The Role of AI in postharvest operations

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Guest lecture for the HOS 5330 Postharvest Technologies for Horticultural Crops

Feb 20, 2025

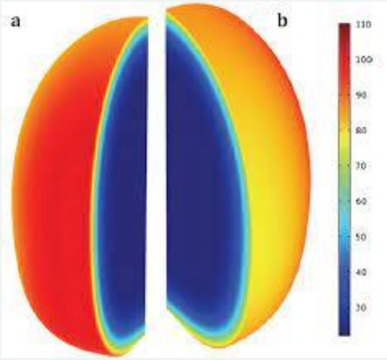
Digital transformation age

Global Automation Market in 2026

$297 BILLION

Food and Beverage Applications

11% of the Market



Statista. 2020. “Industrial automation worldwide.” https://www.statista.com/study/87398/industrial-automation-worldwide

Figure 3: Combinations of 4IR technologies can enable innovation to solve challenges faced in food systems

Digital building blocks

- New computing technologies
- Big data and advanced analytics
- The Internet of Things (IoT)
- Artificial intelligence and machine learning
- Blockchain
- Virtual reality and augmented reality

Advances in science

- Next-generation biotechnologies and genomics
- Energy creation, capture, storage and transmission

Reforming the physical

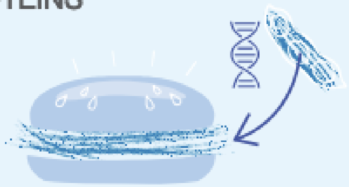
- Autonomous and near-autonomous vehicles
- Advanced, smart robotics
- Additive manufacturing and multidimensional printing
- Advanced materials and nanotechnologies

WEF Transformative Twelve Repor

Figure 1: The 'Transformative Twelve' could deliver significant impacts to food systems by 2030

Changing the shape of demand

ALTERNATIVE PROTEINS



- Reduce GhG emissions by up to 950 megatonnes of CO_2 eq.
- Reduce freshwater withdrawals by up to 400 billion cubic metres
- Liberate up to 400 million hectares of land

FOOD SENSING TECHNOLOGIES FOR FOOD SAFETY, QUALITY, AND TRACEABILITY

- Reduce food waste by up to 20 million tonnes

NUTRIGENETICS FOR PERSONALIZED NUTRITION

- Reduce the number of overweight by up to 55 million

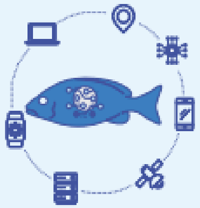
Promoting value-chain linkages

MOBILE SERVICE DELIVERY

- Generate up to $200 billion of income for farmers
- Reduce GhG emissions by up to 100 megatonnes of CO_2 eq.
- Reduce freshwater withdrawals by up to 100 billion cubic metres

BIG DATA AND ADVANCED ANALYTICS FOR INSURANCE

- Generate up to $70 billion of income for farmers
- Increase production by up to 150 million tonnes



IOT FOR REAL-TIME SUPPLY CHAIN TRANSPARENCY AND TRACEABILITY

- Reduce food loss by up to 35 million tonnes

BLOCKCHAIN-ENABLED TRACEABILITY

- Reduce food loss by up to 30 million tonnes

World Economic forum ”transformative twelve”

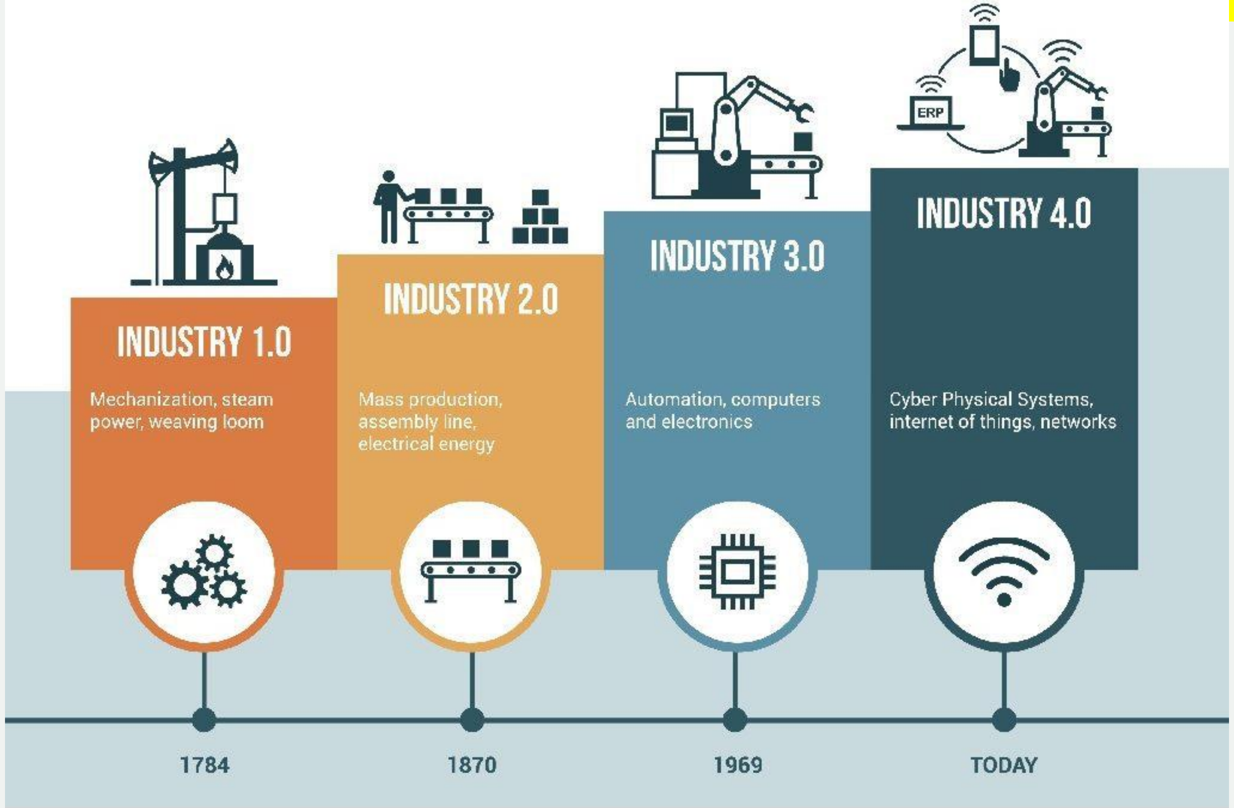
- Food industry has been slow

“14 billion in investments in 1,000 food systems-focused start-ups since 2010, while healthcare attracted $145 billion in investment in 18,000 start-ups during the same time period.” WEF

Figure 5: Summary of impacts by 2030: Changing the shape of demand

	WHAT IF...	THE IMPACT COULD BE...		WHICH IS THE EQUIVALENT OF...	DRIVEN BY...
FOOD SENSING TECHNOLOGIES FOR FOOD SAFETY, QUALITY, AND TRACEABILITY 	30-50% of the consumers in developed countries used food scanning to determine expiration dates by 2030	Reduced food waste Millions of tonnes	10-20	5-7% of total food wasted[33]	Reduced domestic food waste from individualized and real-time expiration dates

Industry 4.0 and society 5



Factfile

History of industrial revolution

1.0 — **1780 – Mechanisation**
Industrial production based on machines powered by water and steam

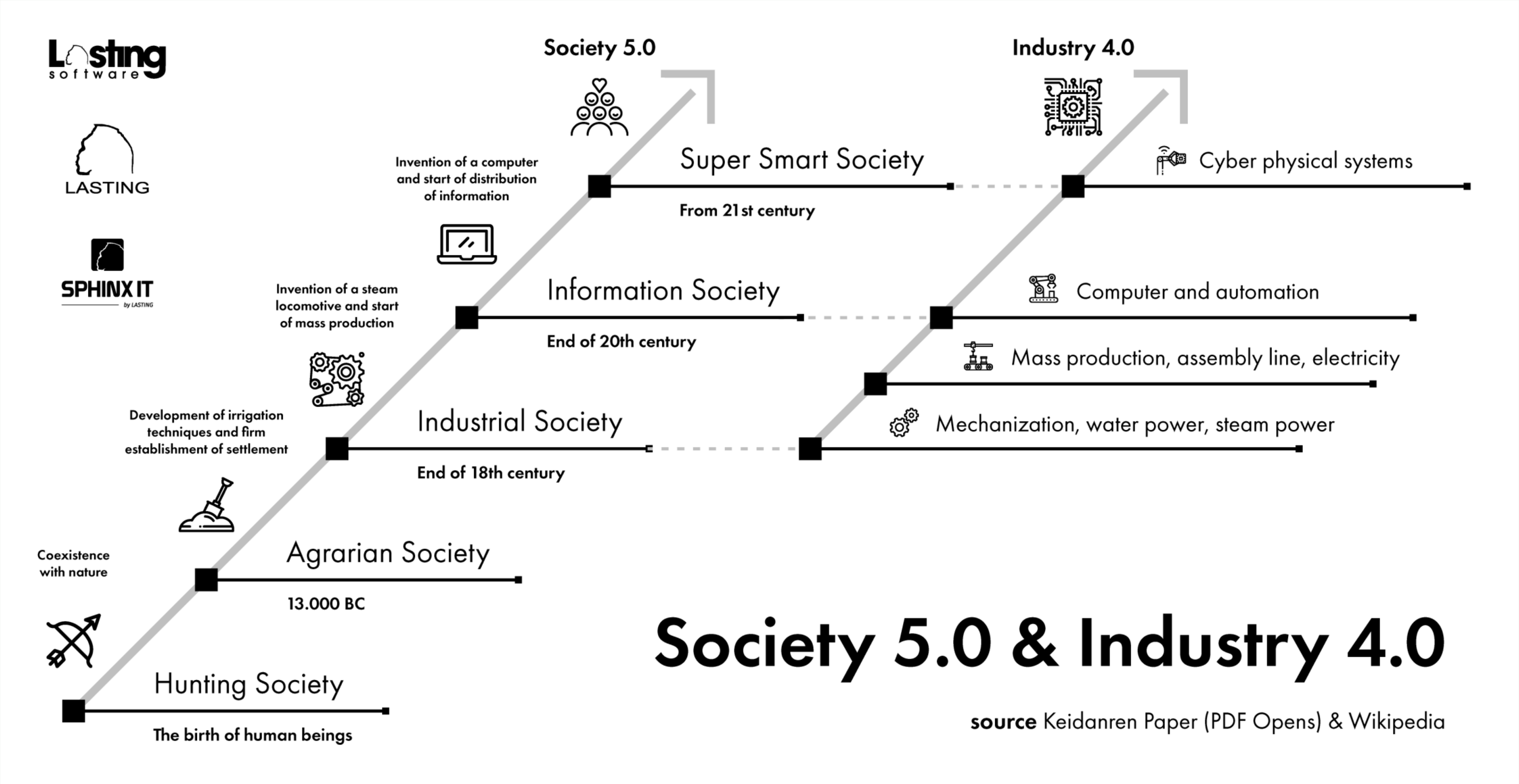
2.0 — **1870 – Electrification**
Mass-production using assembly lines

