THE 16TH INTERNATIONAL WORKSHOP ON NONDESTRUCTIVE QUALITY EVALUATION
OF AGRICULTURAL, LIVESTOCK AND FISHERY PRODUCTS

Non-destructive Measurements of Vegetable and Poultry Products for Quality Assessments: Opportunities of Thermal Imageries using Deep Learning Algorithms

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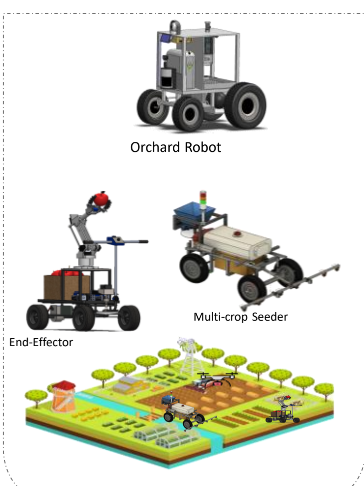
Research Domain: Bioproduction and Machinery Lab

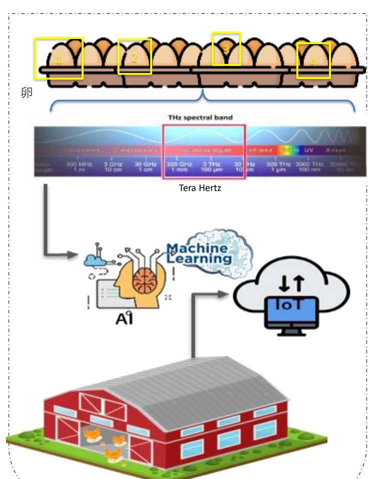
New Ultra-Saving Labor Technology: Robotics

New Decision Systems: IoT x AI

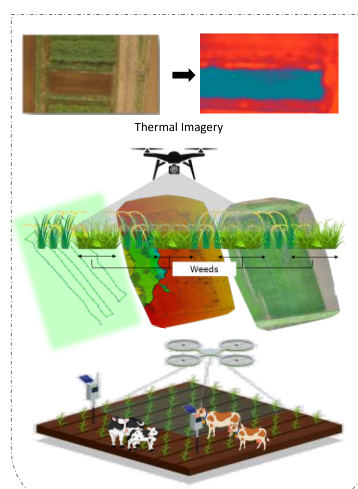
New Sensing Technology: Data to Decisions



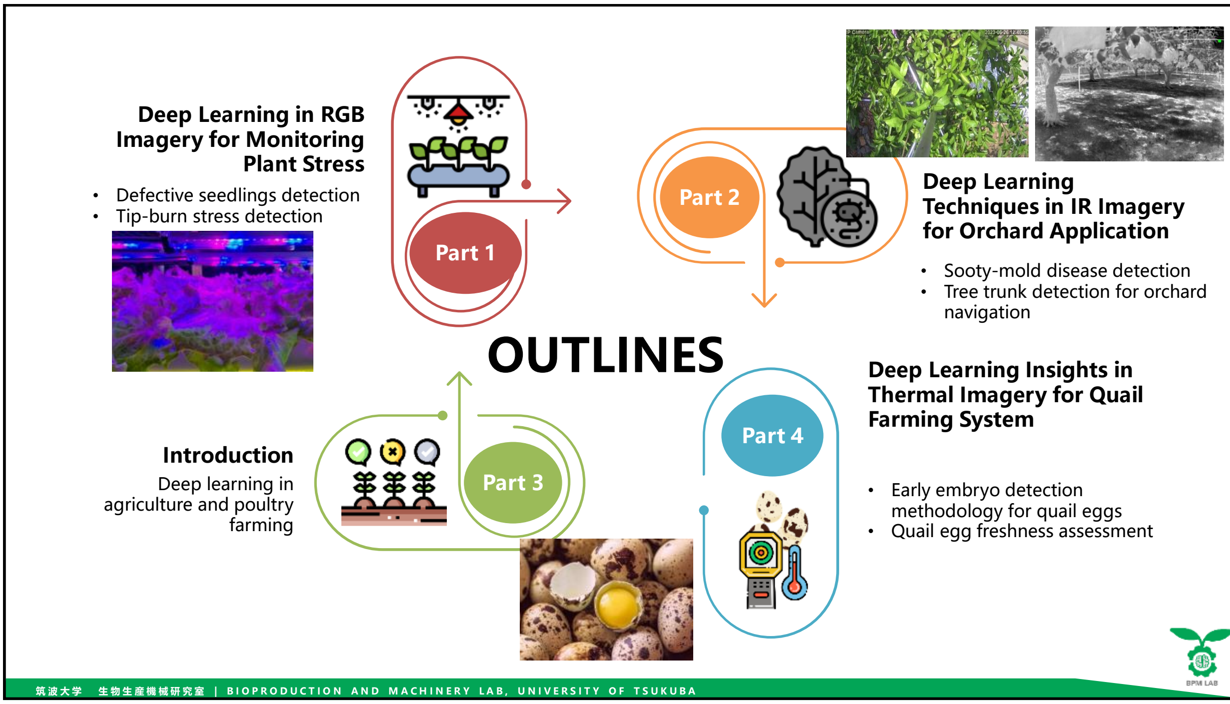
Smart In-Field Production



Smart In-house Production



Smart Big Data Scheme


OUTLINES
Deep Learning in RGB Imagery for Monitoring Plant Stress
• Defective seedlings detection
• Tip-burn stress detection
Part 1
Part 2
Deep Learning Techniques in IR Imagery for Orchard Application
• Sooty-mold disease detection
• Tree trunk detection for orchard navigation
Introduction
Deep learning in agriculture and poultry farming
Part 3
Part 4
Deep Learning Insights in Thermal Imagery for Quail Farming System
• Early embryo detection methodology for quail eggs
• Quail egg freshness assessment
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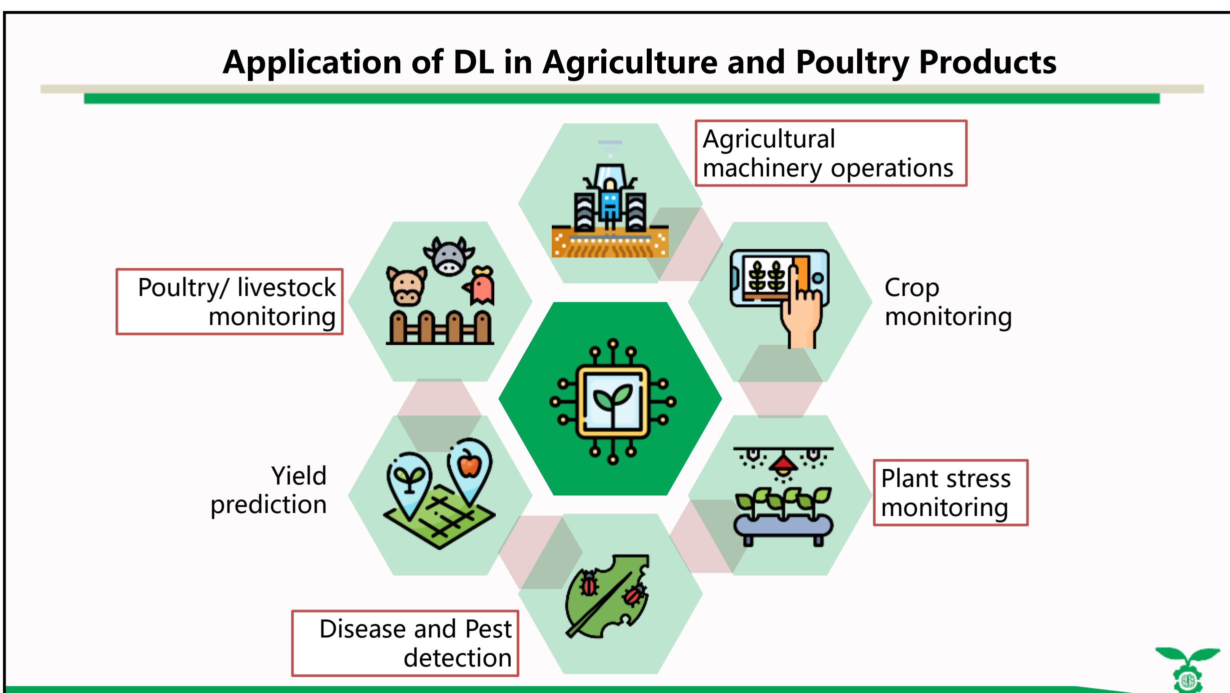
BPM LAB


Application of DL in Agriculture and Poultry Products
Agricultural machinery operations
Poultry/ livestock monitoring
Crop monitoring
Yield prediction
Plant stress monitoring
Disease and Pest detection
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PART 1
From Pixels to Predictions: Deep Learning in RGB Imagery for Monitoring Plant Stress

- **Defective seedlings detection**
- **Tip-burn stress detection on lettuce**

Case Study 1: Defective Lettuce Seedlings Identification

Seedlings nursery

Defective seedlings need to be sorted **manually**.

