Unified Temporal Consistency and Mean Squared Error Loss Function for Predicting Plant Growth Structures through Multimodal Convolutional Long Short-Term Memory: Laying the Groundwork for Digital Twins in Agriculture

John Ivan T. Diaz, Craig Joseph B. Goc-ong, Kaye Louise A. Manilong
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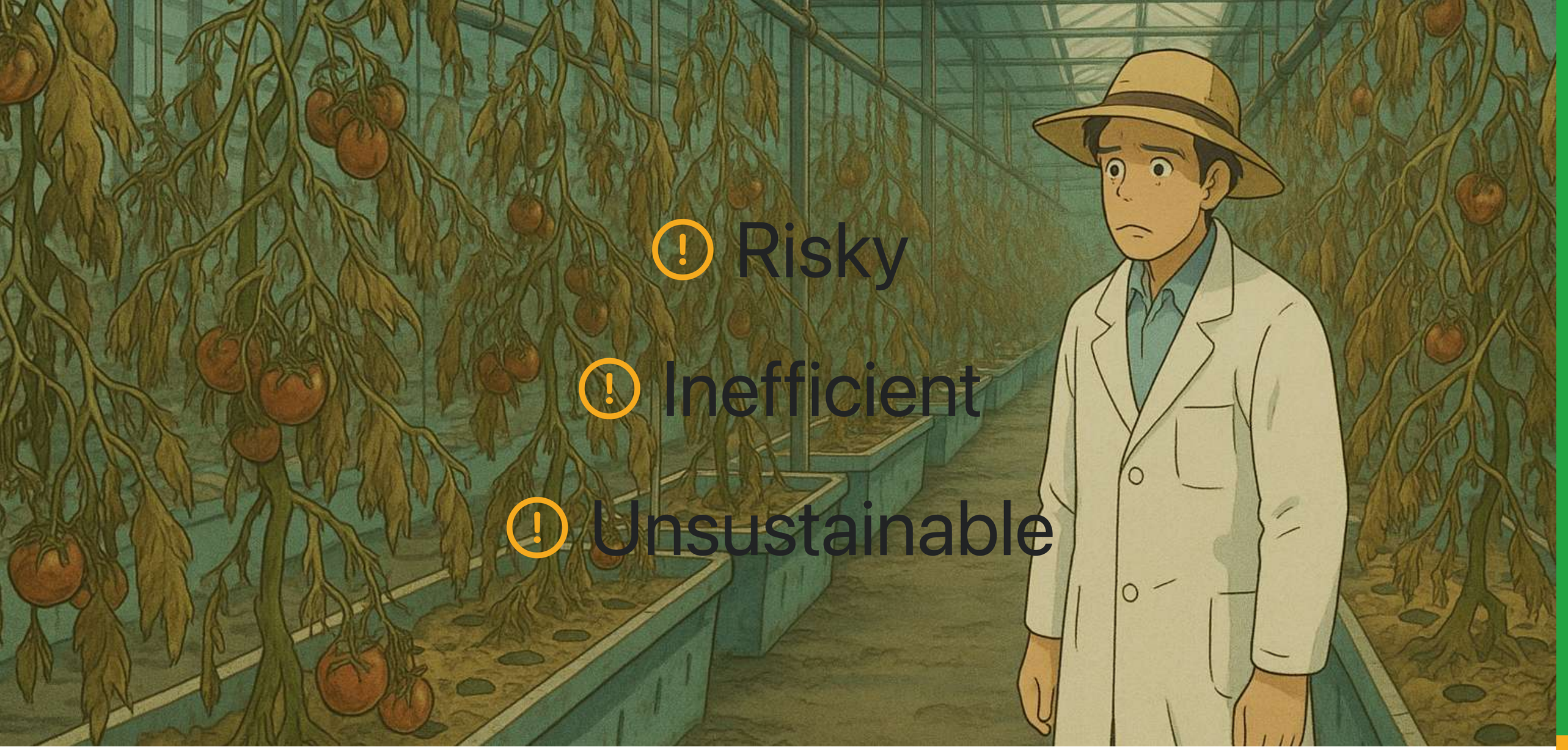

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Digital Twin

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Digital Twin ?

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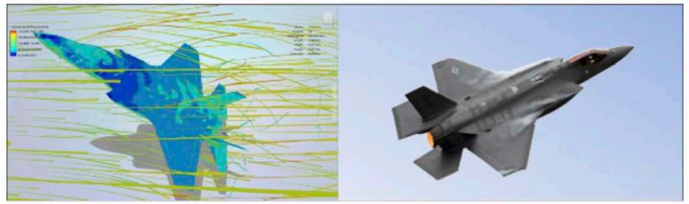
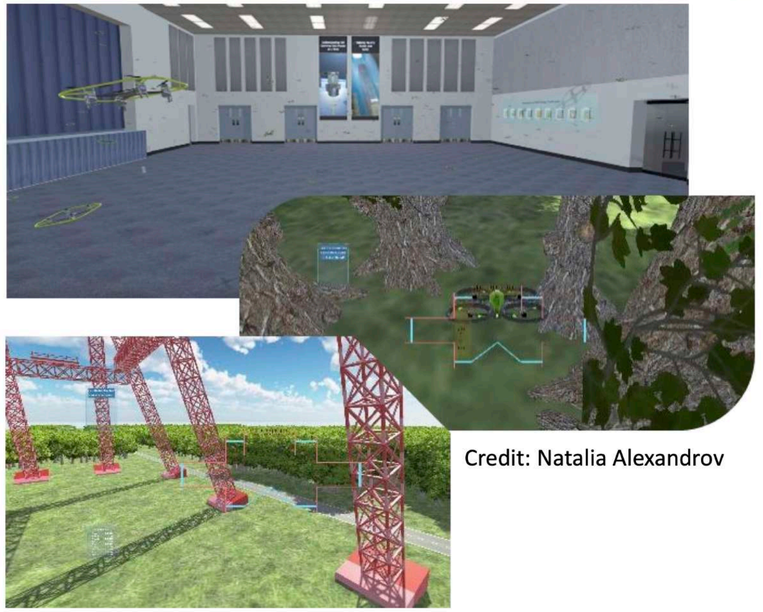
Persistent “TwinSim”

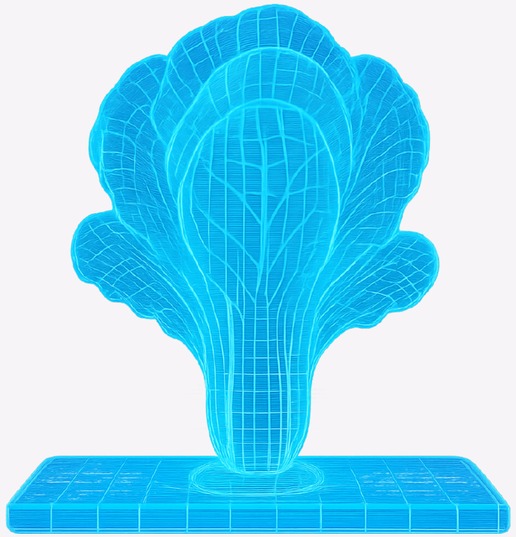


Digital Twin Artifacts/Environments



Credit: Natalia Alexandrov

“Digital Twin” Ecosystem



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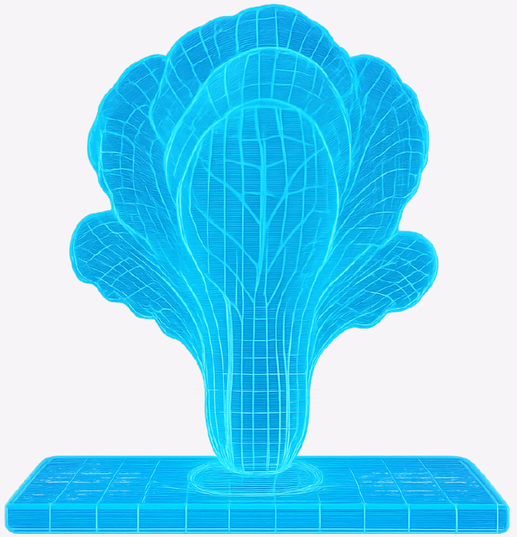
Digital
replica



Actual crop

Digital Twin

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How would my plant respond if I change the temperature to X?

Will growth stagnate if I change the pH level to Y?

