Annex Nr.3

Imaging Process Analysis, Crop Visual Assessment Methodology, Data-Driven / Attēlveidošanas procesa analīze, kultūraugu vizuālās novērtēšanas metodoloģija, datu vadīta pieeja.

Projekts Nr.22-00-A01612-000018

3D fotogrammetrijas pielietošana un energoefektivitāti veicinošu inovāciju ieviešana optimālāku vides apstākļu nodrošināšanai vertikālajā lauksaimniecībā / Application of 3D photogrammetry and implementation of energy efficiency-enhancing innovations to ensure optimal environmental conditions in vertical farming.

NACIONĀLAIS ATTĪSTĪBAS PLĀNS 2020

EIROPAS SAVIENĪBA
EIROPA INVESTĒ LAUKU APVIDOS
Eiropas Lauksaimniecības fonds lauku attīstībai

Atbalsta Zemkopības ministrija un Lauku atbalsta dienests

CONTENTS

SECTION 1 – BROCCOLI VERTICAL FARMING ENVIRONNEMENT

Chapter 1 – Original Project Description

Abstract:

Hydroponic agriculture has emerged as a sustainable and efficient alternative to traditional soil-based agriculture, addressing challenges related to water scarcity, space constraints and climate change. This paper discusses the integration of data collection, image processing and machine learning techniques to optimize hydroponic crop management to increase yield and resource efficiency.

Introduction:

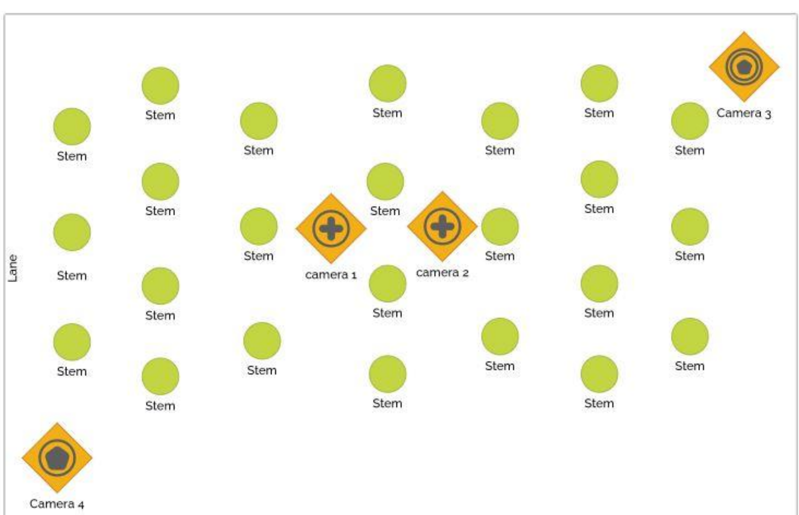
Hydroponic systems offer a controlled environment that promotes optimal plant growth. However, precise monitoring and adjustments are required to achieve these conditions. This study aims to harness the potential of data-driven methods to improve hydroponic farming practices.

Methodology:

The proposed technical methodology involves a multi-step process:

1. **Data collection:** Standardized cameras are strategically placed in the hydroponic environment to capture visual information. This continuous data flow forms the basis for further analysis. 3D photogrammetry monitoring will be provided using 4 cameras – 4K PoE camera, 8 MP, with 1080 viewing angle, EP 66 (moisture protection level), which will be installed at certain points above the system shelves, where plants will be grown (63 plants/m2). Two cameras will be positioned to obtain images from the top (camera 1 and 2), two cameras (camera 3 and 4) will be positioned in the far corners of the system shelf to obtain images from the side. Using such a camera arrangement, it is possible to obtain multi-dimensional visualizations for each plant. It is important that each plant is monitored from multiple angles to obtain objective results. Images will be taken 1 time per hour (total 4 images per 1 hour).

Schematic representation of the system shelf and camera location.



Schematic representation of data processes

Images will be automatically saved as JPG files, which will be converted into EXCEL format using the algorithm.

Information will be obtained on certain parameters for each individual plant, so information on the following parameters will be obtained 63 times per hour (number of plants on one system shelf):

- Height
- Density, width
- Color
- Spots
- Leaf thickness
- Plant surface

The obtained information in EXCEL format will be stored in the AZURE database, from which it will be further transferred to data processing software, where the information will be processed to obtain interpretable data on all determined parameters.

Using this software, average indicators will be obtained for all plants together. Information on all 63 plants will be compared to obtain average values. As well as information on each plant individually will be obtained. Thus, useful and easy-to-use information will be obtained to identify possible factors that promote or, conversely, inhibit plant growth and development.

2.Segmentation: The undistorted images are divided into blocks, each corresponding to a specific crop. This segmentation allows for targeted analysis of individual plants or groups.

3. Image processing: The captured images may be distorted due to camera angles. To eliminate this distortion and ensure accurate data representation, advanced image processing techniques, including camera calibration, are used. Several feature extraction techniques are intended to be applied to the expected data. In each segmented crop block, an array of corresponding features is extracted from the images:

- Green pixel density: An indicator of plant health and density, the density of green pixels reflects growth vigor and overall well-being.
- Abnormal color variations: Deviations from the expected color spectrum can indicate stress or disease, allowing for early detection and intervention.
- Stem width and crop height: When measured using images from sidewall cameras, these indicators provide insight into growth rates and plant development.

Advantages of the current methodology:

- Data analysis and interpretation: Using this software, averages of all plants will be obtained. Information from all 63 plants will be compared to obtain average values. Information about each plant will also be obtained individually. Thus, useful and easy-to-use information will be obtained to clarify possible factors that promote or, conversely, inhibit plant growth and development.
- The collected information forms a comprehensive data set that is the basis for analysis. Machine learning algorithms are used to identify patterns and correlations between environmental parameters (humidity, light, nutrients) and crop growth. These algorithms

generate predictive models that can recommend optimal growing conditions, allowing farmers to fine-tune the environment to increase yields.

- Adaptive environmental management: Real-time data collection and analysis enables an adaptive management approach. Automated systems regulate environmental factors such as humidity, nutrient supply and lighting, ensuring ing optimal conditions for plant growth. Early detection of anomalies prompts immediate action, minimizing potential yield losses.
- Scalability and efficiency: The data-driven approach seamlessly scales to larger systems, enabling a variety of setups, from urban vertical farms to large greenhouse facilities. Precise allocation of resources, including water and nutrients, provides significant efficiency gains, reduces waste, and conserves resources.
- Iterative improvement: The process is iterative, and the collected data improves machine learning models over time. Trends and patterns identified from the accumulated data provide long-term optimization strategies. Furthermore, the iterative process facilitates the development of crop varieties that are uniquely suited to the hydroponic environment.

Conclusion:

The integration of data collection, image processing, and machine learning in hydroponic farming offers a transformative path to higher yields, reduced resource waste, and improved sustainability. By automating the monitoring, analysis, and adaptive control of growing conditions, this approach has the potential to revolutionize modern agriculture and meet the growing global demand for food production. As hydroponic systems continue to evolve, data-driven methodologies will play a key role in shaping the future of sustainable agriculture.

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Chapter 2 – Technical setup

1 Camera setup

1.1 Material selection:

Veezoom PoE Camera - 4K IP Camera for Home Security, Outdoor Surveillance Cameras with Human/Vehicle/Detection, 100ft Night Vision, 2.8mm Lens, IP66 Weatherproof, MicroSD Recording.

