Cost-Effective Cyber-Physical System Prototype for Precision Agriculture with a Focus on Crop Growth

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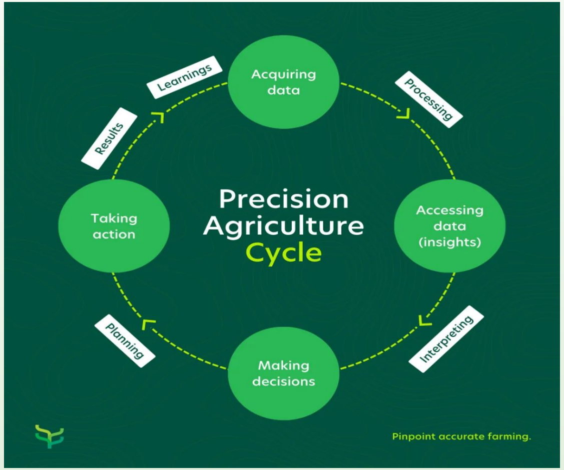
Motivation

To explore rapid prototyping for precision agriculture, which

- ➢ Helps farmers with guidance from machine intelligence,
- ➢ Enhances crop yield while reducing costs,
- ➢ Reduces resource waste,
- ➢ Minimizes destructive practices (killing plants) in farming, and
- ➢ Fosters sustainable practices in farming.

Introduction

What is Precision Agriculture?



- ➢ Leveraging data-driven machine intelligence.
- ➢ For more productive, sustainable farming.

https://www.farm21.com/wp-content/uploads/2022/08/blog-posts-images-3-1024x1024.png.webp
https://humphreymalone.com/wp-content/uploads/2024/01/A-modern-farm-showcasing-precision-agriculture-technology.-The-scene-includes-high-tech-tractors-with-GPS-systems-drones-flying-overhead-surveying-th.webp
https://www.bearingtips.com/wp-content/uploads/2021/06/SMB320-Agricultural-drone.jpg

Introduction

What is plant biomass?

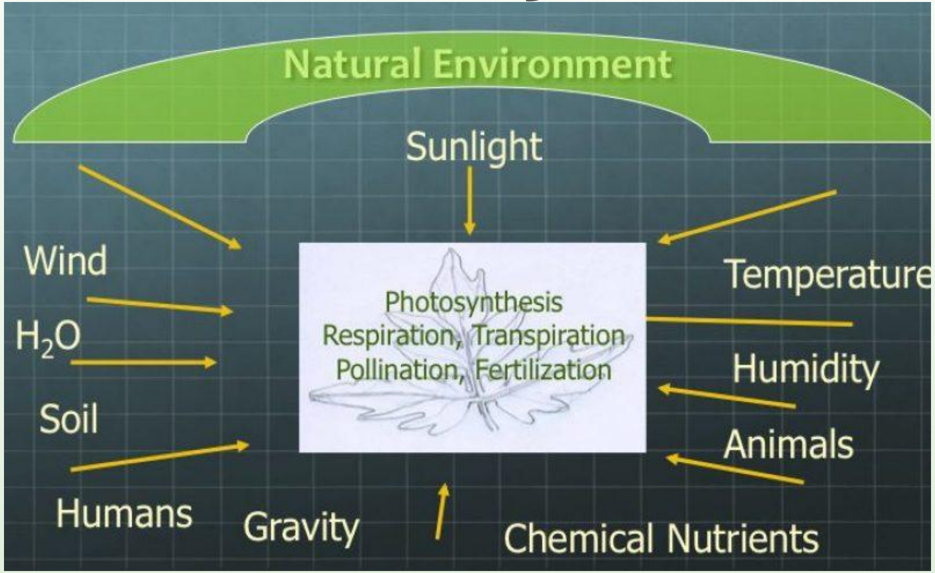
- Biomass is directly related to crop yield.
- **Total mass of living plant material in a given area or volume.**
- Indicator of Ecosystem Productivity.
- Acts as a significant carbon sink.

AI generated images

Introduction

Environmental Factors Affecting Plant Growth

Hydroponic System



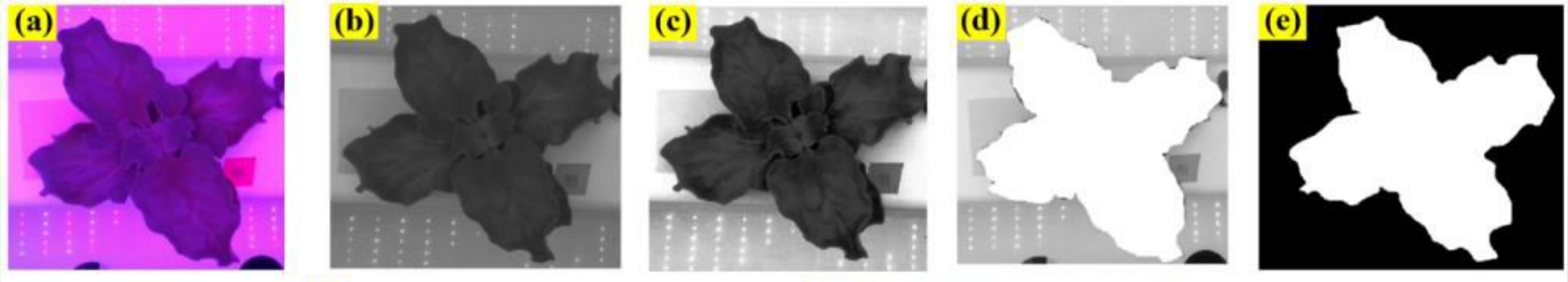
Factors affecting plant growth

https://i0.wp.com/compot.com.au/wp-content/uploads/sites/2/2021/09/environmental-effects-on-plants.jpg?resize=841%2C475

AI generated images

Related Work 1: Non Destructive methods of estimating plant growth via leaf area (by Islam *et al.*)

