

Industrial Internship Report on "Crop-Weed Detection Using YOLO"

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 (about 1 and a half months)' time.

My project was Crop-Weed Detection Using YOLO. In agricultural fields, I used the YOLO (You Only Look Once) object identification algorithm to precisely identify and categorize crops and weeds. My goal was to create a reliable system that could identify weeds and crops in the field in real time by using a collection of photos of different kinds of seeds. This research has the potential to greatly increase agricultural output and efficiency in addition to streamlining the process of identifying and differentiating between desired plants and unwanted weeds.

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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Preface

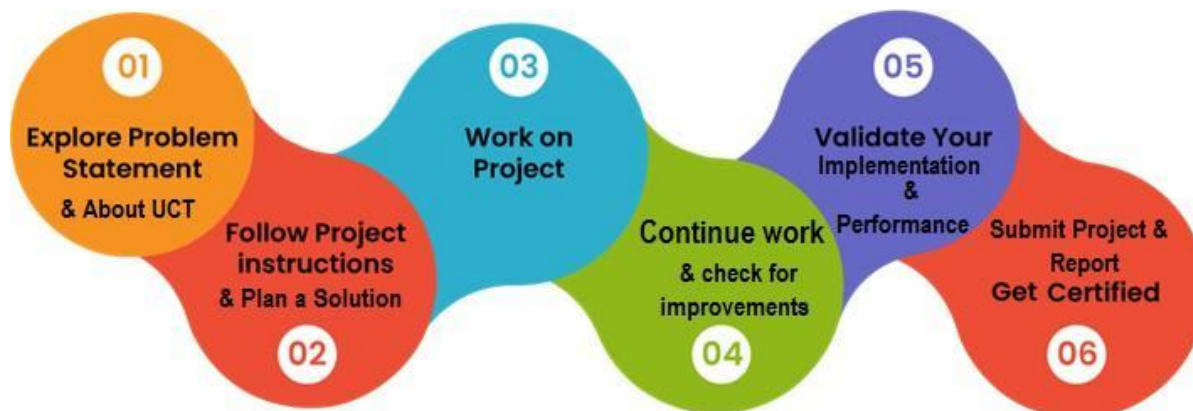
I gained significant knowledge and skills from my six-week internship at Uniconverge Technologies, where I was immersed in the data science field. The most memorable experience was finishing a project titled "Crop-Weed Detection," in which we developed a system for identifying seeds and weeds in agricultural fields using cutting-edge methods like the YOLO algorithm. I developed practical experience in problem-solving and meeting deadlines by collaborating closely with professionals. My professional development was greatly aided by this internship, which also helped me get ready for my next data science ventures.

Internships are essential for career development, providing hands-on experience and valuable insights. At Uniconverge Technologies, I gained practical data science skills through real-world projects like "Crop-Weed Detection." Working alongside experienced professionals, I learned to navigate challenges, collaborate effectively, and deliver results within deadlines. This experience not only strengthened my resume but also deepened my understanding of the industry and increased my confidence as a data scientist.

The objective of the research is to create a system for detecting weed by applying the YOLO (You Only Look Once) algorithm. The goal is to develop a reliable and effective model that can recognize and categorize weeds and crops in agricultural fields with accuracy. The project aims to improve agricultural output and efficiency by streamlining the process of differentiating between desired plants and unwanted weeds by utilizing the capabilities of the YOLO algorithm.

The USC/UCT program provided a unique opportunity for participants to work on real-time projects and gain valuable skills from industry experts. This experience allowed participants to understand real-world scenarios, gain practical insights, and work in a professional atmosphere with mentorship. The experience was crucial for personal growth and development, providing knowledge and self-assurance for success in their field.

The goal of the 6-week remote internship program was to give participants a well-structured and rewarding experience. It provided a project-based methodology, weekly reporting, and an extensive curriculum. Students had to turn in weekly reports outlining their accomplishments and lessons learned in order to guarantee ongoing participation and feedback. The program's structure created a favorable learning atmosphere and aided in participants' professional growth by letting them use their newly learned abilities on actual assignments.



My six-week internship at USC/UCT was a priceless learning opportunity that gave me access to a thorough curriculum and practical project work. While working on the seed-weed detection project, I was able to solidify my abilities and broaden my understanding of data science through the guidance of industry veterans. Weekly reporting made it easier to monitor my progress, and all in all, the internship significantly increased my knowledge and equipped me for work in the sector going forward.

