Seed Incubation Plant

group 10

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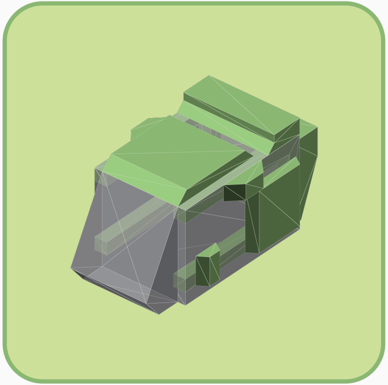
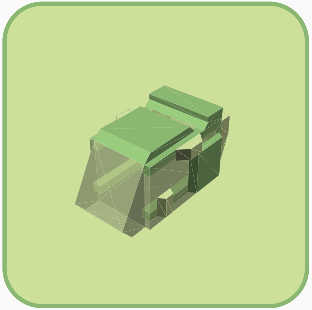
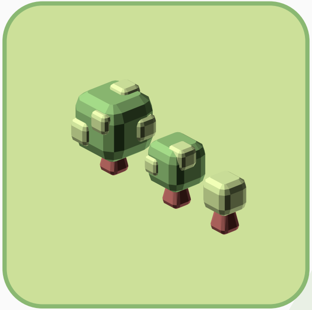
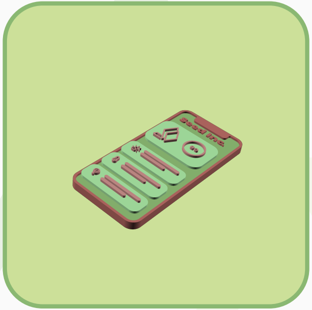


- **Seed Incubation Plant** aims to optimize the germination and growth process of seeds by providing a controlled and monitored environment.
- **Environment Monitoring and Control Unit** (EMCU) part of the incubator takes care of environmental factors such as temperature, humidity, lighting, O_2, etc.
- **Growth Monitoring Unit** (GMU) closely monitors and collects growth related information from each of the germinating saplings.
- With the help of **SINC**, a companion app, the status of the incubator can be closely watched.

Objectives





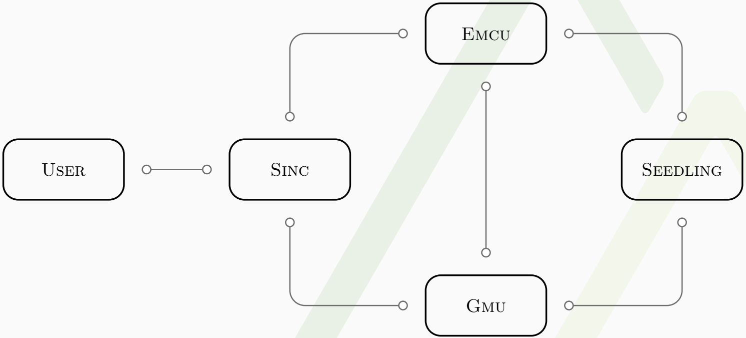


- Implement the sensor and actuator sides of the EMCU, thus driving it into a cohesive system.
- Implement an ESP32 CAM based Growth Monitoring Unit (GMU) powered by a TinyML model.
- Take the development of SINC, a companion app, to the alpha stage.

