Application of Deep Learning Technique to Rice Lodging Identification

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PRAGMA37 @UCSD

Outline

- Introduction
- Related Works
- Methodologies
- Results and Discussion
- Conclusion
- Future Work

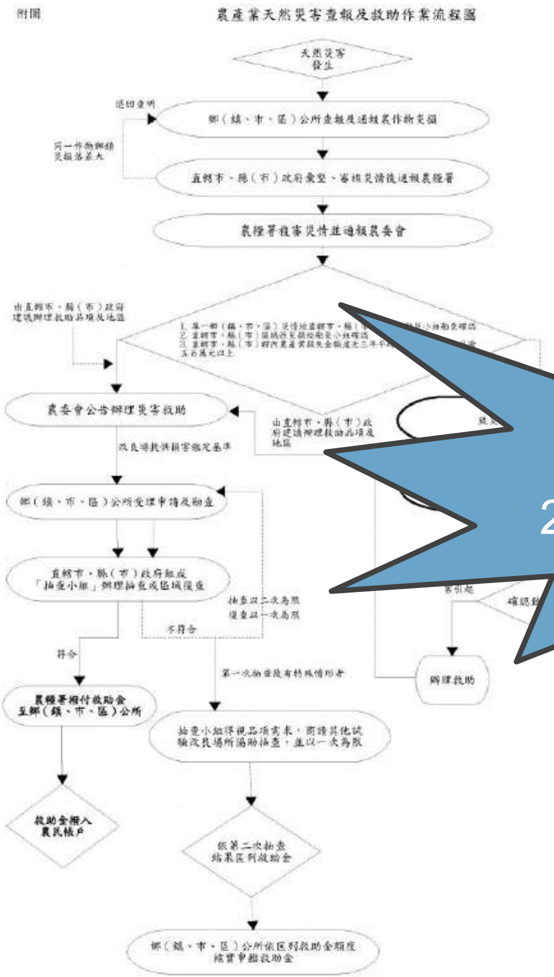
Introduction

Background

In Taiwan, storms and typhoons usually cause crops damage.

Background

Disaster Relief



Takes
2 weeks – 2 months

Background

Fields

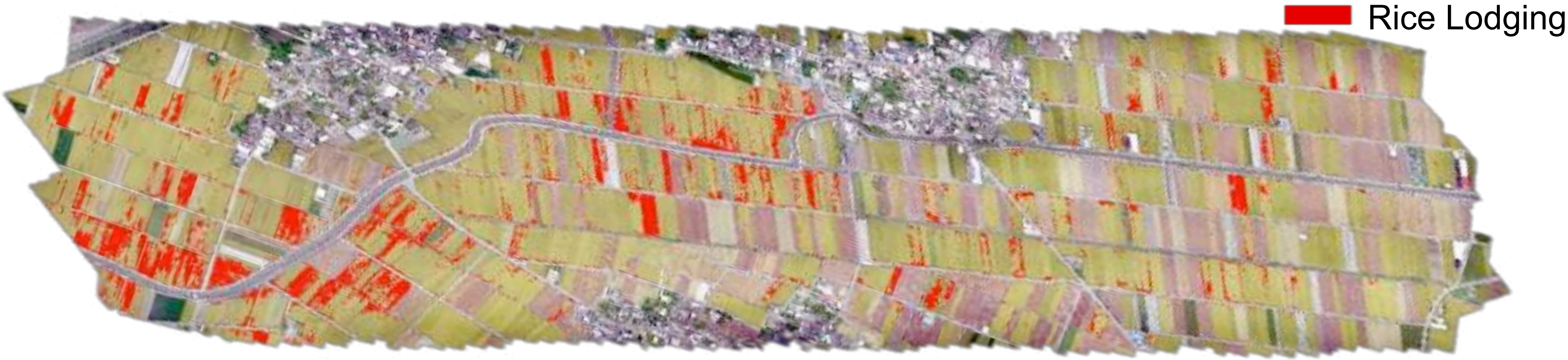
Account for ¼ Taiwan's land area

78% size **<1ha**

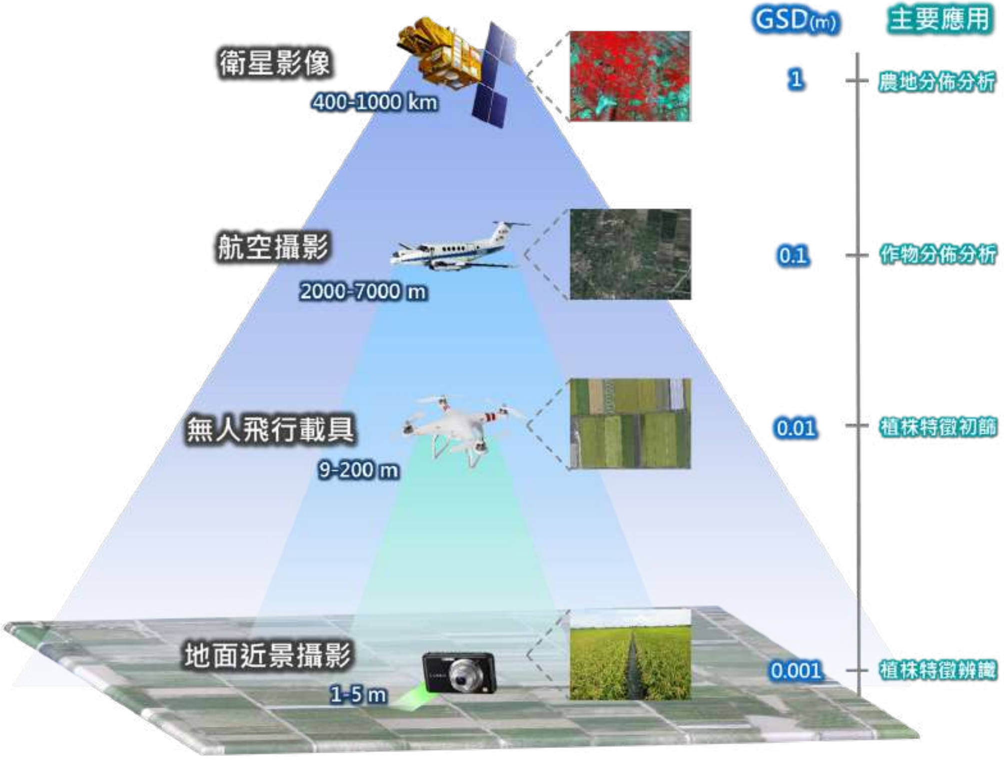
small & **irregular**

multiple cropping
&
crop rotation

Disaster damage assessment/Crop monitoring



Background



Why UAV ?

