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.

The project chosen by myself was to detect the weed and crop from the images given to make sure the pesticides are poured on weed and not on crops. I made a model that detects the weed and crop differentially from the images by displaying boxes on top of them.

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. I hope to work together with them again in the future.

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1 Preface

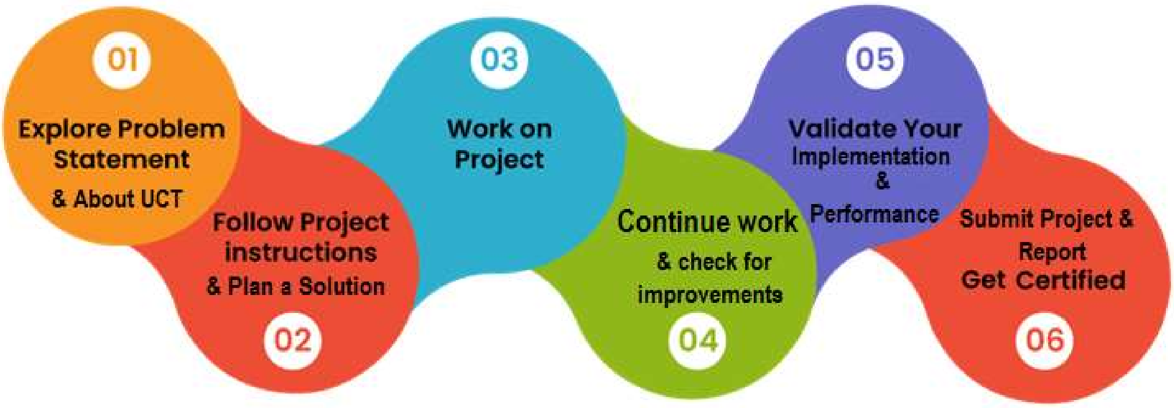
During my first week of internship, I got introduced to several basic topics such as Data Science and Machine Learning. I got to choose the project to do my internship upon and got to discern the problem statement. The next week, I started the implementation of my code by manually annotating the labels with the help of LabelImg and did pre-processing steps with it. Next week comprised of more annotating the labels and creating a model with YOLOV5. The next week, I changed the model to MobileNetV2 as it showed better performance. The following weeks comprised of displaying the outputs of the detected weed and crops.

Internships are vital for career development as they provide hands-on experience and help bridge the gap between academic learning and real-world applications. They offer a platform to develop practical skills, gain industry exposure, and build professional networks. By working on real projects, interns can enhance their technical expertise, learn problem-solving in practical settings, and better understand industry expectations, all of which are essential for a successful career transition.

My project was about detecting the weed and crops from the images to ensure that pesticides are poured on just weed.

This opportunity given my upskillCampus and UniConverge technologies was immensely helpful for my development in this field.

The program was formed in the following way:



My overall experience with this internship, gave me a strong motivation and skills to pursue this field in the future passionately.

I want to thank my parents and friends who pushed me to be a part of this internship and I will be forever grateful to them.

The only message I want to give my peers and juniors is to work hard persistently and not focus on the duration of the hard work.

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)

