### Software Engineering for High Throughput Phenotyping

### Zhiwu Zhang





**Feaching** 

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#### Five ingredients to succeed: CS-VMV

ulture: Trying to understand

trategy: Solve biological problems with analytical and computational challenges. ision: Genomic and phenomic stream data is stationary water for organisms.

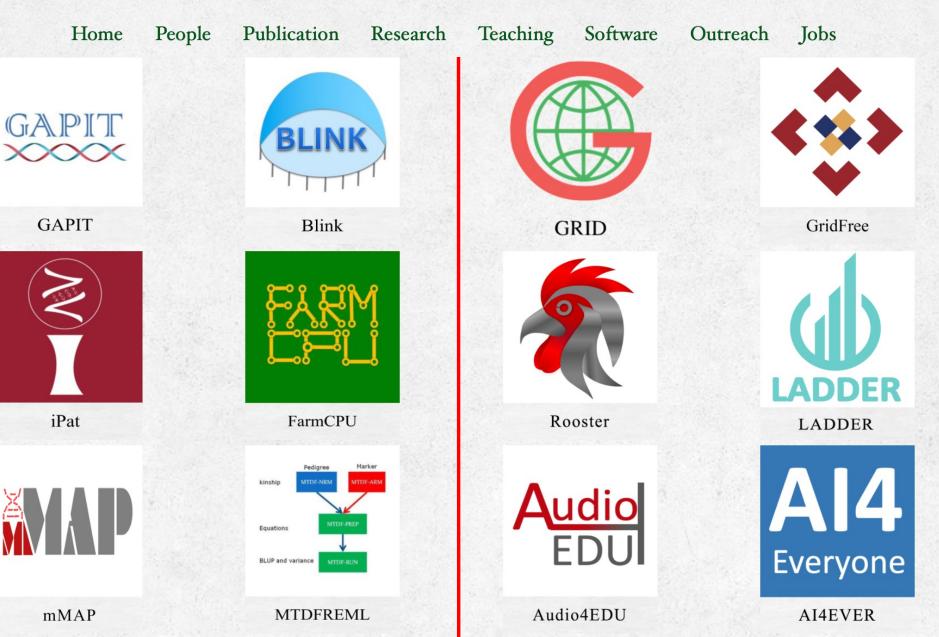
ission: You get data, we help with our analytical methods, tools, and expertise.

alue: Every idea makes sense.

zzlab.net/share







Phenomics

Genomics



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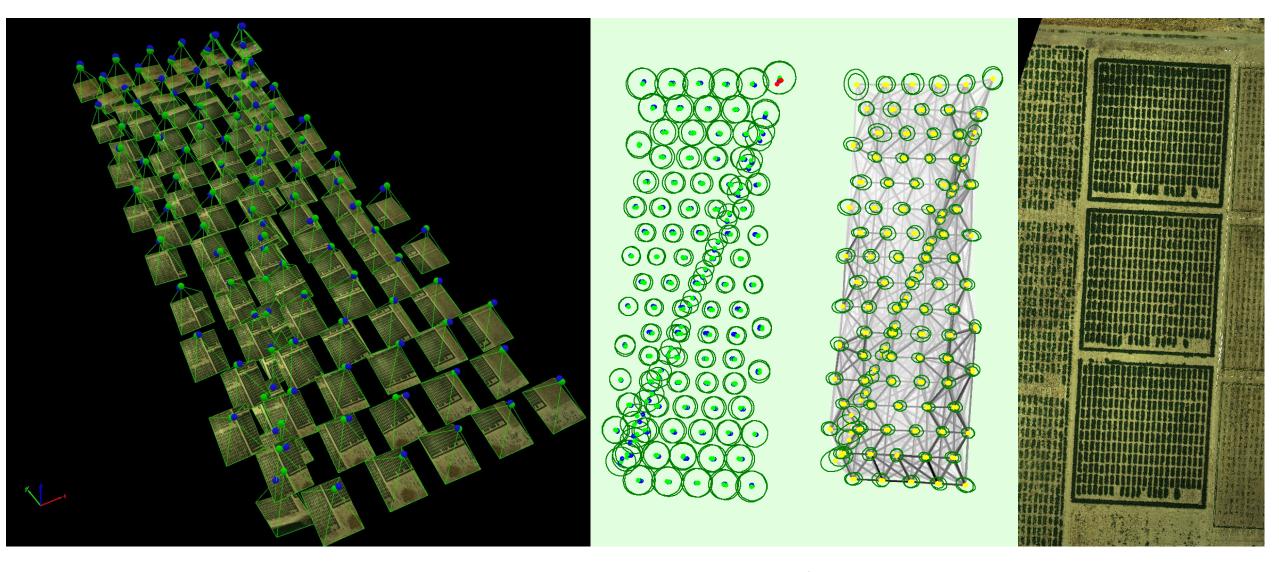




### Phenotyping yield is labor and time expensive

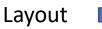


### **Orthomosaic image using PIX4D**



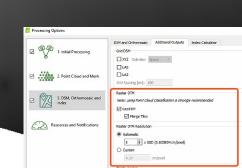
Original images



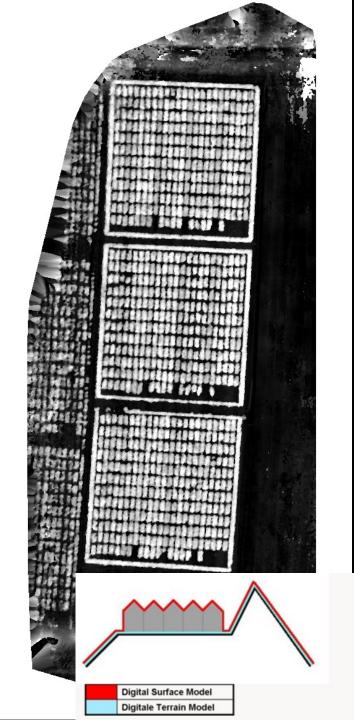


Matching









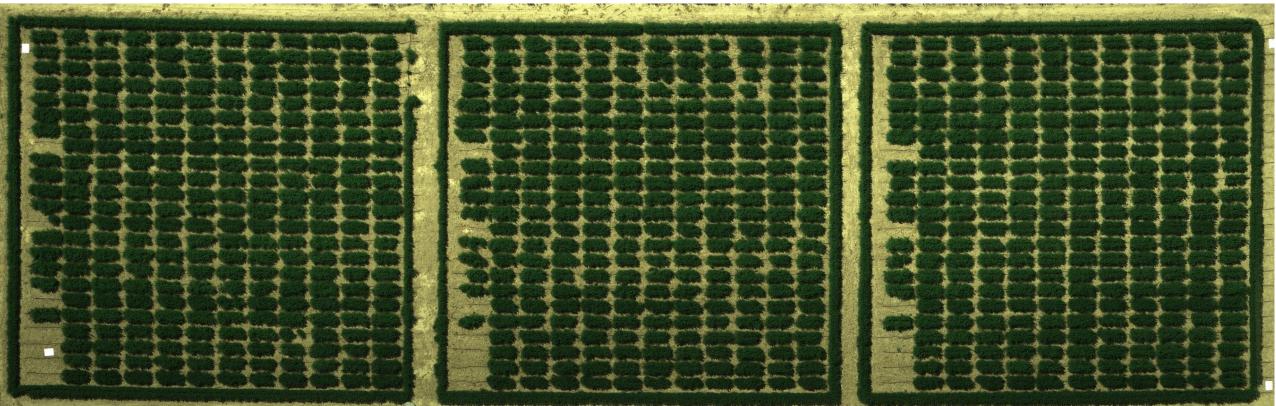
# Drone images (RGB)

(May 5, 2019)

Replicate 3

#### Replicate 2

**Replicate 1** 



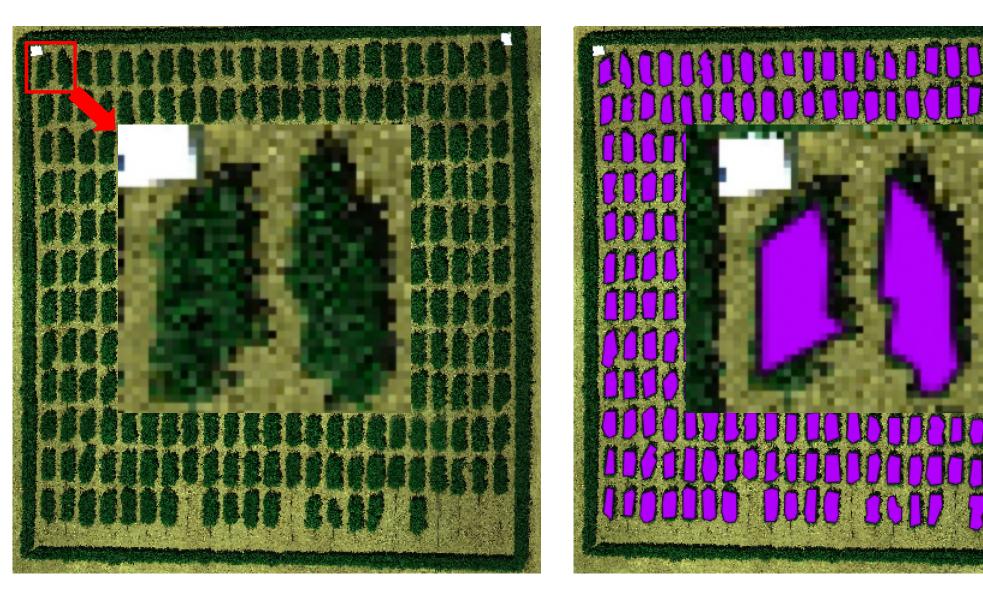
100 feet, ten minutes, ~400 images, joined by PIX4D

