

## Industrial Internship Report on "Crop and Weed Detection using YOLOv8"

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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 projects were Crop and Weed Detection using YOLOv8 and Smart City Traffic Forecasting using XGBoost.

This internship gave me a very good opportunity to get exposure to Industrial problems and design/implement solutions for them. It was an overall great experience to have this internship.

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## 1 Preface

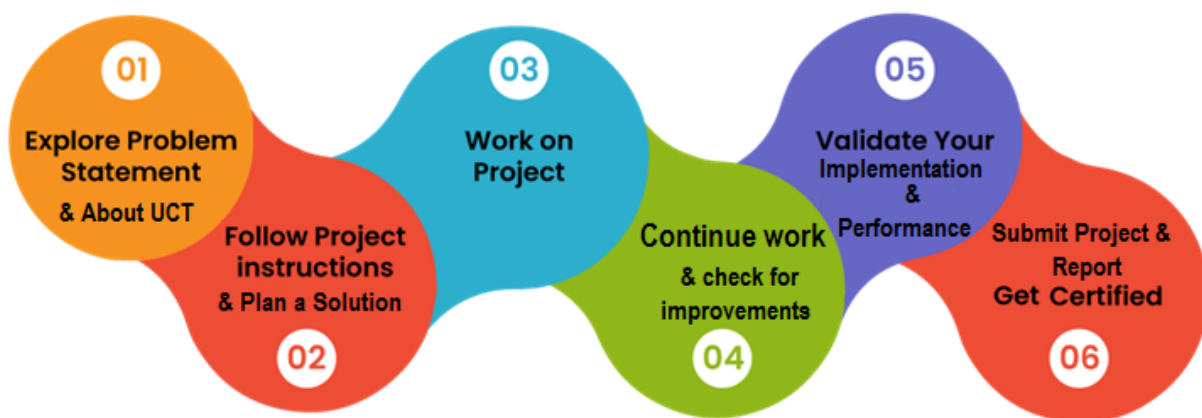
This report summarizes my 6-week Industrial Internship experience under USC/UCT. The internship focused on designing and implementing a YOLOv8-based crop and weed detection system for precision agriculture. The program was planned with weekly milestones and deliverables including weekly report and a final report.

Relevant internships play a critical role in career development by bridging academic knowledge with real-world applications. Through this internship, I practiced end-to-end problem solving—from requirement understanding and data handling to model building, evaluation, documentation, and communication.

I am grateful to my mentors at UniConverge Technologies, and to Upskill Campus and The IoT Academy for the opportunity and guidance. This experience has strengthened my technical confidence and professional skills. To my juniors and peers: embrace projects that challenge you, iterate quickly, and document everything—you will learn the most that way.

The project focused on **Crop and Weed Detection using YOLOv8**. Weeds reduce crop yield by competing for resources, and manual removal is labor-intensive. The problem was to build an automated system that can **differentiate crops from weeds in field images**, enabling precision agriculture and reducing dependence on manual labor and herbicides.

How Program was planned



During this internship, I gained **hands-on experience** in applying machine learning and deep learning to solve real-world problems. I learned how to prepare datasets, train models, evaluate results, and interpret performance metrics in an industrial context. Overall, this internship provided me with valuable exposure to industry practices and boosted my confidence in working on end-to-end projects.

I would like to sincerely thank **Upskill Campus, The IoT Academy, and UniConverge Technologies Pvt. Ltd.** for providing me this opportunity. My special thanks to my peers for their constant support, guidance, and valuable feedback throughout the internship.

