The

Industrial Internship

Report on

”Crop And Weed Detection”

Prepared by

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Executive Summary
This report details the Industrial Internship organized by Upskill Campus and The IoT Academy, in collaboration with the industrial partner UniConverge Technologies Pvt Ltd (UCT). The internship, spanning six weeks, focused on a project/problem statement provided by UCT. The objective was to design and implement a solution within this timeframe. My project involved developing a real-time crop and weed detection system using machine learning. This included preparing and splitting the dataset, training a YOLOv5x model, and converting the best-performing model into TensorFlow Lite and ONNX formats. The final goal was to integrate this model into a mobile application to aid farmers by providing real-time detection of crops and weeds. The internship provided valuable exposure to industrial challenges and hands-on experience in solving complex problems. It was an excellent opportunity to apply theoretical knowledge in a practical setting, gain insights into IoT technologies, and enhance my skills in machine learning and application development. Overall, it was a rewarding experience that significantly contributed to my professional growth.

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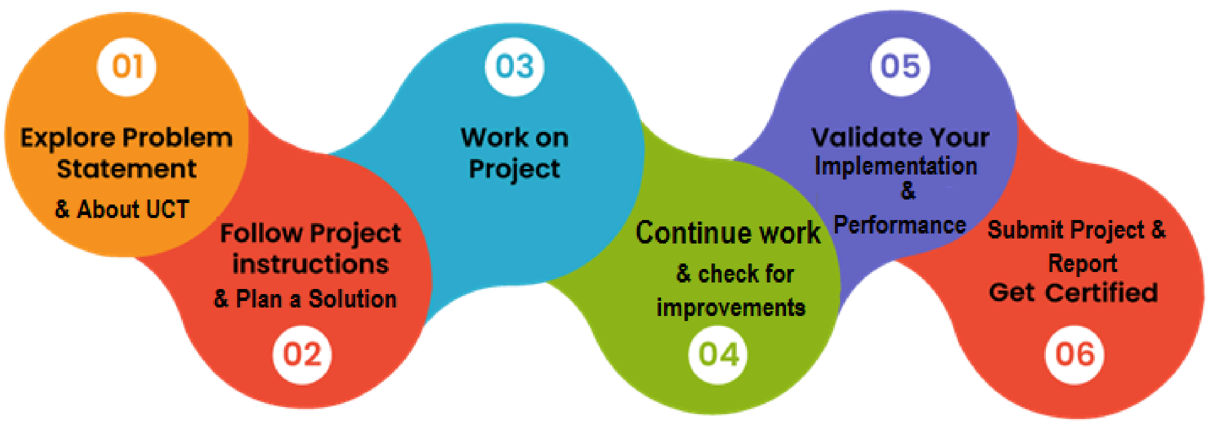
1 Preface

I thoroughly enjoyed my Six-week internship, where I learned essential skills such as Machine Learning, Data Science, Time Management, and IoT. I found myself genuinely interested and engaged throughout the learning process.

Securing a relevant internship at the start of one's career is crucial. It provides valuable knowledge about the IT sector and other industries, paving the way to opportunities in larger companies.

During this internship, I worked on the "Crop and Weed Detection" project. We used YOLO to train the model to distinguish between crop and weed images. This project was a significant opportunity provided by UCT/USC, offering a foundational experience in the IT field.

The internship was well-organized, with an excellent format that included video lectures and study materials, making the learning experience even more enjoyable.



I believe it was an amazing experience to attend this internship. It provided me with fundamental knowledge about Data Science and Machine Learning.

I am very thankful to USC/UCT for giving me this significant opportunity. I am also grateful to some YouTube channels, such as Krish Naik and Harry Bhai, for their valuable content. Additionally, I appreciate the assistance of various AI tools that helped me throughout this internship.

If you get such an opportunity, seize it, work hard, and learn as much as you can. I believe you will truly enjoy the journey.

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.

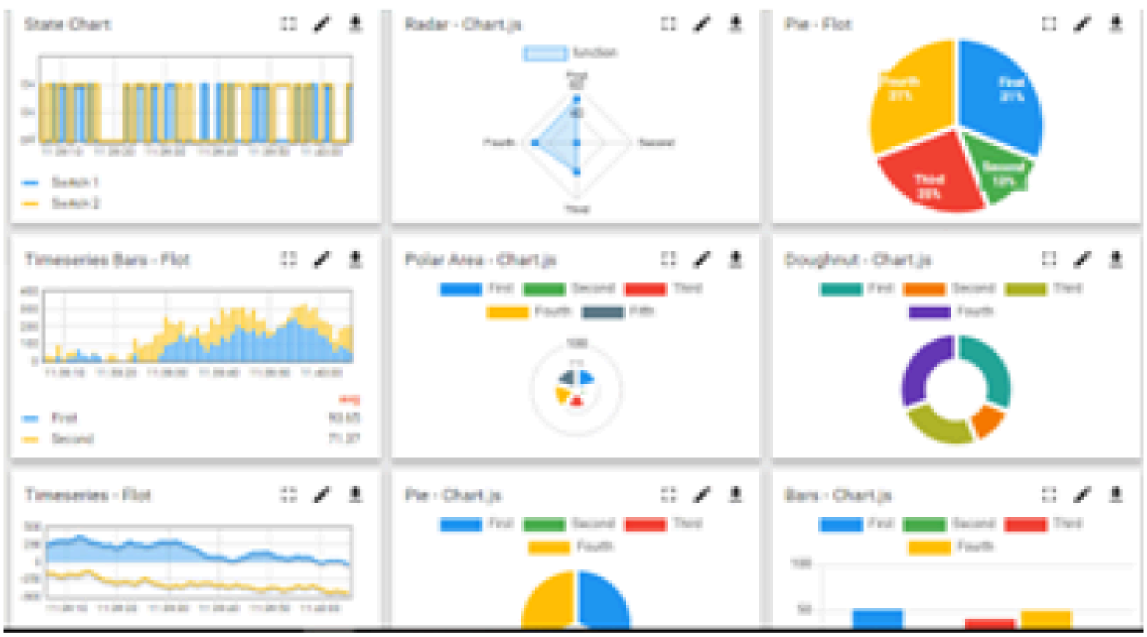
i. UCT IoT Platform ( )