### Manual Curation of shape file (QGIS)

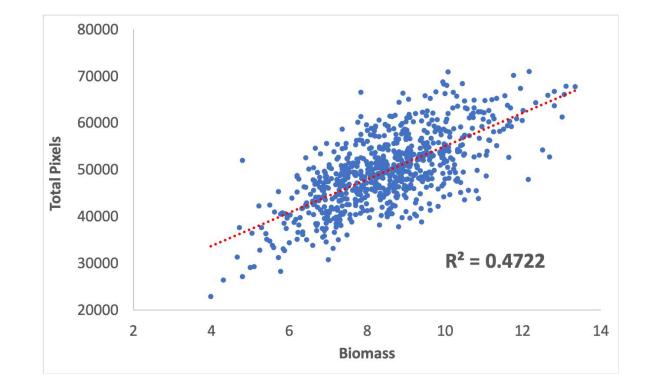


Samuel Revolinski sr.revolinski@uky.edu

1     4850       2     492       3     4679       4     4530       5     5380       6     4580       7     4600	78 93
3         467           4         453           5         538           6         458	93
4 453 5 538 6 458	
5 538 6 458	05
6 458	
	62
7 460	42
	60
8 525	05
9 572	04
10 530	92
11 501:	21
12 540	65
13 361	14
14 383	71
15 412	97
16 467	86
17 439	RQ



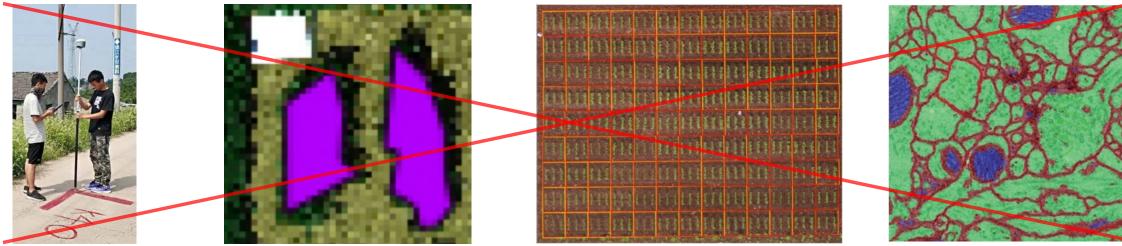
### Canopy area explained 50% of biomass variation



Unpublished data

### Four Roadblocks for Using UAV Images

- Depend on ground devices for geographical information
- Manually draw polygons
- Manually draw lines
- Intensive training to extract pixels of interest

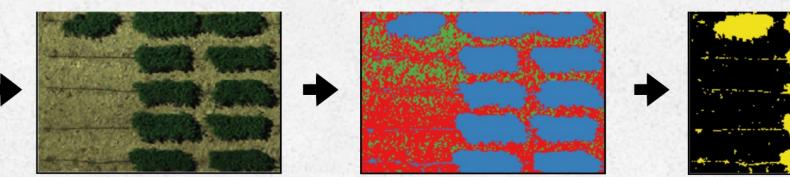


https://www.pix4d.com/blog/large-drone-map-yangtze

https://spj.sciencemag.org/plantphenomics/2019/2591849/

https://academic.oup.com/view-large/figure/118774504/btx180f1.tif





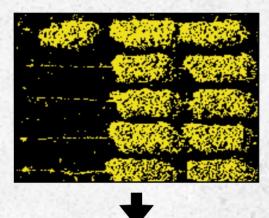


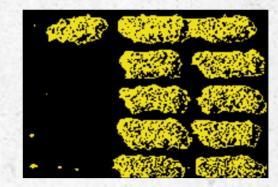
### Easy Way to Extract Info. from Aerial Images



DISCOVER MORE

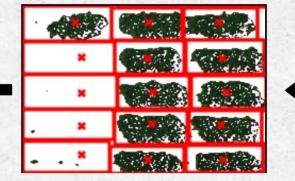
James Chen niche@vt.edu

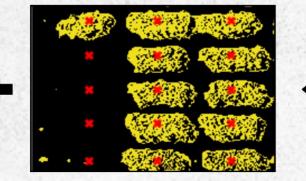




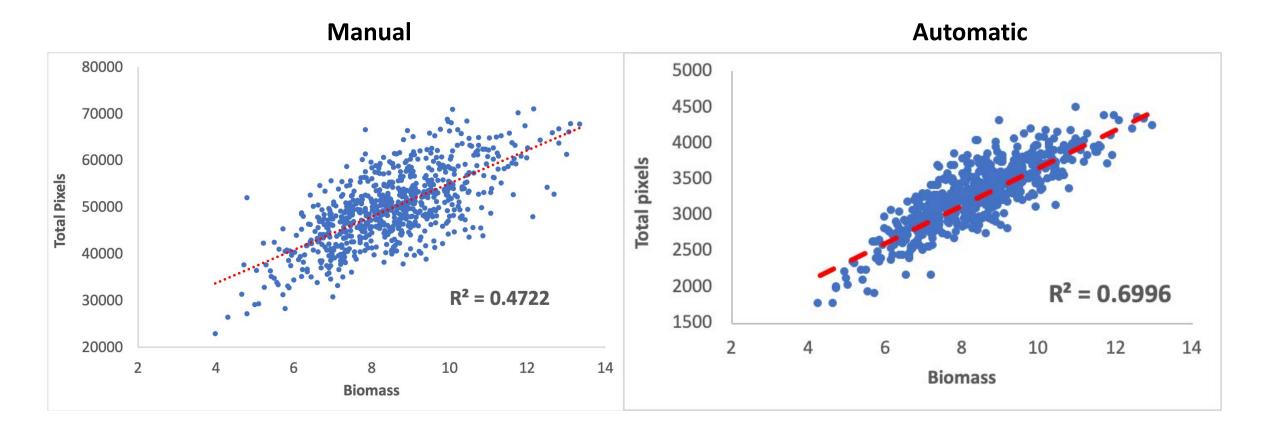
https://doi.org/10.3390/rs12111697

var	row	col	ch 0	ch 1	ch 2	area veg	NDVI
ID 01	0	0	_	87.813	-	10144	0.551
ID 02	0	1	25.397			7018	0.569
ID 03	1	1	22.636	89.053	39.887	7090	0.598
ID 04	2	1	26.187	89.989	40.921	6465	0.555
ID_05	3	1	24.617	87.876	41.833	9786	0.567
ID_06	4	1	23.870	84.696	40.129	4979	0.568
ID_07	0	2	27.664	87.648	42.068	12526	0.525
ID_08	1	2	21.540	91.220	38.632	14689	0.625
ID_09	2	2	24.423	83.188	40.538	11962	0.552