This model was chosen for

- being able to work in difficult environment (high humidity)
- wide angle
- capability to process images at short distances
- high resolution

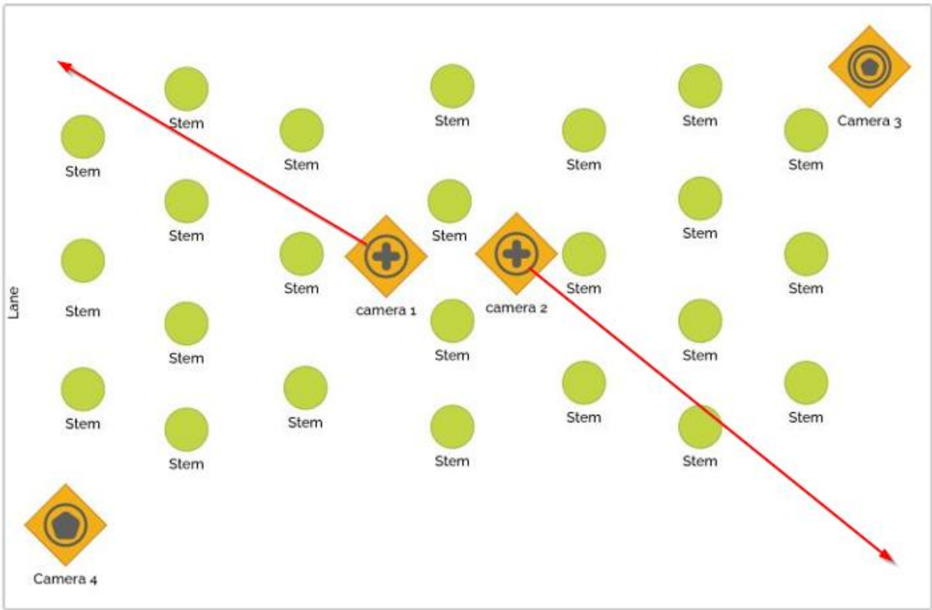
Indoor/Outdoor Usage	Outdoor
Compatible Devices	Smartphone
Power Source	Corded Electric
Connectivity Protocol	Ethernet
Controller Type	APP Controller
Mounting Type	Ceiling Mount
Video Capture Resolution	4k
Color	White
Number of Items	1
Number of Channels	1
Wireless Communication Technology	POE
Viewing Angle	100 Degrees
Installation Type	Surface-Mounted
Night Vision Range	100 Feet

Upper Temperature Rating	55 Degrees Celsius
Frame Rate	25 fps
Material	Mental
Voltage	12 Volts
Wattage	5.5 watts
Item dimensions L x W x H	6.5 x 4 x 3.5 inches
Batteries Required?	No
Item Weight	0.54 Kilograms
Shape	Bullet
Focus Type	Auto Focus
Low light technology	Night Color
Zoom Type	Digital Zoom
Alert Type	Audio and Motion

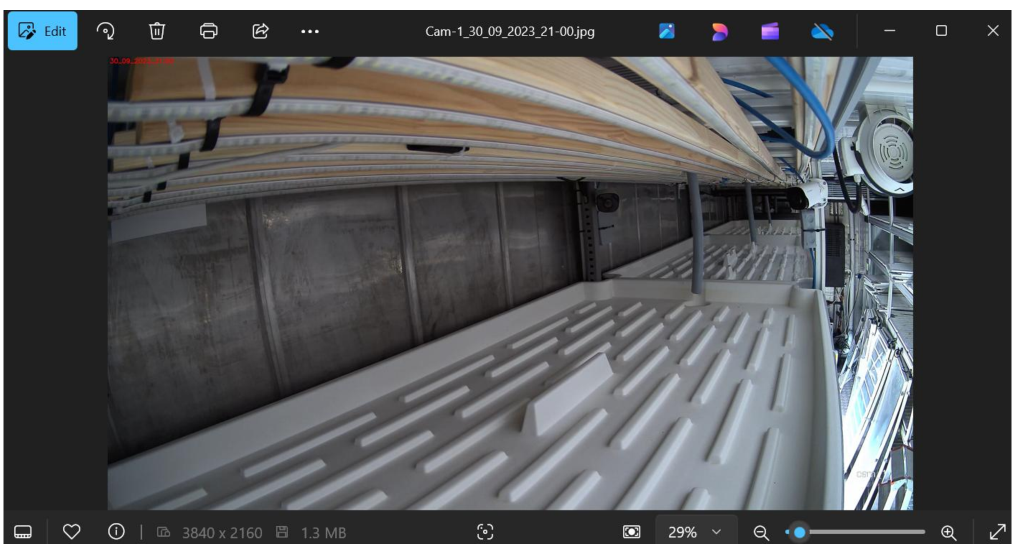
Light Source Type	Infrared/LED
Video Capture Format	MPEG-4
Specific Uses For Product	Ourdoor Use, Indoor Use
Unit Count	16.0 Ounce
Photo Sensor Technology	CMOS
Effective Still Resolution	8 MP
International Protection Rating	IP66
Maximum Webcam Image Resolution	5 MP
Control Method	Remote
Product Dimensions	6.5 x 4 x 3.5 inches
Item Weight	1.19 pounds
ASIN	B0B9FX4DRS
Item model number	WS-N180BS

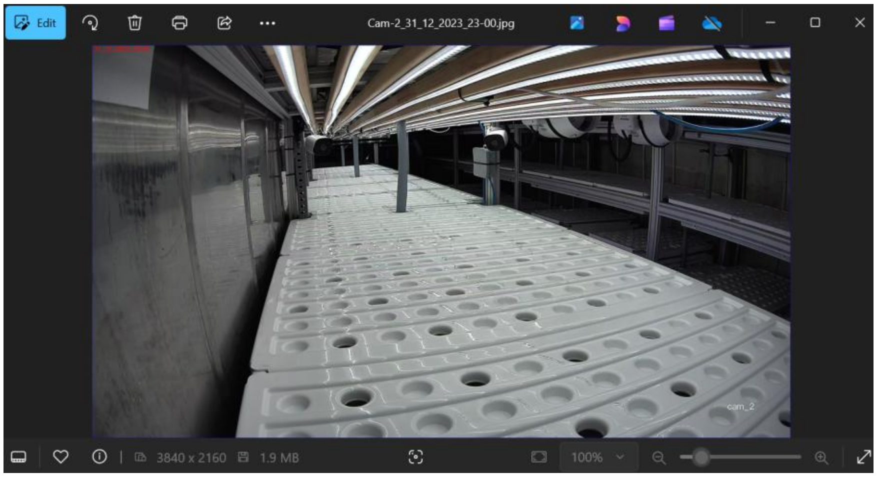
1.2 Camera setup

The original plan setting proved not to be efficient, the positioning of camera 1 and 2 was too close to the plants, did not show enough surface or were partially blocked by the LED lights if they were to be set higher. The team decided to process the images from the 4 corners.



Below images from the 4 cameras after installation




Edit
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cam_2
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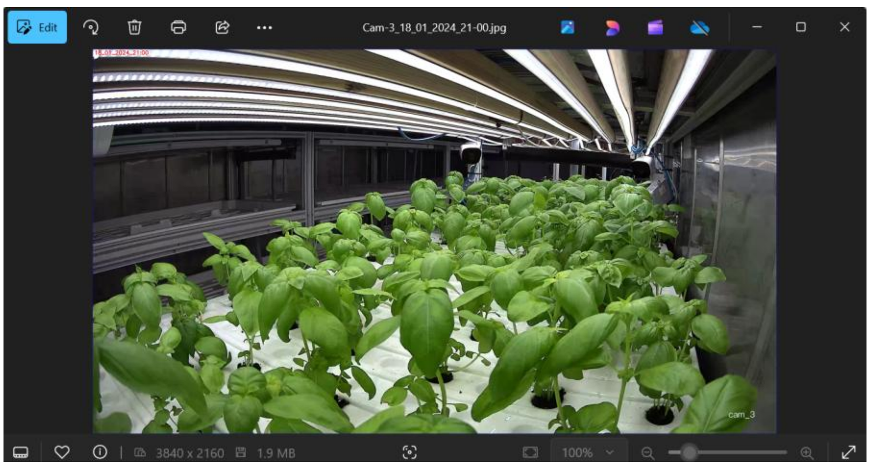
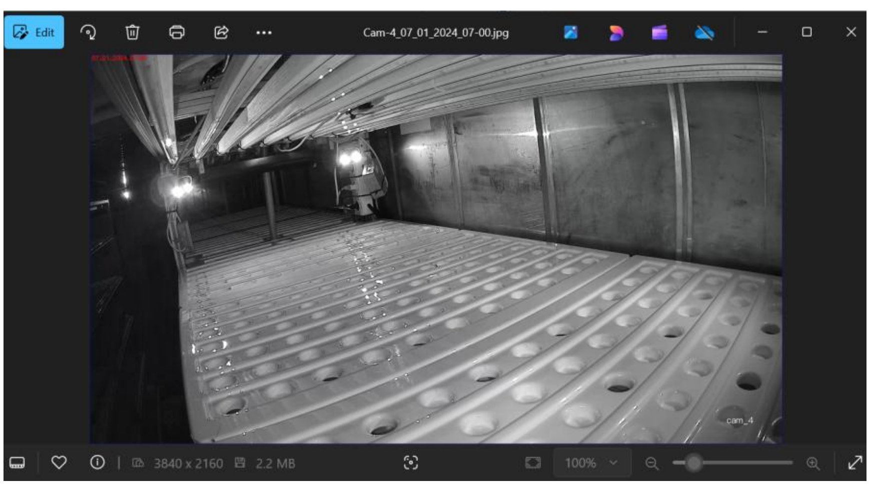
1.9 MB
100%


