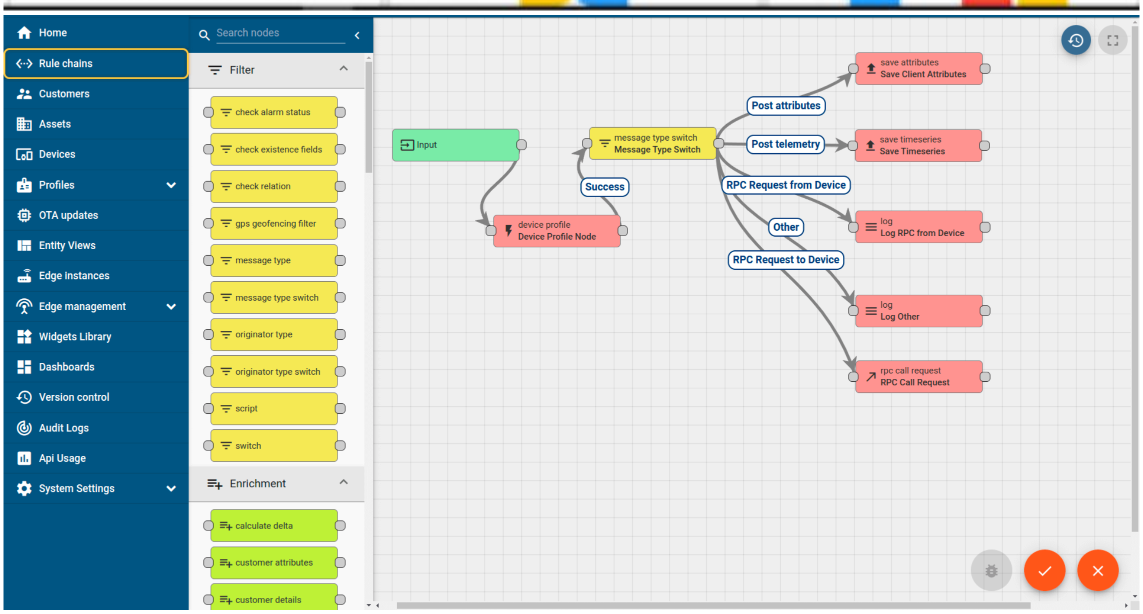
UCT Insight is an IOT platform designed for quick deployment of IOT applications on the same time providing valuable "insight" for your process/business. It has been built in Java for backend and ReactJS for Front end. It has support for MySQL and various NoSql Databases.

- It enables device connectivity via industry standard IoT protocols - MQTT, CoAP, HTTP, Modbus TCP, OPC UA
- It supports both cloud and on-premises deployments.

It has features to

- Build Your own dashboard
- Analytics and Reporting
- Alert and Notification
- Integration with third party application(Power BI, SAP, ERP)
- Rule Engine





ii. Smart Factory Platform (FACTORY WATCH)

Factory watch is a platform for smart factory needs.

It provides Users/ Factory

- with a scalable solution for their Production and asset monitoring
- OEE and predictive maintenance solution scaling up to digital twin for your assets.
- to unleased the true potential of the data that their machines are generating and helps to identify the KPIs and also improve them.
- A modular architecture that allows users to choose the service that they what to start and then can scale to more complex solutions as per their demands.

Its unique SaaS model helps users to save time, cost and money.