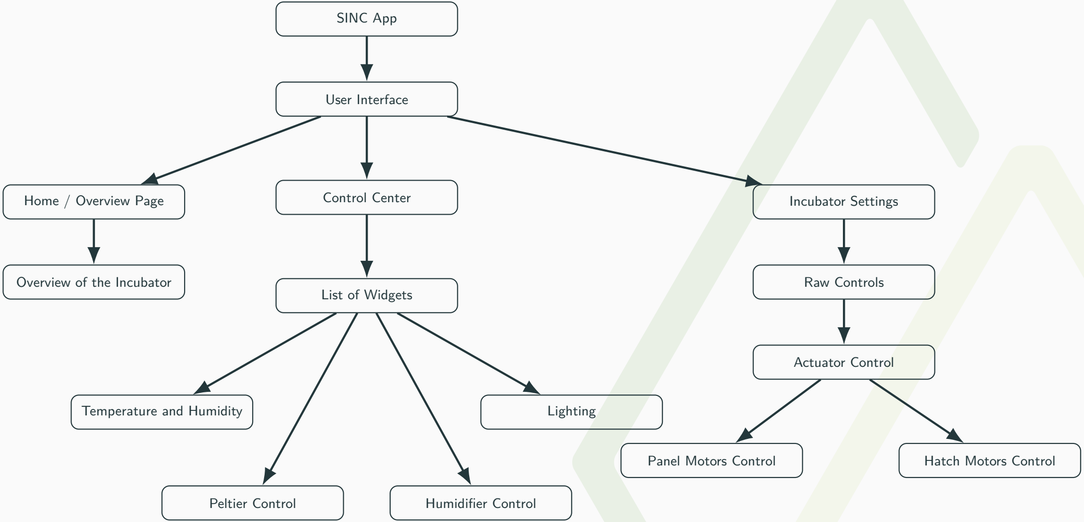
Block Diagram: Overall

Major Components

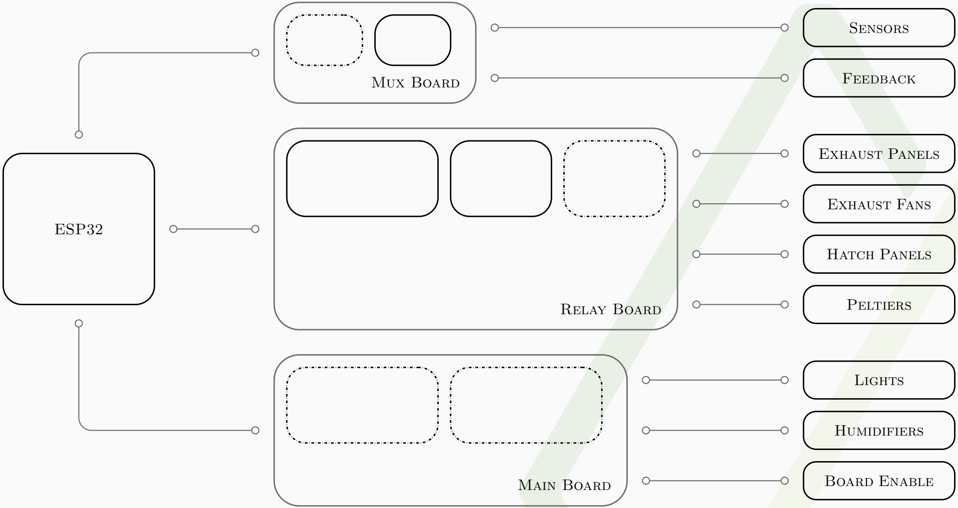
- EMCU
- SINC
- GMU



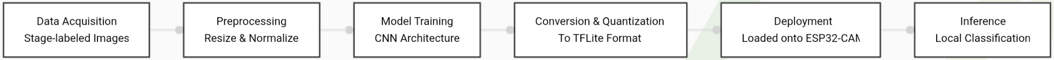
Block Diagram: Sinc App



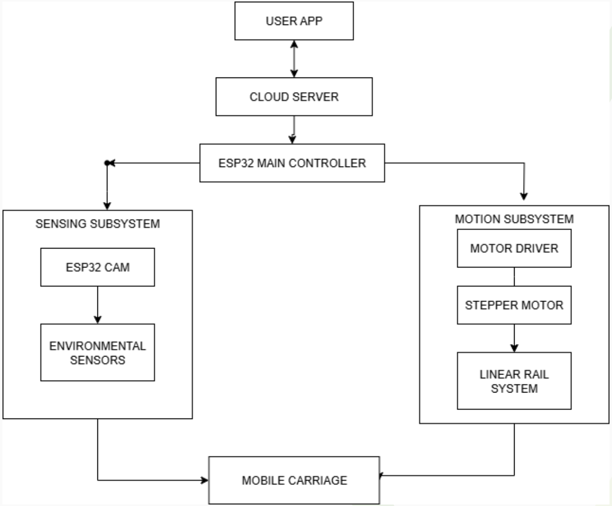
Block Diagram: EMCU



Block Diagram: GMU - TinyML



Block Diagram: GMU - Rail System Architecture



Title:	**Internet of Things (IoT) Based Greenhouse Monitoring and Controlling System Using ESP-32**
Authors:	J. Seetaram, A. Bhavya, C. Tarun and V. Sameera
DOI:	10.17148/IJARCCE.2024.13605
Publisher:	*International Journal of Advanced Research in Computer and Communication Engineering*
Result:	The system successfully performed real-time monitoring and automated environmental control. Demonstrated fully autonomous and remote operation, reducing human intervention.

Relevant Features & Insights:

- IoT-enabled remote control with real-time sensor data visuals.
- User-friendly UI designed on Blynk for farmers.
- Focus on sustainability, resource optimization, and precision agriculture.

Title: **Non Plant Specific Smart Greenhouse with Convective Drying Unit**
Authors: J. Mukherjee et al.
DOI: `10.1109/TQCEBT59414.2024.10545221`
Publisher: *International Conference on Trends in Quantum Computing and Emerging Business Technologies (TQCEBT), 2024*
Result: Developed a smart greenhouse that included an integrated convective drying system, supporting a variety of plant types and optimizing both growth and post-harvest processing.

Relevant Features & Insights:

- Unique addition of convective drying unit supporting post-harvest processing within the smart greenhouse.
- Designed for versatility—accommodates diverse crops beyond plant-specific solutions.
- Included a comprehensive control mechanism for climate and drying, with IoT-based user monitoring.

Title:	**Real-Time Environmental Monitoring in Smart Agriculture Using TinyML and Machine Learning**
Authors:	D. S. Kulkarni and S. Bhudhwale
DOI:	`10.1109/ICISAA62385.2024.10829307`
Publisher:	*2024 International Conference on Intelligent Systems and Advanced Applications (ICISAA), 2024*
Result:	Implemented real-time environmental monitoring in smart agriculture using TinyML, enabling local data processing and actionable insights directly on microcontroller hardware for improved responsiveness and minimized latency.

