Enhancing Sustainable Crop Production with Machine Learning, Synthetic Data, and Digital Twin for Strawberry

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Outline

Optimizing Machine Vision & Robotics in Agriculture Through Virtual Environments

Introduction
- Challenges in Ag Automation
- What is Synthetic Data?

Digital Twins for Strawberry Farming
- How to Create Realistic Synthetic Vegetative Scene
- Creating a Scene: Hardware Control

Similarity between real and synthetic data
- Fruit Detection
- Fruit Sizing
- Lidar Measurement

Conclusion & Discussion


Machine learning and field robotics for precision agriculture
Smart Agriculture Lab
Where Agriculture & Technology Meet to Build Future
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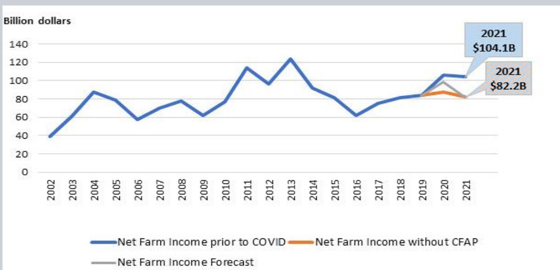
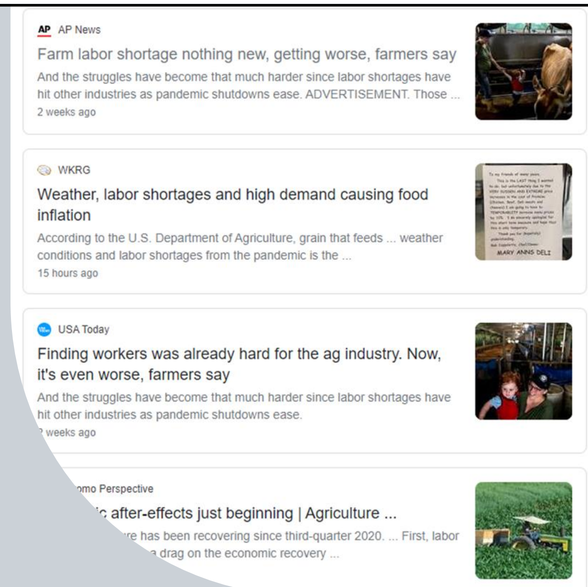
Introduction

Challenges in Agriculture

1. Decrease in agricultural land
2. Labor scarcity in rural areas
3. Price and availability of energy
4. Climate change



Graph from USDA, America's Farmers: Resilient Throughout the COVID Pandemic, Oct 13, 2020



Precision Agriculture

Optimization of Farming Input

- Efficient farming by site-specific crop management
- Increase crop yields
- Maximize profit for growers
- Reduce environmental impact

Technologies for Enhanced Precision Agriculture

- AI and Machine Learning: data analytics and forecasting
- Robotics: Automation with increased efficiency
- Digital Twin: digital representation of your farm

Citrus grove in Lake Wales, Florida

Challenges in Ag Automation & Robotics

Time-Consuming
Testing is limited to few months

Special Expertise
Installation
Maintenance

Costly
Data collection
Travel to farm site

Risk
Bad data
Crop is lost due to disease or frost

How to reduce the turnaround time for autonomous systems?