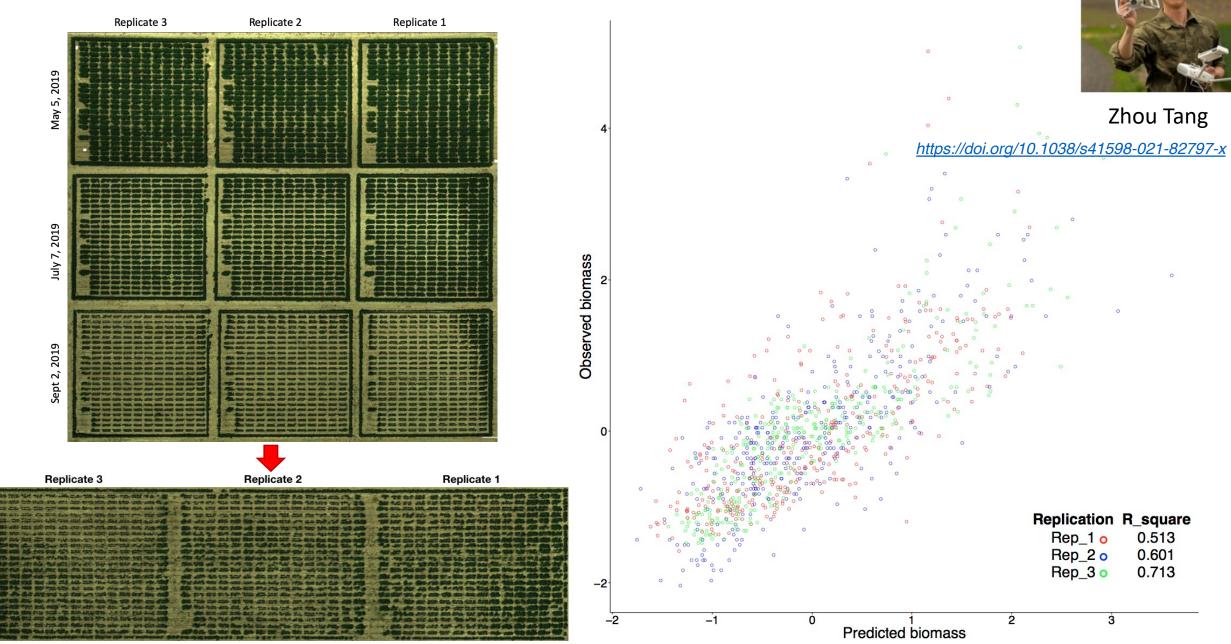


### Canopy area explained 70% of biomass variation



Unpublished data

# Independent validation



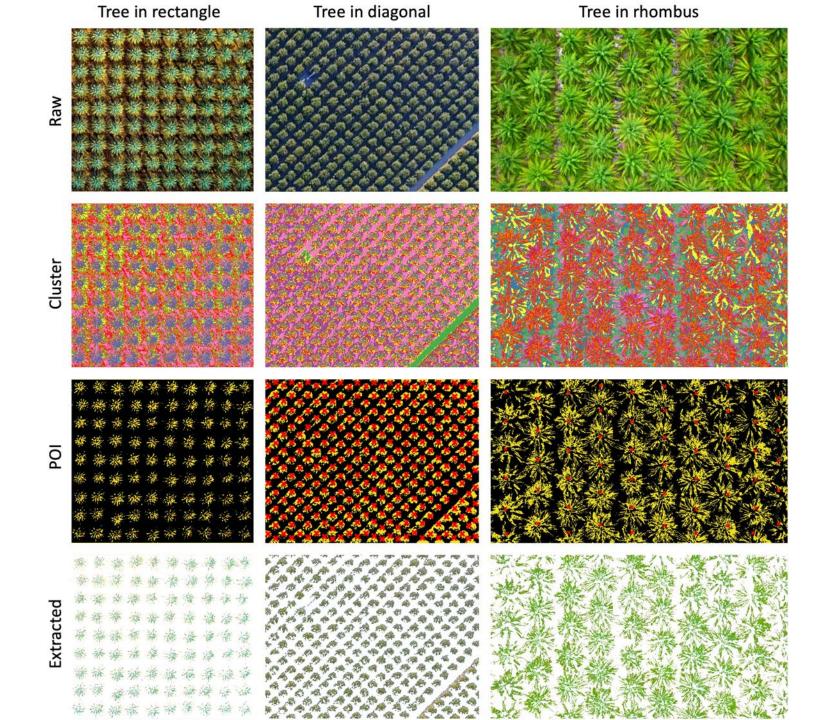
#### Original image

#### Segmented

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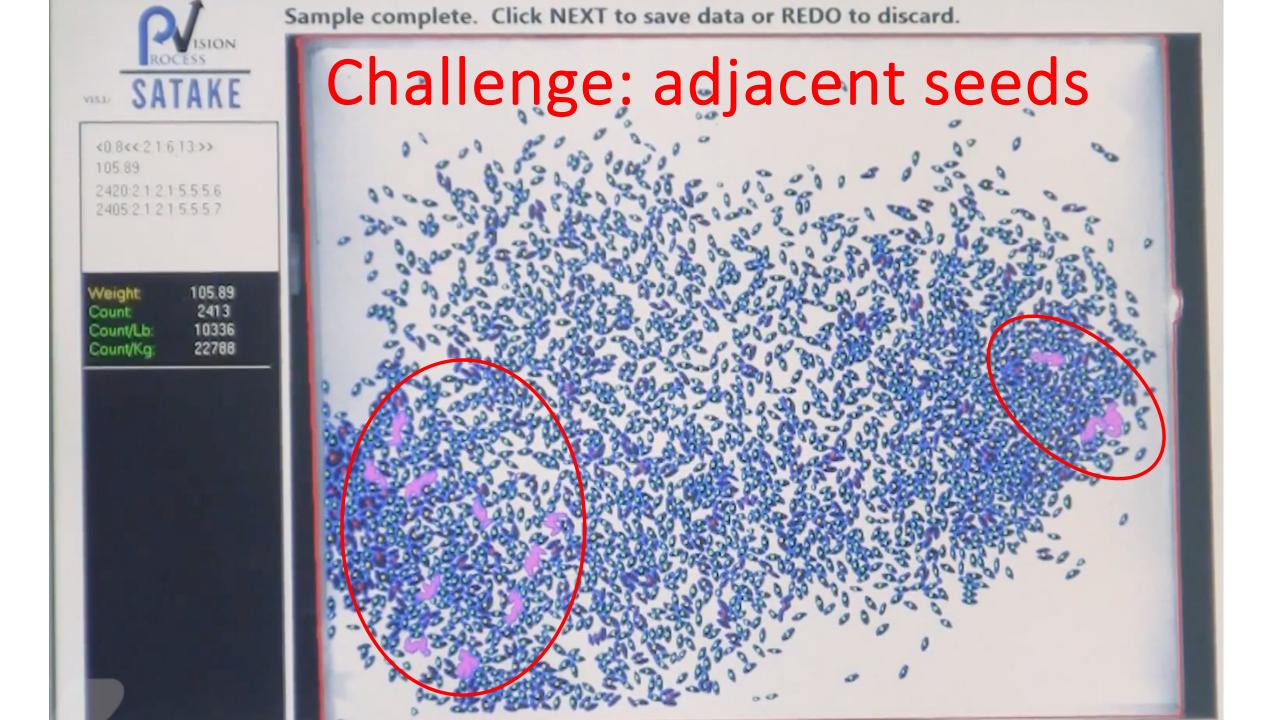
# **Motivation from counting seeds**