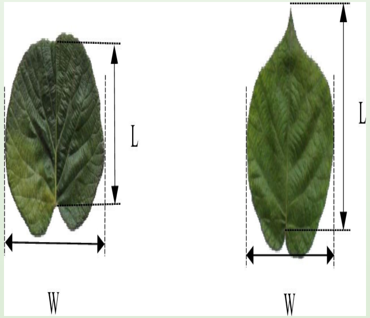
Image acquisition → Image transformation → Histogram equalization → Binary masking of the leaf area → Image segmentation → Calculate pixel → Calculate leaf area

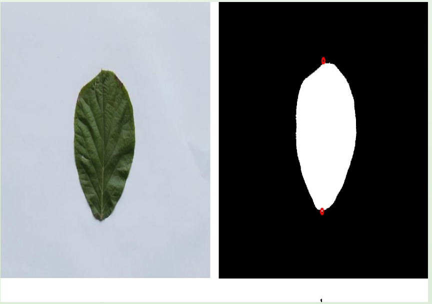


Islam, S, M N Reza, M Chowdhury, M N Islam, M Ali, S Kiraga, and S O Chung. 2021. "Image processing algorithm to estimate ice-plant leaf area from RGB images under different light conditions." IOP Conference Series: Earth and Environmental Science 924 (1): 12013. https://doi.org/10.1088/1755-1315/924/1/012013.

Related Work 2: Method of estimating plant growth via leaf width/length (by Zhang)

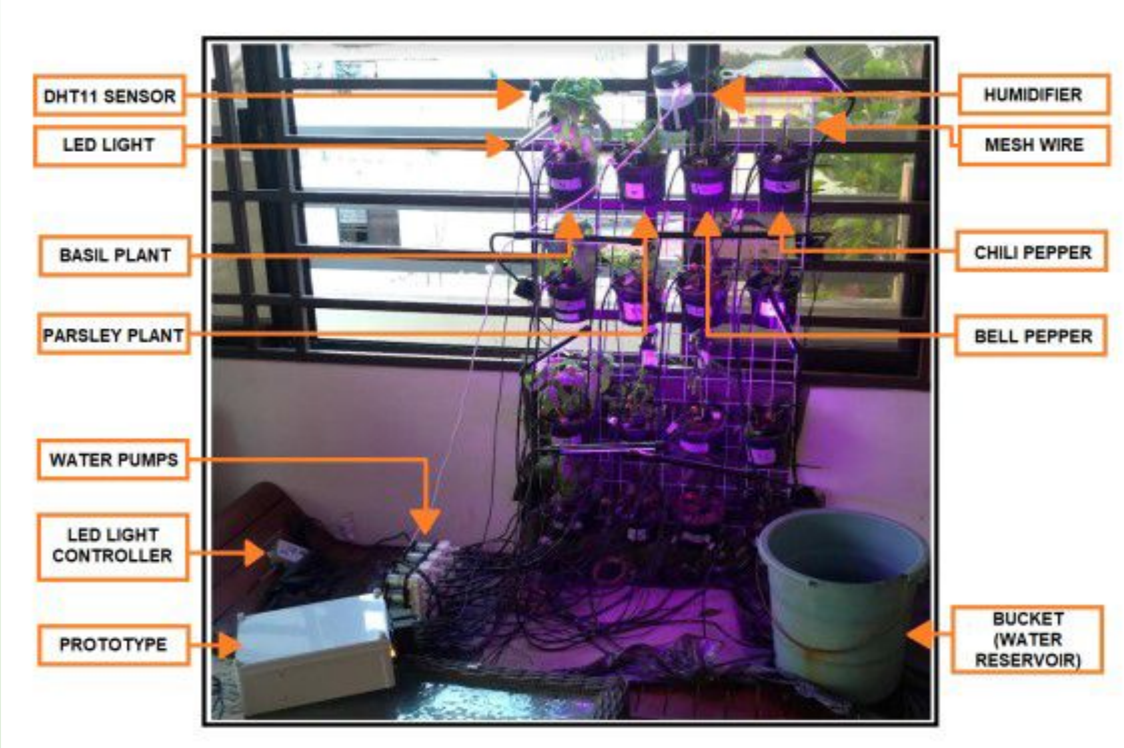
1. Input RGB Images
2. Split color component into R,G and B
3. Remove noise from B channel
4. Image segmentation
5. Image distortion correction
6. Removing the unwanted background
7. Foreground color change to white
8. Skew correction
9. Locating the leaf tip and petiole insertion
10. Calculating leaf length and width





Zhang, Wanhong. 2020. "Digital image processing method for estimating leaf length and width tested using kiwifruit leaves (Actinidia chinensis Planch)." PLOS ONE 15 (7): 1–14. https://doi.org/10.1371/journal.pone.0235499.

Related Work 3: Monitor crop development (by Kagalingan *et al.*)



Kagalingan, Ruby Jon M, Bernard Piolo M Tolentino, and Jessie Jaye R Balbin. 2022. "Aiding Plant Growth Difference for Indoor Vertical Garden against Traditional Outdoor Vertical Garden Setup using DHT11 and Capacitive Soil Moisture Sensor," 96–101. https://doi.org/10.1109/I2CACIS54679.2022.9815472.

Related Work 4: Precision Agriculture through Cyber-Physical Systems (by Castillejo et al.)