3.0 — **1970 – Automation**
Automation using electronics and computers

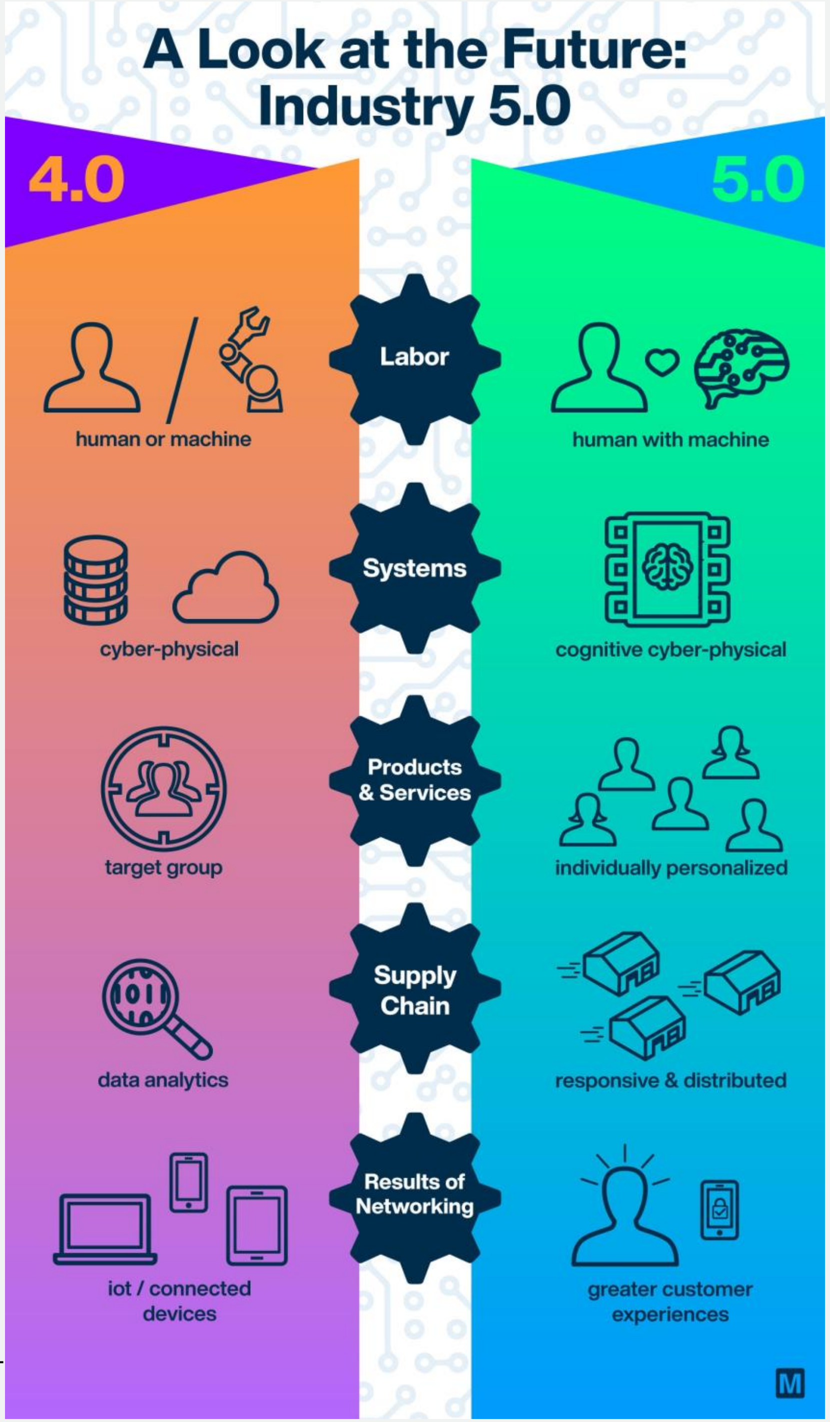
3.5 — **1980 – Globalisation**
Offshoring of production to low-cost economies

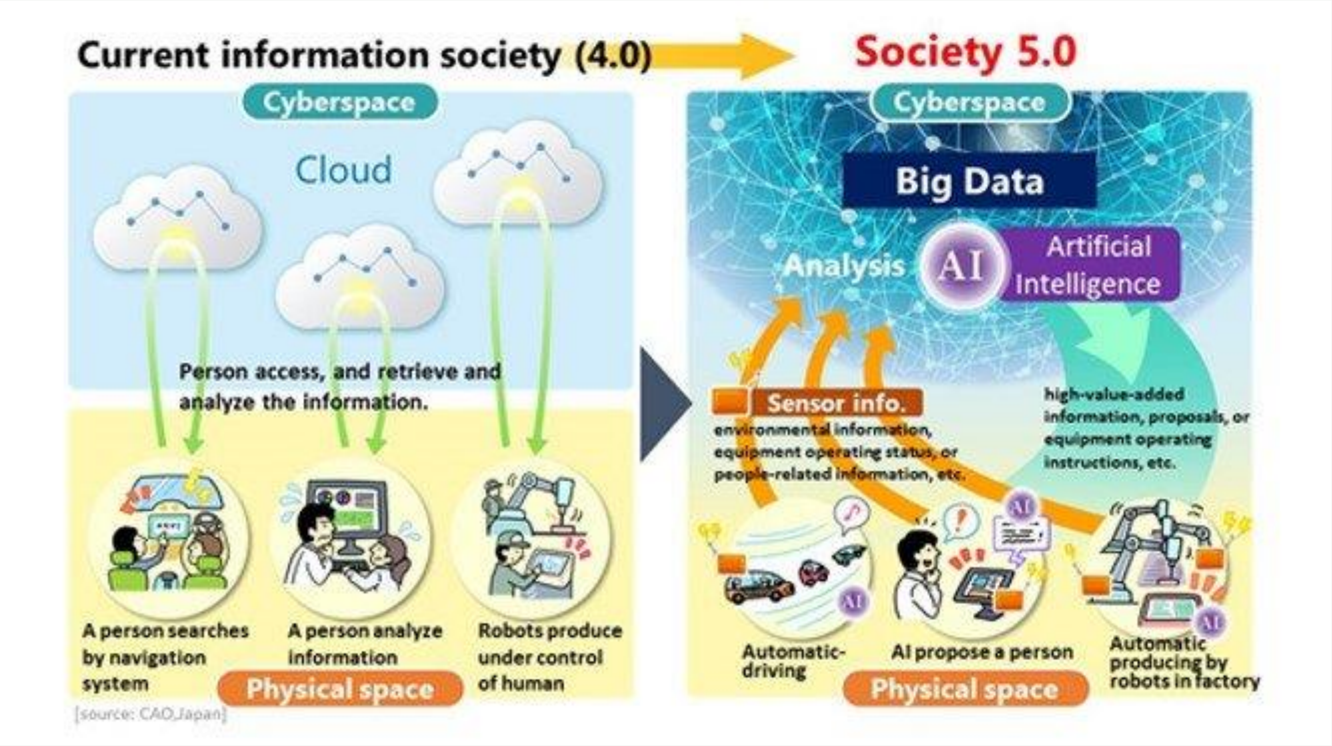
4.0 — **Today – Digitalisation**
Introduction of connected devices, data analytics and artificial intelligence technologies to automate processes further

5.0 — **Future – Personalisation**
The fifth industrial revolution, or Industry 5.0, will be focused on the co-operation between man and machine, as human intelligence works in harmony with cognitive computing. By putting humans back into industrial production with collaborative robots, workers will be upskilled to provide value-added tasks in production, leading to mass customisation and personalisation for customers



Society 5.0
Industry 4.0
Lasting software
LASTING
SPHINX IT by LASTING
Invention of a computer and start of distribution of information
Super Smart Society
From 21st century
Cyber physical systems
Invention of a steam locomotive and start of mass production
Information Society
End of 20th century
Computer and automation
Mass production, assembly line, electricity
Development of irrigation techniques and firm establishment of settlement
Industrial Society
End of 18th century
Mechanization, water power, steam power
Coexistence with nature
Agrarian Society
13.000 BC
Hunting Society
The birth of human beings
Society 5.0 & Industry 4.0
source Keidanren Paper (PDF Opens) & Wikipedia

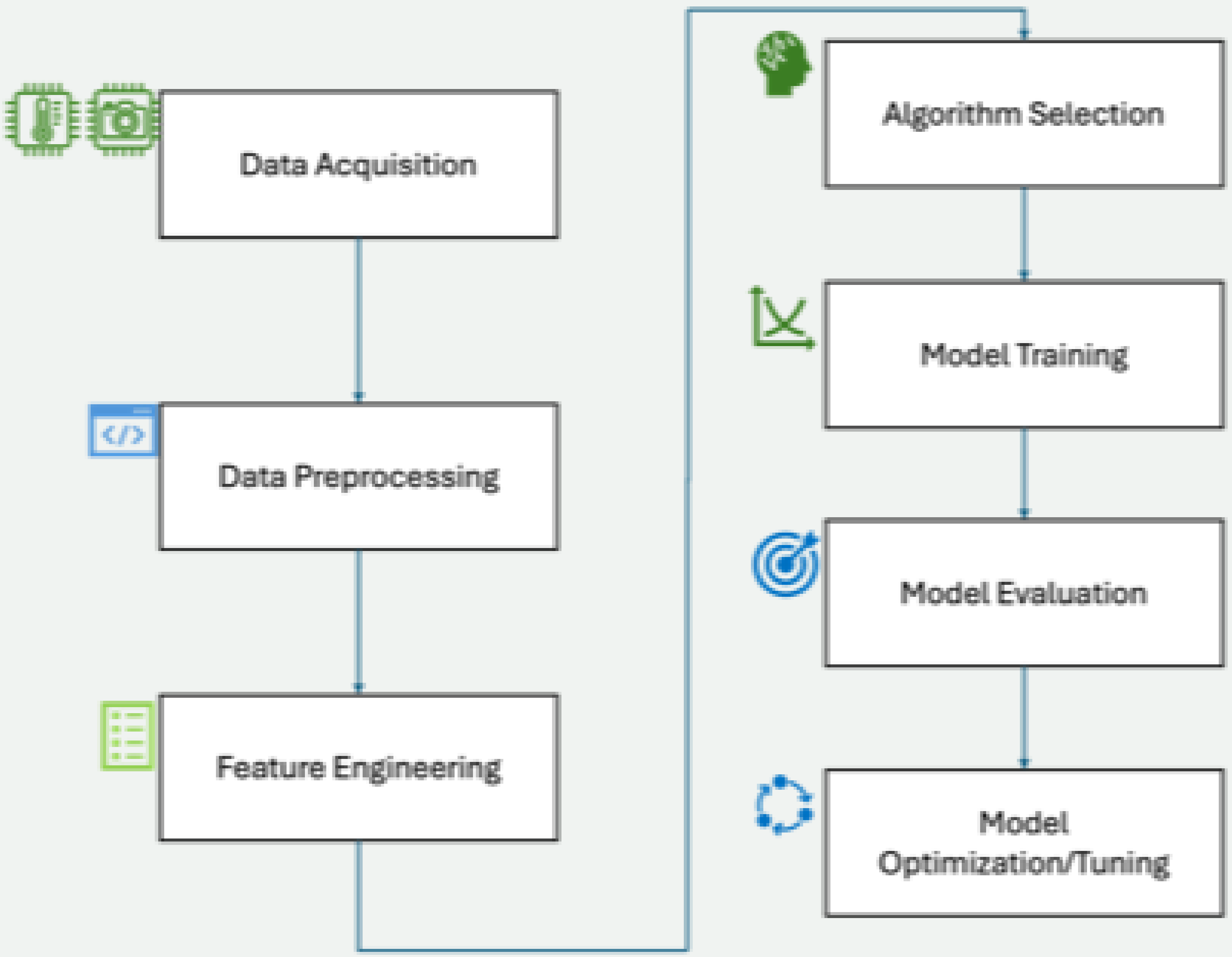

A Look at the Future:
Industry 5.0
4.0
5.0
Labor
human or machine
human with machine
Systems
cyber-physical
cognitive cyber-physical
Products & Services
target group
individually personalized
Supply Chain
data analytics
responsive & distributed
Results of Networking
iot / connected devices
greater customer experiences


Current information society (4.0)
Society 5.0
Cyberspace
Cloud
Person access, and retrieve and analyze the information.
A person searches by navigation system
A person analyze information
Robots produce under control of human
Physical space
[source: CAO,Japan]
Cyberspace
Big Data
Analysis
AI
Artificial Intelligence
Sensor info.
environmental information, equipment operating status, or people-related information, etc.
high-value-added information, proposals, or equipment operating instructions, etc.
Automatic-driving
AI propose a person
Automatic producing by robots in factory
Physical space

But first, What is AI?

