講者簡介

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國立臺灣大學

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郭彥甫副教授現職為國立臺灣大學生物機電工程學系副教授，主要從事機器視覺在農業上監測方面的相關研究。研究主題包含溫室蔬果生長監測、利用葉片影像辨識植物樹種、漁獲物魚種辨識與魚體長量測，與雞豬隻保育與生長監測等。

QUALIFICATIONS

- 普度大學　　機械工程博士　　(2005.05 ~ 2011.08)
- 普度大學　　機械工程碩士　　(2003.08 ~ 2005.05)
- 國立臺灣大學　　農業機械工程學士(1994.08 ~ 1998.07)

PROFESSIONAL EXPERIENCE

- 深度學習、機器學習、機器視覺、機電整合

影像辨識分析
在農林漁牧上的應用

Application of Image Analysis in Agriculture, Forestry, Fishery, and Animal Husbandry

Dr. Yan-Fu Kuo

Aug 22nd, 2019

National Taiwan University
Department of Biomechatronics Engineering

SMART AGRI 智慧農業

Food security

農

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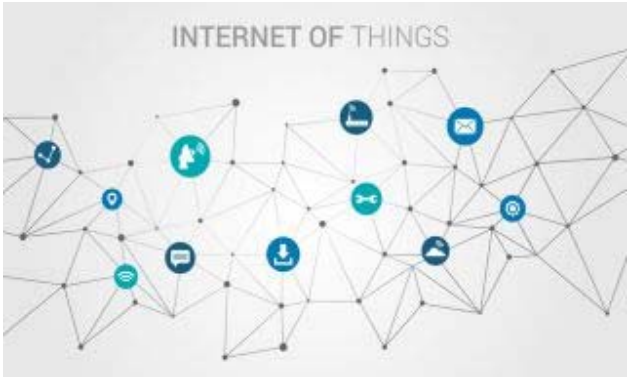
牧

Traditional farming

- Uncertain productivity due to weather, pests, and diseases
- Still high labor-intensive in field inspection

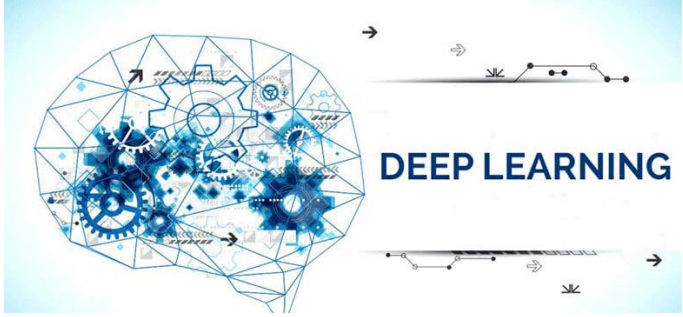
Technologies

Wireless Sensing



IOT

Machine Learning



Deep Learning

Motivation and objective

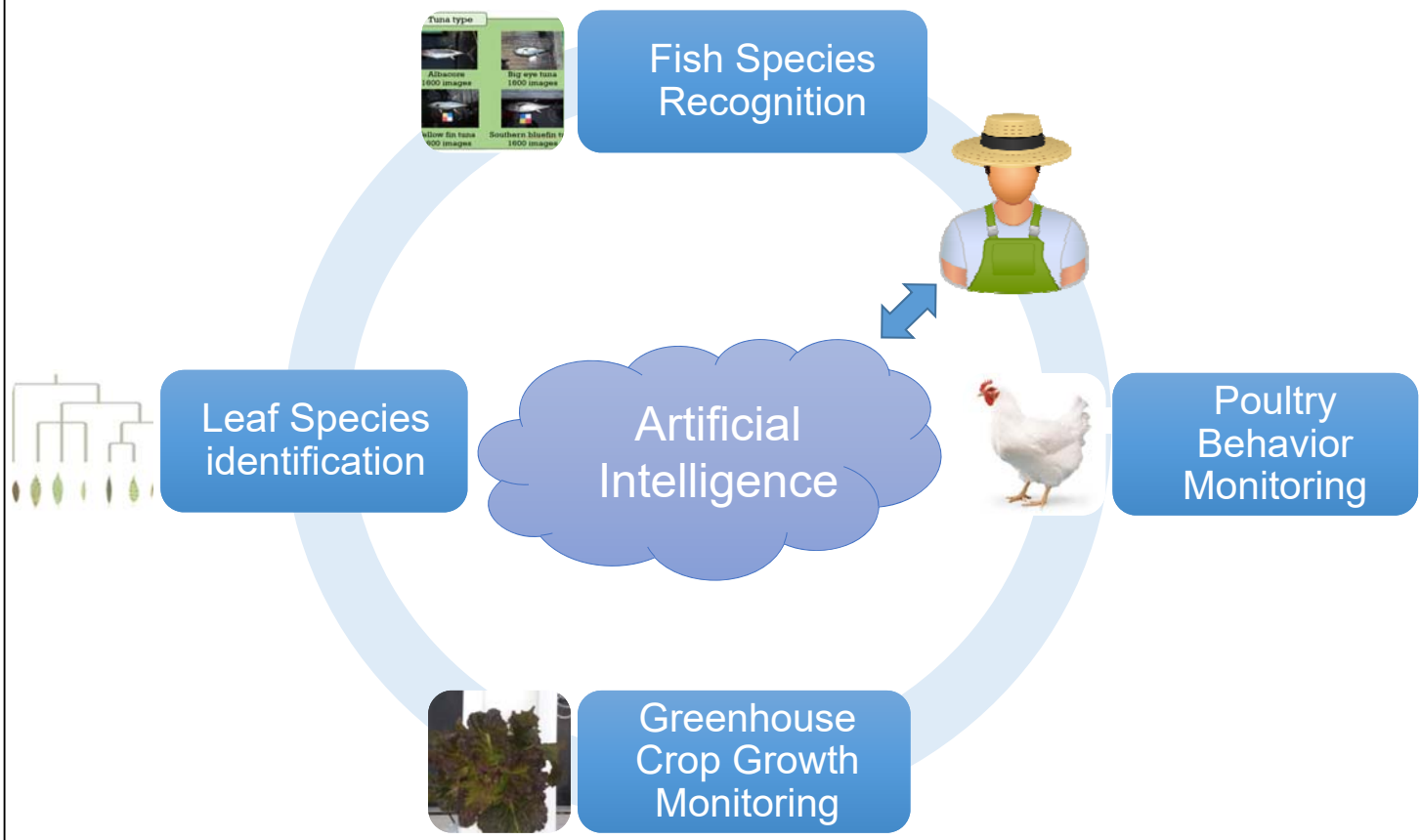
Motivation: Field inspection is **highly labor-intensive**

Developing automatic field inspection approaches

Crop growth monitoring	Livestock monitoring
Production estimation	Disease sensing
Greenhouse management	

Goal: **Reduce labor and increase product quality**

Applications



Growth Monitoring of Lettuce Through Deep Learning

利用深度學習驗控萵苣生長過程

National Taiwan University

Department of Biomechatronics Engineering

Production history of vegetables

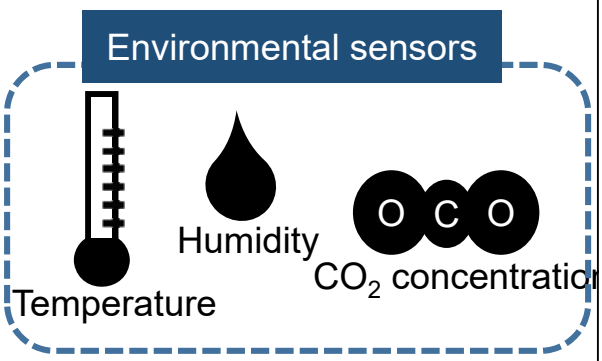
- Vegetable is essential in human diet
- Inadequate vegetable consumption attributed to 3.4 million deaths in 2013

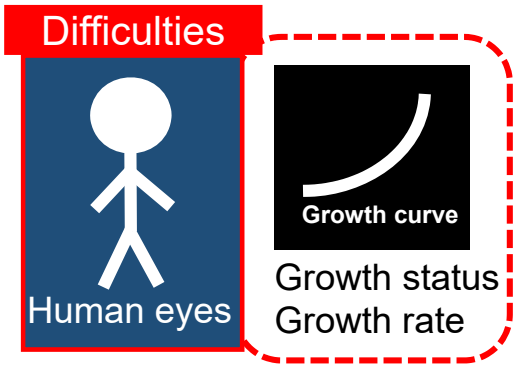
https://www.pexels.com/photo/food-healthy-vegetables-potatoes-5205/