Edit
Cam-3_18_01_2024_21-00.jpg
cam_3
3840 x 2160
1.9 MB
100%


Edit
Cam-4_07_01_2024_07-00.jpg
cam_4
3840 x 2160
2.2 MB
100%

2. Crop meaningful data

The experiment grew basil mariam in the shelve over 12 meaningful growth with success.

Several factors have isolated some growth. The team has selected 8 growth cycle to be meaningful.

The isolated issues were:

- loss of internet connectivity leading to losses of pictures;
- hardware defects.

Chapter 3 – AI Process

1. Data Transformation:

Each image was processed to generate a corresponding JSON file.

Images were converted into numerical data, with variables such as dimensions (e.g., dimensions, frequencies, histograms, etc..) extracted for subsequent calculations.


```
 'image_path': '/content/Crop2_renamed/202310091600_Cam_4.jpg',
 'date': datetime.datetime(2023, 10, 9, 16, 0)},
{'height': 2160,
 'width': 3840,
 'pixel_count': 8294400,
```


The pixel position was derived from these dimensions, and histograms were generated to represent the distribution of pixel frequency intensity. This provides the number of pixel for each color, allowing to define a color map of each picture


```
'color_histogram': array([ 30775,  10259,   8767,   9620,  18360,  26116,  41869,  47155,
        54839,  44381,  36782,  30865,  31411,  30170,  26713,  26410,
        25821,  25630,  30227,  35853,  45821,  53816,  66030,  78180,
        90504, 115161, 135686, 170292, 199188, 213878, 222720, 229245,
       248639, 258935, 261646, 276292, 288906, 289587, 286704, 281334,
       270007, 265640, 269227, 270601, 262615, 250056, 248681, 255631,
       264771, 264194, 264627, 271436, 277398, 277667, 276700, 278178,
       275604, 269859, 261519, 256802, 253382, 247401, 234763, 223335,
       218036, 209252, 200702, 191492, 183968, 179340, 170422, 164045,
       159520, 154896, 147080, 142895, 140419, 142514, 142982, 142192,
       142957, 146768, 147735, 143816, 141493, 141028, 139640, 138609,
       136278, 135228, 131253, 130857, 130759, 129429, 130021, 131486,
       134310, 132688, 132623, 131614, 132661, 130296, 127965, 126013,
       122432, 118139, 113481, 113472, 108493, 107133, 109195, 106125,
       106671, 105381, 104365,  99205,  96177,  93233,  91255,  89836,
        87726,  85751,  84037,  82875,  80620,  78337,  77705,  74651,
        73769,  72556,  70935,  67335,  67662,  66804,  64802,  63878,
        63043,  60583,  60701,  59546,  58361,  56744,  57087,  57350,
        56181,  56179,  56210,  55861,  55043,  55259,  54277,  53458,
        53180,  52081,  51407,  50741,  50099,  50327,  50852,  50407,
        49560,  48149,  48709,  48039,  48550,  47746,  48072,  47219,
        46522,  45370,  44851,  44329,  44269,  43656,  44842,  43347,
        43208,  42231,  41975,  41832,  40482,  39714,  40524,  39775,
        39680,  40152,  39074,  39190,  38519,  38415,  36701,  37209,
        39113,  39156,  38317,  37277,  37120,  38137,  38113,  37681,
        37991,  36969,  34500,  33986,  34015,  32123,  31631,  31293,
        31320,  30350,  30284,  29655,  29032,  27967,  27765,  27275,
        26506,  26397,  27663,  27960,  27257,  27720,  27669,  27951,
```

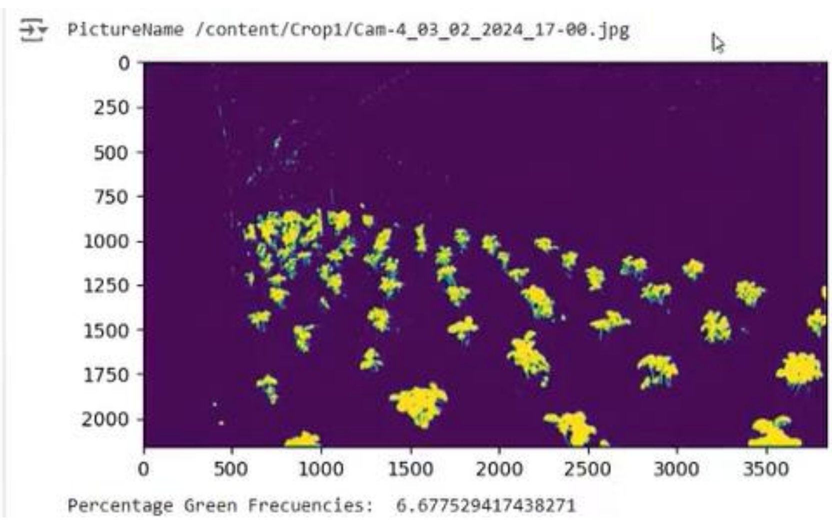
2. Mask Creation:

A mask was created using the crops color frequencies.

```
'edge_pixel_count': 288221,
'green_pixel_count': 0.6769868827160493,
'mask': array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       ...,
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]], dtype=uint8),
'image_path': '/content/Crop2_renamed/202310091900_Cam_4.jpg',
```

Pixels were classified as either within the target spectrum (value = 1) or outside (value = 0). The mask decides what pixel should be selected and which one should not be taken into account.

The masking process effectively isolated the desired crop from its background, leading to a clear identification of each picture, from what is crop and what is not.