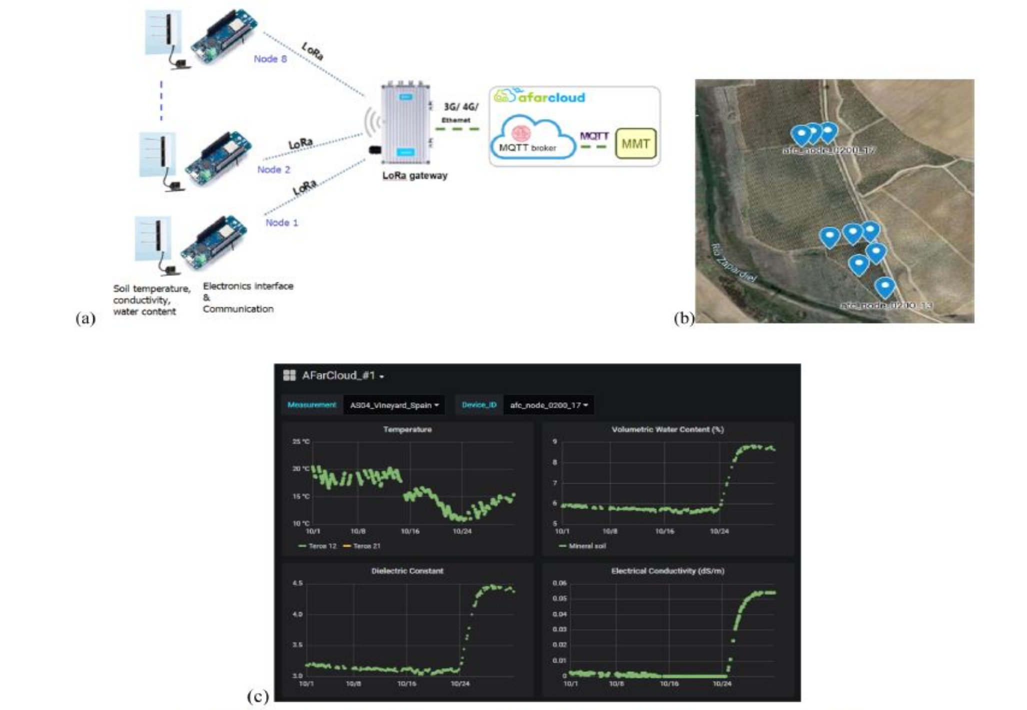


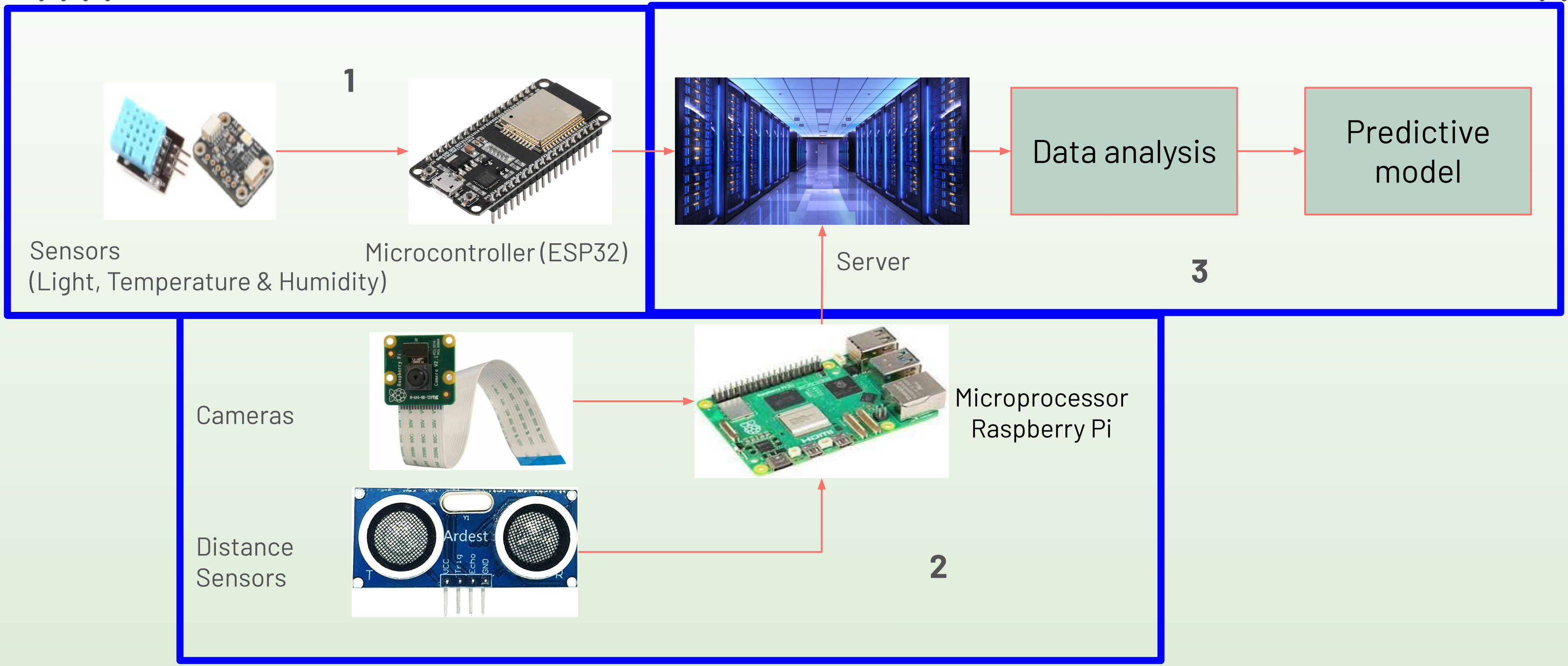
Fig. 9. (a) Example of soil sensors network deployed in the first year; (b) and (c) Real-time locations and measurements.

Castillejo, Pedro, Gorm Johansen, Baran Cürüklü, Sonia Bilbao-Arechabala, Roberto Fresco, Belén Martínez-Rodríguez, Luigi Pomante, et al. 2020. "Aggregate Farming in the Cloud: The AFarCloud ECSEL project." Microprocessors and Microsystems 78 (October): 103218. https://doi.org/10.1016/J.MICPRO.2020.103218.

Summary of Related Work

Paper	Existing work	Takeaways
Islam *et al.*, 2021	Image processing of ice-plant leaf to get its area	Similar image processing to get area of leaf.
Zhang, Wanhong. 2020	Image processing to identify leaf width and length	Similar image processing to identify the leaf in the image.
Kagalingan *et al.*, 2020	Compare indoor and outdoor vertical garden automated system using plant height and average leaf area	Measure environmental data using similar sensors
Castillejo *et al.*, 2020	Created a CPS in which microcontroller collects data and it is sent to cloud via MQTT	Created a CPS which collects data from the microcontroller and microprocessor.