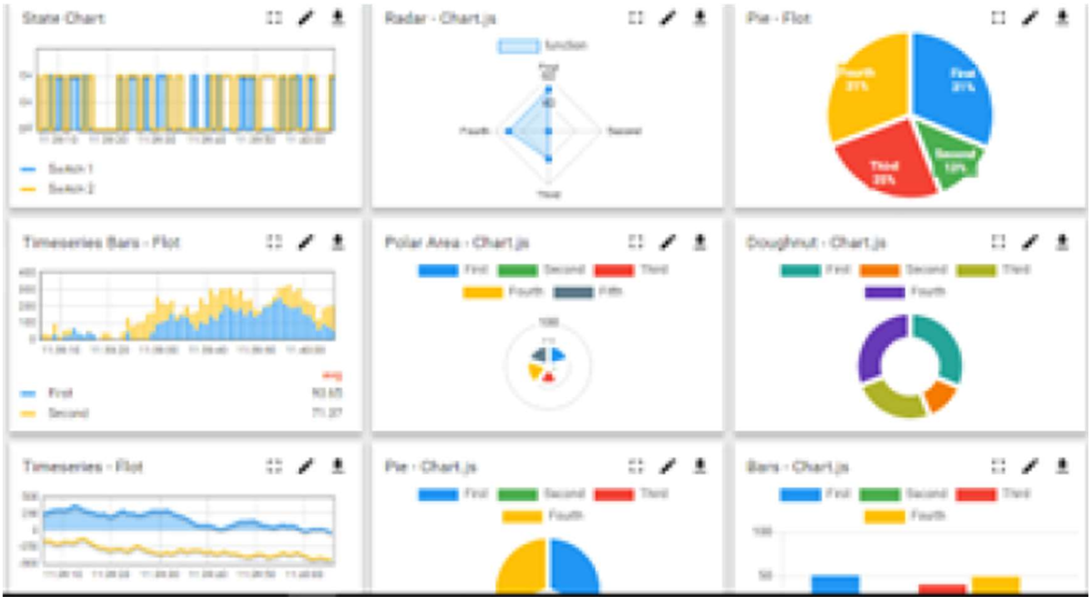
UCT Insight is an IOT platform designed for quick deployment of IOT applications on the same time providing valuable "insight" for your process/business. It has been built in Java for backend and ReactJS for Front end. It has support for MySQL and various NoSql Databases.

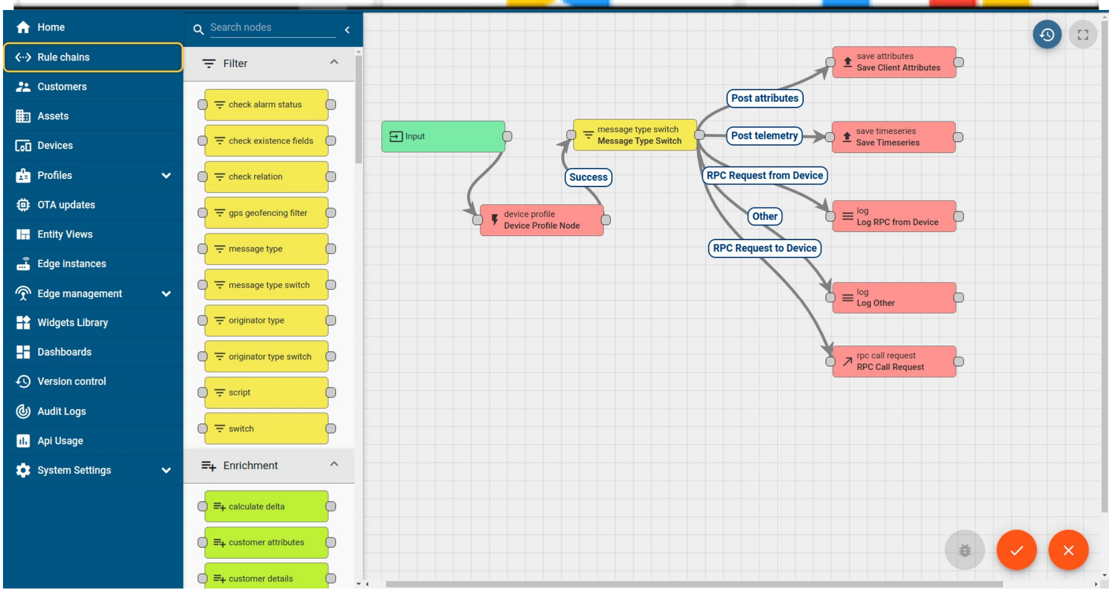
- It enables device connectivity via industry standard IoT protocols - MQTT, CoAP, HTTP, Modbus TCP, OPC UA

- 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.

