Industrial Internship Report on

”Crop and Weed Detection Using YOLOv8 and Deep Learning”

Prepared by

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Executive Summary
This report documents the work carried out during a 4 -week Industrial Internship conducted through upskill Campus and The IoT Academy, in collaboration with UniConverge Technologies Pvt. Ltd. (UCT). The project involved developing an AI-based crop and weed detection system using the YOLOv8 deep learning model. The objective was to automate crop–weed identification from agricultural images to support precision farming and reduce manual effort. The internship provided hands-on experience in dataset preparation, model training, performance evaluation, and industry-oriented problem solving.

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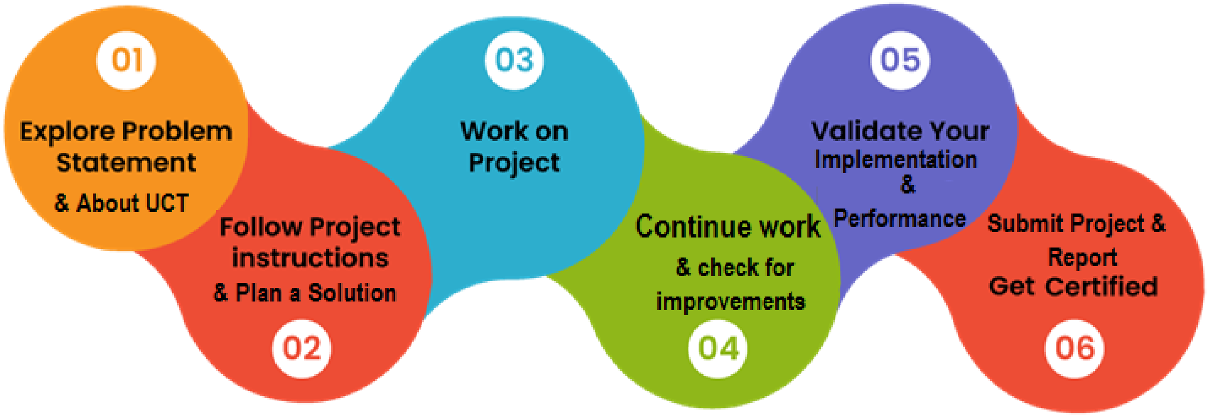
1 Preface



The six-week industrial internship was an important learning experience that bridged the gap between academic knowledge and industrial practices. Modern industries demand engineers who can handle real-world datasets, constraints, and performance trade-offs, which this internship successfully addressed. The opportunity provided by upskill Campus, The IoT Academy, and UniConverge Technologies Pvt. Ltd. allowed me to work on a practical Data Science and Machine Learning project relevant to the agriculture domain.

The program was well structured, starting from problem understanding, followed by data preparation, model design, training, evaluation, and documentation. I would like to express my sincere gratitude to the mentors, coordinators, and technical teams who supported me throughout this internship.

This internship strengthened my technical confidence and motivated me to pursue advanced work in AI-driven real-world applications.

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.