Proposed Prototype Overview



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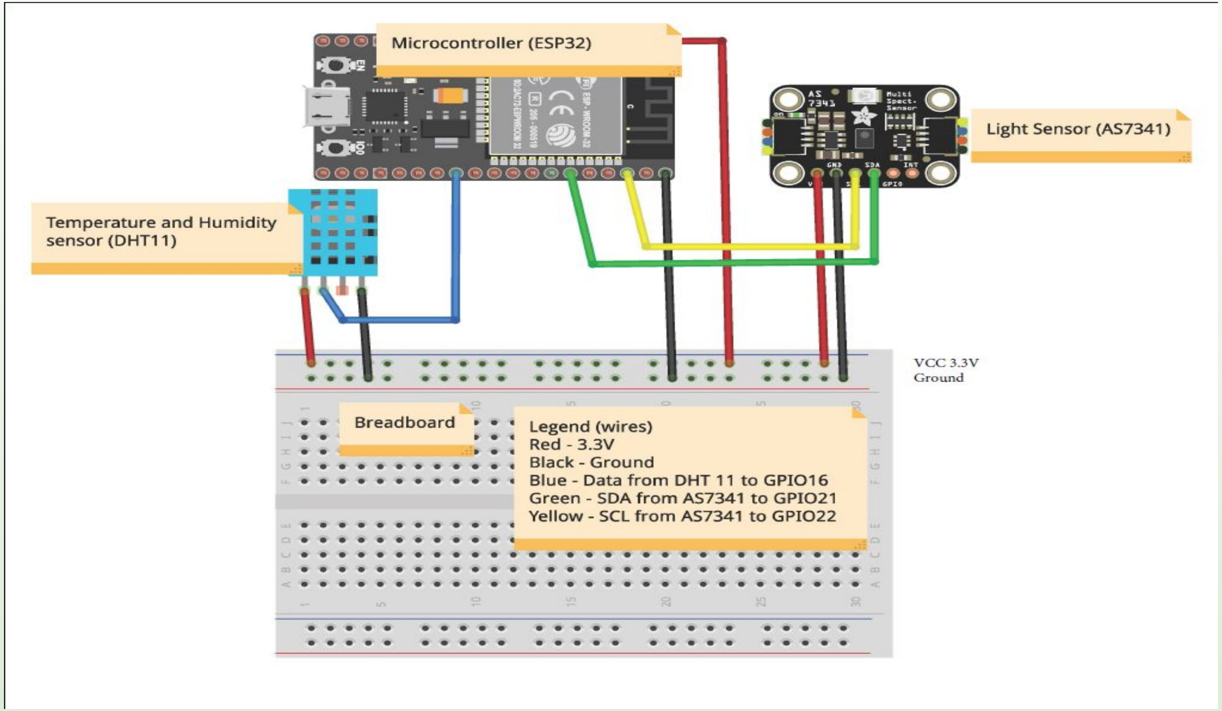
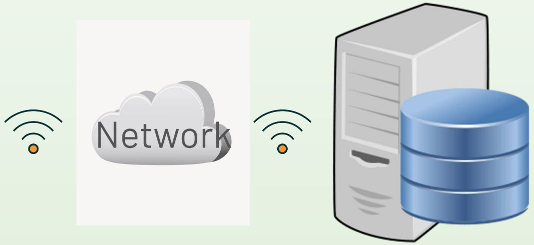
CPS HW Component Design