- Uneven germination rate
- One or more seedlings growing in a single hole
- Artificial damage

Healthy seedling

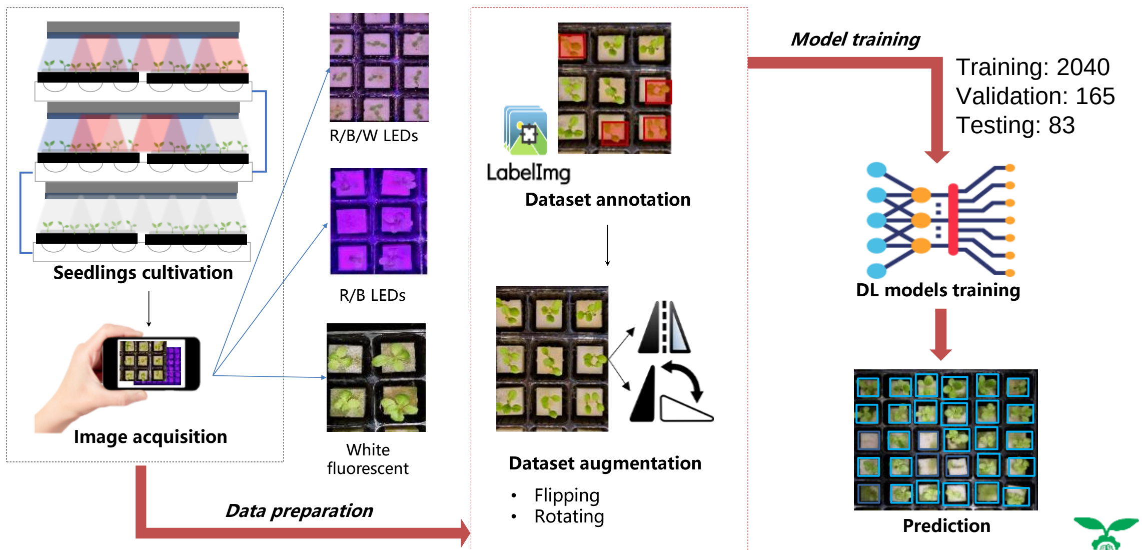
Defective seedling

There is a need for automated solutions

Problems with manual operation:

- Labor-intensive
- Time-consuming
- Highly technical work
- Complex lighting conditions

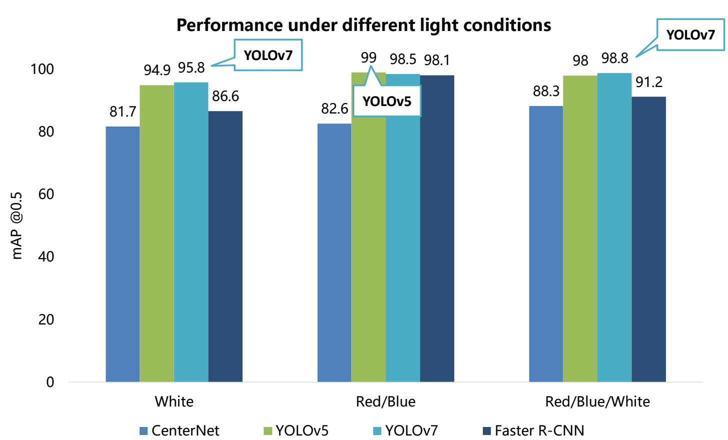
Detection Model Framework



Performance of Different DL Models

Models	mAP @0.5
CenterNet	82.8
YOLOv5	96.5
YOLOv7	97.2
Faster RCNN	88.6

✓ **YOLOv7** obtained the **highest overall accuracy of 97.2 %** compared to other pre-trained models.



✓ **YOLOv7** provides the best accuracy for detecting under **white** and **red/blue/white lights.**
✓ **YOLOv5** performed the best under **red/blue lights.**

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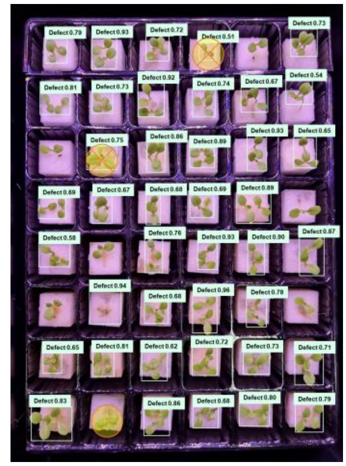
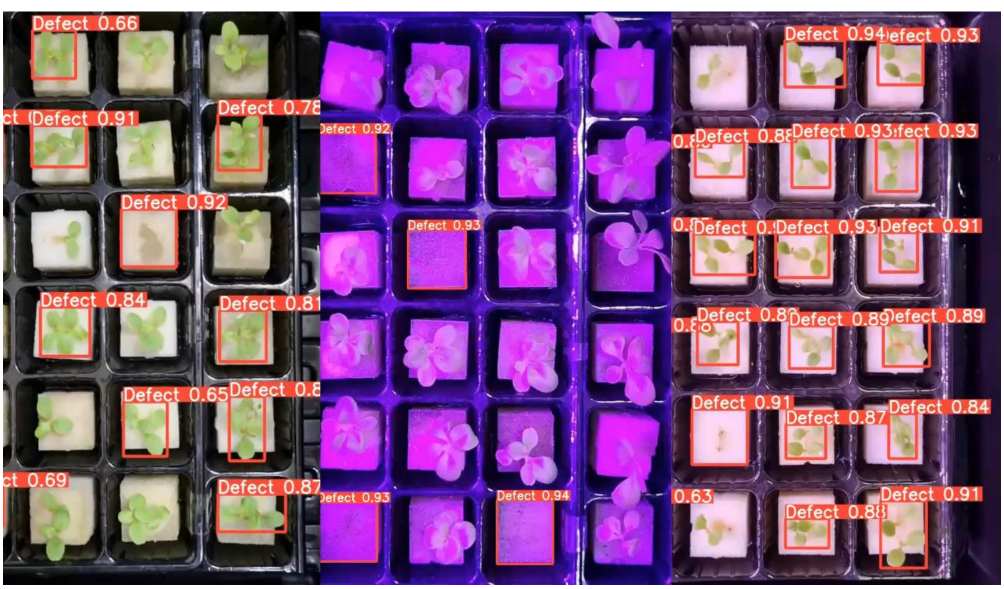
Detection under Different Indoor Lighting Conditions (YOLOv7)

White fluorescent

R/B LEDs



R/B/W LEDs



Case Study 2: Tip-burn Stress Detection On Lettuce Grown Indoors

Tipburn on Lettuce

Indoor-grown lettuce under **artificial light** is **prone** to **tip-burn stress**.

Physiological disorder

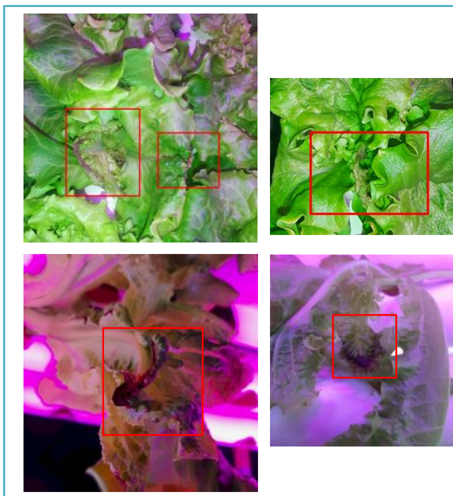
Tip burn is a **physiological disorder,** causes leaf edges to **turn brown or black.**

Causes

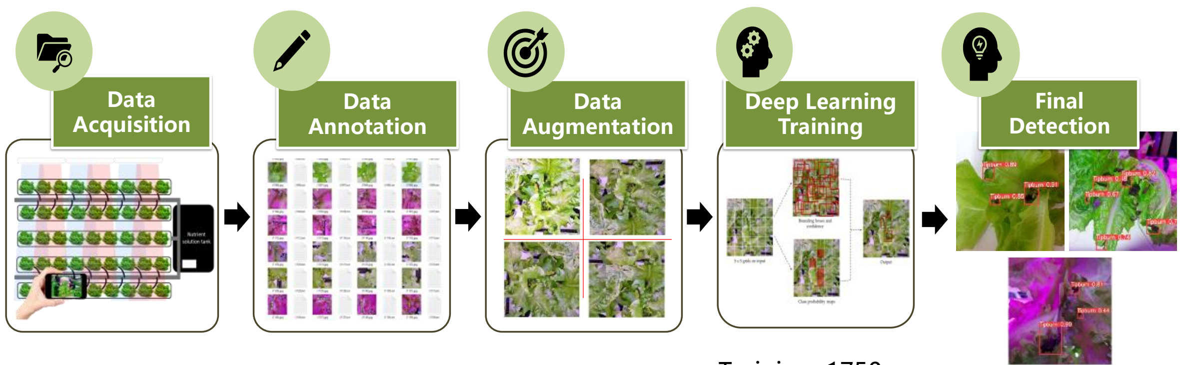
- Light stress
- Nutrient imbalances
- Water stress
- Air flow

Problem in Identifying Tip-burn Manually

Tip-burn is hard to detect manually under complex indoor lighting conditions.

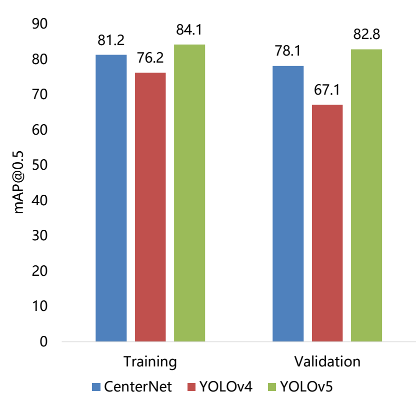


Tip-burn Detection Framework

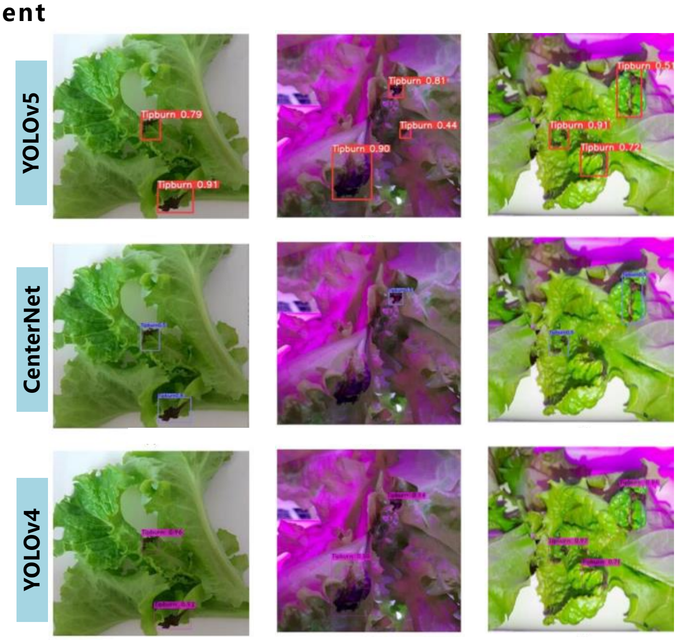


Training: 1750
Validation: 433
Testing: 150

Tip-burn Detection under Different Indoor Lighting Settings



✓ YOLOv5 demonstrated the **highest overall accuracy of 82.8 %** to detect tip-burn.