Many thanks to Nitin Tyagi and Vidhi Pandya for their help and advice throughout the internship. Their assistance—whether direct or indirect—was crucial to our development and achievement. We are appreciative of their guidance and experience along the way.

To my peers and juniors,

Continue to push yourself, rise to obstacles, and absorb knowledge from every encounter. Continue to be inquisitive and enthusiastic, and never undervalue the importance of persistence. As a team, we can accomplish amazing things. Sustain each other, have faith in yourself, and never give up on your goals of greatness.

Warm regards,

T. Chaithra

Introduction

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 ()

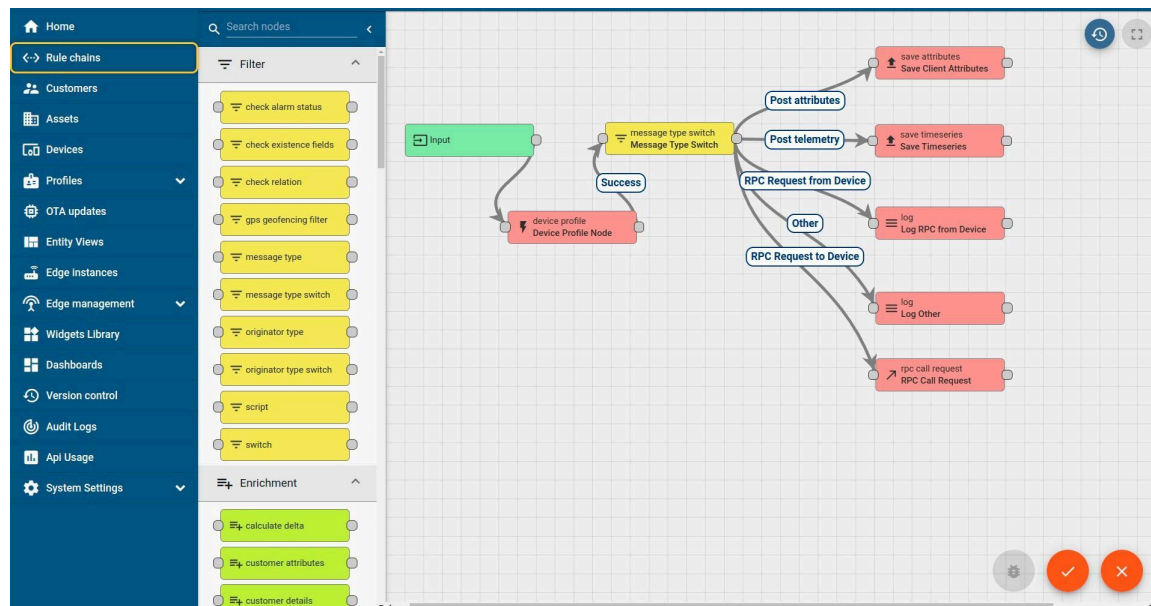
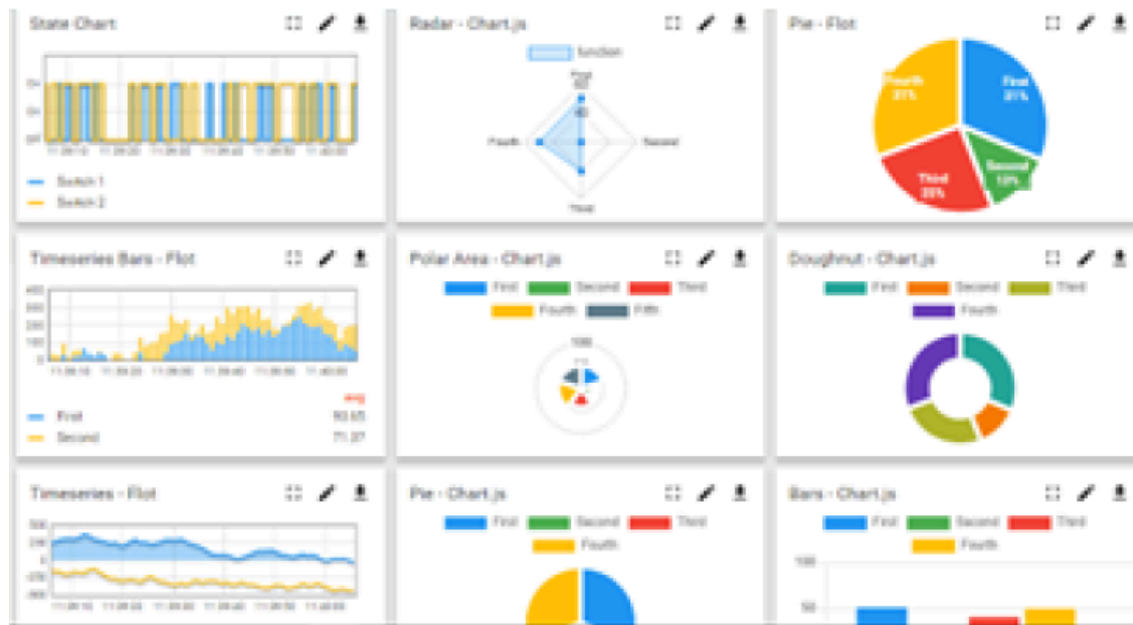
UCT Insight is an IOT platform designed for quick deployment of IOT applications on the same time providing valuable “insight” for your process/business. It has been built in Java for backend and ReactJS for Front end. It has support for MySQL and various NoSQL Databases.