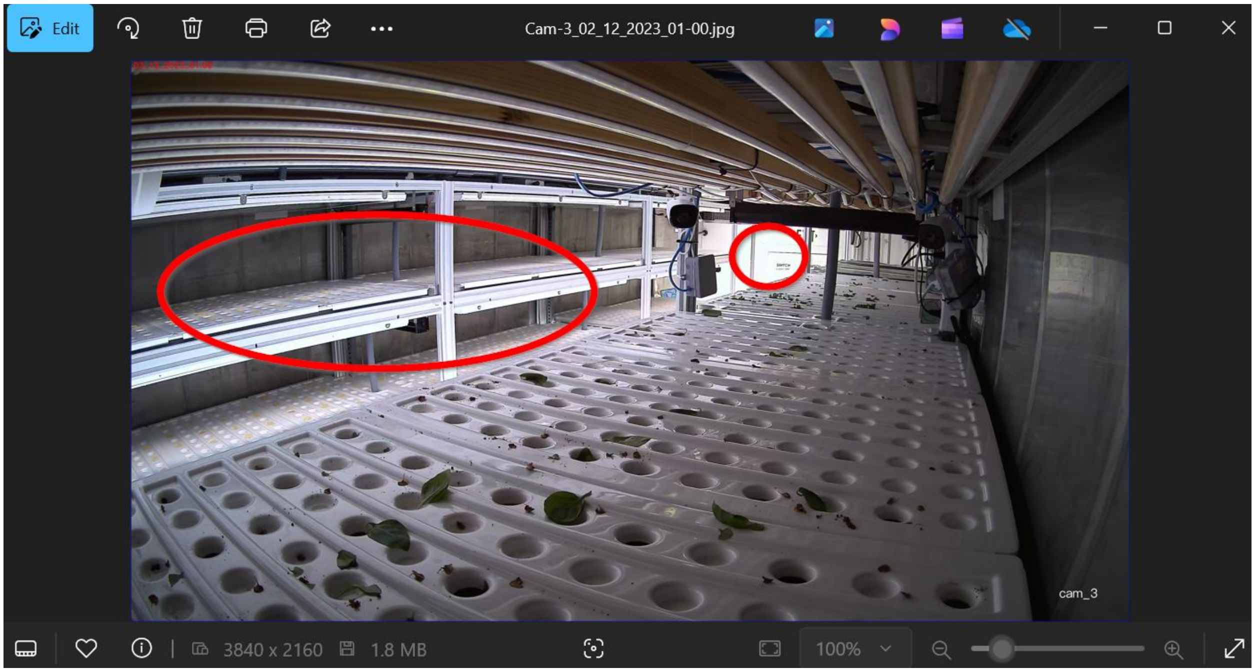


3. Challenges and Refinements:

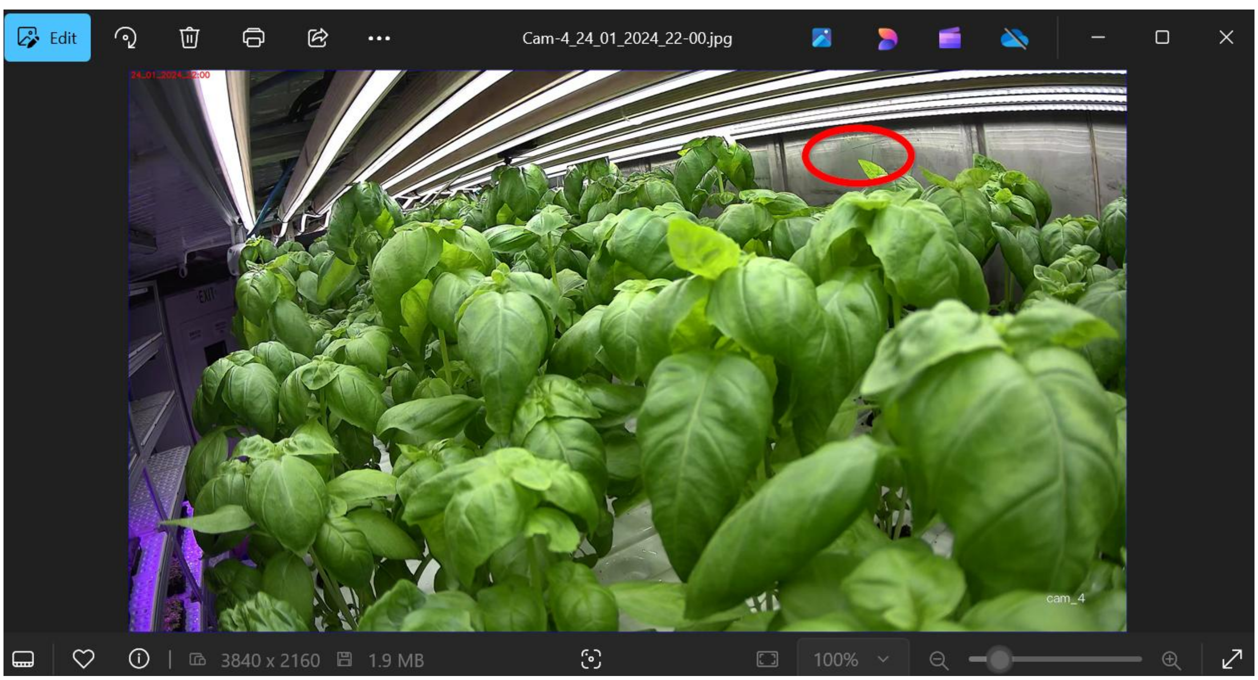
Camera 2 showed some defects. Most pictures had to be abandoned

Camera 3 had meaningful data, however the light pollution after trial, showed that aggregated data with 1,3 and 4 showed lower quality that 1 and 4 alone. The main issues identified were

- Camera 3 had a window in sight. That window reflected other crops from other shelves causing heavy disruptions
- Camera 3 had a broad view on the corridor, generating pollution data



Reflections from shiny surfaces, light variations, and shadows occasionally caused noise and inaccuracies. This is for example due to the walls in metal that reflect slightly the color of the plants.



Manual feedback loops were employed to refine the frequency filtering process, improving the isolation of crops. This has been a tedious process of analysing the color code and isolating the ones that were not relevant.

Night mode pictures had to be abandoned. This is mainly due to the technicity chosen: Night pictures are black and white and the main process of isolation was based on the cololr coding of the pixels. The pictures were hence not compatible with our chosen preferred process

4. Growth Tracking and Data Analysis

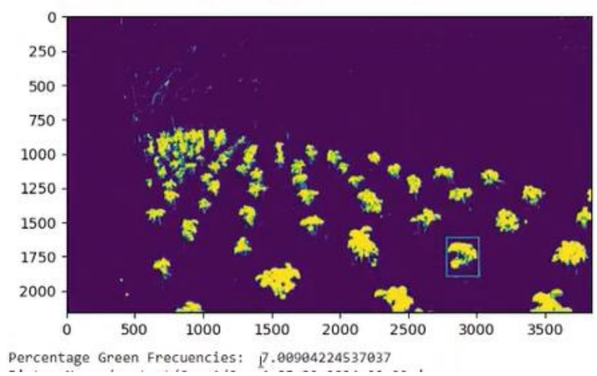
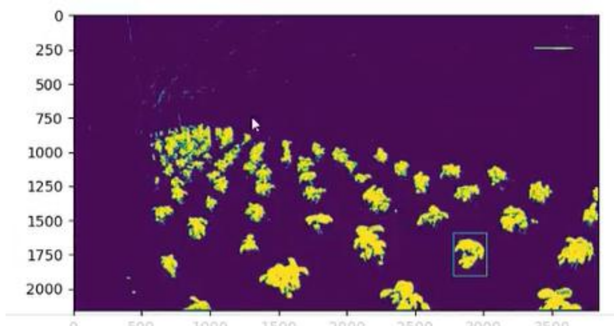
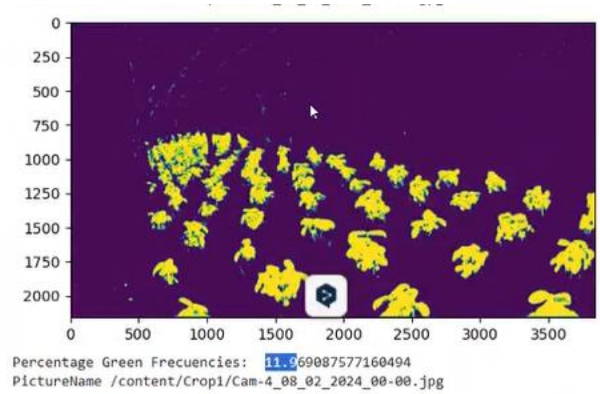
The process for tracking plant growth was explained, with key points highlighted:

Selection of Images:

- Pictures were taken at regular intervals (one picture per hour). However, for this analysis, only one representative image per day was chosen to optimize data relevance in the example here after. The data themselves for the graphical vision are based on hourly data when possible.
- Invalid images, such as those captured with insufficient lighting, were filtered out.

Growth Metrics:

1. The percentage of the image area covered by the crop ("green frequencies") was calculated per picture.
2. This percentage served as a growth metric, demonstrating progressive increases over time.

