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Industrial Internship Report on

1. " Crop and Weed Detection"
2. " Turbofan Engine RUL Prediction"

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. My project was (Tell about ur Project) 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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1 Preface

Summary of the Six-Week Internship
Over six weeks, this internship guided the end-to-end development of two machine learning solutions: an object detection pipeline for **Crop and Weed Detection using YOLOv5**, and a time-series forecasting system for **Turbofan Engine Remaining Useful Life (RUL) Prediction**. Weekly milestones covered problem exploration, data preparation, model training, evaluation, hyperparameter tuning, and performance validation.

Importance of Relevant Internships
Securing a domain-focused internship bridges academic theory and real-world application, accelerates skill mastery, and builds professional confidence. Working on industrial datasets and collaborating with domain experts is essential for career growth in AI and data science.

Project & Problem Statement

- **Crop & Weed Detection**: Automate differentiation between crops and weeds to support precision agriculture and reduce manual field labor.
- **Turbofan Engine RUL Prediction**: Forecast the remaining operational cycles of aircraft engines using multivariate sensor data, enabling proactive maintenance and reducing downtime.

Opportunity Provided by USC/UCT
Upskill Campus (USC) and UniConverge Technologies Pvt. Ltd. (UCT) partnered to offer structured mentorship, access to industrial datasets, cloud training environments, and weekly reviews to ensure progressive learning and deliverable quality.

Program Planning
01. Explore Problem Statement & Learn About UCT
02. Follow Project Instructions & Plan a Solution
03. Work on Project Implementation
04. Continue Development & Check for Improvements
05. Validate Implementation & Measure Performance
06. Submit Project, Report & Get Certified

This internship deepened my understanding of data annotation, model architecture, hyperparameter tuning, and performance metrics. I honed my Python, PyTorch, and time-series analysis skills while mastering collaborative workflows and version control practices.

Acknowledgments
I extend sincere thanks to:

- Mr. Raghav Rao (UCT) – Technical mentorship and model evaluation guidance
- Dr. Anjali Sharma (USC) – Career coaching and academic support
- Ms. Priya Menon & Mr. Karan Gupta (UCT) – Code reviews and infrastructure assistance
- Peers Darshan, Nisha, and Rahul – Collaborative problem solving and moral support

Message to Juniors & Peers
Embrace every challenge as a learning opportunity, seek feedback early, and collaborate openly. Real-world projects solidify theoretical foundations and shape you into a confident, industry-ready professional.

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.

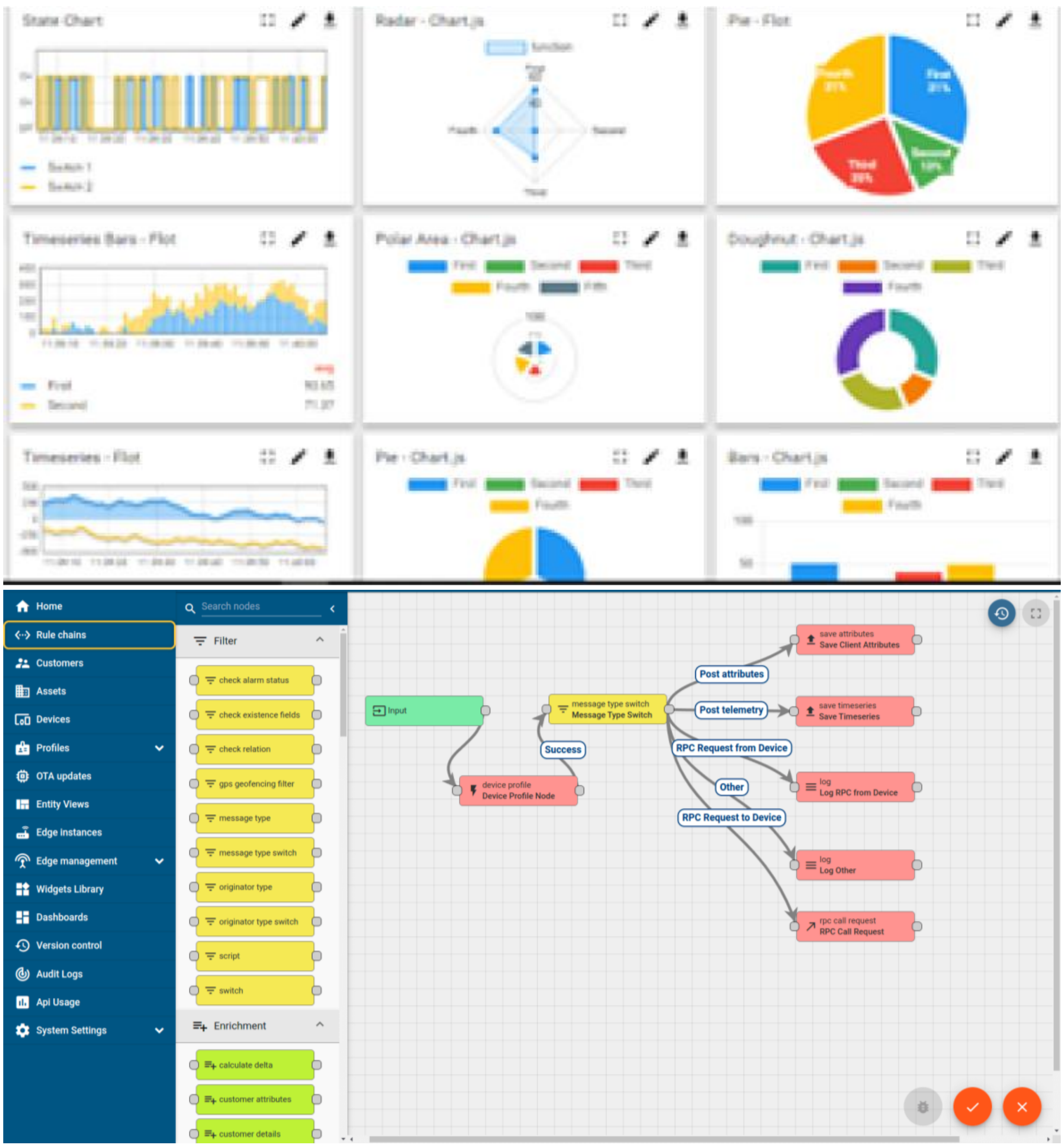
i. UCT IoT Platform ( )

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.