I: Dark age II: Mechanic age III: Electronic age



IV: Computer age

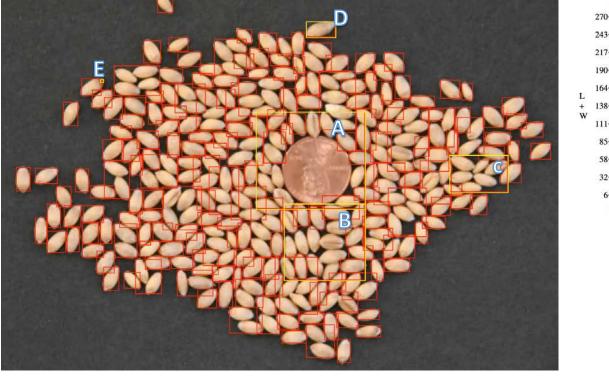


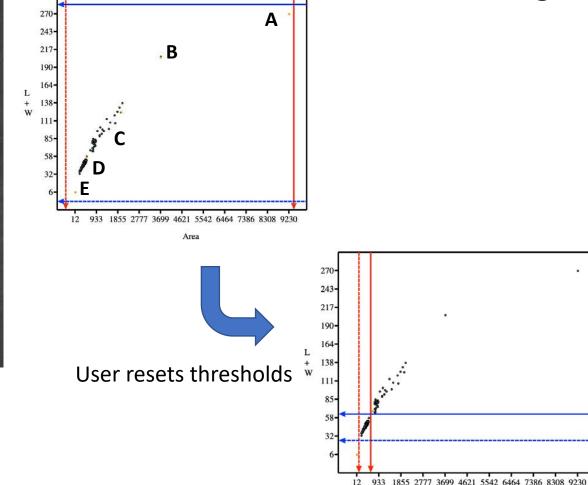




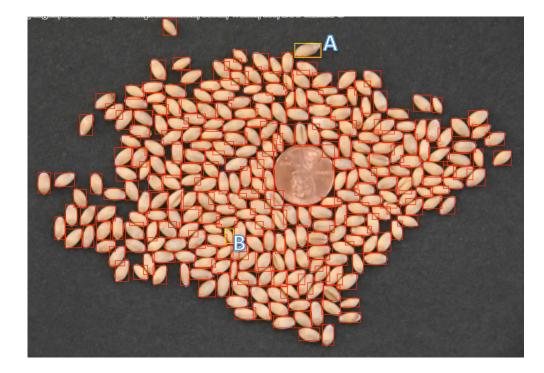


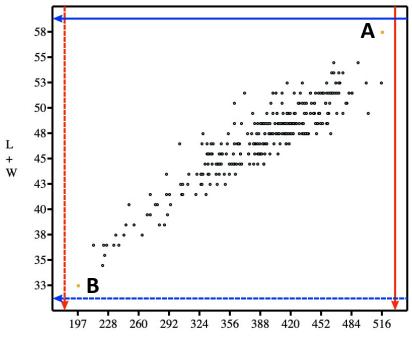
Yang Hu



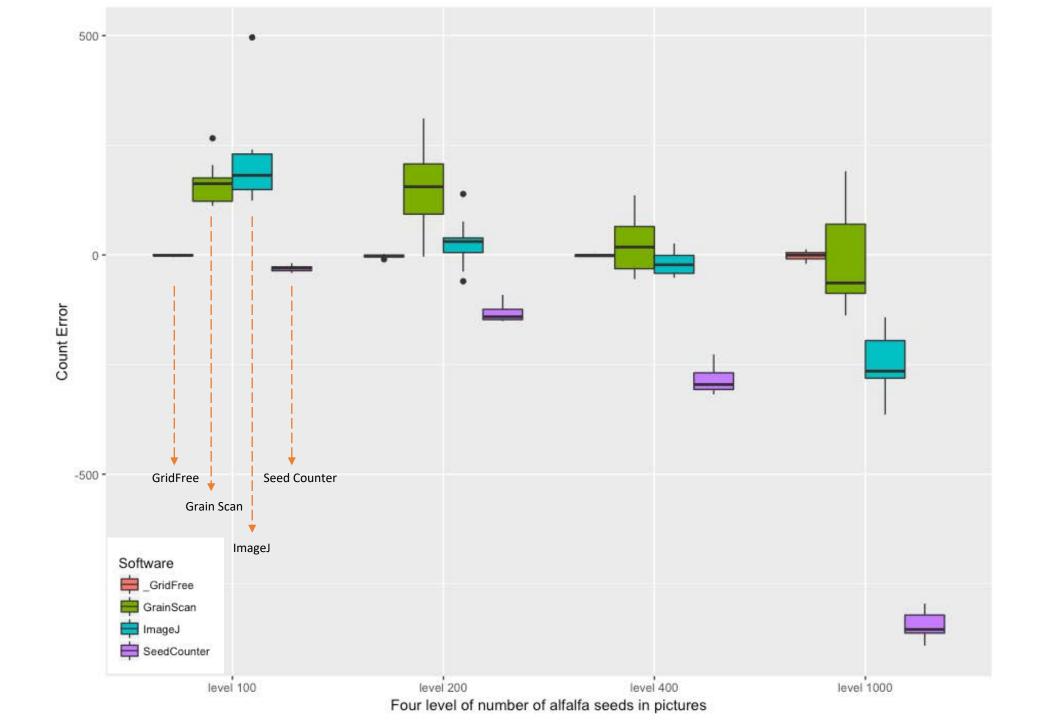


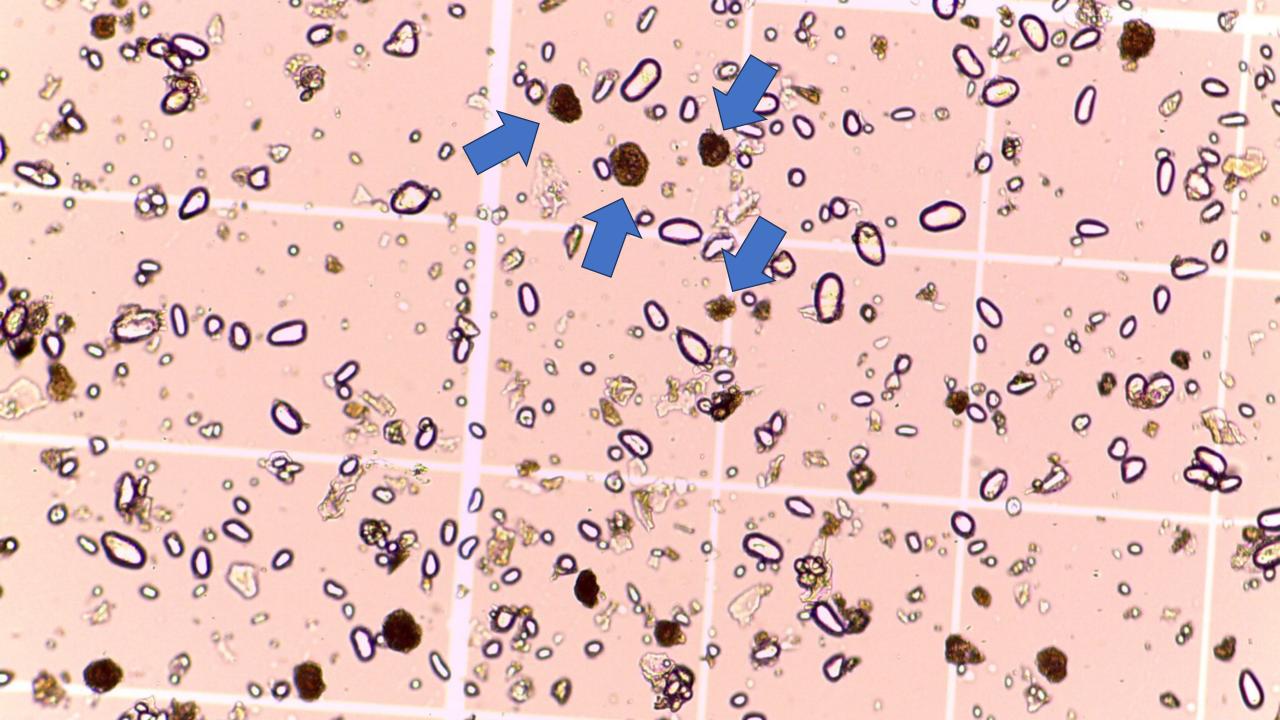
### **Results of user interaction**

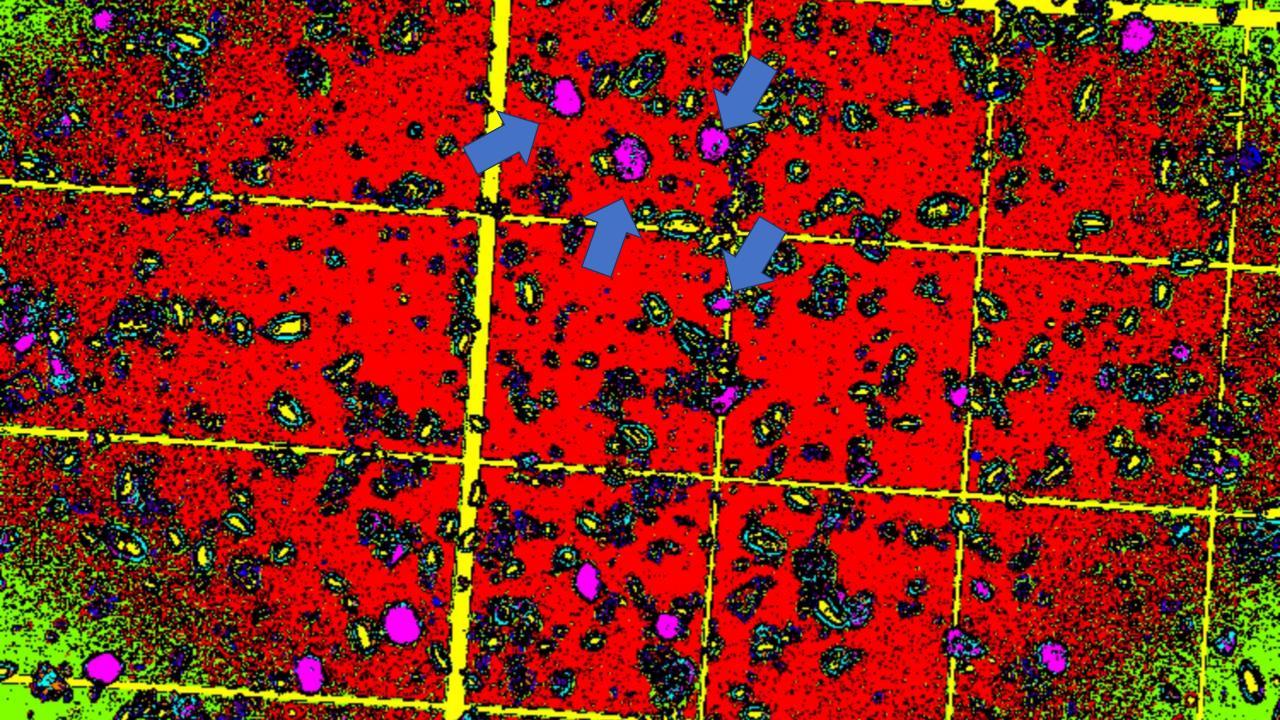




Area







doi:10.1093/plphys/kiab226

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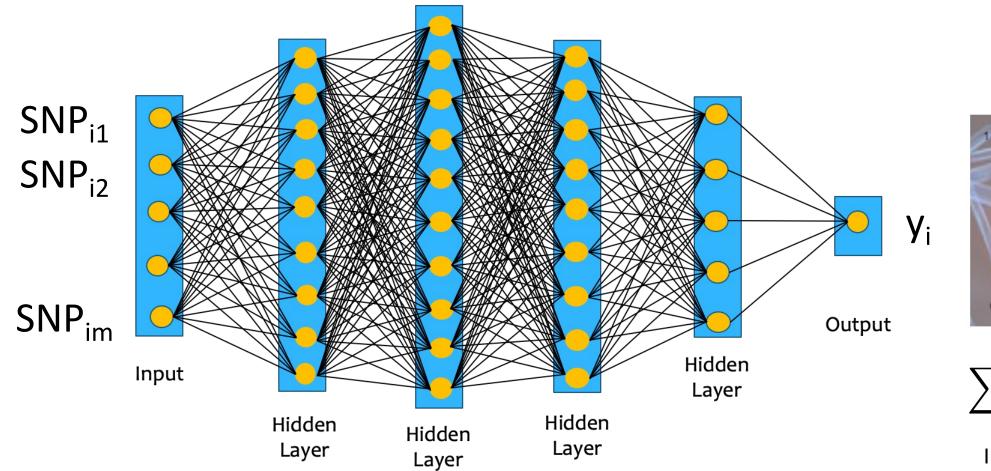
# What stories does this image tell?

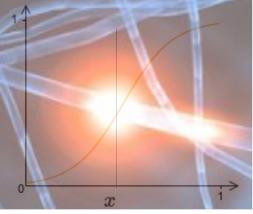


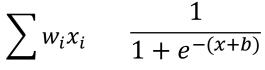


### **Early Detection is critical to control stripe rust**

### **Neural Networks**







Input

Output

≡ Google Scholar

Nature 323 (6088), 533-536



#### **Geoffrey Hinton**

Emeritus Prof. Comp Sci, U.Toronto & Engineering Fellow, Google Verified email at cs.toronto.edu - <u>Homepage</u>

machine learning psychology artificial intelligence cognitive science computer science

TITLE	CITED BY	YEAR
Imagenet classification with deep convolutional neural networks A Krizhevsky, I Sutskever, GE Hinton Advances in neural information processing systems 25	138063 *	2012
Deep learning Y LeCun, Y Bengio, G Hinton Nature 521 (7553), 436-44	66972	2015
Dropout: a simple way to prevent neural networks from overfitting N Srivastava, G Hinton, A Krizhevsky, I Sutskever, R Salakhutdinov The journal of machine learning research 15 (1), 1929-1958	44640	2014
Visualizing data using t-SNE L van der Maaten, G Hinton Journal of Machine Learning Research 9 (Nov), 2579-2605	35659	2008
Learning representations by back-propagating errors DE Rumelhart, GE Hinton, RJ Williams	34206	1986



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#### Frank Rosenblatt (Cornell)



#### Marvin Minsky (MIT)



### Geoffrey Hinton Godfather of Al

B.A., Psychology, Cambridge Ph.D., AI, Edinburgh



UNIVERSITY OF TORONTO

### **George Cybenko's Theorem**

Math. Control Signals Systems (1989) 2: 303-314

Impact factor 1.518 Cited by 17,751 Mathematics of Control, Signals, and Systems © 1989 Springer-Verlag New York Inc.

# Simple neural networks can *represent* a wide variety of interesting functions

#### **Approximation by Superpositions of a Sigmoidal Function\***

#### G. Cybenko†

Abstract. In this paper we demonstrate that finite linear combinations of compositions of a fixed, univariate function and a set of affine functionals can uniformly approximate any continuous function of n real variables with support in the unit hypercube; only mild conditions are imposed on the univariate function. Our results settle an open question about representability in the class of single hidden layer neural networks. In particular, we show that arbitrary decision regions can be arbitrarily well approximated by continuous feedforward neural networks with only a single internal, hidden layer and any continuous sigmoidal nonlinearity. The paper discusses approximation properties of other possible types of nonlinearities that might be implemented by artificial neural networks.