Relevant Features & Insights:

- Leveraged TinyML models on edge devices for on-site data analysis (no constant cloud dependence).
- Enhanced detection and immediate response to abnormal environmental conditions, aiding in automation and safety.
- Demonstrated practical benefits in water and resource optimization, supporting sustainable agricultural practice.

Title: **TinyML for Smart Agriculture: Comparative Analysis of TinyML Platforms and Practical Deployment for Maize Leaf Disease Identification**

Authors: Dan Gookyi et al.

DOI: `10.1016/j.atech.2024.100490`

Publisher: *SSRN (Preprint), April 2024*

Result: Achieved high-accuracy (94.6%) real-time crop disease identification by deploying optimized CNN models on Arduino BLE 33 Sense, validating feasibility of TinyML-based field diagnosis with fast inference and minimal resources.

Relevant Features & Insights:

- Direct comparison of Edge Impulse and TensorFlow Lite for TinyML, with Edge Impulse offering better usability and memory, TensorFlow higher accuracy.
- Large image dataset, rapid 7.6ms inference on microcontrollers.
- Demands no cloud or high-power resources—enabling rich, offline field use, especially in resource-limited areas.

Title:	**TinyML for the Detection of Plant Diseases in Resource-Constrained Areas within West Africa**
Authors:	Chinwe Ibegbu and G. Ayorkor Korsah
DOI:	`10.1109/ICAST61769.2024.10856464`
Publisher:	*IEEE 9th International Conference on Adaptive Science and Technology (ICAST), 2024*
Result:	Developed and field-tested a TinyML-based plant disease detection system for rural West African farmers, enabling offline, low-cost inference. While slightly less accurate than cloud solutions, it outperformed them in accessibility and usability within local constraints.

Relevant Features & Insights:

- Used ESP32-CAM, Edge Impulse, and a Cassava leaf image dataset for on-device ML.
- Compared TinyML system against Plantix cloud app and human experts; recommended cloud-trained/offline-inferred hybrid for best balance.
- Addressed cost, internet inaccessibility, language, user experience, and dataset sourcing—key for real-world adoption in Ghana and similar contexts.