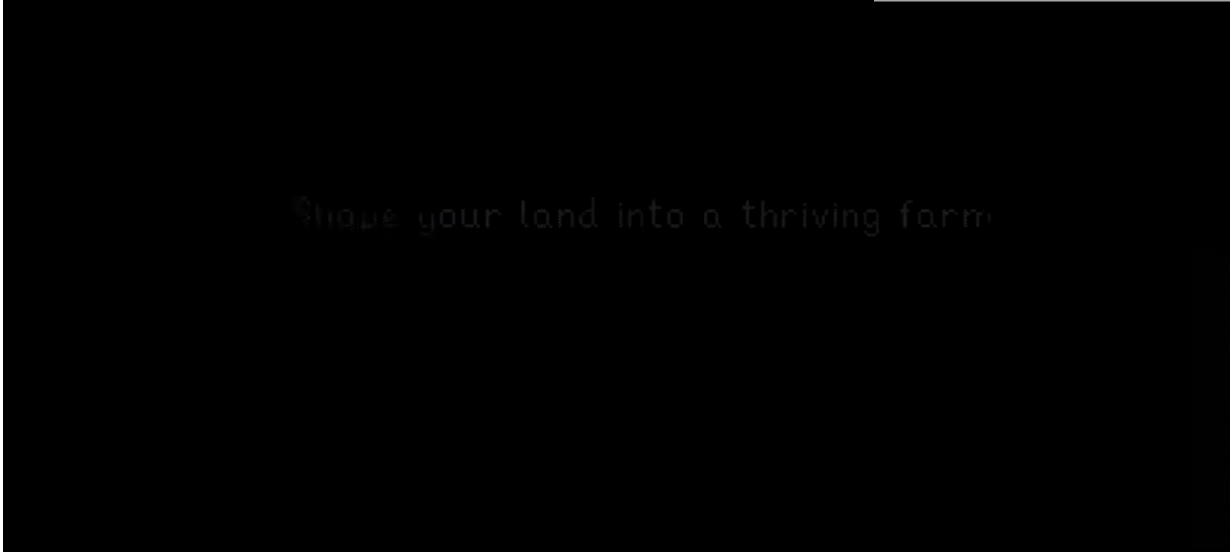
Synthetic Data

Definition:
- Data generated artificially, not from real-world observations

Purpose:
- Can replicate the characteristics of real data
- Useful for enhancing datasets, privacy, and testing

Generation Techniques:
- Statistical methods (e.g., bootstrapping, synthetic regression)
- Generative models (e.g., GANs)
- Simulations & 3D graphics

Digital Twin: a dynamic, virtual representation of a physical objec system, allowing for real-time "artificial" monitoring or simulatior