The use of greenhouses

- High quality vegetables are usually grown in greenhouses

https://www.flickr.com/photos/oregonstateuniversity/33185459271

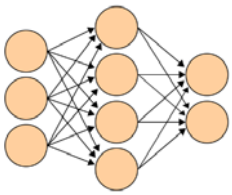




Procedure

Embedded system

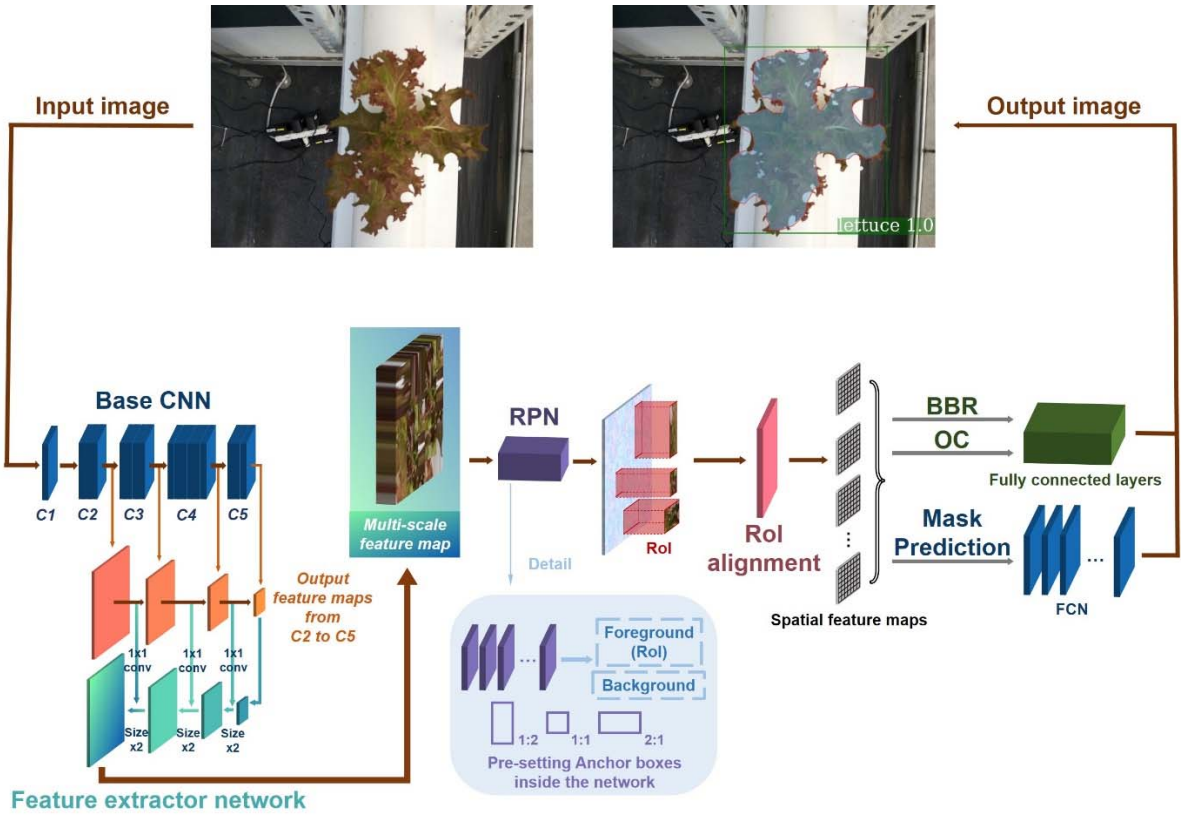
Leaf images



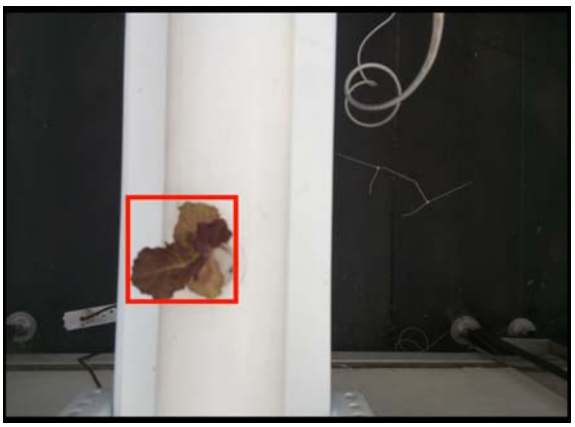
Deep learning algorithms

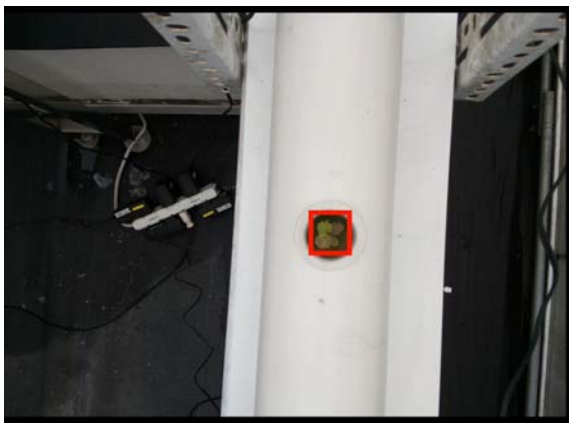
Leaf area estimation

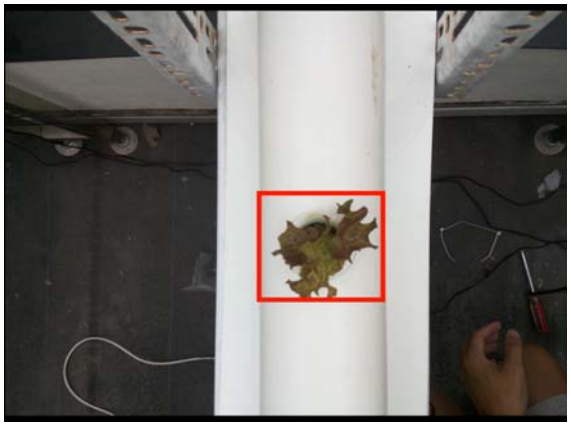
Mask R-CNN architecture



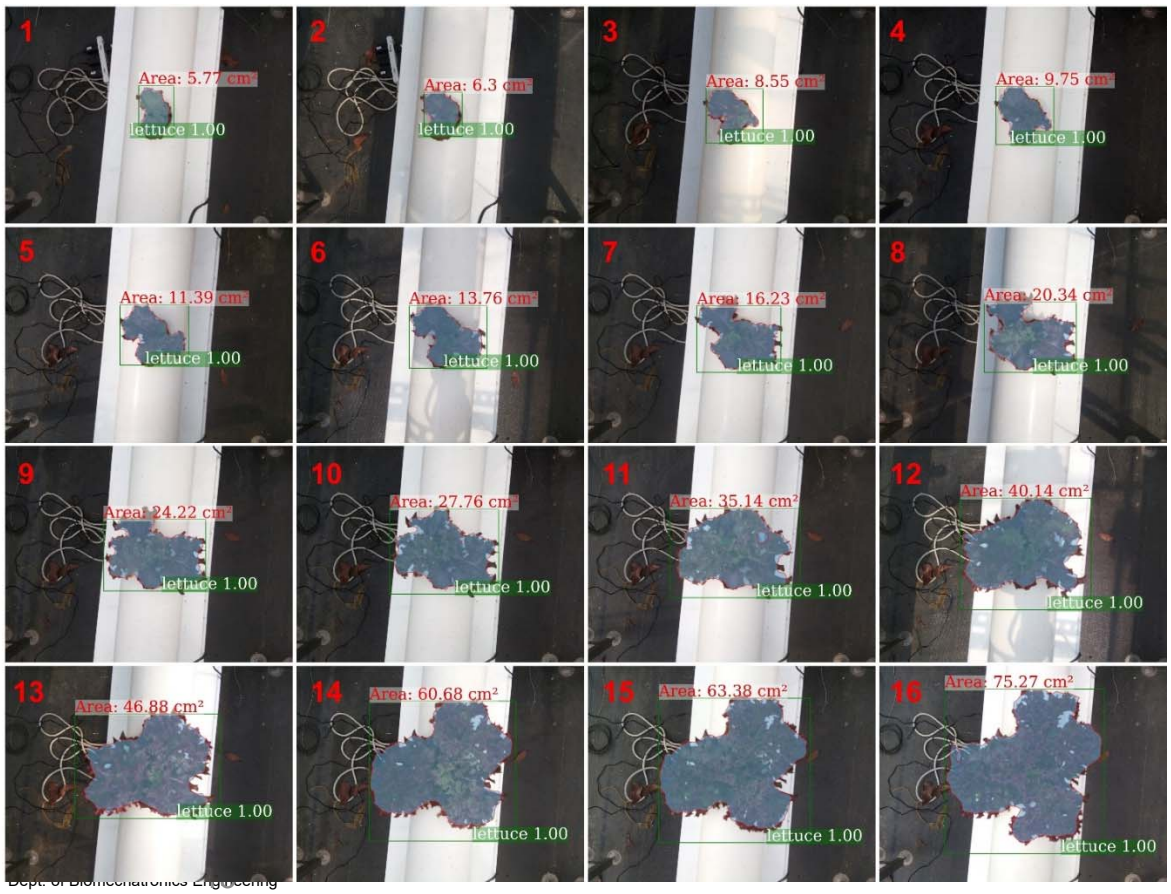
Performance of monitoring





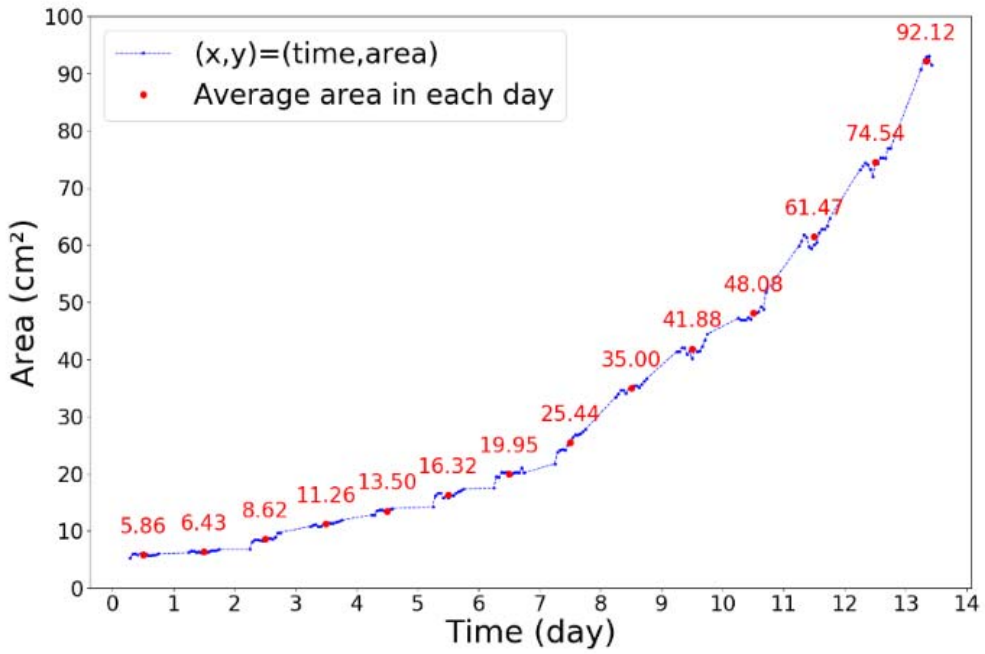


Lettuce growth monitoring



Counting lettuce area

- 18days
- 6:00-18:00 : 1 pic/hr



Identifying Fagaceae and Lauraceae Species in Taiwan Using Leaf Images

利用樹葉影像辨識台灣殼斗科與樟科

National Taiwan University
Department of Biomechatronics Engineering

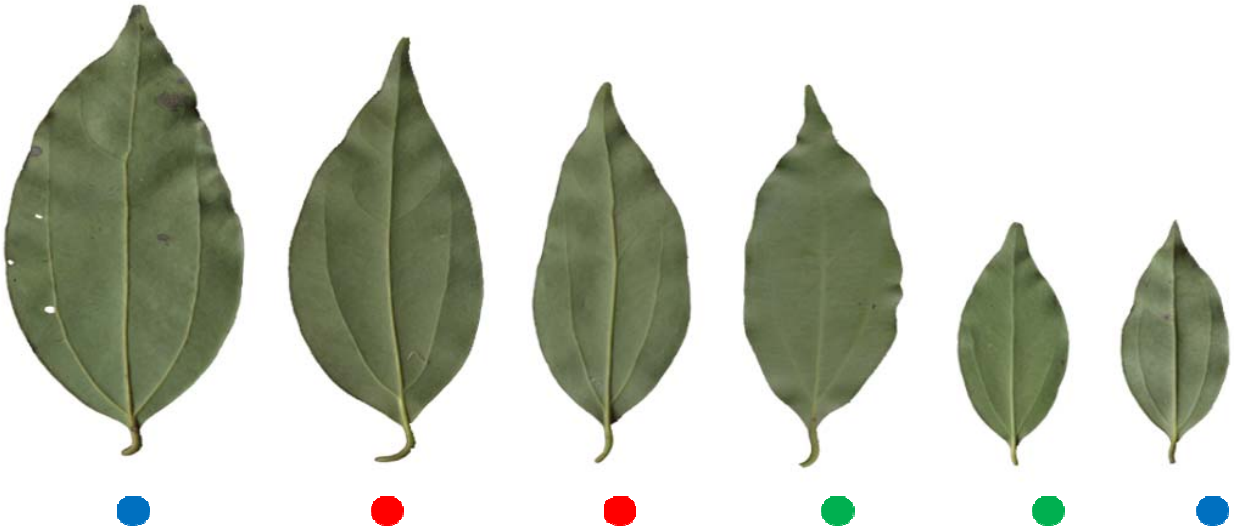
Research background

- Species diversification and ecological speciation
  - More then 1000 species
  - Widespread in north hemisphere
- Tremendous economic values
  - Wine barrel
  - Timber for furniture
  - Medical herbs with bioactivities
  - Food resources

(Stevens, 2001)

Three similar species

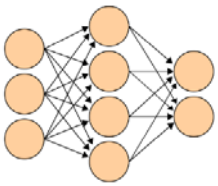
- *C. insulari-montanum* 台灣肉桂
- *C. Osmophloeum* 土肉桂
- *C.Burmannii* 陰香