Item	Count	Price Per Item	Total Price
Plywood 4x6ft 9mm	1	1190	1190
Wood Glue / Fasteners / Nails			418
Waterproof Plywood Coating	1	350	350
2x4ft 5mm Foam Board	7	250	1750
2x4ft 3mm Foam Board	1	180	180
Flex Kwik	6	55	330
Limit Switch	22	12	264
12V DC Fan	8	65	520
Peltier Module	2	271	542
Peltier Cooling System	2	400	800
Humidifier	1	300	300
Ultrasonic Sensors	2	59	118
Grow Light 5V Strip	1	1263	1263
CO2 Sensor	1	2708	2708

Budget: EMCU

Item	Count	Price Per Item	Total Price
400W Power Supply	1	1505	1505
Buck Converters	4	58	116
Stepper Motor	2	102	204
Stepper Motor Driver	2	94	188
Timing Belt	2	92	184
Timing Belt Pully	2	125	250
Rail Roller	8	100	800
PETG Filament	1	999	999
Perf Board	1	80	80
Analog Mux	1	100	100
Wiring			500
Driving Circuits			500
Miscellaneous			1500
Total: EMCU			**17,659**

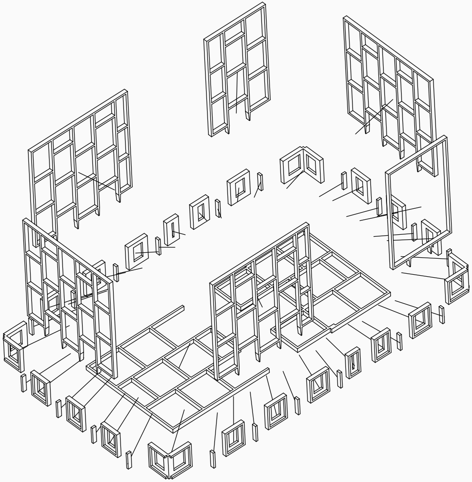
Budget: GMU

Item	Count	Price Per Item	Total Price
ESPCAM	1	750	750
ESPCAM Programmer	1	91	91
SD Card	1	480	480
17HS3401S NEMA17 Stepper Motor	2	544	1088
DRV8825 stepper driver module	2	94	188
GT2 6mm Belt Width 20 Teeth 5mm Bore Timing Pulley	2	42	84
Linear Rail	3	1504	4512
Limit switch	2	23	46
Belt tensioner	1	52	52
Rail mounting brackets	4	69	276
Total: GMU			**7,567**

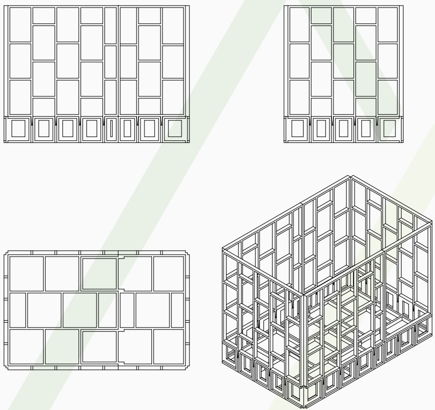
Total Estimated Budget: 25,226

Components Purchased in Phase One: EMCU and GMU

EMCU	GMU
Plywood 4x6ft 9mm.	ESP 32 CAM Module.
Wood Glue.	ESP 32 CAM Programmer.
Nails and Fasteners.	32 GB SD Card.