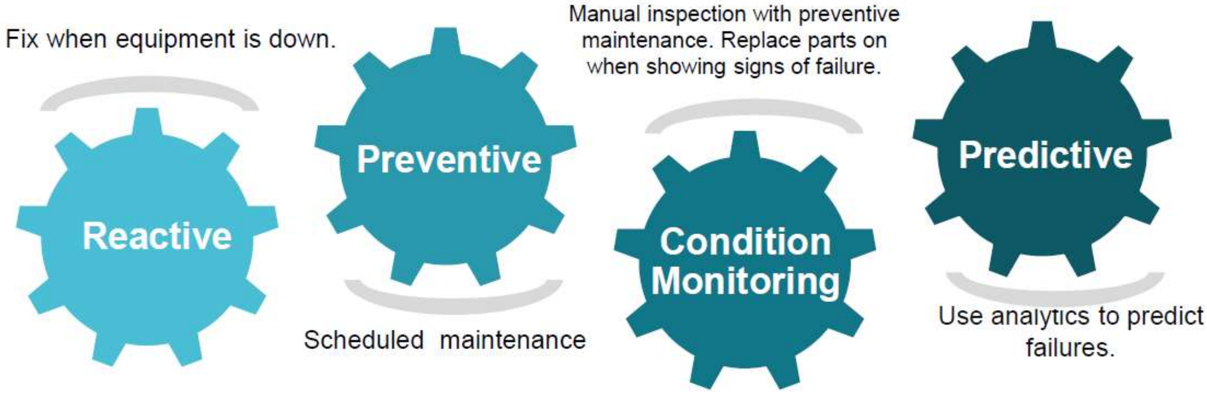
Its unique SaaS model helps users to save time, cost and money.

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

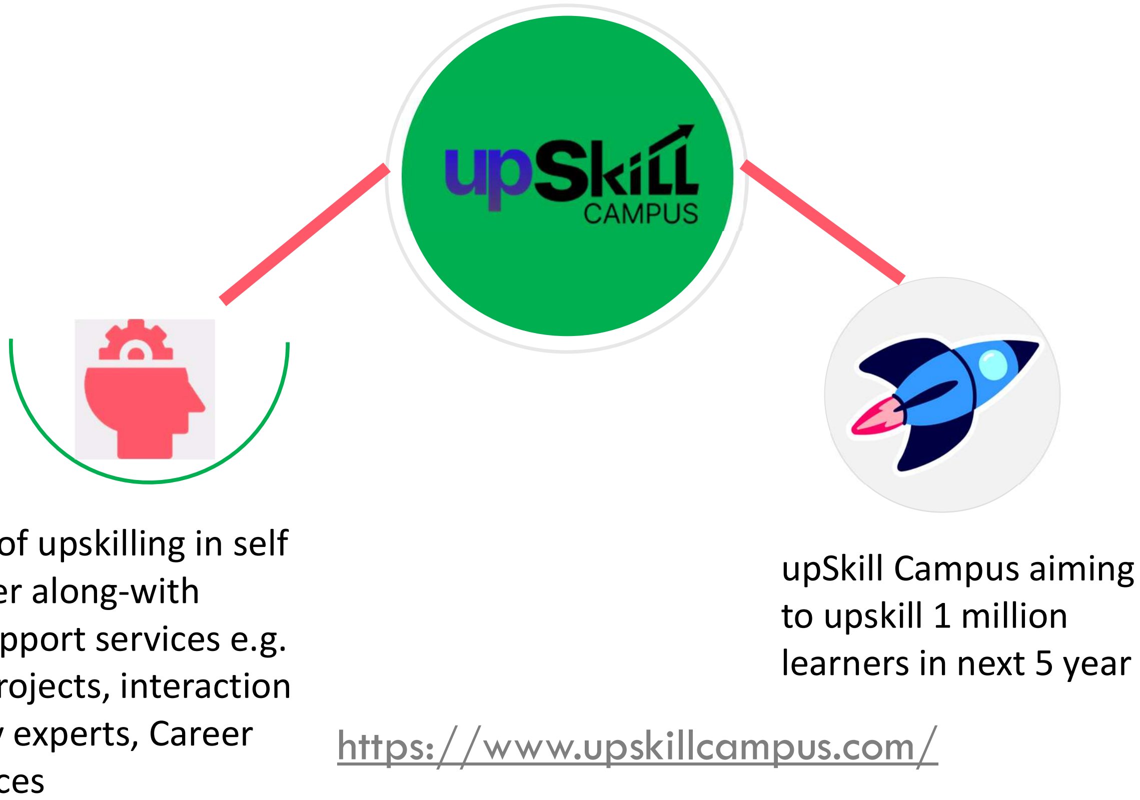
UCT is providing Industrial Machine health monitoring and Predictive maintenance solution leveraging Embedded system, Industrial IoT and Machine Learning Technologies by finding Remaining useful life time of various Machines used in production process.