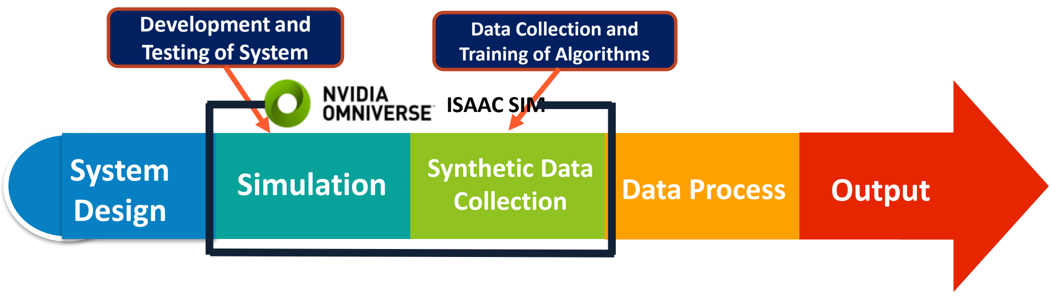


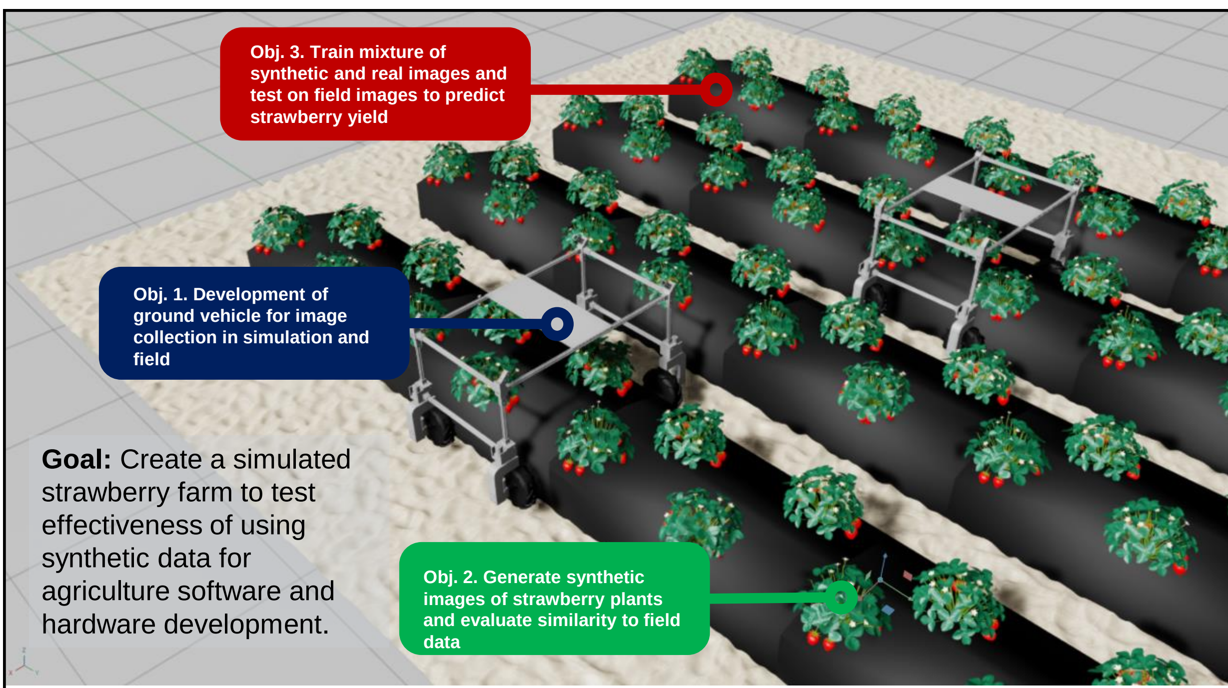
Exploring the Virtual Strawberry Farm

Benefits of Digital Twin

Speed up the development process of robots and AI

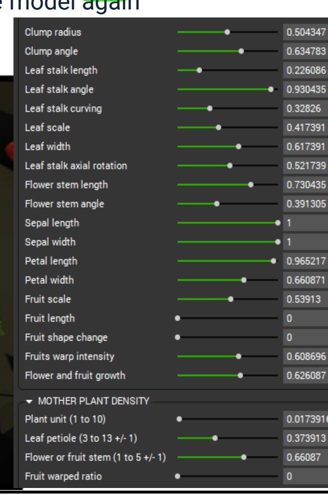
- Data augmentation for limited datasets.
- Training robust machine learning models.
- Testing new agricultural tools without risk.
- Ensuring farmers' data privacy.





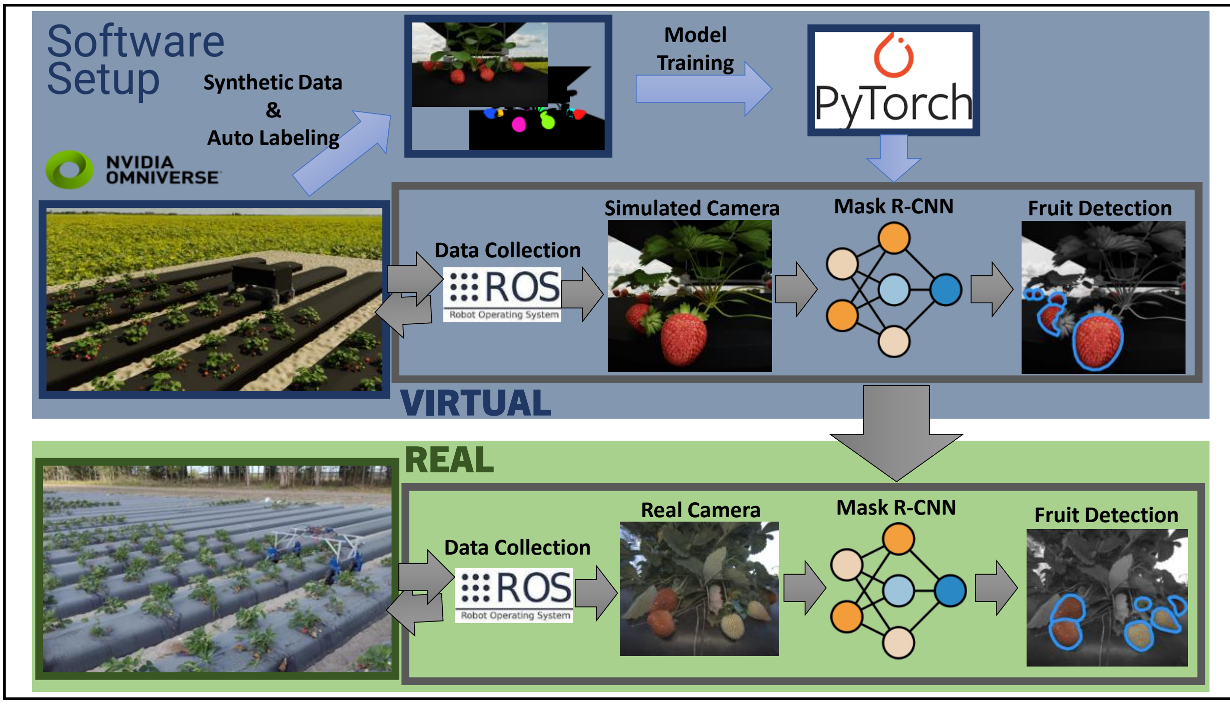
Procedural Modeling

- Rules-based approach for modeling rather than manual design of components
- Flexibility: Easier to modify model components instead of recreating the entire model again
- Randomization: Can randomize model