- Measure environmental data.
- Send data to server via TCP

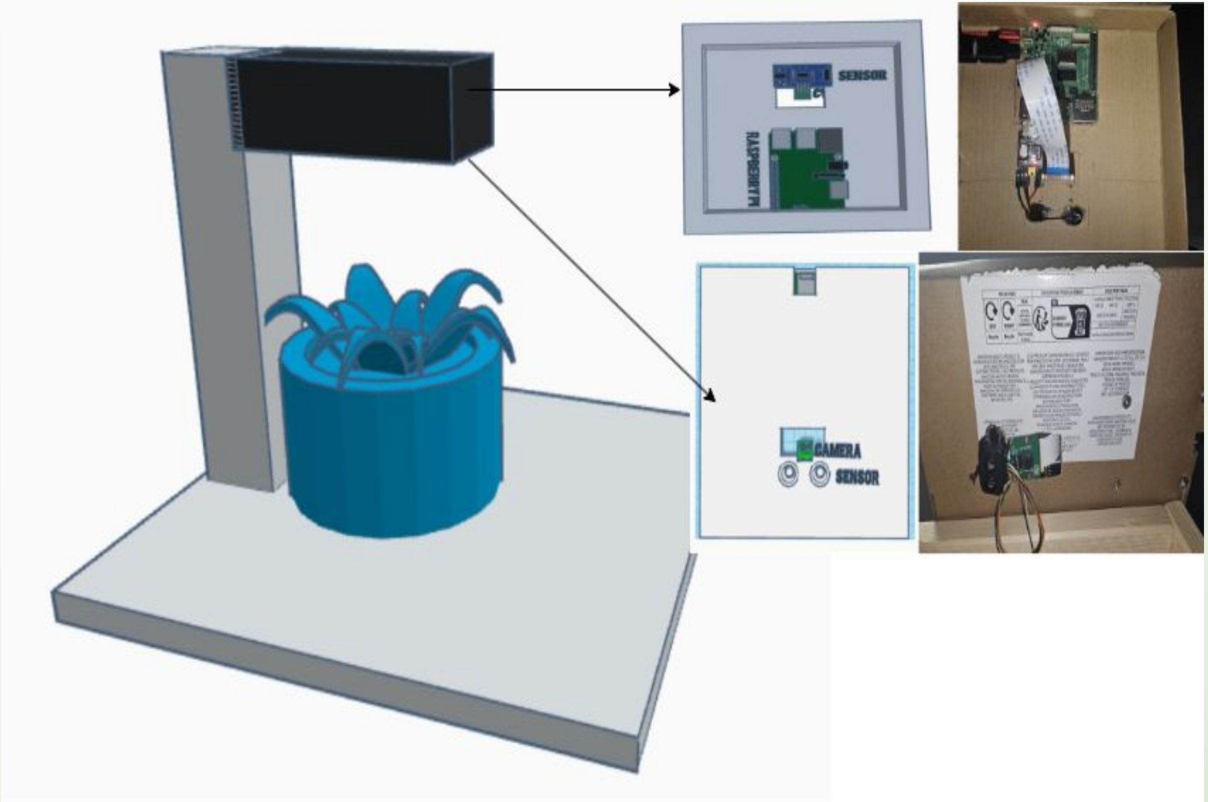


Environmental Factors Dataset

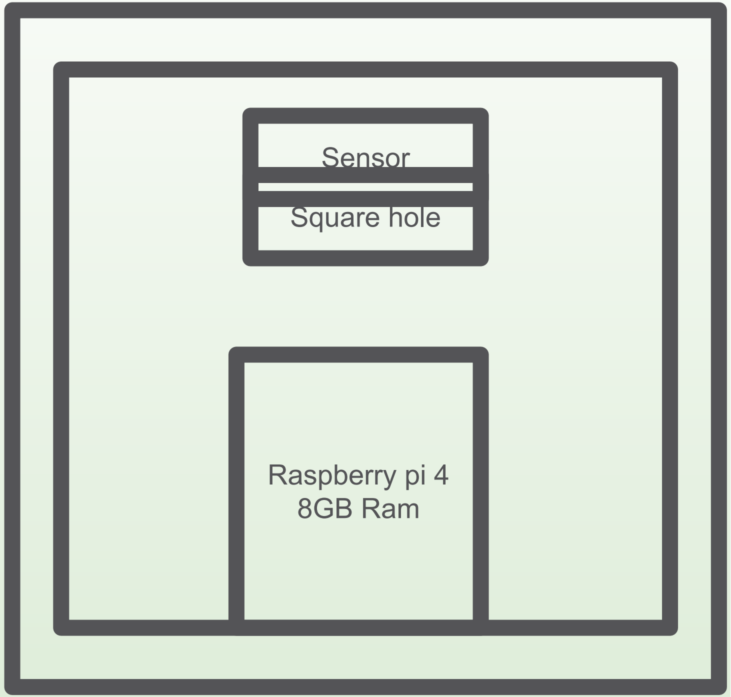
	DHT11		Light Sensor (AS7341)									
Date and time	Temperature(C)	Humidity	f1(430nm)	f2(460nm)	f3(495nm)	f4(530nm)	f5(570nm)	f6(605nm)	f7(645nm)	f8(695nm)	clear	IR (910nm)
3/21/2024 20:50	27	21	61562	65535	65535	65535	65535	65535	65535	65535	65535	65535
3/21/2024 21:50	27	21	61630	65535	65535	65535	65535	65535	65535	65535	65535	65535
3/21/2024 22:50	27	22	0	0	0	1	0	0	0	0	6	0
3/21/2024 23:50	25	23	0	0	0	0	1	0	0	0	7	0
3/22/2024 0:50	24	23	0	0	0	0	0	0	0	0	6	0
3/22/2024 1:50	24	23	0	0	0	0	0	0	0	0	7	0
3/22/2024 2:50	24	23	0	0	0	1	1	0	0	0	7	0
3/22/2024 3:50	24	23	0	0	0	0	0	0	0	0	5	0
3/22/2024 4:50	24	23	0	0	0	0	0	0	0	0	6	0
3/22/2024 5:50	24	23	0	0	0	1	0	0	0	0	6	0
3/22/2024 6:50	24	23	61681	65535	65535	65535	65535	65535	65535	65535	65535	65535
3/22/2024 7:50	26	22	61515	65535	65535	65535	65535	65535	65535	65535	65535	65535

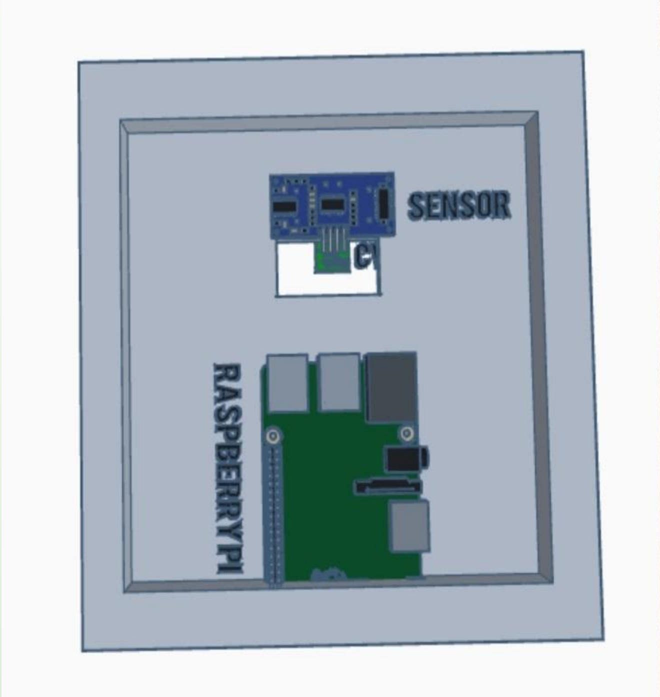
- Collected data for more than 1100 rows
- Data collected for every hour
- Sum all data from the light sensor during feature engineering into a new data