PART 2

Detecting the Invisible: Deep Learning Techniques in IR Imagery for Orchard Application

- **Sooty-mold disease detection**
- **Tree trunk detection for orchard navigation**

Case Study 1: Sooty mold Detection on Citrus Tree Canopy

Disease

30-100 % Yield loss

Sooty Mold

It is **caused by fungi** developed from the **presence of honey dew** produced by **sap-sucking insects**.

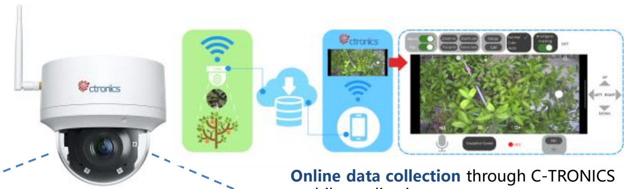
PPFD 44 to 74%

Objectives

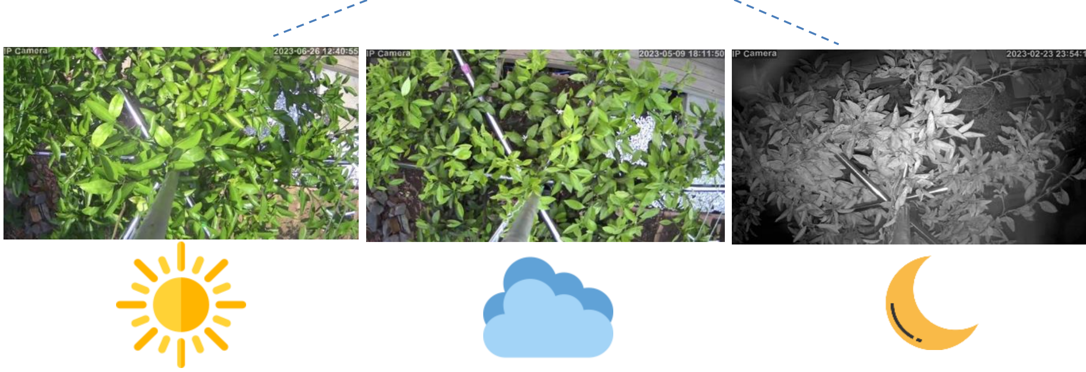
Aims to monitor and detect sooty mold infection on citrus tree canopy using a low-cost surveillance camera system combined with deep learning.

Image Datasets Acquisition

Images were collected using a **low-cost 4MP surveillance home security camera** (CTIPC-530C, Shenzhen C-TRONICS CO., LTD) with 25 M HD night vision capability, 2 pcs IR LEDs and Wi-Fi connectivity.

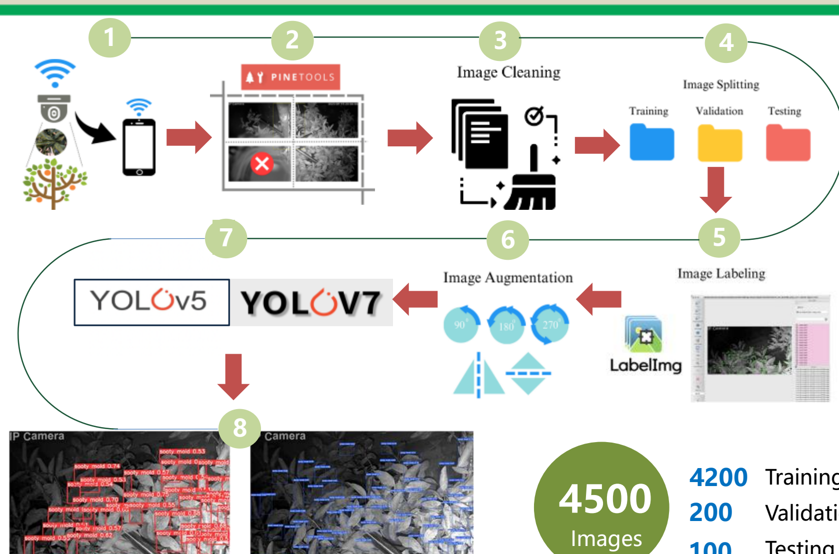


Online data collection through C-TRONICS mobile application



Sooty-mold Detection Framework

1 Collection
2 Slicing
3 Cleaning
4 Splitting
5 Labeling
6 Augmentation
7 Training
8 Detection

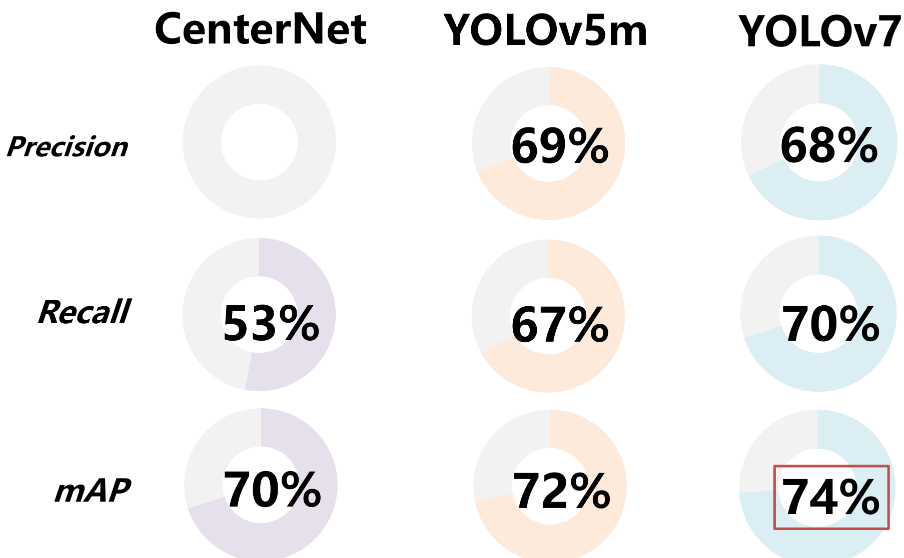


Sliced night images

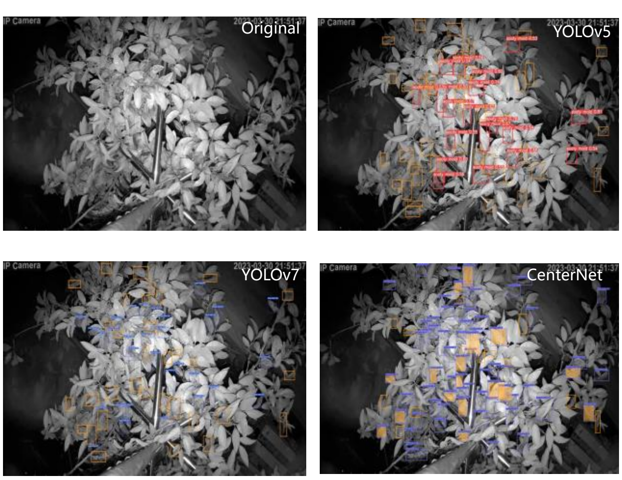
4500
Images

4200 Training
200 Validation
100 Testing

Performance Evaluation



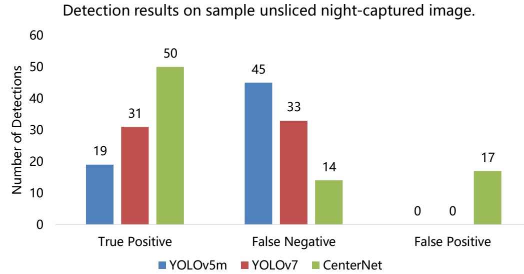
Night-time Detection of Sooty-mold



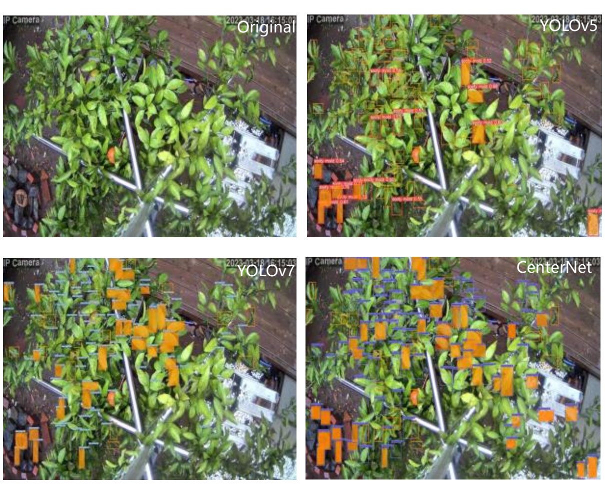
*The orange square in the figure refers to undetected sooty mold infections, and the orange fill indicates false detection.

Model	Night-Unsliced Image		
	Precision (%)	Recall (%)	mAP (%)
YOLOv5m	74.1	24	47.6
YOLOv7	59.7	63.3	60.3
CenterNet	-	25.3	27.5

Detection results on sample unsliced night-captured image.