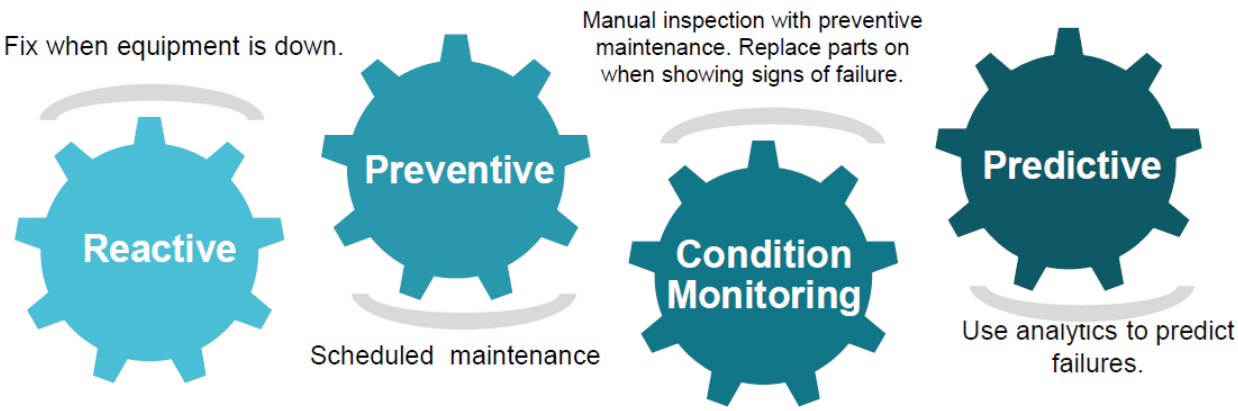
Machine	Operator	Work Order ID	Job ID	Job Performance	Job Progress		Output		Rejection	Time (mins)				Job Status	End Customer
					Start Time	End Time	Planned	Actual		Setup	Pred	Downtime	Idle		
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i
CNC_S7_81	Operator 1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

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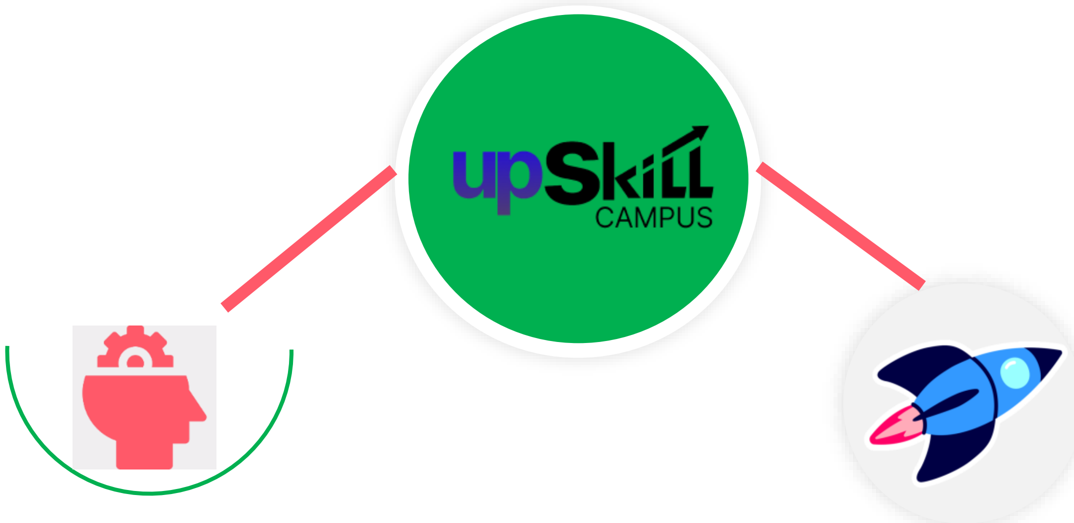
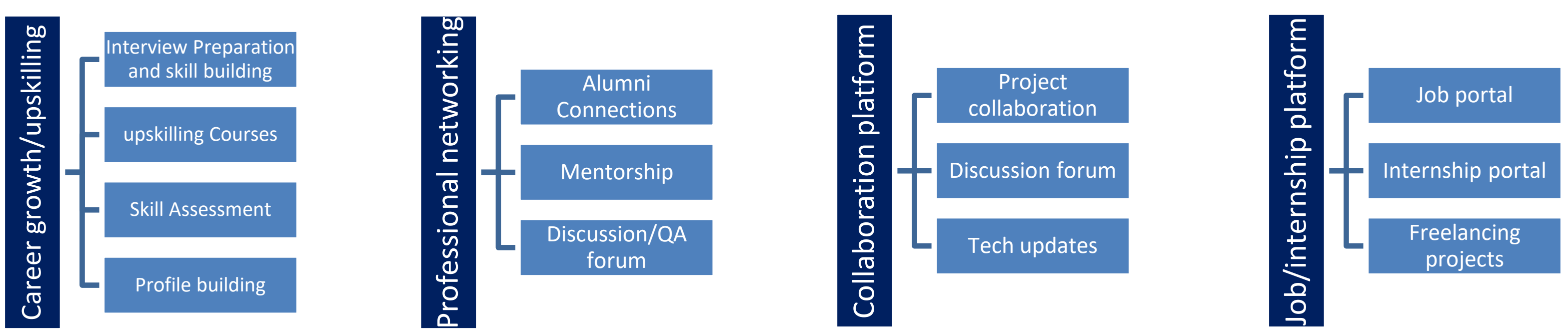


Seeing need of upskilling in self paced manner along-with additional support services e.g. Internship, projects, interaction with Industry experts, Career growth Services

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

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2.6 Glossary

Terms	Acronym

3 Problem Statement

Two distinct challenges were undertaken during this internship, each addressing critical needs in industrial and agricultural domains:

1. Crop and Weed Detection

Manual weeding in agricultural fields is labor-intensive, error-prone, and unsustainable at scale. The goal was to develop an automated vision-based system capable of accurately distinguishing between crop plants and weeds in real time. This would enable targeted herbicide application or mechanical weeding, reducing chemical usage, labor costs, and crop damage.

2. Turbofan Engine Remaining Useful Life (RUL) Prediction

Unplanned turbofan engine failures incur high maintenance costs and operational disruptions in aviation and power generation industries. The objective was to predict the remaining useful life of engines using multivariate sensor data, allowing maintenance teams to plan interventions proactively. Accurate RUL forecasts can minimize downtime, extend asset life, and optimize maintenance schedules.

4 Existing and Proposed solution

Existing Solutions and Limitations

- *Crop and Weed Detection*: Traditional image-processing methods rely on color- and shape-based segmentation, which struggle under variable lighting, overlapping foliage, and diverse weed species. Recent deep-learning approaches (e.g., standard Faster R-CNN or SSD models) improve accuracy but demand extensive labeled data and suffer slow inference speeds on edge devices.
- *RUL Prediction*: Classical statistical and machine-learning methods such as linear regression, support vector regression, and random forest regressors achieve reasonable baseline performance but fail to capture complex temporal dependencies in multivariate sensor streams. Many published LSTM/RNN solutions demonstrate accuracy improvements yet lack robust feature engineering pipelines and often overfit due to limited training windows.