Area Measurement Setup

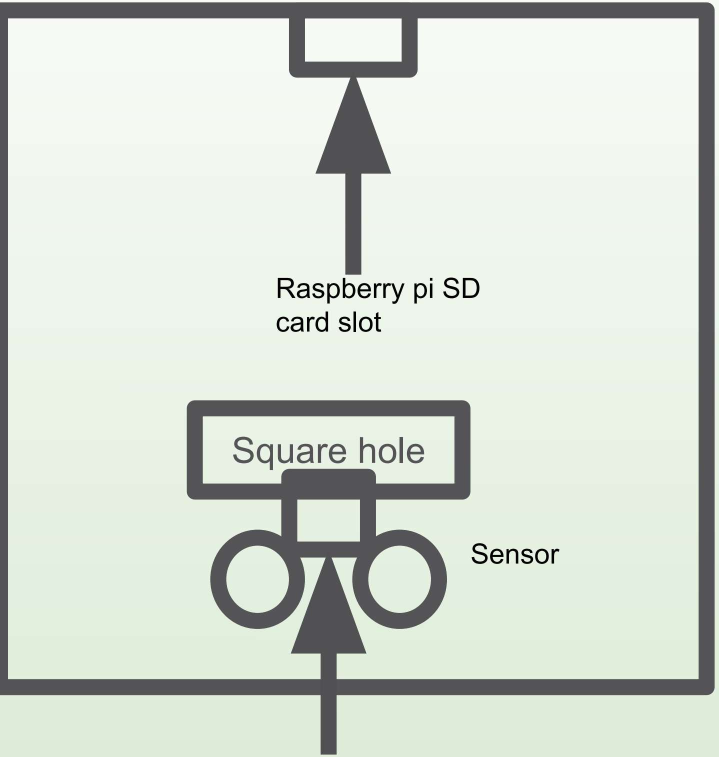


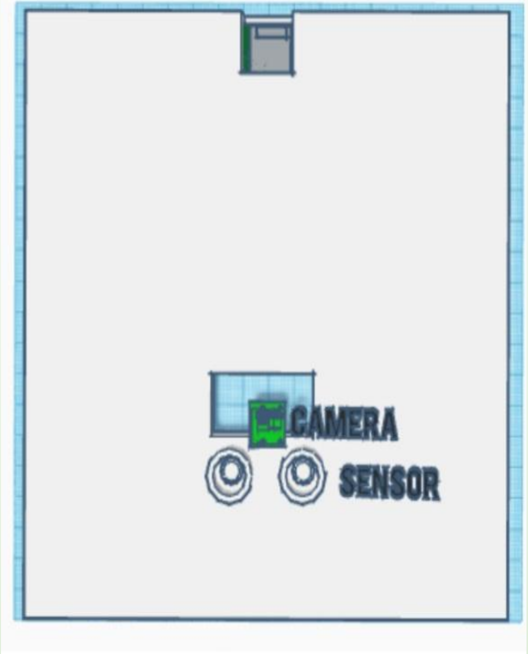
Top View of Setup





Bottom View of Setup





- Camera and distance sensor placed close to each other to reduce angle errors

Image Processing for Leaf Area Measurement

Start

Capture and Process Image

Isolate Target Area with Color Thresholding

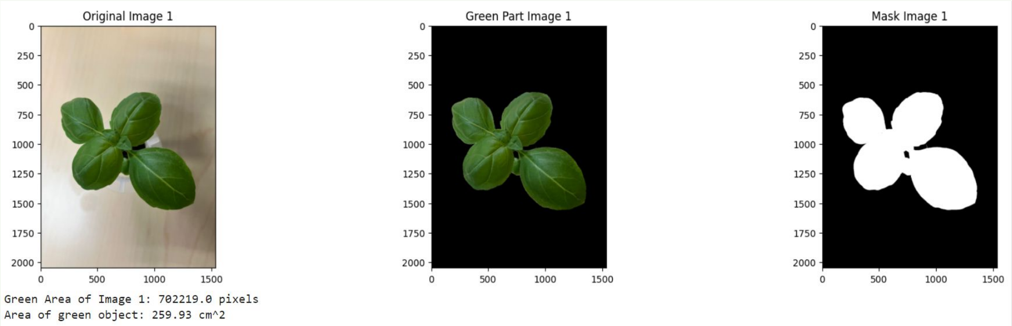
Mask the image

Determine Leaf Area in Pixels

Convert leaf area from pixels to square centimeters

Send Data

End



Leaf Area Measurement

Date and Time	Plant	Distance(cm)	Area(cm^2)
3/25/2024 15:09	B1	20	38.74
3/25/2024 15:09	B1	20	38.36
3/25/2024 15:09	B1	19	38.79
3/25/2024 15:10	B1	19	38.42
3/25/2024 15:10	B1	20	38.45
3/25/2024 15:11	B2	17	77.7
3/25/2024 15:11	B2	17	76.51
3/25/2024 15:11	B2	17	75.86
3/25/2024 15:11	B2	18	79.68
3/25/2024 15:12	B2	18	77.8
3/25/2024 15:12	B3	23	22.62
3/25/2024 15:13	B3	23	22.15
3/25/2024 15:13	B3	23	22.49
3/25/2024 15:13	B3	23	22.51
3/25/2024 15:13	B3	23	22.43

Leaf Area Measurement

Plant far from camera

Plant close to camera

- $\text{base\_ratio} = \dfrac{\text{reference\_object\_pixel\_area}}{\text{reference\_object\_real\_area\_cm}^2}$
- $\text{distance\_adjusted\_ratio} = \text{base\_ratio} * \left(\dfrac{\text{current\_distance}}{\text{reference\_distance}}\right)^2$
- The width and height of the object scale linearly with distance, therefore we square the distance ratio
- Take average of each plant area during preprocessing.

Plant Weight Dataset

Date	Plant	Measured weight(g)	Actual weight(g)
3/25/2024	B1	336.4	236.4
3/25/2024	B2	336.4	236.4
3/25/2024	B3	326.7	226.7
3/26/2024	B1	338.1	238.1
3/26/2024	B2	347.7	247.7
3/26/2024	B3	330.9	230.9
3/27/2024	B1	345.2	245.2
3/27/2024	B2	358.5	258.5
3/27/2024	B3	333.8	233.8

Manual Measurement Plant Weights

Measurement of Weight Using Digital Scale

- Actual weight is Measured weight - (Sponge+basket) weight.
- (Sponge+basket) weight was measured to be 100g on average.

Leaf Area Measurement Setup Evaluation

Ultrasonic ($4.5)

Object	Average of measured area (Cm^2)	Actual Area	% error
2x2 cube	25.63	25	2.46
Leaf 1	2.222	3.42	53.89
Leaf 2	10.34	15.78	52.65
Leaf 3	14.882	18.98	27.55
Leaf 4	4.458	7.85	76.09

TF Luna ($25.98)

Object	Average of measured area (Cm2)	Actual Area	% error
2x2 cube	24.504	25	2.02
Leaf 1	3.048	3.42	12.19
Leaf 2	14.714	15.78	7.27
Leaf 3	20.158	18.98	5.84
Leaf 4	9.53	7.85	17.63

- TF-Luna showed a 58.46% reduction in % error.
- Actual Area is measured by the area of ellipse formula $\pi * \left\langle \frac{L}{2} \right\rangle * \left(\frac{w}{2} \right)$.