To my juniors and peers, I would say: *never hesitate to take on challenging projects*. Even if they seem difficult at first, they are the best way to **learn, grow, and explore** your potential. Stay curious, keep experimenting, and focus equally on **technical skills and soft skills**. Document your work well, seek feedback, and most importantly, enjoy the process of learning—because that's where the real growth happens

## 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 ()

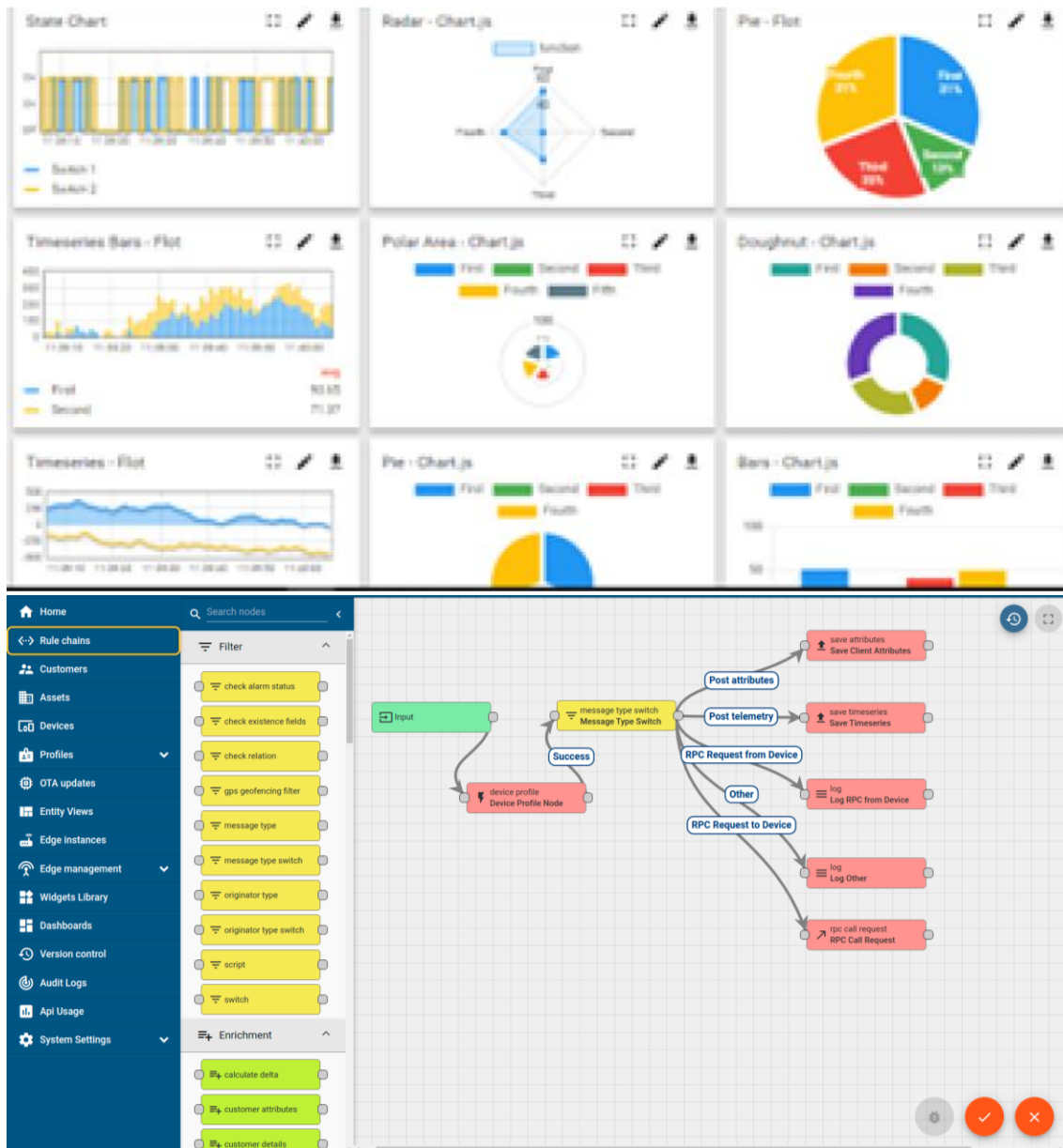
**UCT Insight** is an IOT platform designed for quick deployment of IOT applications on the same time providing valuable “insight” for your process/business. It has been built in Java for backend and ReactJS for Front end. It has support for MySQL and various NoSql Databases.