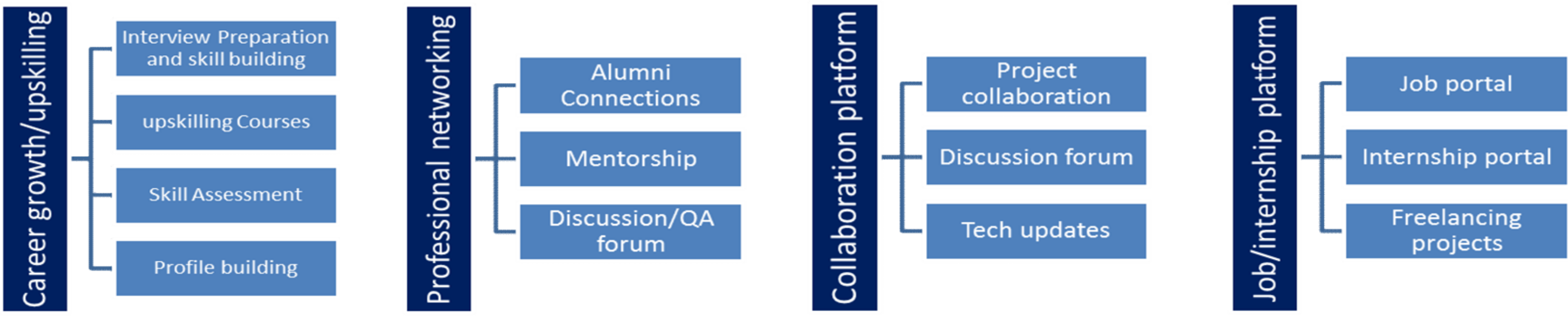
2.2 About upskill Campus (USC)

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.



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] Koushik, K., Venkata Suryanarayana, S. (2023). Crop and Weed Detection From Images Using YOLOv5 Family. In: Sharma, D.K., Peng, SL., Sharma, R., Jeon, G. (eds) Micro-Electronics and Telecommunication Engineering . Lecture Notes in Networks and Systems, vol 617. Springer, Singapore. https://doi.org/10.1007/978-981-19-9512-5_50

[2] Najmeh Razfar, Julian True, Rodina Bassiouny, Vishaal Venkatesh, Rasha Kashef, Weed detection in soybean crops using custom lightweight deep learning models, Journal of Agriculture and Food Research, Volume 8, 2022, 100308, ISSN 2666-1543, https://doi.org/10.1016/j.jafr.2022.100308.

[3] A. Subeesh, S. Bhole, K. Singh, N.S. Chandel, Y.A. Rajwade, K.V.R. Rao, S.P. Kumar, D. Jat, Deep convolutional neural network models for weed detection in polyhouse grown bell peppers, Artificial Intelligence in Agriculture, Volume 6, 2022, Pages 47-54, ISSN 2589-7217, https://doi.org/10.1016/j.aiia.2022.01.002.

2.6 Glossary

Terms	Acronym
MobileNetV2	A lightweight deep learning architecture designed for mobile and embedded vision applications, known for its efficiency and performance in image classification and object detection tasks.
Bounding Box	A rectangle used to define the position of detected objects (weed or crop) in an image.
CNN (Convolutional Neural Network)	A class of deep neural networks, typically used for analyzing visual imagery.
Object Detection	A computer vision technique that involves identifying and locating objects within an image or video frame.
Labels	In object detection, labels are annotations that specify the class (weed or crop) and location of each object in an image

3 Problem Statement

"Crop and weed detection"

I had to make a model to detect weed and crop from the images so that the pesticides are just poured to weed and not crops. I had to perform several pre-processing steps along with manual annotation of labels which was performed with the help of LabelImg.