- Artificial Intelligence mimics human intelligence processes through algorithms and machine learning. In horticulture, AI’s relevance extends from predictive analytics to robotic automation, transforming traditional practices.

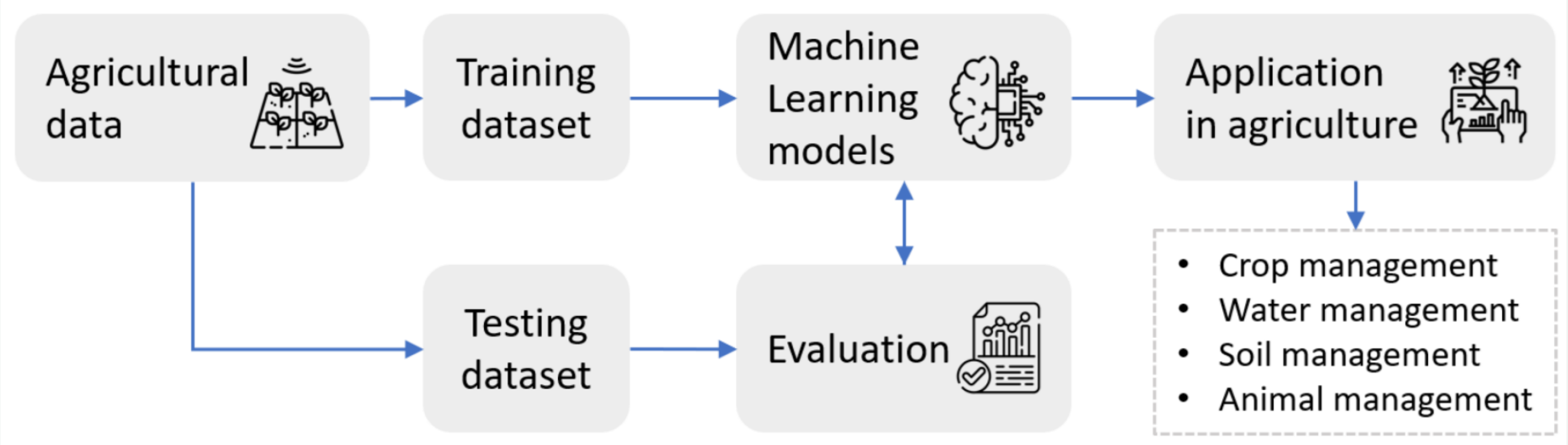
Year	Definition of AI	Reference
1950	The ability of a machine to exhibit intelligent behaviour equivalent to, or indistinguishable from, that of a human.	(Turing, 1950)
1956	The science and engineering of making intelligent machines.	(McCarthy et al., 2006)
1980s	The science of making machines capable of performing tasks that would require intelligence if done by humans.	(Minsky, 1961)
1990s	A machine with the ability to solve problems that are done by humans with our intelligence.	(Russell & Norvig, 2010)
2000s	AI is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment.	(Nilsson, 1998)
2018	AI is the science of making machines that are capable of performing tasks that would require intelligence if done by humans.	(Chollet, 2021)


Data Acquisition
Data Preprocessing
Feature Engineering
Algorithm Selection
Model Training
Model Evaluation
Model
Optimization/Tuning

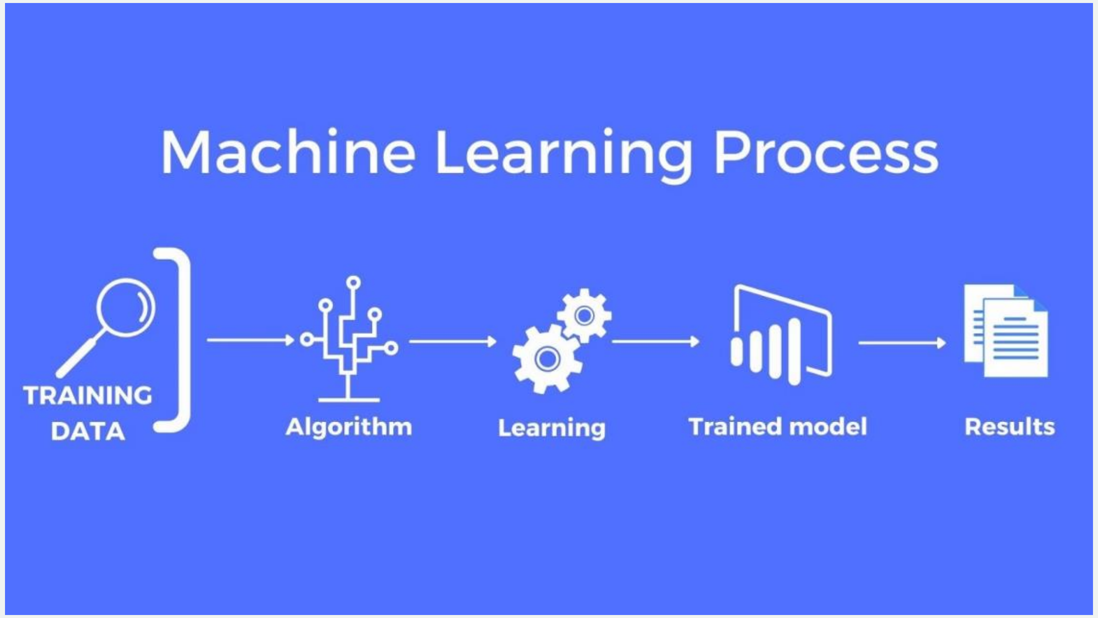
Mechanistic Methods	AI Methods
Rule-based: **Operate on explicit rules created by humans. rules are based on logical statements and clear, deterministic algorithms**	Learning-based: AI, particularly machine learning, operates on algorithms that allow the system to learn from data and improve over time
Predictability: **Outcomes are predictable and repeatable because the system operates within the confines of its programmed instructions.**	Adaptability AI systems can adapt to new and changing environments or data patterns without being explicitly reprogrammed.
Rigidity: **They cannot learn or adapt to new data or environments unless explicitly reprogrammed.**	Generalization Advanced AI systems, especially those using deep learning, can generalize from one task to another, applying learned knowledge to different but related problems
Domain-specific **Often designed for specific tasks and cannot generalize beyond the scope of their predefined rules, assumptions, and boundaries.**	Probabilistic and non-deterministic AI often deals with uncertainties and probabilities, making decisions based on statistical likelihoods rather than fixed rules.
Transparency **The decision-making process is transparent and can be traced through the rules and algorithms applied.**	Opacity Some AI systems, particularly those involving complex neural networks, can be opaque, making it difficult to understand the exact decision-making process (often referred to as "black box" models)
First principles **Often designed based on fundamental theories and laws from physics, chemistry, or other domains, which dictate the system's behaviour.**	Data-driven AI systems are primarily driven by data, learning patterns, and relationships within the data that may not be apparent or derivable from first principles.

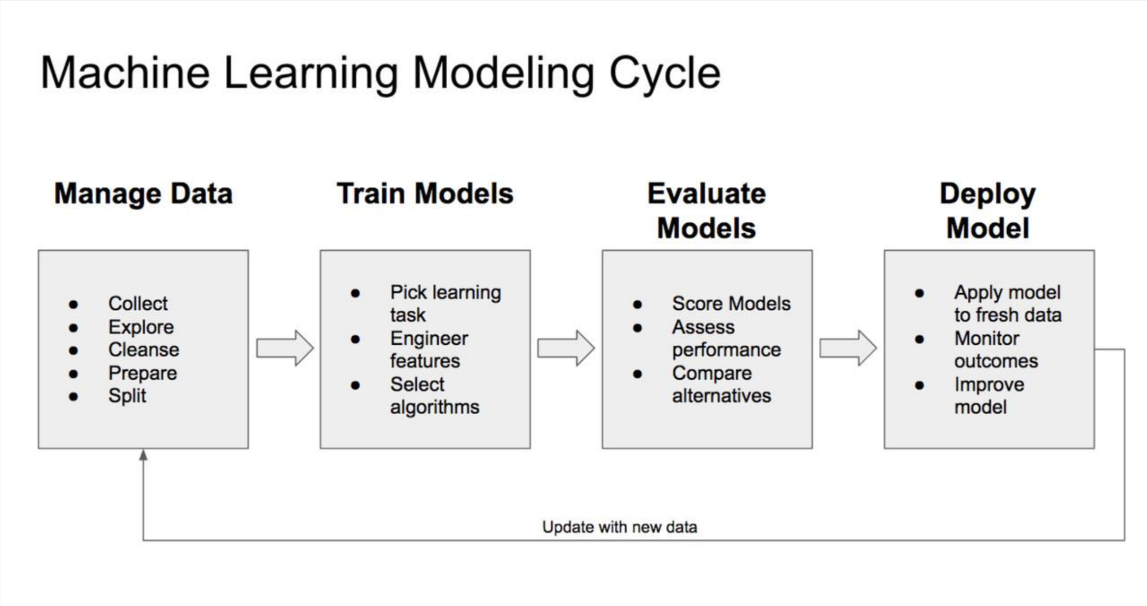
AI's Role in Agriculture

- Precision agriculture
- Pest control
- Crop health monitoring
- Smart farming and components
- AI integration with IoT devices and sensors in the field