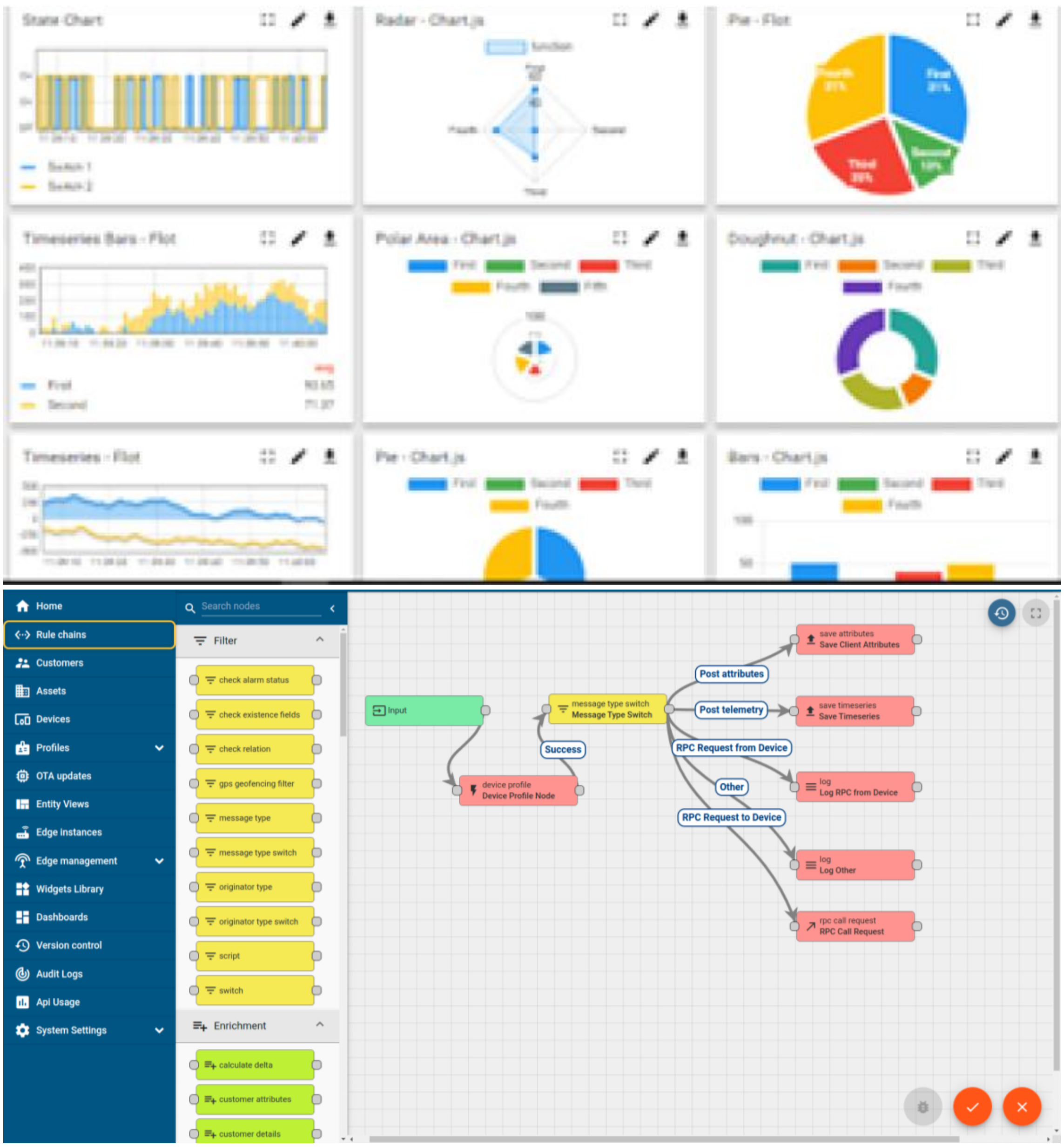
i. UCT IoT Platform (uct Insight)

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



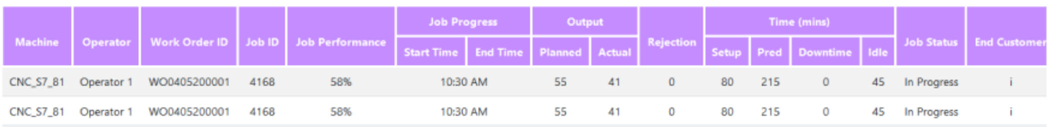
ii. Smart Factory Platform (FACTORY WATCH)

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.