High resolution

High mobility

Low price

Object

Large-area Investigation

Visible Band Camera

Process Fast

Related Works

Related Works

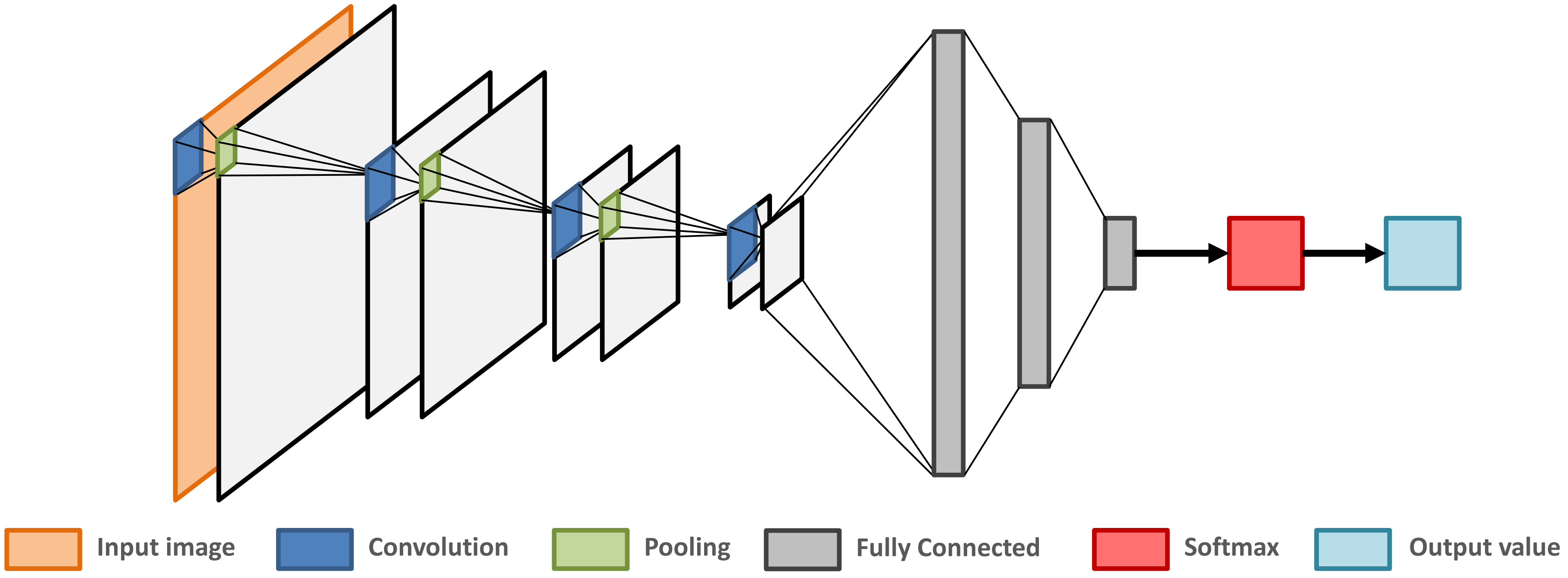
Convolutional Neural Network

Semantic Segmentation Architecture

Application on Precision Agriculture

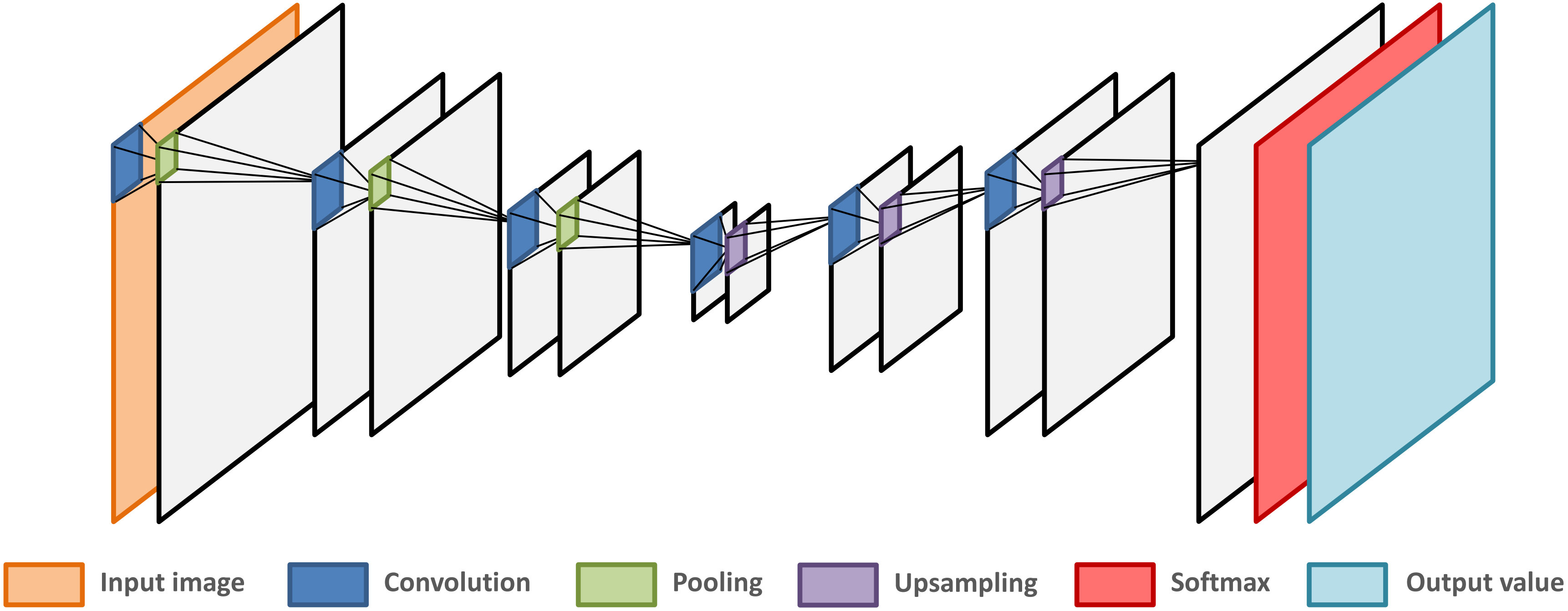
Convolutional Neural Network

Composition of CNN



Semantic Segmentation Architecture

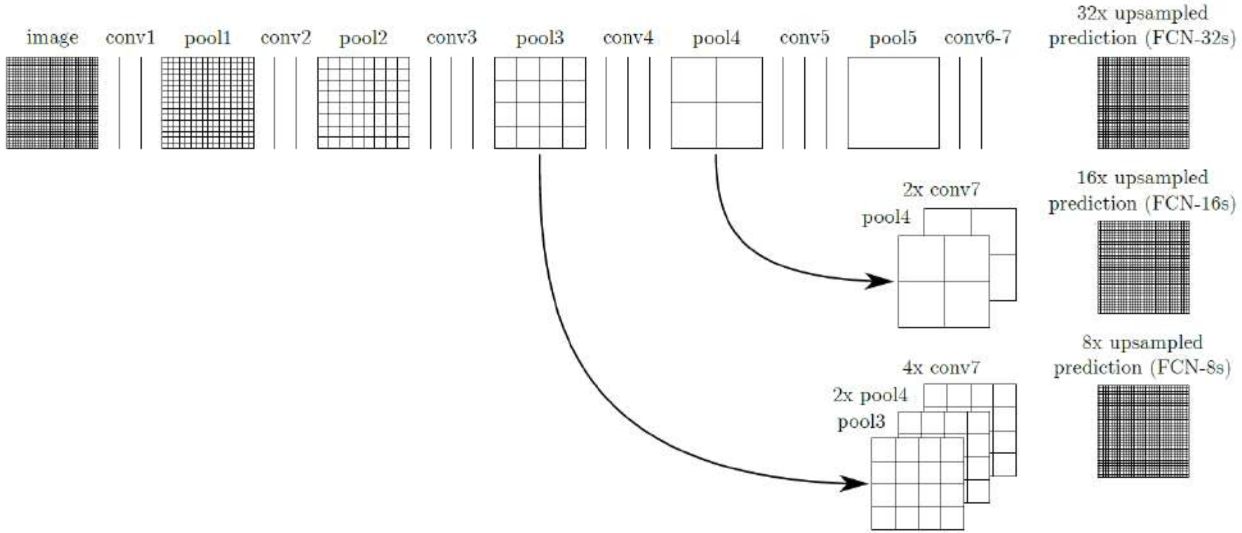
Modification from CNN to become FCN



Semantic Segmentation Architecture

Long, Shelhamer and Darrell(2015)

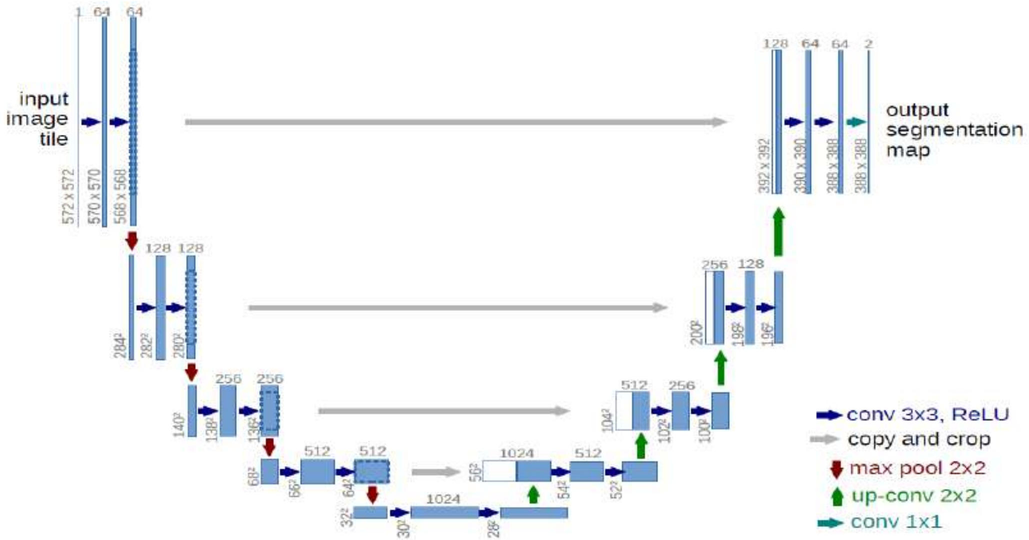
- Proposed FCN
- Pixel-wise classification with no image size limitation
- The skip architecture is robust for detecting multiscale features



Semantic Segmentation Architecture

Ronneberger, Fischer and Brox (2015)

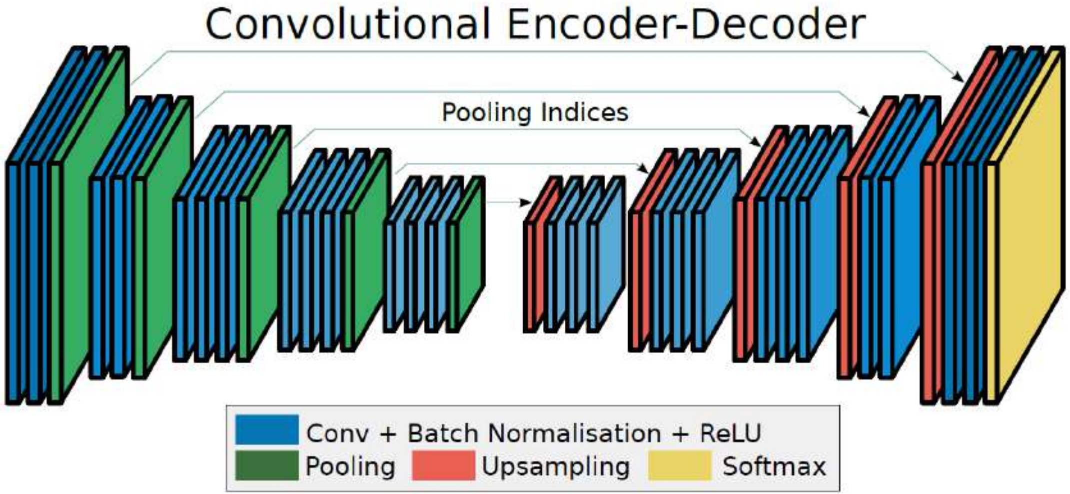
- Proposed U-Net
- Encoder-Decoder architecture
- Biomedical image binary segmentation



Semantic Segmentation Architecture

Badrinarayanan, Kendall and Copula (2015)

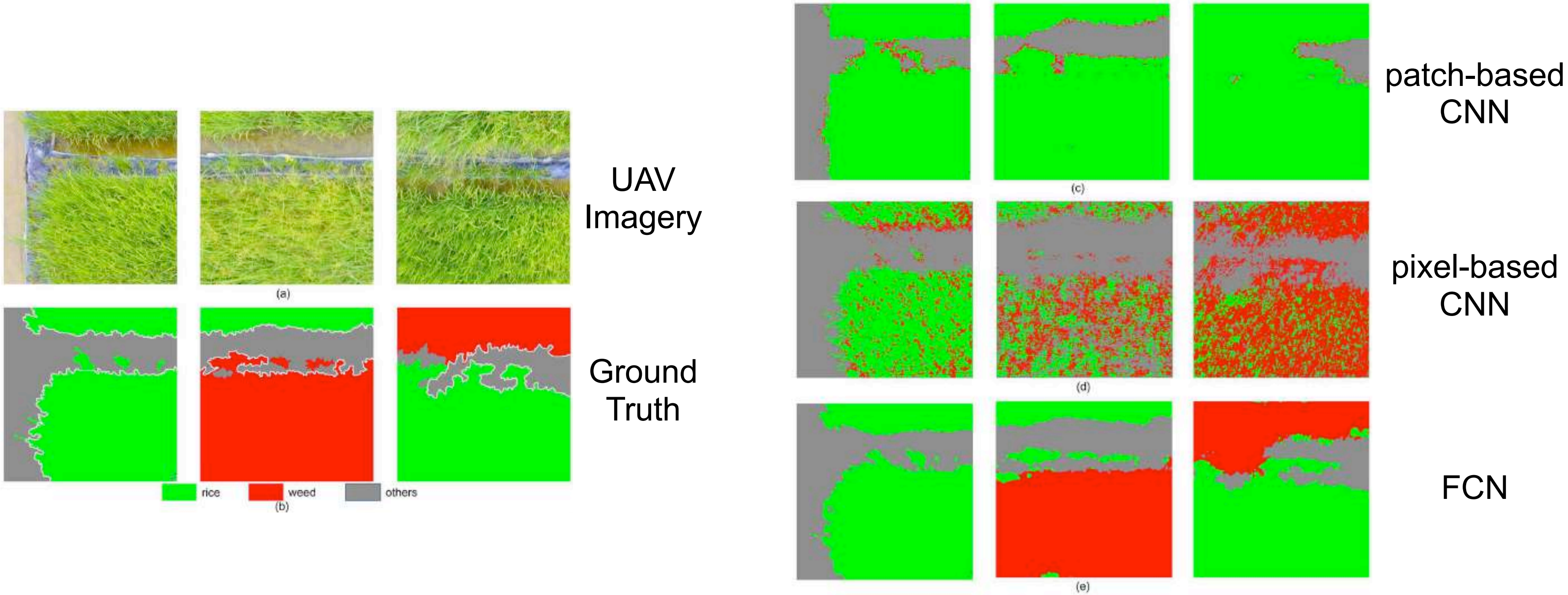
- Proposed SegNet
- Encoder-Decoder architecture based on VGG-16
- Pooling indices eliminates the learning for upsample