Procedure

Picking leaves

Imaging leaves

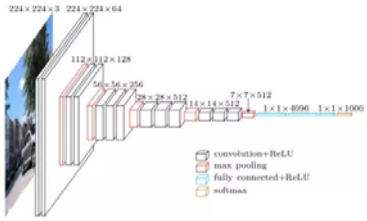


Deep learning algorithms

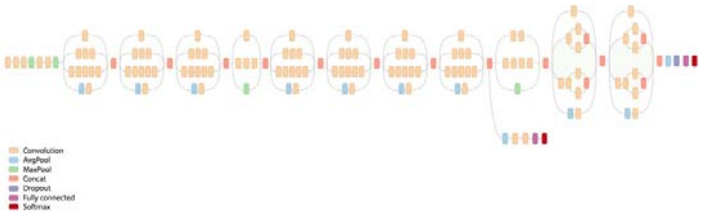
Classifying species

Pre-trained models

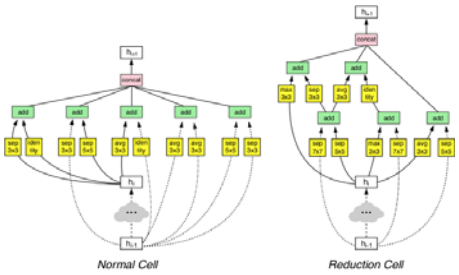
- VGG-16
  - Convolutional block



- Inception-V3
  - Inception module



- NASNet
  - Normal cell, reduction cell

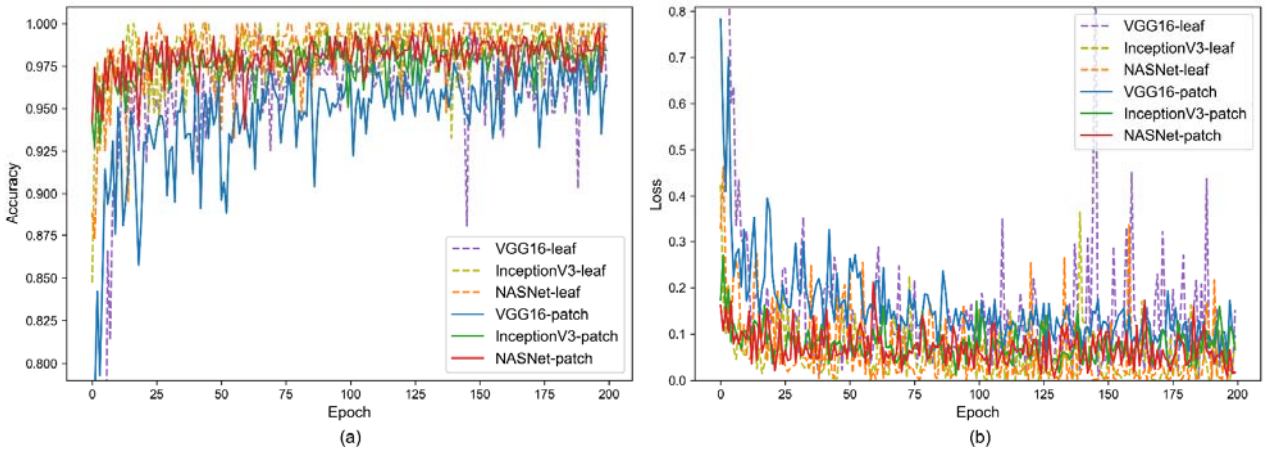


Dataset

Leaf	C. insulari-montanum	C. osmophloeum	C. burmannii
training	451	628	466
validation	50	50	50
test	100	100	100

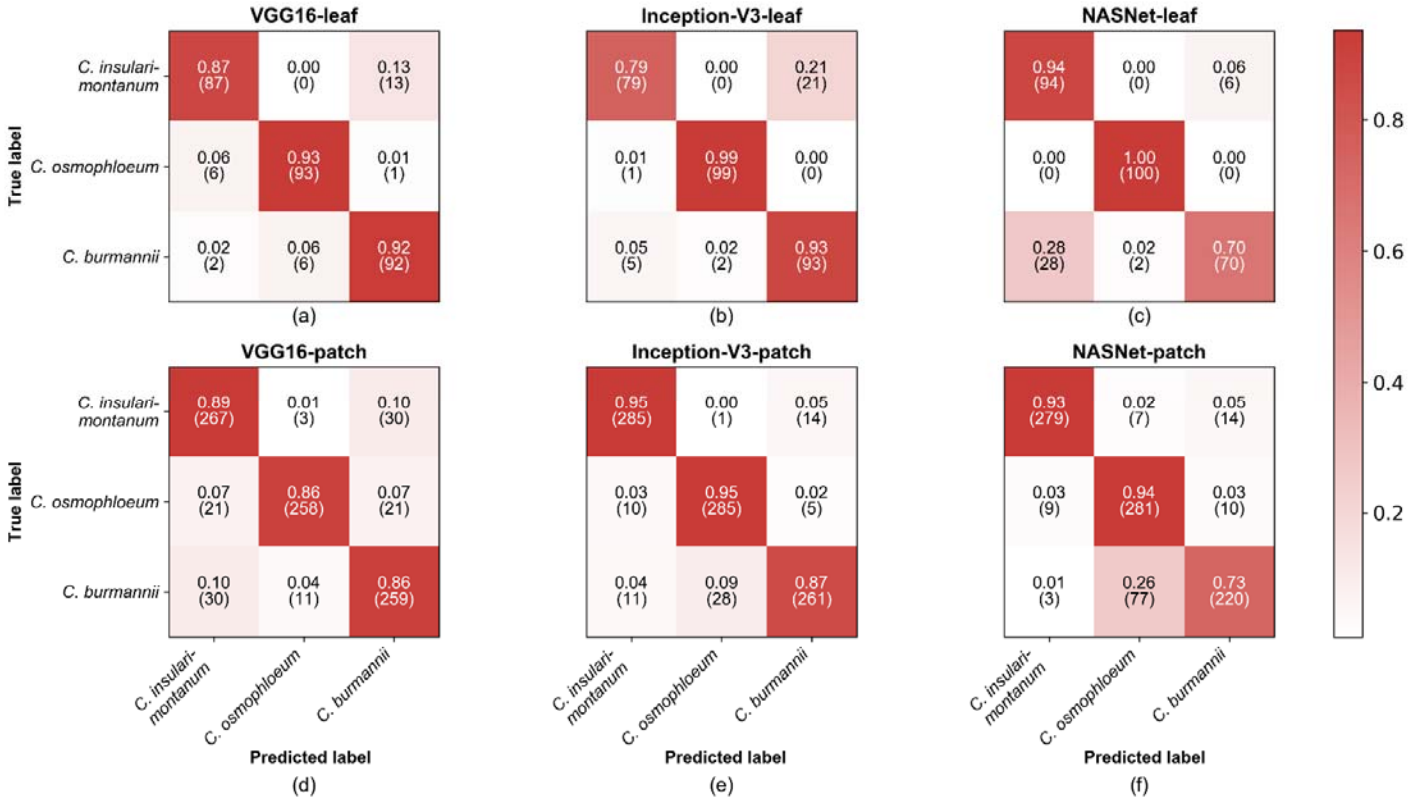
Patch	C. insulari-montanum	C. osmophloeum	C. burmannii
training	1353	1884	1398
validation	150	150	150
test	300	300	300

Performance



	Model	Validation accuracy	Validation loss	Test accuracy	Parameters
leaf	VGG16-leaf	0.973 ± 0.019	0.120 ± 0.106	0.907	14.78 M
	Inception-V3-leaf	0.990 ± 0.009	0.037 ± 0.041	0.903	21.81 M
	NASNet-leaf	0.991 ± 0.010	0.036 ± 0.060	0.880	4.27 M
patch	VGG16-patch	0.963 ± 0.014	0.105 ± 0.032	0.871	14.07 M
	Inception-V3-patch	0.981 ± 0.007	0.073 ± 0.030	0.923	8.98 M
	NASNet-patch	0.985 ± 0.007	0.062 ± 0.035	0.866	0.87 M

Performance



Fish species identification and body length estimation

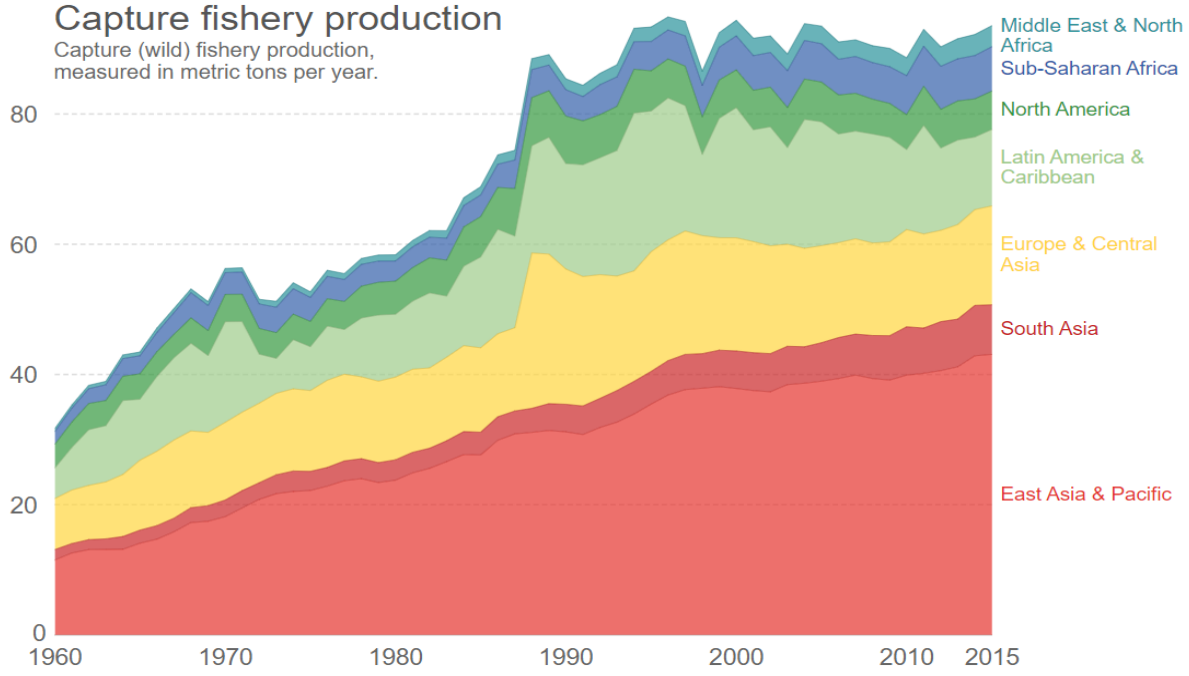
魚種辨識與魚體長量測

National Taiwan University

Department of Biomechatronics Engineering

Fish catch

- In 2014, there were about 93.6 MT of aquatic products caught in marine worldwide

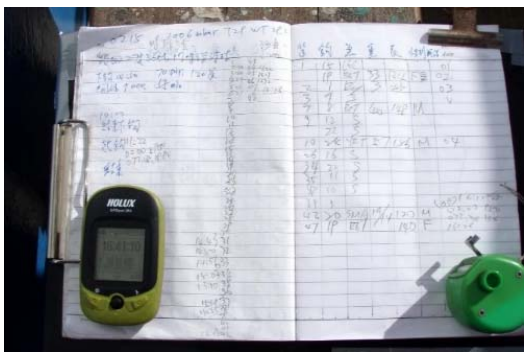


Fish sustainability

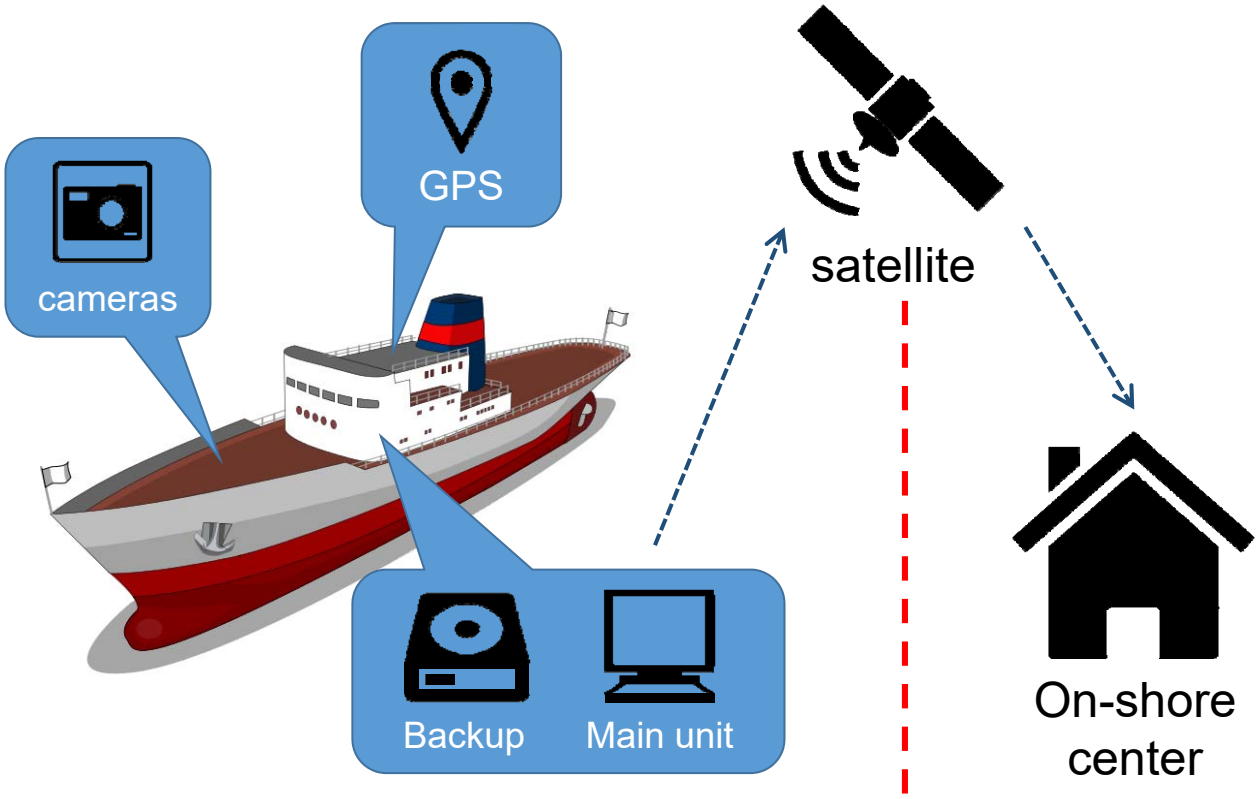
- Many fishing boat were involved in illegal, unreported and unregulated (IUU) activities
- 31.4% of the fish stocks were overfished