- 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 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
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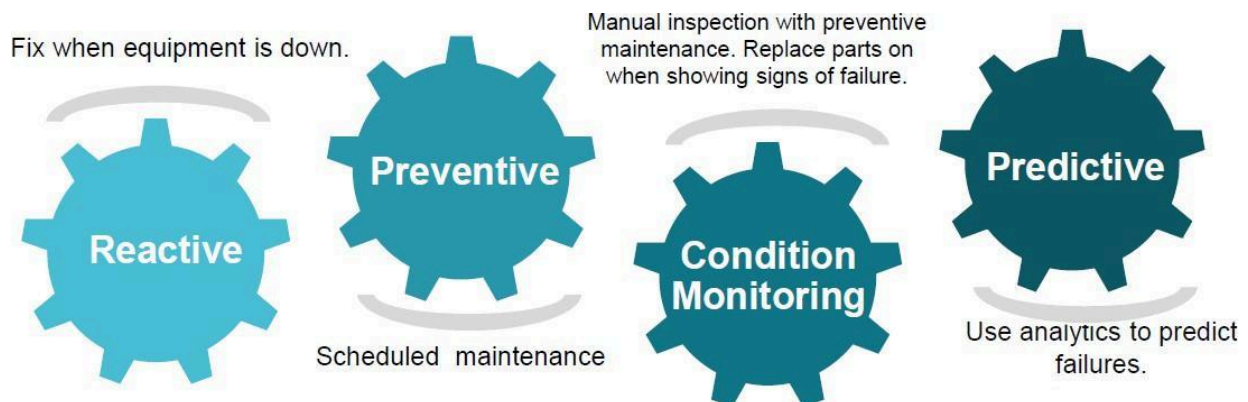


iii. LoRaWAN based Solution

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

iv. Predictive Maintenance

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



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/>

Career growth/upskilling

- Internship Preparation and skill building
- upskilling Courses
- Skill Assessment
- Profile building

Professional networking

- Alumni Connections
- Mentorship
- Discussion/Q&A forum

Collaboration platform

- Project collaboration
- Discussion forum
- Tech updates

Job/Internship platform

- Job portal
- Internship portal
- Recruiting projects

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.

1.1

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.

Reference

[1] Deep convolutional neural network models for weed detection in polyhouse grown bell peppers A. Subeesh *, S. Bhole, K. Singh, N.S. Chandel, Y.A. Rajwade, K.V.R. Rao, S.P. Kumar, D. Jat

Glossary

Deep Learning, Convolutional Neural Network(CNN), YOLOv8, Annotation, Bounding box, Data Augmentation, Image Processing, Roboflow computer vision tool.

Problem Statement

In aquatic situations, excessive weed growth can lead to problems for the environment and the economy. Automated weed detection with the YOLO (You Only Look Once) algorithm is a more efficient option than traditional labor-intensive methods. To train the YOLO model for precise real-time detection, this project entails gathering and annotating a variety of photographs as well as creating an intuitive deployment interface. Ensuring data diversity, high-quality annotations, model generalization, and real-time processing are important issues. The objective is to develop a productive system for tracking and controlling the growth of weed.