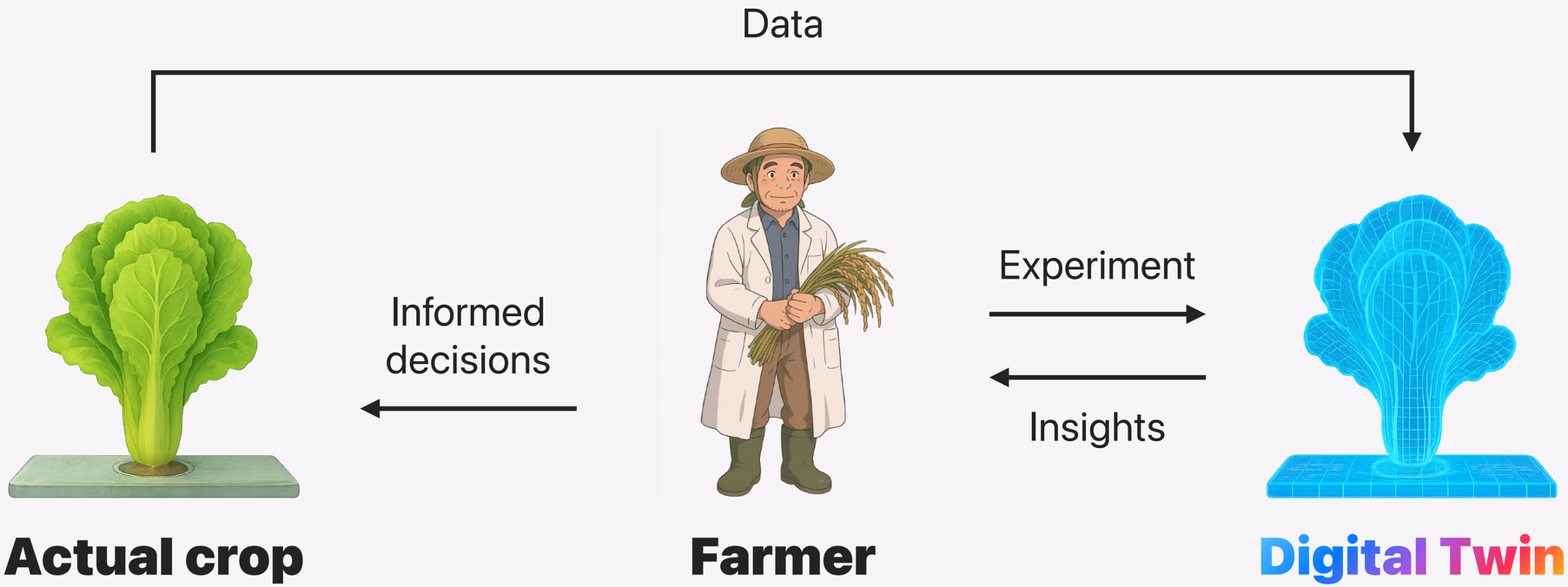
Current farming practice

Actual crop

Direct decisions

Farmer

Our vision


Data
Informed decisions
Experiment
Insights
Actual crop
Farmer
Digital Twin

Technological impacts

Farmers can make informed agricultural decisions

More Sustainable and Efficient farming

Healthier crops

Higher yields

SUSTAINABLE DEVELOPMENT GOALS

2 ZERO HUNGER

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

12 RESPONSIBLE CONSUMPTION AND PRODUCTION

Entrepreneurial opportunities for developers

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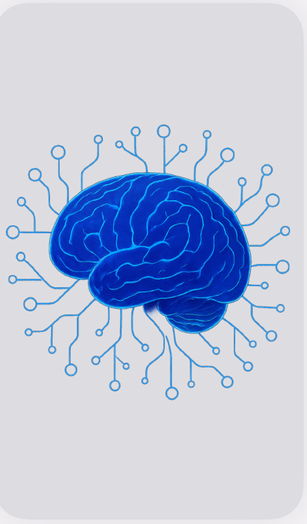
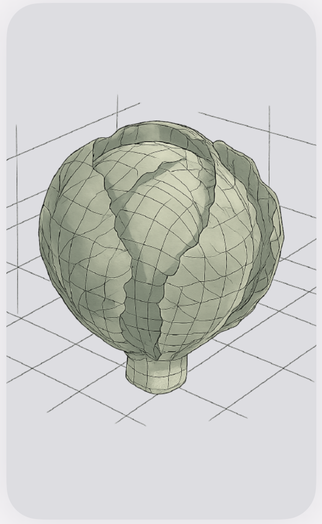
Laying the groundwork

R&D roadmap

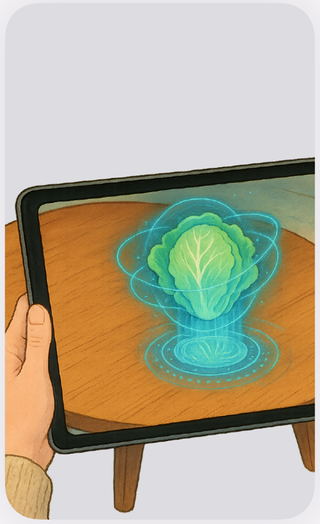
Data Collection



Artificial Intelligence



3D Modeling



Augmented Reality

User Interface

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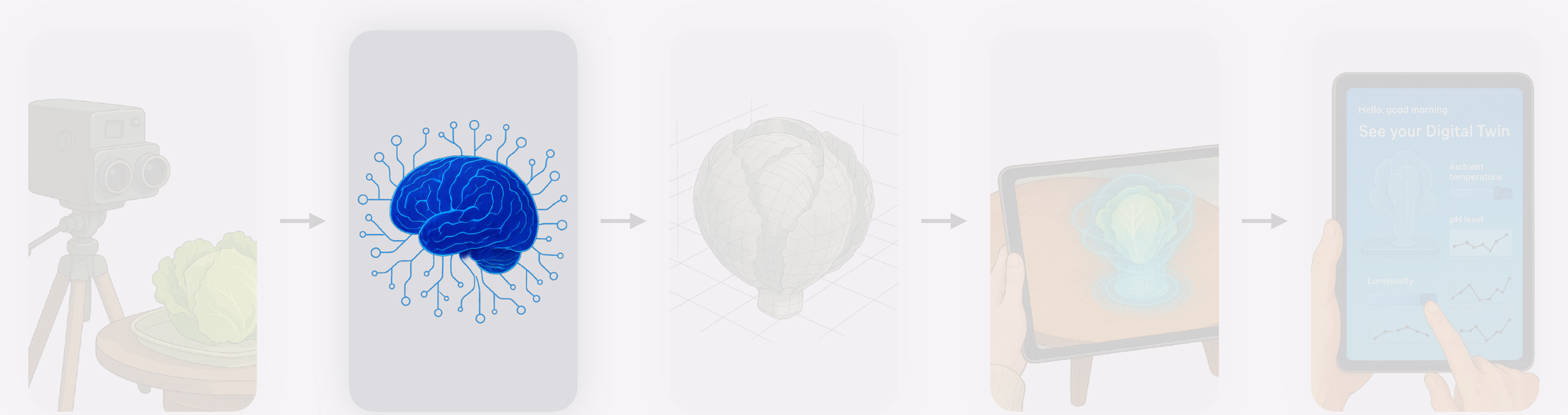
In this presentation



Artificial Intelligence

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In this presentation

1. Data collection process
2. Model architecture
3. Training and testing results
4. Unified loss function
5. Conclusions and recommendations

In this presentation

1. Data collection process

A deep learning model that predicts future appearances of crops with respect to external conditions around them

A deep learning model that predicts future appearances of crops with respect to external conditions around them

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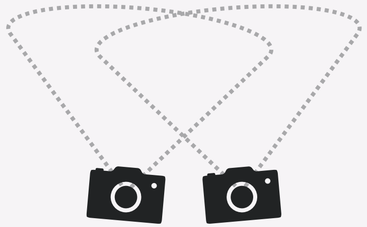
Collecting data

Images



Stereo cameras

Numerical data

Ambient temperature	25°C
pH level	7.5
Soil moisture	50%
Luminosity	700 lux

Sensors

Collecting data

Frame 1

25°C
7.5
50%
700 lux

12 hours

Frame 2

25°C
7.5
50%
700 lux

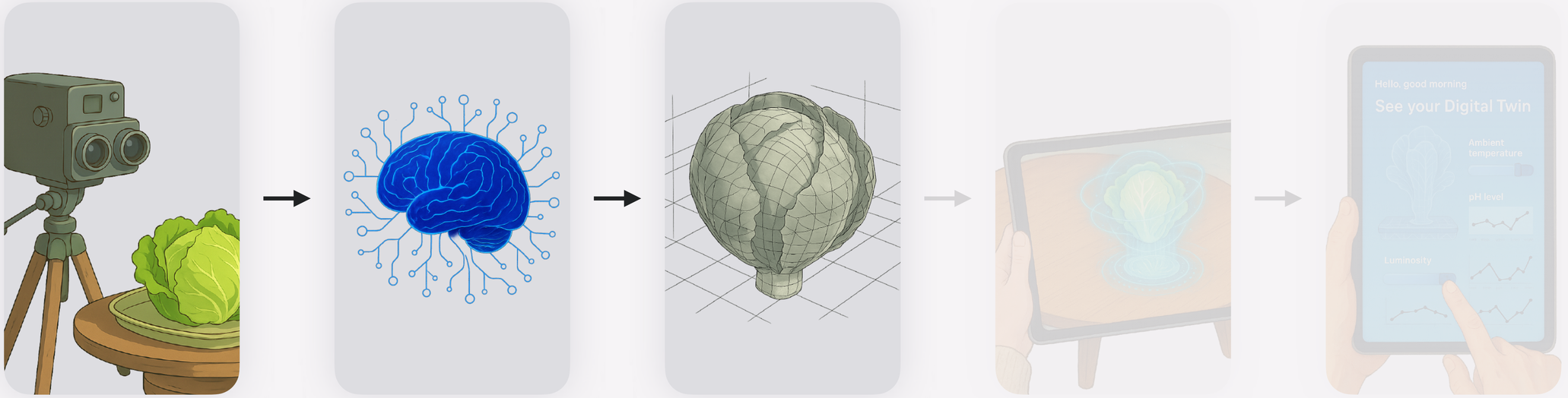
12 hours

Frame 3

25°C
7.5
50%
700 lux

...