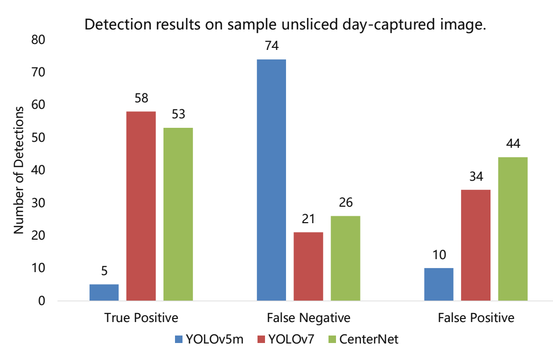


Day-time Detection of Sooty-mold



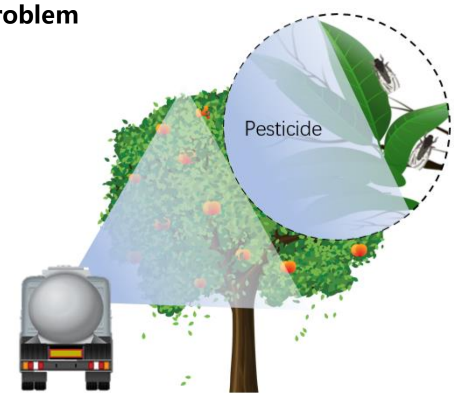
* The orange square in the figure refers to undetected sooty mold infections, and the orange fill indicates false detection.

Model	Day-Unsliced Image		
	Precision (%)	Recall (%)	mAP (%)
YOLOv5m	35.1	5.4	19.1
YOLOv7	30.6	48.0	26.7
CenterNet	-	17.8	13.8



Case Study 2: Tree Trunks Detection for Orchard Navigation

Problem



- Sprayer uses large quantities of pesticides, most of which do not reach the targets

Insects

- Insects have different habits
- For some insects, the best time to spray pesticide is thought to be during the night and early morning

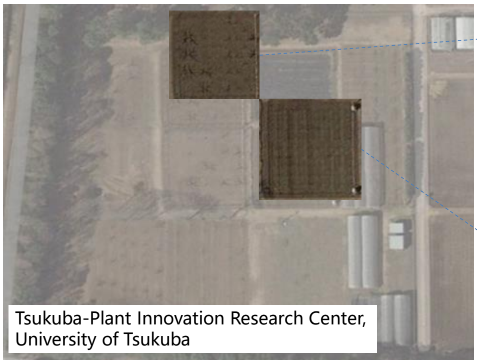
Purpose

- To develop an **autonomous navigation** spraying robot for orchard that can be used under **varies light conditions.**

FLIR ADK

- The camera develop for the **automotive thermal vision** for advanced driver assistance systems (ADAS) and autonomous vehicles (AV).
- Images can be used in deep learning to identify objects.

Data Collection in Orchard



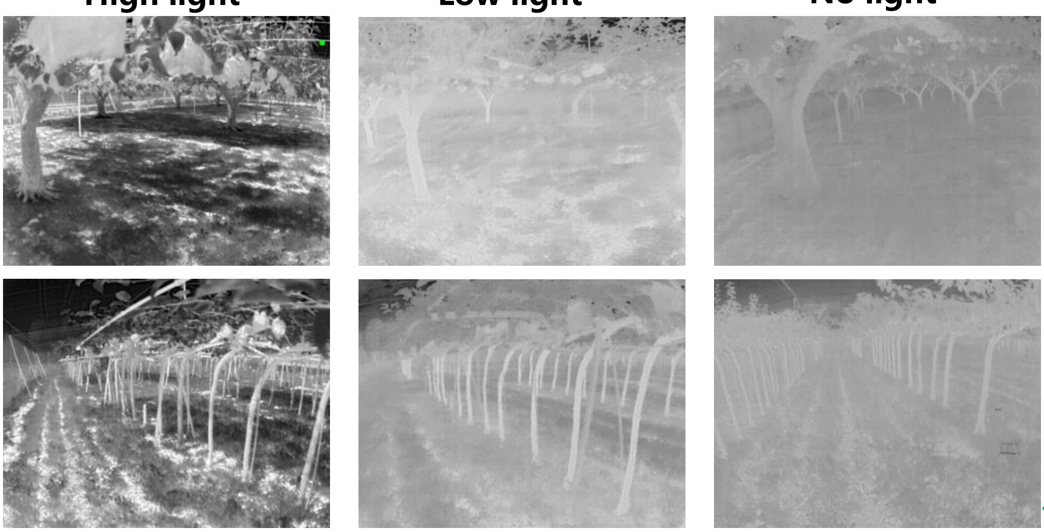

Conventional pear orchard


Joint-tree training pear orchard

Date	Time	Light Condition
2021.8.24	19:00-20:00	No light
2021.8.26	13:00-14:00	Strong light
2021.9.06	17:00-18:00	Low light

Thermal Images in Different Light Conditions

High light **Low light** **No light**



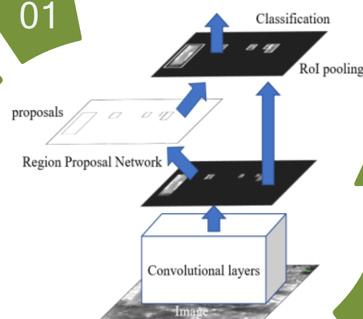
Faster R-CNN to Detect Tree Trunk

01 Convolutional layers

- To extract feature maps of images for training datasets

02 Region proposal network (RPN)

- To obtained the approximate position of the objects from the feature maps



Faster R-CNN
(Region Based Convolutional Neural Networks)

03 Region of interest pooling (ROI pooling)

- To obtained the fixed-size objects feature map

04 Classification

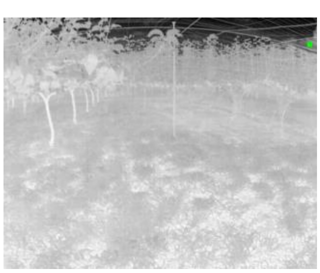
- To classify the objects of tree trunk detection

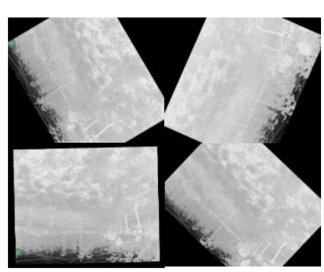
Data Preparation

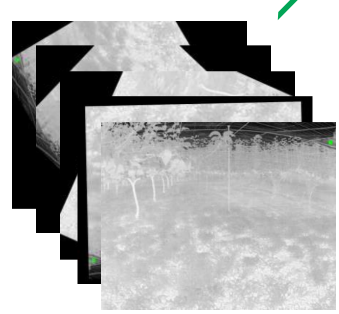
Original image: 5313

Augmented image: 7563

Total image: 12876



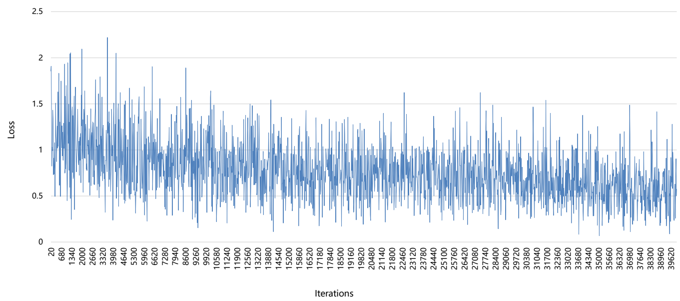




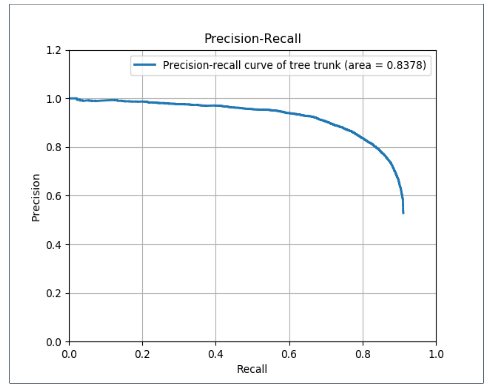
Training: 9270
Validation: 2318
Testing: 1288

Performance Evaluation

Total loss of Faster RCNN (40000 iterations)