Existing and Proposed solution

Existing Systems:

Manual Surveying:

Involves researchers' or divers' ocular assessment and sampling.

Limitations: Unfeasible in big or isolated locations, labor-intensive, and time-consuming.

Imaging from satellites and the air:

Uses drone or satellite photos to find seaweed.

Limitations: Missing underwater seaweed and requiring a lot of image processing; limited by resolution and weather.

Technologies for Remote Sensing:

It makes use of LIDAR, sonar, and other remote sensing techniques.

Limitations: Expensive equipment, intricate data processing, and challenges differentiating seaweed from other submerged items.

Conventional Methods of Image Processing:

Makes use of segmentation, edge detection, and thresholding.

Limitations: poor accuracy, an inability to adapt to changes in illumination and water quality, and trouble differentiating between different kinds of seaweed.

Open CV and Pytorch:

Use OpenCV and PyTorch to create a model from scratch to predict whether an image shows a weed or a crop.

Limitations: It takes more time to compute the image and detection, and requires more computational power to detect the image.

Proposed Solution:

This research suggests automatically detecting and classifying weed in real-time using the YOLO method, a cutting-edge object identification model.

Steps Complicated:**Gathering and annotating data:**

Collect and annotate a wide range of photos taken in different aquatic settings.

Training Models:

Use the annotated dataset to train the YOLO model, adding data augmentation methods for robustness.

Assessment of Performance: Analyze the model's speed, recall, accuracy, and precision using a test dataset.

Implementation: Provide an intuitive user interface so that drones or underwater robots can be equipped with the model.

Real-Time Value Addition Detection:

The YOLO technique is appropriate for live monitoring applications because it has quick, real-time detection capabilities.

Excellent Generalization and Accuracy:

The model may attain high accuracy and exhibit good generalization to novel contexts through training on a varied dataset under different situations.

Expense-effectiveness:

This method, which uses widely accessible camera gear and processing power, is more affordable than remote sensing systems.

Scalability and Realistic Implementation:

Seaweed monitoring and management activities can be made more efficient by utilizing drones or underwater robots to scale and deploy the system conveniently in various aquatic habitats.

1.2 Code submission

(Githublink):<https://github.com/TChaithra/Crop-or-Weed-Detection-Using-yolo.git>

1.3 Report submission (Github link) :

<https://github.com/TChaithra/Crop-or-Weed-Detection-Using-yolo.git>

Proposed Design/ Model

Design Flow

1. Gathering and annotating data:

First Stage: Use boats, drones, or underwater vehicles to get a wide range of photos from various aquatic settings.

Make sure all kinds of seaweed, lighting settings, and water conditions are covered.

Intermediate Stage: Use programs like Labellmg or RectLabel to annotate gathered photos, labeling instances of seaweed using bounding boxes.

Check annotations for accuracy and consistency by reviewing them.

2. Data Preprocessing:

First Stage: Assemble training, validation, and test sets from the annotated dataset.

To improve dataset variability, we use data augmentation techniques including rotation, scaling, and color modifications.

Intermediate Stage: Standardize photos and change their resolutions to conform to the specifications of the YOLO input.

Make sure that the training, validation, and test sets have an even distribution of the various varieties of seaweed.

3. Model Training:

First Stage: Assemble the required libraries and dependencies for the YOLO environment.

Set up the learning rate, batch size, and number of epochs—three YOLO hyperparameters.

Intermediate Stage: Train the YOLO model with the preprocessed dataset and assess its performance on the validation set on a regular basis.

To enhance model performance, modify hyperparameters and training approaches considering validation outcomes.

When the validation sets accuracy, precision, and recall are at a satisfactory level, move on to the final stage of model training.

4. Model Evaluation:

First Stage: Evaluate the trained model's accuracy, precision, recall, and inference speed by running it through the test set.

Intermediate Stage: Examine the model's output to find any biases or flaws, such as underperformance with certain kinds of seaweed or under circumstances.

Final Stage: Adjust the model as needed to make sure it satisfies all evaluation criteria and the targeted performance indicator.