4 Existing and Proposed solution

There were several solutions available but almost all of them had higher computation. Some did not provide the bounding box required for this solution.

My proposed solution consists of pre-processing steps such as removing noise from the images using fastNlMeansDenoisingColored() function, resizing the images to increase accuracy and decrease computation, sharpen the images using filter2D() function, and augmenting the images. Then a function was made to load the .xml files consisting of the labels from the Drive. Then, MobileNetV2 model was used for detection. Then the model was trained and evaluated and probabilities were predicted and those probabilities were converted to labels. Then, I displayed the 4 images showing the inaccuracy of the model and 5 outputs showing the accurate detection of the weed and crop.

The value addition in this is displaying the inaccurate images, sharpening and denoising the images, and using the probabilities to predict the classes.

4.1 Code submission (Github link)

https://github.com/OmPatel1891/upskillcampus/blob/main/WeedandCropDetection.ipynb

4.2 Report submission (Github link):

https://github.com/OmPatel1891/upskillcampus/blob/main/WeedandCropDetection_Om_Mehulbhai_Patel_USC_UCT.pdf

5 Proposed Design/ Model

1. System Architecture

1.1. Input Pipeline

- **Image Acquisition**:
  - Images are captured from the field, either by drones or ground-based cameras.
  - Images are saved in .jpeg format, and corresponding annotation files are stored in XML format.

1.2. Preprocessing

- **Image Preprocessing**:
  - Images are resized to 512x512 pixels.
  - **Denoising**: Uses OpenCV's fastNlMeansDenoisingColored function to remove noise.
  - **Sharpening**: Uses a sharpening filter to enhance image clarity with a custom kernel.
- **Annotation Parsing**:
  - Bounding boxes and class labels (weed/crop) are extracted from XML annotation files.
  - Labels are converted to binary classes (1 for weed, 0 for crop).

1.3. Data Augmentation

- **Augmentation Techniques**:
  - Rotation (up to 20 degrees), zoom, shear, horizontal flips, and shifts (width/height) are applied to the training data for better generalization.

1.4. Data Split

- **Train-Test Split**: The dataset is split into 80% training and 20% testing using train_test_split. Both images and corresponding bounding boxes are divided accordingly.

2. Model Architecture

2.1. MobileNetV2 Backbone

- The pre-trained MobileNetV2 is used as the feature extractor, without the top fully-connected layers (include_top=False).
- Only the last 10 layers are fine-tuned, while the rest are frozen to retain learned features from the ImageNet dataset.

2.2. Custom Layers

- **Flatten Layer**: Flattens the output of the MobileNetV2 feature extractor.
- **Dense Layer**: A fully connected dense layer with 256 units and relu activation, added to learn more abstract features.
- **Dropout Layer**: Dropout with a rate of 0.5 to reduce overfitting.
- **Output Layer**: A final dense layer with a single output node and sigmoid activation for binary classification (weed/crop).

3. Training Pipeline

3.1. Loss Function

- **Binary Cross-Entropy**: Since it's a binary classification problem, binary cross-entropy is used as the loss function.

3.2. Optimizer

- **Adam Optimizer**: The Adam optimizer with a learning rate of 0.0001 is used for efficient training.

3.3. Learning Rate Scheduling

- **ReduceLROnPlateau**: This callback reduces the learning rate by a factor of 0.5 when the validation loss plateaus, allowing for finer adjustments during later epochs.

3.4. Data Augmentation

- The augmented training data is generated on-the-fly using ImageDataGenerator, which applies various augmentations (rotation, shift, zoom, etc.) to increase dataset diversity.

3.5. Training Parameters

- The model is trained over 15 epochs, with a batch size of 8.
- Training is performed using augmented data for better generalization to unseen field conditions.

4. Evaluation and post-processing

4.1. Evaluation

- After training, the model is evaluated on the test set using accuracy as the primary metric.