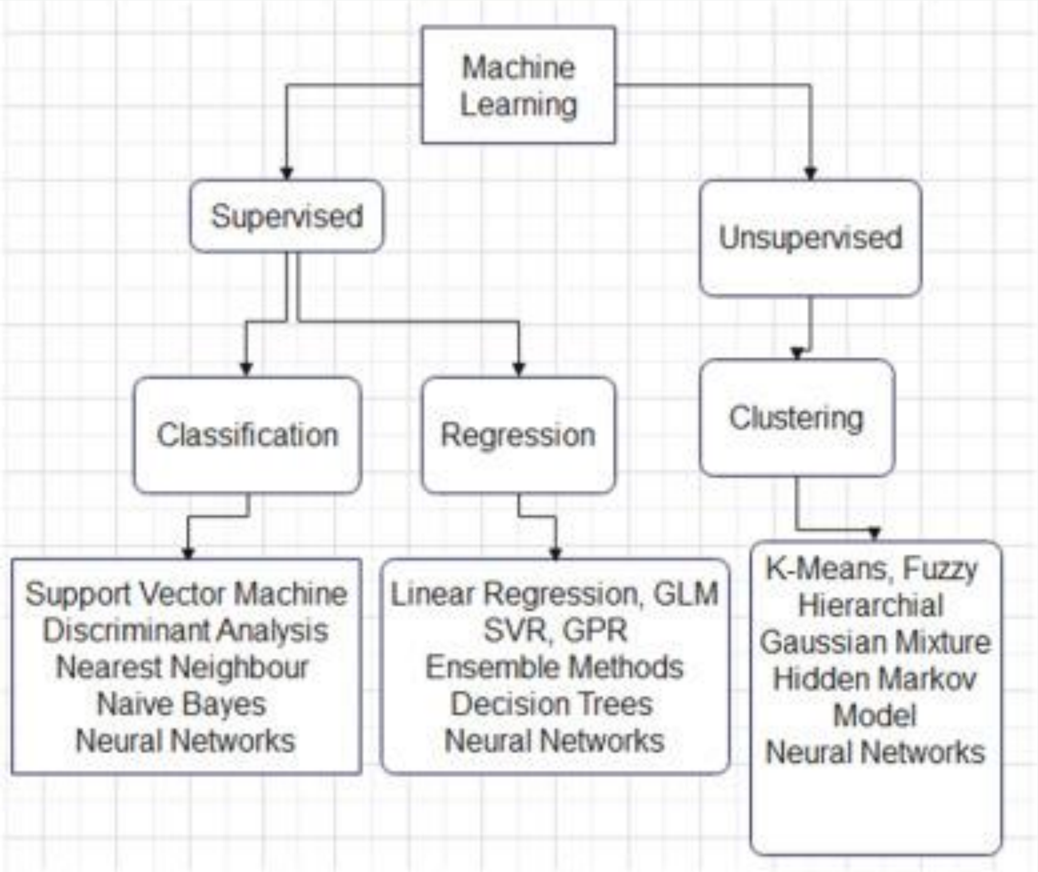


Model Training and Machine Learning



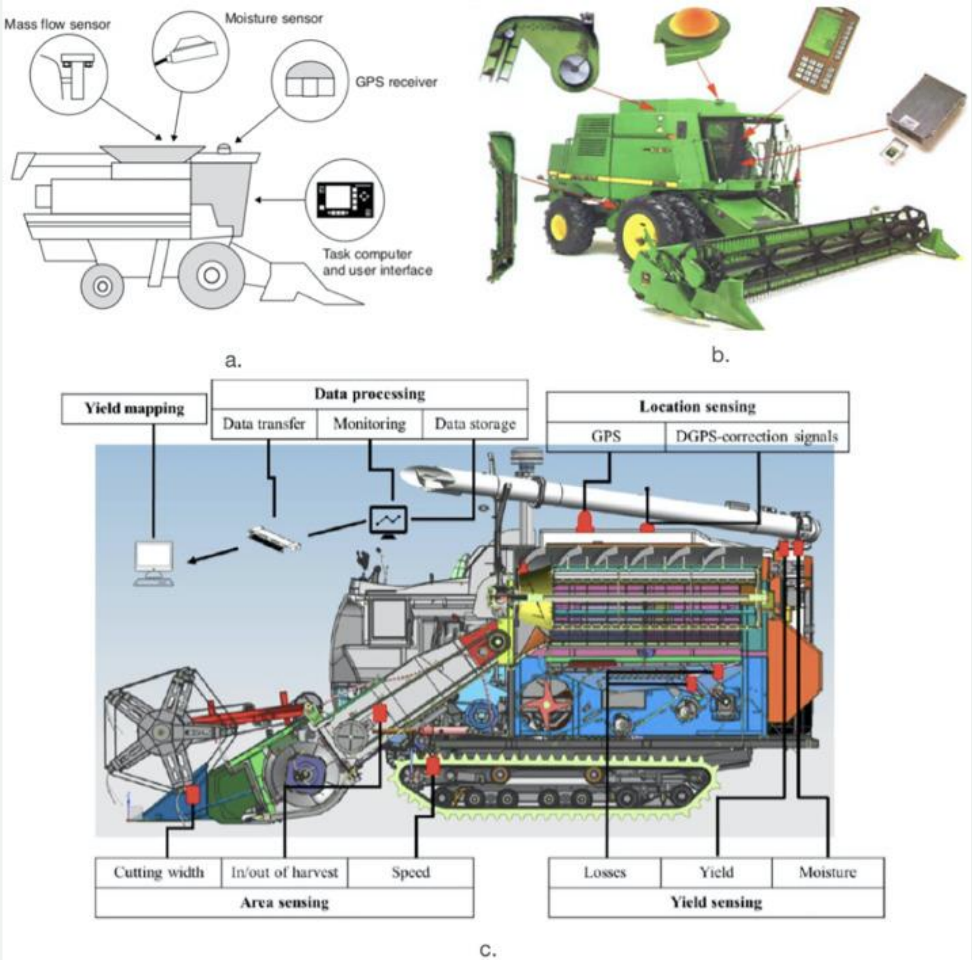


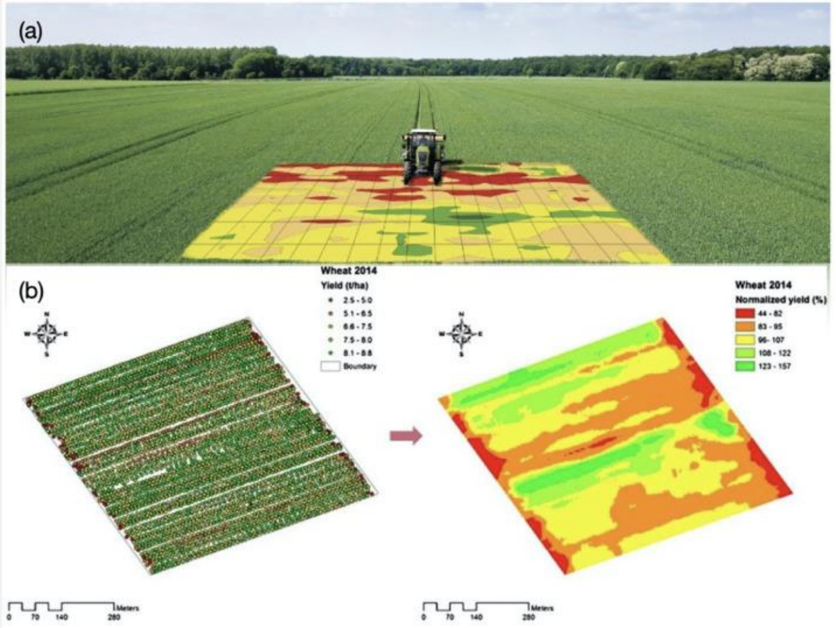
Model Training and Machine Learning



Applications of AI in harvest operations

- Optimization of timing and methods of harvest

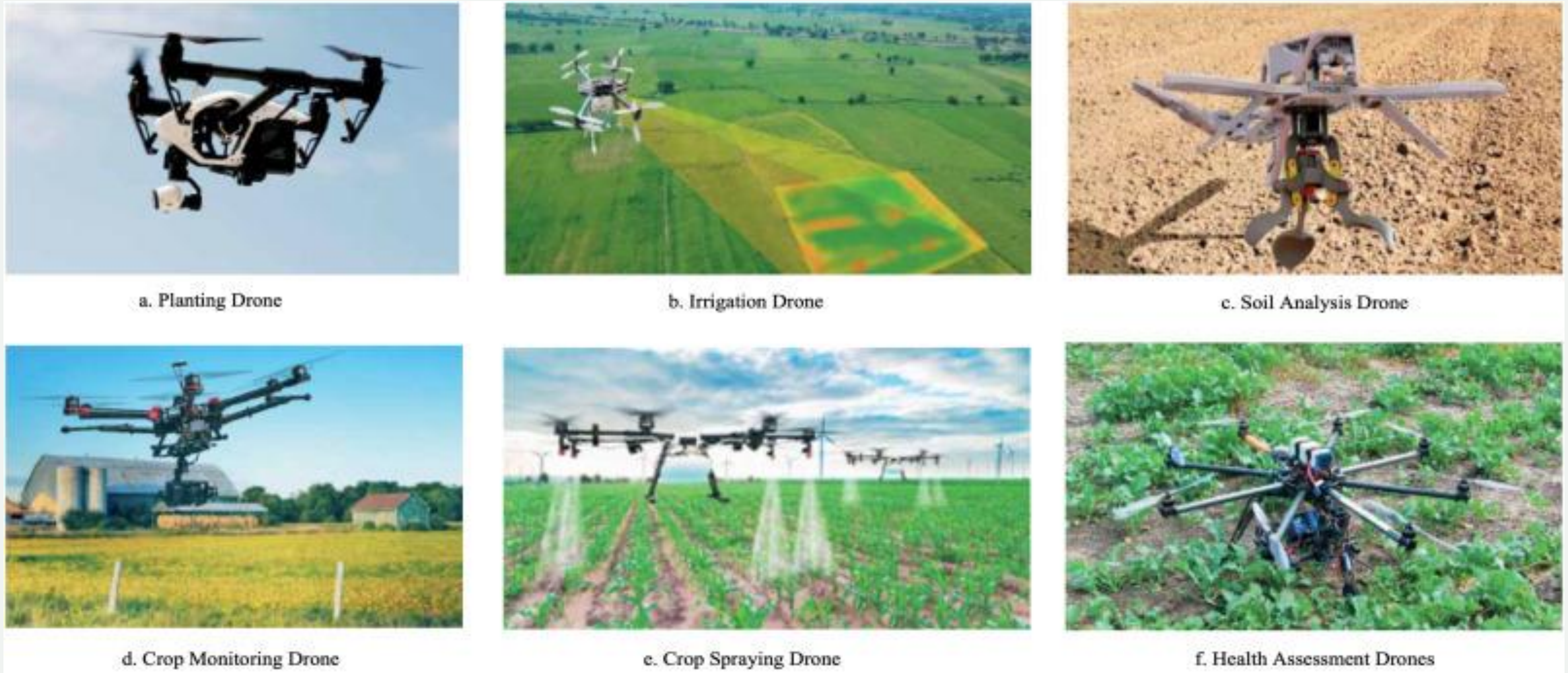




Talaviya et al. 2020

Applications of AI in harvest operations

- AI-driven machinery and drones

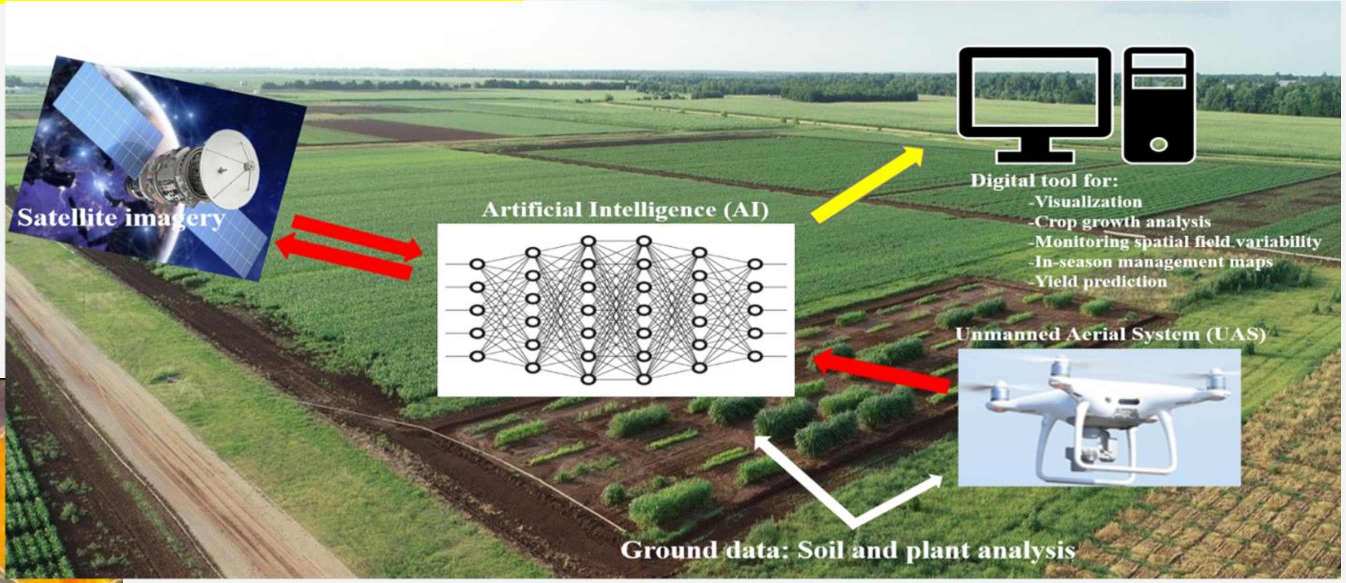


a. Planting Drone
b. Irrigation Drone
c. Soil Analysis Drone
d. Crop Monitoring Drone
e. Crop Spraying Drone
f. Health Assessment Drones