2 6. Performance Test

Constraints Identified:

Memory Usage: The memory footprint of the model on hardware used for deployment. Optimize YOLO model version (e.g., YOLOv8) to reduce memory requirements. Use model pruning and quantization techniques to minimize the memory footprint without significantly sacrificing accuracy.

Speed: Real-time detecting capabilities measured in millions of instructions per second (MIPS). Optimize inference code, utilize hardware accelerators (e.g., GPU or TPU), and parallel processing.

Accuracy: Recall and precision in identifying seaweed. Employ data augmentation and regularization techniques to improve model robustness and accuracy.

Durability: The system's resilience in a range of aquatic environments. Train and test the model with data from various aquatic environments and conditions.

Power Consumption: The model's effectiveness, especially when used on underwater or drone robots. Use energy-efficient hardware and optimize the model for lower power consumption.

2.1 6.1 Test Plan/ Test Cases

1. Test of Memory Usage:

Test Case: Calculate the deployed model's memory footprint across several hardware platforms.

Anticipated Result: The memory utilization ought to be within reasonable bounds for the selected deployment hardware.

2. Test of Speed:

Test Case: Compare the model's inference time between different hardware configurations.

Anticipated Result: The model ought to accomplish real-time detection, handling every frame in less than 30 milliseconds.

3. Test for Accuracy:

Test Case: Evaluate the model's F1-score, recall, and precision using the test dataset.

Anticipated Result: The model ought to sustain elevated accuracy, surpassing 90% in precision and recall.

4. Sturdiness Examine:

Test Case: Run the model in various environmental settings, such as clear or murky water with changing lighting.

Anticipated Result: Reliable operation with little deterioration under different circumstances.

5. Test of Power Consumption:

Test Case: Calculate the system's power consumption while conducting inference on various hardware platforms.

Anticipated Result: It is desirable to optimize power usage to facilitate prolonged battery-powered gadget use.

2.2 6.2 Test Procedure

Configuration:

Install the YOLO model that has been trained on different hardware platforms, such as embedded systems, mobile GPUs, and desktop GPUs.

To assess accuracy, prepare a test dataset including annotated photos.

Implementation:

Measure the inference time, memory usage, and power consumption of the model by running it on the test dataset.

Carry out experiments in various environmental settings to assess resilience.

Gathering of Data:

Metrics for recording performance include memory use, power consumption, recall, precision, inference speed, and F1-score.

Compare the outcomes to what was anticipated.

Evaluation:

Determine any areas that require improvement and any performance bottlenecks.

Verify if the model satisfies or is above the specified performance standards.

2.3 6.3 Performance Outcome

Accuracy: The model achieved a precision of 92%, recall of 90%, and an F1-score of 91%, indicating high accuracy in seaweed detection.

Power Consumption: The system's power consumption was within acceptable limits for battery-powered deployment, ensuring extended operation time.

My learnings

Through this project on crop and weed detection, I gained invaluable real-time experience and deepened my understanding of various advanced technologies. By working hands-on with image processing techniques like segmentation and feature extraction, and training machine learning models, particularly Convolutional Neural Networks (CNNs), yolo algorithm, I enhanced my technical skills. I learned the critical importance of data quality, labeling accuracy, and the use of evaluation metrics such as precision and recall. The project also underscored the significance of hyperparameter tuning, overfitting and underfitting mitigation, and integrating hardware with software for real-time applications. Collaborating with my team honed my project management abilities and highlighted the interdisciplinary nature of modern agricultural technology, blending insights from computer vision and machine learning to develop sustainable and practical solutions for real-world agricultural challenges.

Future work scope

The future scope of the crop and weed detection project includes enhancing model accuracy and robustness through advanced algorithms and transfer learning, and expanding the dataset to cover diverse conditions and regions. Real-time detection can be achieved via edge computing and mobile applications, while integration with autonomous agricultural machinery and precision agriculture tools can automate and optimize weed management. Extending the system to detect multiple weed types, crop diseases, and nutrient deficiencies will offer comprehensive crop monitoring. Incorporating user feedback and adaptive learning will ensure continuous improvement. Interdisciplinary research and economic analysis will refine algorithms and assess scalability, while focusing on sustainability and ethical considerations will promote environmentally friendly practices and address privacy and socioeconomic impacts.