4.2. Prediction and Bounding Box Visualization

- **Prediction**: The model predicts whether an image contains a weed or a crop, outputting a probability score that is rounded to 0 (crop) or 1 (weed).

- **Bounding Box Visualization**:
  - Predictions and true labels are visualized alongside the corresponding bounding boxes.
  - **Misclassified Samples**: Images that are misclassified (incorrect weed/crop prediction) are displayed for further analysis, showing both predicted and true labels.

4.3. Error Analysis

- Misclassified samples are highlighted, allowing visualization of the differences between the model's predictions and actual labels, which can be used for future model improvements.

5. Deployment Pipeline

5.1. Real-time Application

- **Field Deployment**: The trained model is deployed on edge devices like drones or automated sprayers.
- **Image Input**: The system captures real-time images of the field, which are processed by the model to detect weeds and crops.
- **Pesticide Application**: Weed-detected regions are targeted by the sprayer, minimizing pesticide use on crops.

5.2. Post-Processing

- After detection, Non-Maximum Suppression (NMS) is applied to eliminate overlapping bounding boxes, ensuring that only the most confident predictions are retained.

6. Visualization Design

6.1. Misclassification Plot

- Misclassified images are plotted with bounding boxes around the detected weed/crop. The predicted class is shown in red alongside the true class for easy comparison.

6.2. Sample Image Plot

- Random samples from the test set are displayed with their bounding boxes and predicted labels. Weed labels are displayed in red, and crop labels are displayed in green for intuitive visualization.

6 Performance Test

Performance testing is critical for demonstrating the usefulness of this weed and crop detection system in real-world industrial settings. The system goes beyond an academic prototype by addressing specific constraints that might affect its acceptance in real-world circumstances.

Identified Constraints

1. **Memory Consumption**
   The MobileNetV2 model is chosen because it is lightweight and memory-efficient, making it suitable for deployment on devices with limited resources such as drones, field robots, or edge devices.

2. **Processing Speed (Operations per Second / MIPS)**
   Processing speed is critical for real-time weed and crop detection in the field. MobileNetV2, with its efficient architecture, ensures faster inference times.

3. **Accuracy**
   While MobileNetV2 provides a good trade-off between performance and accuracy, achieving high accuracy in diverse environmental conditions, like varying lighting or occlusion, remains a challenge.

How These Constraints Were Addressed in the Design

1. **Memory Management**
   - By using MobileNetV2, a lightweight deep learning model, the memory requirements are significantly reduced compared to heavier models like ResNet or YOLOV5. This ensures the system can be run on edge devices with limited memory resources.
   - Images are resized to a standard resolution of 512x512 pixels, optimizing memory usage without compromising too much on detail for accurate classification.

2. **Processing Speed**

   Additionally, only the last 10 layers are unfrozen for fine-tuning, reducing the amount of computation needed during training and making the model suitable for real-time detection.

3. **Accuracy Optimization**

- To improve accuracy, data augmentation techniques such as rotation, zoom, and shifts were applied to create more diverse training data, making the model more robust to real-world variations.
- The design uses ReduceLROnPlateau to optimize learning rates, improving the model's ability to generalize by adjusting learning dynamically when the validation loss plateaus.

4. **Power Consumption**

   The reduction in the number of trainable layers further minimizes power requirements during the fine-tuning process, making it feasible for battery-powered devices.

Test Results and Potential Impacts

1. **Memory and Speed Testing**
   - **Memory Usage**: The model was tested on a system with sufficient memory, and the memory footprint of MobileNetV2 remained manageable, even with augmentation applied. Up to 5 GB of RAM was used.
   - **Speed**: Real-time testing on edge devices (like Nvidia Jetson) would be required to ensure the system meets the required MIPS for real-world deployment. Up to 7 minutes were required to run the code.
2. **Accuracy Testing**
   - **Accuracy**: The test accuracy reached was over 78% during evaluations on the dataset. However, real-world field conditions (lighting changes, occlusions, different weed types) might lower this accuracy.