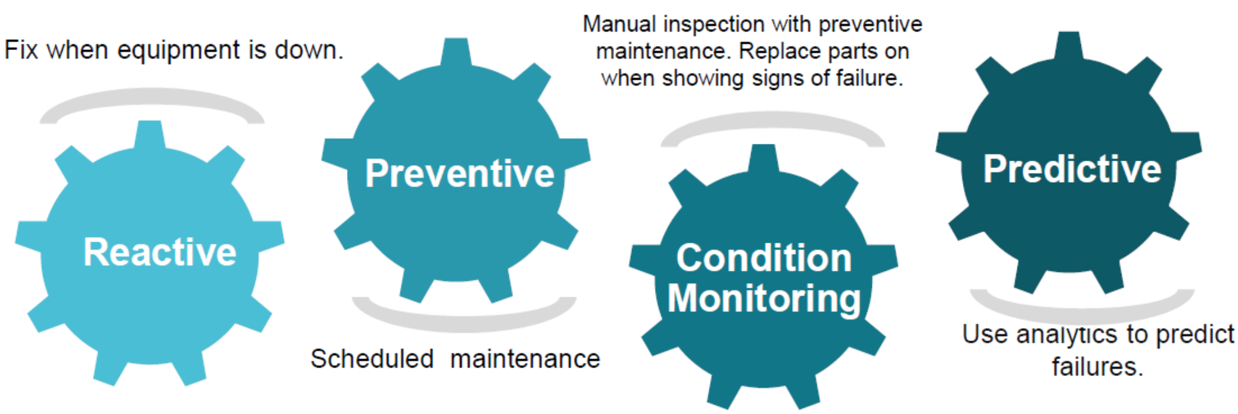
Machine	Operator	Work Order ID	Job ID	Job Performance	Job Progress		Output		Rejection	Time (mins)				Job Status	End Customer
					Start Time	End Time	Planned	Actual		Setup	Pred	Downtime	Idle		
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i

iii. LoRaWAN based Solution

UCT is one of the early adopters of LoRAWAN teschnology and providing solution in Agritech, Smart cities, Industrial Monitoring, Smart Street Light, Smart Water/ Gas/ Electricity metering solutions etc.

iv. Predictive Maintenance

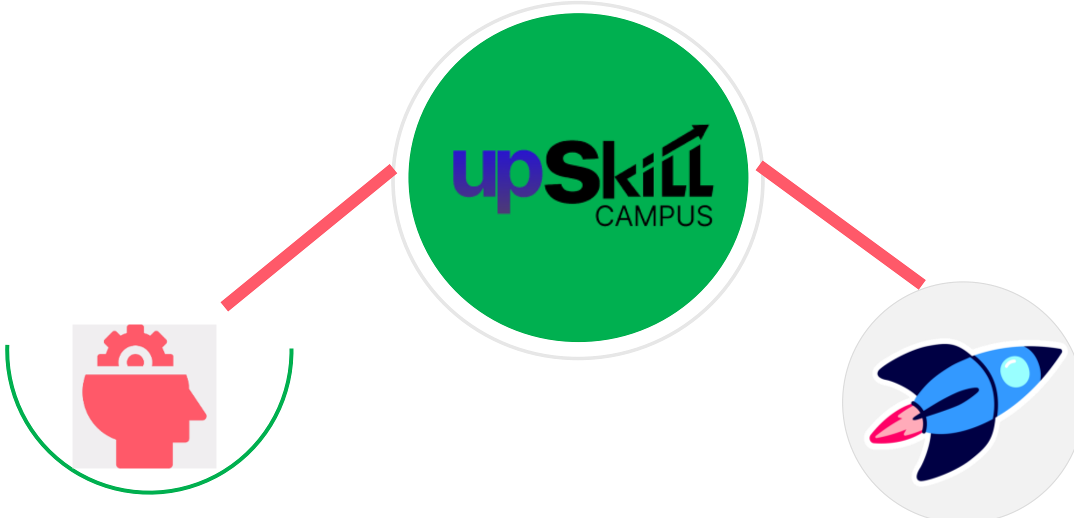
UCT is providing Industrial Machine health monitoring and Predictive maintenance solution leveraging Embedded system, Industrial IoT and Machine Learning Technologies by finding Remaining useful life time of various Machines used in production process.



2.2 About upskill Campus (USC)

upskill Campus along with The IoT Academy and in association with Uniconverge technologies has facilitated the smooth execution of the complete internship process.