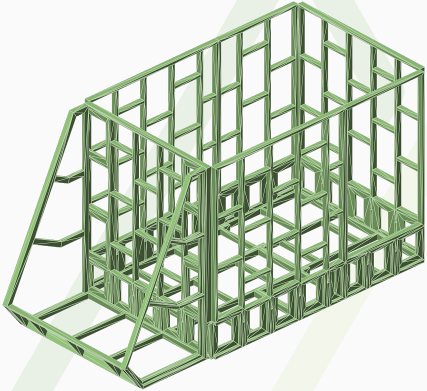


Exploded View of Incubator Frame



Side, Front, Top and Orthographic Views

Front and Back Bases Attached



Frame with Electronics Bay

Output Obtained: GMU - CNN Model Architecture

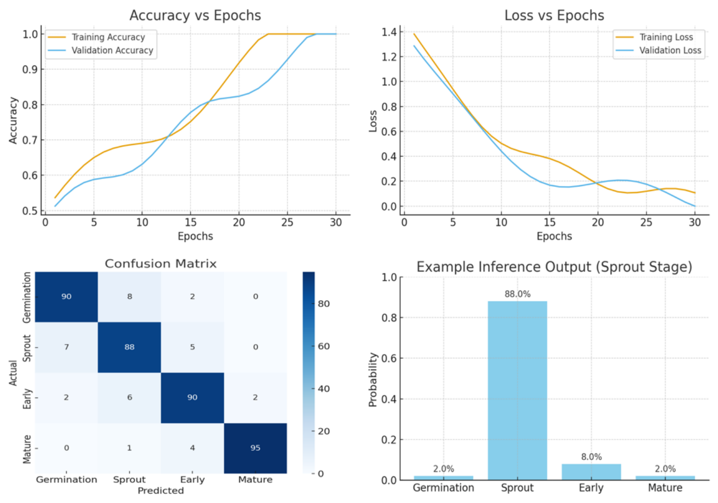
```
/usr/local/lib/python3.12/dist-packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning:
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model architecture:
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 62, 62, 16)	448
max_pooling2d (MaxPooling2D)	(None, 31, 31, 16)	0
conv2d_1 (Conv2D)	(None, 29, 29, 32)	4,640
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_2 (Conv2D)	(None, 12, 12, 64)	18,496
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 64)	0
flatten (Flatten)	(None, 2304)	0
dense (Dense)	(None, 128)	295,040
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 4)	516