Application on Precision Agriculture

Huang et al. (2018)

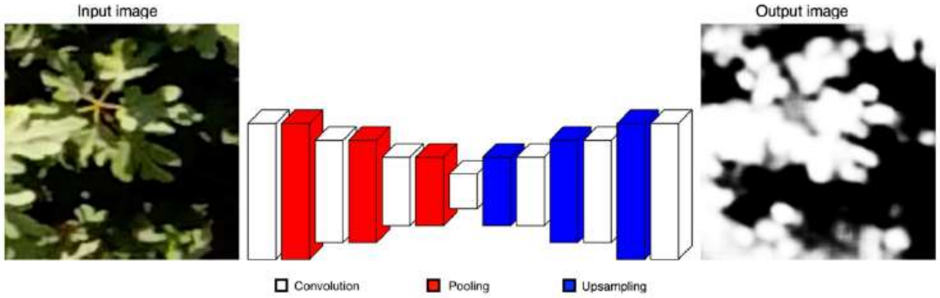
- FCN outperforms than patch-based CNN and pixel-based CNN in UAV imagery

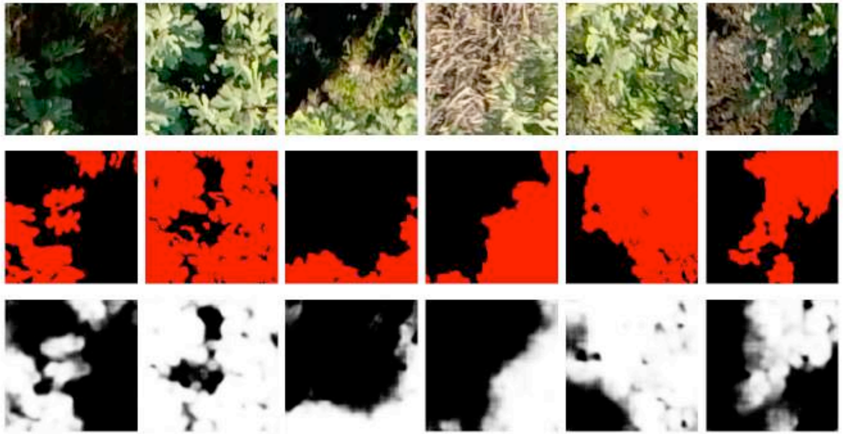


Application on Precision Agriculture

Fuentes-Pacheco et al. (2019)

- Successfully simplified SegNet for binary vegetation identification

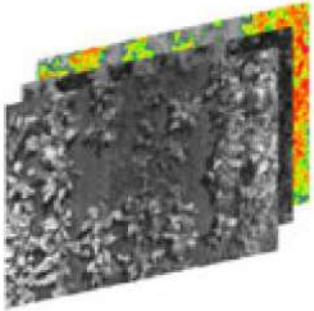




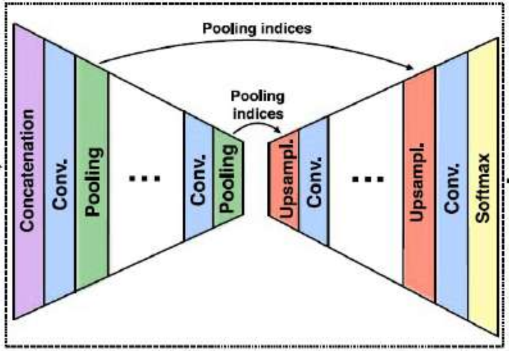
Application on Precision Agriculture

Sa et al. (2018)

- GPU embedded system performs well on SegNet inference (1.8 fps)

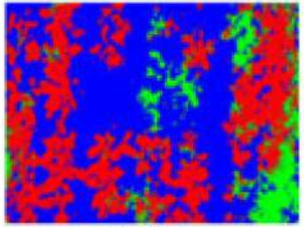


Input Img=[NIR:Red:NDVI]

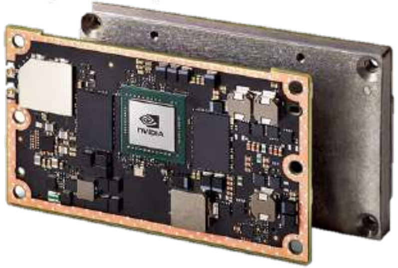


SegNet: Conv.(26), Max pooling(5), Upsampling(5)

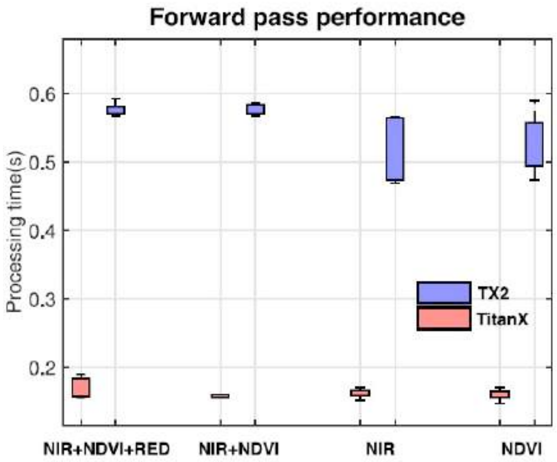
Conv. layers include: Convolution, Batch Norm., and ReLU



Output: Pixel-wise class probability



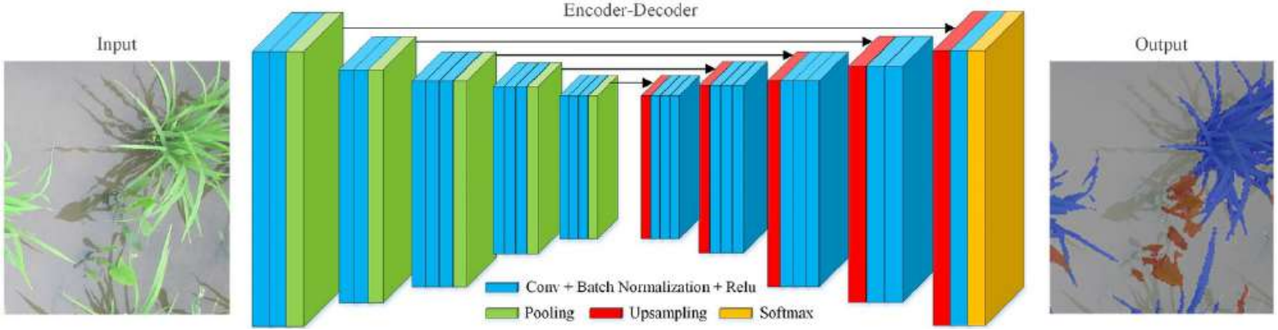
Nvidia Jetson TX2



Application on Precision Agriculture

Ma et al. (2019)

- SegNet was well-suited for pixel-classification on tiny and abnormally shaped object

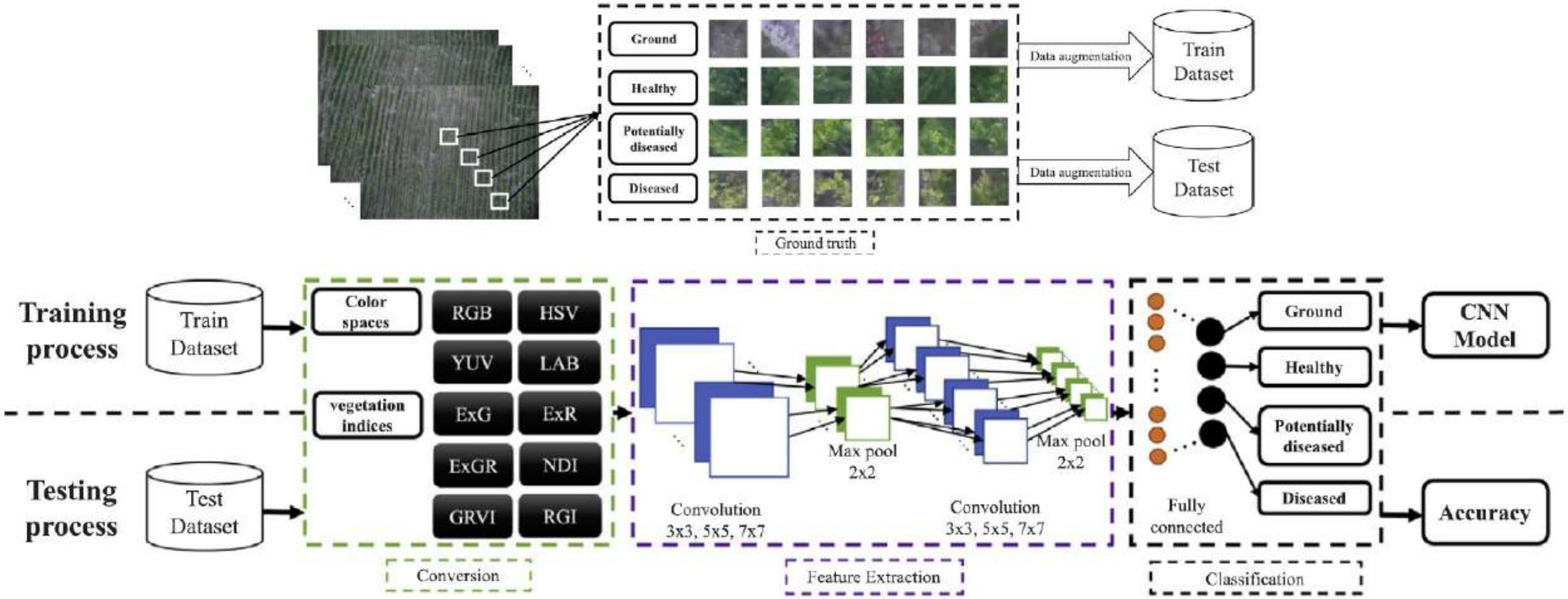


Approach	GT/Predicted Class	Rice	Background	Weed
SegNet	Rice	**0.936**	0.015	0.049
	Background	0.061	**0.907**	0.032
	Weed	0.042	0.019	**0.939**
FCN	Rice	**0.921**	0.022	0.056
	Background	0.120	**0.834**	0.046
	Weed	0.053	0.018	**0.929**
U-Net	Rice	**0.462**	0.182	0.356
	Background	0.014	**0.977**	0.010
	Weed	0.173	0.143	**0.685**

Application on Precision Agriculture

Kerkech, Hafiane and Canals (2018)