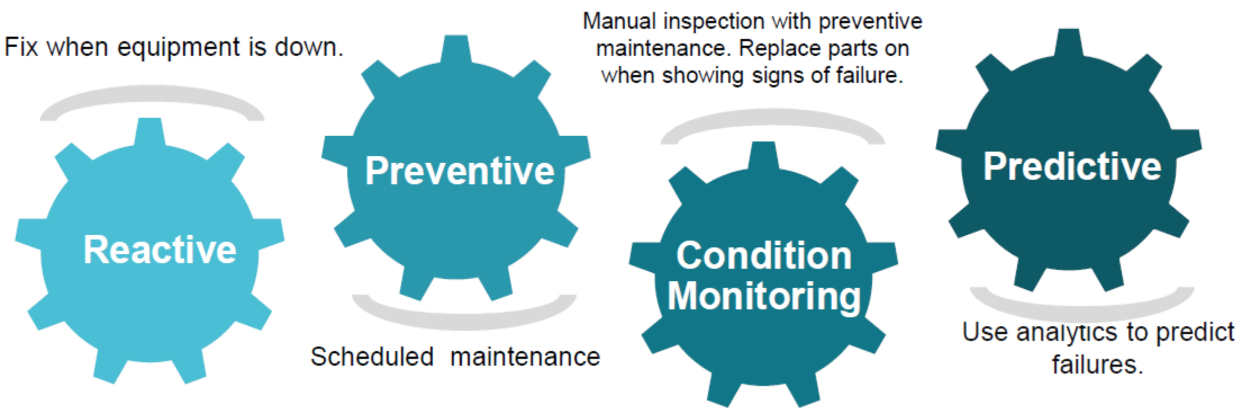
Machine	Operator	Work Order ID	Job ID	Job Performance	Job Progress		Output		Rejection	Time (mins)				Job Status	End Customer
					Start Time	End Time	Planned	Actual		Setup	Pred	Downtime	Idle		
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i
CNC_S7_81	Operator 1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

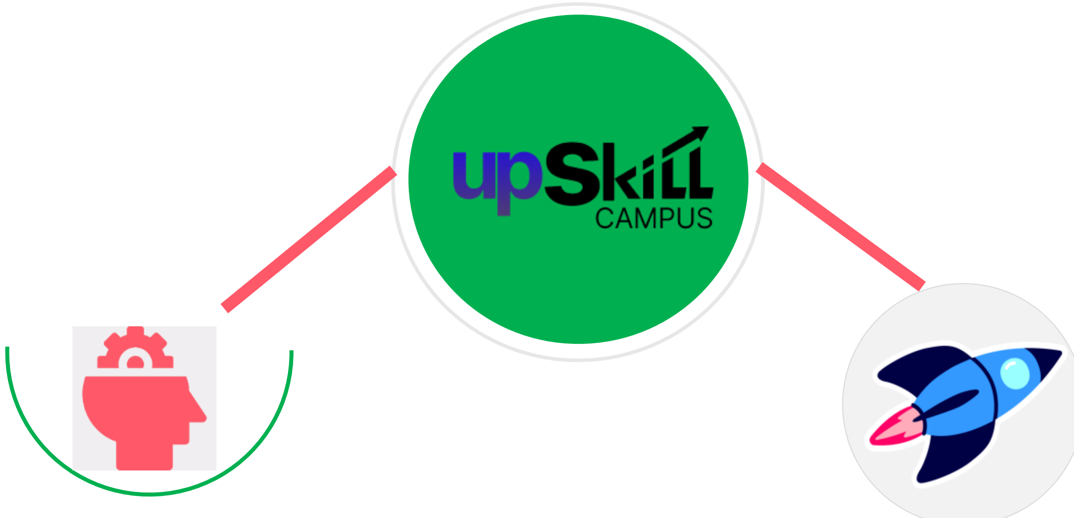
UCT is providing Industrial Machine health monitoring and Predictive maintenance solution leveraging Embedded system, Industrial IoT and Machine Learning Technologies by finding Remaining useful life time of various Machines used in production process.



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.