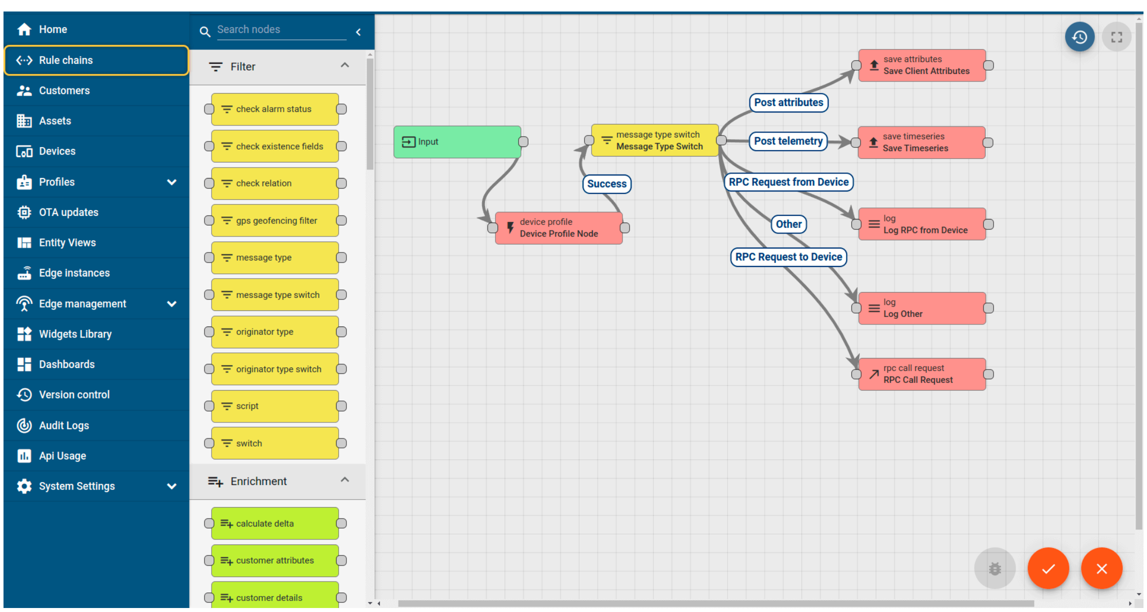
UCT Insight is an IOT platform designed for quick deployment of IOT applications on the same time providing valuable "insight" for your process/business. It has been built in Java for backend and ReactJS for Front end. It has support for MySQL and various NoSql Databases.

- 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.

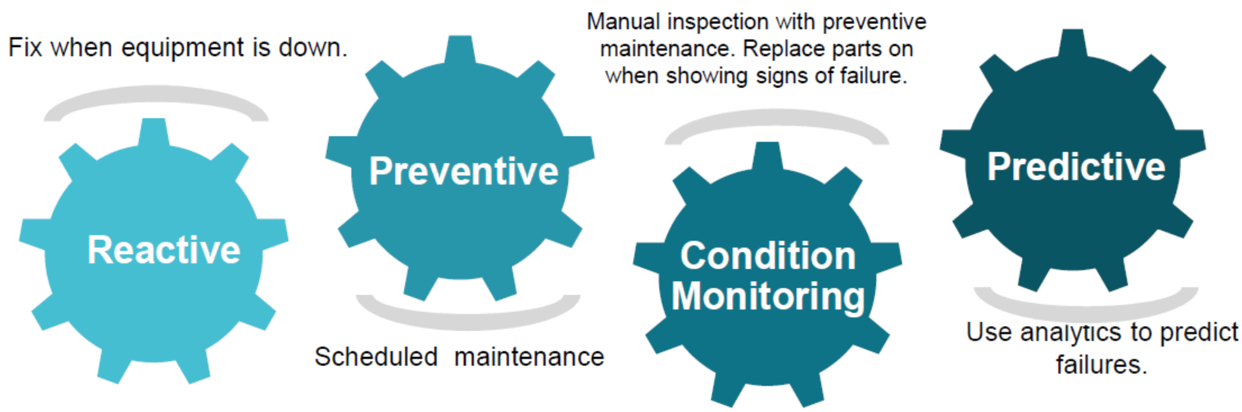
Machine	Operator	Work Order ID	Job ID	Job Performance	Job Progress		Output		Rejection	Time (mins)				Job Status	End Customer
					Start Time	End Time	Planned	Actual		Setup	Pred	Downtime	Idle		
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i
CNC_S7_81	Operator 1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