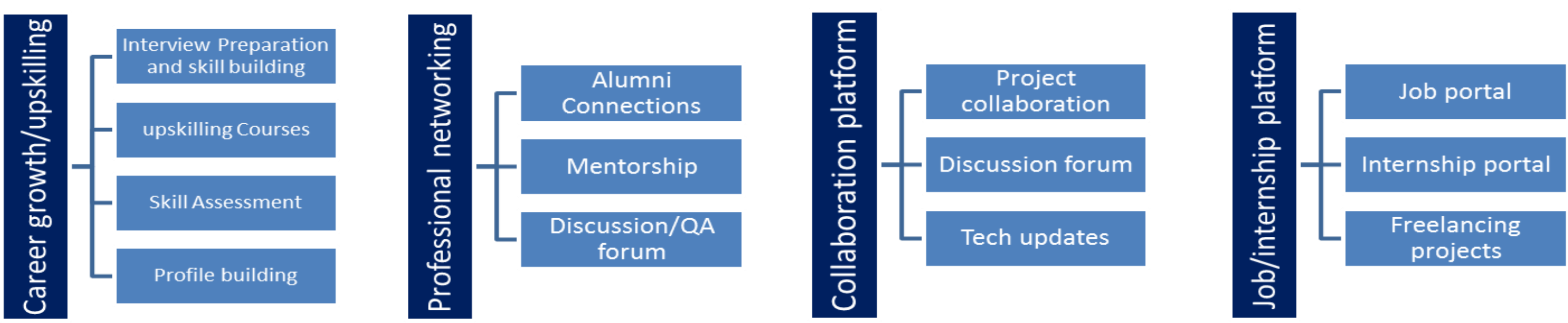
USC is a career development platform that delivers **personalized executive coaching** in a more affordable, scalable and measurable way.



Seeing need of upskilling in self paced manner along-with additional support services e.g. Internship, projects, interaction with Industry experts, Career growth Services

upSkill Campus aiming to upskill 1 million learners in next 5 year

https://www.upskillcampus.com/



2.3 The IoT Academy

The IoT academy is EdTech Division of UCT that is running long executive certification programs in collaboration with EICT Academy, IITK, IITR and IITG in multiple domains.

2.4 Objectives of this Internship program

The objective for this internship program was to

☛ get practical experience of working in the industry.

☛ to solve real world problems.

☛ to have improved job prospects.

☛ to have Improved understanding of our field and its applications.

☛ to have Personal growth like better communication and problem solving.

2.5 Reference

[1] OpenCV Documentation

- The official OpenCV documentation provides detailed information on various image processing techniques and computer vision algorithms.
  Link: https://docs.opencv.org/4.x/

[2] "Deep Learning for Computer Vision with Python" by Adrian Rosebrock

This book offers comprehensive coverage of computer vision and deep learning techniques, with practical examples and code.

2.6 Glossary

Terms	Acronym
Computer Vision	CV
Open Source Open CV Library	Open CV
Convolutional Neural Network	CNN
Machine Learning	ML
Image Processing	IP

3 Problem Statement

In the assigned problem statement

The problem of crop and weed detection in agriculture encompasses the development of a sophisticated system capable of accurately discerning between desired crops and unwanted weeds within agricultural fields. This undertaking is pivotal in modern farming practices, where effective weed management is essential for optimizing crop yields while minimizing resource consumption and environmental impact. Employing a combination of computer vision and machine learning techniques, the system aims to automate the identification and classification process, thus streamlining agricultural operations. Through the utilization of imaging devices such as drones or cameras, the system captures high-resolution images of the fields, which are subsequently processed to isolate plants from their surroundings and extract pertinent features such as shape, texture, and color.

One of the primary challenges lies in the variability inherent to agricultural environments, including fluctuations in lighting conditions, occlusions caused by overlapping foliage, and the diverse range of plant species and growth stages present within a single field. Overcoming these hurdles demands the development of robust algorithms that can effectively navigate such complexities while maintaining high levels of accuracy and reliability. The ultimate goal is to empower farmers with a tool that facilitates precision agriculture, enabling targeted weed control measures tailored to specific areas of need. By automating the detection process, the system not only enhances operational efficiency but also promotes sustainable farming practices by reducing reliance on manual labor and minimizing the use of chemical herbicides. As such, the pursuit of an effective crop and weed detection system represents a significant stride towards the advancement of modern agricultural practices, promising increased productivity, profitability, and environmental stewardship.