- 
Percentage Green Frecuencies: 7.00904224537037


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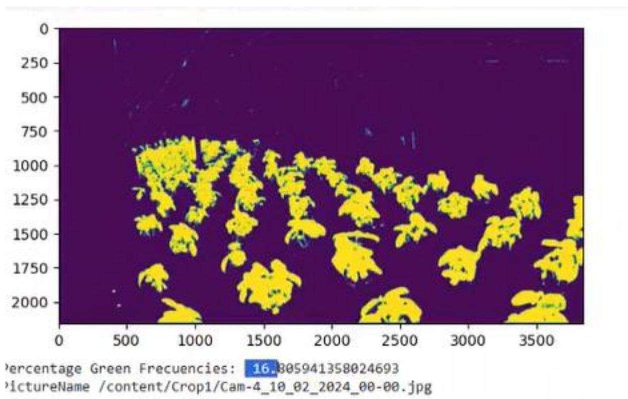
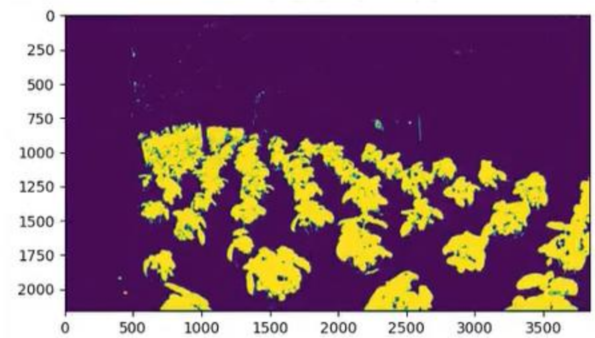

ercentage Green Frecuencies: 16.805941358024693
ictureName /content/Crop1/Cam-4_10_02_2024_00-00.jpg
-
-



Percentage Green Frecuencies: 19.47585117669753
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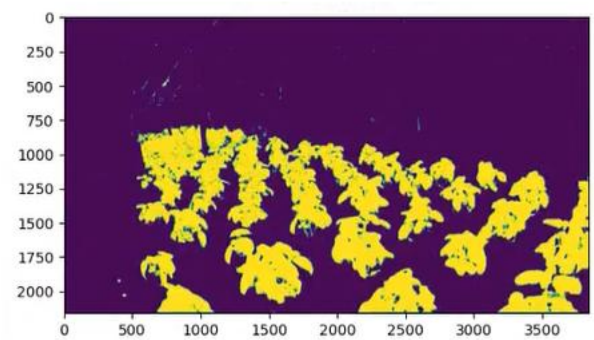
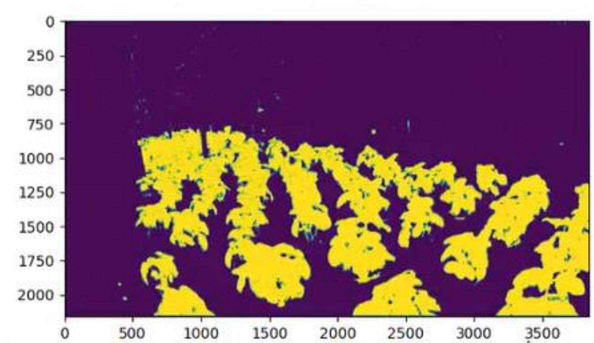
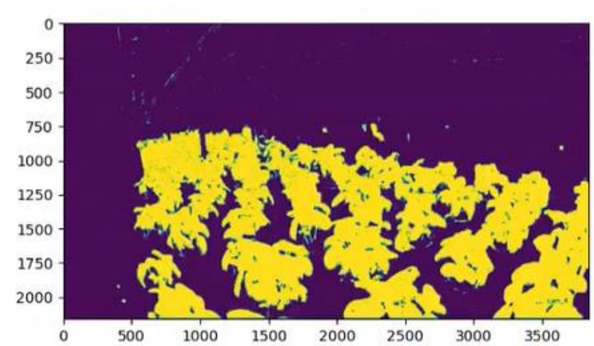


Percentage Green Frecuencies: 22.870201581790123
PictureName /content/Crop1/Cam-4_1[illegible]_02_2024_03-00.jpg



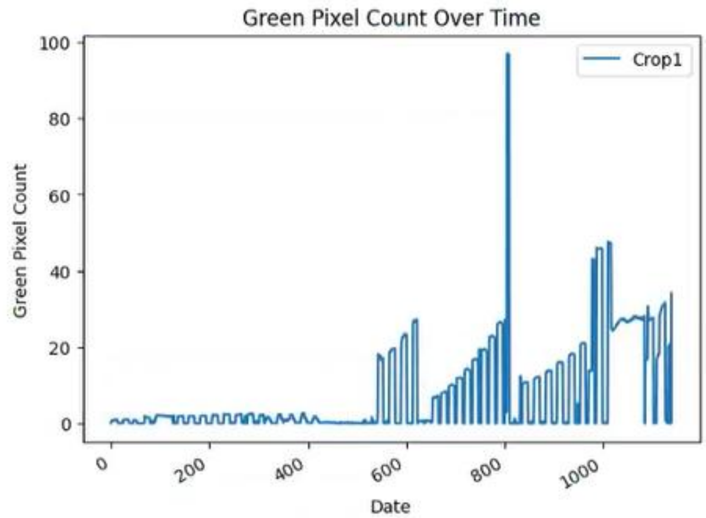
Percentage Green Frecuencies: 26.191430362654323
PictureName /content/Crop1/Cam-4_13_02_2024_00-00.jpg



Percentage Green Frecuencies: 31.356589988425927

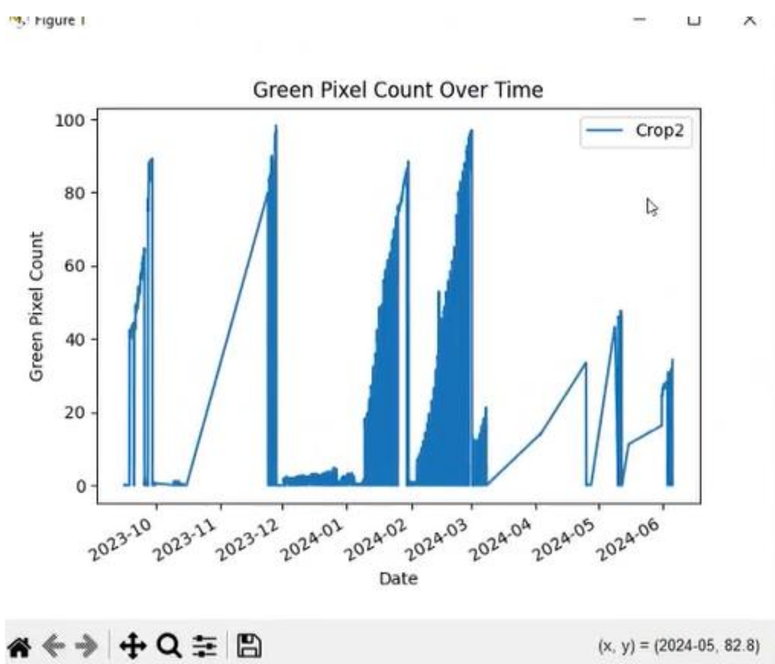
5. Growth Rate Observations:

- Initially, growth was incremental, with daily increases of 0.5% to 1.5%.
- The rate accelerated mid-way through the observation period, reaching daily growth rates of 3% or higher.



6. Graphical Representation:

- Graphs plotted growth rates over time, showing fluctuations caused by external factors such as light variations.
- A smoothed signal was derived by removing noise, providing a clearer depiction of growth trends.



7. **Multi-Camera Integration:**

- Data from three cameras were combined to enhance accuracy. Averages, maximums, and minimums were computed across cameras.
- Synchronization of timestamps ensured consistency, particularly during lighting inconsistencies.

Future Steps

The presenter outlined the next steps for further development:

Graph Refinement:

- Enhance graphical representations for better clarity and usability.
- Integrate findings with other platforms for broader analysis.

Algorithm Application:

- Adapt the existing algorithm to analyze images of different crops (e.g., tomatoes), adjusting parameters (e.g., focusing on red frequencies instead of green).

Knowledge Expansion:

- Use historical data from multiple seasons to identify patterns and generate insights.
- Explore the implications of growth curve variations for agricultural decision-

SECTION II : MEZVIDI VERTICAL FARMING GREENHOUSE

Introduction

This report details the experiment conducted to detect tomatoes using image processing and machine learning techniques. Various approaches were tested, including color detection, shape recognition, and deep learning solutions. The experiment aimed to identify make a parallel with the methods used for Basil, the limitations of existing methods and explore potential improvements.

Image Processing Methods and Challenges

Several approaches were tested to detect tomatoes in images, building upon previous work done with basil detection. However, significant challenges were encountered, particularly due to color variability, light pollution, inconsistencies in shape recognition, and camera quality limitations.