- 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



## FACTORY WATCH

### ii. Smart Factory Platform ( )

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 unleash 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 want 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





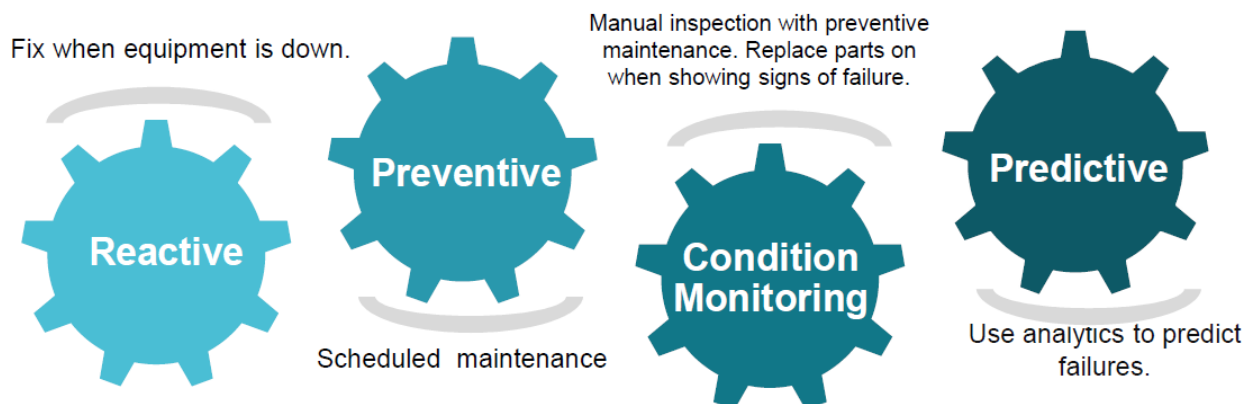


### iii. LoRaWAN based Solution

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

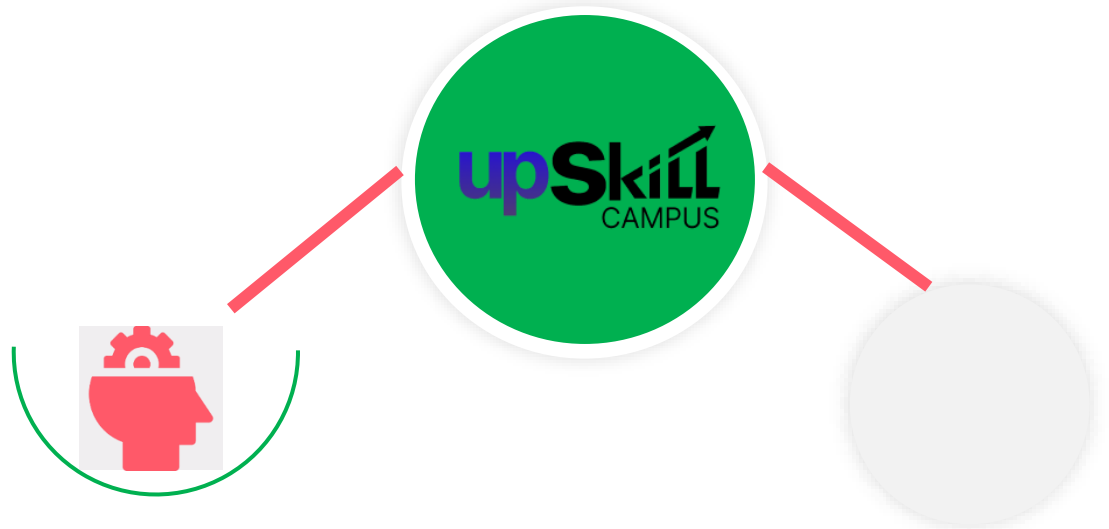
UCT is providing Industrial Machine health monitoring and Predictive maintenance solution leveraging Embedded system, Industrial IoT and Machine Learning Technologies by finding Remaining useful life time of various Machines used in production process.