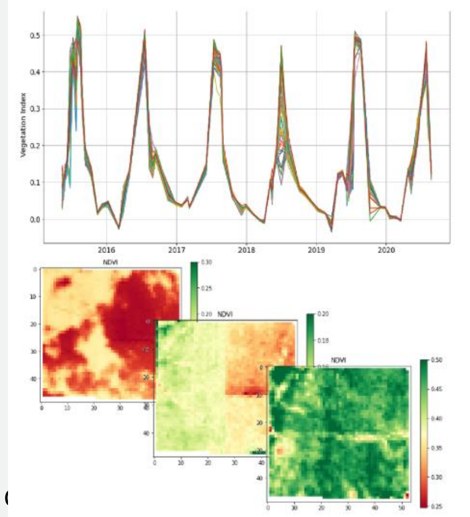
Talaviya et al. 2020

Applications of AI in harvest operations

- [Satellite imagery]

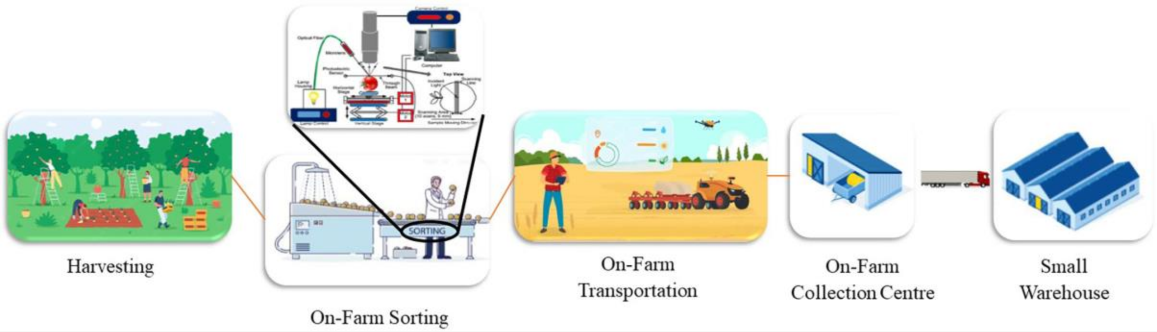


Texas A&M



Satellite imaging (

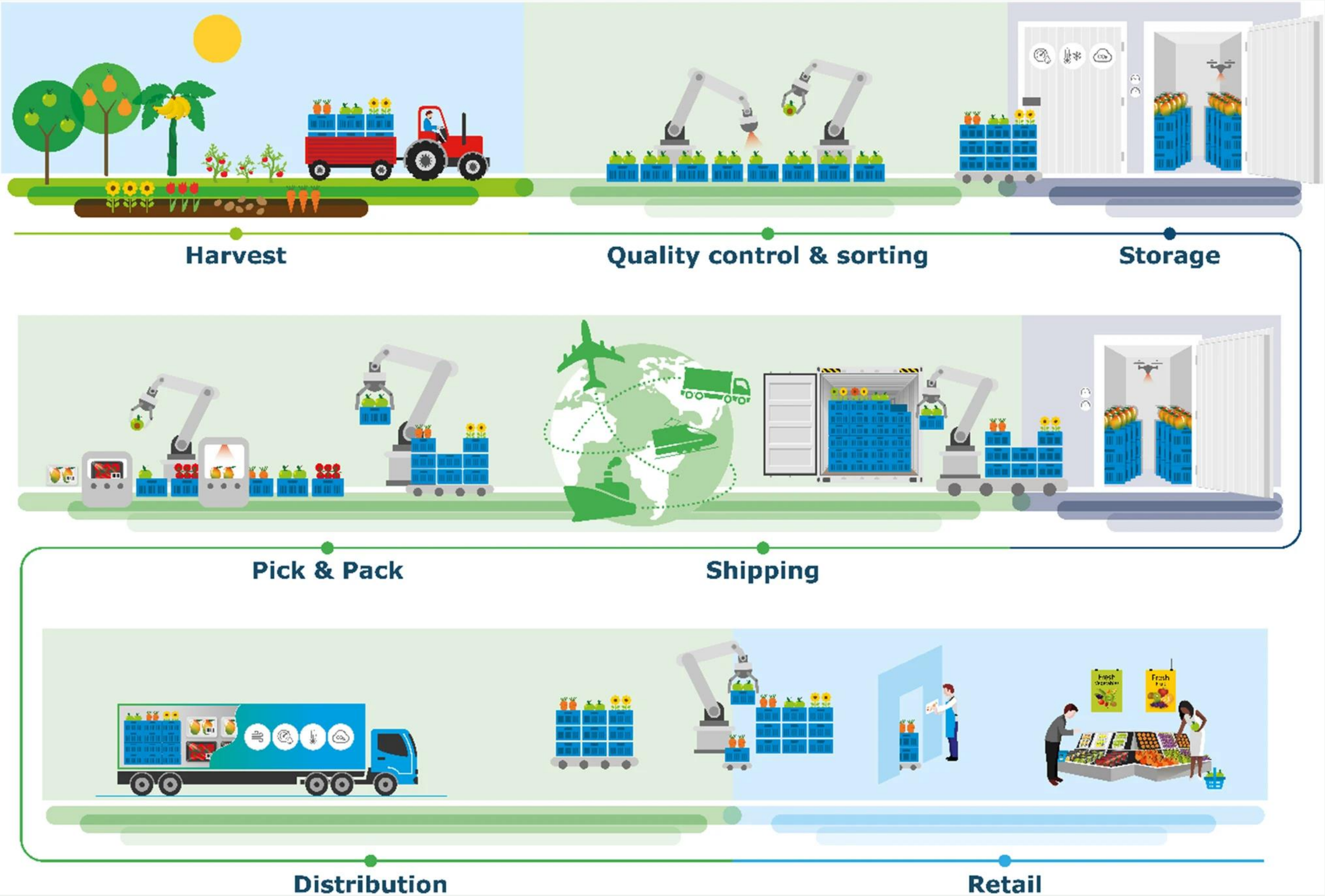
On-farm sorting and transportation



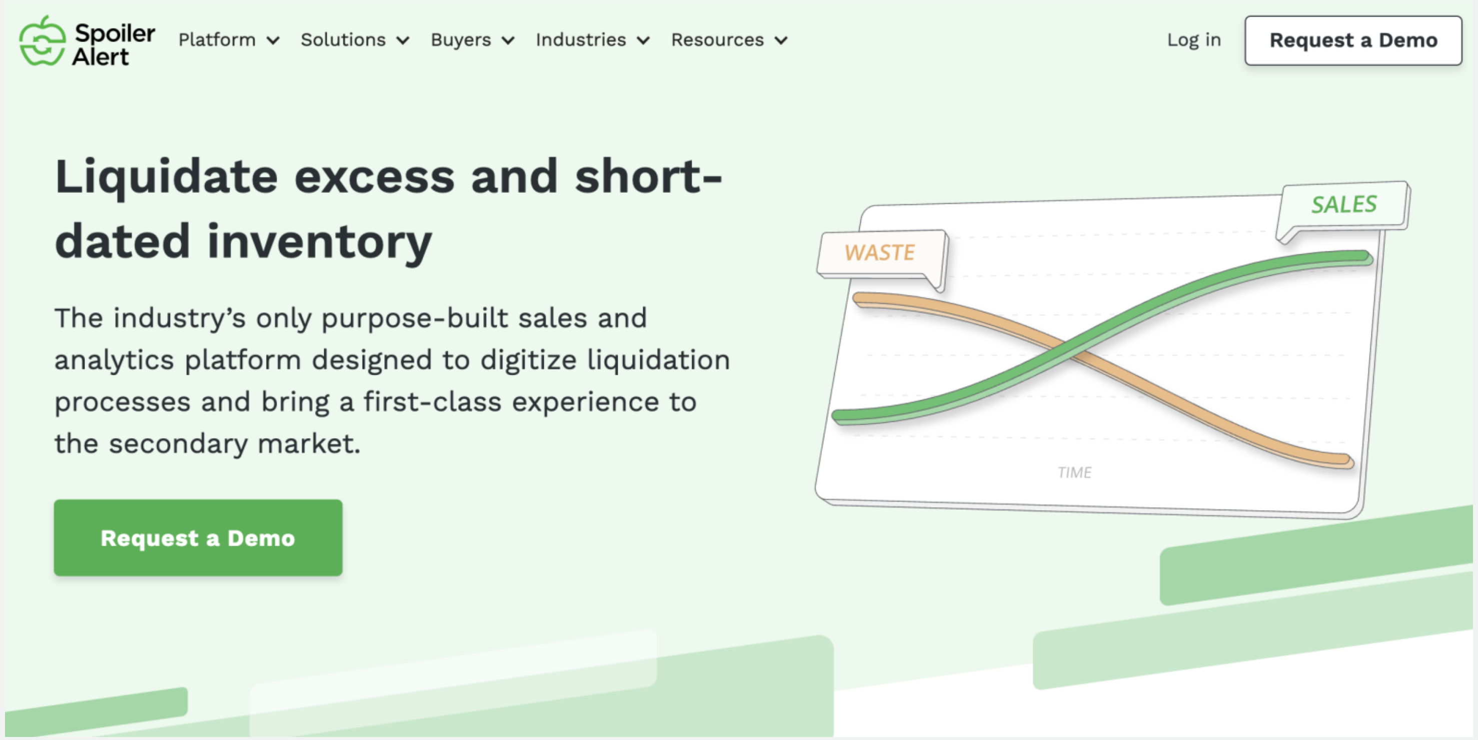
Objectives	On-farm Handling Problems	References
Defect detection	Classifying rotting and fresh fruits	Kang and Gwak (2021)
	Internal browning in mangoes	Gabriëls et al. (2020)
	Internal bruise detection in blueberries Internal defect detection in mangoes	Kuzy et al. (2018); Raghavendra et al., (2021)
Content detection	Detection of soluble solids in "Medjool" dates Chlorophyll degradation and anthocyanin detection in cherries Determination of soluble solids, starch pattern index, and Streif Index in apples Determination of soluble solids in apples	Ben-Zvi et al. (2017) Overbeck et al. (2017); Çetin et al. (2022); Wang et al. (2022)
Maturity and ripeness detection	Kiwi firmness classification	Torkashvand et al. (2017)
	Philippine coconut maturity grading	Caladcad et al. (2020)
	Firmness identification in avocadoes	Jaramillo-Acevedo et al. (2020)
	Cherry ripeness detection	Overbeck et al. (2017)
	Mango ripeness estimation	Wendel et al. (2018)
Quality (size, mass, and color) evaluation	Mass grading of mangoes	Momin et al. (2017)
	Infield grading and sorting system for apples	Zhang et al. (2021)
	Developing bin filler and on-farm sorting machine for apple harvesting	Zhang et al. (2017)