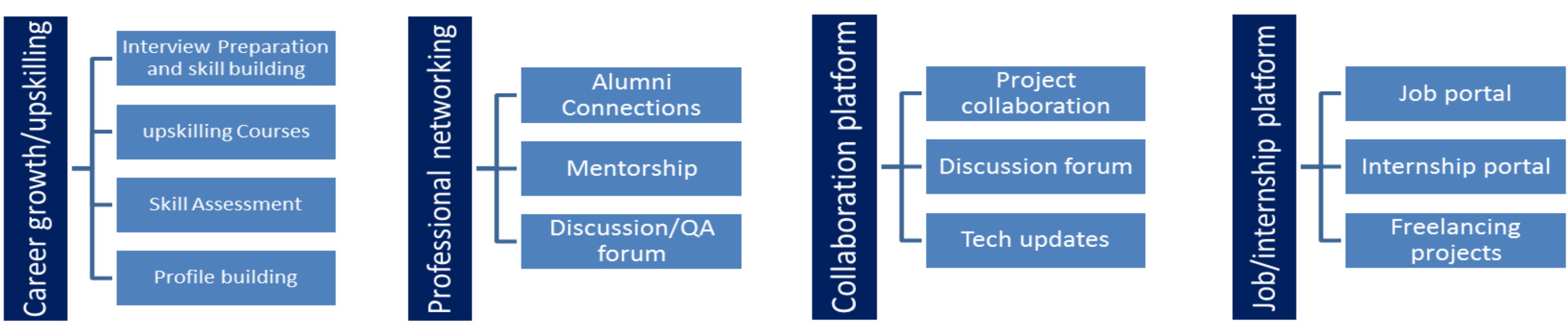
USC is a career development platform that delivers **personalized executive coaching** in a more affordable, scalable and measurable way.



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/



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.

2.3 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.

2.4 Reference

- YOLOv8 Documentation
- Ultralytics GitHub Repository
- Research papers on AI in Precision Agriculture

2.5 Glossary

Terms	Acronym
YOLO	You Only Look Once
Map	Mean Average Precision
CNN	Convolutional Neural Network
IoU	Intersection over Union

3 Problem Statement

Manual identification of crops and weeds in agricultural fields is a **time-consuming, labor-intensive, and error-prone process**, especially when performed over large farming areas. Traditional methods rely heavily on human observation, which can lead to inconsistent results and increased operational costs. Additionally, incorrect identification often results in excessive or improper use of herbicides, negatively impacting crop health and the environment.

To address these challenges, there is a strong need for an **automated and intelligent system** capable of accurately detecting and classifying crops and weeds from agricultural images. The objective of this project is to design and implement a **deep learning-based object detection system**, using modern computer vision techniques, that can achieve high accuracy and support **precision agriculture practices** by improving efficiency and reducing manual effort.

4 Existing and Proposed solution

- **Existing Solutions**
- Manual inspection by farmers
- Traditional image processing techniques
- Limited accuracy under varying lighting and backgrounds

Limitations

- Low scalability
- High labor cost
- Poor generalization

Proposed Solution

An **AI-based object detection system** using **YOLOv8** is proposed.
The model is trained on labeled agricultural images resized to **512 × 512** resolution to detect **crop** and **weed** classes efficiently.

Value Addition

- High detection accuracy
- Fast inference speed
- Scalable and deployable solution

4.1 Code submission (Github link):

https://github.com/Crazen1411/upskillcampus/tree/main/CODE

4.2 Report submission (Github link):

https://github.com/Crazen1411/upskillcampus/tree/main/Results

5 Proposed Design/ Model

The system follows the workflow below:

1. Dataset collection and annotation
2. Image preprocessing (512 × 512 resolution)
3. YOLOv8 model training and fine-tuning
4. Model validation and testing
5. Performance evaluation