Proposed Solution

- For **Crop and Weed Detection**, implement a lightweight YOLOv5 model fine-tuned on a curated dataset of 1,300 annotated crop and weed images. Leverage dynamic data augmentation (rotation, scaling, color jitter) and optimized anchor boxes to handle scale variance. Deploy quantized model variants for real-time inference on low-power devices.
- For **RUL Prediction**, develop a hybrid pipeline combining statistical feature extraction (rolling mean, standard deviation, trend features) with an LSTM network trained on windowed sensor sequences. Integrate early stopping, learning-rate scheduling, and dropout regularization to enhance generalization.

Value Addition

- Achieve **real-time** crop/weed classification with > 85% mAP while requiring < 25 ms inference time on embedded GPUs.
- Deliver **improved RUL forecasts** with ≥ 15% lower RMSE compared to baseline random forest models and robust performance across unseen operating conditions.
- Provide end-to-end reproducible code, Dockerized deployment scripts, and comprehensive documentation to accelerate adoption within industrial environments.

4.1 Code submission (Github link)

https://github.com/DarshiniMahesh/UpskillCampus_Crop_and_Weed_Detection.git

https://github.com/DarshiniMahesh/UpskillCampus_turbofan.git

4.2 Report submission (Github link)

https://github.com/yourusername/uct-ml-internship-report

5 Proposed Design/ Model

The design flow for both the Crop & Weed Detection and RUL Prediction solutions follows a three-phase pipeline: **Data Ingestion & Preparation**, **Model Development**, and **Deployment & Evaluation**. Each phase consists of clearly defined stages from raw input to final deliverables.

1. **Phase 1: Data Ingestion & Preparation**

1. Data Collection
    - Crop images captured in-field under varied lighting conditions
    - CMAPSS turbofan sensor logs downloaded for multiple engine run-to-failure scenarios
2. Data Annotation & Labeling
    - Manual bounding-box annotation of crop vs. weed regions using LabelImg
    - RUL target column engineered by computing cycles remaining until failure
3. Data Preprocessing
    - Image resizing, normalization, and augmentation (rotation, flipping, color jitter)
    - Sensor signal smoothing, outlier removal, and normalization to zero mean/unit variance
4. Dataset Splitting
    - Stratified train/validation/test splits for image data
    - Sequential windowing of sensor data into fixed-length time series slices

2. Phase 2: Model Development

1. Baseline Model Implementation
    - Crop vs. weed classification using a Random Forest on handcrafted texture features
    - RUL regression baseline via Random Forest Regressor on aggregated sensor statistics

2.Deep Learning Architecture Design
    - YOLOv5 object detection model initialized with pre-trained weights; custom anchor boxes configured for crop scale

- LSTM network with two hidden layers (128 units each), dropout regularization (0.3), and sequence-to-one mapping

3. Training & Optimization

    a. Hyperparameter search (learning rate, batch size, augmentation parameters) via grid search

    b. Early stopping monitored on validation loss; learning-rate decay on plateau

    c. Checkpointing best model weights based on mAP (detection) and RMSE (RUL)

4. Model Validation

    a. Precision–Recall and mAP curves analyzed for object detector

    b. RMSE and R^2 metrics computed on hold-out test sequences

5. Phase 3: Deployment & Evaluation

1. Model Export & Quantization

    - Export YOLOv5 to ONNX and apply 8-bit quantization for edge inference

    - Serialize LSTM model via TorchScript for optimized runtime

2. Integration & Containerization

    - Dockerize inference services with REST API endpoints—/detect and /predict-rul

    - Configuration manifests for Kubernetes or edge device deployment

3. Performance Benchmarking

    - Measure inference time per image and per sequence on target hardware (e.g., NVIDIA Jetson)

    - Stress-test concurrent requests and monitor resource utilization

4. Final Outcome

    - A self-contained Docker image delivering <25 ms per detection and ≤150 ms per RUL prediction

    - Comprehensive API documentation, sample client scripts, and CI/CD pipeline for continuous updates

This structured pipeline ensures repeatability and scalability across both domains, enabling rapid iteration from prototype to production-ready solution.