```
 Total params: 319,140 (1.22 MB)
 Trainable params: 319,140 (1.22 MB)
 Non-trainable params: 0 (0.00 B)
/usr/local/lib/python3.12/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: Us
  self._warn_if_super_not_called()
```

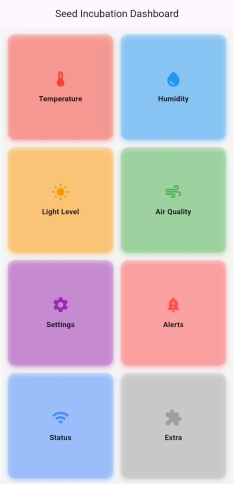
CNN Model Architecture

Output Obtained: GMU - Accuracy, Loss Graphs, and Confusion Matrix

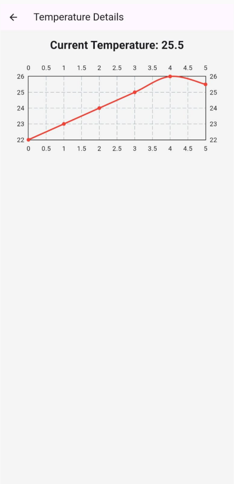


Accuracy, Loss Graphs, and Confusion Matrix

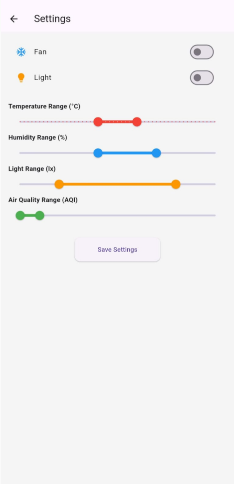
Output Obtained: SINC App UI



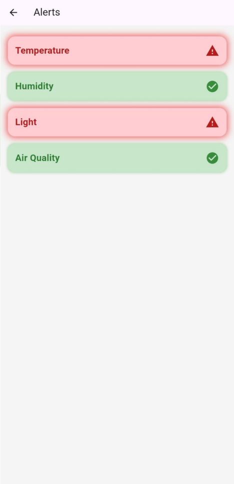
Home



Status



Settings



Alerts

Work Plan: Completion Status

Week 01 - 02	▪ Refined Enclosure design. ▪ Data collection for TinyML - Done. ▪ Purchased components for GMU: ESP32 CAM, SD Card, Programmer Board. ▪ SINC UI specification done, protocol specification in progress.
Week 03 - 04	▪ Reimplementation of Electronics Bay in progress. ▪ Completed frame designing. ▪ Started developing SINC App and GMU.
Week 05 - 06	▪ Purchased materials for outer frame: PlyWood, Glue, Fasteners. ▪ Completed Enclosure Front Base.
Week 07 - 08	▪ Completed Enclosure Back Base. ▪ App UI using Flutter is Done. ▪ Started Developing GMU Rail Mechanism.

[1] J. Seetaram1, A. Bhavya, C. Tarun, and V. Sameera, **"Internet of things (iot) based greenhouse monitoring and controlling system using esp-32,"** *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 13, pp. 29–35, 2024. DOI: `10.17148/IJARCCE.2024.13605`.

[2] A. Battikh et al., **"Greenhouse automation using esp32: A comprehensive study on monitoring and controlling environmental parameters for optimal plant growth,"** in *2nd International Engineering Conference on Electrical, Energy, and Artificial Intelligence (EICEEAI)*, 2023. DOI: `10.1109/EICEEAI60672.2023.10590110`.

[3] J. Mukherjee et al., **"Non plant specific smart greenhouse with convective drying unit,"** in *International Conference on Trends in Quantum Computing and Emerging Business Technologies (TQCEBT)*, 2024. DOI: `10.1109/TQCEBT59414.2024.10545221`.

[4] D. S. Kulkarni and S. Bhudhwale, **"Real-time environmental monitoring in smart agriculture using tinyml and machine learning,"** in *2024 International Conference on Intelligent Systems and Advanced Applications (ICISAA)*, 2024, pp. 1–6. DOI: `10.1109/ICISAA62385.2024.10829307`.

[5] C. Ibegbu and G. A. Korsah, **"Tinyml for the detection of plant diseases in resource-constrained areas within west africa,"** in *2024 IEEE 9th International Conference on Adaptive Science and Technology (ICAST)*, vol. 9, 2024, pp. 1–8. DOI: 10.1109/ICAST61769.2024.10856464.

[6] I. Ihoume, R. Tadili, N. Arbaoui, M. Benchrifa, A. Idrissi, and M. Daoudi, **"Developing a multi-label tinyml machine learning model for an active and optimized greenhouse microclimate control from multivariate sensed data,"** *Artificial Intelligence in Agriculture*, vol. 6, pp. 129–137, 2022, ISSN: 2589-7217. DOI: https://doi.org/10.1016/j.aiia.2022.08.003.

[7] Q. M. Nguyen, V. T. Le, M. N. Lai, and H. B. Vo, **"Resource-constrained intelligent trap: Fruit flies surveillance framework with tinyml integration,"** in *2024 Tenth International Conference on Communications and Electronics (ICCE)*, 2024, pp. 415–420. DOI: 10.1109/ICCE62051.2024.10634657.

[8] S. Chhorn, S. Tep, C. Hel, and R. Pec, **"Development of esp32-based smart greenhouse controller,"** in *2022 IEEE 8th World Forum on Internet of Things (WF-IoT)*, 2022, pp. 1–6. DOI: 10.1109/WF-IoT54382.2022.10152112.

[9] C. H. Hidalgo, A. González-Vidal, and A. F. Skarmeta, **"Edge computing in smart agriculture scenario based on tinyml for irrigation control,"** in *2023 IEEE 9th World Forum on Internet of Things (WF-IoT)*, 2023, pp. 01–08. DOI: `10.1109/WF-IoT58464.2023.10539452`.

[10] D. A. N. Gookyi et al., **"Tinyml for smart agriculture: Comparative analysis of tinyml platforms and practical deployment for maize leaf disease identification,"** *Smart Agricultural Technology*, vol. 8, p. 100 490, 2024, ISSN: 2772-3755. DOI: `https://doi.org/10.1016/j.atech.2024.100490`. [Online]. Available: `https://www.sciencedirect.com/science/article/pii/S2772375524000959`.

Thank You