- Combination of Vegetation index outperforms RGB-only



Summary

CNN does well in visual recognition

A stack of convolution layers with small filter performs better

SegNet

FCN outputs pixel-wise classification

FCNs are feasible for real-time classification

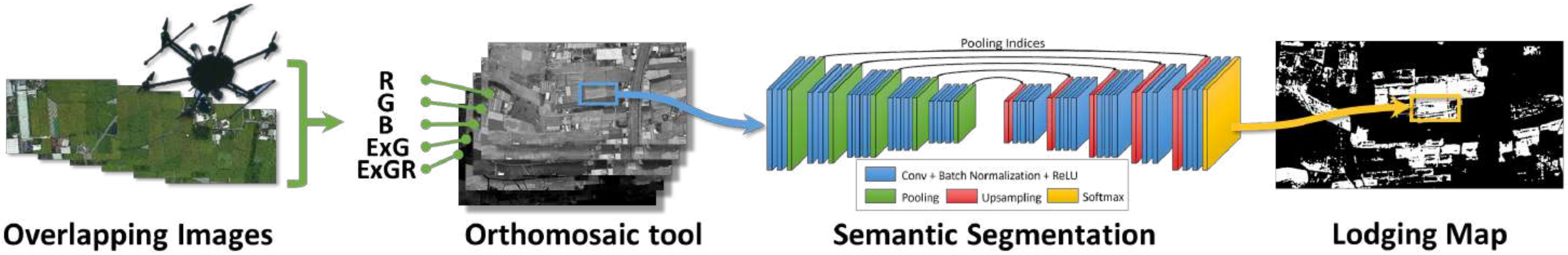
FCN-AlexNet

Combination of vegetation index outperforms RGB-only

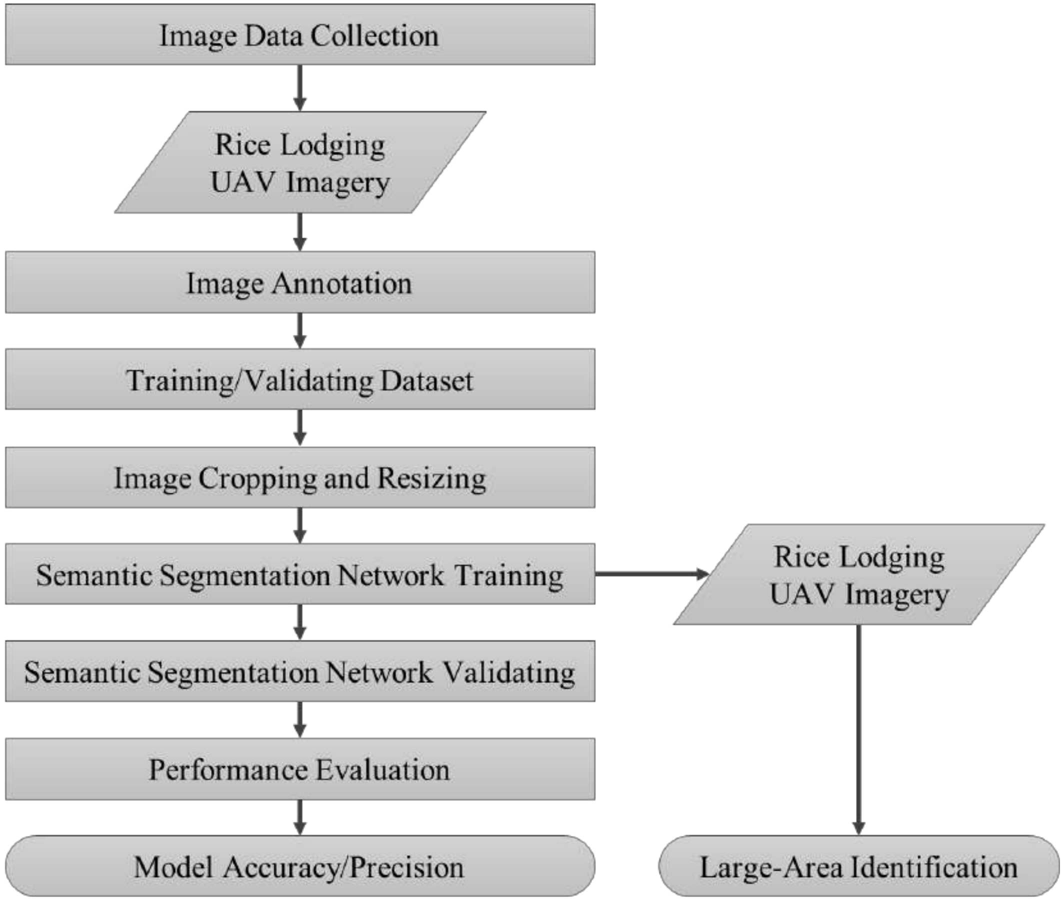
Multi-source

Methodologies

Research Pipeline

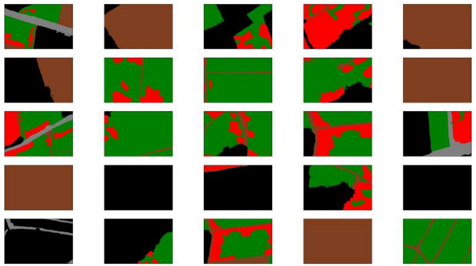


Research Flow

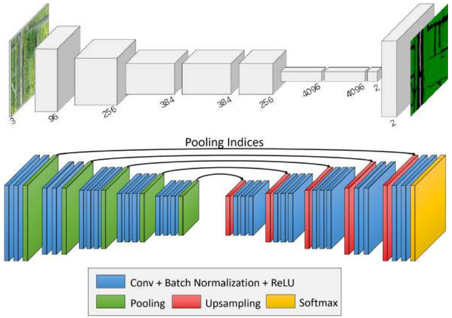


3 phases of Methodologies

Data Collection



Training and Validating Dataset



Semantic Segmentation Network

Data Collection (for Training)

Camera Spec.	
Model	SONY QX-100
Resolution	5472 x 3648
HFOV	64.8°

Flight Task		
Height (m)	GSD (cm/pix)	Front-overlap (%)
230	5.27	85

Mozihdunyuan, Taichung

Rice Lodging event

Date : Jun.8th, 2017

Area : 430 ha

Height : 230m

GSD : 5.27 cm/pix

Image # : 522

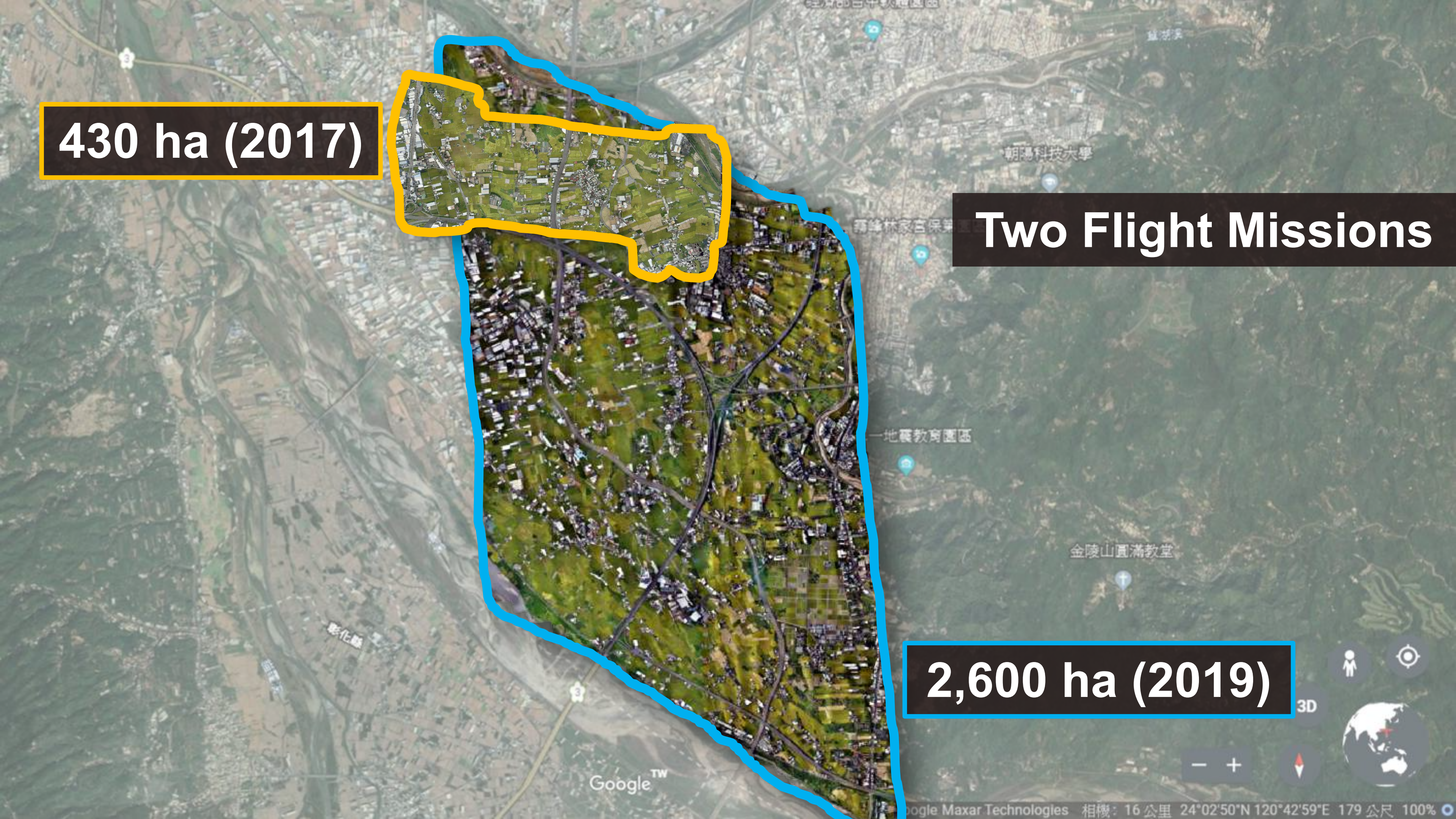
Data Collection (for Testing)

Camera Spec.	
Model	SONY A7R MK2
Resolution	7952 x 5304
HFOV	100.4°

Flight Task		
Height (m)	GSD (cm/pix)	Front-overlap (%)
180	4.68	85

Wu Feng, Taichung
Rice Lodging event

Date : May.26th, 2019
Area : 2600 ha
Height : 180m
GSD : 4.68 cm/pix
Image # : 2500


Two Flight Missions
430 ha (2017)
2,600 ha (2019)
朝陽科技大學
金陵山圓滿教堂
3D
Google

Training and Validating Dataset

- Total 522 Hi-Res images, 179 annotated image of quarter part (179/2088)
- Ratio invariant (3:2)
- Images are spitted to 480x320
- Training samples : Training 1764 / Validating 742 (70/30 split)