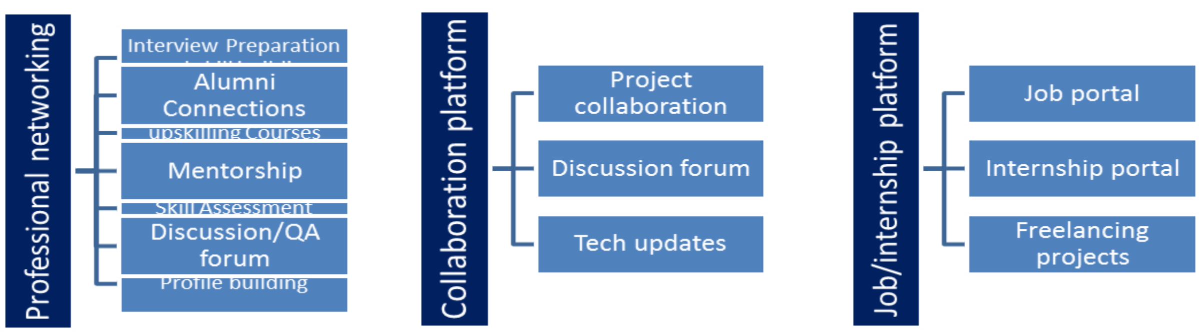
upskill Campus along with The IoT Academy and in association with Uniconverge technologies has facilitated the smooth execution of the complete internship process.

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] https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-3180.2010.00829.x

[2] https://www.sciencedirect.com/science/article/abs/pii/S0168169922007207

[3] https://elibrary.asabe.org/abstract.asp?aid=53312

[4] https://www.kaggle.com/

2.6 Glossary

Terms	Acronym
ML(Machine Learning)	A field of AI focused on building systems that learn from data.
DL(Deep Learning)	A subset of ML involving neural networks with many layers.
APIs (Application Programming Interfaces)	Tools and protocols for building and interacting with software applications.
MIPS (Million Instructions Per Second)	A measure of the performance of a computer processor.
SDK(Software Development Kit)	A collection of tools and libraries for developing applications.

3 Problem Statement

Weed is an unwanted thing in agriculture. Weed use the nutrients, water, land and many more things that might have gone to crops. Which results in less production of the required crop. The farmer often uses pesticides to remove weed which is also effective but some pesticides may stick with crop and may causes problems for humans.

"Automated Detection and Differentiation of Crops and Weeds Using Deep Learning for Agricultural Optimization"

Explanation

Weeds are an unwanted presence in agricultural fields, competing with crops for essential resources such as nutrients, water, and space. This competition often leads to reduced crop yields, as weeds can significantly outcompete crops for these vital inputs, resulting in lower agricultural productivity. Additionally, weeds can harbor pests and diseases that may further threaten crop health.

To combat this issue, farmers typically rely on chemical herbicides to remove weeds. While effective, these chemicals pose several challenges and risks. Some herbicides can remain on the crops, potentially entering the food chain and posing health risks to consumers. Moreover, the overuse of herbicides can lead to environmental issues such as soil degradation, water contamination, and harm to non-target organisms.

The aim of this project is to develop an automated system that can accurately detect and differentiate between crops and weeds in real-time using advanced deep learning techniques. By leveraging the YOLOv5x architecture. The model will be trained on a diverse dataset of crop and weed images, ensuring robust performance under different conditions.

Once trained, the model will be deployed on a mobile platform using TensorFlow Lite, allowing farmers to use the system directly in the field. This deployment will provide a real-time, non-chemical solution for weed management, enabling farmers to target weeds more precisely and potentially reduce the need for herbicides. By improving the efficiency and accuracy of weed detection, this project aims to enhance overall crop yields, reduce environmental impact, and contribute to safer food production practices.

This project will address key challenges such as dataset preparation, model training, and deployment, offering valuable insights and advancements in the field of agricultural technology. The ultimate goal is to provide a sustainable and efficient tool that aids farmers in their efforts to manage weeds and improve crop production.

4 Existing and Proposed solution

Existing Solutions

1. **Manual Weed Removal:**
   - **Overview:** This traditional method involves physically removing weeds by hand or with tools. It is labor-intensive and time-consuming, often requiring significant manual labor, especially in large fields.
   - **Limitations:**
     - Labor-intensive and costly.
     - Not feasible for large-scale farming.
     - Potential for human error and inconsistency.
2. **Chemical Herbicides:**
   - **Overview:** Chemical herbicides are widely used to control weed populations by selectively targeting unwanted plants. This method is efficient and relatively easy to apply.
   - **Limitations:**
     - Potential health risks due to chemical residues on crops.
     - Environmental concerns, such as soil degradation and water contamination.
     - Development of herbicide-resistant weed species.
3. **Mechanical Weeding:**
   - **Overview:** This method uses machinery to remove weeds. It is more efficient than manual weeding and can cover larger areas.
   - **Limitations:**
     - Can be costly due to equipment and maintenance.
     - May not be effective for all types of weeds or in all field conditions.
     - Potential damage to crops during the weeding process.
4. **Existing Automated Detection Systems:**
   - **Overview:** Some systems use image processing and basic machine learning techniques to detect weeds. These systems may use conventional cameras and simpler algorithms.
   - **Limitations:**
     - Often limited in accuracy and specificity.
     - Struggle with varying environmental conditions, such as lighting and weather.
     - May not distinguish well between similar-looking crops and weeds.

Proposed Solution

Our proposed solution involves the development of an advanced deep learning-based system using the YOLOv5x architecture to detect and differentiate between crops and weeds in real-time. The system will leverage a well-labeled dataset containing images of various crops and weeds to train a robust object detection model.