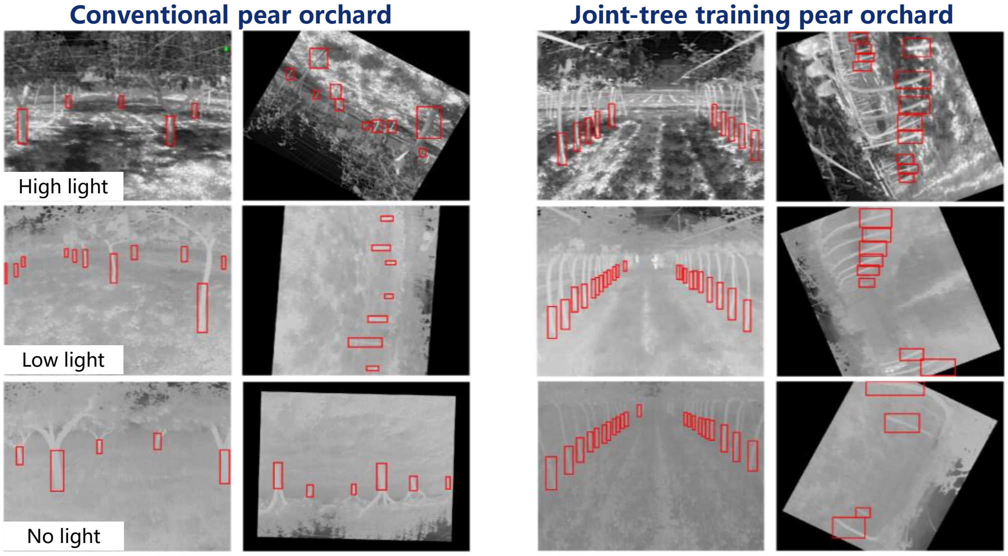
Precision-recall curve of testing



Tree Trunks Detection- Validation

Conventional pear orchard

Joint-tree training pear orchard



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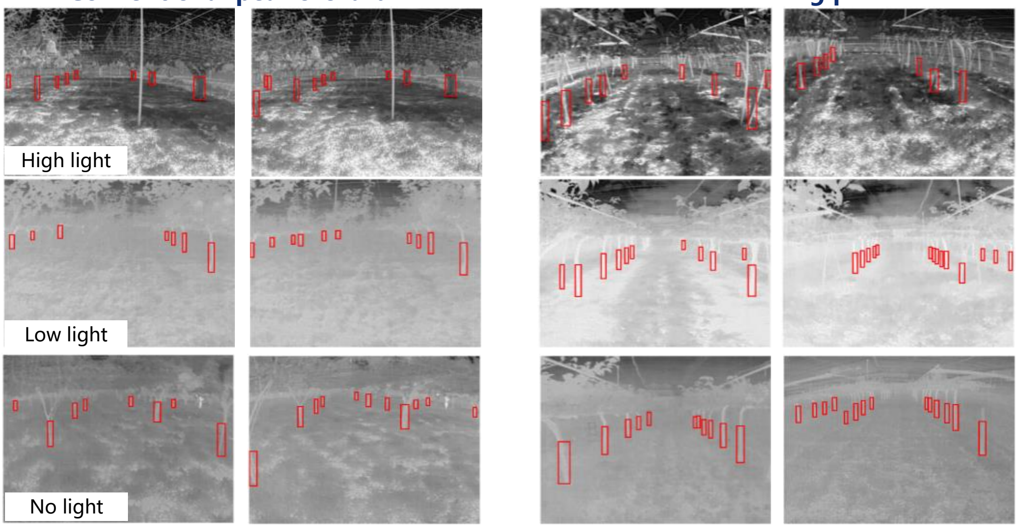
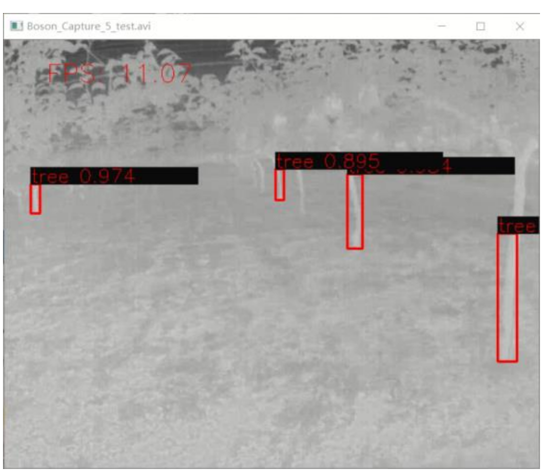
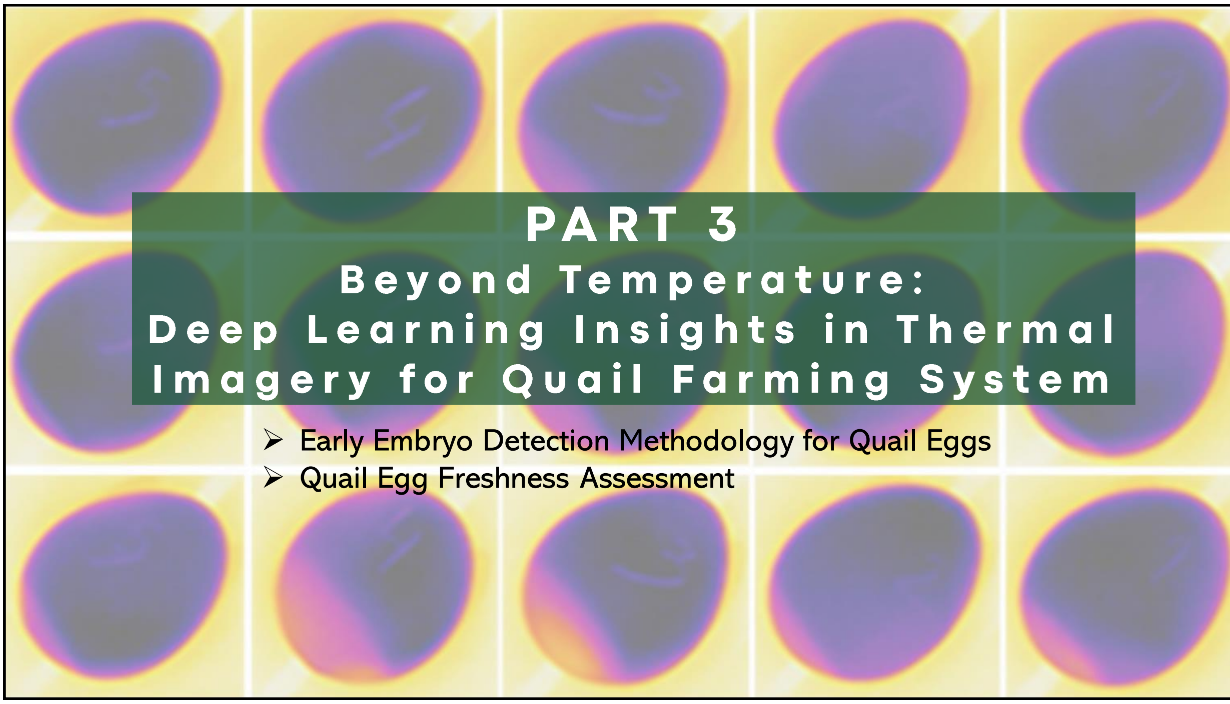
Tree Trunks Detection- Test

Conventional pear orchard | **Joint-tree training pear orchard**



Detection under Low-light Conditions





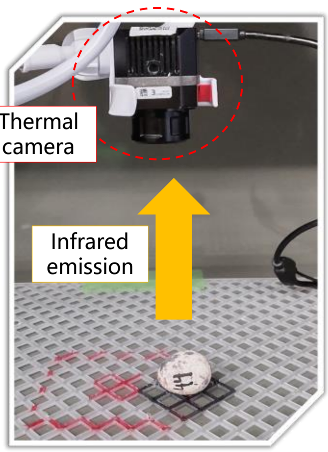
PART 3

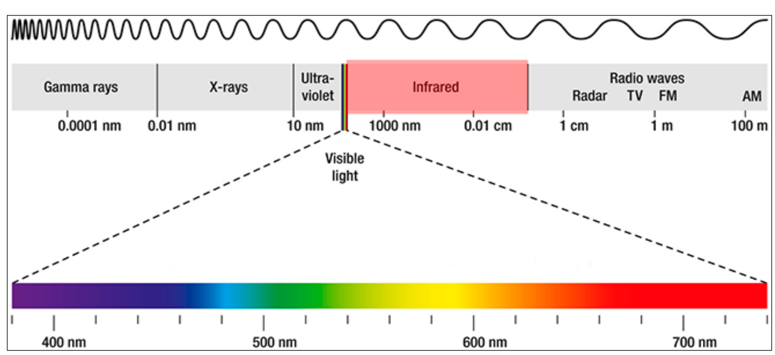
Beyond Temperature: Deep Learning Insights in Thermal Imagery for Quail Farming System

- Early Embryo Detection Methodology for Quail Eggs
- Quail Egg Freshness Assessment

Thermal Imaging – Basic Concepts

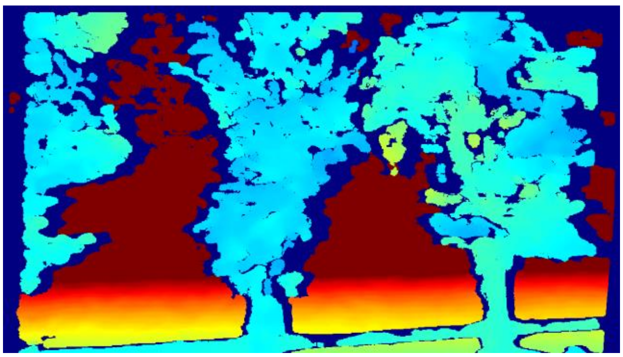
Thermal imaging, also known as **infrared thermography** or thermal vision, detects and visualizes **infrared radiation (heat) emitted by objects and organisms**.

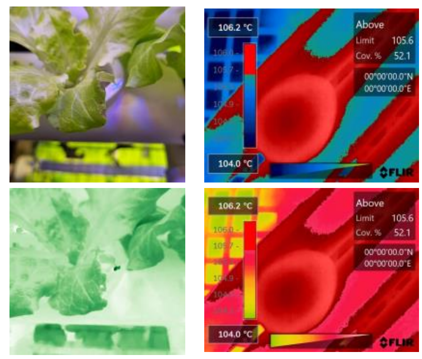


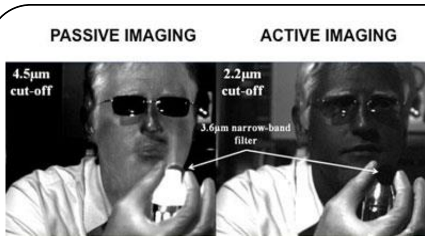


https://www.utwente.nl/en/news/2015/12/208853/plants-show-stress-in-thermal-spectrum

- All objects with a **temperature above absolute zero** (-273.15°C or -459.67°F) **emit infrared radiation**.
- To make the thermal image more understandable, various color schemes are used.
- Typically, **warm objects** are shown in shades **of red, orange, or yellow**, while **cooler objects** appear in shades of **blue or green.**







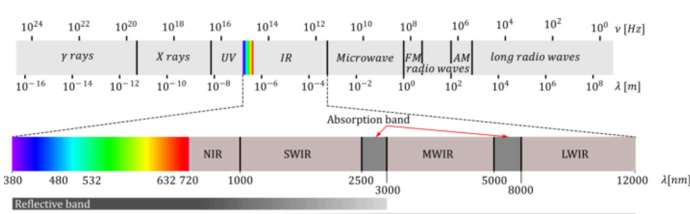
https://www.photonics.com/images/Web/Articles/2013/1/21/IMS_IRCamera.jpg

Properties: (1) Source of thermal radiation:

Passive thermal imaging
- Captures the natural thermal radiation.