Manual monitoring

- Observers were sent to record fish catch information, including species and sizes
- Fish catch may underreported or misreported



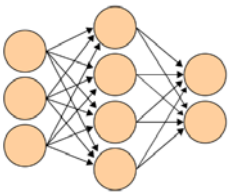
Electronic monitoring system



Procedure

Catchin
g fish

Imaging
fish body



Deep
learning
algorithms

Generating
fishery
report

Species identification

- Step:
  - Fish body detection
  - Fish species identification

Load image → Fish body detection → Fish body segmentation → CNN model classification → Result

Image collection

Tuna type


Albacore
1600 images


Big eye tuna
1600 images


Yellow fin tuna
1600 images


Southern bluefin tuna
1600 images

Billfish type


Blue marlin
1000 images


Sailfish
400 images


Swordfish
1000 images


Other billfish
900 images

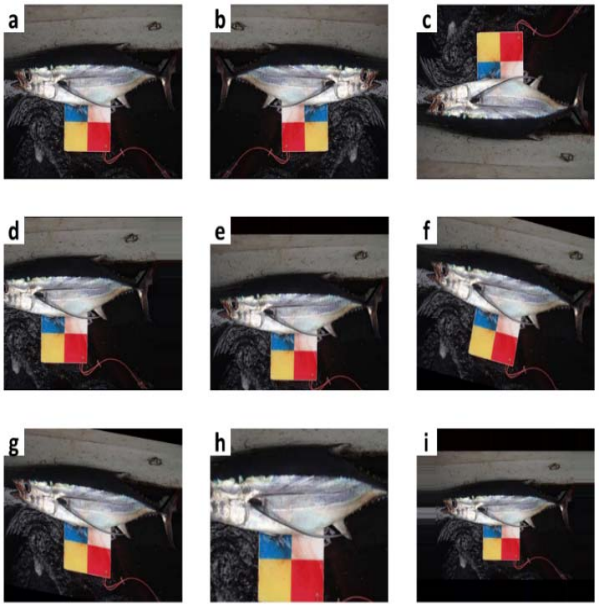
Other type


Dolphin fish
1000 images


Shark
1600 images


Others
1600 images

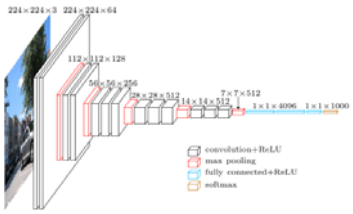
Augmentation



- Horizontal/vertical flipping
- Width/height shift
- Rotation
- Shearing
- Zoom in/out

Pre-trained models

➢ VGG-16
- Inherit the thought of AlexNet
- Add more layer



Simonyan& Zisserman, 2014

➢ DenseNet-201
- Feature reuse
- Summation → Concatenation

Huang et al., 2017

➢ MobileNet
- Depthwise separable convolution:
- Depthwise and pointwise convolution

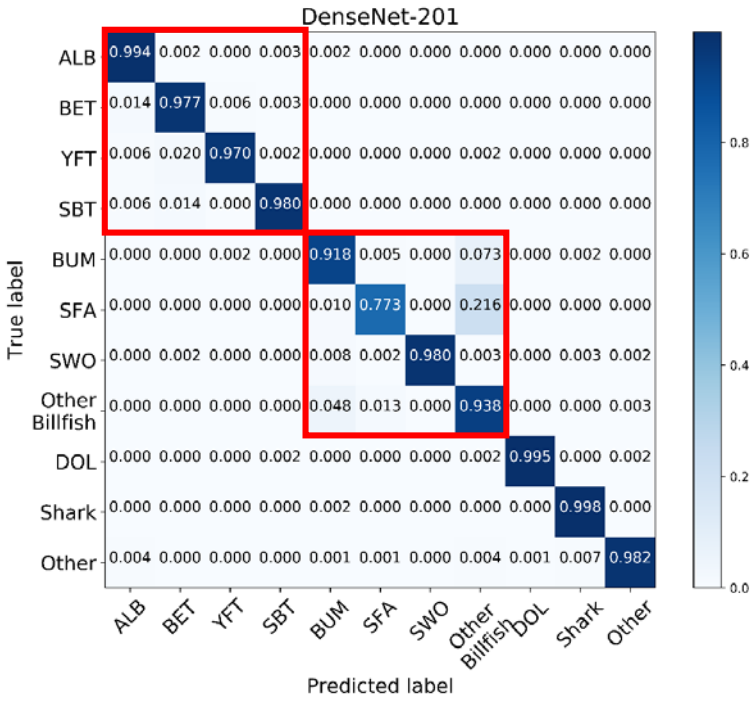
Standard convolution

Depthwise separable convolution

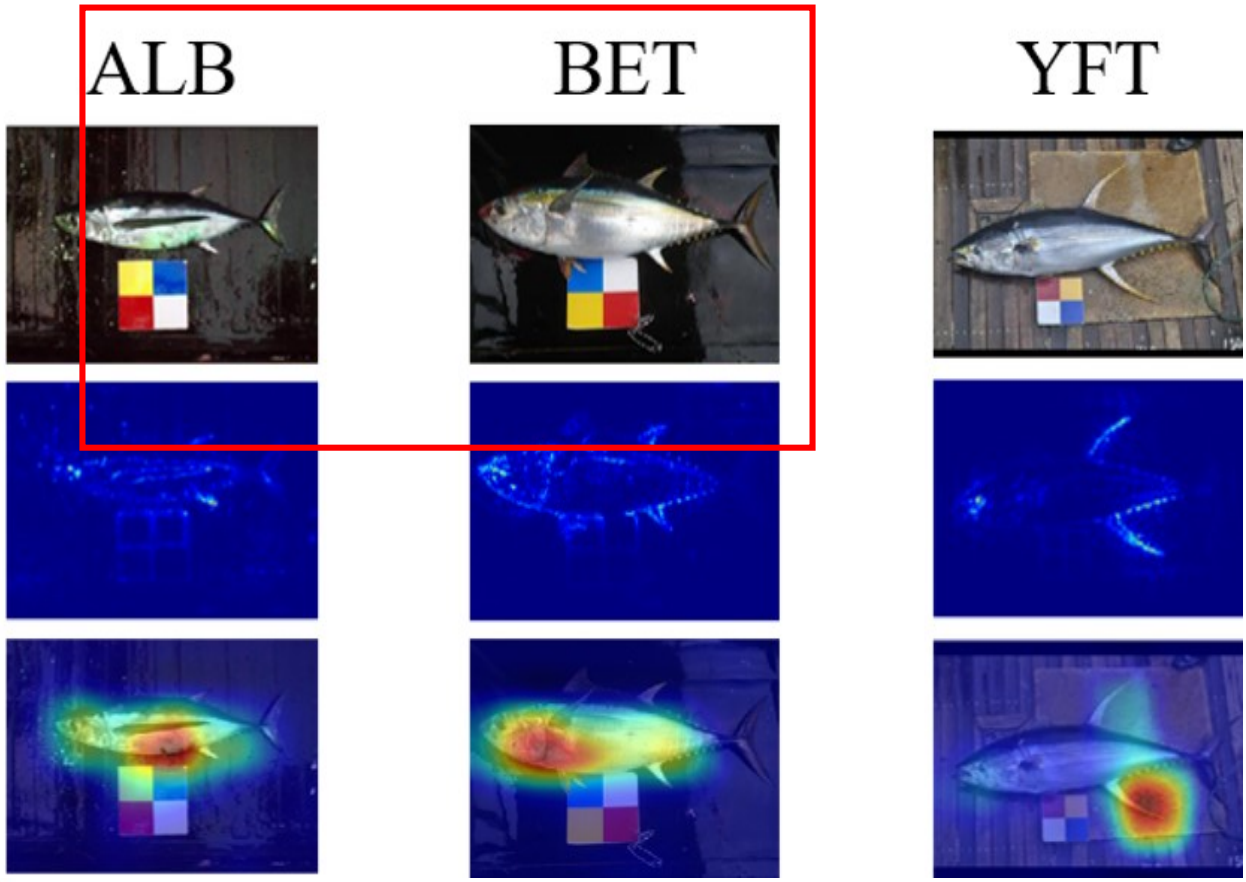
Howard et al., 2017

Performance

	VGG-16	DenseNet-201	MobileNet
Accuracy (%)	95.44	96.89 ✓	92.27
Time (sec/images)	0.02	0.05	0.014 ✓

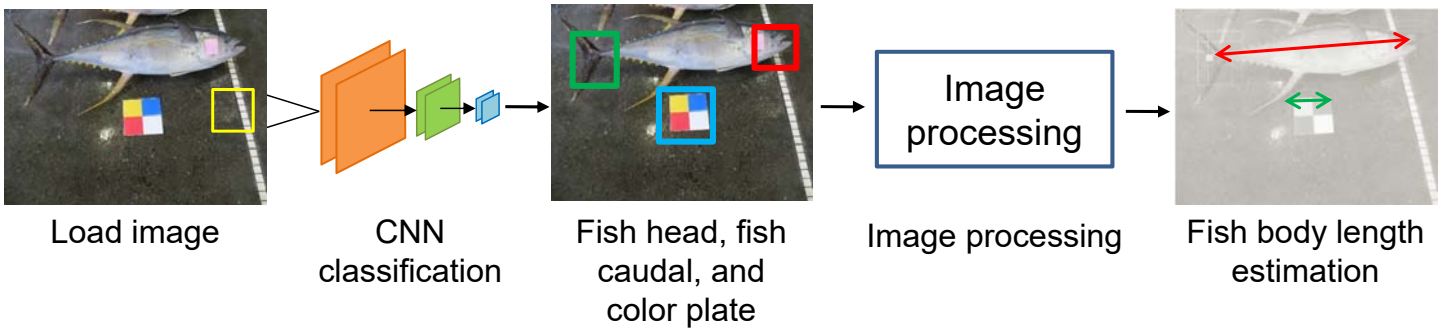


Model visualization

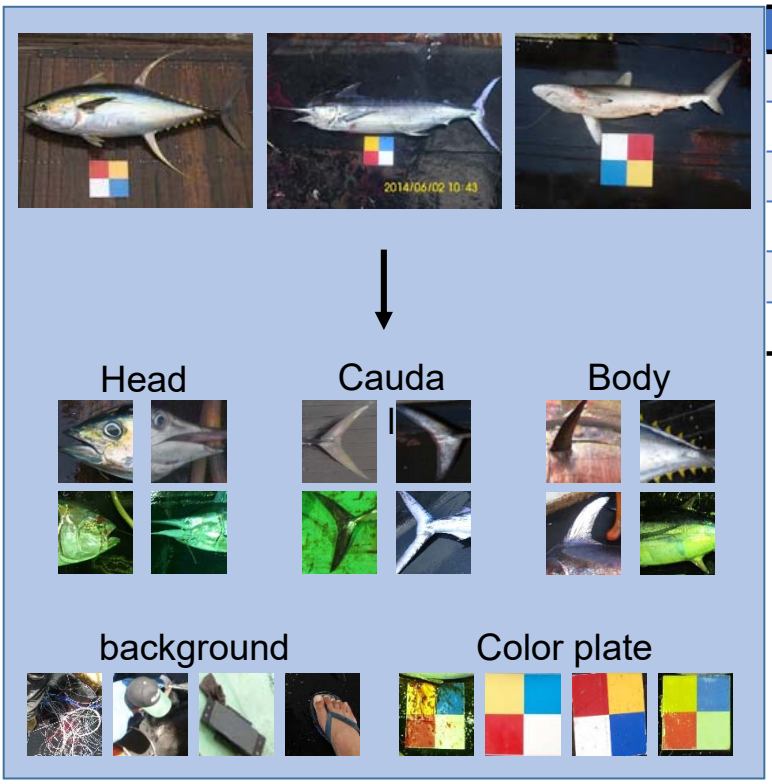


Fish body length estimation

- Step:
  1. Fish head, caudal, and color plate detection
  2. Fish body length estimation