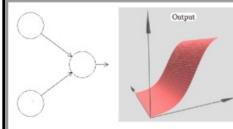


### **Computer demonstration**

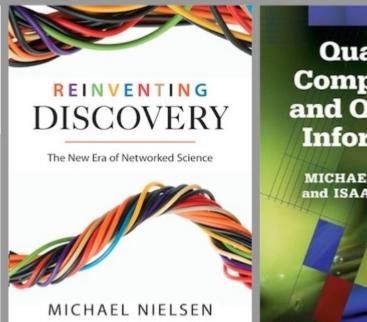
#### **CHAPTER 4**

A visual proof that neural nets can compute any function

#### **Books**



Neural Networks and Deep Learning: A free online book explaining the core ideas behind artificial neural networks and deep learning. Code.



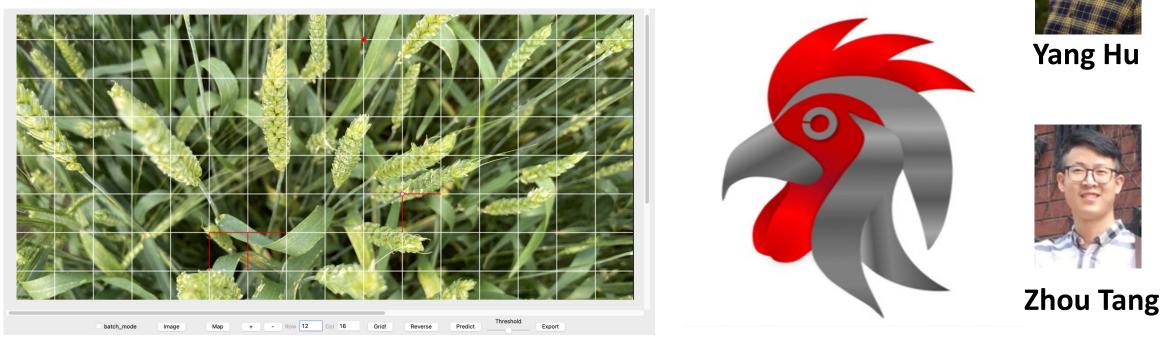
#### Quantum Computation and Quantum Information

MICHAEL A. NIELSEN and ISAAC L. CHUANG



#### By Michael Nielsen / Dec 2019

### Wheat stripe rust early detection

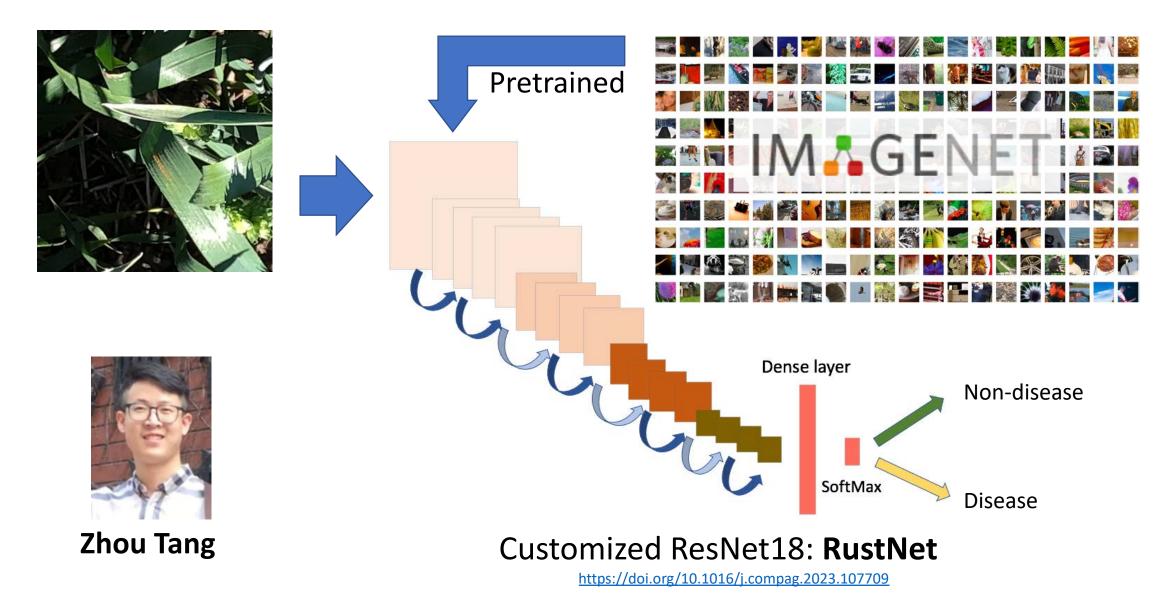


#### https://zzlab.net/Rooster

#### Affordable High Throughput Field Detection of Wheat Stripe Rust Using Deep Learning Based on Semi Automatic Image Labeling

Zhou Tang<sup>1</sup>, Meinan Wang<sup>2</sup>, Michael Schirrmann<sup>3</sup>, Karl-Heinz Dammer<sup>3</sup>, Robert Brueggeman<sup>1</sup>, Xianran Li<sup>1</sup>, Sankaran, Sindhuja<sup>4</sup>, Mike Pumphrey<sup>1</sup>, Yang Hu<sup>1\*</sup>, Xianming Chen<sup>2,5\*</sup>, and Zhiwu Zhang<sup>1\*</sup>

# **Residual Neural Network Architecture**





# ROOSTER



#### Yang Hu



batch\_mode

Map

Image

- Row 24

+

Col 32

Grid!

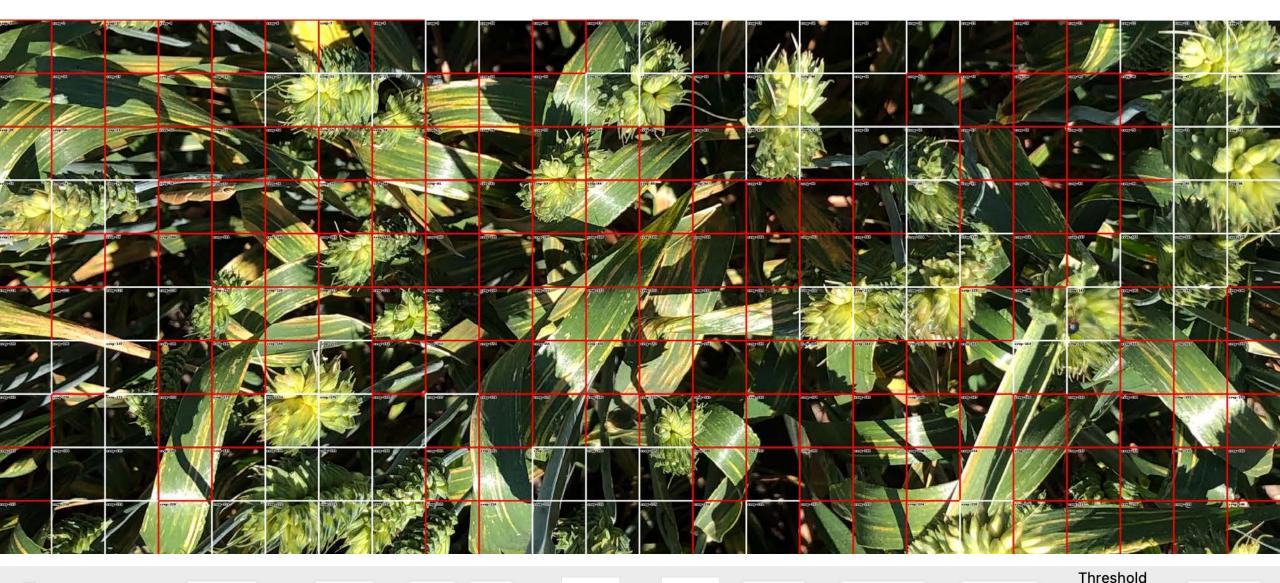
Reverse

Predict

Export

Threshold

### **Revers and customization**



batch\_mode

Map

Image

- Row 24

+

Col 32

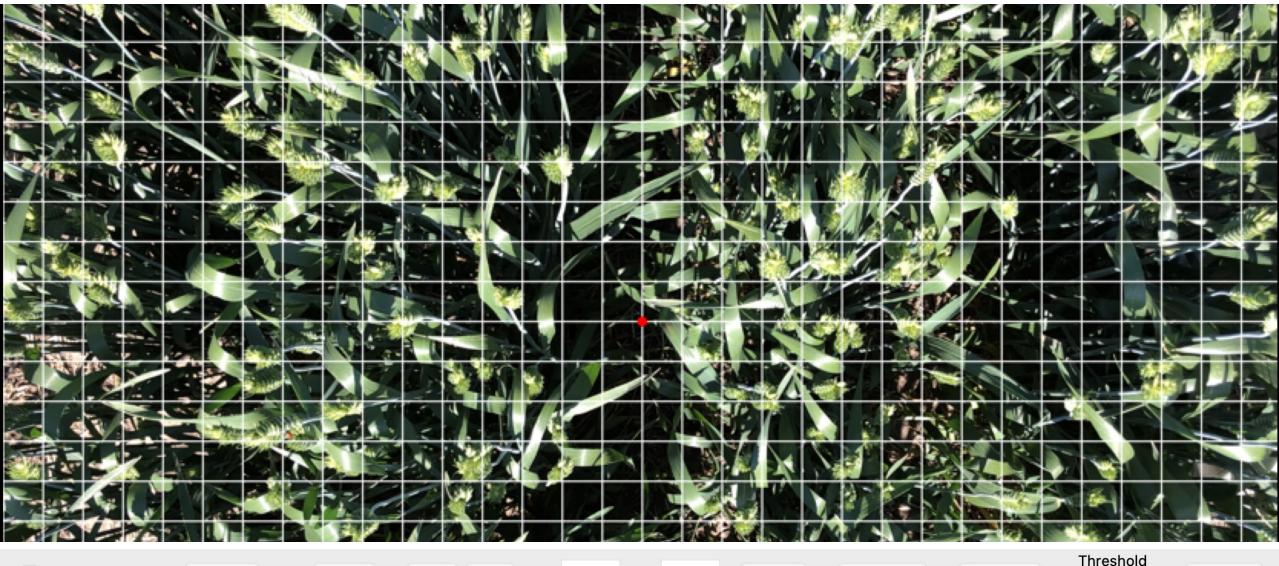
Grid!