1. Color-Based Detection

- The initial approach involved detecting red frequencies in the images, similar to how green frequencies were used for basil detection.
- Challenges encountered included:
    - Artificial light pollution, including ultraviolet reflections, making it difficult to isolate the true color of the tomato.

    - Variability in tomato coloration, changing from green to red as they ripen.

    - Adjusting the frequency spectrum led to a loss of relevant information and misclassification.

- Unlike basil, which maintains a relatively stable green color, tomatoes undergo significant color transitions, making spectral-based methods unreliable.

2. Shape-Based Detection

- Combining color analysis with shape recognition was attempted.
- However, shape-based detection was ineffective due to:
    - Tomatoes having inconsistent shapes that vary in curvature and size, especially during different growth phases.

    - Shadows and reflections interfering with edge detection algorithms.

- Partial obstructions by leaves, making it difficult for the algorithm to detect a complete shape in dense foliage.

- For an ML system, an occluded tomato no longer appears as a tomato, limiting the effectiveness of shape-based methods.

3. Manual Fine-Tuning Process

- The experiment initially required iterative adjustments (feedback loops) to isolate the correct color frequencies.
- The frequency filtering process was manually refined through trial and error to optimize detection.

4. Noise in Image Processing

- Green noise in dark images was noted as a persistent issue, affecting baseline readings.

- Some reflections from light sources also interfered with the detection process, creating false positives.

5. Growth Tracking in Initial Tests

- A methodology was developed for tracking plant growth using time-series image comparisons.
- Growth was observed through daily snapshots, but minor daily variations made visual comparison difficult.
- The model initially struggled to detect differences in early growth stages.

6. Data Filtering and Selection

- Useless images were removed from the dataset, such as those captured in poor lighting conditions.
- One image per day was selected for tracking, avoiding redundant data.

7. Graphical Representations of Growth

- Initial attempts at creating graphs for growth patterns showed inconsistencies due to lighting variations.
- The graphs revealed fluctuations due to external factors, leading to the need for data smoothing.

8. Multi-Camera Integration and Image Cropping

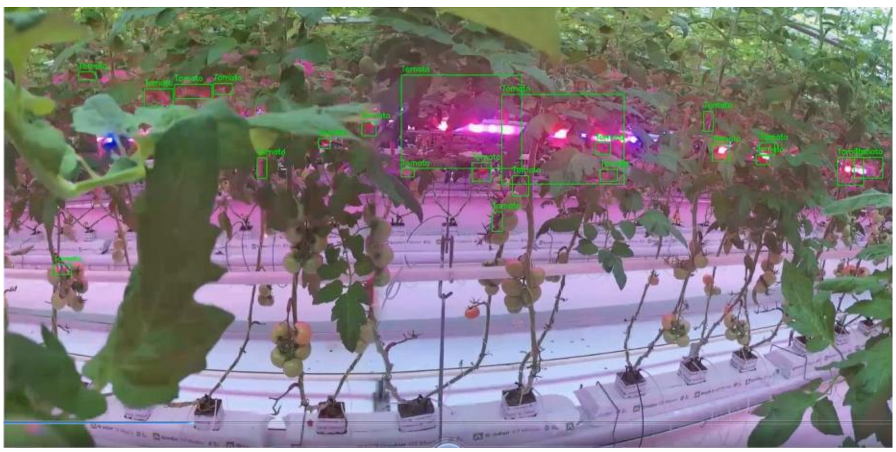
- Alternative strategies were explored to mitigate detection issues:
    - Using multiple cameras with narrower angles to reduce distortions.
    - Cropping images into smaller overlapping sections to increase detection accuracy.

- Capturing images under different lighting conditions to reduce contrast-related issues.

- These solutions require extensive computational resources and additional hardware investments.
- Switching from wide-angle cameras to multiple focused cameras may improve accuracy but increases processing time and complexity.

9. Impact of Lighting Conditions

- Differences between daytime and nighttime image capture affected detection quality.
- Artificial lights in the environment introduced additional spectral noise that complicated the analysis.
- The tests were conducted under two conditions:
    - **Day mode:** with artificial lighting turned on.



    - **Night mode:** using only the camera's built-in lights.

- These variations impacted the consistency of detection and required adjustments to the image processing pipeline.

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10. Comparison Between Plant Types

- The previous method used for basil detection did not translate well to tomatoes due to differences in color consistency and shape variation.
- Basil presented a more uniform green signature, while tomatoes required different detection criteria.

11. Annotation and Tracking Complexity

- The detection challenge does not stop at identifying tomatoes; tracking them over time adds a significant complexity layer.
- The need for a unique identifier per tomato (to track changes over time) was noted as a critical missing element in the current methodology.
- Tracking remains unsolved because of environmental changes—tomatoes are continuously harvested, making it difficult to establish a persistent dataset.

12. Dataset Limitations and Business Implications

- The experiment highlighted the necessity of collecting a massive dataset of annotated tomato images.
- Unlike basil, which has a uniform dataset available, tomatoes lack extensive pre-labeled machine learning datasets.
- Business side note — if such a dataset were built and owned, it could provide a major competitive advantage in agricultural AI.

Machine Learning and Deep Learning Approaches

Since traditional methods (color and shape detection) proved ineffective, preexisting open AI-driven solutions were considered.

1. Existing AI Models

- No pre-trained datasets specifically designed for tomato detection were found.
- General object detection models like YOLO (You Only Look Once) were tested, but they lacked training for tomato identification.
- Unlike basil, tomatoes require more complex feature extraction due to their varied appearance.
- Most machine learning models are trained on simple, well-centered objects, while tomatoes exist in a dynamic, cluttered environment, making detection more challenging.

2. Potential AI Training Strategies

- Training a custom deep learning model would require:
    - A large dataset of labeled tomato images covering various growth stages and lighting conditions.
    - Infrastructure capable of handling deep learning computations.
    - Collaboration with agricultural research institutions to gather annotated datasets.
- A key takeaway was that owning a unique dataset could provide competitive advantages in the agricultural sector.

Key Findings and Next Steps

1. **Color detection is unreliable** due to light pollution, spectral variations, and artificial reflections.
2. **Shape detection is ineffective** due to occlusions, reflections, and irregular forms.
3. **Camera limitations impact image quality**, making tomato detection harder.
4. **HDR imaging may improve clarity**, but the current cameras do not support it.
5. **Multi-camera setups with HDR imaging** could improve data quality but require additional investments.
6. **Existing AI models do not cover tomato detection**, making a custom solution necessary.
7. **A large-scale dataset** is essential to develop a reliable machine learning model.
8. **Tomatoes present unique challenges compared to basil**, requiring a fundamentally different detection approach.
9. **Tracking tomatoes over time remains an unsolved challenge**, as environmental changes make it difficult to establish a consistent dataset.
10. **Dataset ownership provides a business advantage**, offering a potential competitive edge in agricultural AI.

Conclusion

The tomato detection experiment highlighted the complexities of adapting image processing techniques to agricultural settings. Traditional color and shape detection methods proved insufficient, necessitating more advanced machine learning approaches. A fundamental challenge remains the lack of a comprehensive tomato dataset, which will be a focus for future efforts. Improvements in hardware, lighting conditions, and deep learning models will be required to develop a fully functional tomato detection system.