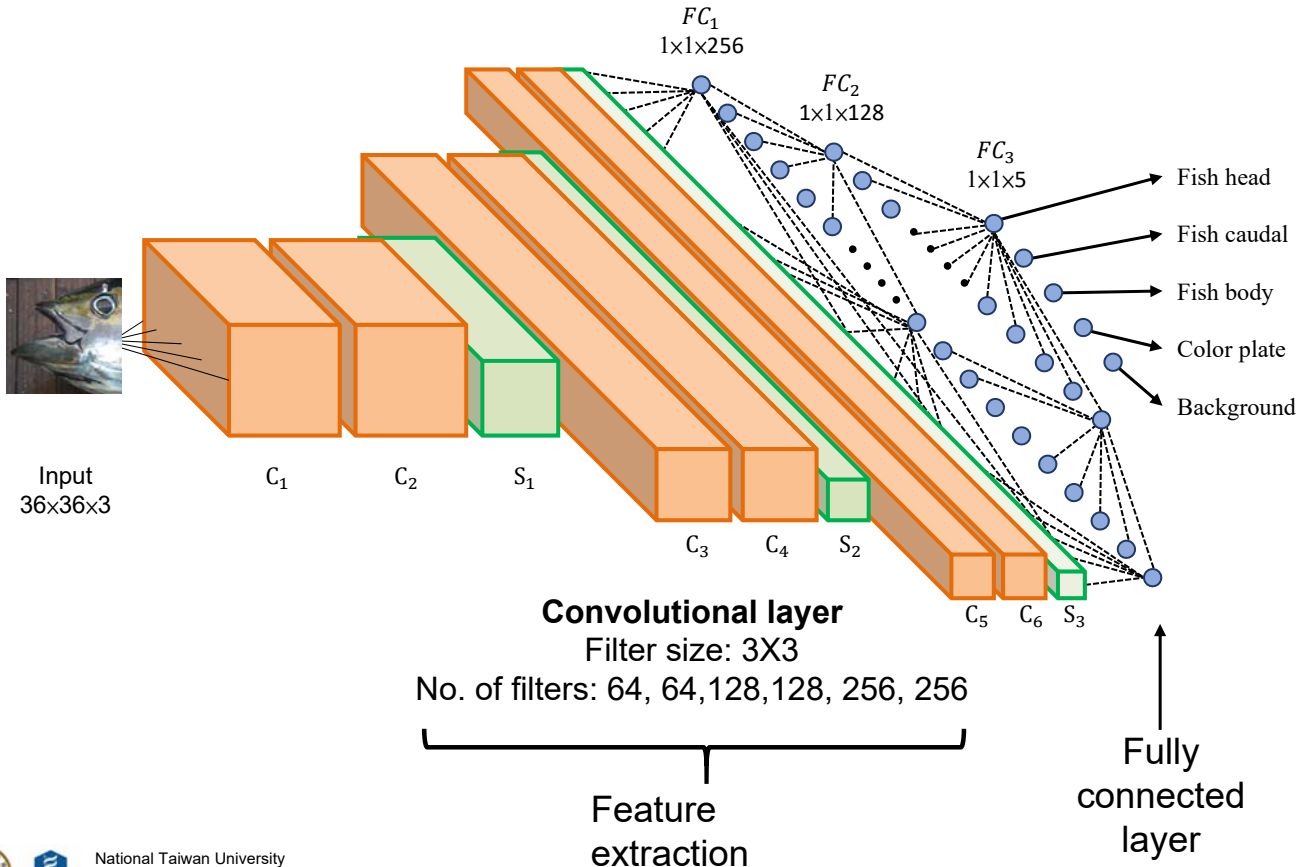
Training patch preparation



Class	Training	Validation	Total
Head	3500	500	4000
Caudal	3500	500	4000
Body	3500	500	4000
Color plate	3500	500	4000
Background	13500	500	14000
Total	27500	2500	30000

Patch size: 36x36 (pixels x pixels)
Images source: (FA·COA)

Architecture of the CNN

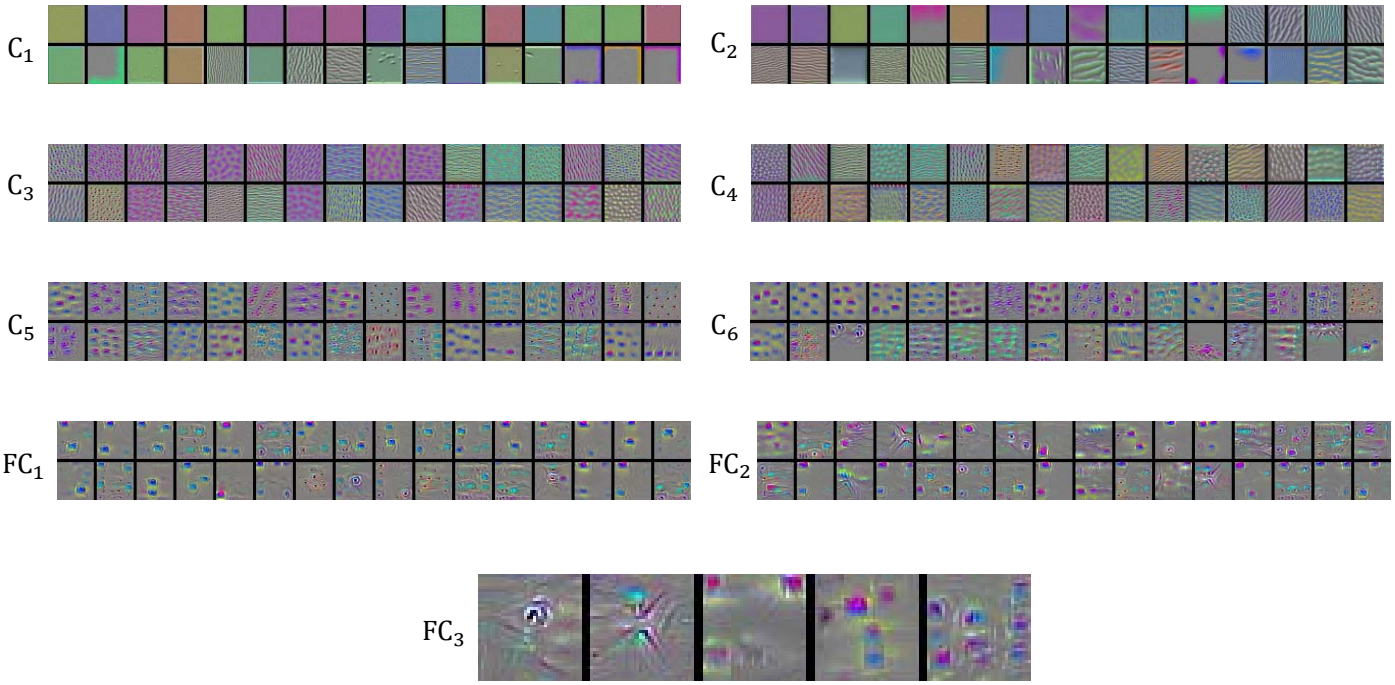


Performance comparison

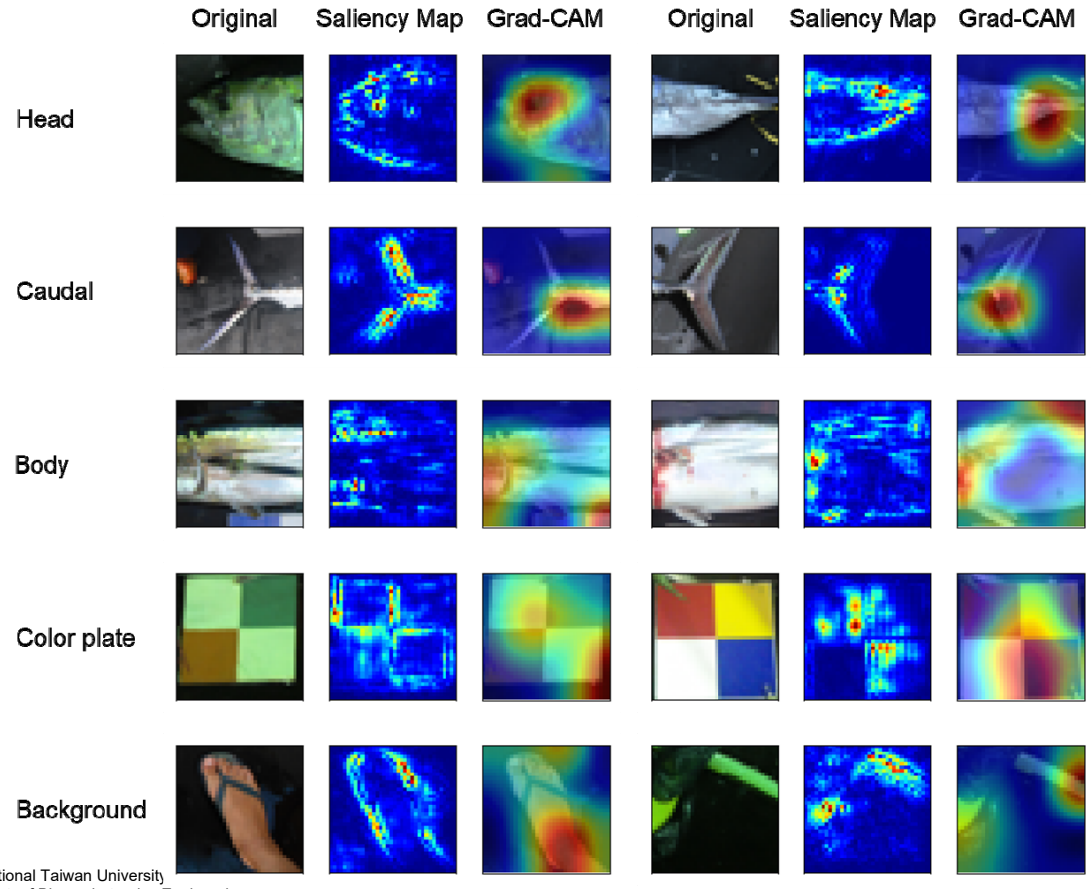
➢Comparison to other well-known CNN architecture

CNN architecture	Training time (s/epoch)	Validation accuracy (%)	Parameters (M)
Proposed	**10.0**	**97.70**	**2.2**
AlexNet	30.0	97.50	37.9
VGG-16	44.0	96.93	65.0