Key Features:

- **High Accuracy and Efficiency:** YOLOv5x is known for its high performance in object detection tasks, offering real-time processing capabilities and high accuracy in distinguishing between different objects.
- **Real-Time Mobile Deployment:** The model will be converted to TensorFlow Lite and deployed on a mobile application, enabling farmers to use the system directly in the field. This provides real-time weed detection, allowing for immediate action.
- **Non-Chemical Solution:** By providing accurate weed detection, this system can reduce the reliance on chemical herbicides, promoting safer and more sustainable farming practices.

Value Addition

- **Precision Agriculture:** The system enhances precision agriculture by enabling targeted weed management, thus optimizing the use of resources such as water, nutrients, and space.
- **Environmental and Health Benefits:** By reducing the need for chemical herbicides, the system helps minimize environmental contamination and potential health risks to consumers.
- **Cost-Effectiveness:** The mobile-based solution is cost-effective compared to traditional methods, as it reduces labor costs and the need for expensive chemical treatments.
- **Scalability:** The system can be scaled to different types of crops and agricultural settings, making it versatile and applicable in various farming scenarios.

4.1 Code submission (Github link)

https://github.com/hi10vi10/upskillCampus

4.2 Report submission (Github link) .

https://github.com/hi10vi10/upskillCampus/blob/master/Hiten_Hasmukhbhai_Patel_InternshipReport_USC_UCT%20.pdf

5 Proposed Design/ Model

1. Data Collection and Preprocessing:

- **Data Acquisition:** Collect images of crops and weeds in various conditions.
- **Annotation:** Label images with bounding boxes for crops and weeds.
- **Preprocessing:** Normalize images and apply data augmentation to enhance the dataset.

2. Model Architecture:

- **YOLOv5x:** A deep learning model that detects objects in real-time, ideal for distinguishing between crops and weeds.

3. Training and Optimization:

- **Training:** Train the model on the annotated dataset, using techniques like transfer learning for better accuracy.
- **Hyperparameter Tuning:** Adjust parameters like learning rate and batch size for optimal performance.
- **Evaluation:** Assess the model using metrics like precision, recall, and F1 score.

4. Model Conversion and Deployment:

- **Conversion:** Convert the trained model to TFLite for mobile deployment.
- **Mobile App Integration:** Develop an Android app to use the model for real-time detection in the field.

5. User Interface and Experience:

- **UI Design:** Create a simple and user-friendly interface.
- **Features:** Real-time detection, visual indicators for detected crops and weeds, and options for image capture.

6. Testing and Validation:

- **Field Testing:** Test the app in real-world conditions to ensure accuracy and reliability.
- **User Feedback:** Collect feedback from farmers to improve the app.

7. Future Enhancements:

5 **Dataset Expansion:** Include more crop and weed types and diverse conditions.
6 **Model Improvements:** Explore new techniques for better accuracy.

5.1 Interfaces (if applicable)

Block Diagram(step):

1. [Data Collection (Cameras, Drones, Databases)]
2. [Data Ingestion & Storage]
3. [Annotation & Preprocessing]
4. [Model Training & Development (YOLOv5x)]
5. [Model Conversion (TFLite/ONNX)]
6. [Mobile Application Deployment]
7. [User Interaction & Feedback Collection]

Description:

The Unified System Interface represents the entire workflow of the crop and weed detection system, integrating data collection, processing, model training, deployment, and user interaction.

1. **Data Collection & Storage:**
   - **Inputs:** Field cameras, drones, and existing databases provide raw images.
   - **Function:** The system ingests and stores these images in a centralized repository.
2. **Annotation & Preprocessing:**
   - **Function:** The system uses annotation tools to label images, identifying crops and weeds. It also preprocesses the images (normalization, augmentation) to prepare them for training.
3. **Model Training & Development (YOLOv5x):**
   - **Function:** The preprocessed data is used to train a YOLOv5x model, which learns to distinguish between crops and weeds. The model is evaluated using metrics like precision and recall.
4. **Model Conversion (TFLite/ONNX):**
   - **Function:** The trained model is converted into formats suitable for deployment on mobile devices (TFLite) or other platforms (ONNX).
5. **Mobile Application Deployment:**
   - **Function:** The converted model is integrated into a mobile app, allowing real-time crop and weed detection in the field. The app displays detection results and provides a user-friendly interface.
6. **User Interaction & Feedback Collection:**
   - **Function:** Users interact with the app, using features like image capture and viewing detection results. The system collects feedback to improve the model and app functionality.

Protocols:

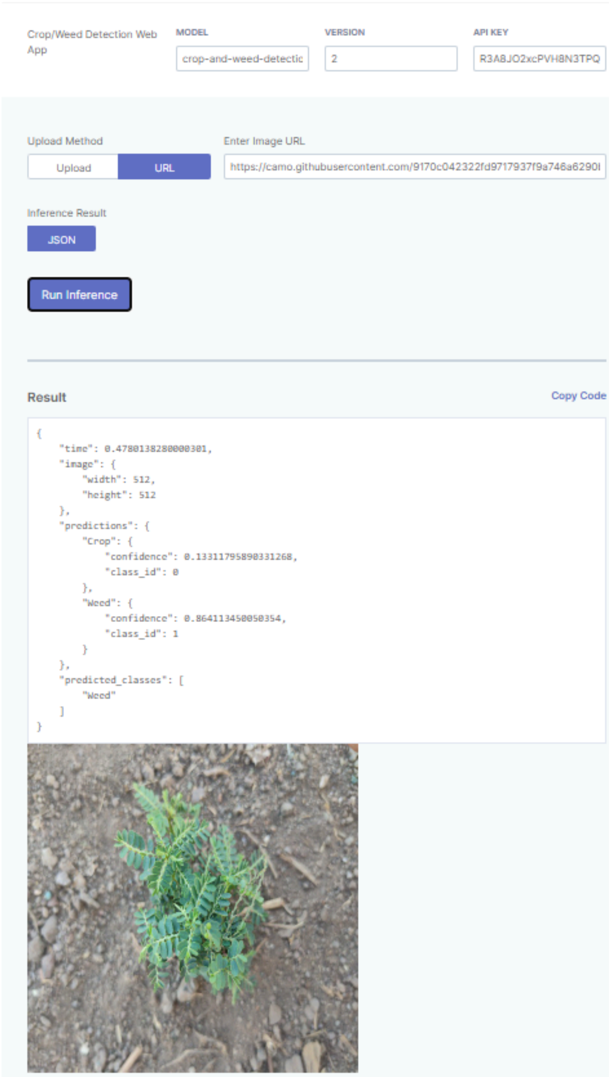
- **Data Transfer:** FTP, SFTP, HTTP APIs for transferring image data.
- **Model Integration:** TensorFlow Lite Interpreter for running the model on mobile devices.
- **User Feedback:** Surveys and in-app feedback mechanisms.