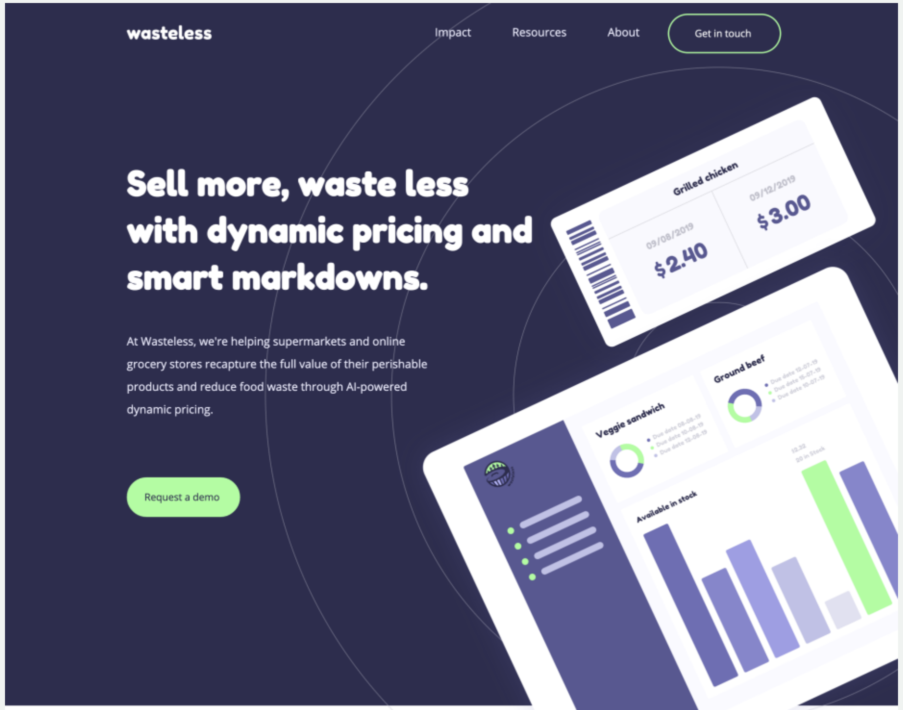
Applications of AI in postharvest operations

- Crop quality and shelf life
- Sorting, grading, packaging and beyond




GROWING
TRANSFORMING
PACKAGING
SELLING
HOSPITALITY & CATERING
HOUSEHOLD
FOOD WASTE PREVENTION
Airponix
Fresh Pod
wasteless
winnow
GROWING UNDERGROUND
mimica
ConsumAI
satis
FOOD SURPLUS REUSE
ODDBOX
TOAST
RUBIES RUBBLE
Elysia
ZHEROES
Too Good To Go
OLIO
FOOD WASTE UPCYCLING & RECYCLING
FRUU..
BIOHM
IntelliDigest
bio-bean
LEAP micro AD
Chip[s] Board
ENTOCYCLE





Accenture AI

Sorting

- Supply chain integration of Hyperspectral Imaging is in full swing
- Miniaturization and imaging capabilities, real-time monitoring capabilities

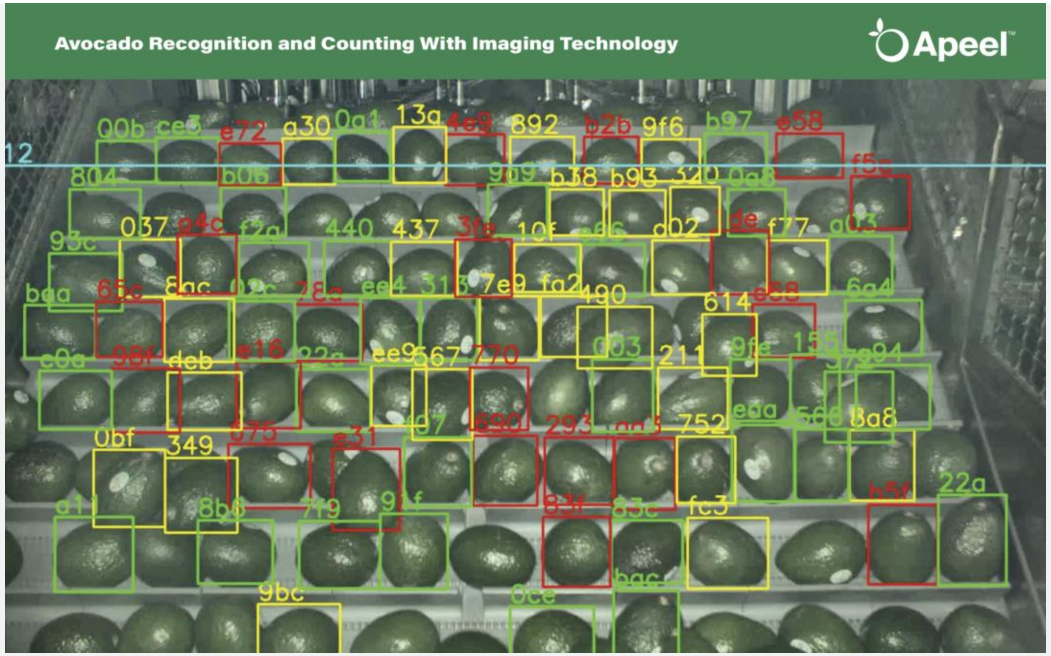
Image credit: Apeel Sciences

Apeel Sciences acquires ImpactVision to look inside fruit & veg for freshness

May 12, 2021 Louisa Burwood-Taylor

Disclosure: AgFunder (AFN's parent company) is an investor in ImpactVision. Learn more here.

Apeel Sciences, the food waste technology company, has acquired hyperspectral imaging startup ImpactVision. This is Apeel's first acquisition, and the Santa Barbara-based company says it stands to dramatically reduce the 40% of produce that's wasted globally each year.



Simbe Robotics Announces New Tally 3.0 Shelf-Scanning Robot

by Chris Albrecht

- OCTOBER 22, 2020
- FILED UNDER:
  BEHIND THE BOT
  FUTURE OF GROCERY
  GROCERY
  ROBOTICS, AI & DATA

RipeLocker Raises $5M for its Low Atmosphere Approach to Extending Food Freshness

by Chris Albrecht

- APRIL 22, 2021
- FILED UNDER:
  NEWS

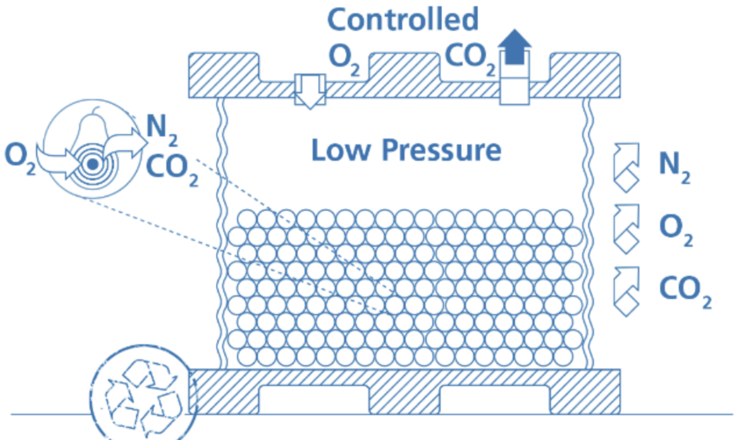


Image property of RipeLocker. Used with permission.

Automatic surface temperature measurement and detection

Contents lists available at ScienceDirect

Postharvest Biology and Technology

journal homepage: www.elsevier.com/locate/postharvbio

Continuous surface temperature monitoring of refrigerated fresh produce through visible and thermal infrared sensor fusion

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A R T I C L E I N F O

Keywords:
Temperature monitoring
Precision retail
Thermal imaging
Infrared camera
Object detection
Computer vision

A B S T R A C T

Temperature is a critical parameter affecting the safety and quality of food products, with deviations leading to spoilage, food safety issues, and increased food waste, presenting significant economic and sustainability challenges. Conventional temperature sensors such as thermometers, thermistors, and thermocouples are accurate but often invasive, measuring the temperature of proxy media or storage environments rather than individual products. To address this limitation, we developed a non-destructive temperature measurement system using thermal infrared (IR) and visible (RGB) imaging sensors. The system integrates a thermal camera module, an RGB sensor, and a single-board computer, employing homography matrix-based RGB-thermal fusion, real-time object detection, and temperature monitoring to isolate product surface temperatures from the background. The system was validated with thermocouple measurements by monitoring the surface temperature profiles of apples, peppers, and individually packaged broccoli under cold storage conditions. When compared to thermocouple measurements, average root mean square error values were 0.63, 0.81 and 1.86°C for apple, bell pepper, and individually wrapped broccoli, respectively. These results emphasize the importance of further addressing reflective materials and surface emissivity effects to enhance accuracy. This tool demonstrates potential for real-time, individual surface temperature monitoring, providing a practical solution for precision retail and supply chain applications. Future system enhancements are also proposed; including addressing material reflectivity and emissivity, and system calibration methods to improve its accuracy and broaden its applicability across diverse operational scenarios.

https://doi.org/10.1016/j.postharvbio.2024.113354

Automatic surface temperature measurement and detection

01 Read Images

- Read the RGB Image and Resize
- Read the IR image

02 Select Control Points in Images

- Select four control coordinates using the "cpselect" function in MATLAB
- Save the selected point coordinates

03 Obtain the Transformation Matrix

- Load the control coordinates in RGB and IR images
- Find the homography between loaded coordinates using the "findHomography" function in OpenCV Python