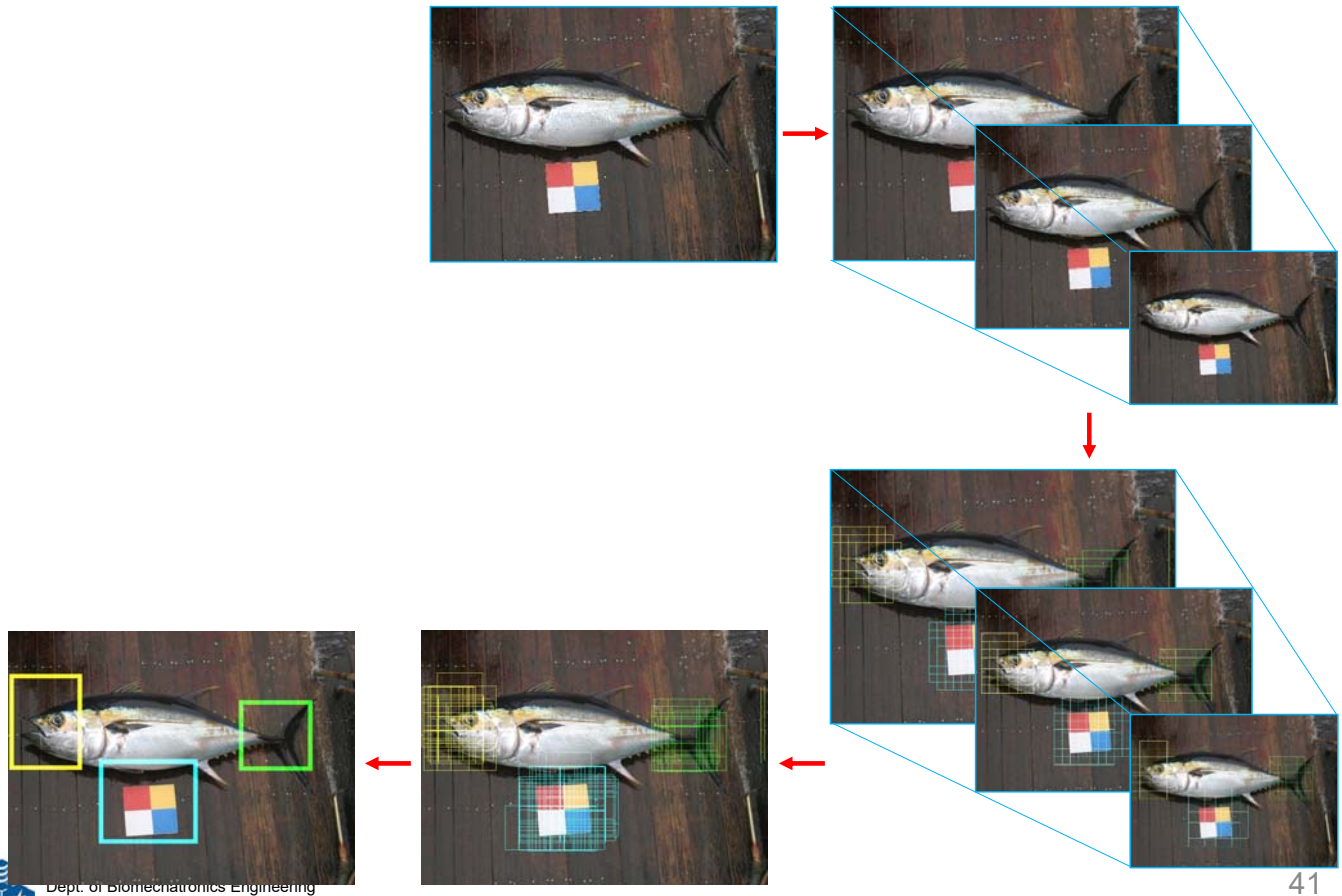
Filter visualization



Visualization



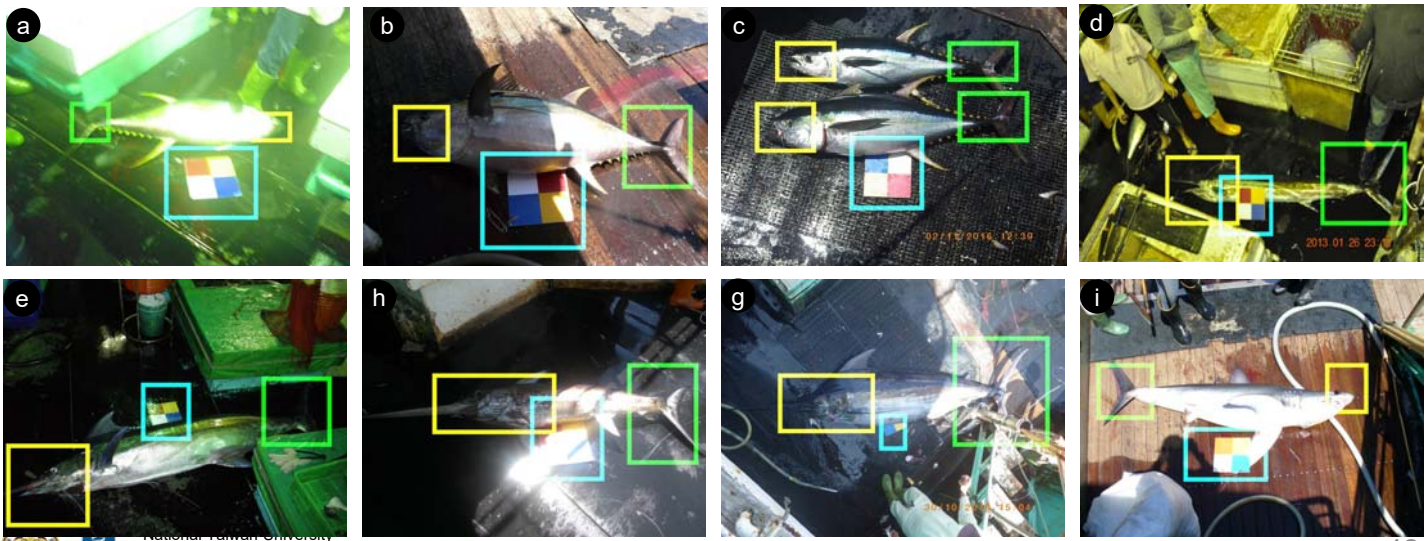
Detection of head and caudal



Performance

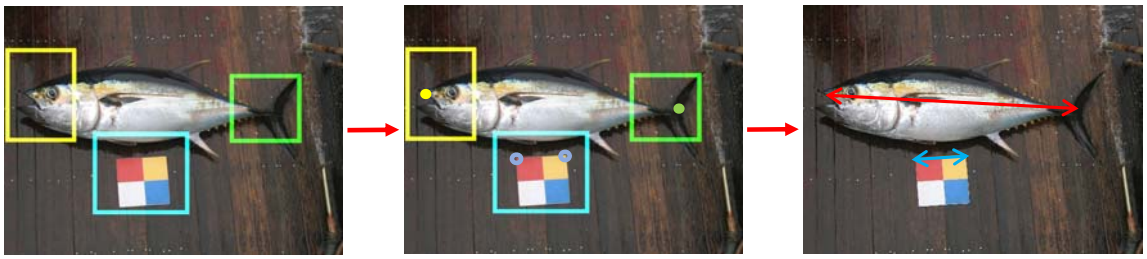
➢Detection rates:

Spatial pyramid ratio	Head (%)	Caudal (%)	Color plate (%)
0.5	89.83	87.37	98.77
0.4	98.80	96.67	99.20
0.3	97.14	97.97	98.78
Combined	**99.62**	**99.23**	**99.93**

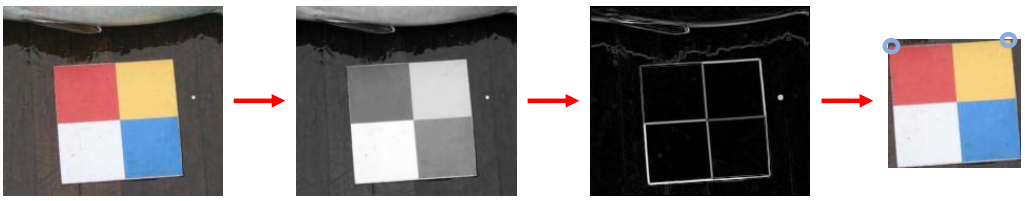


Body length estimation

- The snout point and fork point localization

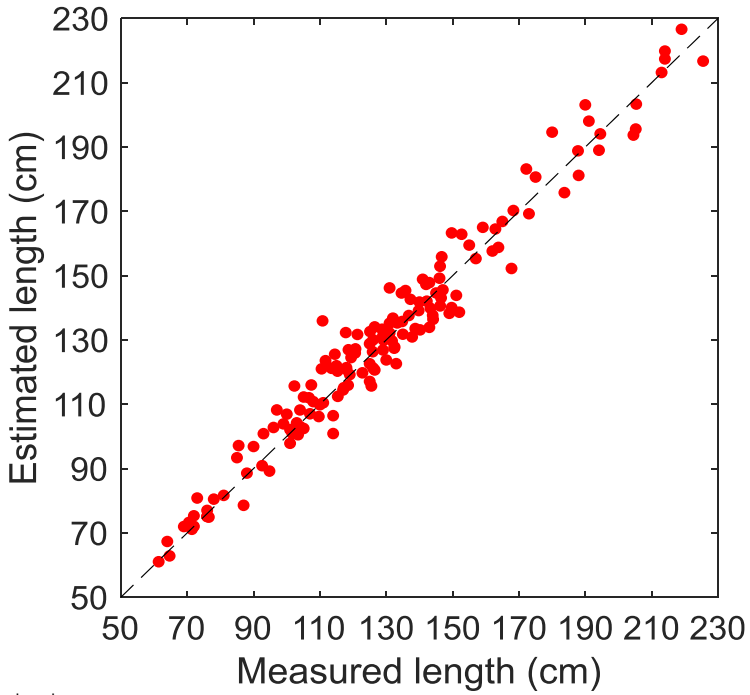


- Meter-to-pixel ratio calculation



Performance

- Test images: 154
- Body length estimation error: 5.36±0.33 cm



Detecting animal behavior - chicken and pig
監控雞隻與豬隻行為

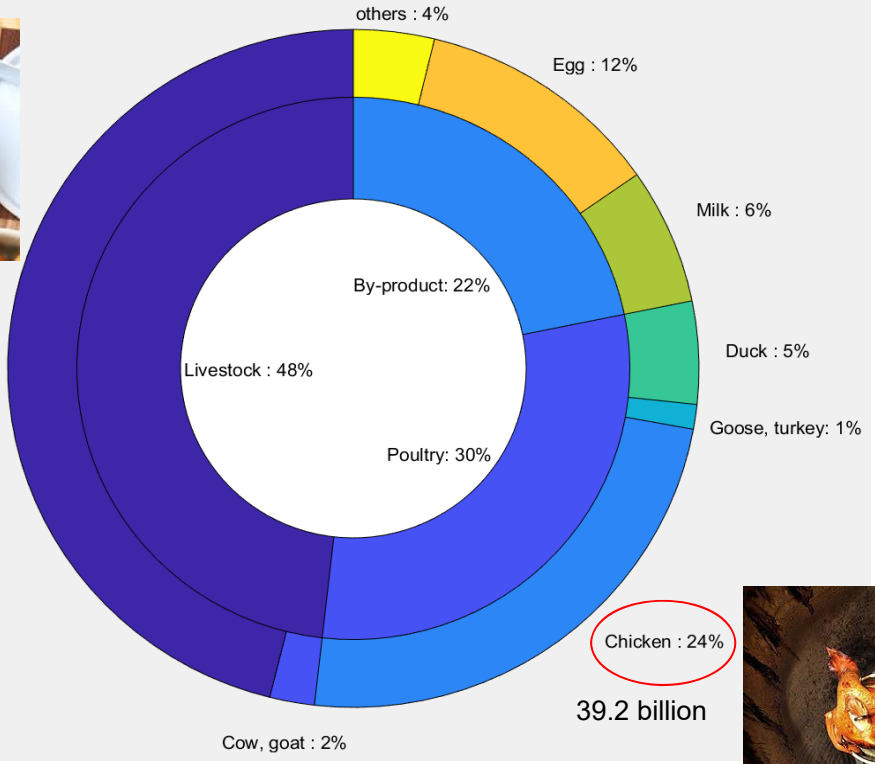
National Taiwan University

Department of Biomechatronics Engineering

Animal husbandry sales in Taiwan

Pig : 46%

75.5 billion



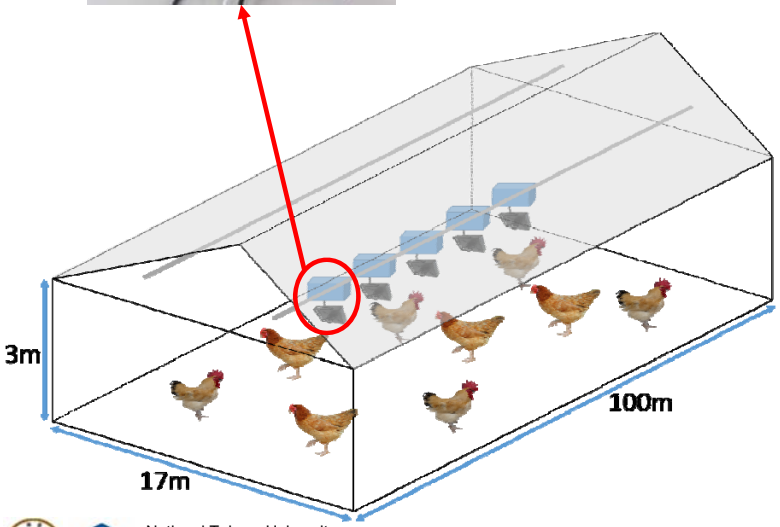
Manually monitoring

- Inactive chicken:
  - under heat stress, injure in fights
  - reduce feeding and movement
    ⇒ increase mortality
- Nursing piglet:
  - newborn pigs need to be taken care of
- Patrol and naked-eye observation are laborious and time-consuming