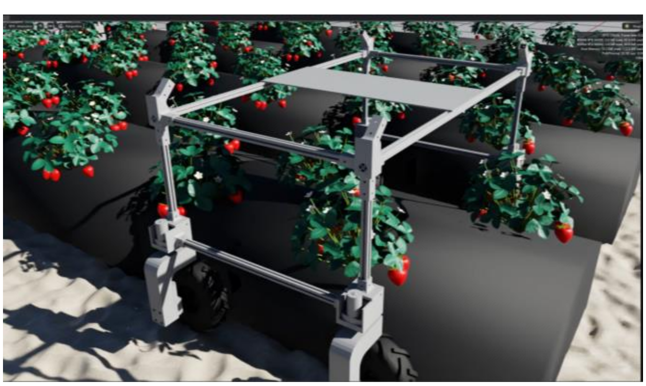


Hardware Setup in the Field

Hardware Setup in Isaac Sim



Data Acquisition (Gen1 & Gen2)



Gen 1

Gen 2

Field

Simulation

NVIDIA OMNIVERSE

Camera Perspectives

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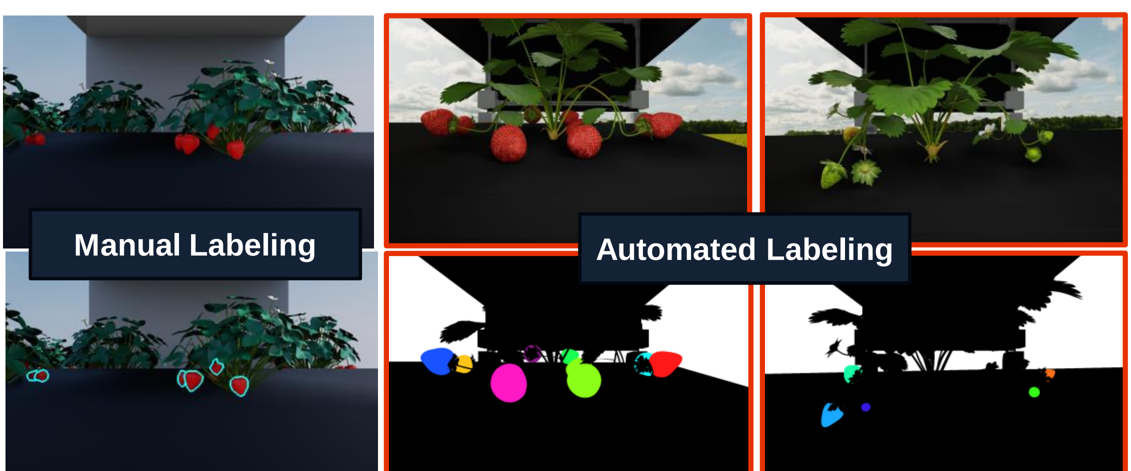
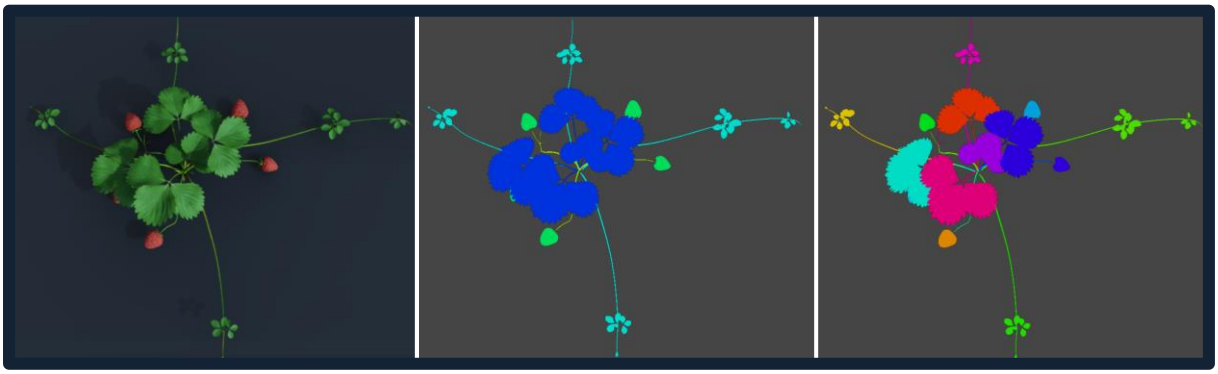
Automated Labeling