5.1 High Level Diagram (if applicable)

Diagram 5.1 Prediction results

5.2 Interfaces (if applicable)

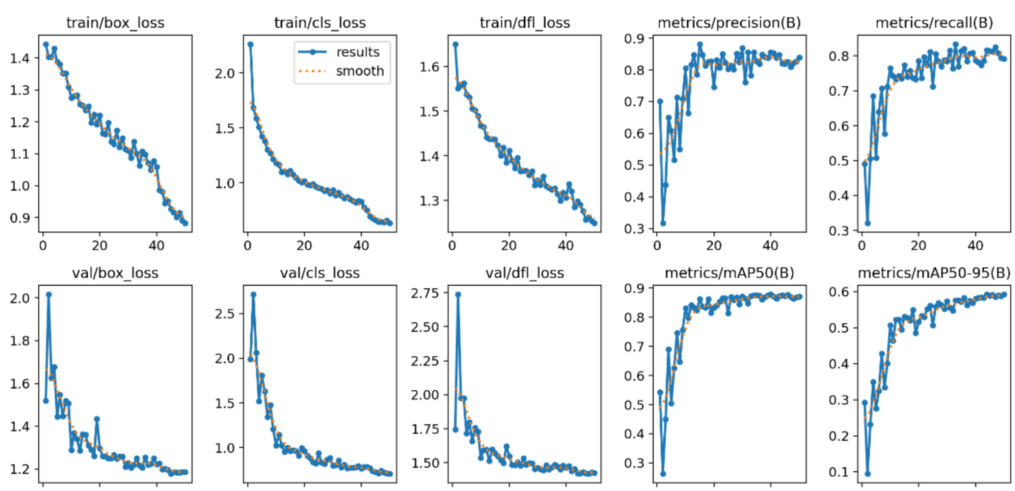


Diagram 5.2 Training Curves

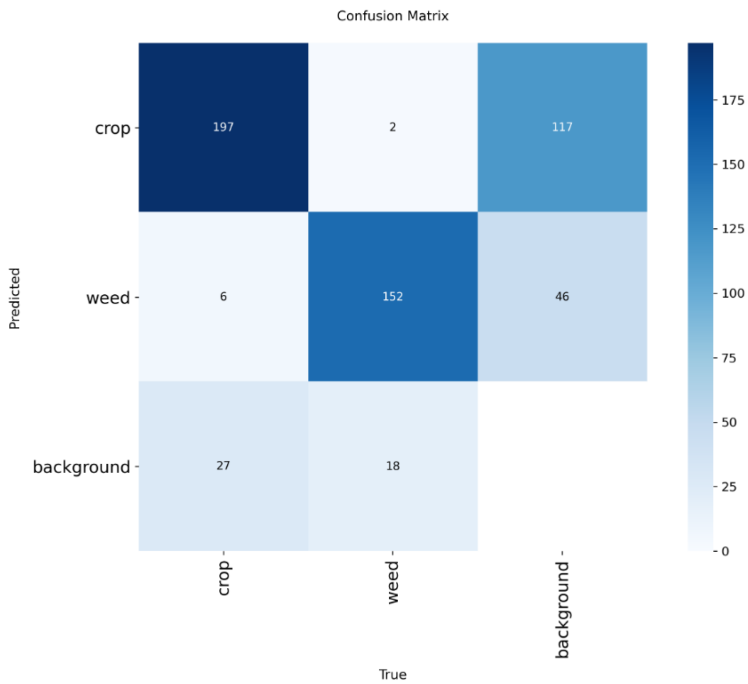


Diagram 5.3 Validation Results – Confusion Matrix

6. Performance Evaluation and Industrial Constraints

This section explains the practical relevance of the proposed crop–weed detection system and justifies its applicability in real industrial environments. Unlike a purely academic project, this work considers real-world constraints such as computational limitations, power efficiency, and real-time performance requirements commonly faced in precision agriculture systems.