Image acquiring system

Embedded system

Henhouse image

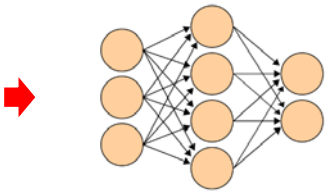


Router

Server

Procedure

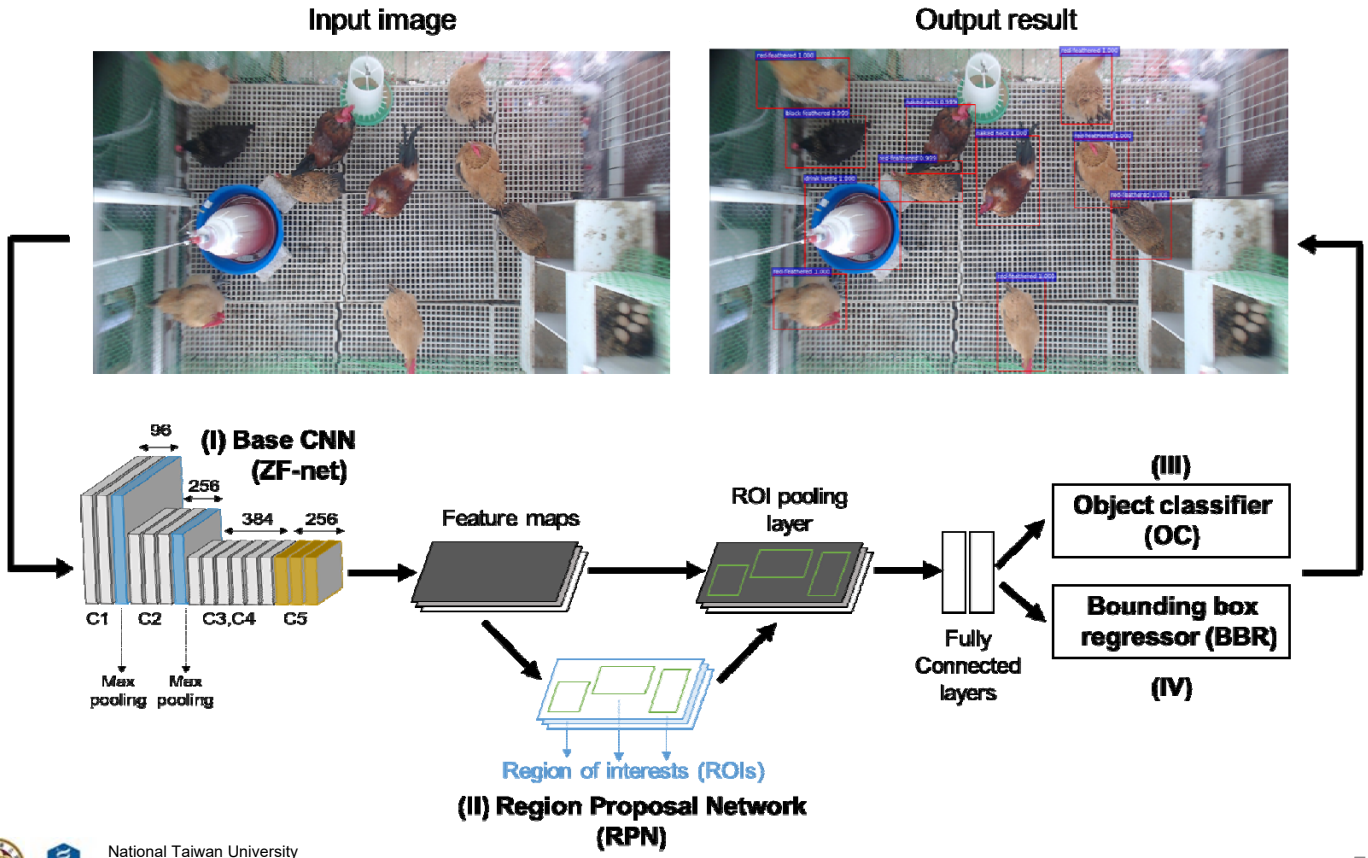
Image acquiring system



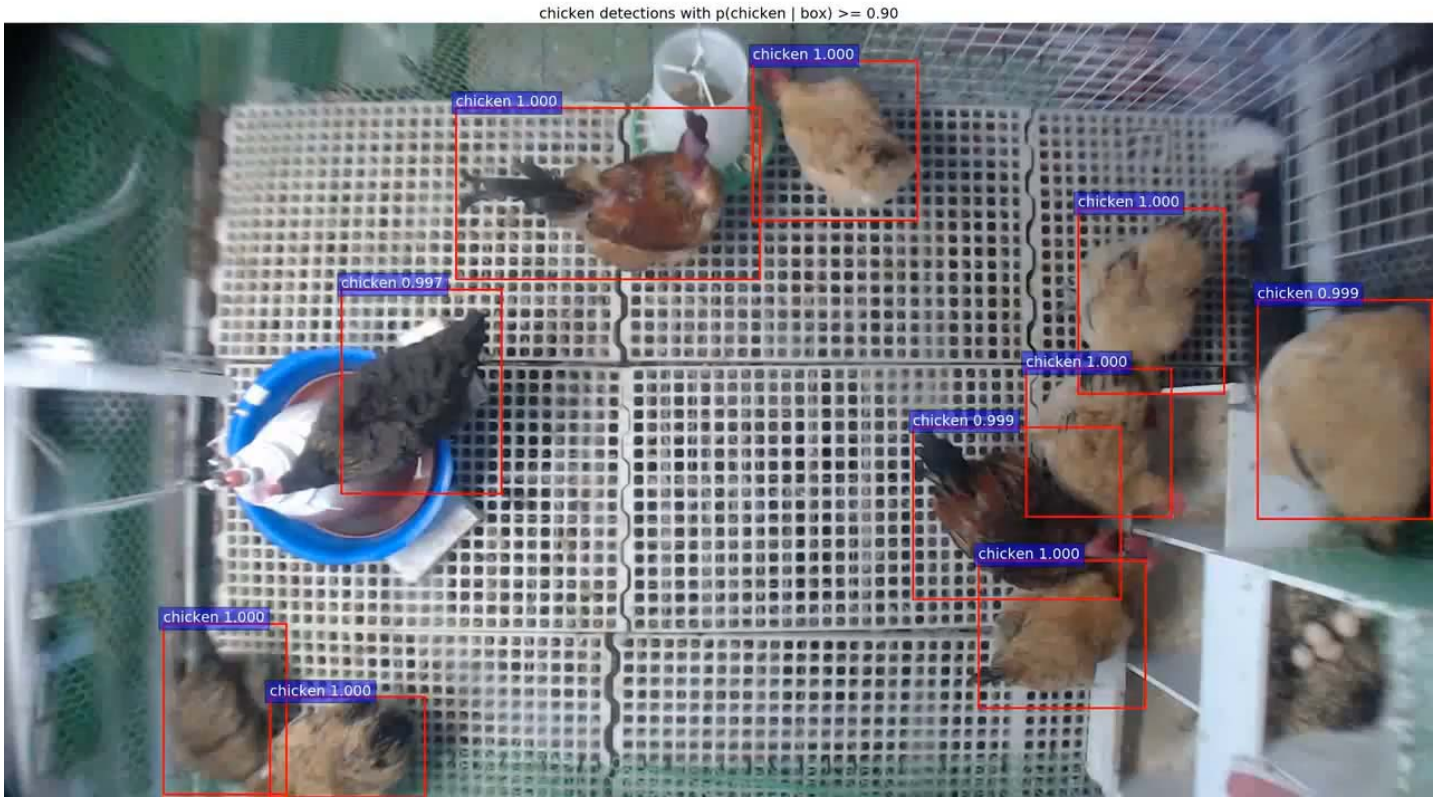
Deep learning algorithms

Detecting animal behavior

Faster R-CNN architecture

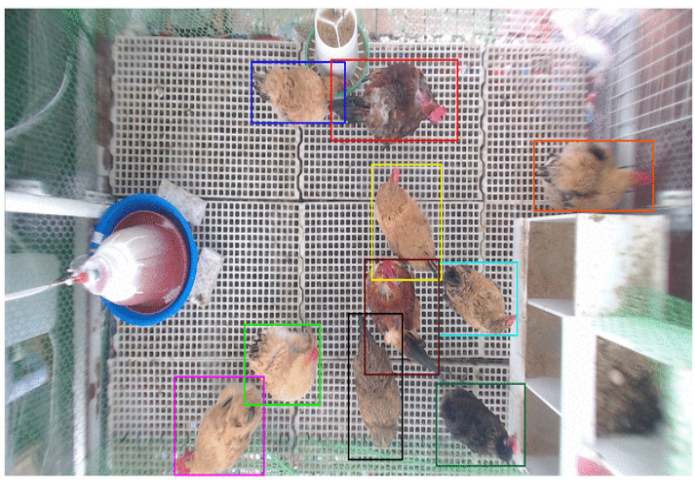


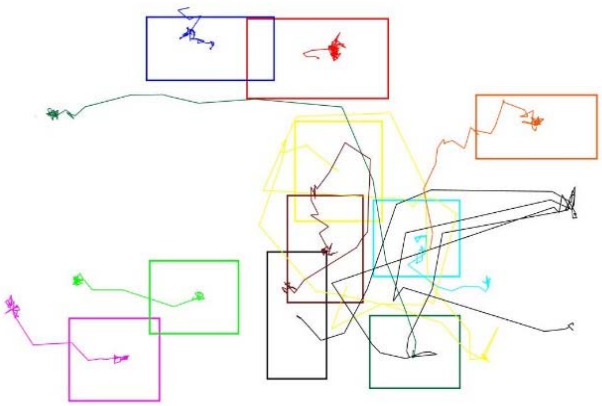
Performance of chicken detection



Result of tracking

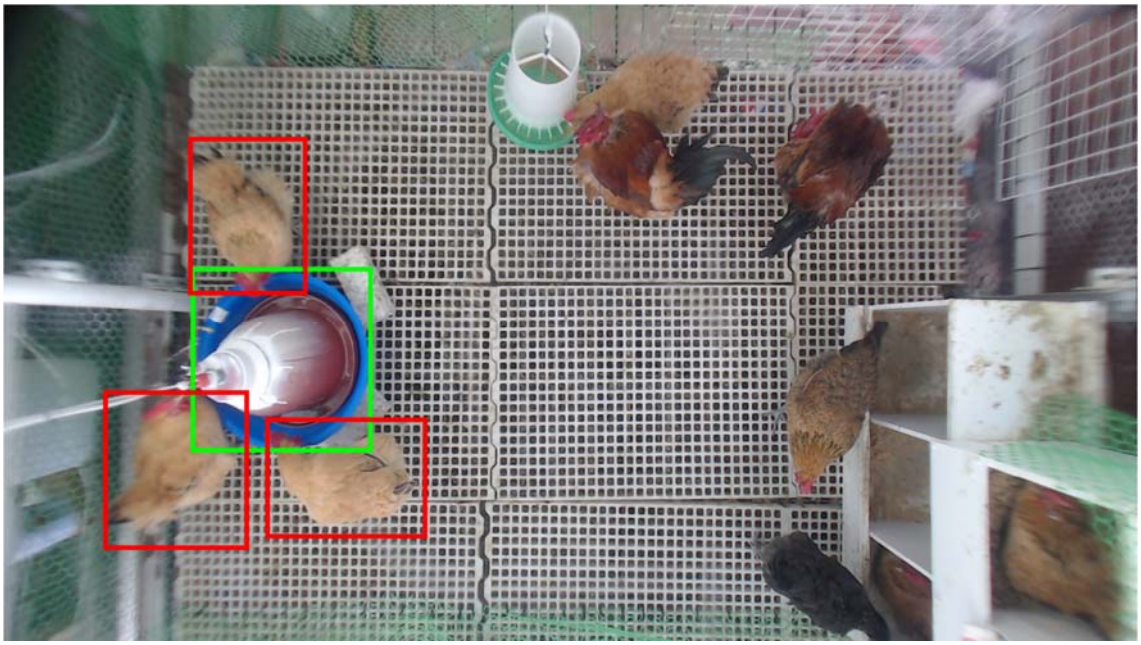
- 360 images for test
- Tracking accuracy: 98.94%