Reverse

Predict

Export

### **Prediction with RustNet**



batch\_mode

Map

Image

Row 24

-

+

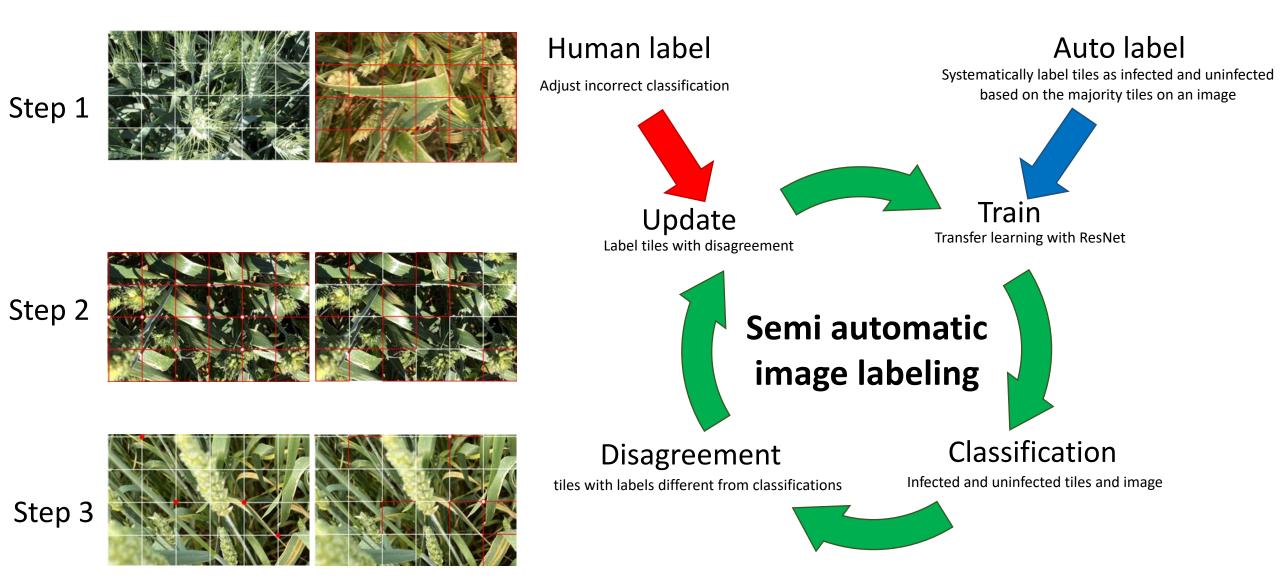
Col 32 Grid!

Reverse

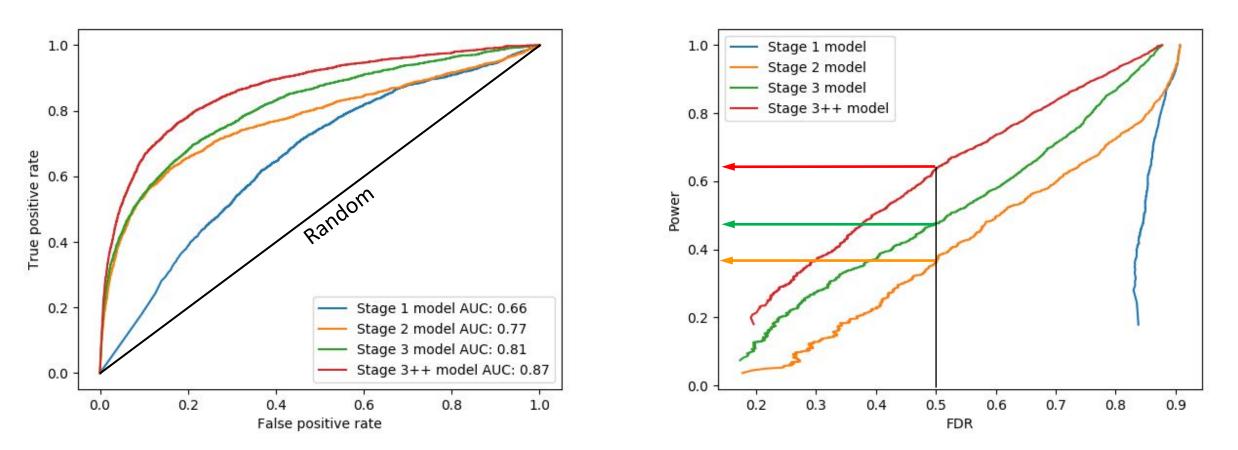
Predict

Export

### **Online learning**



### **Prediction accuracy**



https://zzlab.net/Rooster

## What does it mean for farmers?

Stage	FDR	False+	Power	Images	Time (m)
2	50%	10	35%	1,429	48
3	50%	10	50%	1,000	33
3++	50%	10	65%	769	26

#### Assumptions

- To find ten infected leaves on average
- Confidence to find at least one: 99.99%
- Taking images every two seconds
- Leaves per image: 200
- Frequency: 0.01%



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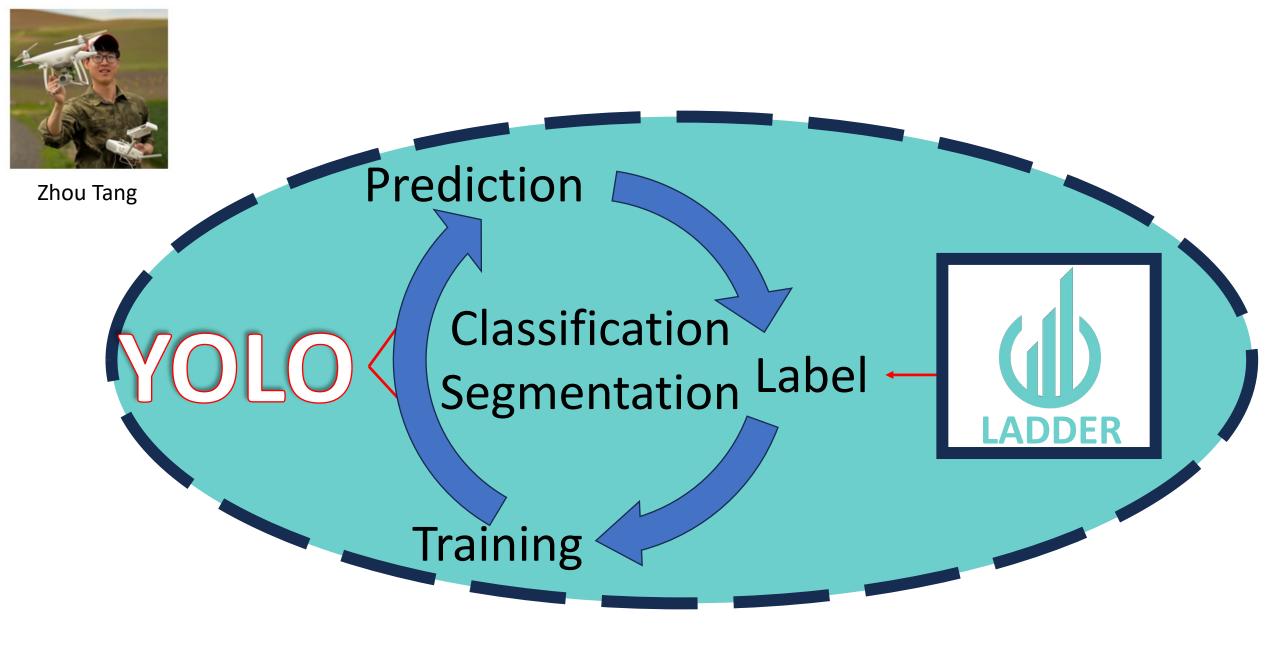




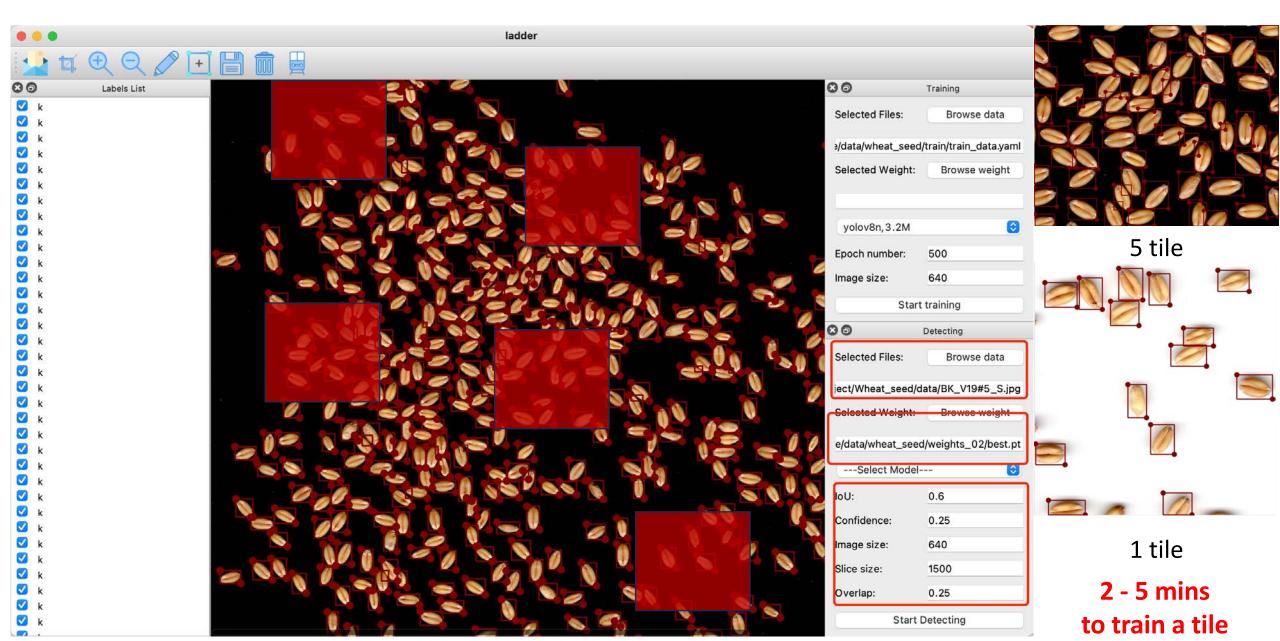


Harv 1  $G \rightarrow D \rightarrow 2 \rightarrow 3 \rightarrow 0 \rightarrow 1 \rightarrow 5$ 