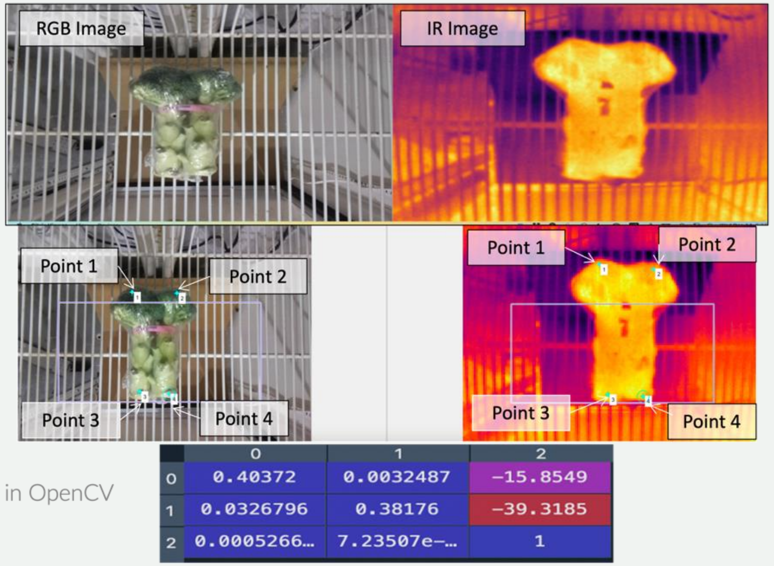
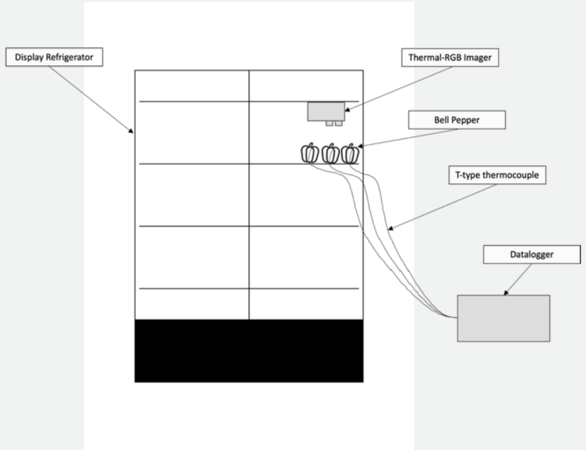
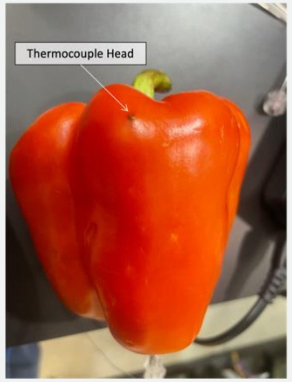
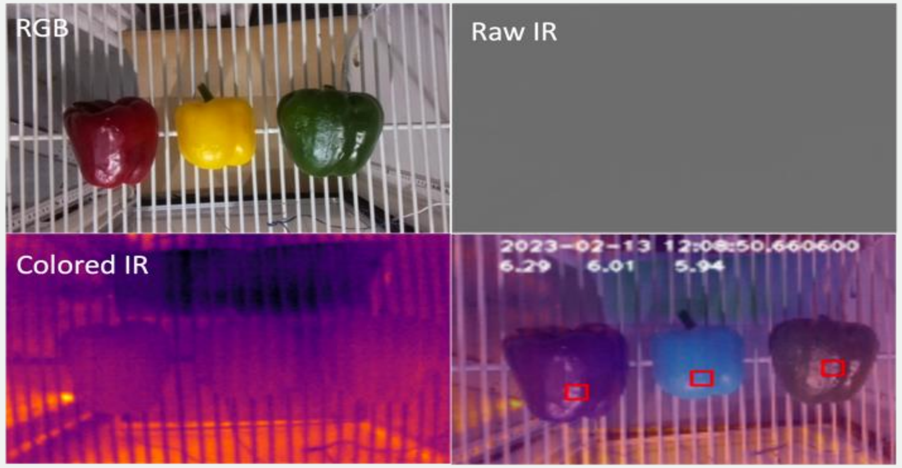
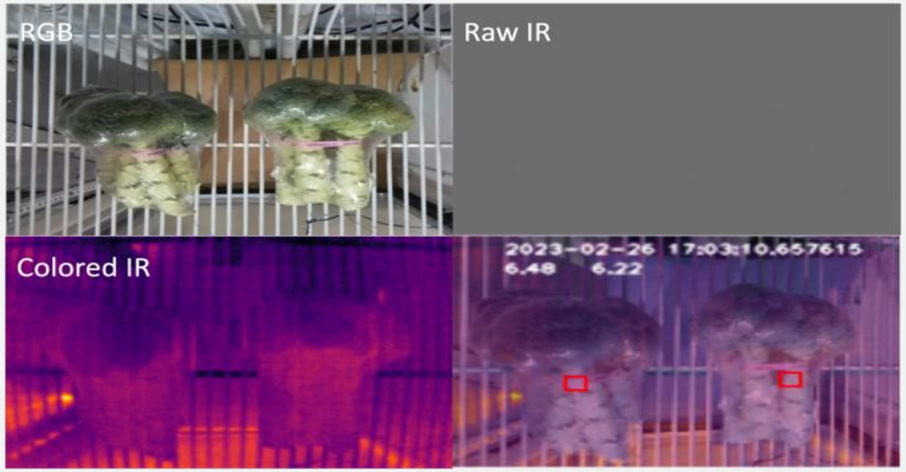


Figure 2. Construction of the camera module (left), 3D mockup design of the sensor housing (right).









01 Initialize Cameras and Object Detection Model

- Import libraries (NumPy, OpenCV, TFLite
- Setup camera indices and camera spatial solutions
- Setup the thermal camera raw temperature data acquisition
- Initialize the object detection model for the RGB camera

02 Streaming data from both cameras

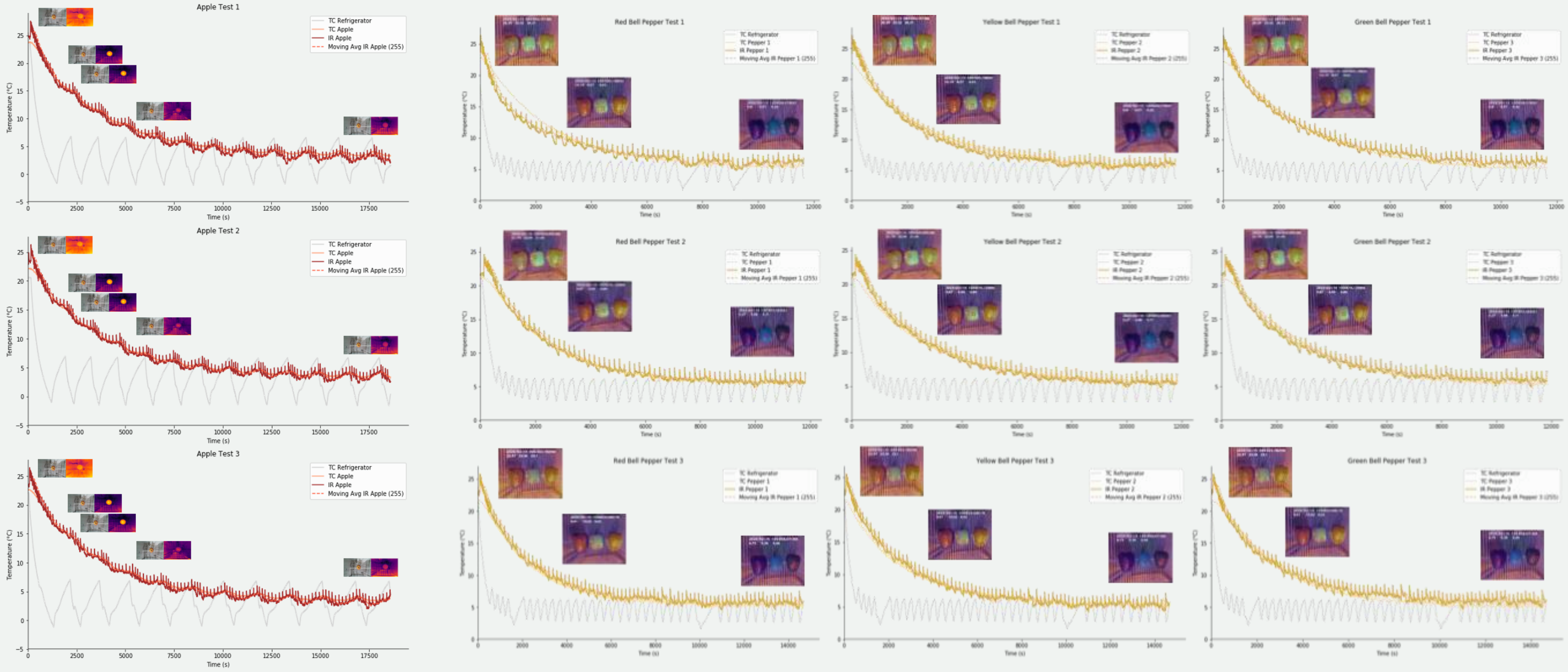
- Grab frames from RGB and thermal cameras
- Convert the default BGR color format in OpenCV into RGB
- Normalize the 16-bit raw thermal image to an 8-bit grayscale image
- Apply a colormap to the 8-bit grayscale temperature image for visualization purposes

03 Image Registration and Object Detection

- Warp and overlay RGB image using the homography matrix into the 8-bit colored thermal image
- Perform object detection on warped and overlayed RGB-thermal image
- Obtain temperature values from 16-bit raw thermal images using the bounding box locations on the detected object
- Display the mean value of the detected bounding box on the screen

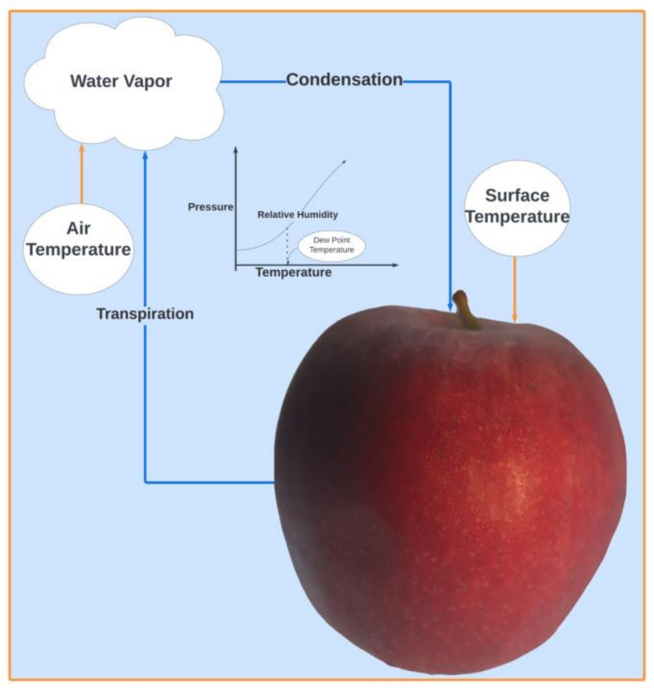
04 Temperature Data Logging and Finalization

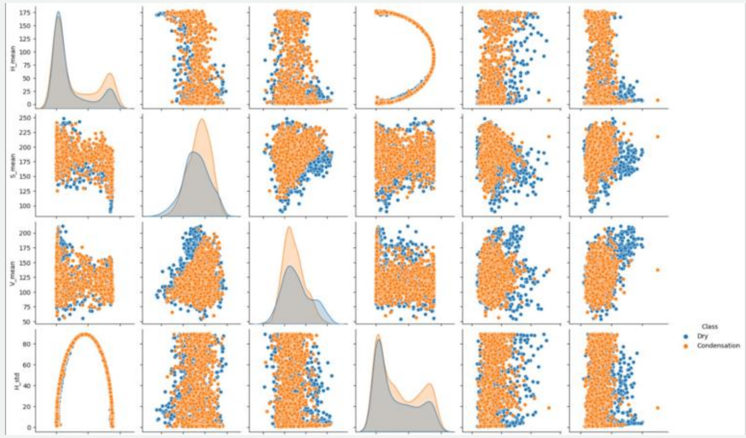
- Record min, max, and mean of the returned bounding box locations
- Stop streaming from both cameras



Apple Test 1
TC Refrigerator
TC Apple
IR Apple
Moving Avg IR Apple (255)
Temperature (°C)
Time (s)
Apple Test 2
Apple Test 3
Red Bell Pepper Test 1
Yellow Bell Pepper Test 1
Green Bell Pepper Test 1
Red Bell Pepper Test 2
Yellow Bell Pepper Test 2
Green Bell Pepper Test 2
Red Bell Pepper Test 3
Yellow Bell Pepper Test 3
Green Bell Pepper Test 3
TC Pepper 1
IR Pepper 1
Moving Avg IR Pepper 1 (255)
TC Pepper 2
IR Pepper 2
Moving Avg IR Pepper 2 (255)
TC Pepper 3
IR Pepper 3
Moving Avg IR Pepper 3 (255)