R&D roadmap



Data Collection → **Artificial Intelligence** → **3D Modeling**

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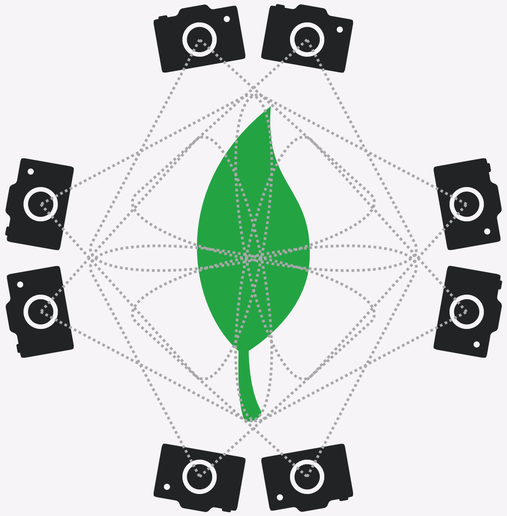
Imaging setup

Front stereo image

Left stereo image



Right stereo image

Back stereo image

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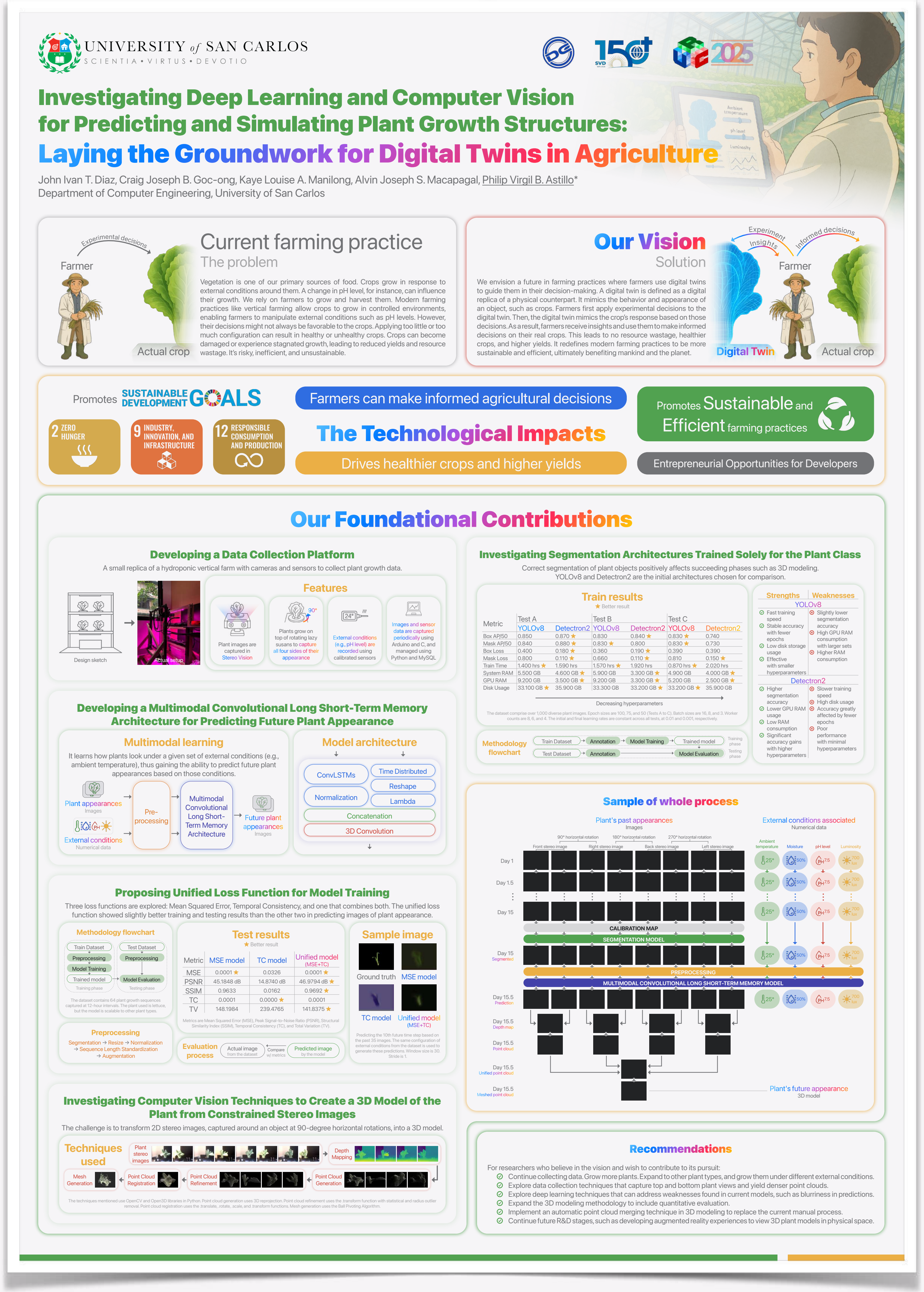
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Investigating Deep Learning and Computer Vision
for Predicting and Simulating Plant Growth Structures:
Laying the Groundwork for Digital Twins in Agriculture
John Ivan T. Diaz, Craig Joseph B. Goc-ong, Kaye Louise A. Manilong, Alvin Joseph S. Macapagal, Philip Virgil B. Astillo*
Department of Computer Engineering, University of San Carlos
Current farming practice
The problem
Vegetation is one of our primary sources of food. Crops grow in response to external conditions around them. A change in pH level, for instance, can influence their growth. We rely on farmers to grow and harvest them. Modern farming practices like vertical farming allow crops to grow in controlled environments, enabling farmers to manipulate external conditions such as pH levels. However, their decisions might not always be favorable to the crops. Applying too little or too much configuration can result in healthy or unhealthy crops. Crops can become damaged or experience stagnated growth, leading to reduced yields and resource wastage. It's risky, inefficient, and unsustainable.
Experimental decisions
Farmer
Actual crop
Our Vision
Solution
We envision a future in farming practices where farmers use digital twins to guide them in their decision-making. A digital twin is defined as a digital replica of a physical counterpart. It mimics the behavior and appearance of an object, such as crops. Farmers first apply experimental decisions to the digital twin. Then, the digital twin mimics the crop's response based on those decisions. As a result, farmers receive insights and use them to make informed decisions on their real crops. This leads to no resource wastage, healthier crops, and higher yields. It redefines modern farming practices to be more sustainable and efficient, ultimately benefiting mankind and the planet.
Experiment
Insights
Informed decisions
Digital Twin
Farmer
Actual crop
Promotes SUSTAINABLE DEVELOPMENT GOALS
2 ZERO HUNGER
9 INDUSTRY, INNOVATION, AND INFRASTRUCTURE
12 RESPONSIBLE CONSUMPTION AND PRODUCTION
Farmers can make informed agricultural decisions
The Technological Impacts
Drives healthier crops and higher yields
Promotes Sustainable and Efficient farming practices
Entrepreneurial Opportunities for Developers
Our Foundational Contributions
Developing a Data Collection Platform
A small replica of a hydroponic vertical farm with cameras and sensors to collect plant growth data.
Features
Investigating Segmentation Architectures Trained Solely for the Plant Class
Correct segmentation of plant objects positively affects succeeding phases such as 3D modeling.
YOLOv8 and Detectron2 are the initial architectures chosen for comparison.
Train results
Strengths
Weaknesses
Developing a Multimodal Convolutional Long Short-Term Memory Architecture for Predicting Future Plant Appearance
Multimodal learning
Model architecture
Sample of whole process
Proposing Unified Loss Function for Model Training
Test results
Sample image
Investigating Computer Vision Techniques to Create a 3D Model of the Plant from Constrained Stereo Images
Day 15.5
Unified point cloud
Day 15.5
Meshed point cloud
Plant's future appearance
3D model
Recommendations
For researchers who believe in the vision and wish to contribute to its pursuit:
Continue collecting data. Grow more plants. Expand to other plant types, and grow them under different external conditions.
Explore data collection techniques that capture top and bottom plant views and yield denser point clouds.
Explore deep learning techniques that can address weaknesses found in current models, such as blurriness in predictions.
Expand the 3D modeling methodology to include quantitative evaluation.
Implement an automatic point cloud merging technique in 3D modeling to replace the current manual process.
Continue future R&D stages, such as developing augmented reality experiences to view 3D plant models in physical space.

Collecting data

	Frame 1	Frame 2	Frame 3	Frame 4	...
Sequence 1					
Sequence 2					
Sequence 3					
...					