Cost Evaluation

Equipment	**Cost per Unit (USD)**
Garden cube & seeds of plant	42.56
Raspberry pi 4 8GB	74.68
ESP32 DEVBOARD-J	8.99
TF-Luna (LIDAR sensor)	25.98
AS7341 (Light sensor)	15.95
DHT11	2.23
Raspberry pi camera V2	14.99
Wires	6.98
USB-C cable	9.99
Total	**202.35**

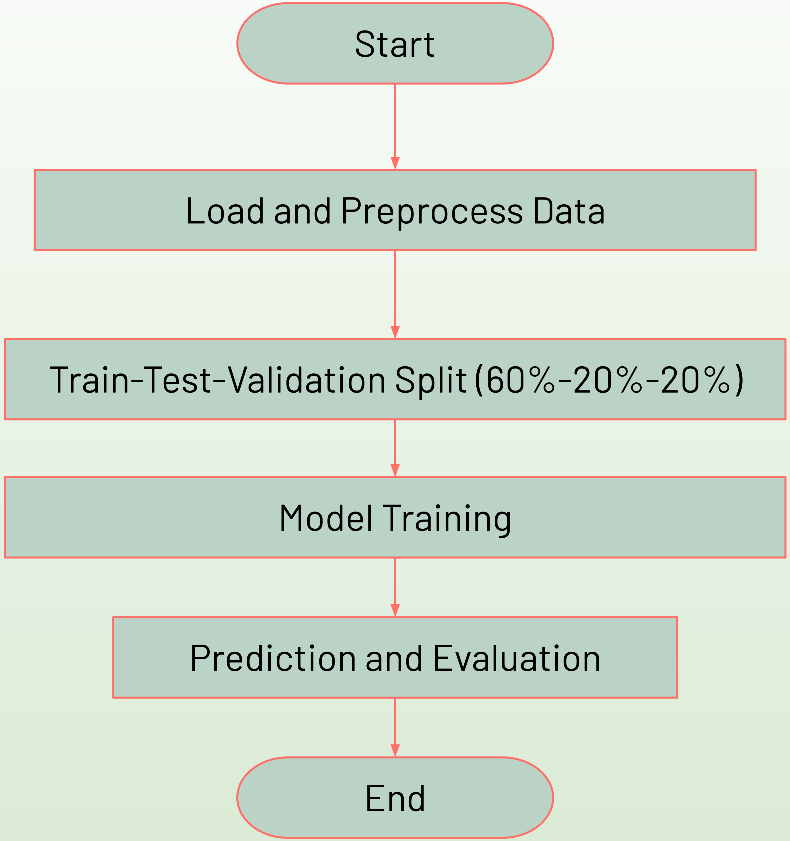
Equipment	Cost per Unit (USD)
Raspberry Pi Camera Module 3D (DIY Setup)	**139**

Equipment	Cost per Unit (USD)
ASTRA PRO PLUS	**149.99**

Equipment	Cost per Unit (USD)
Tf-Luna	25.98
Raspberry pi camera V2	14.99
Total	**40.97**

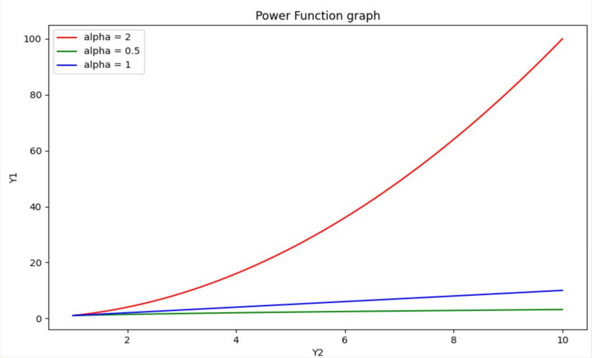
- Compared to employing a depth camera, the cost of my equipment is 70.5% less.

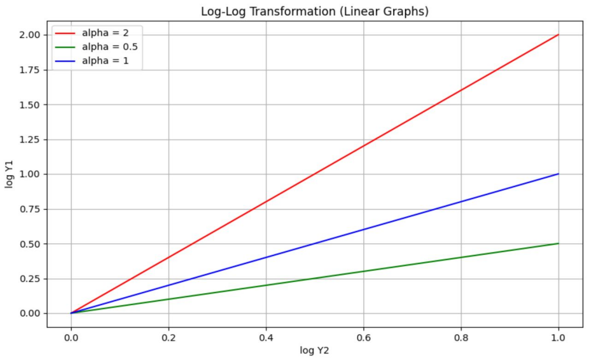
Flowchart of Prediction model



Why Linear Regression?

$Y_1 = \beta Y_2^{\alpha}$ (Power Function Equation) $\log Y_1 = \log \beta + \alpha \log Y_2$