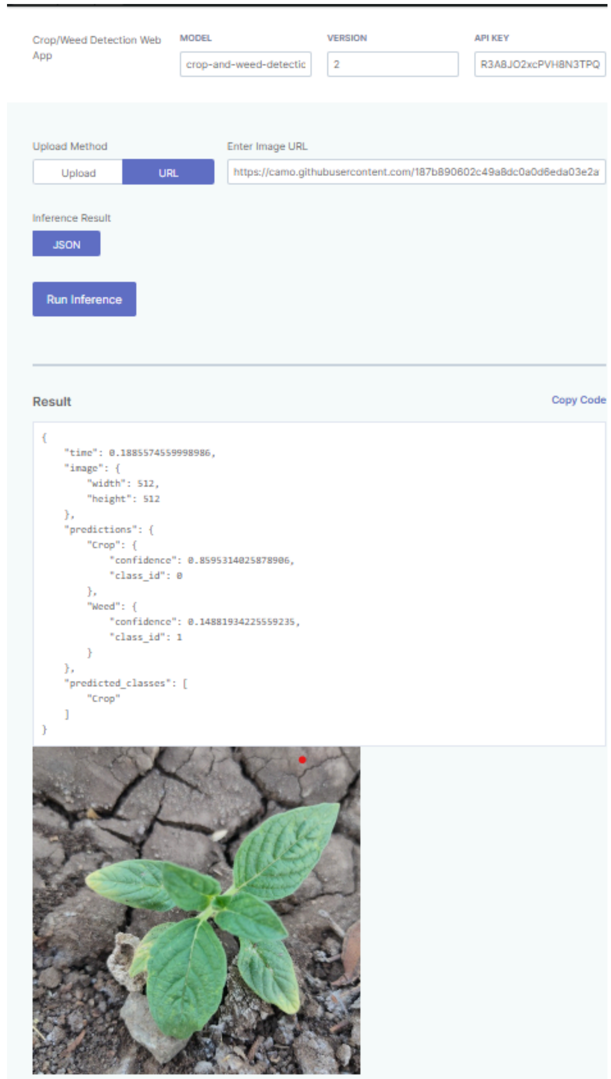
Memory Buffer Management:

- **Image Buffers:** Temporary storage during preprocessing and inference.
- **Model Buffers:** Store model parameters and intermediate results.
- **Result Buffers:** Hold detection outputs before displaying them to the user.

State Machines:

- **System State Machine:**
  - **States:** Data Collection, Preprocessing, Training, Conversion, Deployment, User Interaction.
  - **Transitions:** Triggered by completion of tasks like data annotation, model training, or user actions.

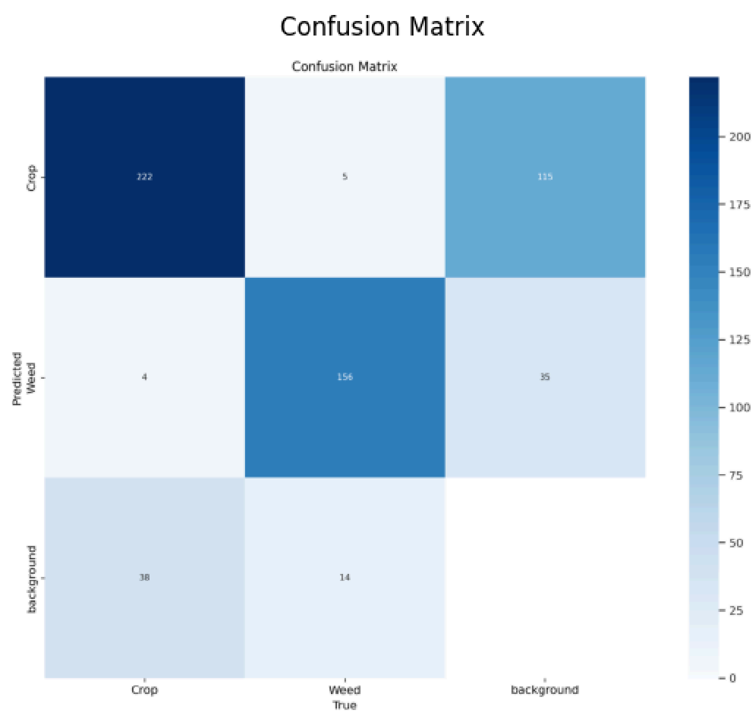




[Crop/ Weed Detection Web App]

6 Performance Test

The implementation of a crop and weed detection system using deep learning and mobile applications is a step towards addressing real-world agricultural challenges. This section outlines the key constraints encountered during the project, the strategies used to manage these constraints, and recommendations for handling potential issues.