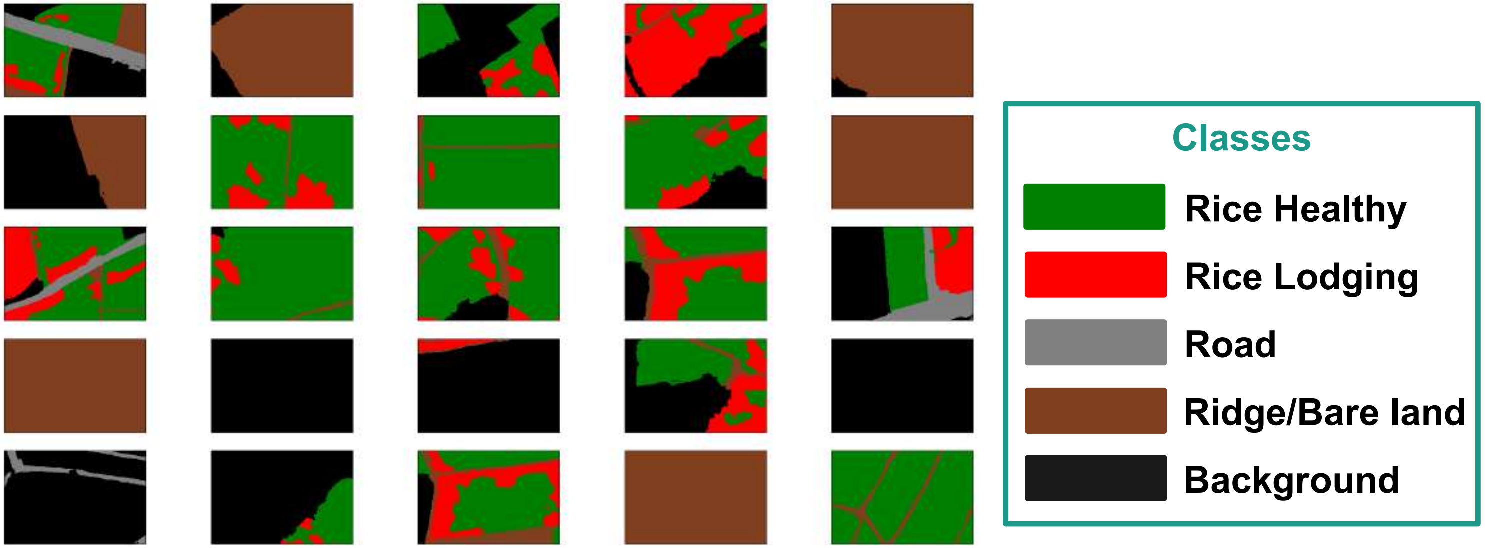


Image Stitching

- Commercial software: **Agisoft Metashape**
- Image based modeling
- Networking process (distributed computing)
- 2 physical machines, 5 computing nodes (4+1)
- 3 GPU nodes, 2 CPU nodes
- 10Gbps network between physical machines
- 40TB Hybrid storage (SSD cache)

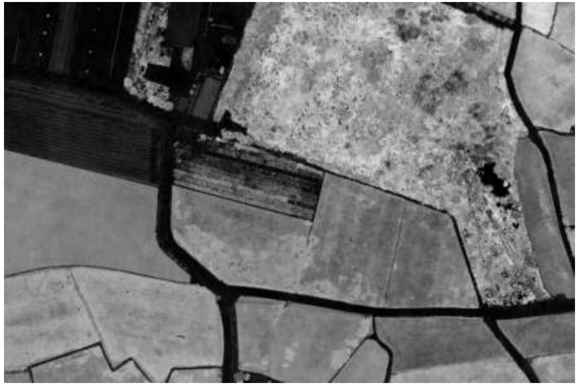
Metashape

Training and Validating Dataset

- Combination of visible band and vegetation index
- Excess Green index (ExG)
- Excess Green minus Excess Red index (ExGR)

$$ExG = 2 * G - R - B$$
$$ExGR = ExG - ExR = 3 * G - 2.4 * R - B$$

RGB

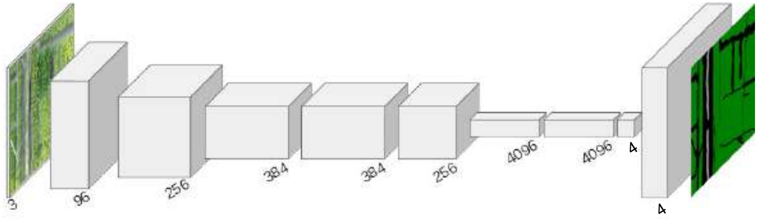


ExG

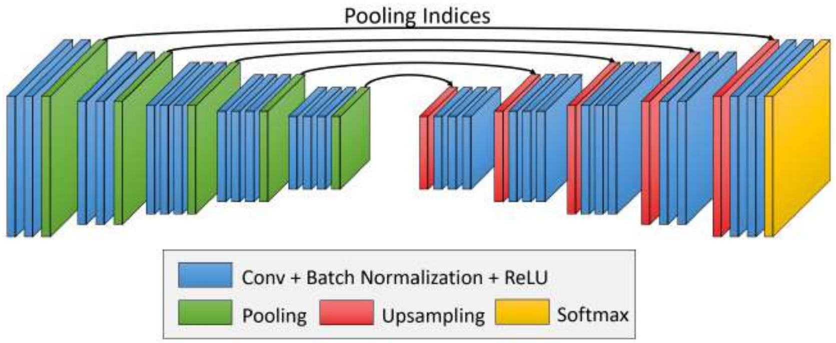
ExGR

Semantic Segmentation Architecture

2 Fully Convolutional Network

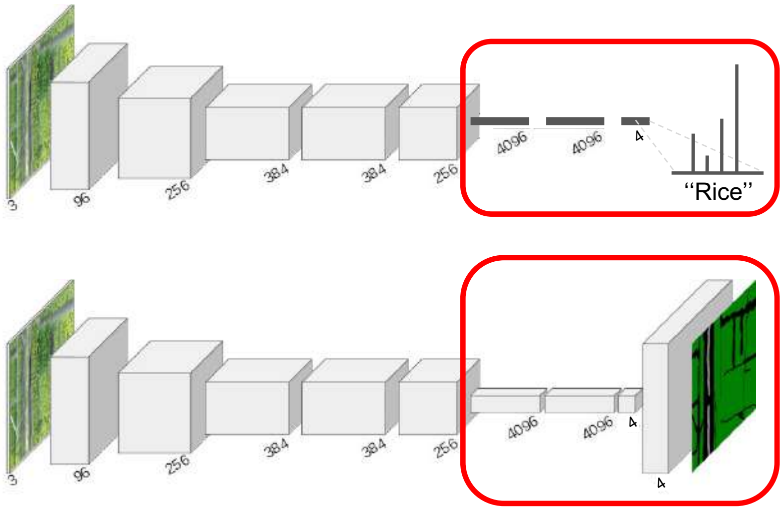


FCN-AlexNet



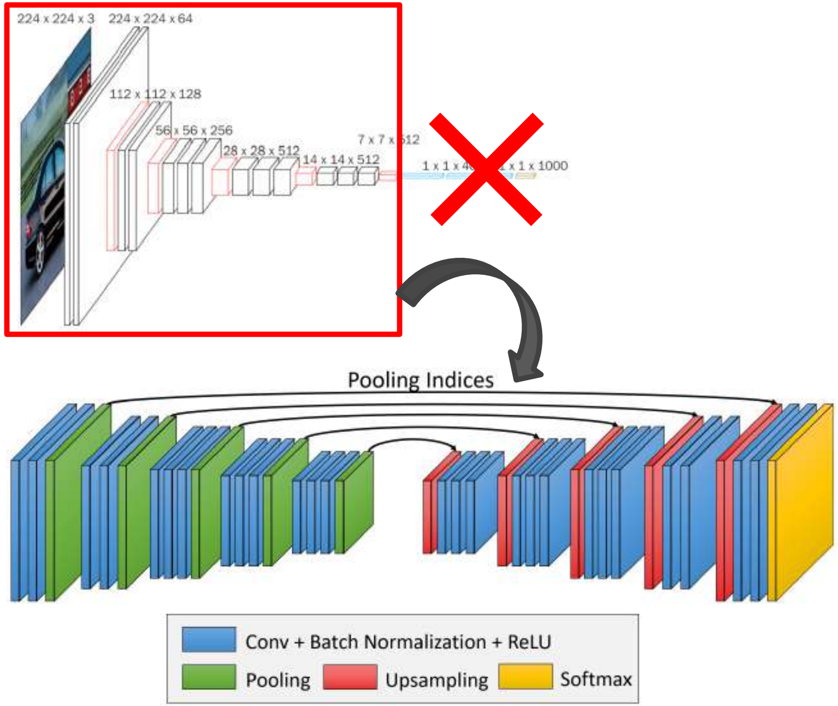
SegNet

FCN-AlexNet



- Based on AlexNet
- Adjustment :
  - Three 1x1 convolution layer
  - One 32x deconvolution layer
  - One softmax activation layer

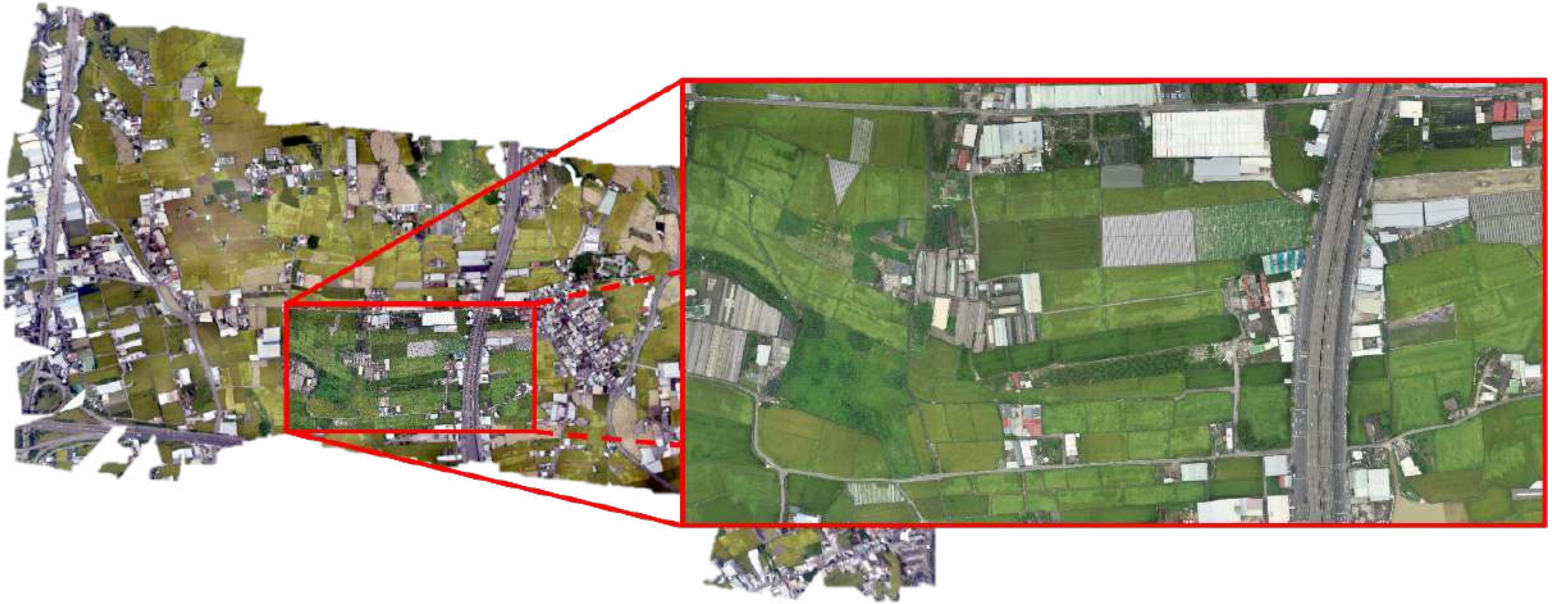
SegNet



- Based on VGG-16
- Adjustment :
  - A mirrored convolution structure
  - Encoder-Decoder FCN
  - Pooling indices