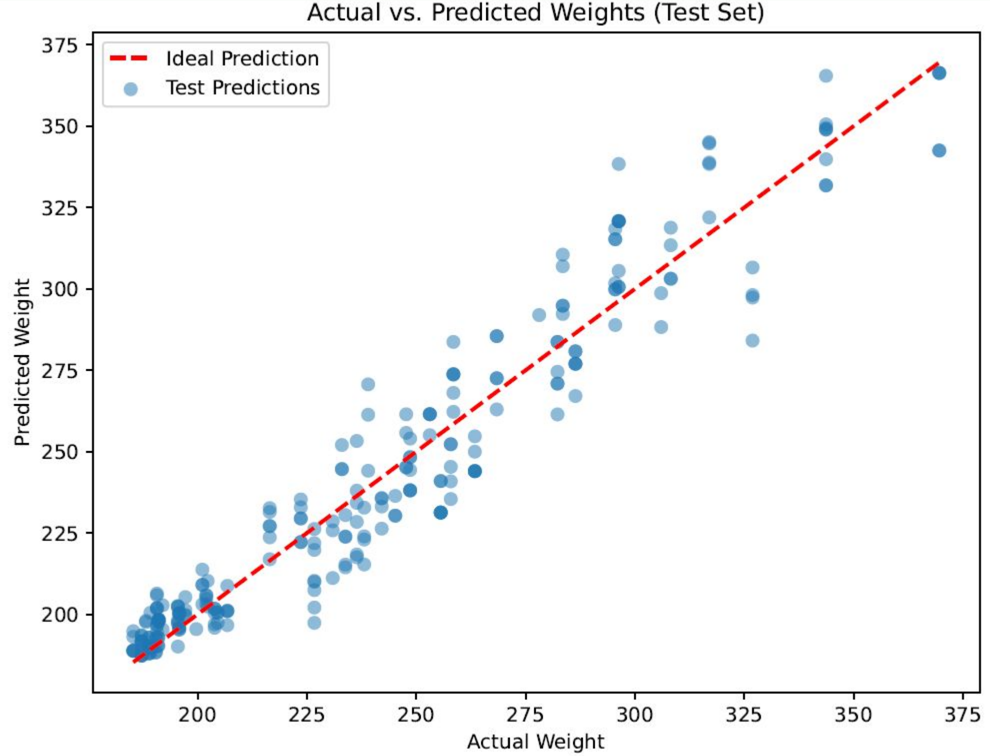
- Y_1 : Variable of particular interest.
- Y_2: Variable measuring size.
- α and β: Parameters describing the functional relation between Y_1 and Y_2.

- Log transformation can simplify complex relationships between variables in plants.
- Linear regression gives statistical significance of the parameters.
- On log-transformed data can help account for this variability.
- Bayesian linear regression offers a probabilistic framework that can effectively handle uncertainties in the data.

Niklas J., Karl. 1994. Plant Allometry: The Scaling of Form and Process. Chicago: University of Chicago Press.

Linear regression of plant growth stages

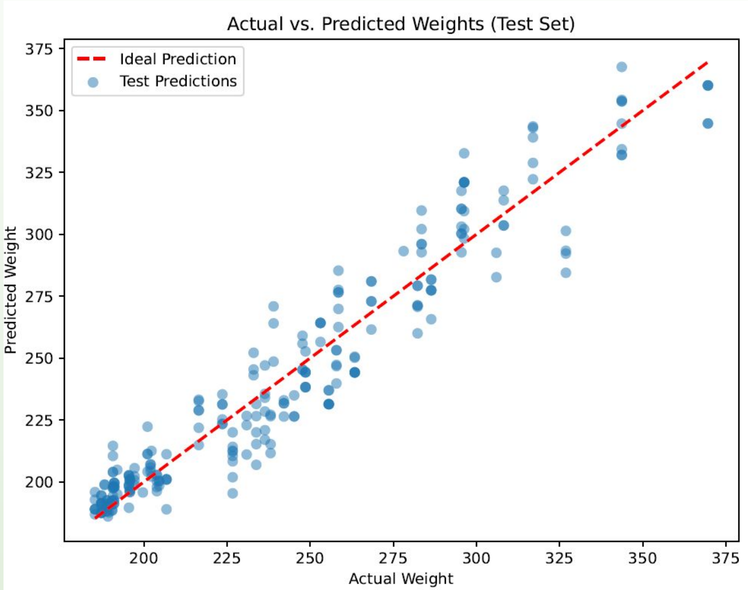
	Mean Squared Error (MSE)	R-squared values
Validation	171.37	0.906
Test	156.12	0.93



Bayes Linear regression of plant growth stages

Linear Regression	Mean Squared Error (MSE)	R-squared values
Validation	171.37	0.906
Test	156.12	0.93

Bayes Linear Regression	Mean Squared Error (MSE)	R-squared values
Validation	185.61	0.899
Test	169.90	0.924



- Linear regression has better accuracy due to lower MSE
- Linear regression and bayes linear regression have similar variance in the data
- Linear regression did a better than bayes linear regression.

Discussion on Applicability

- ➢ Can be adapted to manage and optimize vertical farming, aeroponic, aquaponic systems and outdoor plants. [1]
- ➢ Can be applied to monitor and adjust conditions in storage environments by controlling temperature, humidity, and ethylene concentrations. [2]
- ➢ Can be trained in identifying plant illnesses, which are typically visible in the leaves of the plant. [3]

[1] Yanes, A. R., Martinez, P., & Ahmad, R. (2020). Towards automated aquaponics: A review on monitoring, IoT, and smart systems. Journal of Cleaner Production, 263, 121571. https://doi.org/10.1016/j.jclepro.2020.121571

[2] Yanghui Ou, Xifu Wang, Jingyun Liu; Warehouse multipoint temperature and humidity monitoring system design based on Kingview. AIP Conf. Proc. 28 April 2017; 1834 (1): 040009. https://doi.org/10.1063/1.4981605

[3] Aldakheel EA, Zakariah M and Alabdalall AH (2024) Detection and identification of plant leaf diseases using YOLOv4. Front. Plant Sci. 15:1355941. doi: 10.3389/fpls.2024.1355941

Conclusion

- ➢ Integrated CPS and advanced sensors for real-time plant growth and environmental monitoring in hydroponics.
- ➢ Highlighted the role of machine learning in enhancing CPS for hydroponics agriculture.
- ➢ Solutions adaptable to various hydroponic scales from home gardens to commercial farms.
- ➢ Cost-effective setup with high-precision components, enhancing practicality and accessibility in agriculture.

Future Work

- ➢ Incorporate Low-Cost Depth Camera.
- ➢ Expand Plant Variety Studied.
- ➢ Integrate Additional Environmental Sensors.
- ➢ Explore Various Growing Conditions.
- ➢ Develop Fully Automated System including Control.
- ➢ Work with Vivid Machines (Agricultural technology company) to facilitate prediction using a rover and drone.

Thank you

- I would like to thank, Deeksha Prahlad, Chanhee Lee, and Rishab Kashyap, for their support during the research, including NSF I/UCRC for Intelligent, Distributed, Embedded Applications and Systems (IDEAS) from NSF grant #2231620.
- Special thanks to Prof. Hokeun Kim for helping me during different phases of the research.