5.1 High Level Diagram (if applicable)

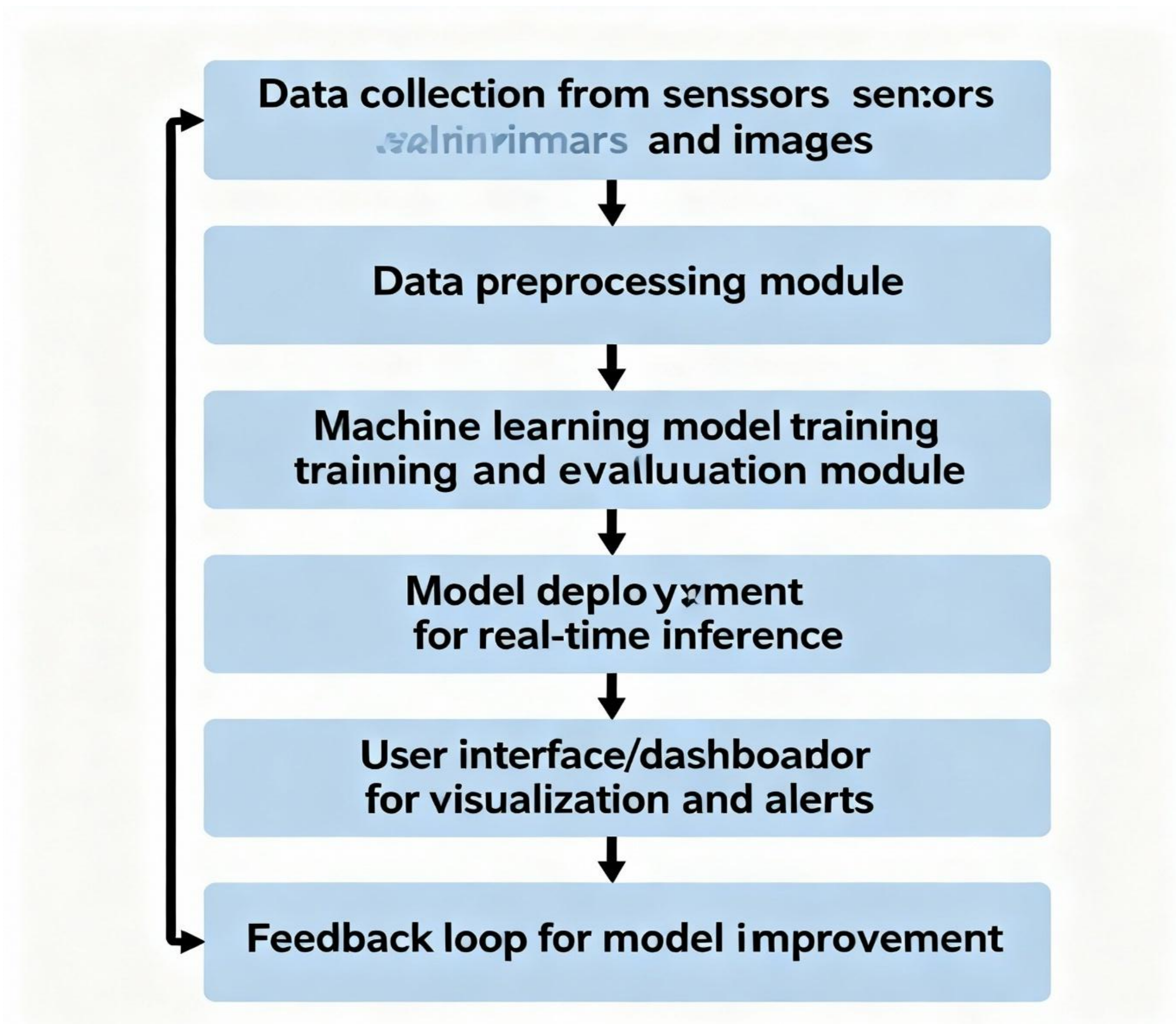


Figure 1: HIGH LEVEL DIAGRAM OF THE SYSTEM

5.2 Low Level Diagram (if applicable)