Preprocessing pipeline

Segmentation

↓

Resize

↓

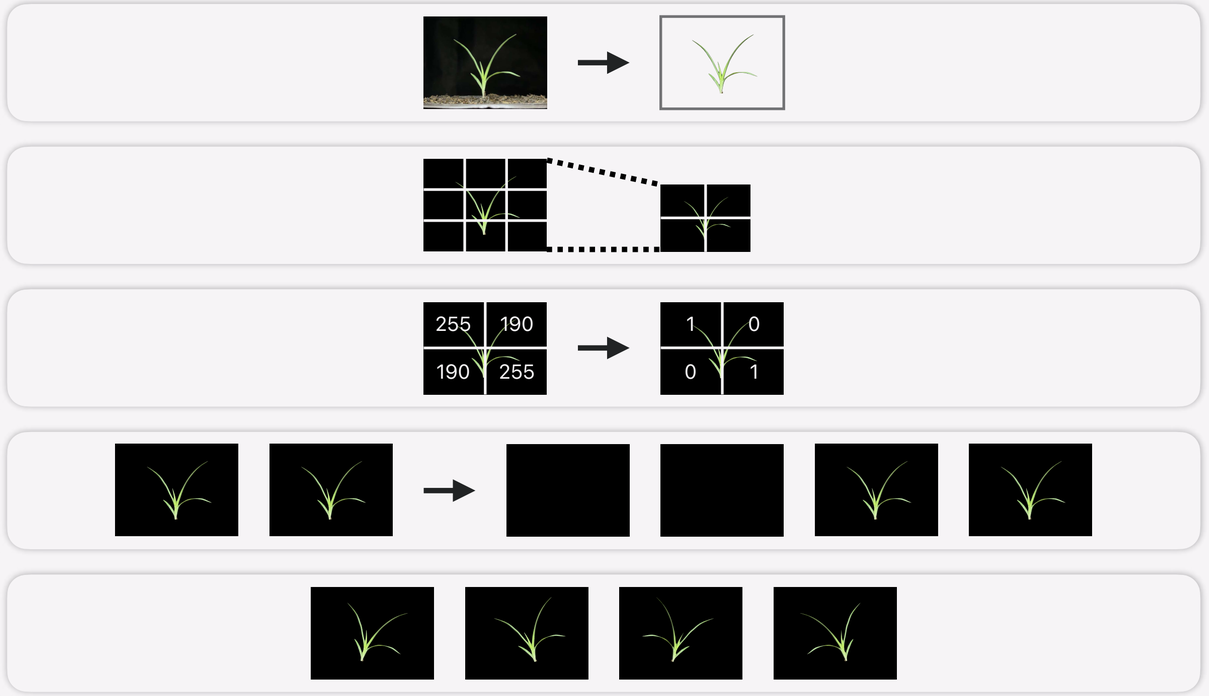
Normalization

↓

Sequence length standardization

↓

Augmentation



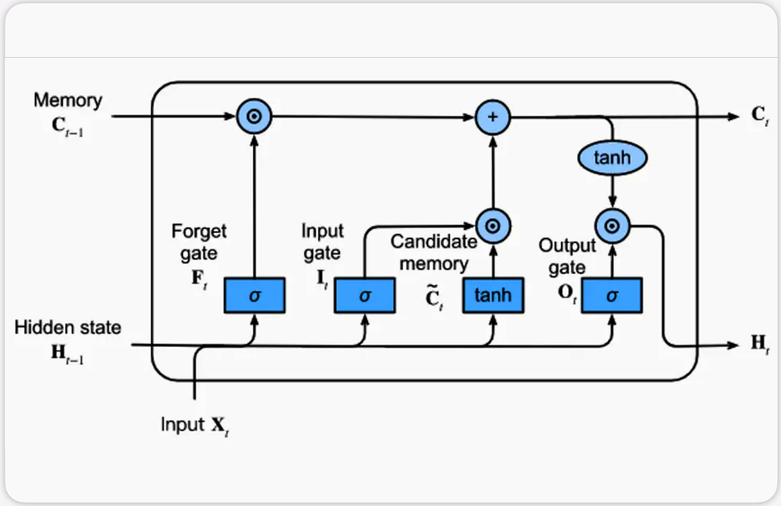
In this presentation

1. Data collection process

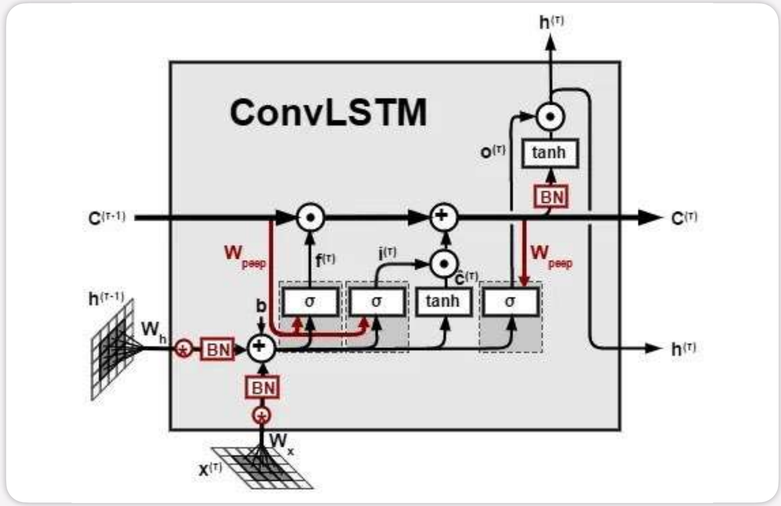
In this presentation

2 Model architecture

Recent deep learning advancements



Traditional LSTM



Convolutional LSTM

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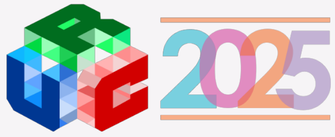
Convolutional LSTM



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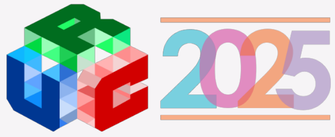
Multimodal Convolutional LSTM



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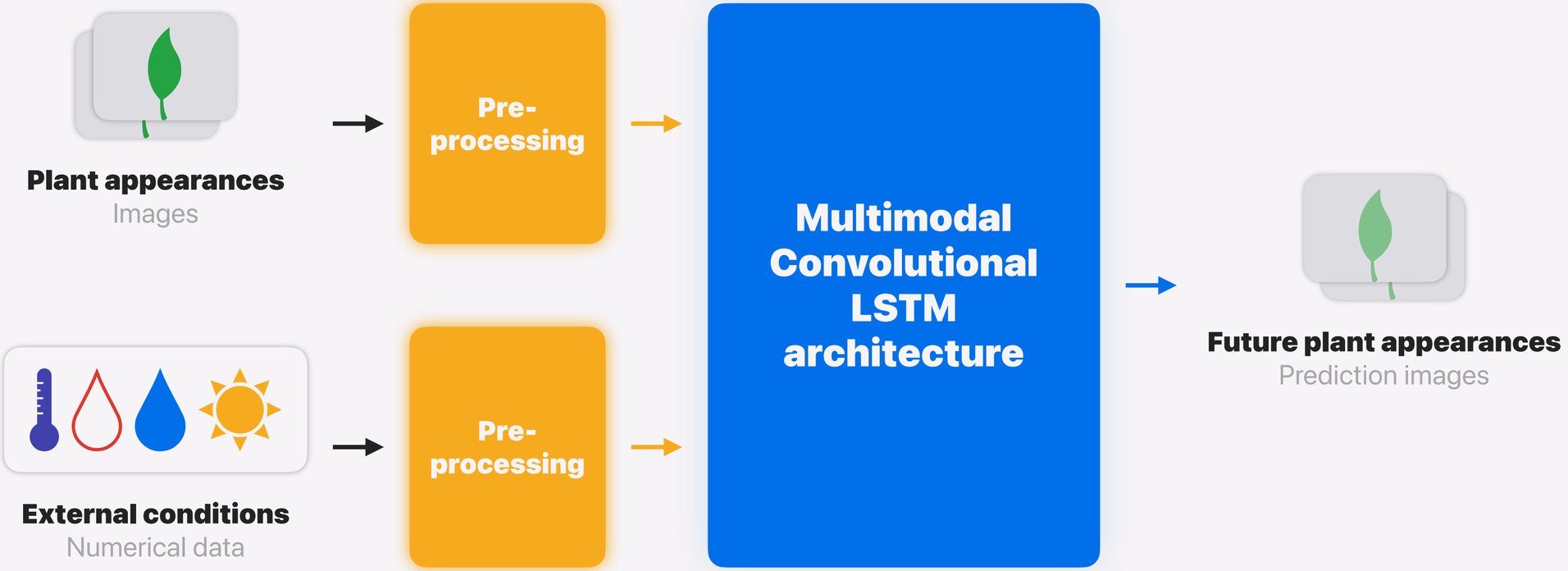
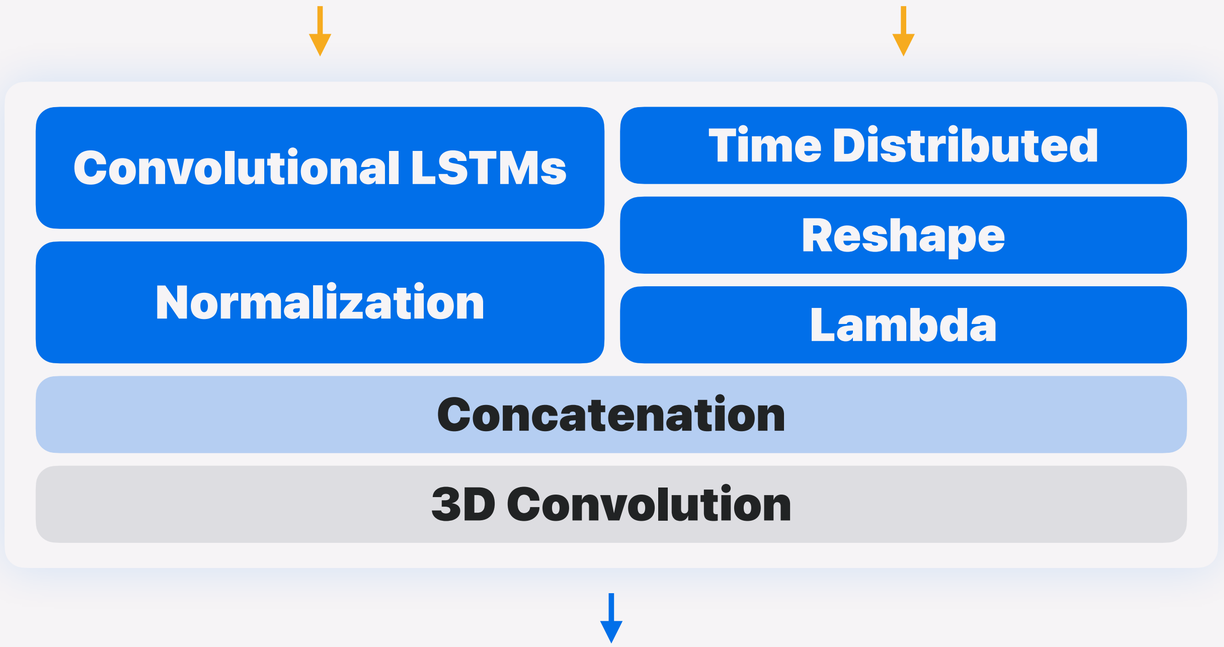
Multimodal learning