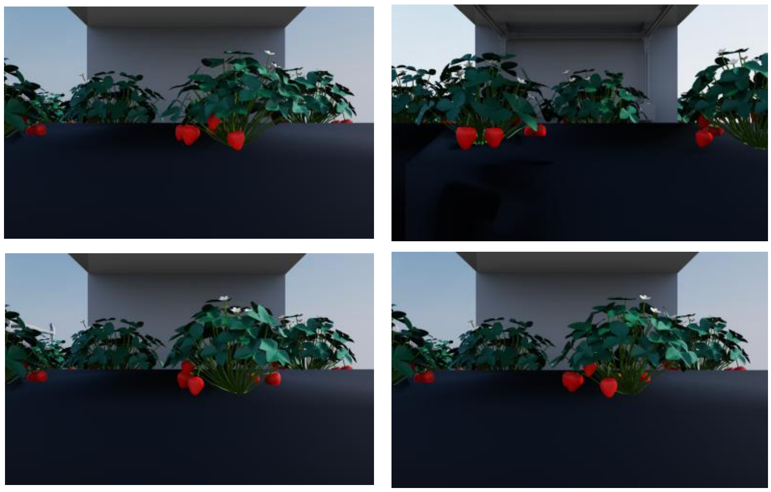


Automated Labeling

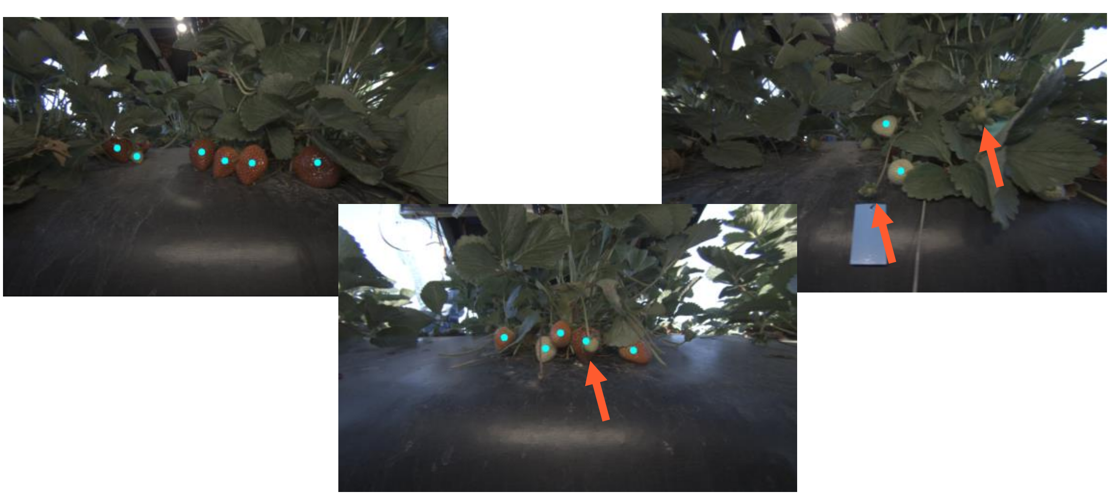
RGB | Semantic Segmentation | Instance Segmentation



Results: Sample Training Images - Gen 1



Results: Fruit Detection on Field Images



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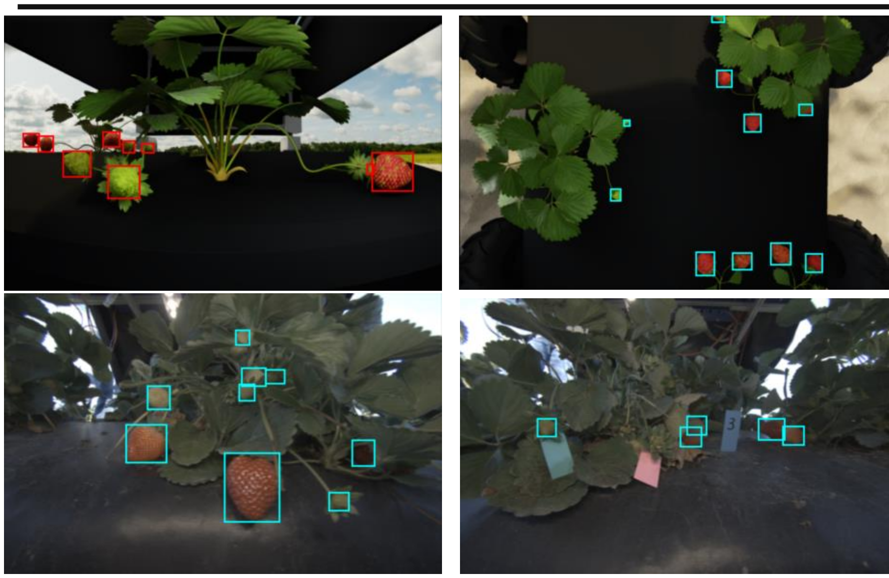
Sample Training Images - Gen 2