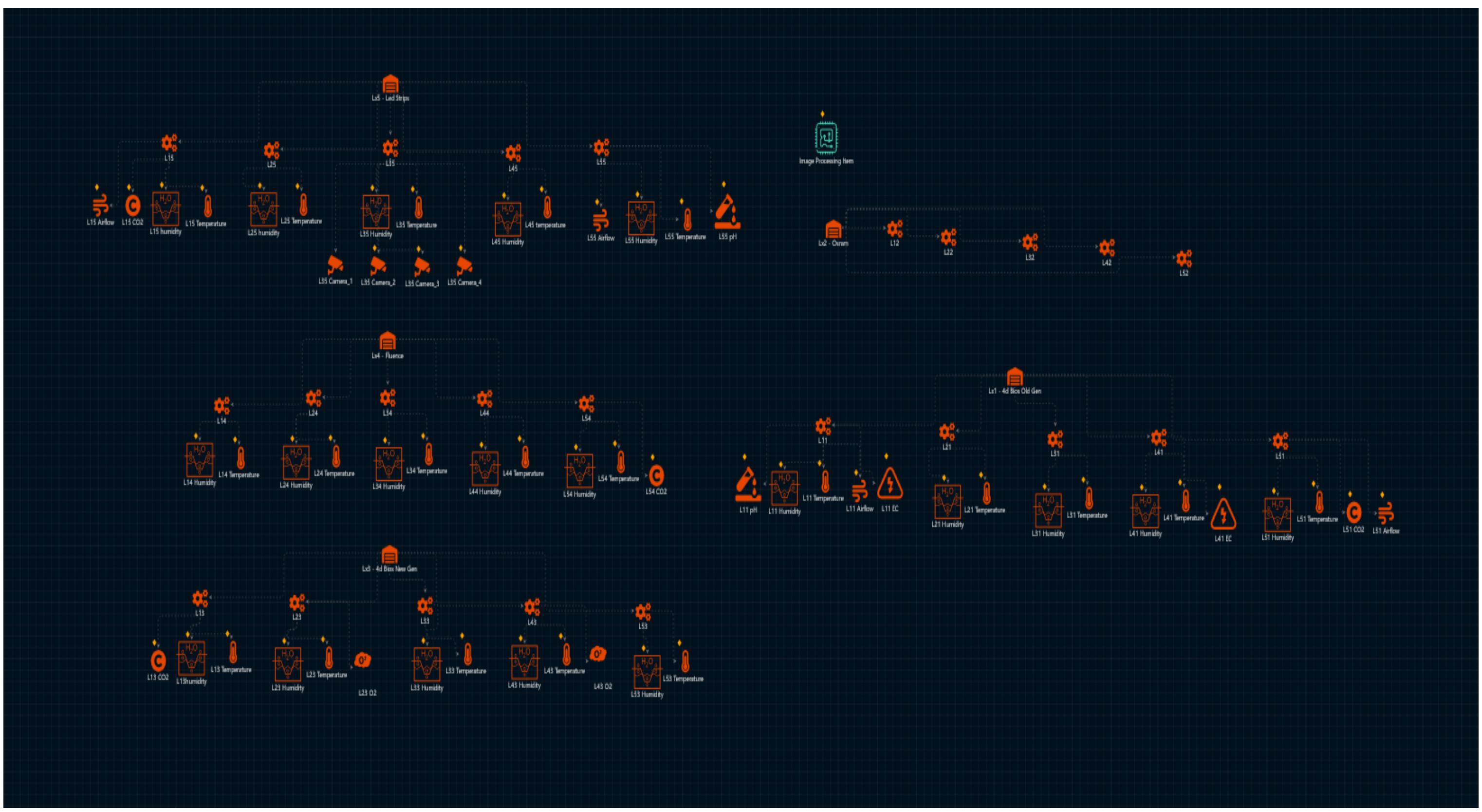
SECTION III: DATA STORAGE IN PLATFORM

The data is securely stored within a Microsoft Azure Data Lake, a scalable storage solution designed to handle vast amounts of structured and unstructured data. This setup ensures efficient management and retrieval of extensive datasets, including thousands of images and millions of recordings.

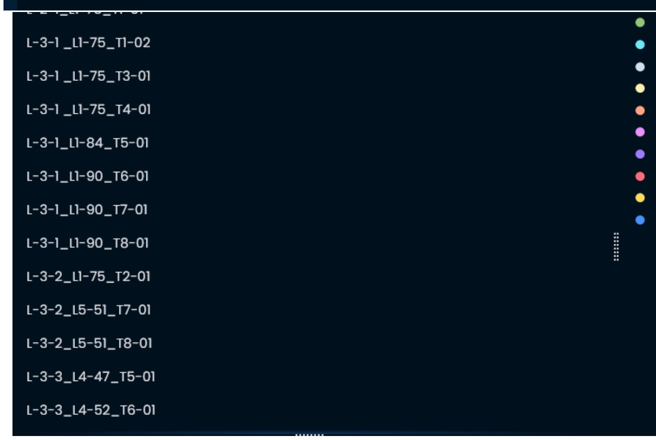
Access to this data is facilitated through the Wizata platform, which integrates seamlessly with Azure Data Lake. Wizata's architecture allows for real-time data ingestion, processing, and analysis, enabling users to visualize and interpret data without the need for manual exports. The platform supports advanced analytics and machine learning applications, providing tools for data-driven decision-making.

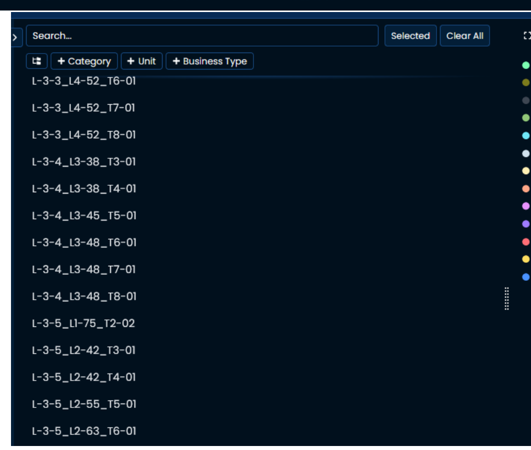
Given the substantial volume of data, direct transmission is impractical. Below the detailed summaries of the available datasets.