Model architecture



In this presentation

2 Model architecture

In this presentation

3 Training and testing results

Evaluation

MSE
model

Model trained with
Mean Squared Error
loss function

TC
model

Model trained with
Temporal Consistency
loss function

Evaluation

MSE
model

TC
model

$$L_{\text{MSE}} = \frac{1}{N}\sum_{i=1}^{N}\left(x_{s,L,i} - \hat{x}_{s,L,i}\right)^2$$

$$L_{\text{TC}} = \frac{1}{N(T_S-1)}\sum_{t=2}^{T_S}\sum_{i=1}^{N}\left[(x_{s,t,i} - x_{s,t-1,i}) - (\hat{x}_{s,t,i} - \hat{x}_{s,t-1,i})\right]^2$$

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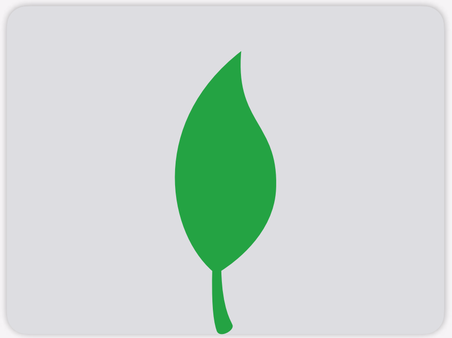
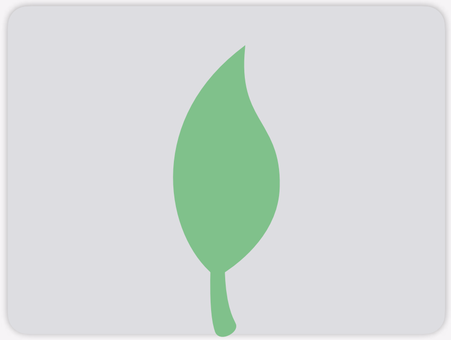
Evaluation



Day 1

Compare



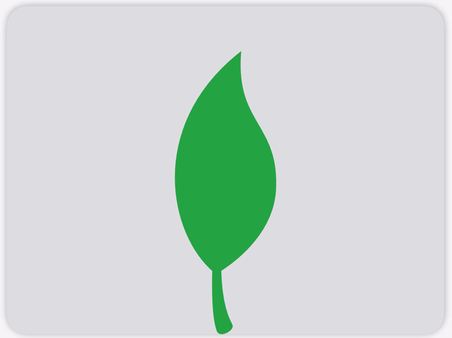
Day 1

Actual image
from the dataset

Predicted image
by the model

Evaluation

Metrics



Day 1

Actual image
from the dataset

Mean Squared Error

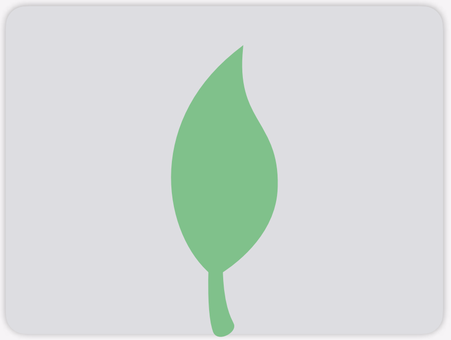
Peak Signal-to-Noise Ratio

Structured Similarity Index

Temporal Consistency

Total Variation

Visual inspection



Day 1

Predicted image
by the model

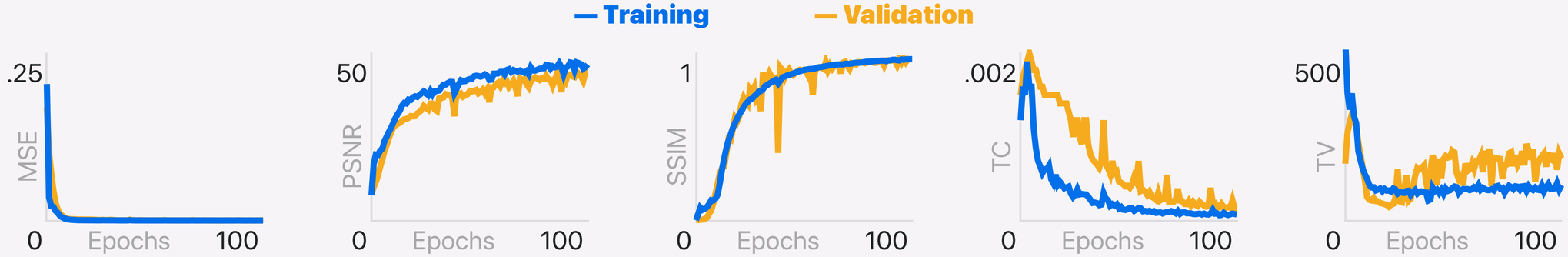
Evaluation

Quantitative metrics

Bad		Good
Greater than 0	MSE	0
Below 40 dB or above 50 dB	PSNR	Within 40-50 dB
Lesser than 1	SSIM	1
Greater than 0	TC	0
Greater than 0	TV	0

Training results

Metric curves of **MSE model**



MSE

✓ Met good benchmarks

PSNR

✓ Met good benchmarks

SSIM

✓ Met good benchmarks

TC

✓ Met benchmarks but slower than TC model

TV

✓ Met good benchmarks

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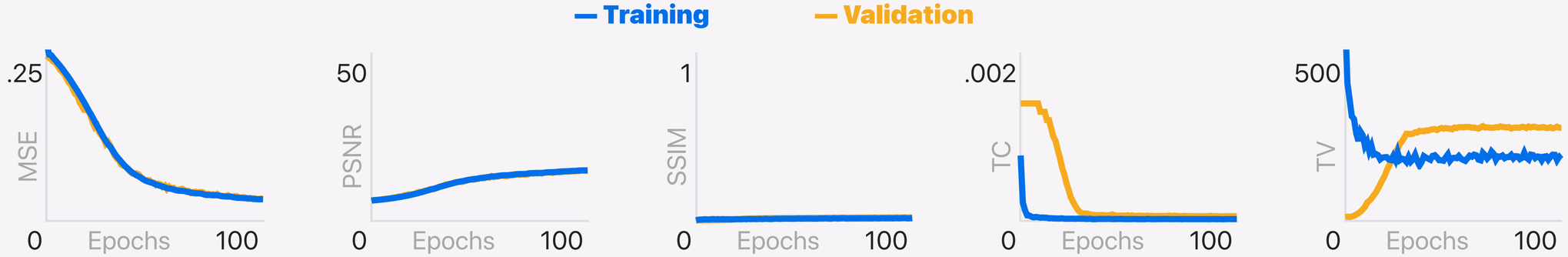
Training results

Metric curves of **TC model**



MSE

⊗ Did not meet good benchmarks

PSNR

⊗ Did not meet good benchmarks

SSIM

⊗ Did not meet good benchmarks

TC

✓ Met good benchmarks

TV

⊗ Slightly worse than MSE model

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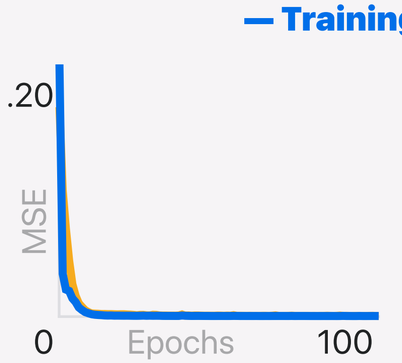
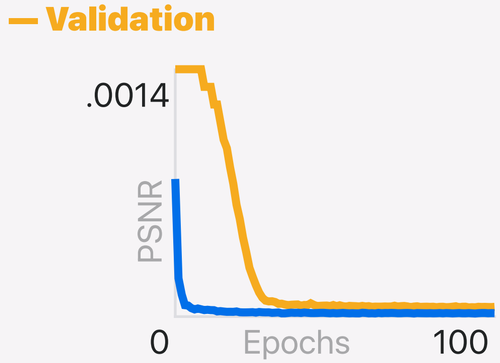
Training results

Loss curves



MSE model



TC model

ⓘ Early convergence

Test results

Quantitative metrics

	MSE model	TC model
MSE ★ Lower is better	0.0001 ★	0.0326
PSNR ★ Higher is better	45.1848 dB ★	14.8740 dB
SSIM ★ Higher is better	0.9633 ★	0.0162
TC ★ Lower is better	0.0001	0.0000 ★
TV ★ Lower is better	148.1984 ★	239.4765

MSE
model

Model trained with
Mean Squared Error
loss function

TC
model

Model trained with
Temporal Consistency
loss function

Unified loss function

MSE
model

Model trained with
Mean Squared Error
loss function

TC
model

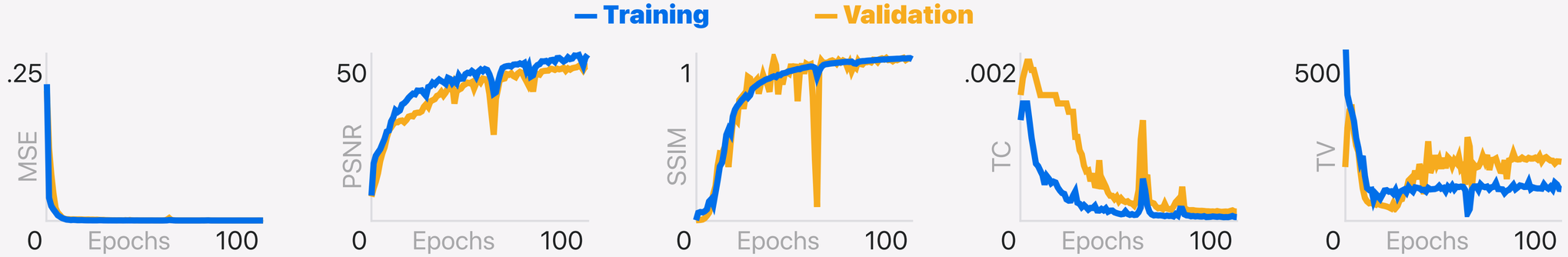
Model trained with
Temporal Consistency
loss function