Detection of Condensation





HSV features overlap

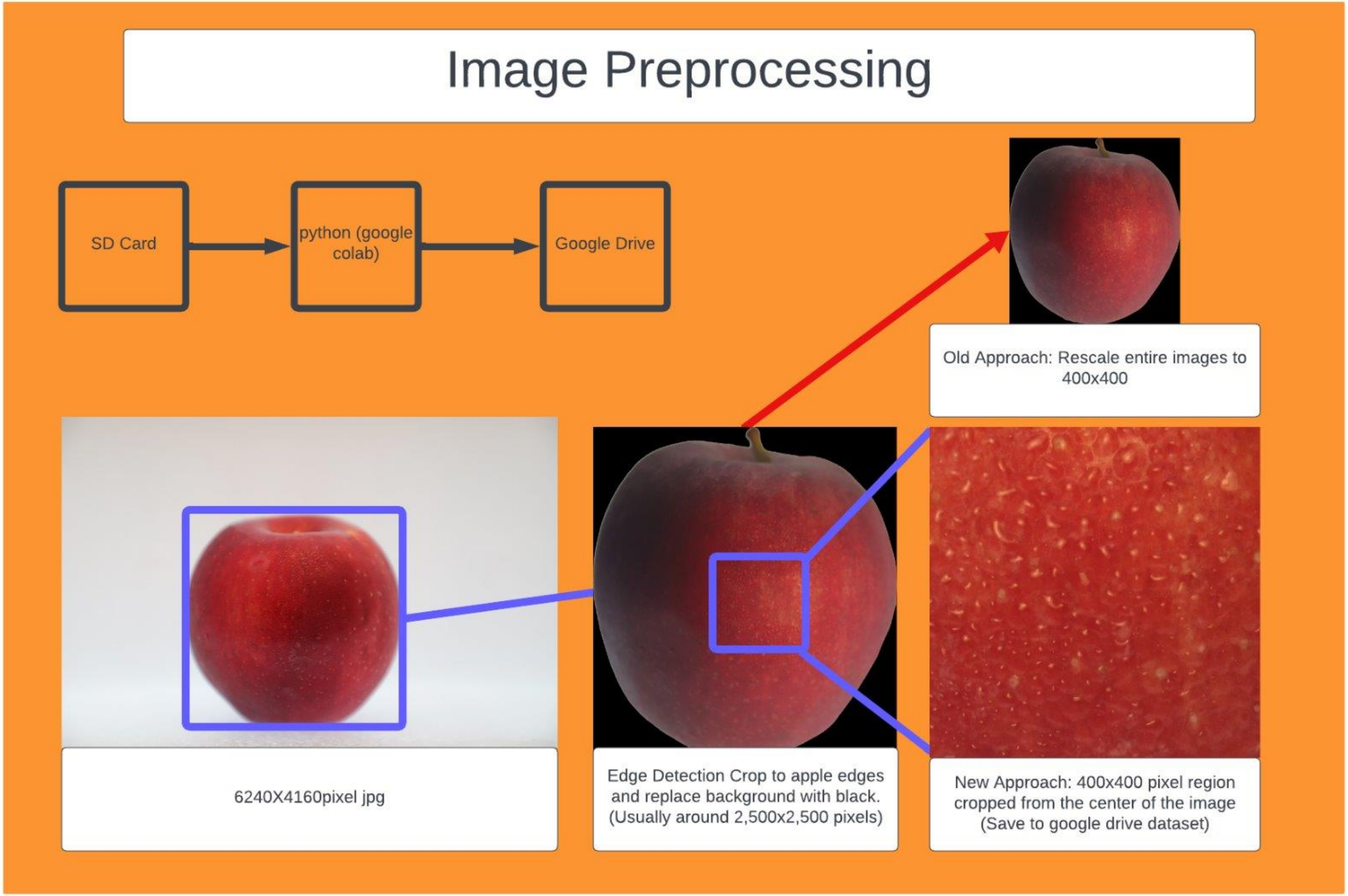
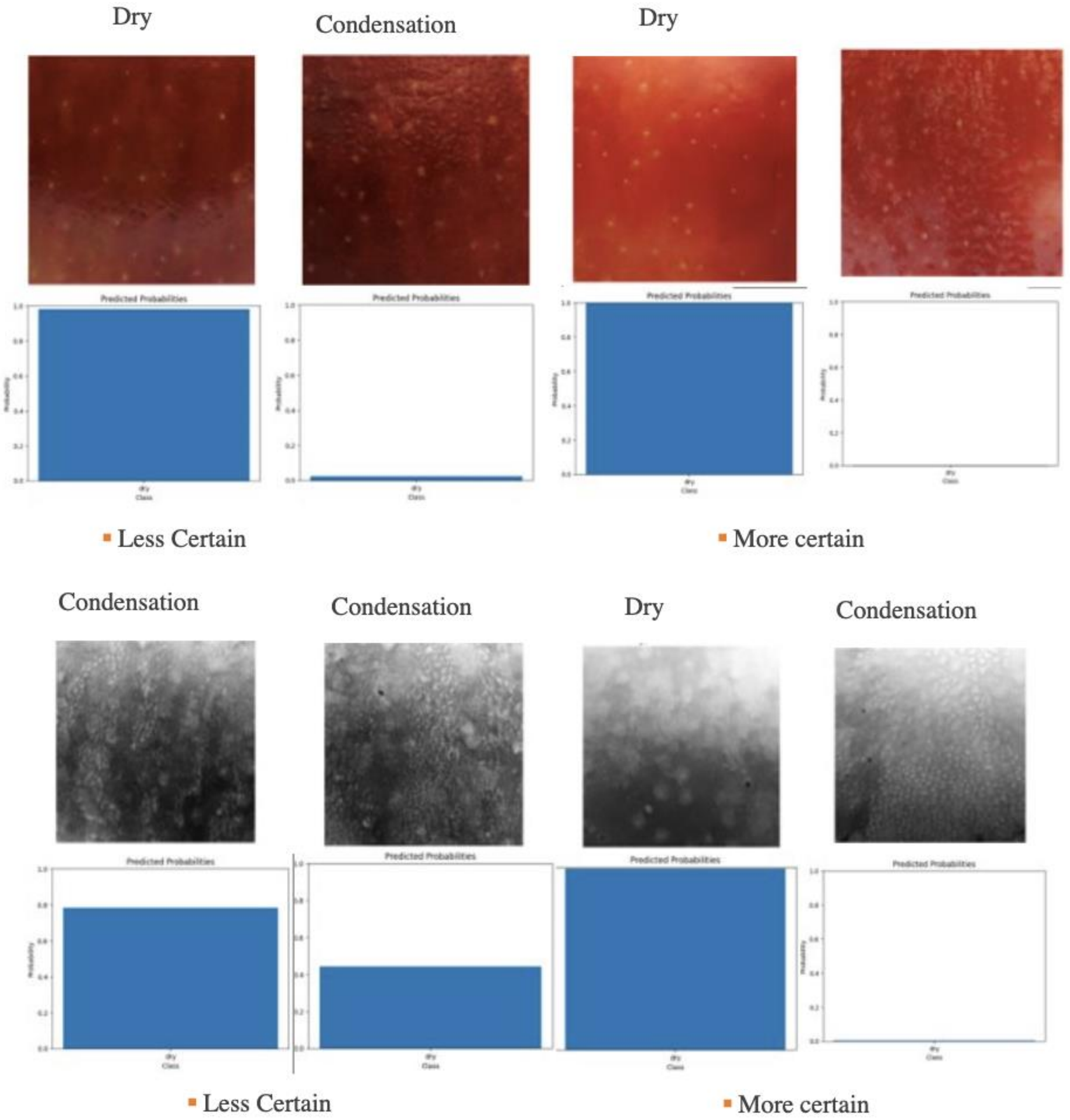


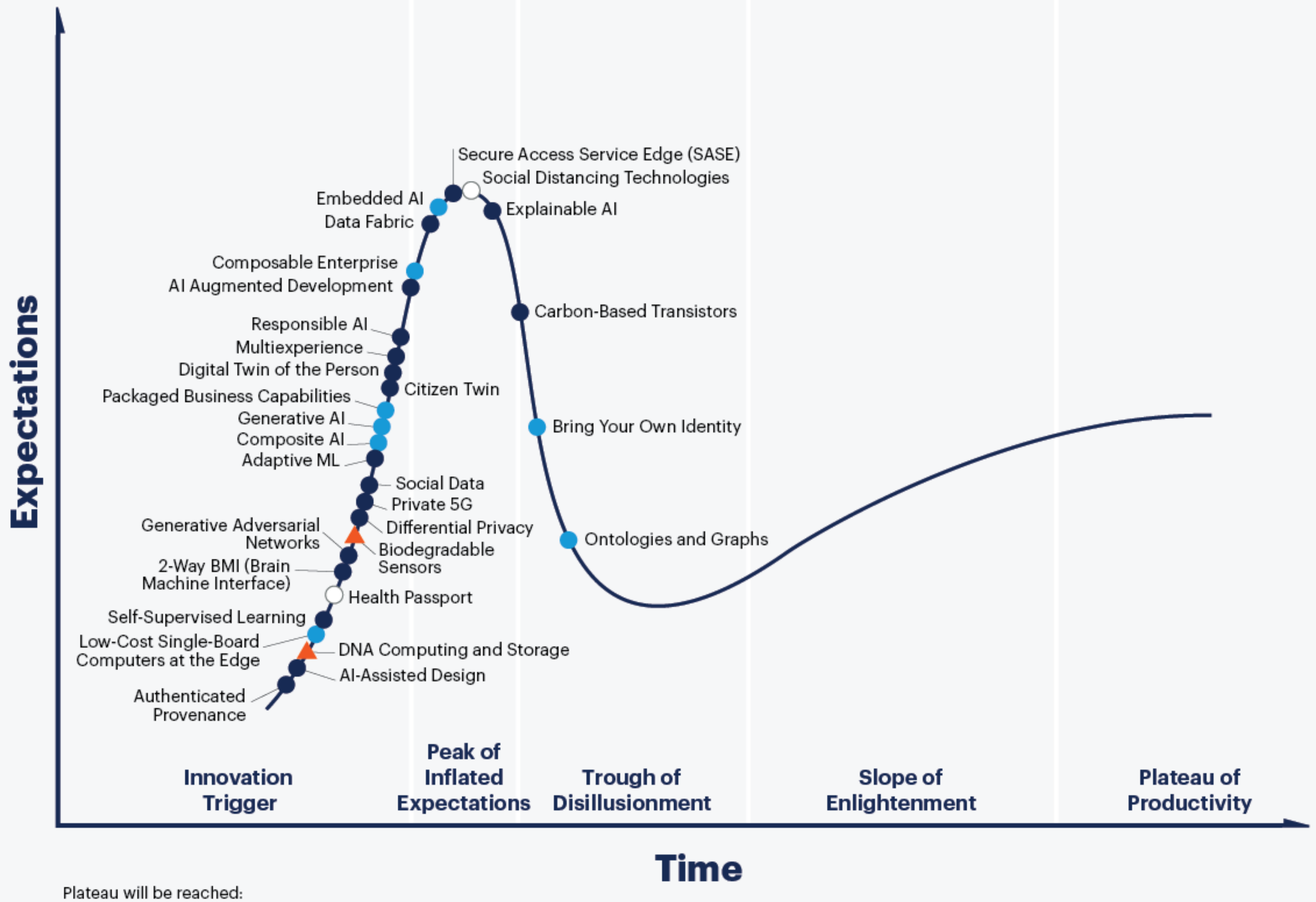
Image Preprocessing
SD Card
python (google colab)
Google Drive
Old Approach: Rescale entire images to 400x400
6240X4160pixel jpg
Edge Detection Crop to apple edges and replace background with black. (Usually around 2,500x2,500 pixels)
New Approach: 400x400 pixel region cropped from the center of the image (Save to google drive dataset)

Predictions



Model	RGB		Grayscale	
Dataset	Red Apples	Granny Smith	Red Apples	Granny Smith
Threshold	0.5	0.7	0.5	0.7
Accuracy	0.911	0.479	0.916	0.792
Precision	0.933	0.479	0.979	0.722
F1 Score	0.901	0.647	0.915	0.929
ROC_AUC	0.979	0.631	0.976	0.811

Hype Cycle for Emerging Technologies, 2020



Plateau will be reached:

○ less than 2 years ● 2 to 5 years ● 5 to 10 years ▲ more than 10 years ⊗ obsolete before plateau

As of July 2020

gartner.com/SmarterWithGartner

Source: Gartner

Gartner