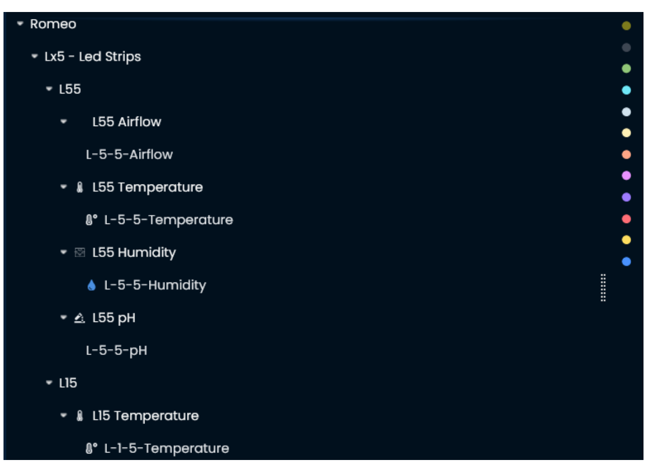
General picture of sensors and datasets

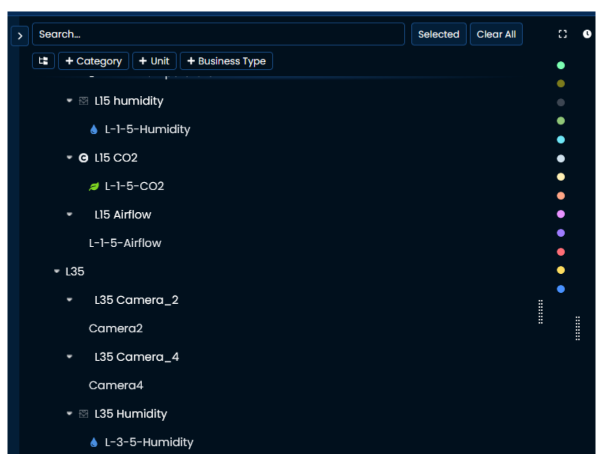


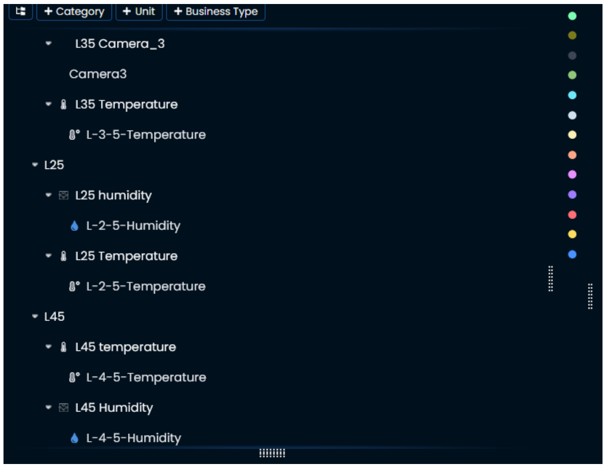
List of data sets – sensors - Broccoli







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Camera3
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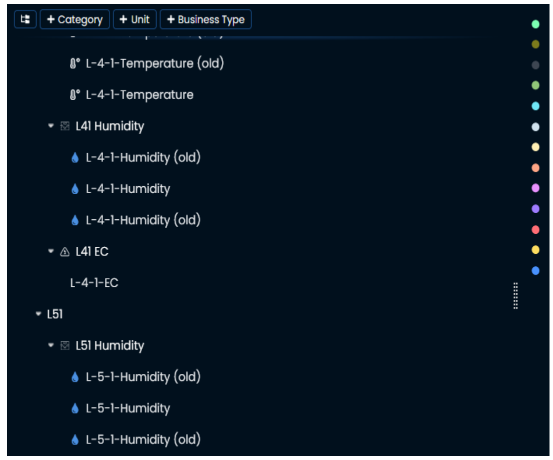
L-3-5-Temperature
L25
L25 humidity
L-2-5-Humidity
L25 Temperature
L-2-5-Temperature
L45
L45 temperature
L-4-5-Temperature
L45 Humidity
L-4-5-Humidity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L-4-1-Humidity (old)
L41 EC
L-4-1-EC
L51
L51 Humidity
L-5-1-Humidity (old)
L-5-1-Humidity
L-5-1-Humidity (old)


L11 pH
L-1-1-pH
L31
L31 Temperature
L-3-1-Temperature (old)
L-3-1-Temperature
L-3-1-Temperature (old)
L31 Humidity
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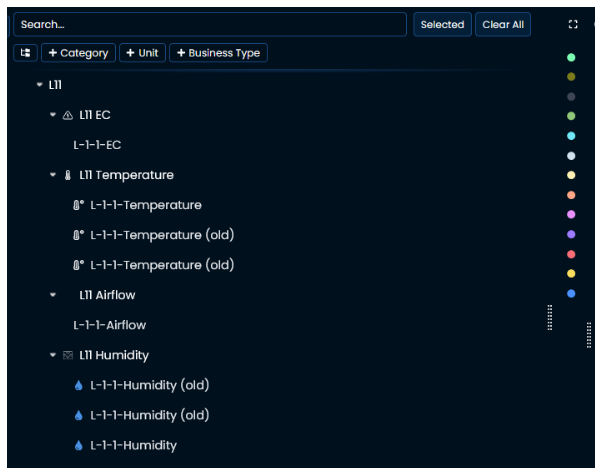
L41
L41 Temperature
L-4-1-Temperature (old)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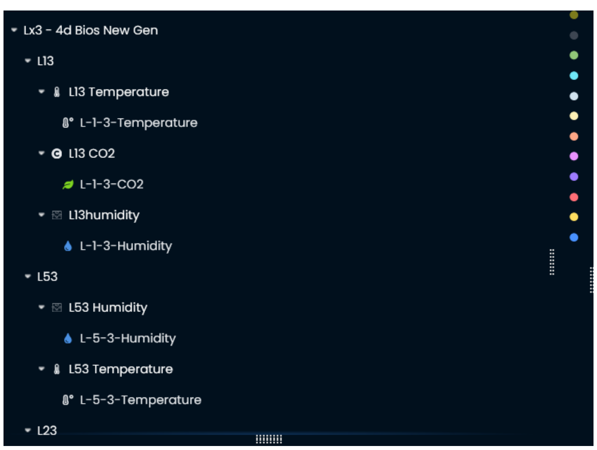
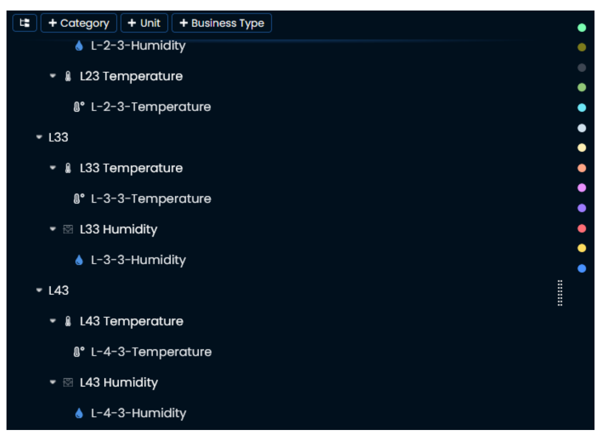

Lx3 - 4d Bios New Gen
L13
L13 Temperature
L-1-3-Temperature
L13 CO2
L-1-3-CO2
L13humidity
L-1-3-Humidity
L53
L53 Humidity
L-5-3-Humidity
L53 Temperature
L-5-3-Temperature
L23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+ Unit
+ Business Type
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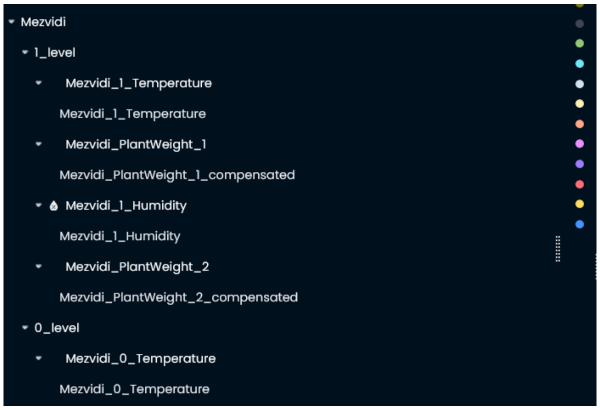
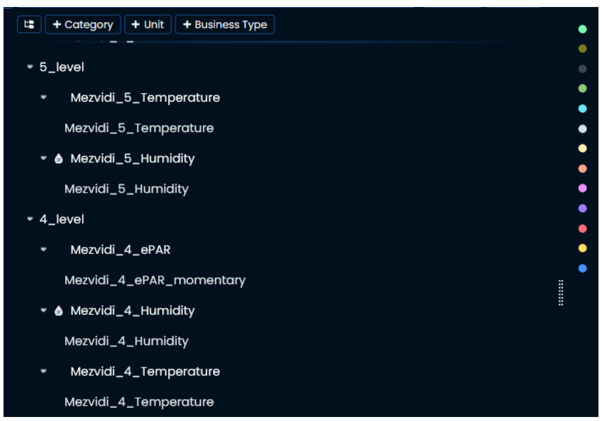
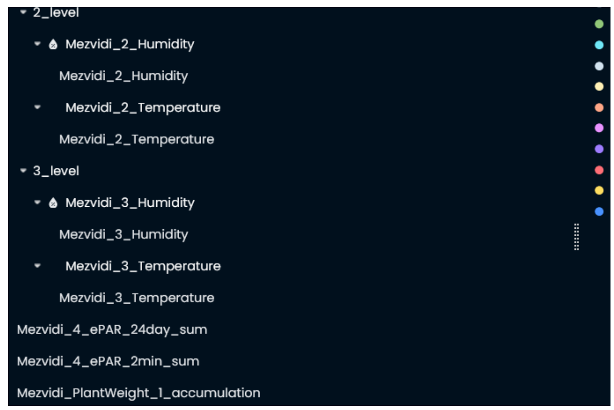
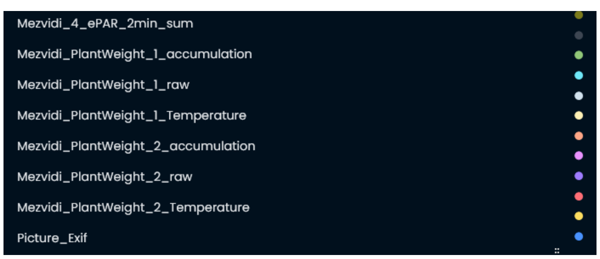
L23 Temperature
L-2-3-Temperature
L33
L33 Temperature
L-3-3-Temperature
L33 Humidity
L-3-3-Humidity
L43
L43 Temperature
L-4-3-Temperature
L43 Humidity
L-4-3-Humidity

List of data sets – sensors - Mezvidi









List of data sets – Images