MSE+TC
model

Model trained with
unified MSE and TC
loss functions

Training results

Metric curves of Unified model



MSE

✓ Similar to MSE model

PSNR

✓ Slightly faster than MSE model

SSIM

✓ Similar to MSE model

TC

✓ Similar to MSE model

TV

✓ Similar to MSE model

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Test results

Quantitative metrics

	MSE model	TC model	Unified model
MSE ★ Lower is better	0.0001 ★	0.0326	0.0001 ★
PSNR ★ Higher is better	45.1848 dB	14.8740 dB	46.9794 dB ★
SSIM ★ Higher is better	0.9633	0.0162	0.9692 ★
TC ★ Lower is better	0.0001	0.0000 ★	0.0001
TV ★ Lower is better	148.1984	239.4765	141.8375 ★

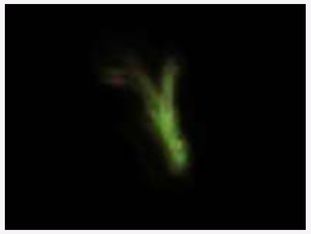
Test results

Qualitative inspection

Predicting one future time step

Based on past 35 images

Ground truth



MSE model

TC model

Unified model

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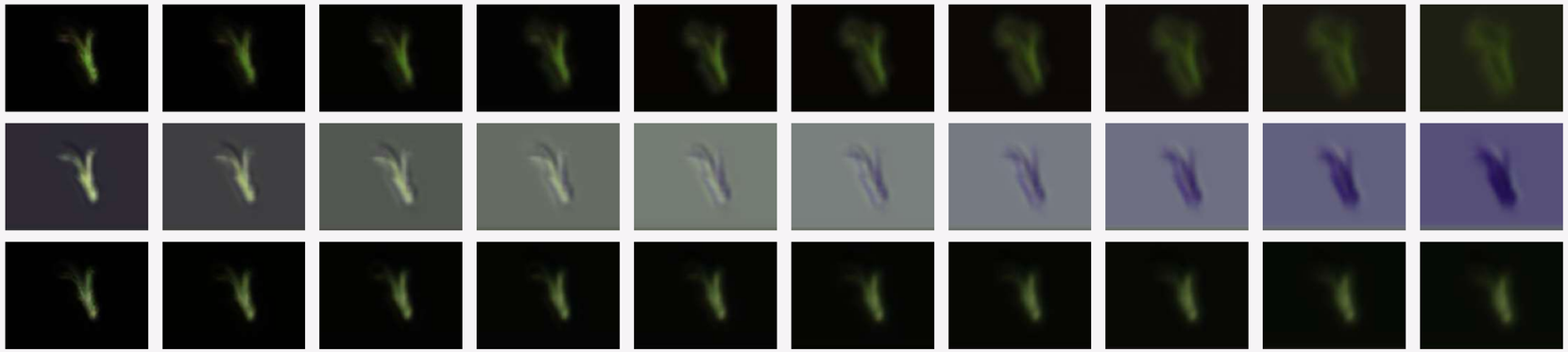
Test results

Qualitative inspection

MSE model

TC model

Unified model



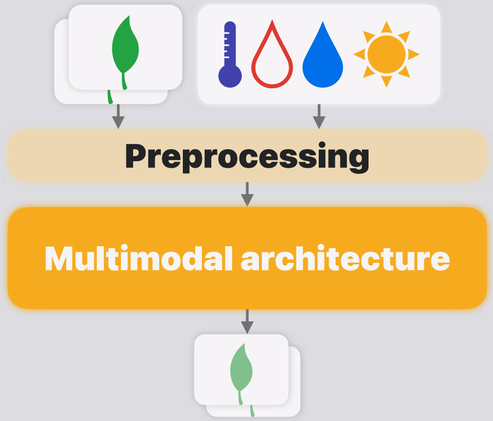
Future time steps

Recap

Predicting future plant growth appearances with

Multimodal Convolutional Long Short-Term Memory

Multimodal learning



Model architecture

- ConvLSTM
- Time Distributed
- Reshape
- Normalization
- Lambda
- Concatenation
- 3D Convolution

MSE — **Mean Squared Error**
Excels image quality

TC — **Temporal Consistency**
Excels smoothness in changing frames of plant appearance

MSE +TC — **Unified MSE + TC**
Surpasses other models with slightly better train & test results

Unified Loss Function

A unique approach by blending MSE and TC as a single loss function

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Limitations

- Dataset lacks diversity in plant images
  The causal of early convergence during model training

- Dataset lacks plant images grown in different external conditions
  The causal why multimodality feature remain untested

Recommendations

For succeeding researchers,

- Continue collecting data (i.e., add more sequences)
- Expand the dataset with other plant types (i.e., beyond lettuce)
- Grow them in different external conditions (e.g., cooler temperatures)
- Explore other techniques that help solve the weaknesses found in current models (e.g., blurry predictions)

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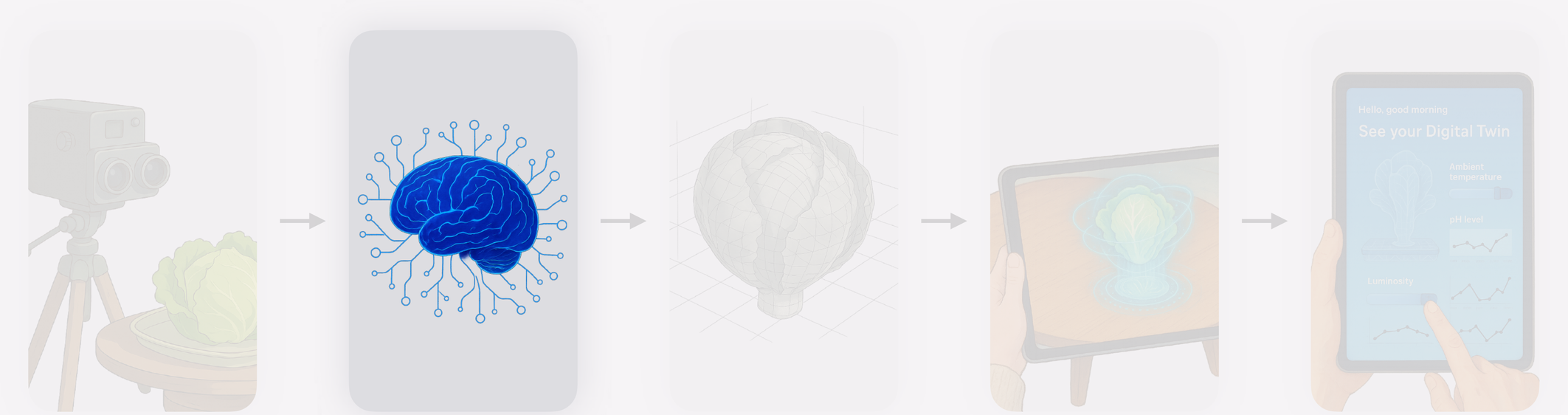
R&D roadmap



Artificial Intelligence

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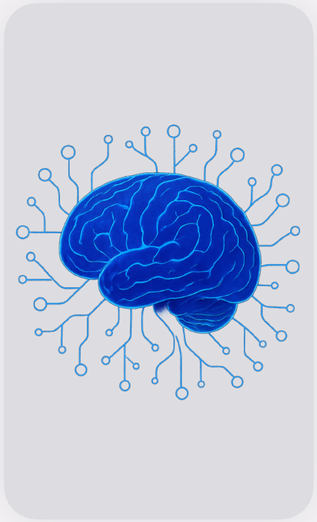
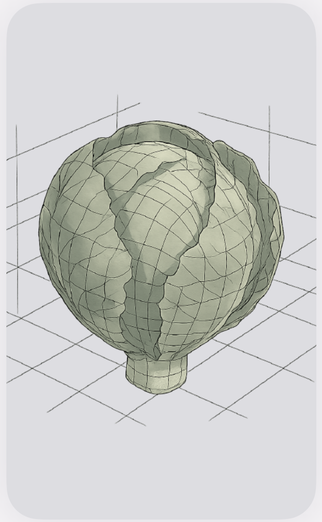
R&D roadmap