Results: Fruit Detection on Field Images



Results: Fruit Detection

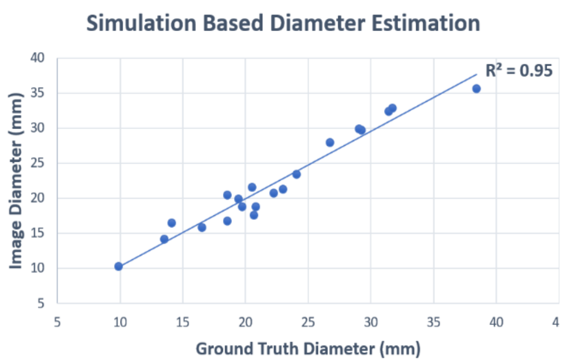
Training using Synthetic Data only

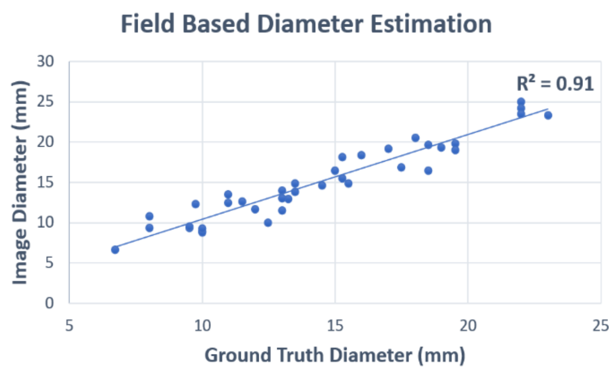
	TP	FP	FN	Precision	Recall	F1-Score
 **Synthetic Data Gen-1**	56	2	86	0.96	0.39	0.56
 **Synthetic Data Gen-2**	127	17	15	0.88	0.89	0.89
Gen-1 + Gen 2	96	3	44	0.97	0.69	0.80
Real Images	129	2	12	0.98	0.91	0.95

Results: Fruit Detection

	Trial 1 (March 16)			
	Fruit Count	Precision	Recall	F1-Score
All Fruit	295	0.95	0.89	0.92
Red Fruit	167	0.95	0.99	0.97
White Fruit	61	1.00	0.87	0.93
Green Fruit	67	0.94	0.72	0.82
Trial 2 (March 20)				
All Fruit	134	0.89	0.75	0.81
Red Fruit	39	0.87	0.95	0.91
White Fruit	52	0.98	0.81	0.89
Green Fruit	43	0.83	0.58	0.68