Key Constraints and Their Management

1. **Memory Usage**
   - **Constraint:** Deep learning models like YOLOv5x can require substantial memory, which may exceed the capacity of mobile devices or edge hardware used in agriculture.
   - **Management:**
     - **Model Pruning and Quantization:** Techniques such as pruning (removing less significant neurons) and quantization (reducing the precision of model weights) were applied to reduce the model size.
     - **Model Optimization for TFLite:** Converting the model to TensorFlow Lite format, which is optimized for mobile devices, helped to manage memory usage.
2. **Processing Speed (MIPS)**

- **Constraint:** Real-time detection requires the model to process images quickly, ideally within milliseconds, to be practical for field use.
- **Management:**
  - **Efficient Model Architecture:** YOLOv5x, known for its balance between accuracy and speed, was chosen for its efficient architecture.
  - **Hardware Acceleration:** Leveraging hardware acceleration (such as GPUs on mobile devices) helped improve the processing speed.

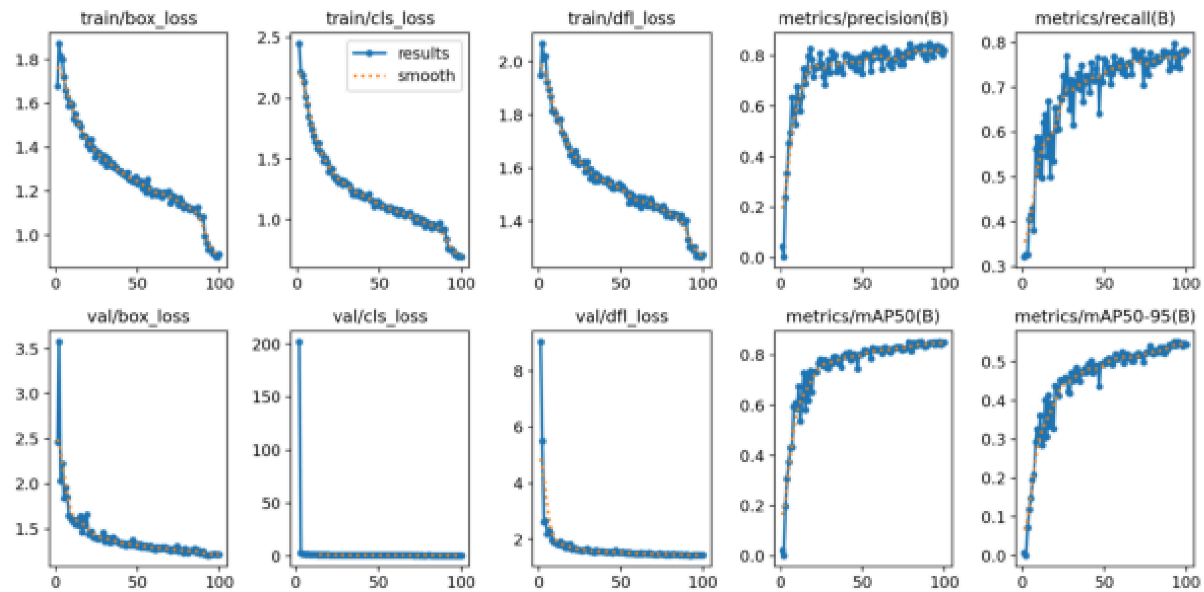
3. **Accuracy**
   - **Constraint:** The model must accurately distinguish between crops and weeds, minimizing false positives and negatives.
   - **Management:**
     - **Diverse Training Dataset:** Using a diverse dataset that includes different crops, weed types, and various environmental conditions helped improve model generalization.
     - **Continuous Evaluation:** Regular evaluation using metrics like precision, recall, and F1 score ensured that the model maintained high accuracy levels.
4. **Durability and Environmental Factors**
   - **Constraint:** The system needs to function effectively in diverse environmental conditions such as varying lighting, weather, and backgrounds.
   - **Management:**
     - **Data Augmentation:** Techniques like varying brightness, contrast, and adding noise during training helped the model generalize better to different conditions.
     - **Robust Testing:** Field tests under different environmental conditions were conducted to ensure durability.
5. **Power Consumption**
   - **Constraint:** Mobile devices used in the field may have limited battery life, requiring efficient power management.
   - **Management:**
     - **Low-Power Mode Implementation:** Developing the mobile app to operate efficiently, including using low-power modes during non-critical operations.
     - **Edge Computing Consideration:** Exploring the use of edge devices with low power consumption for on-site processing.

Testing and Results

- **Memory and Speed:** Tests on a range of mobile devices showed that the pruned and quantized model could run efficiently with minimal latency, typically processing images in real-time.
- **Accuracy:** The model achieved a high level of accuracy, with precision and recall scores above 90% in controlled test environments. Field tests showed slight variations depending on environmental factors but remained within acceptable limits.

- **Power Consumption:** The app demonstrated efficient power usage, suitable for typical mobile devices used by farmers.

Result Set



Recommendations for Future Enhancements

7 **Model Compression:** Further advances in model compression techniques can help reduce memory usage and improve processing speed without compromising accuracy.