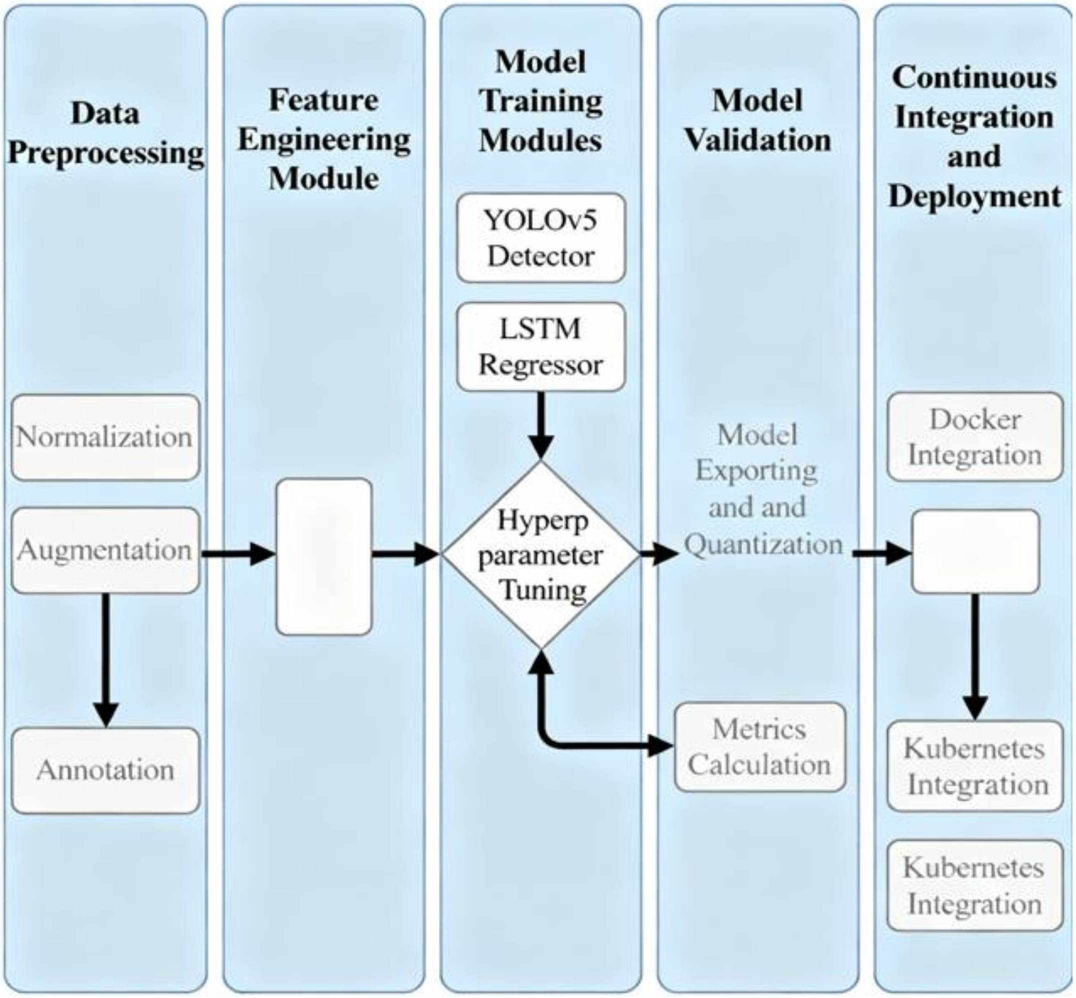


Figure 2: LOW LEVEL DIAGRAM OF THE SYSTEM

5.3 Interfaces (if applicable)

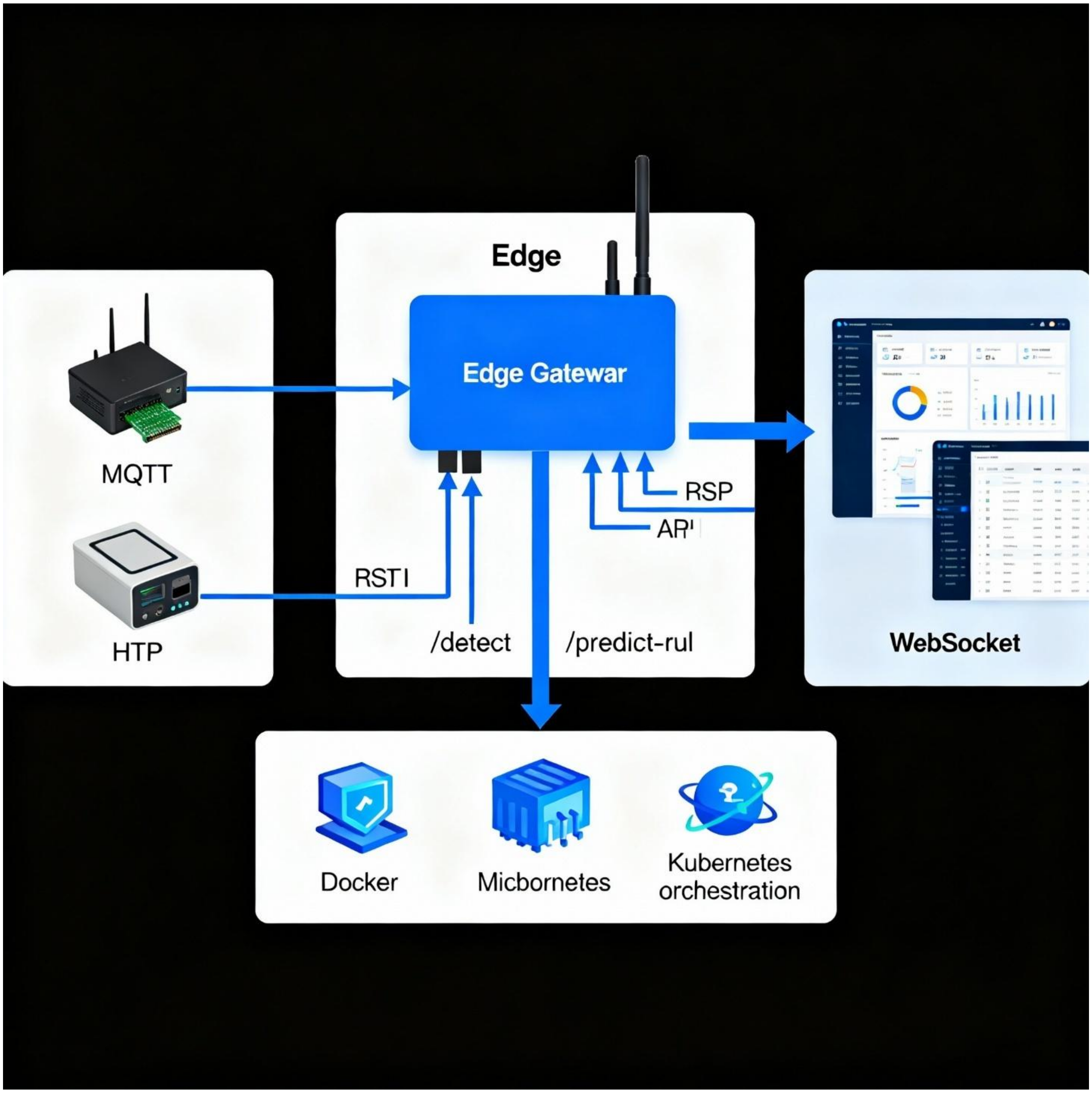