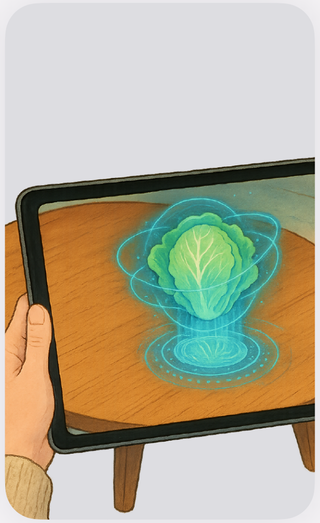
Data Collection



Artificial Intelligence



3D Modeling



Augmented Reality

User Interface

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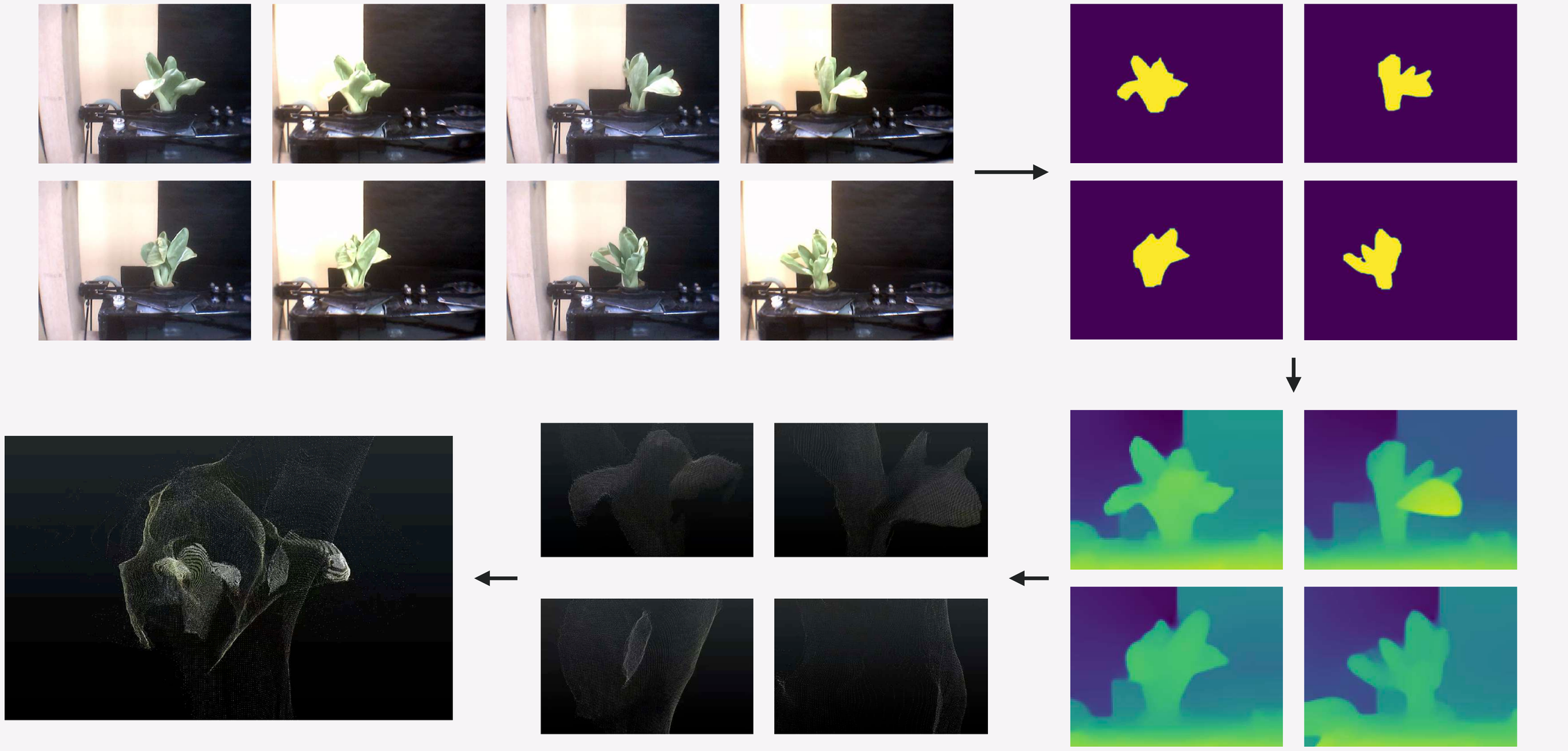
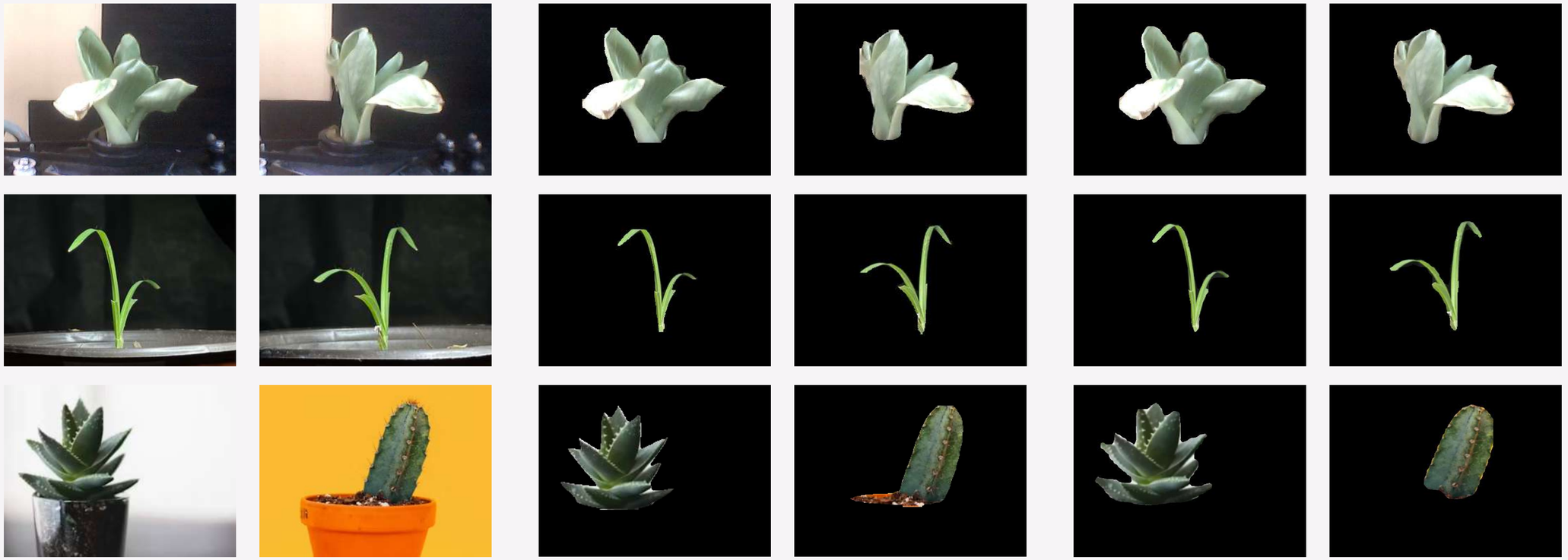


Training images

YOLOv8

Detectron2



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Investigating Deep Learning and Computer Vision for Predicting and Simulating Plant Growth Structures: Laying the Groundwork for Digital Twins in Agriculture

John Ivan T. Diaz, Craig Joseph B. Goc-ong, Kaye Louise A. Manilong, Alvin Joseph S. Macapagal, Philip Virgil B. Astillo*
Department of Computer Engineering, University of San Carlos

Current farming practice

The problem

Vegetation is one of our primary sources of food. Crops grow in response to external conditions around them. A change in pH level, for instance, can influence their growth. We rely on farmers to grow and harvest them. Modern farming practices like vertical farming allow crops to grow in controlled environments, enabling farmers to manipulate external conditions such as pH levels. However, their decisions might not always be favorable to the crops. Applying too little or too much configuration can result in healthy or unhealthy crops. Crops can become damaged or experience stagnated growth, leading to reduced yields and resource wastage. It's risky, inefficient, and unsustainable.

Farmer — Environmental decisions — Actual crop

Our Vision

Solution

We envision a future in farming practices where farmers use digital twins to guide them in their decision-making. A digital twin is defined as a digital replica of a physical counterpart. It mimics the behavior and appearance of an object, such as crops. Farmers first apply experimental decisions to the digital twin. Then, the digital twin mimics the crop's response based on those decisions. As a result, farmers receive insights and use them to make informed decisions on their real crops. This leads to no resource wastage, healthier crops, and higher yields. It redefines modern farming practices to be more sustainable and efficient, ultimately benefiting mankind and the planet.

Farmer — Experiences — Insights — Informed decisions — Digital Twin — Actual crop

Promotes SUSTAINABLE DEVELOPMENT GOALS

2 ZERO HUNGER
9 INDUSTRY, INNOVATION, AND INFRASTRUCTURE
12 RESPONSIBLE CONSUMPTION AND PRODUCTION

The Technological Impacts

- Farmers can make informed agricultural decisions
- Drives healthier crops and higher yields
- Promotes Sustainable and Efficient farming practices
- Entrepreneurial Opportunities for Developers

Our Foundational Contributions

Developing a Data Collection Platform

A small replica of a hydroponic vertical farm with cameras and sensors to collect plant growth data.

Design sketch

Features

- Plant images are captured in Stereo Vision
- Plants grow on top of rotating lazy susans to capture all four sides of their appearance
- External conditions (e.g. pH level) are recorded using calibrated sensors
- Images and sensor data are captured periodically using Arduino and C, and managed using Python and MySQL

Developing a Multimodal Convolutional Long Short-Term Memory Architecture for Predicting Future Plant Appearance

Multimodal learning

It learns how plants look under a given set of external conditions (e.g., ambient temperature), thus gaining the ability to predict future plant appearances based on those conditions.

Plant appearances (Images) + External conditions (Numerical data) → Pre-processing → Multimodal Convolutional Long Short-Term Memory Architecture → Future plant appearances (Images)

Model architecture

- ConvLSTMs
- Time Distributed
- Reshape
- Normalization
- Lambda
- Concatenation
- 3D Convolution

Proposing Unified Loss Function for Model Training

Three loss functions are explored: Mean Squared Error, Temporal Consistency, and one that combines both. The unified loss function showed slightly better training and testing results than the other two in predicting images of plant appearance.

Methodology flowchart

Train Dataset → Preprocessing → Model Training → Trained model → Model Evaluation (Training phase)
Test Dataset → Preprocessing → Model Evaluation (Testing phase)

The dataset contains 64 plant growth sequences captured at 32 hours intervals. The plant used is lettuce, but the model is scalable to other plant types.