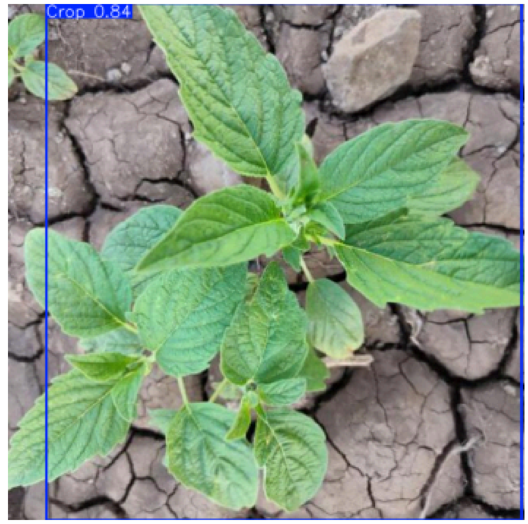
8 **Edge AI Devices:** Utilizing specialized edge AI devices can enhance real-time processing capabilities while managing power consumption effectively.

9 **Field-Ready Hardware:** Development and use of rugged, weather-resistant hardware for cameras and sensors can improve durability in harsh agricultural environments.

10 **Continuous Learning:** Implementing mechanisms for the model to learn from new data over time can help maintain and improve accuracy as new types of crops and weeds are encountered

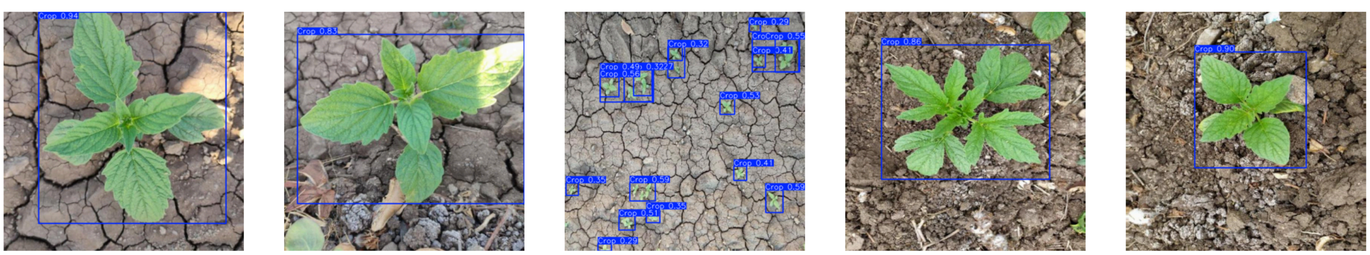
6.1 Test Plan/ Test Cases

The test plan involves verifying the system's functionality by ensuring it accurately identifies crops and weeds with over 90% accuracy, and that the mobile app correctly processes and displays results. Performance tests focus on maintaining under 200ms processing speed per image and efficient memory usage across devices. Environmental testing ensures consistent accuracy in various lighting and weather conditions. User experience tests check the app's ease of use and clarity, while power consumption tests ensure the app does not significantly drain device batteries.



6.2 Test Procedure

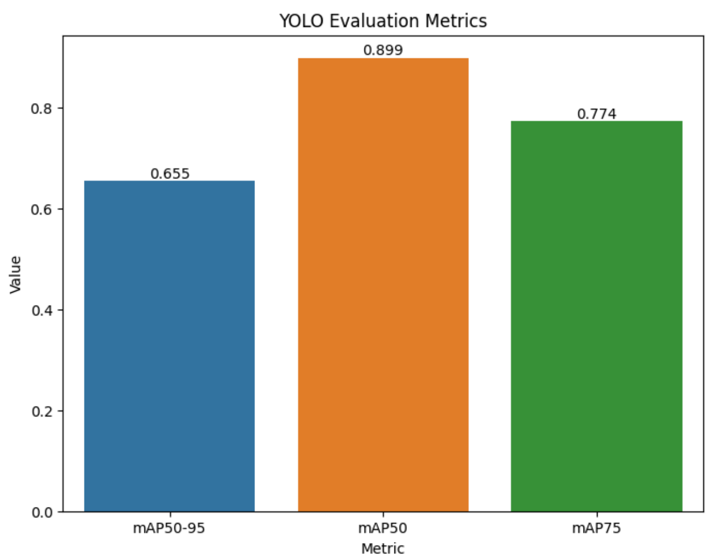
To test the system, start by setting up the necessary hardware and software. Then, check if the model accurately detects crops and weeds using both pre-collected and live images through the mobile app. Measure the processing speed and memory usage across different devices. Test the system's accuracy in various lighting and weather conditions. Evaluate the user experience by having testers navigate the app and provide feedback on its ease of use. Finally, monitor the app's