Recommendations for Future Improvements

1. **Memory**:
   - If memory constraints become more severe in real-world deployment, using techniques such as model pruning, quantization, or distillation can reduce the model size further.
   - Consider downsampling images to a smaller resolution (e.g., 256x256) during inference for speed-memory trade-offs, especially for real-time applications.
2. **Speed**:

- Deploy the model using TensorFlow Lite for real-time mobile applications, which can optimize speed and efficiency.
- Use hardware acceleration (such as GPUs on edge devices) to further enhance the processing time.

3. **Accuracy**:
    - Incorporating additional sensor data (such as multi-spectral or thermal imaging) can improve accuracy in challenging conditions where visual data alone may not be sufficient.
    - Consider using ensemble methods with multiple lightweight models or incorporating attention mechanisms to improve detection of hard-to-see weeds or crops.

6.1 Test Plan/ Test Cases

Test Case ID	Test Description	Expected Outcome	Actual Outcome	Pass/Fail
TC1	Accuracy Test: Evaluate accuracy on the test dataset	The model should achieve an accuracy of at least 75%	78.9%	Pass
TC2	Memory Test: Measure the memory usage during training and inference	Memory usage should be within limits (e.g., < 4GB)	5GB	Fail
TC3	Speed Test: Evaluate the total time to run the model	It should execute within 10 minutes	7 minutes	Pass
TC4	Robustness Test: Test model robustness under different environmental conditions (lighting, weather)	Model accuracy should not degrade significantly	Did not degrade	Pass

6.2 Test Procedure

Test Case TC1: Accuracy Test

Objective: Measure the accuracy of the weed and crop detection model on unseen test data.

Steps:

1. Train the model on the training dataset.
2. Evaluate the model using the testing dataset (20% split from original data).
3. Record the accuracy and analyze any misclassifications.

Expected Outcome: The accuracy should be at least 75%.

Test Case TC2: Memory Test

Objective: Measure the memory footprint during training and inference.

Steps:

1. Run the model during training and log the memory usage using system monitoring tools.
2. Perform inference on a batch of images and measure memory usage during the process.

Expected Outcome: Memory usage should remain below 5GB during training and inference.

Test Case TC3: Speed Test

Objective: Evaluate the speed of the model.

Steps:

1. Deploy the model.
2. Measure the time taken for the model to execute.

Expected Outcome: It should execute within 10 minutes

6.3 Performance Outcome

- **Accuracy**:
  The model achieved an accuracy of 78.9% on the test dataset during initial evaluations, demonstrating high performance in detecting crops and weeds under controlled conditions.
- **Memory Usage**:
  Memory usage during training peaked at around 5GB.
- **Speed Test:**
  The model was successfully executed within 7 minutes.

7 My learnings

Developing and deploying the weed and crop detection model using MobileNetV2 provided me with important insights into various critical areas of machine learning and its application in real-world contexts. The decision to use MobileNetV2 highlighted the significance of balancing model efficiency with computational constraints, especially for deployment on edge devices. Fine-tuning the model and using picture preprocessing approaches improved its performance, while data augmentation indicated how to improve robustness and generalizability. Testing the system on several criteria (accuracy, speed, and memory consumption) revealed the constraints and implications of real-time and resource-efficient deployment. Furthermore, coordinating the project workflow from data collection to system validation improved my expertise of integrating software and hardware and dealing with realistic restrictions. These experiences have highlighted the importance of rigorous testing, documentation, and the ethical implications of using technology to solve practical problems, notably in agriculture.

8 Future work scope

The future scope of the weed and crop detection model using MobileNetV2 includes a number of fascinating areas for improvement and application. One major area is to increase the model's robustness and accuracy by expanding the dataset to include more different environmental conditions and plant varieties, which would improve the system's performance in real-world scenarios. Integrating advanced approaches like transfer learning with more complicated architectures or ensemble methods has the potential to improve accuracy further. Furthermore, refining the model for faster inference and lower memory consumption will make it more suitable for use on edge devices and in low-power applications. Integrating with real-time data sources, such as drones or automated farming equipment, may enable more dynamic and responsive agricultural management systems. Furthermore, combining user feedback and system learning capabilities could result in adaptive models that improve over time, providing farmers with more precise and actionable insights.