Rice Lodging Identification

- Area for experiments (40ha)



Rice Lodging Identification

- Histogram matching for color similarity

2019 Before Histogram matching

2019 After Histogram matching

2017 (same as training)

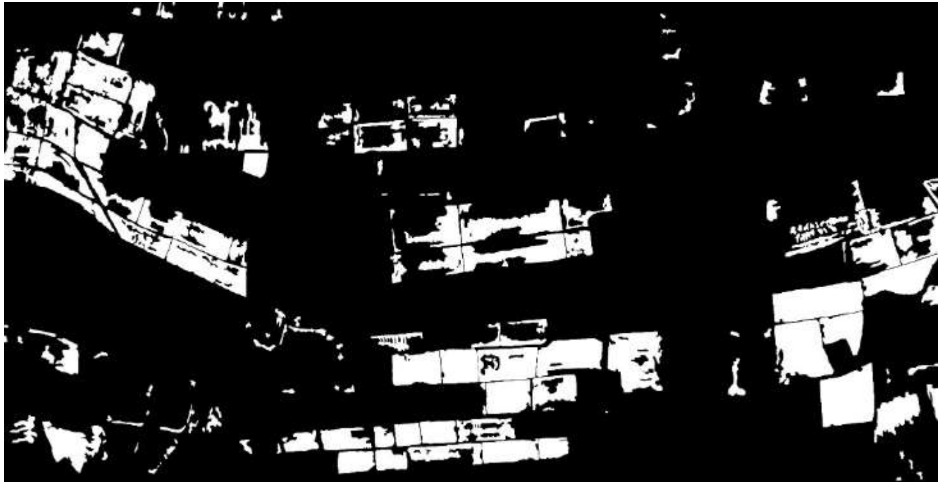
Rice Lodging Identification

- Crop image to tiles because the limitation of GPU memory
- Each tile is 320x480

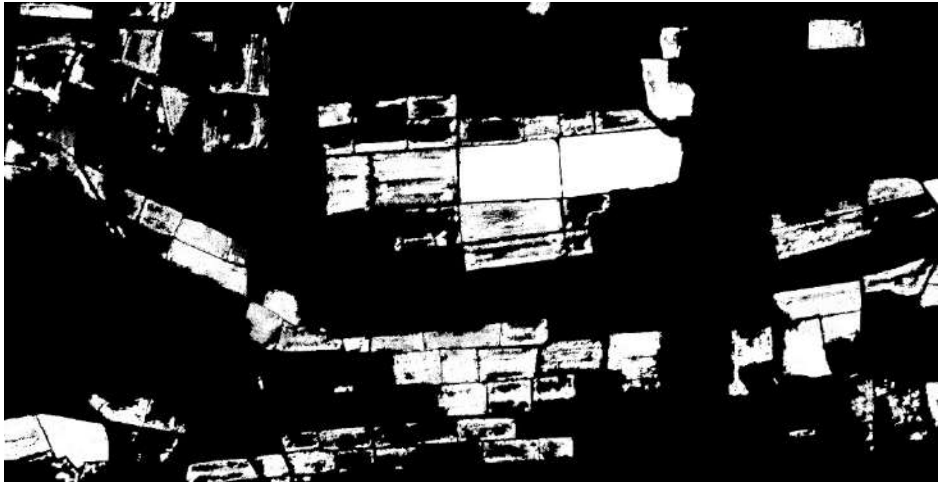
Rice Lodging Identification

- Well annotated ground truth for model evaluation
- Compared with Maximum Likelihood Classification (MLC)

2017



2019



Training Environment (TWGC service)

Compute Hardware	
CPU	Intel Xeon Gold 6154 @3.00GHz (8 cores/GPU node)
Memory	60 GB/GPU node
Accelerator	NVIDIA Tesla V100 16GB /GPU node

Software Environment	
OS	Ubuntu 16.04
Container Soft.	Docker EE
Containerized Image	nchc-tensorflow-18.07-py3
Libraries	Python 3.5.2 TensorFlow 1.10.1 Keras 2.2.2 Numpy 1.15 Scikit-image 0.15.0 Jupyter Notebook CUDA 9.0

Training Parameter

Source: Kingma, Diederik P., and Jimmy Ba. "Adam: A method for stochastic optimization." *arXiv preprint arXiv:1412.6980*(2014).

Training Parameter	
Optimizer	Adam (Adaptive Moment Estimation)
Learning rate	10E-3
B1	0.9
B2	0.999
Epsilon	10E-8
Decay	0.05
Epoch	50
Batch size	24

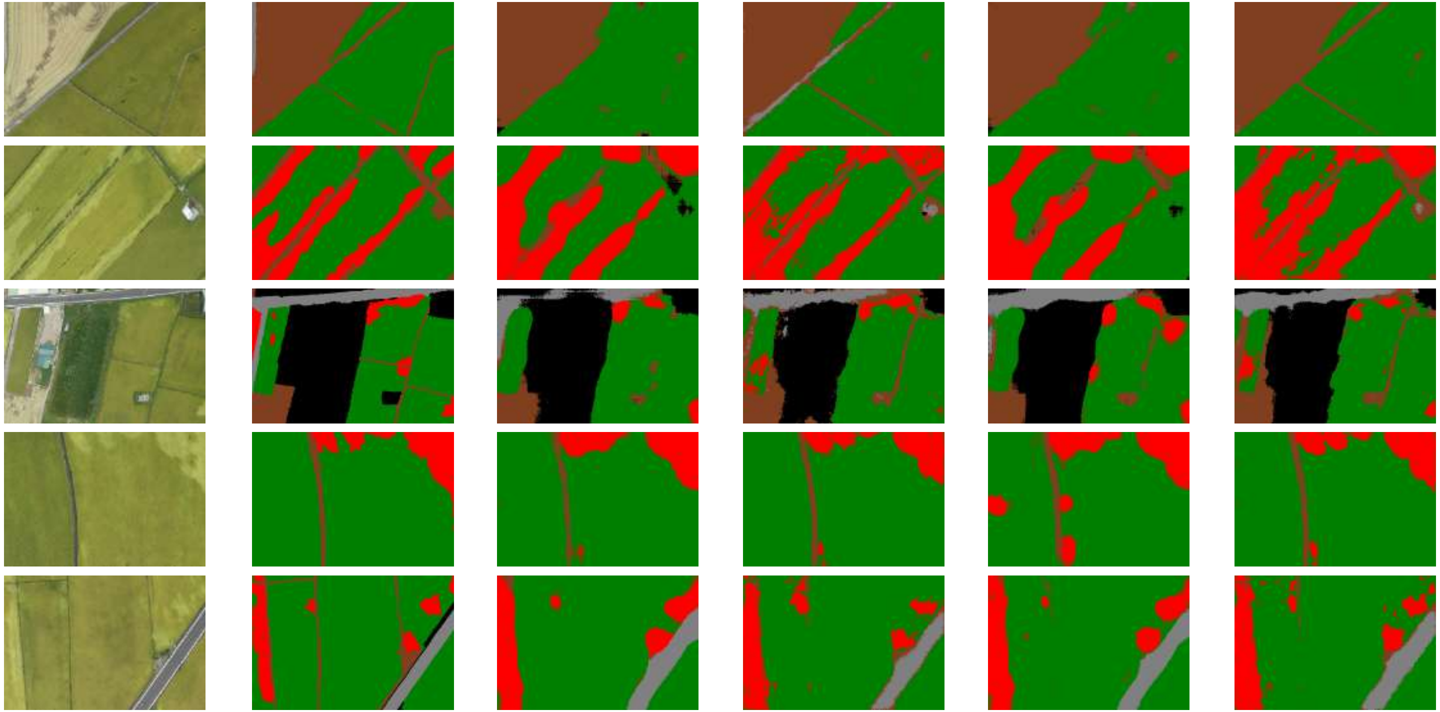
Results and Discussion

Evaluation and Discussion

Precision and OA of Rice Lodging Identification (%)

Model	Information	Rice Paddy	Rice Lodging	Road	Ridge	Unmarked	OA
FCN-AlexNet	RGB	**92.97**	68.12	**68.49**	74.37	91.05	85.25
	RGB+ExG	89.09	84.51	40.25	75.00	95.11	84.78
	RGB+ExGR	87.75	**84.58**	37.84	76.87	**96.19**	85.00
	RGB+ExG+ExGR	92.11	81.63	40.69	**79.41**	95.46	**86.68**
SegNet	RGB	94.90	61.74	50.90	61.74	**92.59**	**87.67**
	RGB+ExG	**95.77**	57.38	63.99	**87.96**	88.96	87.07
	RGB+ExGR	92.04	76.71	41.86	86.55	92.04	87.17
	RGB+ExG+ExGR	85.57	**80.82**	**67.12**	87.59	88.89	85.74

Results (Rice Lodging Identification)



UAV Imagery | Ground Truth | FCN-AlexNet (RGB) | SegNet (RGB) | FCN-AlexNet (RGB+ExG) | SegNet (RGB+ExG)

Evaluation and Discussion

- Precision

$$precision_c = \frac{TP_c}{TP_c + FP_c}$$

- Recall

$$recall_c = \frac{TP_c}{TP_c + FN_c}$$

- Overall Accuracy

$$OA = \sum_{c=1}^{n} \frac{TP_c}{TP_c + TN_c + FP_c + FN_c}$$

- F1-score

$$F_1 = \frac{2 \cdot precision \cdot recall}{precision + recall}$$

Rice Lodging Identification

Performance Comparison on 2017 Rice Lodging Mosaic Image

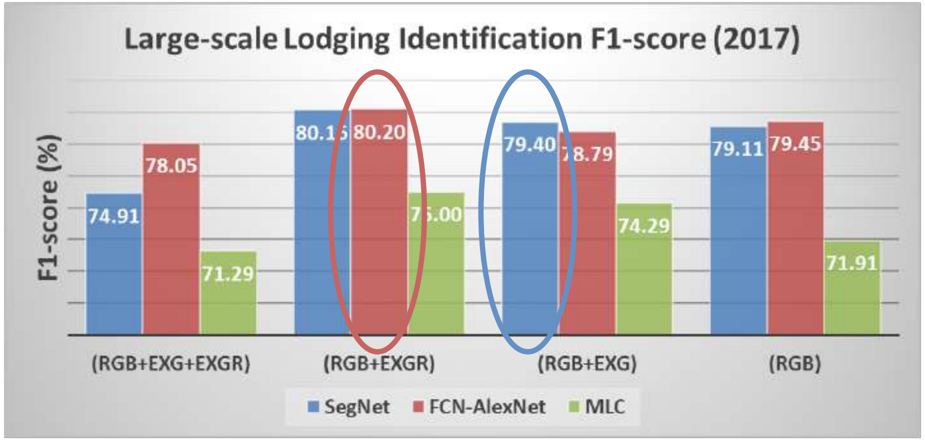
Classifier	Information	Precision(%)	Recall(%)	F1-score(%)	Time(s)
SegNet	RGB+ExG+ExGR	61.63	95.49	74.91	126
	RGB+ExGR	71.35	91.44	80.16	119
	RGB+ExG	73.55	86.27	79.40	134
	RGB	**80.42**	77.85	79.11	121
FCN-AlexNet	RGB+ExG+ExGR	68.64	90.46	78.05	**96**
	RGB+ExGR	71.29	91.65	**80.20**	135
	RGB+ExG	72.01	86.98	78.79	141
	RGB	73.30	86.72	79.45	101
MLC	RGB+ExG+ExGR	56.47	**96.64**	71.29	1526
	RGB+ExGR	63.42	91.76	75.00	1492
	RGB+ExG	61.75	93.23	74.29	1511
	RGB	57.43	96.16	71.91	1342