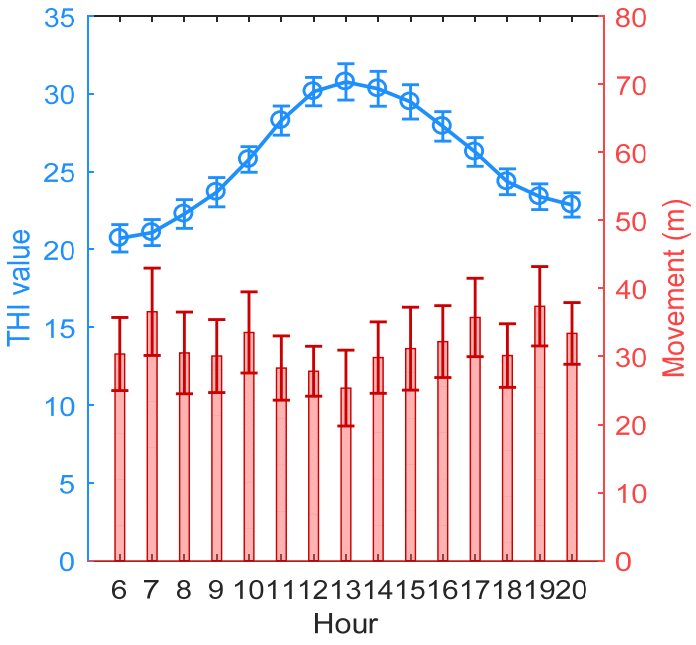
Chicken drinking time

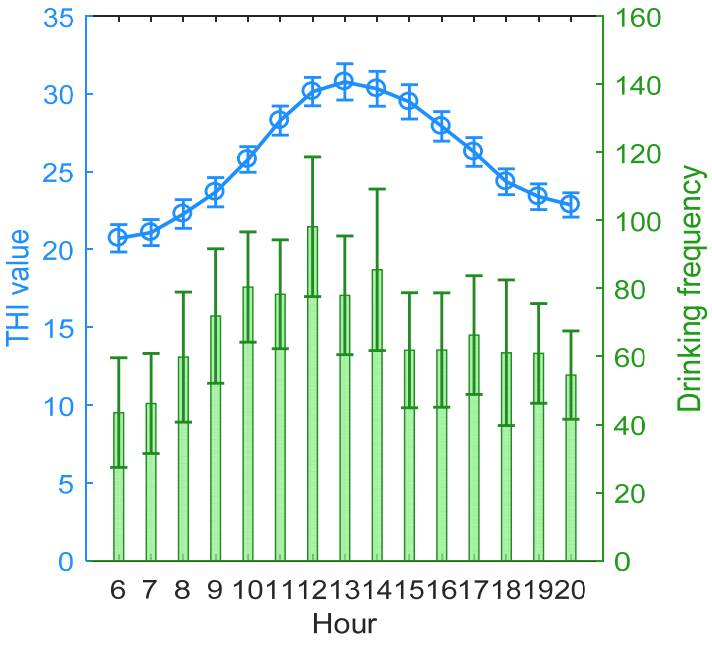
- Tracking the distance of the chickens and drinking kettle in each frame



Chicken activities and THI

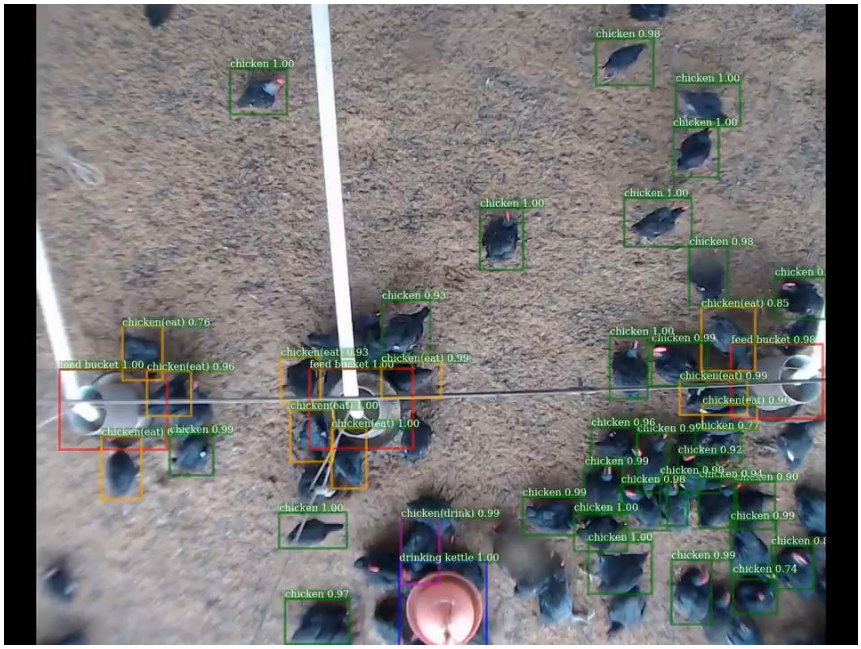
- Correlation between chicken activities and THI





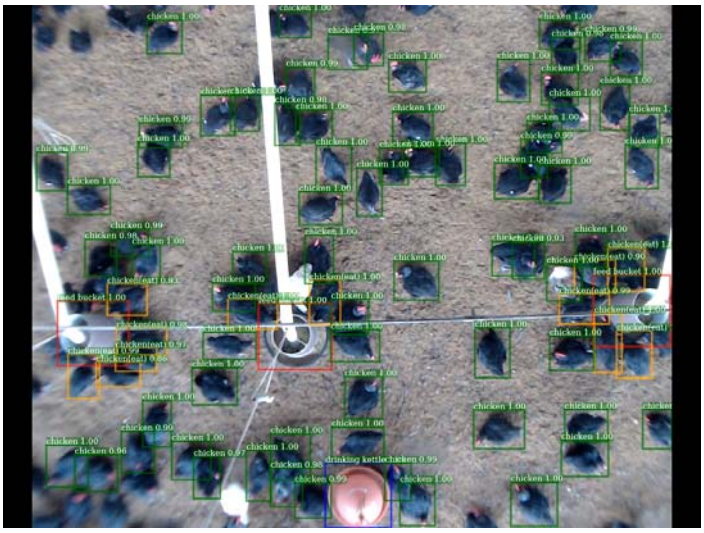
Chicken detection in henhouse

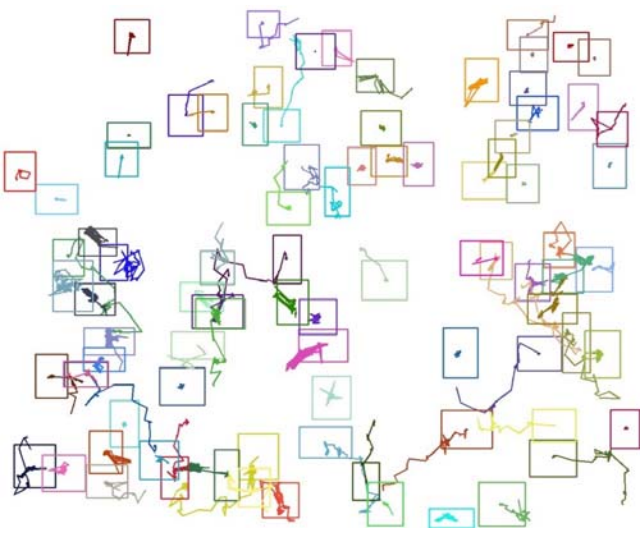
- 18 images for testing
- 0.081 seconds per frame (Nvidia 1080Ti)
- Overall accuracy: 80.54%



Chicken tracking in henhouse

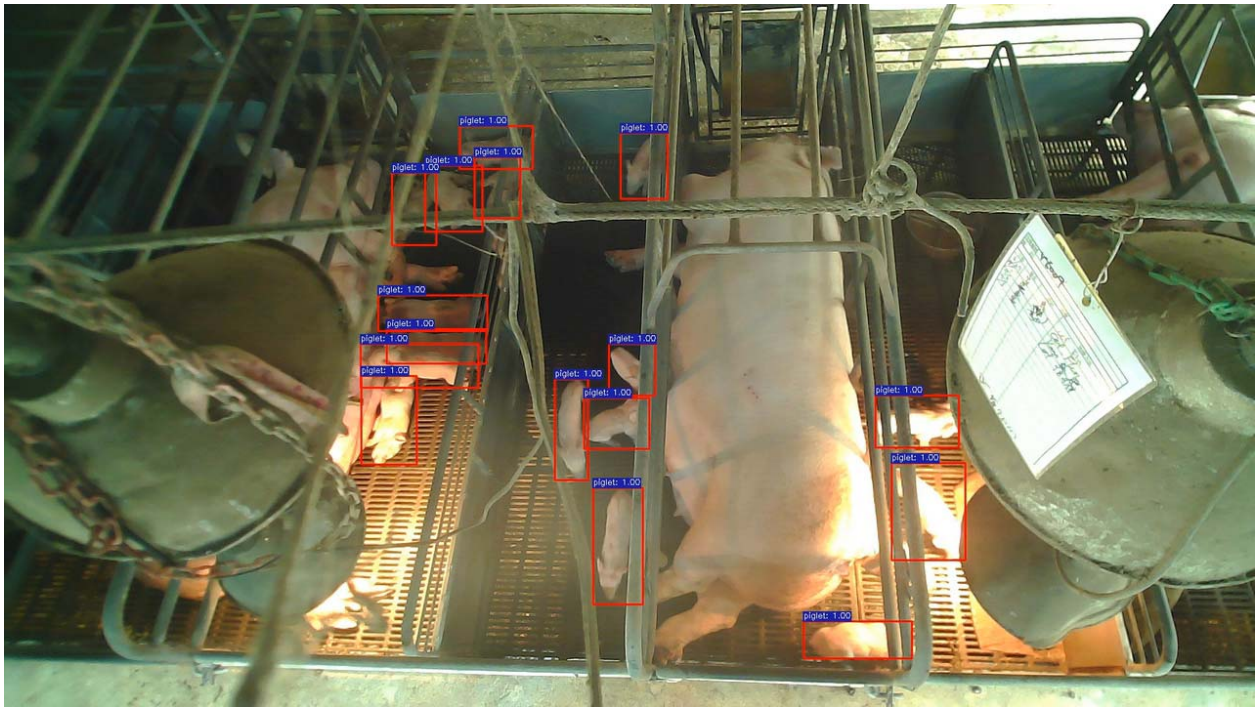
- Tracking the chickens in commercial henhouse





Piglet detection

- Detecting piglet in farrowing house



Conclusion

- Growth Monitoring of Lettuce – Achieved an error of 2.37% for estimating Lettuce area
- Identifying Fagaceae and Lauraceae Species in Taiwan – Achieved an accuracy of 99.1%, 98.7% for identifying 3 species
- Fish species identification and body length estimation – Achieved an accuracy of 96.9% for identifying 11 fish species
- Detecting animal behavior – Achieved an mean average precision of 80.4%, 81.4% for chicken detection, piglet detection respectively

Acknowledgement

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Overseas Fisheries Development Council of the Republic of China

Thanks for listening !