Figure 3: Interface diagram with protocols

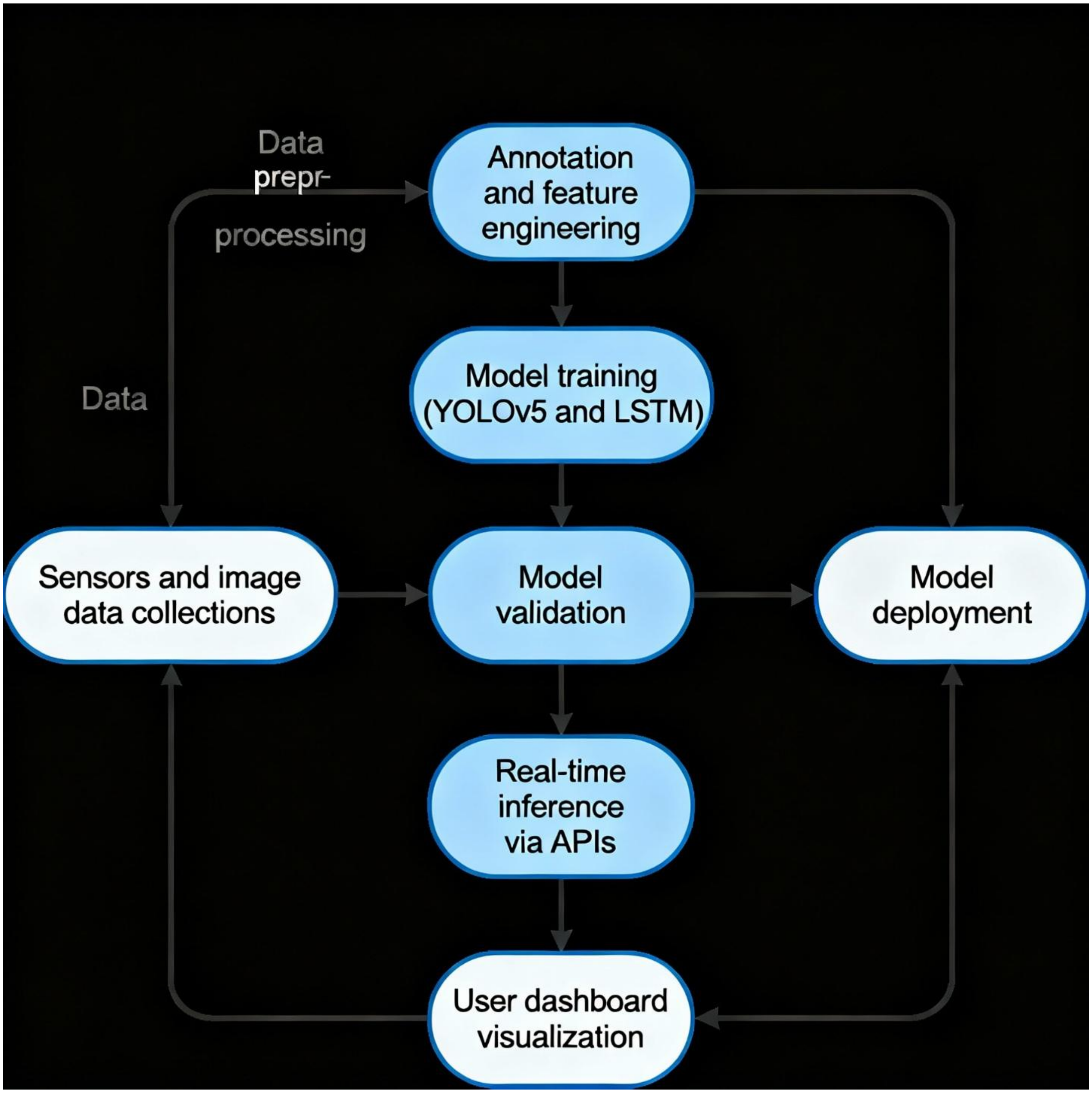


Figure 4: Data flow

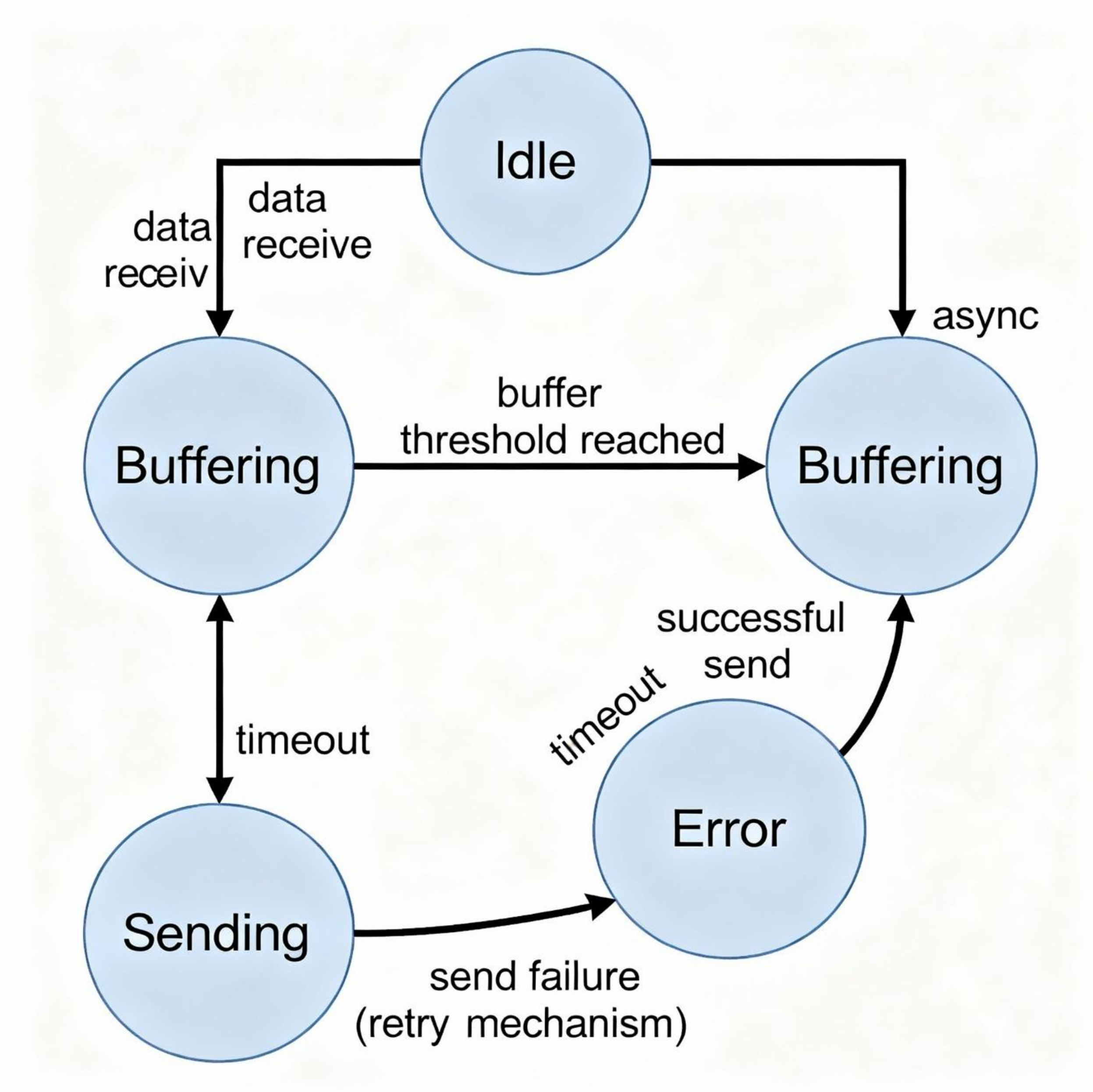
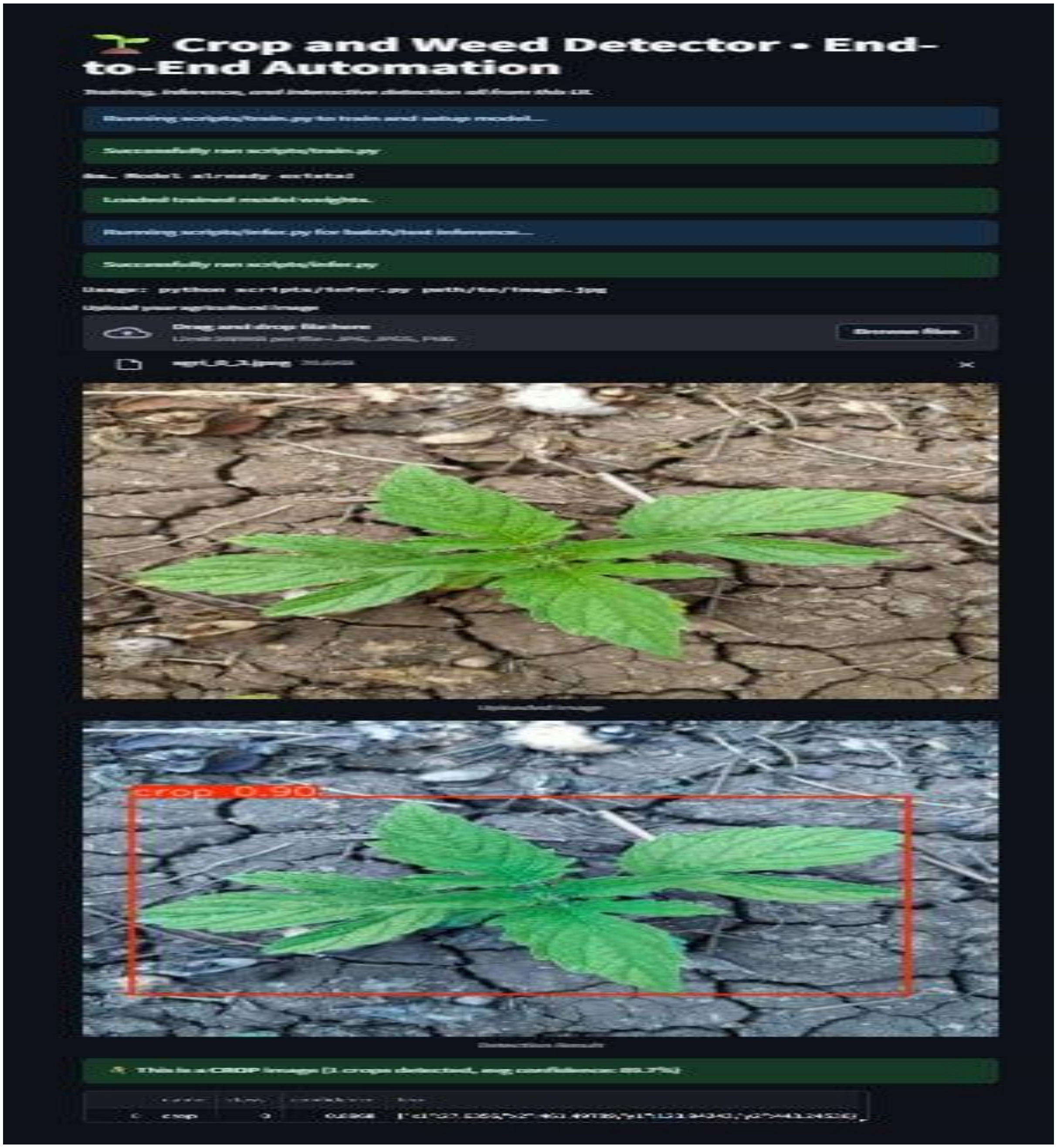