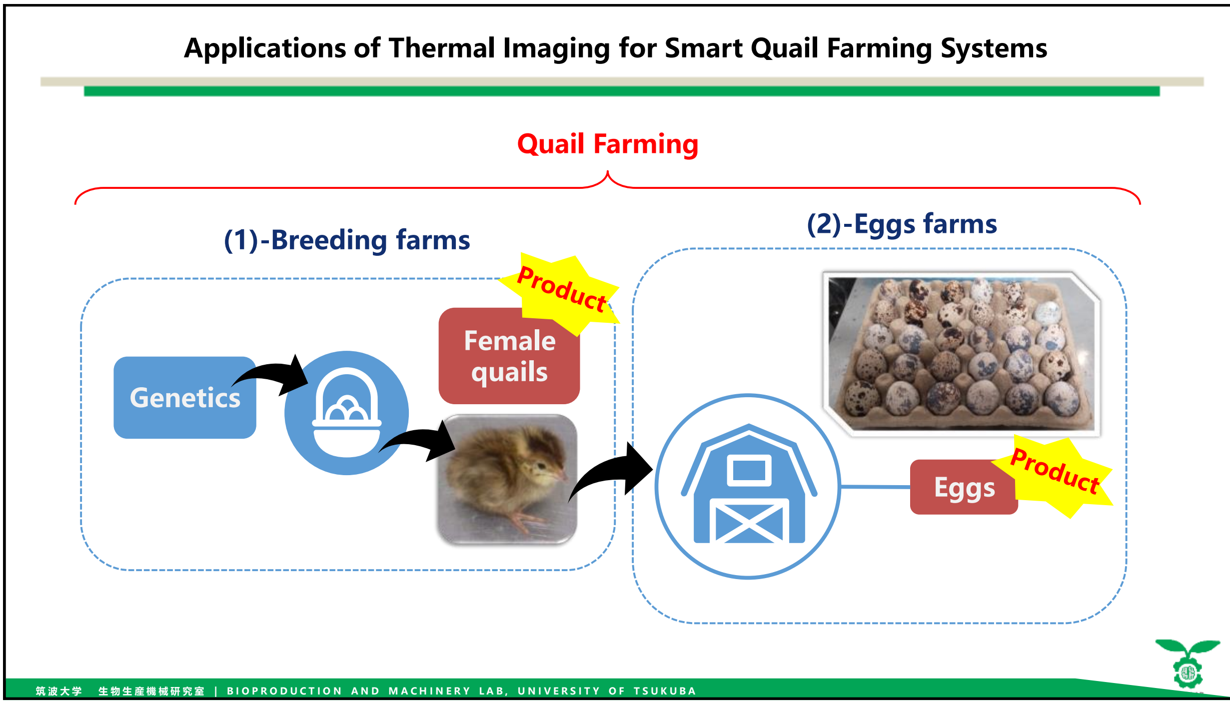
Active thermal imaging
- Involves the emission of a controlled source of thermal radiation, usually in the form of heat or infrared light.

(2) Sensors:
- Long-Wave Infrared (LWIR) Cameras
- Mid-Wave Infrared (MWIR) Cameras
- Short-Wave Infrared (SWIR) Cameras



https://nedinsco.com/technologies/swir-camera-technology/

https://www.pass-thermal.co.uk/media/revslider/hompage-slider/flir-thermals.png


Applications of Thermal Imaging for Smart Quail Farming Systems
Quail Farming
(1)-Breeding farms
(2)-Eggs farms
Genetics
Product
Female quails
Eggs
Product
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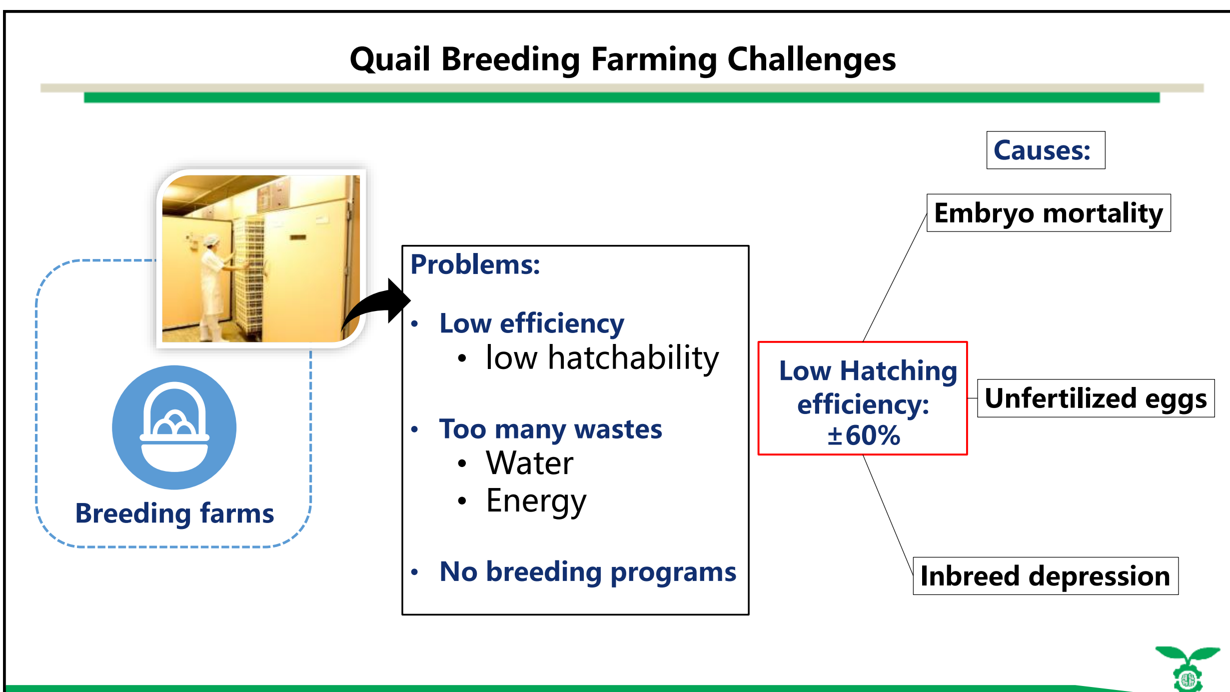
Quail Breeding Farming Challenges
Breeding farms
Problems:
• Low efficiency
• low hatchability
• Too many wastes
• Water
• Energy
• No breeding programs
Low Hatching efficiency: ±60%
Causes:
Embryo mortality
Unfertilized eggs
Inbreed depression
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Quail Eggs Farming Challenges

Quality Standards

Eggs farms

Multiple sources of variation
- Size
- Weight
- Color
- Eggshell defects
- **Freshness**

Lack of Freshness:
- Water
- CO_2
- pH
- Osmotic exchange

Albumen

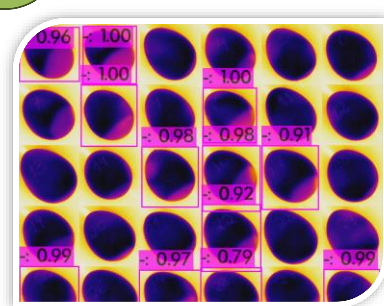
Yolk

Quail Farming Deep Learning based Thermal Sensing Systems

1 Breeding farms

Embryo detection

2 Eggs farms



Freshness assessment

Case Study 1: Thermal Sensing Embryo Detection Methodology

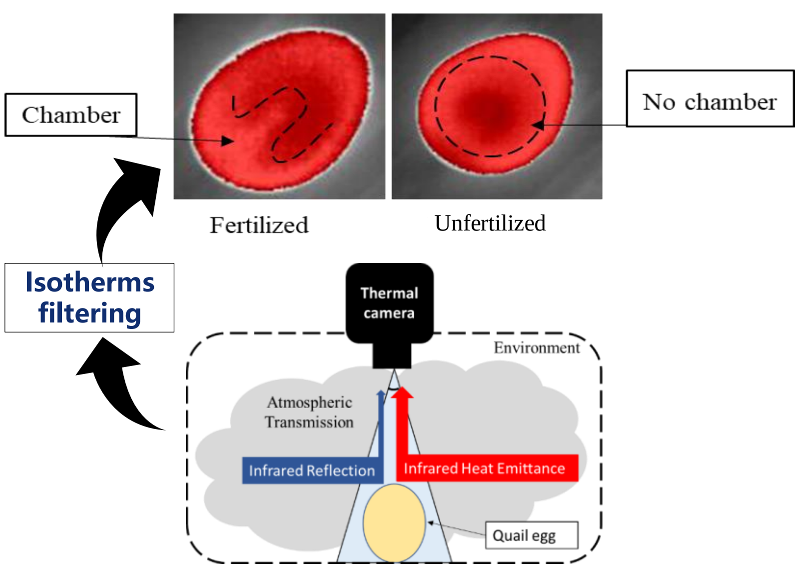
Objective:

Detect Unfertilized eggs during the incubation period at the early stages

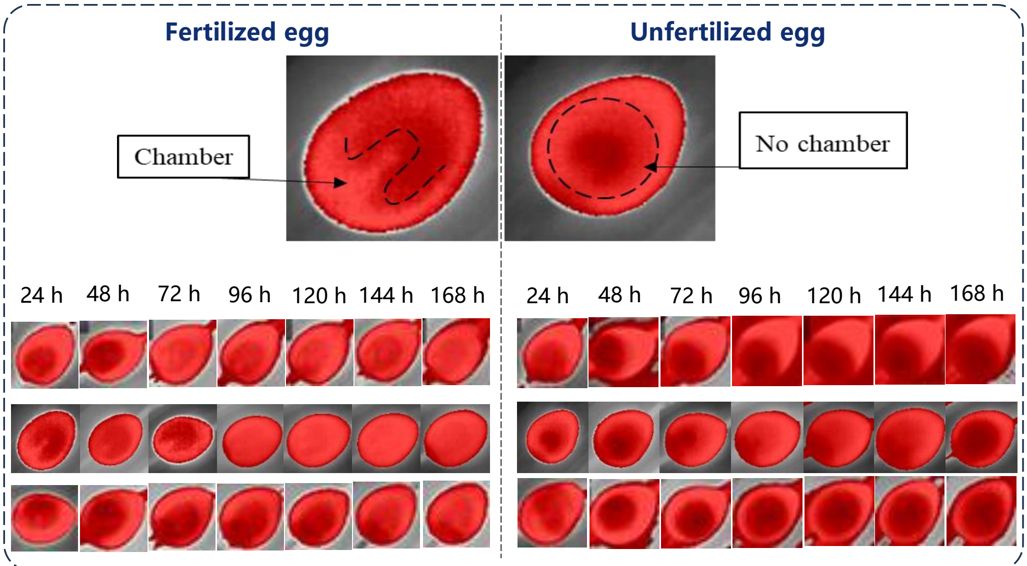
FLIR® (Teledyne FLIR LLC, Wilsonville, Oregon, U.S.) Model VUE™ 336, 6.8 mm.

*data collected every 12h.

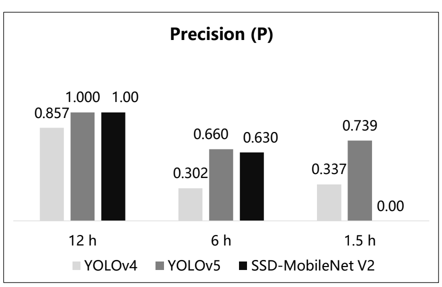
Images Dataset Collection

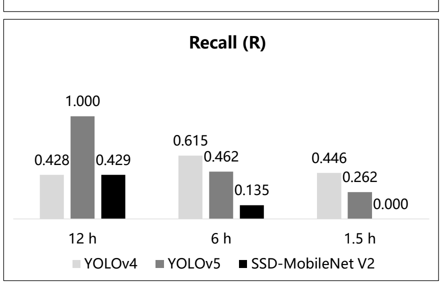


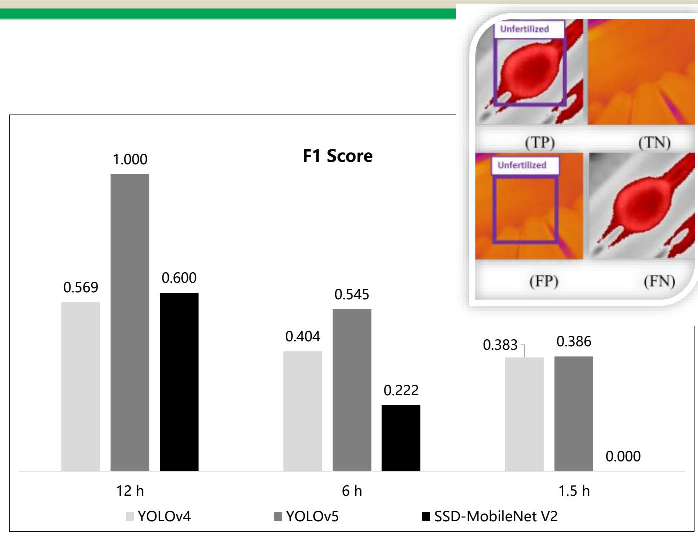
Images Dataset Collection



Performance Evaluation







*12h, 6h, and 1.5 Turning eggs period comparison

Case Study 2: Thermal Sensing Freshness Assessment

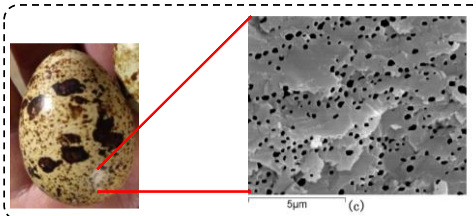
Deep learning freshness methodology:

1st: Deep learning training dataset
- 178 eggs stored for 60 days
- Data collection after 30, 50 and 60 days
- Image augmentation – 3610 in total

2nd: Air cell size assessment – **Method validation**
- 148 eggs under accelerated aging
- (10 days – summer room temperature)

3rd: Testing dataset
- 60 eggs stored for 15 days after the expired label.

Concept Background

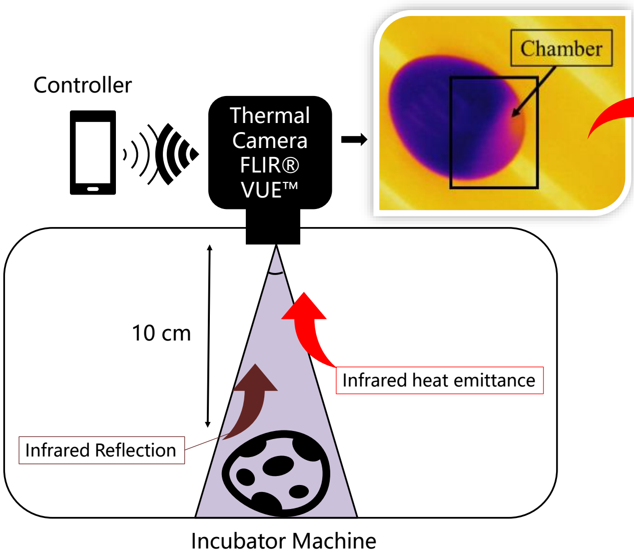


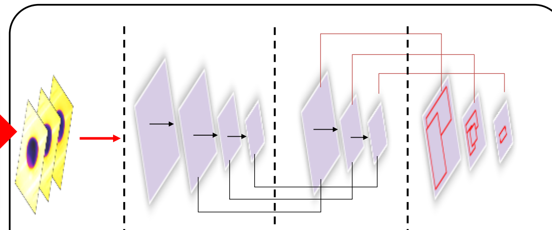
Eggs pores allow transmission of gases

Wang, D., Li, Y., Liu, L., Liu, J., Bao, M., Yang, N., Zhuo-Cheng, H., & Ning, Z. (2017). Traits of eggshells and shell membranes of translucent eggs. Poultry Science, 96, 351–358.

Env. Temp = target temp | Env. Temp = target temp | Env. Temp ≠ target temp

Detection Framework



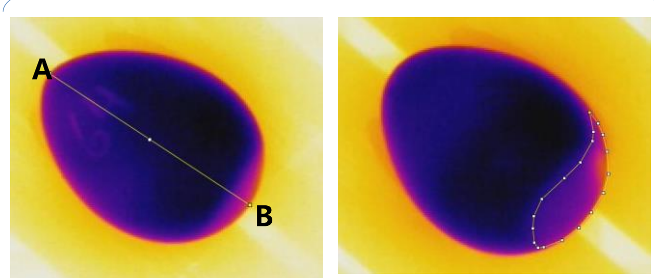


	Backbone	Neck	Dense Prediction
YOLOv4	• CSPDarknet53	• PANet • SPP block	• YOLO layer
YOLOv5	• CSPDarknet	• PANet • Modified FPN	• YOLO layer
EfficientDet	• EfficientNet	• BiFPN	• Box prediction net