6.1 Identified Constraints and Design Considerations

The major constraints identified for this project include **memory usage, processing speed (MIPS), detection accuracy, and power consumption**. In real agricultural applications, models are often deployed on edge devices such as drones, smart cameras, or autonomous robots, where computational resources are limited. To address these constraints, the **YOLOv8-Nano** model was chosen due to its lightweight architecture and low memory footprint. The input image resolution was standardized at **512 × 512**, ensuring a balance between feature detail and computational efficiency. Additionally, the use of a single-stage object detection model minimized inference latency, making the system suitable for real-time operation.

Table 6.1: Identified Constraints and Design Handling

Constraint Type	Description	Impact on System	Design Choice / Mitigation
Memory Usage	Limited memory on edge/embedded devices	Large models may not fit	YOLOv8-Nano chosen for low memory footprint
Processing Speed (MIPS)	Real-time detection required	Slow inference reduces usability	Single-stage YOLO detector used
Accuracy	Misclassification affects crop yield	False weed detection	Trained with labeled dataset and validation
Power Consumption	Battery-powered devices	High power drain	Lightweight architecture preferred
Deployment Environment	Field conditions vary	Noise, lighting changes	Data augmentation and robust training

6.2 Performance Test Plan and Test Procedure

The performance testing focused on evaluating the model’s ability to accurately and efficiently detect crops and weeds under realistic conditions. The test plan involved validating the trained model on a separate validation dataset containing unseen images. Key performance metrics such as **precision, recall, mAP50, and mAP50–95** were selected to measure detection accuracy and robustness. The test procedure included running inference using the trained model, recording prediction outputs, and analyzing the results generated by the YOLO evaluation pipeline. This approach ensured consistent and repeatable performance assessment.

Table 6.2: Performance Test Plan / Test Cases

Test Case ID	Test Description	Input	Expected Output
TC-01	Crop detection accuracy	Field image	Correct crop bounding box
TC-02	Weed detection accuracy	Field image	Correct weed bounding box
TC-03	Multi-object detection	Mixed crop & weed image	Both objects detected
TC-04	Model validation	Validation dataset	Performance metrics generated
TC-05	Speed evaluation	Batch inference	Fast inference time

6.3 Performance Outcomes and Industrial Relevance

The performance evaluation demonstrated that the model achieved a **precision of 0.816**, **recall of 0.816**, and a **mAP50 of 0.876**, indicating reliable detection performance for both crop and weed classes. The inference speed was sufficiently fast to support near real-time applications, even on limited GPU resources. While direct testing of power consumption and long-term durability was not conducted due to hardware constraints, the lightweight nature of the model suggests low energy requirements suitable for edge deployment. For industrial implementation, it is recommended to integrate the model with optimized inference frameworks and energy-efficient hardware platforms to further enhance performance and reliability.

Table 6.3: Test Procedure

Step No	Procedure Description
1	Load trained YOLOv8 model
2	Provide validation dataset
3	Run inference on validation images
4	Record predictions and metrics
5	Analyze precision, recall, mAP

Table 6.4: Performance Outcome

Metric	Value Obtained
Precision	0.816
Recall	0.816
mAP@50	0.876
mAP@50–95	0.592
Inference Speed	~1.6 ms per image
Deployment Suitability	Real-time capable

7 My learnings

During this internship, I gained hands-on experience in the practical implementation of **YOLOv8 for object detection**, including end-to-end dataset preparation, annotation, and organization in the required format. I learned how to train and fine-tune deep learning models, adjust hyperparameters, and analyze training behavior to improve performance.

Additionally, I developed skills in evaluating model performance using industry-standard metrics such as precision, recall, and mAP. This internship significantly enhanced my understanding of **Machine Learning and Computer Vision concepts** and improved my confidence in applying these techniques to real-world agricultural and industrial problems.

8 Future work scope

- Increase dataset size for better generalization
- Deploy model on edge devices (Jetson / Raspberry Pi)
- Integrate with drone-based imaging
- Extend to multi-crop classification
- Add real-time video detection