Preprocessing

Segmentation → Resize → Normalization → Sequence Length Standardization → Augmentation

Test results

★ Better result

Metric	MSE model	TC model	Unified model (MSE+TC)
MSE	0.0001 ★	0.0206	0.0001 ★
PSNR	45.1648 dB	14.8740 dB	46.9794 dB ★
SSIM	0.9633	0.0162	0.9650 ★
TC	0.0001	0.0000 ★	0.0001
TV	148.1984	239.4765	141.8375 ★

RMSE=Root Mean Squared Error (RMSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Temporal Consistency (TC), and Total Variation (TV)

Evaluation process: Actual image (from the dataset) — Forecast (10 frames) — Predicted image (from the model)

Sample image

Ground truth | MSE model
TC model | Unified model (MSE+TC)

Predicting the 10th frame of a sequence using the past 30 images. The same configuration of external conditions from the dataset is used to generate these images. The frame size is 30 × 30 pixels.

Investigating Computer Vision Techniques to Create a 3D Model of the Plant from Constrained Stereo Images

The challenge is to transform 2D stereo images, captured around an object at 90-degree horizontal rotations, into a 3D model.

Techniques used

Plant stereo images → Depth Mapping → Point Cloud Generation → Point Cloud Refinement → Point Cloud Registration → Mesh Generation

The techniques mentioned can OpenCV and OpenGL libraries in Python. Point cloud generation uses 3D reprojection. Point cloud refinement uses the Iterative Function with statistical and radius outlier removal. Point cloud registration uses the translate, rotate, scale, and transform functions. Mesh generation uses the Ball Pivoting Algorithm.

Investigating Segmentation Architectures Trained Solely for the Plant Class

Correct segmentation of plant objects positively affects succeeding phases such as 3D modeling. YOLOv8 and Detectron2 are the initial architectures chosen for comparison.

Train results

★ Better result

Metric	Test A		Test B		Test C	
	YOLOv8	Detectron2	YOLOv8	Detectron2	YOLOv8	Detectron2
Box AP50	0.850	0.870 ★	0.830	0.840 ★	0.830 ★	0.740
Mask AP50	0.840	0.860 ★	0.830 ★	0.800	0.830 ★	0.720
Box Loss	0.400	0.180 ★	0.360	0.190 ★	0.390	0.190 ★
Mask Loss	0.800	0.170 ★	0.680	0.170 ★	0.870	0.150 ★
Train Time	1,400 hrs ★	1,590 hrs	1,570 hrs ★	1,920 hrs	1,870 hrs ★	2,020 hrs
System RAM	5,300 GB ★	4,600 GB ★	5,900 GB ★	3,300 GB ★	5,900 GB ★	4,600 GB ★
GPU RAM	31,000 GB ★	31,000 GB ★	31,000 GB ★	31,000 GB ★	31,000 GB ★	31,000 GB ★
Disk Usage	33,500 GB ★	35,900 GB	33,300 GB ★	33,200 GB ★	33,200 GB ★	35,900 GB

Decreasing hyperparameters

This dataset contains more than 10,000 plant images, found in rows at 100, 75, and 50 Pixels-to-CU. Batch sizes are 16, 8, and 2. Worker counts are 8, 4, and 2. The train and test images were processed at levels of 10,000 and 1,000 respectively.

Methodology flowchart: Train Dataset → Annotation → Model Training → Trained model (Training phase); Test Dataset → Annotation → Model Evaluation (Testing phase)

Strengths | Weaknesses

YOLOv8
- Fast training speed
- Stable accuracy with fewer epochs
- Low disk storage usage
- Effective with smaller hyperparameters
- Slightly lower segmentation accuracy
- High GPU RAM consumption with larger sets
- Higher RAM consumption

Detectron2
- Higher segmentation accuracy
- Lower GPU RAM usage
- Stable RAM consumption
- Significant accuracy gains with higher hyperparameters
- Slower training speed
- High disk usage
- Accuracy greatly affected by fewer epochs
- Poor performance with minimal hyperparameters

Sample of whole process

Plant's past appearances (Images) — External conditions associated (Numerical data)

Ambient temperature | Moisture | pH level

Day 1 … Day 15

CALIBRATION MAP
SEGMENTATION MODEL
Segmented Images
MULTIMODAL CONVOLUTIONAL LONG-SHORT-TERM MEMORY MODEL

Day 15.1 Predicted
Day 15.5 Depth Map
Day 15.5 Point Map
Day 15.5 Refined point cloud
Day 15.5 Meshed point cloud

Plant's future appearance 3D model

Recommendations

For researchers who believe in the vision and wish to contribute to its pursuit:

- Continue collecting data. Grow more plants. Expand to other plant types, and grow them under different external conditions.
- Explore data collection techniques that capture top and bottom plant views and yield denser point clouds.
- Explore deep learning techniques that can address weaknesses found in current models, such as blurriness in predictions.
- Expand the 3D modeling methodology to include quantitative evaluation.
- Implement an automatic point cloud merging technique in 3D modeling to replace the current manual process.
- Continue future R&D stages, such as developing augmented reality experiences to view 3D plant models in physical space.

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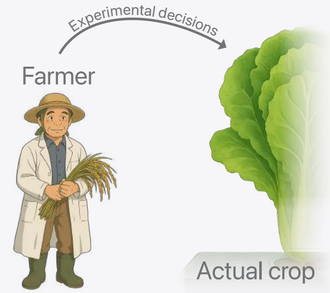

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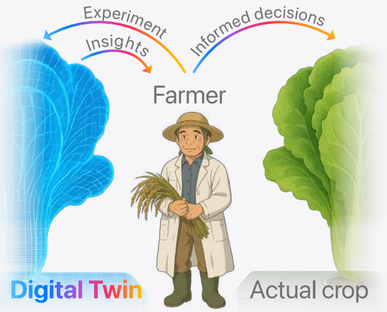

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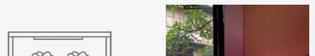

Features

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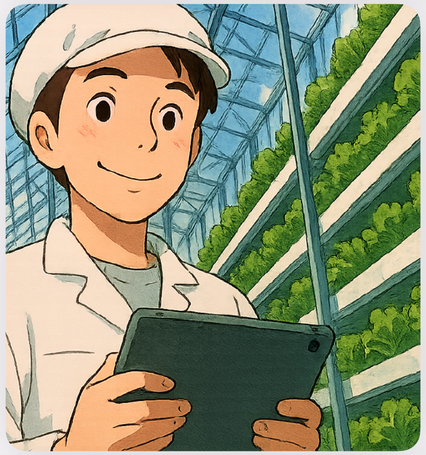
Train results

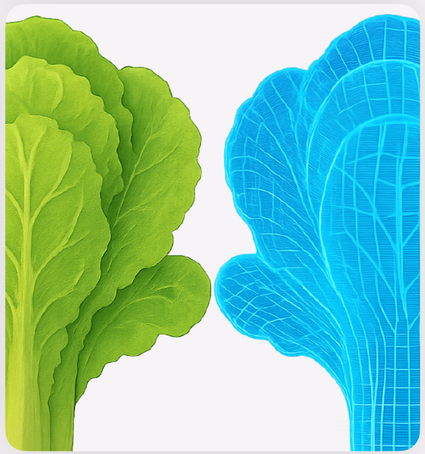
Strengths	Weaknesses

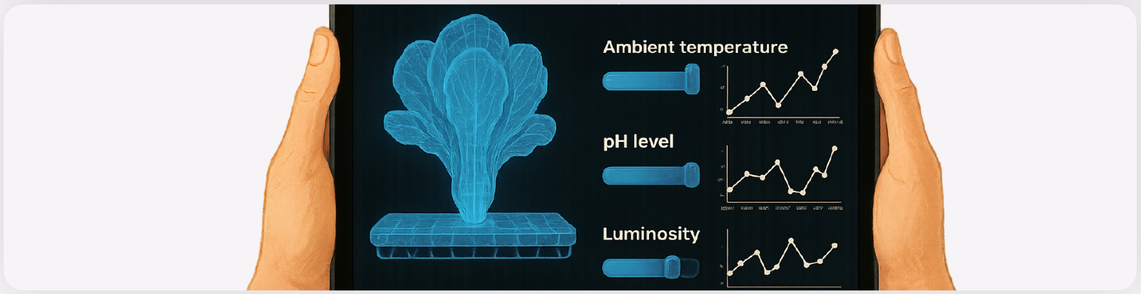


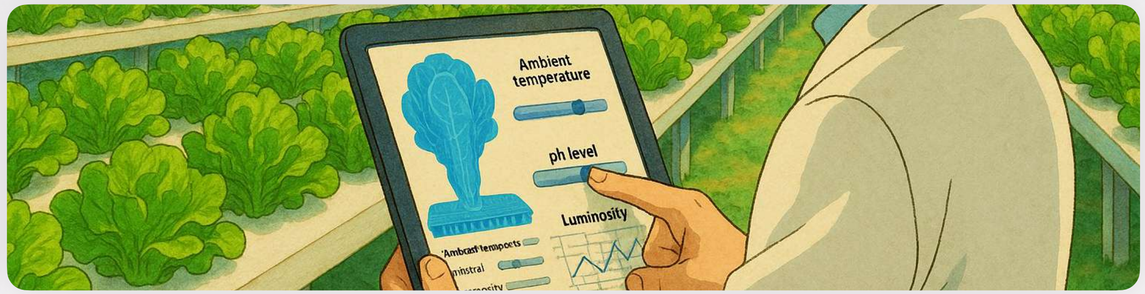
Our vision

Digital twins in agriculture

Empowering farmers with informed decisions.
Promoting sustainability and efficiency.
For humanity. For the planet.







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Unified Temporal Consistency and Mean Squared Error Loss Function for Predicting Plant Growth Structures through Multimodal Convolutional Long Short-Term Memory: Laying the Groundwork for Digital Twins in Agriculture

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