## 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.

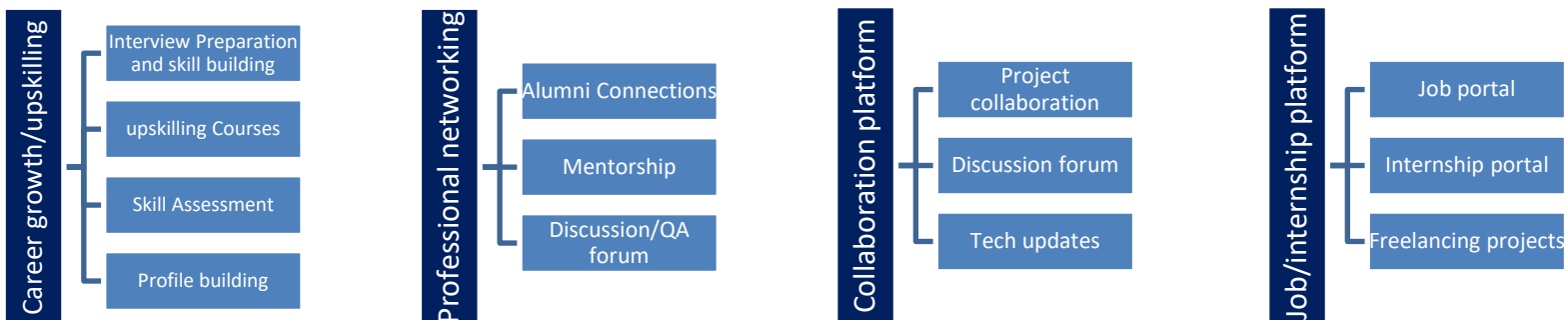
USC is a career development platform that delivers **personalized executive coaching** in a more affordable, scalable and measurable way.



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.

### 3 Problem Statement

In modern agriculture, weeds compete with crops for nutrients, light, and water, resulting in reduced yield and increased cost of cultivation. Manual inspection and weeding are labor-intensive, time-consuming, and error-prone. The problem is to build an automated, robust, and scalable system that detects weeds in sesame crop fields from RGB images and distinguishes them from crops in real time to support precision agriculture workflows such as targeted spraying or mechanical removal.

## 4 Existing and Proposed solution

### Existing Solutions:

Manual scouting and weeding—accurate but slow, laborious, and costly.

Classical image processing (thresholding, morphology)—sensitive to lighting and background variations.

Generic object detectors without agricultural adaptation—limited accuracy on crop-weed discrimination.

### Proposed Solution:

Adopt YOLOv8-based object detection tuned for agricultural imagery (sesame crop and weed classes).

Create a carefully labeled dataset in YOLO format with quality control and augmentation for robustness.

Train with transfer learning, apply class weighting/augmentations, and validate with agricultural metrics (precision/recall per class, mAP).

Package inference into a lightweight pipeline that can run on Colab/CPU and be containerized for field deployment.

### Value Addition:

Higher detection accuracy under varying illumination and canopy density.

Reduced manual effort and faster decisions, enabling targeted weeding (cost/time savings).

Reusable dataset and pipeline for other crops with minimal additional labeling.

#### 4.1 Code submission (Github link):

[https://github.com/Paperfloat/upskillcampus/blob/main/Crop and weed detection.ipynb](https://github.com/Paperfloat/upskillcampus/blob/main/Crop%20and%20weed%20detection.ipynb)

#### 4.2 Report submission (Github link) :

[https://github.com/Paperfloat/upskillcampus/blob/main/Crop and weed detection Srishti USC UCT.pdf](https://github.com/Paperfloat/upskillcampus/blob/main/Crop%20and%20weed%20detection%20Srishti%20USC%20UCT.pdf)



## 5 Proposed Design/ Model

The solution follows a clear pipeline from **data acquisition to deployment**. Key stages and artifacts are listed below:

1. **Data Collection** – Agricultural field images of sesame crops containing both crops and weeds.
2. **Image Annotation** – Manual labeling of weeds and crops using bounding boxes in YOLO format.
3. **Dataset Preparation** – Train/validation/test split, augmentations (flips, rotations, brightness adjustments).
4. **Model Training** – Training YOLOv8 with transfer learning for crop–weed classification and detection.
5. **Model Evaluation** – Performance tested using precision, recall, F1-score, mAP50, and mAP50-95.
6. **Inference & Deployment** – Predictions visualized with bounding boxes and confidence scores, packaged for use in field applications.