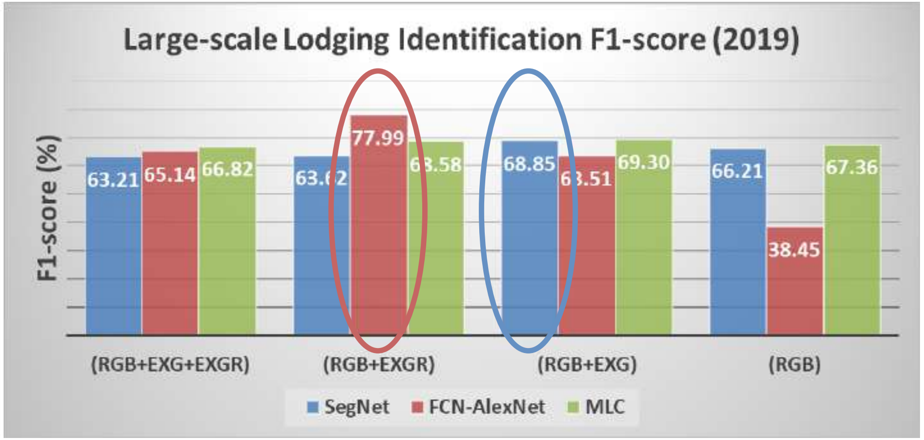
Rice Lodging Identification

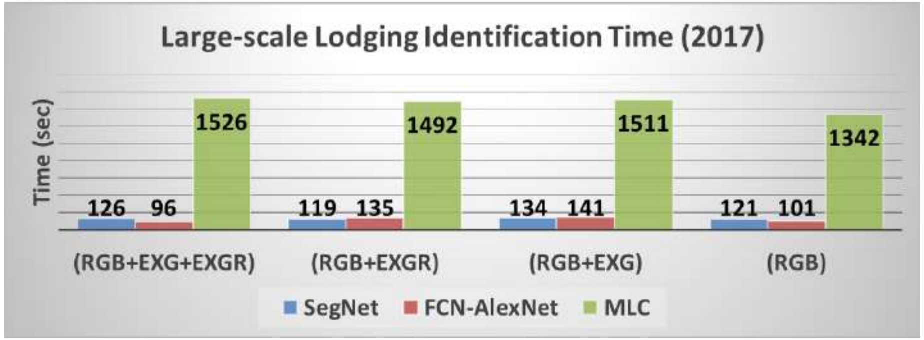
Performance Comparison on 2019 Rice Lodging Mosaic Image

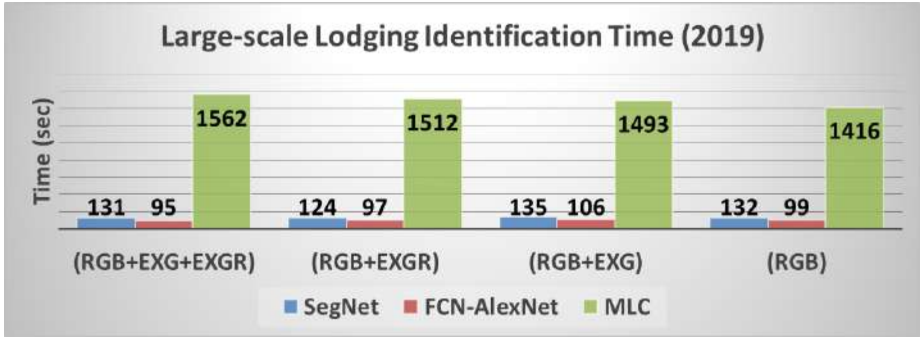
Classifier	Information	Precision(%)	Recall(%)	F1-score(%)	Time(s)
SegNet	RGB+ExG+ExGR	50.62	84.14	63.21	131
	RGB+ExGR	55.93	73.77	63.62	124
	RGB+ExG	68.55	69.15	68.85	135
	RGB	79.07	47.66	66.21	132
FCN-AlexNet	RGB+ExG+ExGR	57.40	75.29	65.14	**95**
	RGB+ExGR	73.31	83.30	**77.99**	97
	RGB+ExG	81.87	51.87	63.51	106
	RGB	**89.78**	24.46	38.45	99
MLC	RGB+ExG+ExGR	57.03	80.67	66.82	1562
	RGB+ExGR	56.88	86.33	68.58	1512
	RGB+ExG	58.40	**85.21**	69.30	1493
	RGB	58.67	79.07	67.36	1416