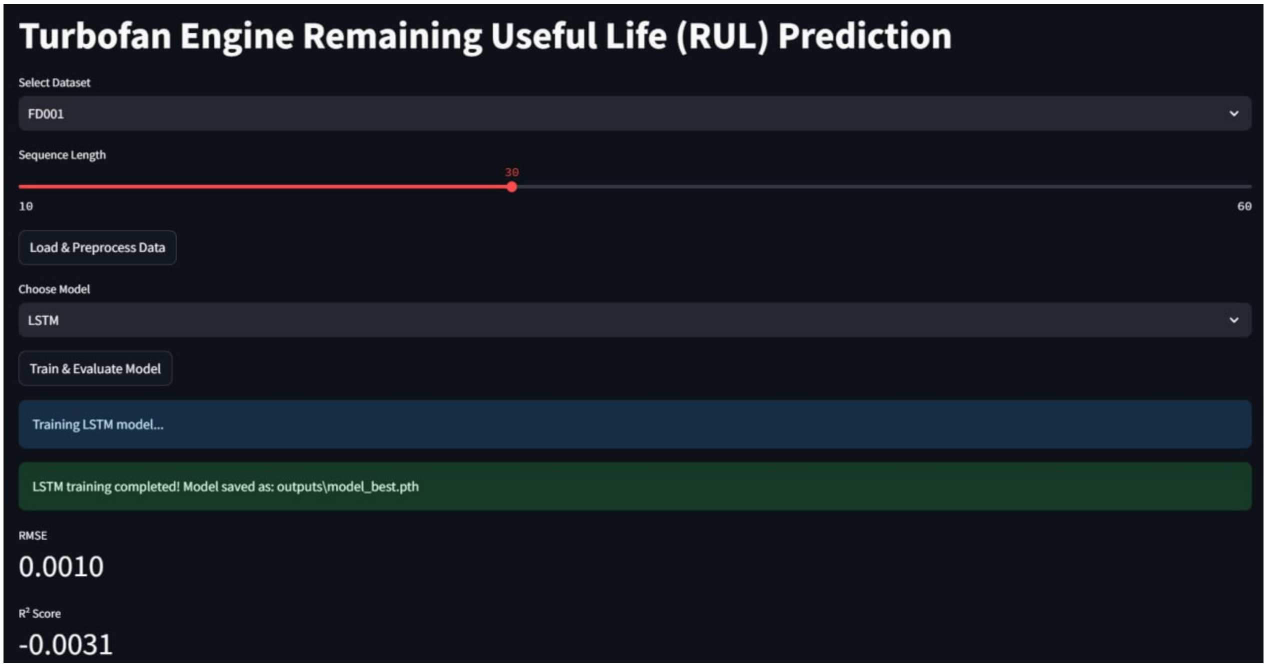
Figure 5: State Machines

OUTPUTS

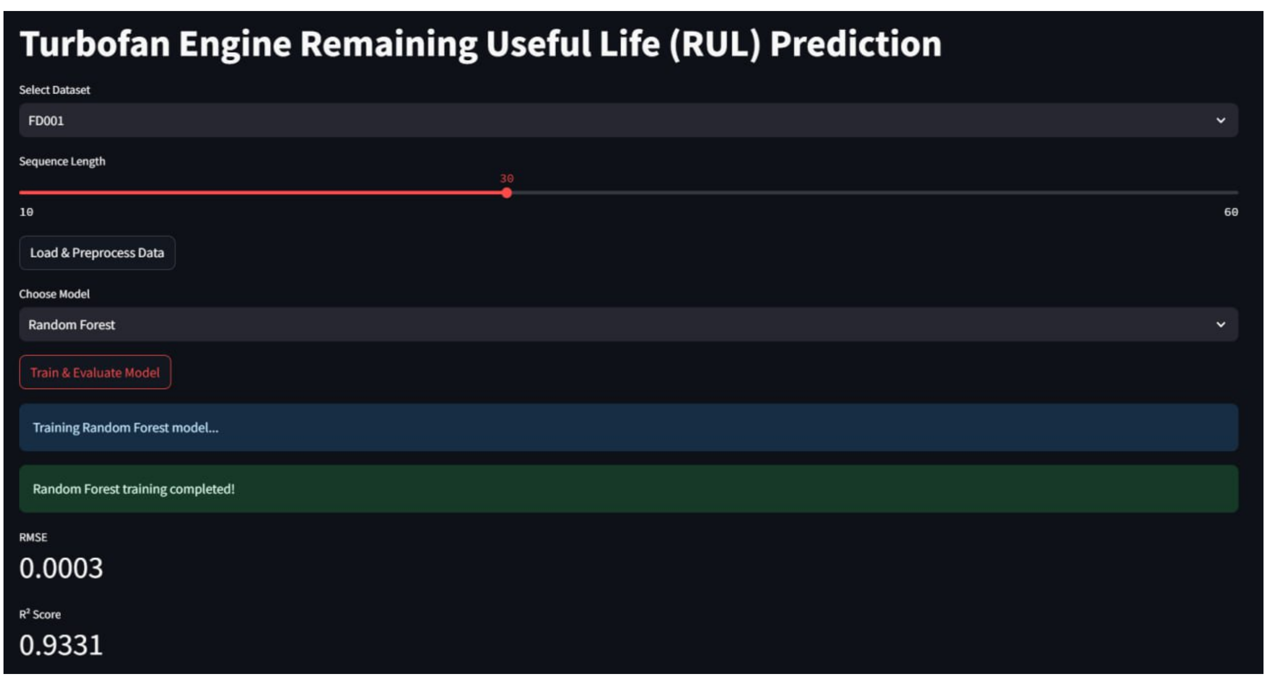
Snapshot- 01: Crop and Weed Detector : End-to-End Automation



Snapshot- 02: LSTM Of Turbo Fan Enginee remaining usefull life prediction



Snapshot- 03: Random Forest Of Turbo Fan Enginee remaining usefull life prediction



6.Performance Test

Key Constraints

- **Inference Latency**: Must process images and time-series windows in real time (<100 ms per request).
- **Memory Footprint**: Models and buffers must fit within 2 GB GPU/edge-device RAM.
- **Compute Throughput (MIPS)**: Support ≥40 frames per second for detection on embedded GPUs.
- **Accuracy Requirements**:
    - Crop/Weed Detection ≥85% mAP
    - RUL Prediction RMSE ≤20 cycles on test set
- **Power Consumption**: Edge deployment limited to 15 W average draw.