#### Rabbit holes!

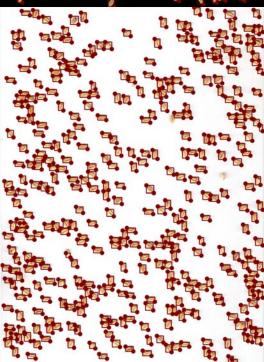


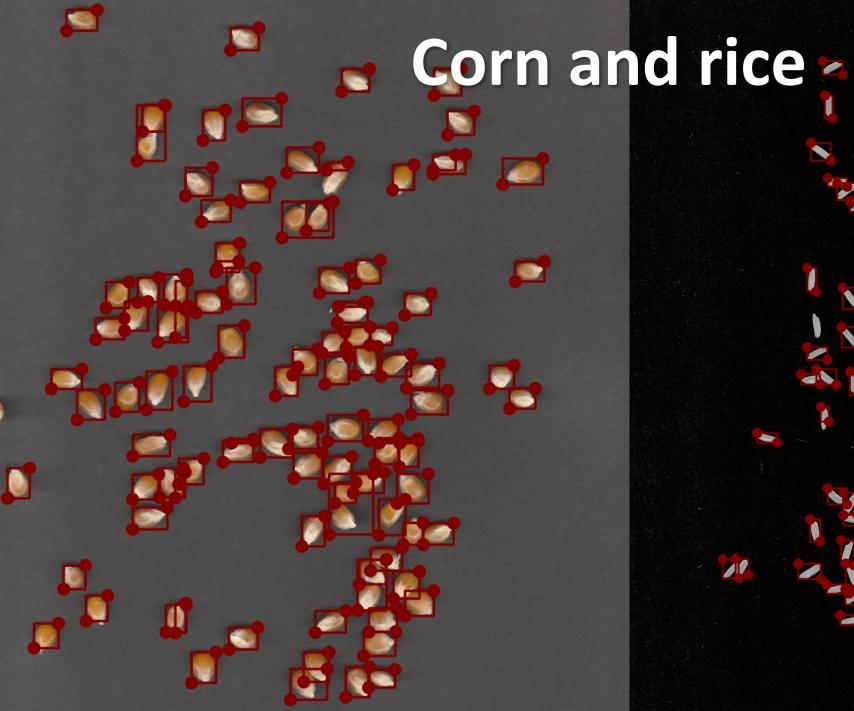
#### Build a computer vision system within an hour