Pixel area estimation

Real size

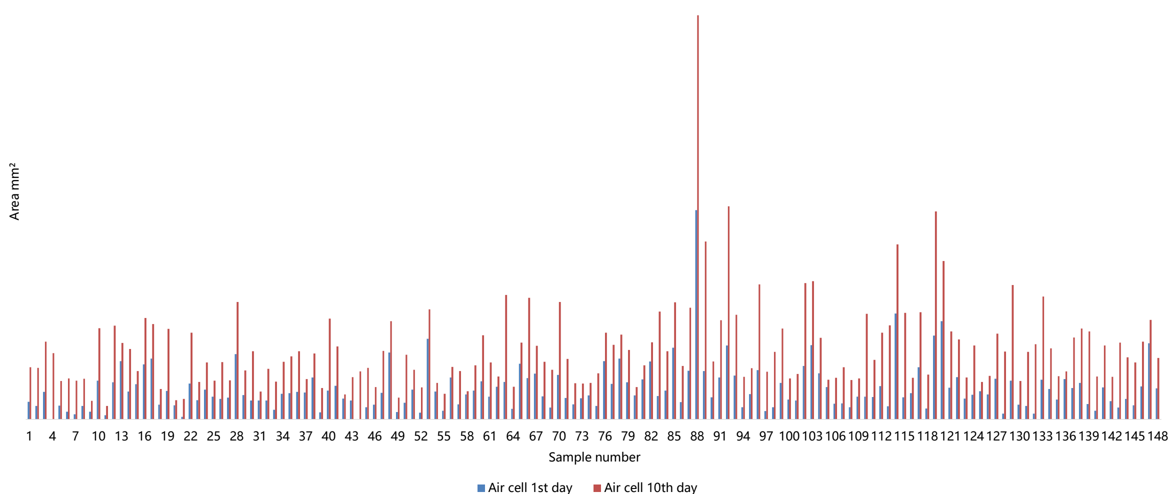
Weight

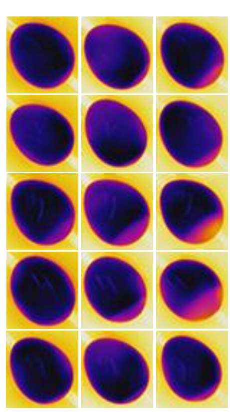


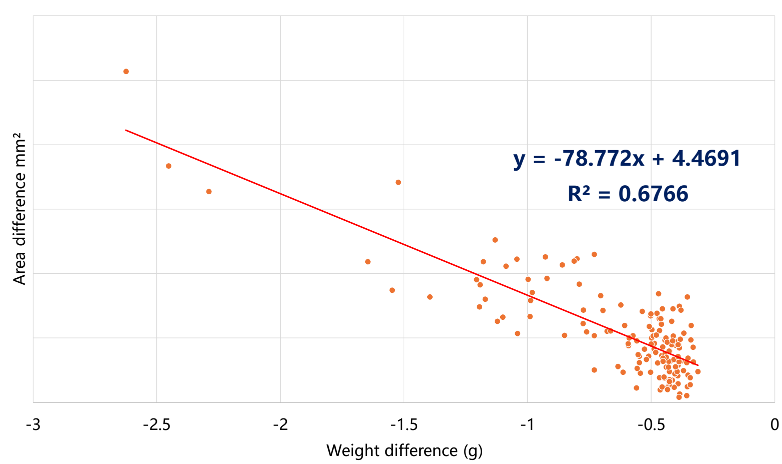
Real size = x pixels

x pixels^2 = real area mm^2

Variation in The Air Cell Size







Weight Difference (Mean)	Pixel Area Difference (Mean)	Degrees of Freedom (n-2)	T-Statistic	Coefficient (r)	p Value
−0.620	53.300	146	17.47713	−0.82256	1.3 × 10−37

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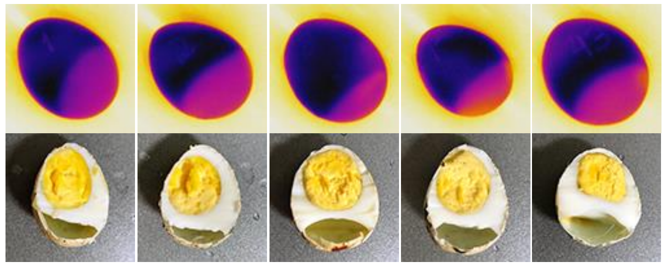
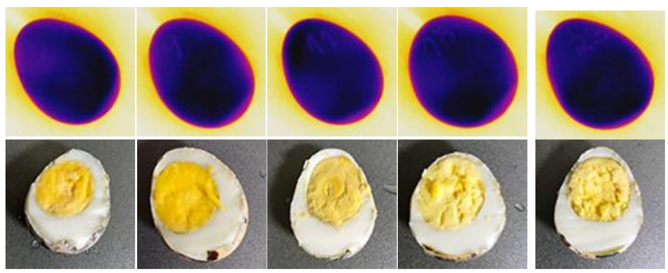
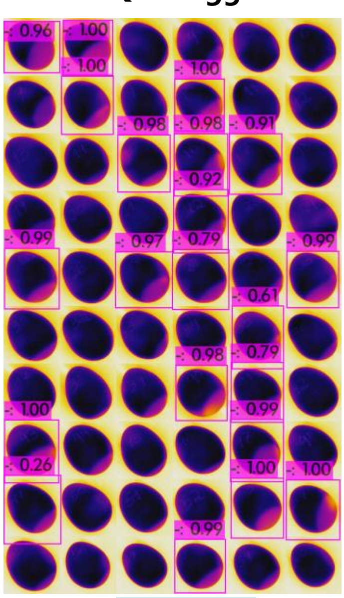


Nonfresh eggs

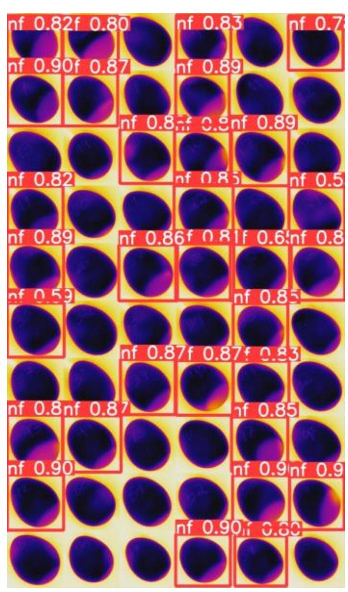


Fresh eggs

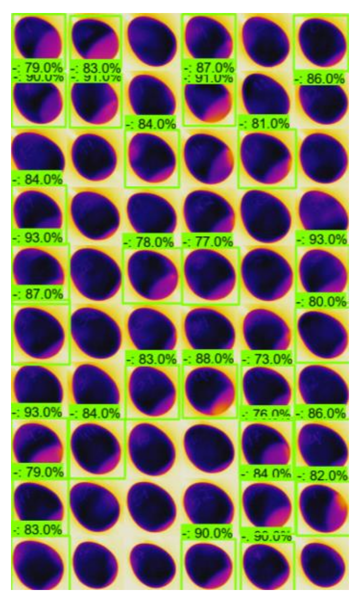
Nonfresh Quail Eggs Detection



YOLOv4



YOLOv5



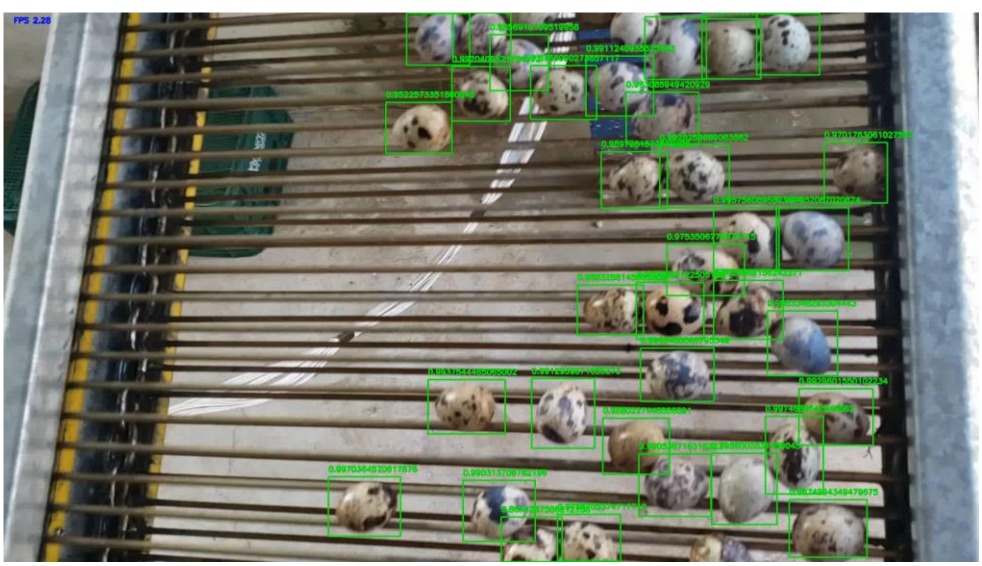
EfficientDet

Deep learning (DL) revalidation was given by **{[(TN+FN)/Total eggs] × 100}**

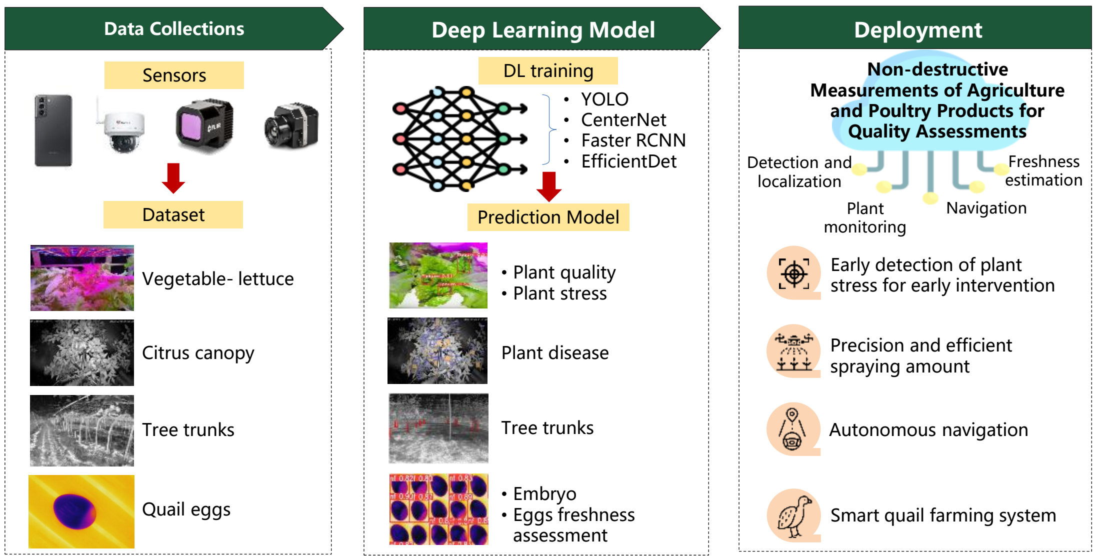
True revalidation was defined as **[(TN/Total eggs) × 100]**

Model	Total Eggs	Not Fresh (bbox)	DL Fresh (TN + FN)	True Negative (TN)	DL Revalidation	True Revalidation	Revalidation Error
YOLOv4	60	20	40	22	66.67%	36.67%	30.00%
YOLOv5	60	31	29	22	**48.33%**	**36.67%**	**11.67%**
EfficientDet	60	29	31	22	51.67%	36.67%	15.00%

Revalidation of label expiry date



Summary



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