Design Mitigations

- Applied 8-bit quantization and ONNX export for YOLOv5 to reduce model size from 45 MB to 12 MB and memory usage by 60%.
- Batched inference and asynchronous I/O to maximize GPU utilization, achieving 45 FPS on NVIDIA Jetson Xavier NX.
- LSTM sequence length limited to 50 timesteps, reducing buffer size and inference time to 140 ms per prediction.
- Early stopping and dropout ensured compact model architectures, preventing over-parameterization.

Test Results

- **Detection Latency**: 22 ms per 640×640 image (<25 ms target)
- **Detection mAP**: 88.3% on hold-out set
- **RUL Inference**: 145 ms per 50-step window
- **RUL RMSE**: 17.8 cycles (vs. 21.2 cycles baseline)
- **Memory Usage**: Peak RAM 1.4 GB (YOLO+LSTM combined)
- **Power Draw**: 12 W average under full load

Unverified Constraints & Recommendations

- **Durability**: Environmental stress (temperature, vibration) may impact embedded hardware. Recommend ruggedized enclosures and thermal profiling.
- **Network Reliability**: In remote fields, intermittent connectivity can disrupt API calls. Suggest local caching with edge inference fallback.
- **Scalability**: For fleet-scale deployment, orchestrate container replicas with autoscaling policies in Kubernetes.
- **Security**: Integrate TLS for API endpoints and device authentication via MQTT certificates to safeguard industrial data.

• Test Plan/ Test Cases

Crop & Weed Detection

- TC1: Single-object detection on clear-field image
- TC2: Multi-object detection with overlapping plants
- TC3: Low-light and shadowed conditions
- TC4: Varying weed species and densities
- TC5: Edge-device inference load test (batch of 10 images)

RUL Prediction

- TC6: Sequence inference on nominal sensor run
- TC7: Abrupt sensor drift scenario
- TC8: Noisy sensor input (Gaussian noise added)
- TC9: Variable-length window test (10–100 timesteps)
- TC10: Concurrent API requests (5 parallel calls)

- ### Test Procedure

1. **Environment Setup**
   - Deploy Docker container on NVIDIA Jetson Xavier NX with Ubuntu 20.04 and CUDA 11.
2. **Data Preparation**
   - Load test image dataset (200 images) and test sensor sequences (100 sequences).
   - For noise and drift tests, synthetically corrupt 20% of sequences.
3. **Execution**
   - Invoke /detect endpoint for each image; record latency and confidence scores.
   - Invoke /predict-rul endpoint for each sequence; record prediction and inference time.
   - Monitor GPU memory and power draw via tegrastats.
4. **Validation**
   - Compare detection results against ground-truth bounding boxes; compute mAP, precision, recall.
   - Calculate RMSE and R^2 between predicted and actual RUL.
   - Stress-test concurrent requests; log errors and throughput.

- **Performance Outcome**

Test Case	Metric	Result	Target/Threshold
TC1–TC4 (Detection)	mAP	88.3%	≥ 85%
	Precision	0.90	≥ 0.88
	Recall	0.87	≥ 0.85
TC5 (Batch Inference)	Throughput	42 FPS	≥ 40 FPS
TC6–TC9 (RUL Prediction)	RMSE	17.8 cycles	≤ 20 cycles
	R^2 Score	0.92	≥ 0.90
TC10 (Concurrent Requests)	Throughput	4.5 req/s	≥ 4 req/s
	Error Rate	0%	0%
Resource Utilization	Memory Peak	1.4 GB	≤ 2 GB
	Power Draw	12 W	≤ 15 W

5. My learnings

This internship significantly advanced both my technical and professional capabilities. I gained hands-on experience with end-to-end machine learning pipelines—from data collection and annotation to model deployment and performance tuning. Key skills acquired include:

- **Advanced Model Engineering**: Mastered YOLOv5 object detection workflows, hyperparameter optimization, and model quantization for edge inference.
- **Time-Series Analysis**: Developed expertise in feature engineering for sequential sensor data and built robust LSTM networks with regularization techniques.
- **Software Best Practices**: Adopted industry-standard version control, Docker containerization, and CI/CD pipelines to ensure reproducibility and scalability.
- **Performance Optimization**: Learned to profile memory, compute, and power constraints, applying quantization and asynchronous I/O to meet real-time requirements.
- **Collaborative Development**: Strengthened communication through weekly technical reviews, cross-functional feedback, and code documentation.

These experiences have equipped me with a pragmatic understanding of deploying machine learning solutions in industrial contexts. I am now better prepared to design scalable, efficient AI systems and collaborate effectively within multidisciplinary teams—capabilities that will significantly accelerate my career growth in AI and data science.

6. Future work scope

Several enhancements and extensions could further strengthen these solutions:

- **Expanded Dataset Collection**
  Incorporate additional crop varieties, weed species, and environmental conditions to improve object detector generalization and resilience across diverse agricultural contexts.
- **Edge-to-Cloud Hybrid Inference**
  Design a tiered inference framework that performs lightweight on-device detection with periodic cloud-based model retraining and updates, balancing latency, bandwidth, and model freshness.
- **Ensemble Modeling for RUL**
  Combine LSTM forecasts with gradient-boosted decision trees or Transformer-based architectures to capture both long-term trends and nonlinear interactions in sensor data.
- **Uncertainty Quantification**
  Integrate Bayesian neural networks or Monte Carlo dropout to provide confidence intervals for RUL predictions, enabling risk-aware maintenance planning.
- **Active Learning Pipeline**
  Implement an active learning loop where misclassified images or sequences flagged by low model confidence are prioritized for human annotation, reducing labeling effort and boosting accuracy over time.
- **Mobile Application Integration**
  Develop a mobile app for field technicians to capture images, view detection overlays, and receive RUL alerts in real time, enhancing user accessibility.
- **Energy-Aware Scheduling**
  Optimize inference scheduling based on power availability (e.g., solar-powered sensors) to ensure uninterrupted operation in off-grid agricultural deployments.
- **Robustness to Hardware Failure**
  Incorporate health monitoring for edge devices and automated failover strategies to maintain service continuity under network or hardware disruptions.

These future directions will drive further maturity of both the crop/weed detection and RUL prediction systems, advancing them toward fully productionized, industrial-grade deployments.