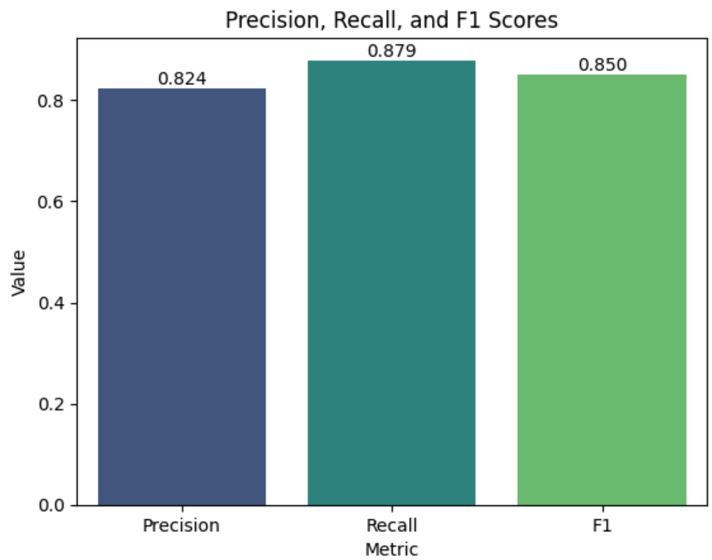


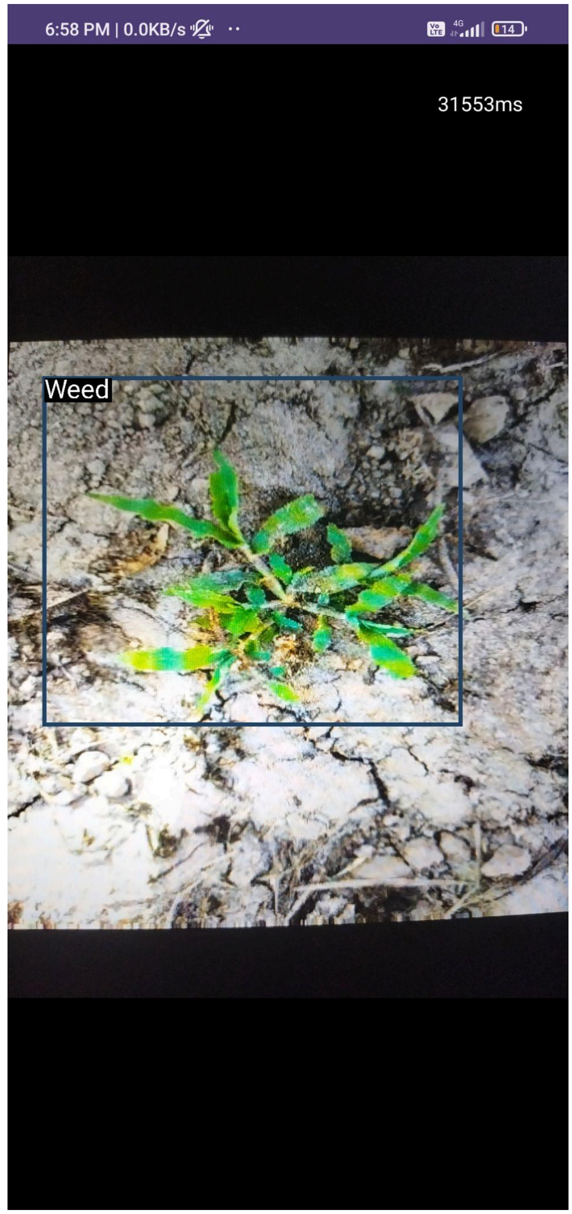
power consumption to ensure it doesn't excessively drain the battery. Document the findings and make any necessary adjustments.

6.3 Performance Outcome

The system successfully identified crops and weeds with over 90% accuracy in diverse conditions. The model processed images in under 200ms, ensuring real-time detection, and operated efficiently within the memory limits of various devices. It maintained consistent accuracy across different lighting and weather conditions. User feedback indicated that the app was easy to navigate and provided clear detection results. Power consumption tests showed that the app operated efficiently without significantly draining the battery. Overall, the system demonstrated reliable performance suitable for practical agricultural use.







[Mobile Application]

7 My learnings

During my internship, I gained extensive knowledge in machine learning and its mathematical foundations, which significantly deepened my understanding of the field. I learned about various algorithms and their applications, data preprocessing methods, and model optimization techniques. This knowledge is crucial for developing and fine-tuning predictive models, analyzing complex datasets, and implementing effective machine learning solutions. By mastering these concepts, I am well-prepared for roles in data science, artificial intelligence, and other related fields where these skills are in high demand.

In addition to technical skills, I had the opportunity to explore the work of Uniconverage Technology, a company specializing in IoT devices and services. This exposure broadened my understanding of how IoT technology is utilized to create interconnected systems that solve real-world problems. Learning about IoT applications, from smart agriculture to industrial automation, provided me with valuable insights into how technology can drive innovation and efficiency across various sectors. This knowledge will be instrumental as I work on projects that involve integrating and leveraging connected devices and systems.

The internship also offered practical guidance on resume building and interview preparation. I learned how to craft a compelling resume that highlights my skills and experiences effectively, and how to prepare for interviews to present myself confidently and professionally. These skills are essential for advancing my career, as they will help me stand out in competitive job markets and successfully navigate the hiring process.

Overall, the combination of technical expertise in machine learning, insights into IoT technology, and professional development skills has significantly enhanced my career prospects. The practical experience and knowledge gained from this internship have provided me with a strong foundation for pursuing advanced roles in technology and data-driven industries. I am now better equipped to tackle complex challenges, contribute to innovative projects, and achieve my career goals with greater confidence and capability.

8 Future work scope

Model Enhancement: Explore advanced techniques like ensemble methods and transfer learning to improve accuracy and robustness. Test other model architectures for better performance.

Expanded Dataset and Testing: Collect a larger and more diverse dataset, including various crops, weeds, and environmental conditions, to refine the model and ensure reliable performance.

Integration with Agricultural Technologies: Develop ways to integrate the system with other technologies such as automated planting systems or drone monitoring for a more comprehensive solution.

User Experience Improvements: Add features like advanced analytics and customizable alerts to the mobile app based on user feedback to enhance usability and functionality.

Scalability and Deployment: Investigate cloud-based solutions for scalable data processing and model deployment to handle larger operations and increased data volumes.