### 5.1 Interfaces

#### □ Data I/O:

- Input: Images and YOLO-format annotation files (.txt)
- Output: Labeled bounding boxes (crop/weed), detection confidence scores

#### 🔍 System Interfaces:

- **Training Interface:** Ultralytics YOLOv8 Python API in Google Colab/VS Code
- **Evaluation Interface:** Matplotlib/Seaborn plots for confusion matrix, PR curves, mAP
- **User Interface (optional):** Streamlit app or Jupyter notebook for displaying detection results

#### 🔍 Block Diagrams & Data Flow:

- Raw Images → Annotation → Dataset Split → YOLOv8 Training → Evaluation → Deployment → Field Application.

## 2 Protocols / State Flow:

- State machine: *Idle* → *Data Preparation* → *Training* → *Evaluation* → *Deployed Model (Inference)*
- Memory buffer management for batch training handled by PyTorch backend during YOLOv8 training.

## 6 Performance Test

We identified constraints relevant to real deployments: accuracy, inference latency, and robustness to lighting/occlusion. The design uses augmentations and threshold tuning to mitigate these constraints; smaller YOLO variants reduce latency.

### 6.1 Test Plan/ Test Cases

The performance of the Crop and Weed Detection model was validated using the following test cases:

- **Test Case 1:** Evaluate detection accuracy on unseen validation dataset (780 images).
- **Test Case 2:** Generate precision, recall, and mAP scores for both *crop* and *weed* classes.
- **Test Case 3:** Confusion matrix analysis to identify false positives and false negatives.
- **Test Case 4:** Measure inference speed on GPU (Tesla T4) for batch size = 1.
- **Test Case 5:** Visual inspection of bounding box predictions on random validation samples.

### 6.2 Test Procedure

- Prepare dataset with 3120 training images and 780 validation images.
- Train YOLOv8 model on sesame crop dataset with augmentation (flip, rotation, brightness/contrast).
- Use validation set for model evaluation.
- Record metrics: Precision, Recall, F1-score, mAP50, and mAP50-95.

- Generate confusion matrix and PR curves to analyze class-wise performance.
- Test inference speed per image on GPU.
- Compare results against baseline (manual observation/earlier models if available).

### 6.3 Performance Outcome

The YOLOv8-based crop and weed detection model achieved the following results on the validation set (780 images, 1218 instances):

- **Overall Metrics:**
  - Precision: **0.861**
  - Recall: **0.821**
  - mAP50: **0.900**
  - mAP50-95: **0.643**
- **Class-wise Performance:**
  - **Crop:** Precision = 0.823, Recall = 0.830, mAP50 = 0.897, mAP50-95 = 0.676
  - **Weed:** Precision = 0.900, Recall = 0.812, mAP50 = 0.904, mAP50-95 = 0.610
- **Inference Speed:**
  - ~3.1 ms inference per 512×512 image on Tesla T4 GPU.
- **Confusion Matrix:**
  - Showed strong discrimination between classes, with low misclassification rate between crop and weed.

These results indicate that the model is reliable for real-world deployment in **precision agriculture**, capable of differentiating crops from weeds with high accuracy and efficiency.

## 7 My learnings

YOLOv8 training lifecycle: data curation, augmentation, hyperparameter tuning, and evaluation.

Model debugging via error analysis (false positives/negatives) and targeted dataset fixes.

Reproducible experiments (versioning configs, seeds, and metrics).

Collaboration skills—async updates, code reviews, and presenting results to non-ML stakeholders.

## 8 Future work scope

Grow dataset with edge cases (early growth stages, heavy occlusion, low light).

Experiment with additional architectures (RT-DETR, YOLOv10) and knowledge distillation for edge devices.

Integrate GPS-anchored detections for geospatial maps and route planning for weeding operations.

Deploy a lightweight Streamlit app with on-device inference (CPU) and offline mode for field usage.