Rice Lodging Identification

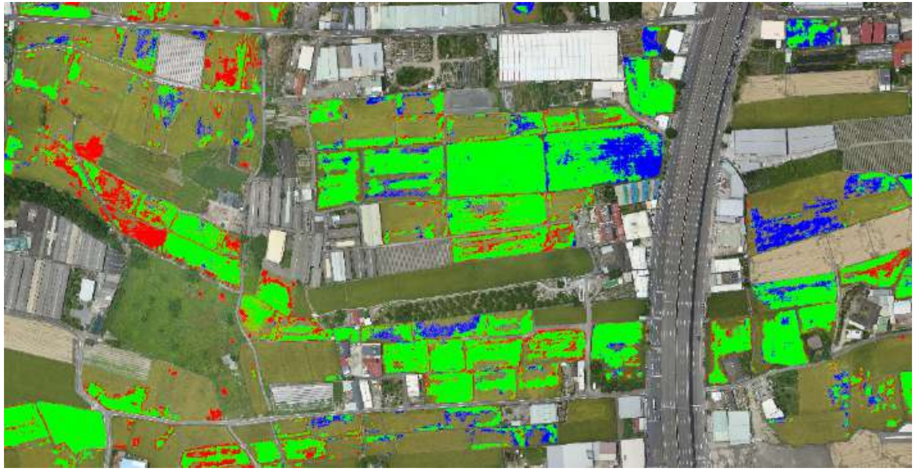




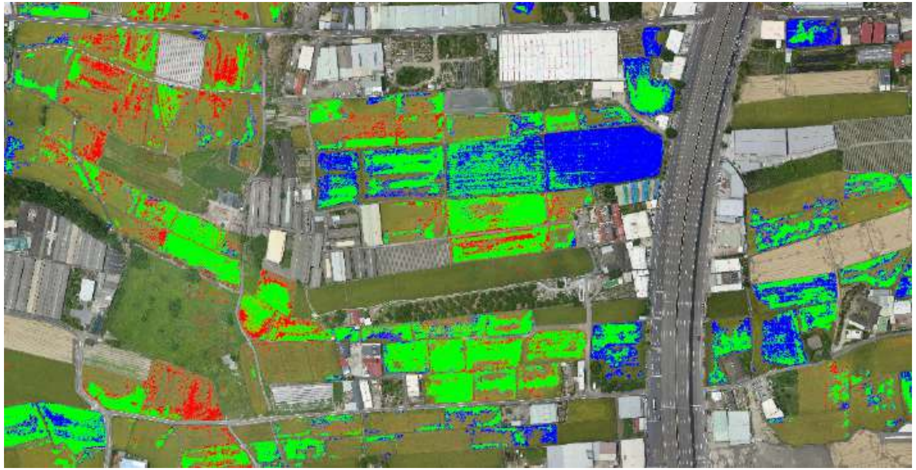




Rice Lodging Identification

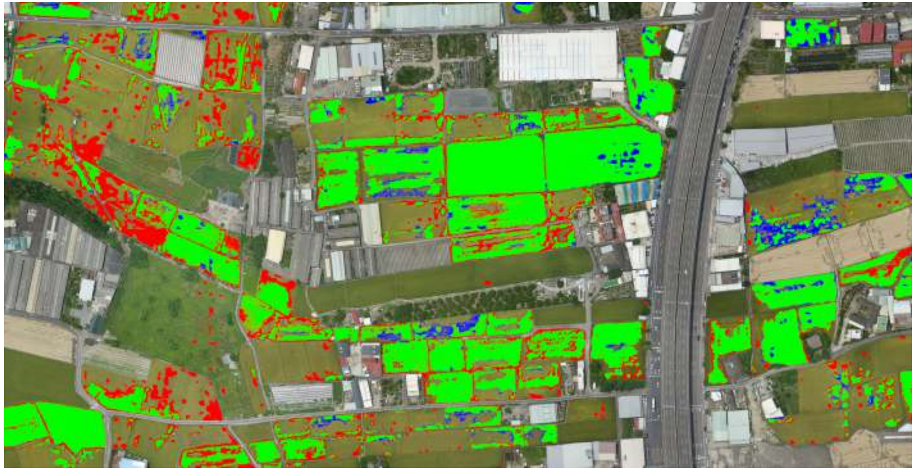


2017 SegNet (RGB+ExG)

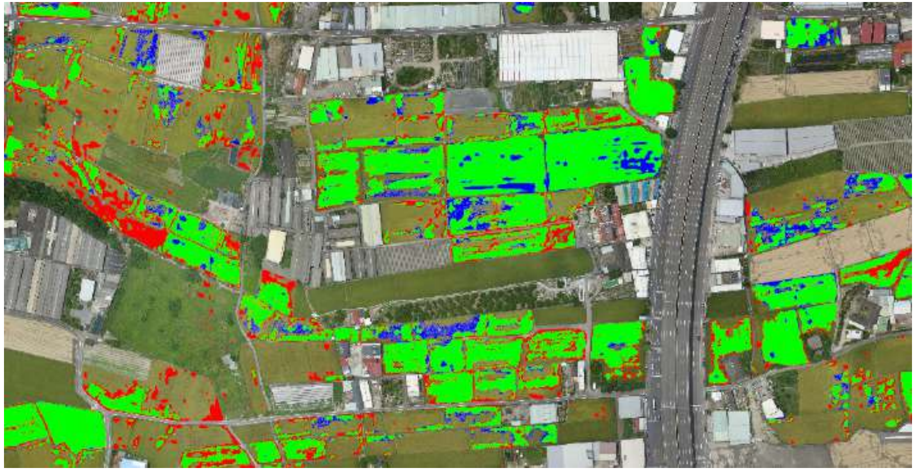


2017 SegNet (RGB)

Rice Lodging Identification

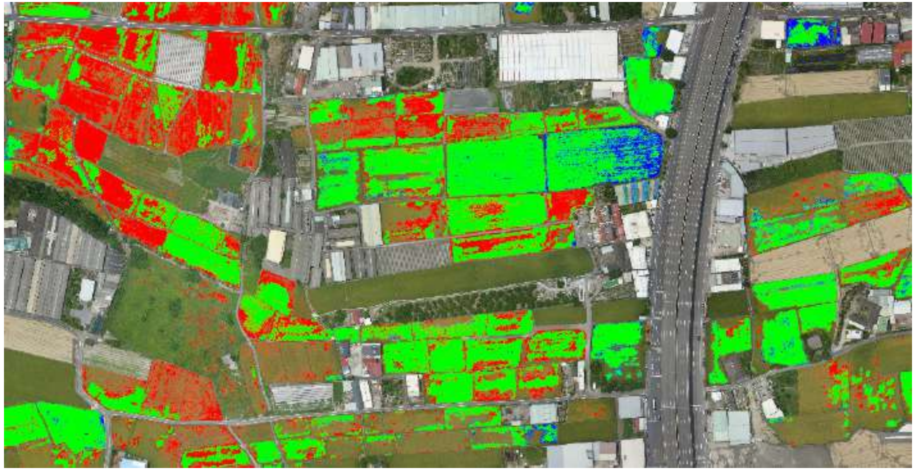


2017 FCN-AlexNet (RGB+ExGR)

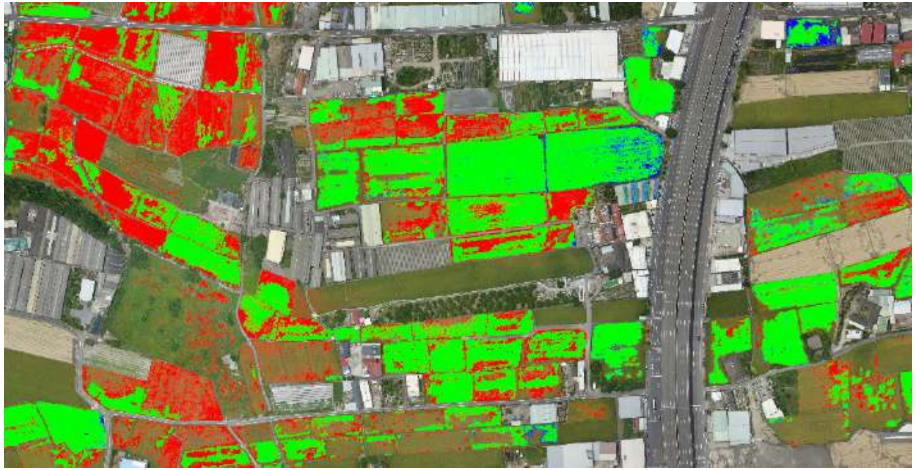


2017 FCN-AlexNet (RGB)

Rice Lodging Identification

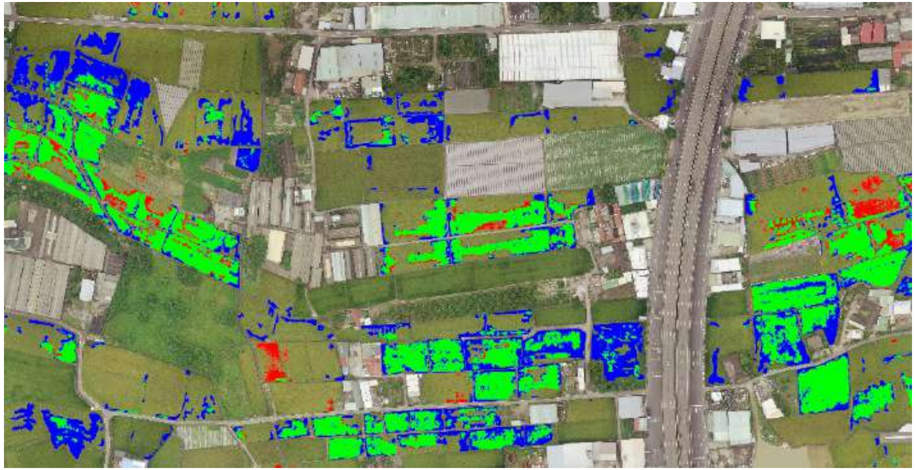


2017 MLC (RGB+ExG)

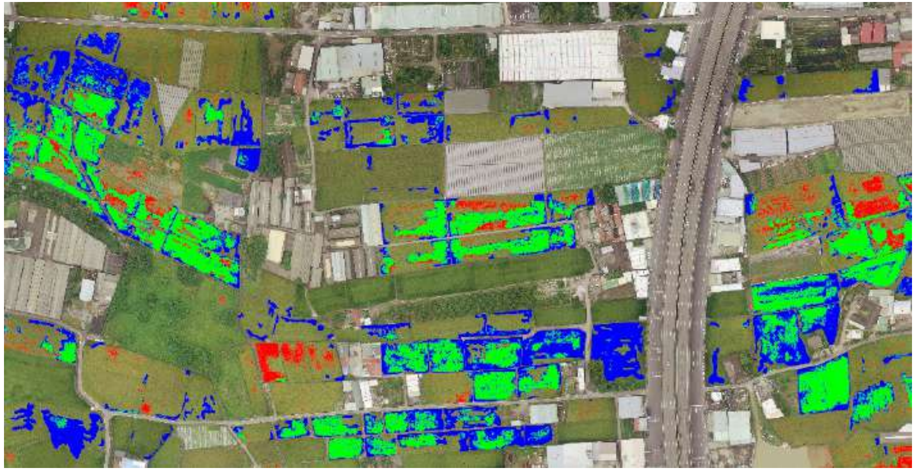


2017 MLC (RGB)

Rice Lodging Identification

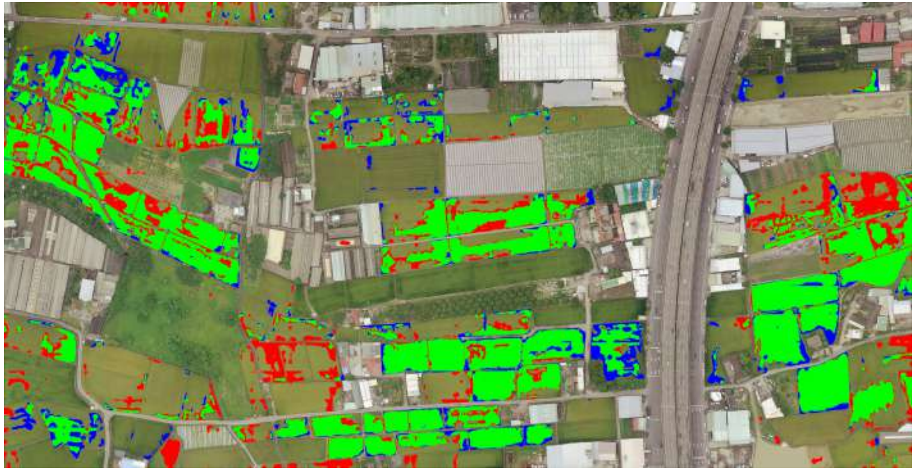


2019 SegNet (RGB+ExG)

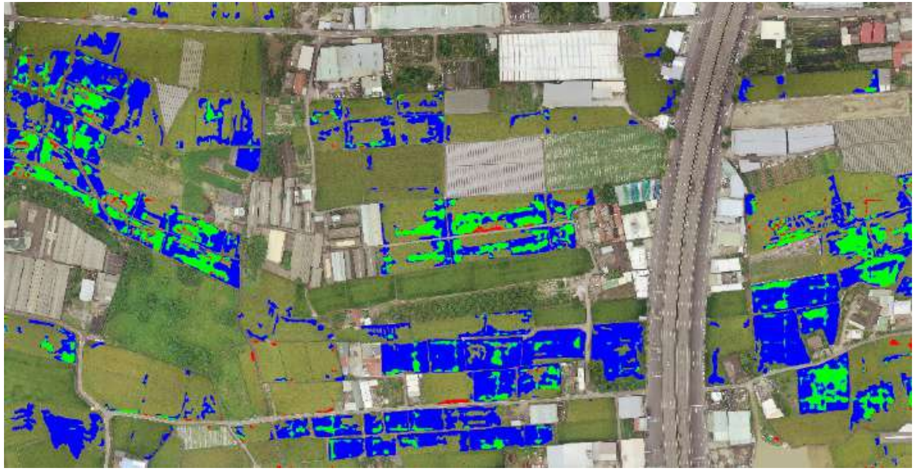


2019 SegNet (RGB)

Rice Lodging Identification



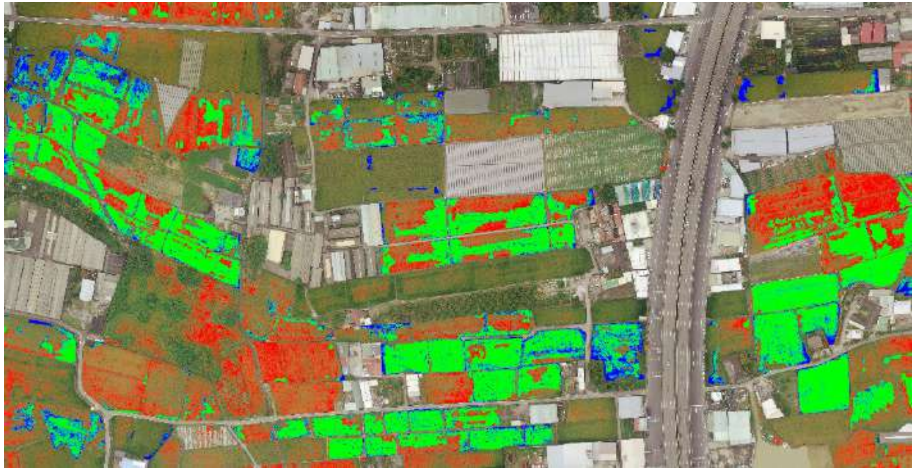
2019 FCN-AlexNet (RGB+ExGR)



2019 FCN-AlexNet (RGB)

Rice Lodging Identification

2019 MLC (RGB+ExG)



2019 MLC (RGB)

Rice Lodging Identification

2600 ha area
Investigation & Process
within 1 day

80ha for 2 min

Conclusion

Conclusion

1) UAVs help the large-area investigation and also lower the cost of labor and money.

2) With the deep learning technique, data can be reused and the classifier can be reinforced, which means the experience can be accumulated.

3) Adding vegetation index makes the classification model robust.

4) Image tile eliminates the memory insufficient problem of processing large-scale images.

5) The variant of illumination, white balance and saturation are still the challenges for image classification tasks.

Future Work

Future Work

1) Test other networks, such as Enet, EDANet.

2) Edge devices integration

3) Distributed computing for faster results.

4) Autonomous identification and pathfinding

5) Paddy field mapping for lodging rate calculation.

6) Preparing an article for submission

Future Work

Nvidia Jetson TX2

Nvidia Jetson AGX Xavier

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Thanks for your attention !

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