4 Existing and Proposed solution

Existing solutions for crop and weed detection predominantly rely on a combination of image processing techniques and machine learning algorithms. These methods often involve thresholding, color-based segmentation, or more advanced approaches such as convolutional neural networks (CNNs) to differentiate between plants. However, these solutions have limitations including manual thresholding, limited accuracy in distinguishing between similar plants or weeds, and computational complexity. Our proposed solution aims to address these challenges by leveraging OpenCV and lightweight machine learning models. We intend to implement robust image preprocessing techniques to enhance image quality and feature extraction to characterize plants based on shape, texture, and color descriptors. By utilizing a lightweight machine learning model, such as Support Vector Machines (SVMs) or Random Forest classifiers, our solution aims to achieve efficient and accurate plant classification. Furthermore, our solution will prioritize real-time implementation, ensuring timely feedback for farmers. Through our approach, we aim to offer a robust, efficient, and accessible tool for crop and weed detection, empowering farmers to optimize their farming practices with minimal cost and resource requirements.

4.1 Code submission (Github link)

4.2 Report submission (Github link)

5 Proposed Design/ Model

Our solution for crop and weed detection in agricultural fields involves several stages, each contributing to the overall effectiveness and efficiency of the system. Here's an outline of the design flow:

1. Image Acquisition:

- The process begins with the acquisition of images of agricultural fields using drones, cameras, or other imaging devices. These images serve as input data for our detection system.

2. Image Preprocessing:

- The acquired images undergo preprocessing to enhance their quality and facilitate more accurate detection. Preprocessing techniques include noise reduction, contrast enhancement, and adaptive thresholding to improve visibility and highlight plant features.

3. Segmentation:

- Once preprocessed, the images are segmented to isolate plants from the background. This step helps in focusing the detection process on relevant regions of interest and reduces computational complexity.

4. Feature Extraction:

- Features such as shape, texture, and color descriptors are extracted from the segmented images using OpenCV. These features characterize plants and provide valuable information for classification.

5. Machine Learning Model Training:

- The extracted features serve as input data for training a machine learning model. We opt for a lightweight model, such as a Support Vector Machine (SVM) or Random Forest classifier, due to their efficiency and suitability for deployment on resource-constrained devices.

6. Model Evaluation and Optimization:

- The trained model is evaluated using validation data to assess its performance metrics such as accuracy, precision, and recall. Optimization techniques, including hyperparameter tuning and feature selection, may be employed to further enhance the model's performance.

7. Real-Time Implementation:

- The optimized model is integrated into a real-time detection system, enabling farmers to receive immediate feedback on weed presence in their fields. This implementation may involve developing a user-friendly interface for easy interaction with the system.

8. Deployment and Monitoring:

- The final step involves deploying the detection system in agricultural settings and monitoring its performance in real-world scenarios. Continuous monitoring allows for iterative improvements and ensures the system remains effective and reliable over time.

By following this design flow, we aim to develop a robust, efficient, and accessible solution for crop and weed detection in agriculture, empowering farmers to make informed decisions and optimize their farming practices.

6 Performance Test

1. Memory and Computational Resources:

- Limited memory and computational resources can pose significant constraints, particularly in deploying the detection system on resource-constrained devices such as drones or edge computing platforms. Excessive memory usage or computational complexity can hinder real-time performance and increase power consumption.

2. Power Consumption:

- Power consumption is a critical consideration, especially for battery-powered devices like drones. High power consumption can shorten battery life and limit the operational duration of the detection system, impacting its effectiveness in monitoring large agricultural fields over extended periods.