Results: Fruit Sizing

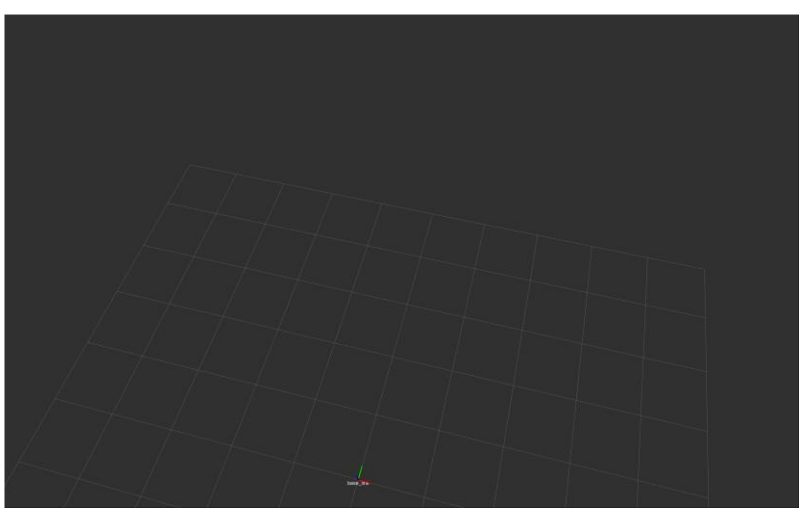




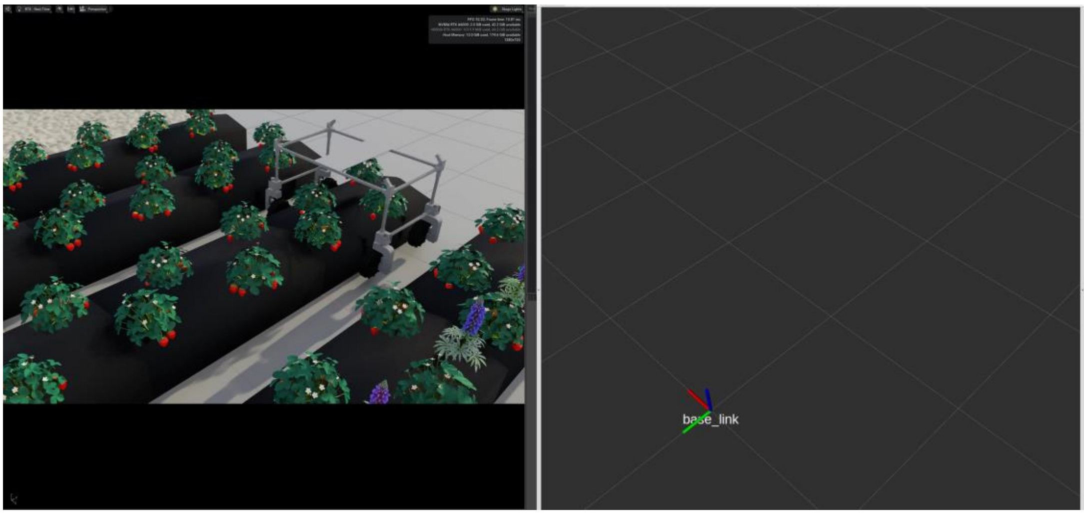
Average Diameter Error: **1.5 mm**

Average Diameter Error: **1.6 mm**

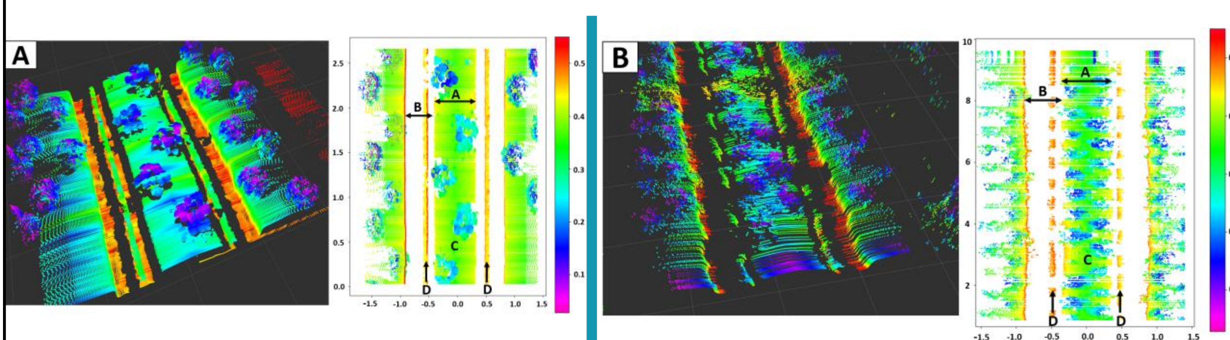
Results: Lidar Data In Field



Results: Lidar Data In Simulation



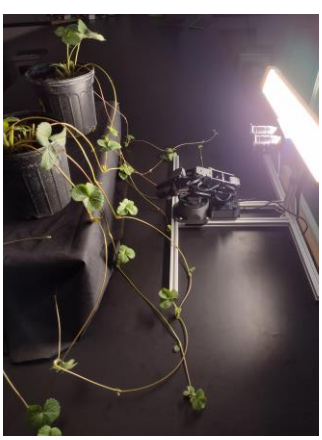
Results: Lidar Data Comparison

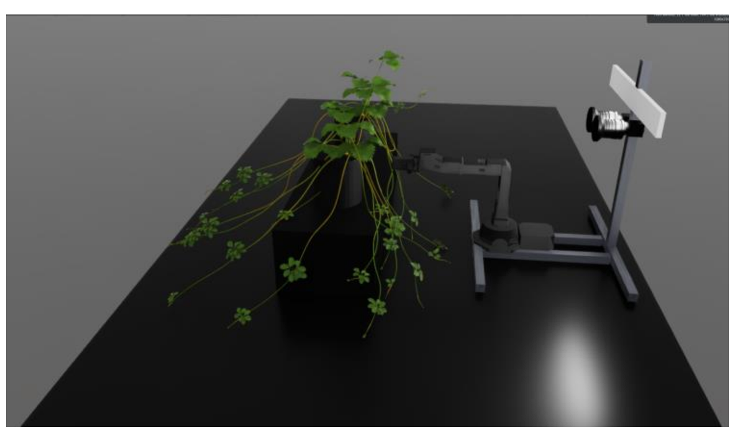


Label	Description	Simulated Lidar Sensor (m)	Real Lidar Sensor (m)	Ground Truth Measurement (m)
A	Bed Spacing	0.50	0.53	0.51
B	Bed Width	0.72	0.71	0.74
C	Bed Height	0.26	0.29	0.25

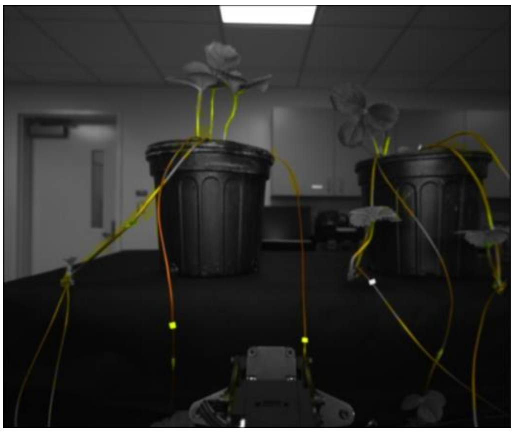
More realistic strawberry Plant - Runner

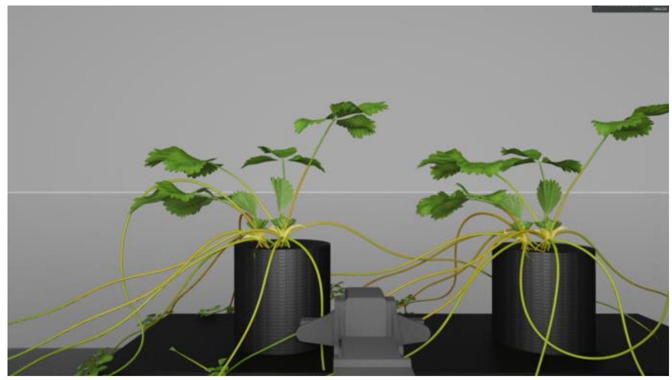
Digital Twin for Runner Cutting

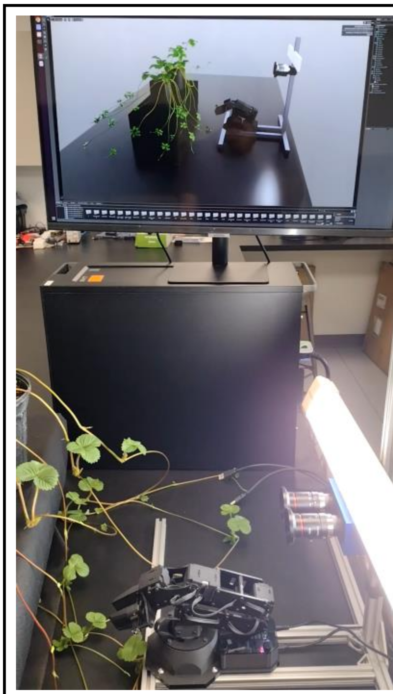




Digital Twin for Runner Cutting







Digital Twin for Runner Cutting

Bidirectional communication between ROS and the hardware, as well as its reflection in the virtual environment of Isaac Sim

Robotics Simulation for Runner Detection

Summary

Turnaround time from concept to product in the AgTech industry is costly and time-consuming.

- There is a limited window to test prototypes each year, which adds to the challenges.
- The risk of crop limitations due to disease or weather further complicates the development process.
- Labor costs associated with collecting data and obtaining reliable ground truth are significant.

Leveraging synthetic agricultural data and better simulation tools can help mitigate risks.

- Utilizing synthetic data allows for more frequent and extensive testing, reducing reliance on limited real-world opportunities.
- Improved simulation tools provide a more efficient and cost-effective way to evaluate product performance.

Acknowledgement

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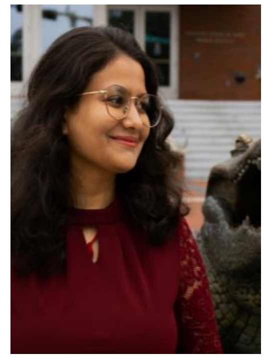

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Thank You!

ANY QUESTIONS?

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