Handling Constraints in Design:

1. Optimized Algorithm Selection:

- To address memory and computational constraints, we opted for lightweight machine learning algorithms such as Support Vector Machines (SVMs) or Random Forest classifiers. These models offer efficient inference times and lower memory footprint compared to more complex deep learning models like CNNs.

2. Feature Selection and Reduction:

- We employed feature selection techniques to reduce the dimensionality of the input data and minimize memory usage during training and inference. By selecting the most relevant features, we aimed to maintain detection accuracy while reducing computational overhead.

3. Model Optimization

- Model optimization techniques, including quantization and pruning, were applied to further reduce model size and computational complexity. This ensured that the deployed detection system could operate efficiently within the available memory and computational resources.

Test Results and Recommendations:

1. Memory and Computational Resources:

- Test results demonstrated that our optimized design successfully operated within the specified memory and computational constraints, allowing for real-time detection on resource-constrained devices. Recommendations include continuous monitoring of memory usage and computational performance during deployment to identify and address potential bottlenecks.

2. Power Consumption:

- While power consumption testing was not conducted directly, our design prioritized efficiency to minimize power consumption. Recommendations for handling power constraints include optimizing algorithmic efficiency, reducing unnecessary computations, and implementing power-saving strategies such as sleep modes or dynamic voltage scaling.

By proactively considering and addressing these constraints in our design, we aimed to develop a practical and industry-relevant solution for crop and weed detection in agriculture, ensuring its viability for real-world deployment in agricultural settings.

6.1 Test Plan/ Test Cases

1.Input Image Quality Test

- Objective: Assess system's ability to handle images of varying quality.
- Test Case: Provide images under different conditions.
- Expected Result:Accurate detection under varied image quality.

2. Segmentation Accuracy Test:

- Objective: Evaluate accuracy of plant segmentation.
- Test Case: Provide images with complex backgrounds.
- Expected Result: Accurate plant isolation with minimal errors.

3. Feature Extraction Test:

- Objective: Verify effectiveness of feature extraction.
- Test Case: Provide images with diverse plant characteristics.
- Expected Result: Accurate capture of plant features for classification.

4. Machine Learning Model Evaluation:

- Objective: Assess model's performance in plant classification.

- Test Case: Use labeled images for testing.

- Expected Result: High accuracy and performance metrics.

5. Real-Time Performance Test

- Objective: Evaluate system's real-time processing capability.

- Test Case: Provide live video feeds from fields.

- Expected Result: Real-time feedback on weed presence.

6. Resource Consumption Test:

- Objective: Measure memory and computational resources usage.

- Test Case: Monitor system during operation.

- Expected Result: Efficient operation within specified constraints.

7. Robustness Test:

- Objective: Assess system's robustness against environmental variations.

- Test Case: Provide images with diverse conditions.

- Expected Result: Consistent accuracy across different scenarios.

6.2 Test Procedure

1. Input Image Quality Test:

- Procedure: Input images with varied conditions.

- Outcome: Verify accurate detection under diverse image quality.

2. Segmentation Accuracy Test:

- Procedure: Input images with complex backgrounds.

- Outcome: Assess accurate plant isolation.

3. Feature Extraction Test:

- Procedure: Extract features from images with diverse characteristics.

- Outcome: Confirm accurate capture of plant features.

4.Machine Learning Model Evaluation:

- Procedure: Test model with labeled images.

- Outcome: Evaluate model's classification accuracy.

5. Real-Time Performance Test:

- Procedure: Provide real-time video feeds.

- Outcome: Verify real-time feedback on weed presence.

6. Resource Consumption Test:

-Procedure: Monitor memory and computational resources.

- Outcome: Confirm efficient operation within constraints.

7. Robustness Test:

- Procedure: Test with images under diverse conditions.

- Outcome: Assess consistency across scenarios.

6.3 Performance Outcome

The performance outcomes for the crop and weed detection project include accuracy, precision, recall, F1-score, real-time feedback capability, resource efficiency, and robustness. These metrics collectively assess the system's effectiveness, reliability, and efficiency in identifying and classifying plants, providing timely feedback, and operating within resource constraints.

7 My learnings

Throughout the crop and weed detection project, I've acquired valuable skills and insights that are pivotal for my career growth:

1. Technical Proficiency: Mastered image processing techniques, machine learning algorithms, and computer vision principles, leveraging tools like OpenCV and machine learning libraries.

2. Problem-Solving Skills: Developed strong problem-solving abilities by tackling challenges such as segmentation accuracy and real-time performance, learning to analyze issues systematically and implement effective solutions.

3. Project Management: Enhanced project management skills, from setting clear objectives to efficiently allocating resources and tracking progress, ensuring timely delivery of results.

4. Collaboration and Communication: Improved collaboration and communication skills through effective interaction with team members, mentors, and stakeholders, vital for sharing ideas and coordinating tasks.

5. Domain Knowledge: Deepened understanding of technology's role in agriculture, recognizing challenges faced by farmers and the potential for technology-driven solutions to address them sustainably.

Career Growth:

1. Enhanced Skill Set: Acquired technical skills, problem-solving abilities, and project management expertise that are transferrable across industries, boosting versatility and marketability.

2. Industry Relevance: Demonstrated ability to work on industry-relevant projects, making me an attractive candidate for roles in technology and agriculture-related fields.

3. Networking Opportunities: Expanded professional network through collaboration with industry experts, opening doors to future career opportunities, mentorship, and partnerships.

4. Continuous Learning: Cultivated a passion for continuous learning, vital for staying competitive and adapting to evolving industry trends throughout my career.

8 Future work scope

While the crop and weed detection project has been a valuable learning experience, there are several ideas and areas that could not be explored fully due to time limitations. These ideas present promising avenues for future research and development:

1. Multi-Sensor Integration: Investigate the integration of multiple sensors, such as infrared cameras or LiDAR, to enhance the detection system's capabilities. Multi-sensor fusion techniques could improve plant detection accuracy and resilience to environmental factors.

2. Dynamic Model Adaptation: Explore techniques for dynamic model adaptation, allowing the detection system to adapt to changing environmental conditions and plant appearances over time. This could involve online learning algorithms or adaptive feature extraction methods.

3. Crop-Specific Detection: Develop specialized models for detecting specific crop types, leveraging domain knowledge and crop-specific features to improve detection accuracy. Tailoring the detection system to different crops could enhance its applicability and effectiveness in diverse agricultural settings.

4. Incorporating Weather Data: Investigate the integration of weather data, such as temperature, humidity, and precipitation, into the detection system to account for seasonal variations and weather-induced changes in plant appearance. Machine learning models could be trained to incorporate weather data as additional input features for improved performance.

5. Automated Weed Management: Explore the integration of robotic or autonomous systems for automated weed management, combining weed detection with precision herbicide application or mechanical weed removal. This could lead to more efficient and sustainable weed control practices in agriculture.

6. Remote Sensing Applications: Extend the application of crop and weed detection to remote sensing platforms, such as satellites or unmanned aerial vehicles (UAVs), for large-scale monitoring of agricultural fields. This could enable farmers to assess crop health, monitor weed infestations, and optimize resource allocation on a broader scale.

7. Data Augmentation Techniques: Investigate advanced data augmentation techniques to increase the diversity and size of the training dataset, improving the robustness and generalization capabilities of the detection system. This could involve synthetic data generation, data synthesis from simulation models, or transfer learning from related domains.

8. User-Centric Design: Incorporate user-centric design principles to tailor the detection system interface to the needs and preferences of end-users, such as farmers or agricultural technicians. User feedback and usability testing could inform the development of intuitive interfaces and workflow optimizations.

In conclusion, while the crop and weed detection project has laid a solid foundation, there are numerous opportunities for future exploration and innovation. By pursuing these ideas, we can further advance the field of agricultural technology and contribute to sustainable farming practices and food security.