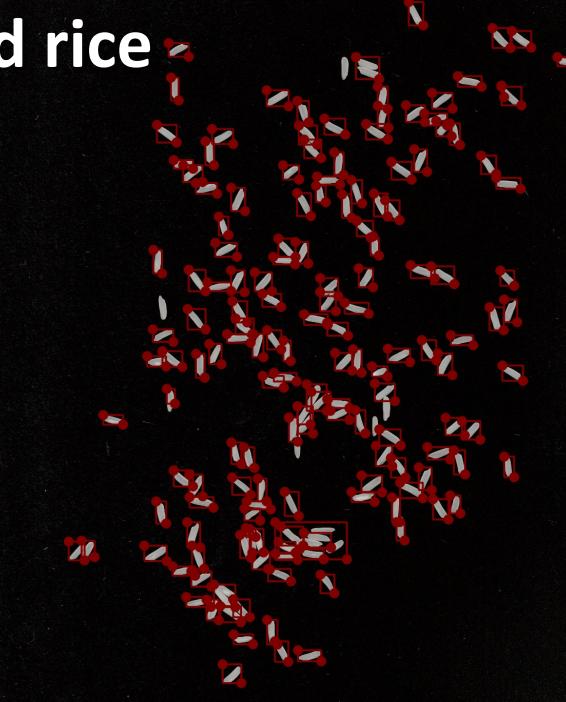




Each image take ~ 2 mins



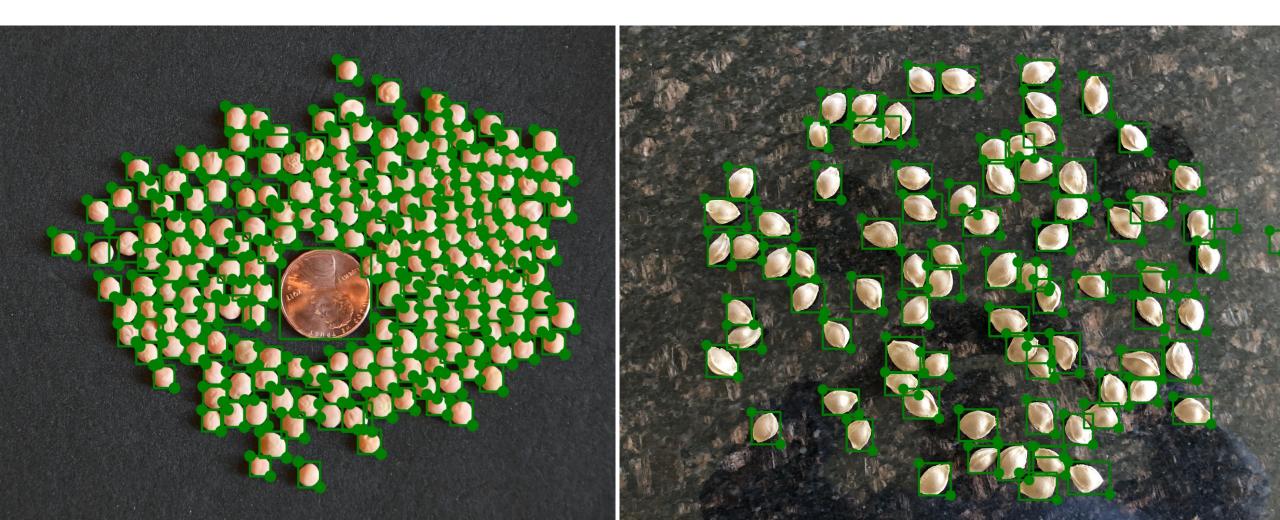




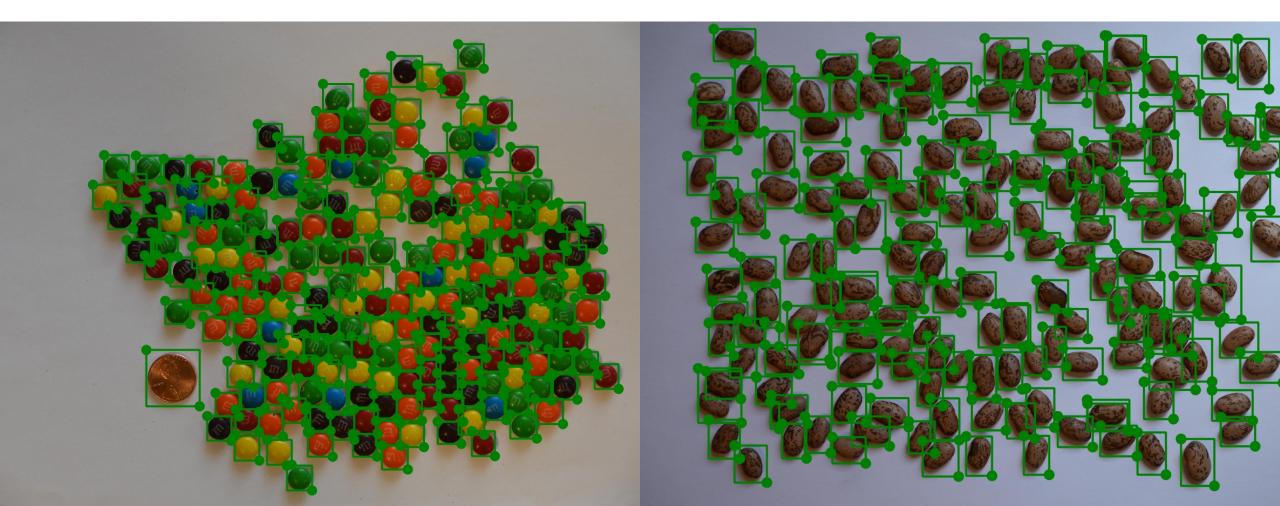
#### **Chesnutt and chickpea**

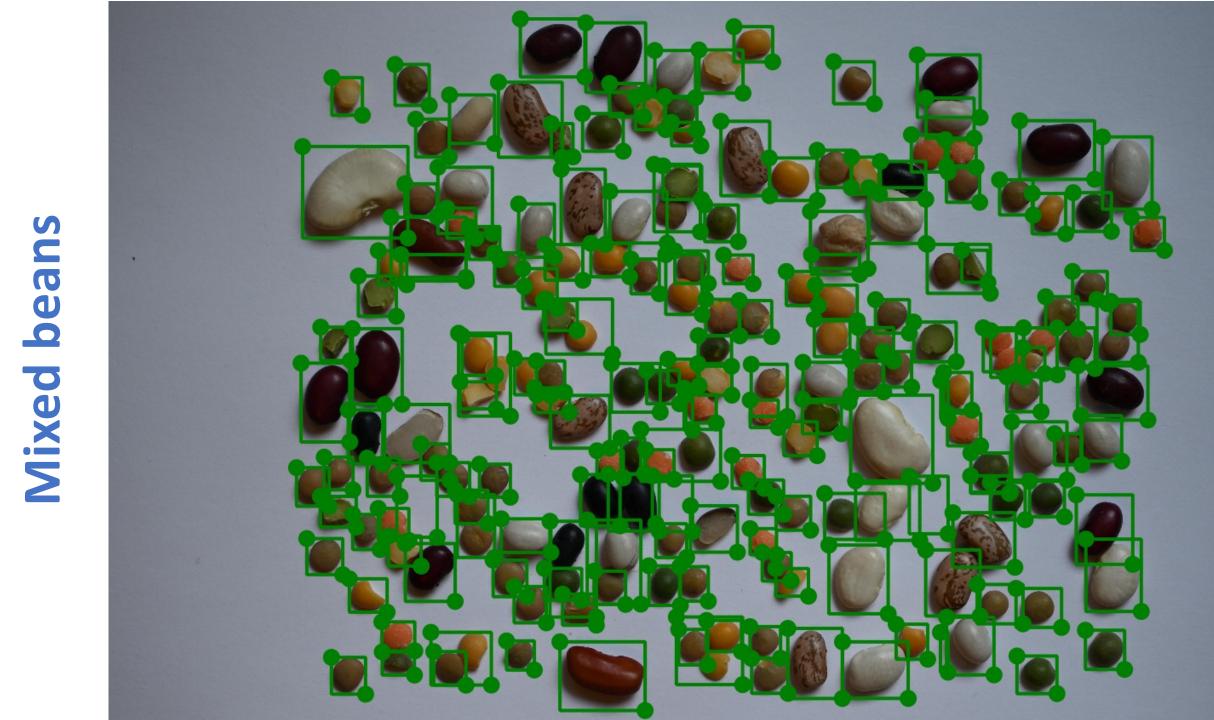


#### **Lentil and Apricot**



#### **Cands and Beans**

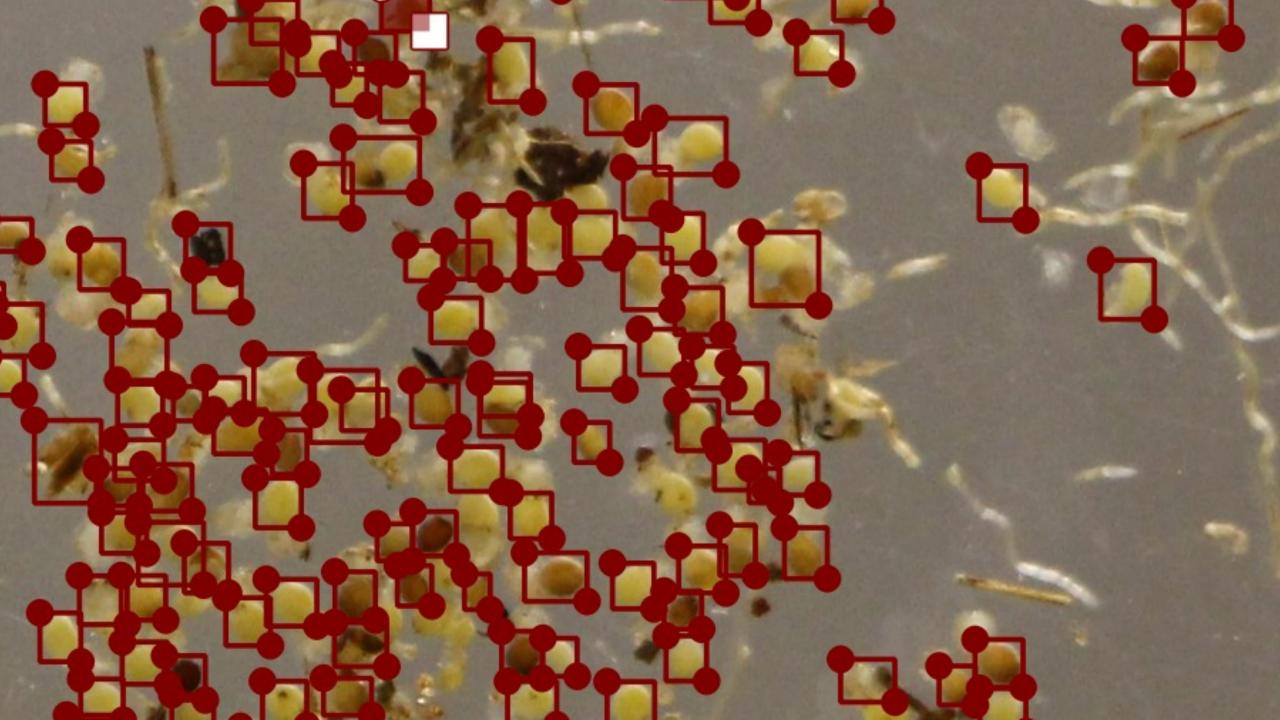




### **Customized System**

PGAS11

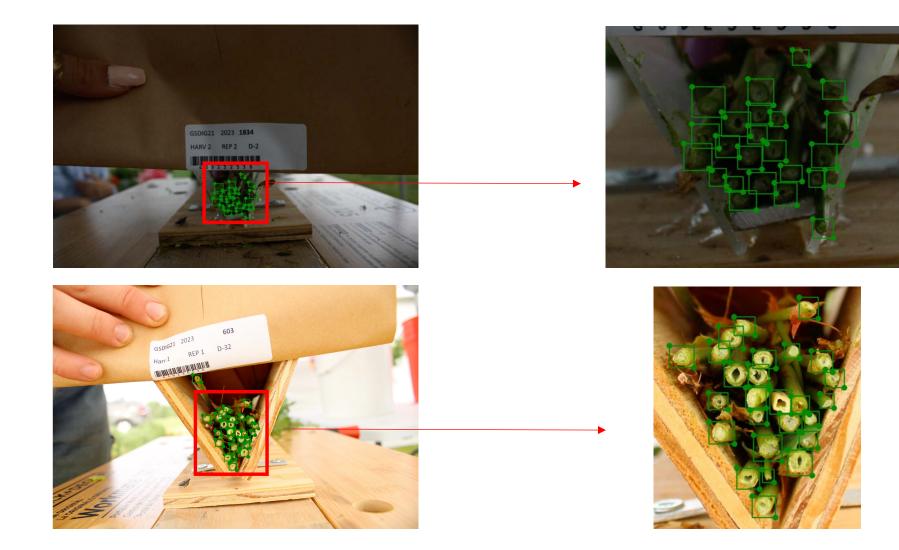
Soybean cyst nematode



	Training set	Testing set
Alfalfa flower	3 (2 dark, 1 light)	2 (1 dark, 1 light)



	Training set	Testing set
Alfalfa Stem	6 (3 dark, 3 light)	4 (2 dark, 2 light)





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Mosaic







# Plug & Play









- Bran separates more cleanly from the endosperm for milling
- High flour yield
- Low water absorption
- Low gluten strength







AI4 Everyone 80%







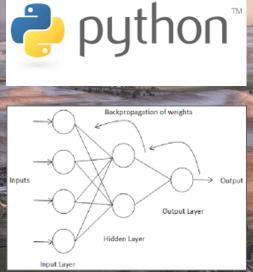
Build a path for everyone to succeed in Al

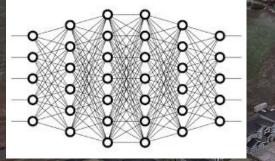


**A|4** 

Everyone

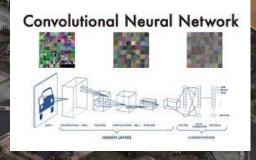
Plug&Play











### **Models for Transfer Learning**

	AI4EV	ER
		Name: input_3
		Class: InputLayer
		Input:
		Name: conv1_pad
		Class: ZeroPadding2D
		Input: Input_1
		A Research of the second of the second of the
		Name: conv1_conv
		Class: Conv2D Input: conv1_pad
		input convi_pad
re-trained model		
		Name: conv1_bn
ResNet50	Layer configuration	Class: BatchNormalization
	Name conv1_conv	Input: conv1_conv
	activation linear	
	strides 2 x 2	
ustomize model		
New Model	dilation_rate 1 x 1	Name: conv1_relu
dd node class:	kernel_size 7 x 7	Class: Activation
	trainable true 🕑	Input: conv1_bn
Gnerate ML Model		
	padding valid	
aining Strategy	filters 64	
	Input conv1_pad	Name: pool1_pad
		Class: ZeroPadding2D
	Update Layer	Input: conv1_relu
	Remove Layer	
Strategy Config		
		Name: pool1_pool
		Class: MaxPooling2D
		Insut nool, and
		Input Model Label Train Result Output

Click "Model" click "OK" do not choose any model Load pre-trained model "ResNet50" **Neural Network Model editing:** 

Mouse click on layer component to display layer configuration \*Pre-trained model layers cannot be removed AI4EVER pre-trained (ImageNet) neural-network models

Model	Size (MB)	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth	Time (ms) per inference step (CPU)	Time (ms) per inference step (GPU)
Xception	88	79.0%	94.5%	22.9M	81	109.4	8.1
<u>VGG16</u>	528	71.3%	90.1%	138.4M	16	69.5	4.2
<u>VGG19</u>	549	71.3%	90.0%	143.7M	19	84.8	4.4
ResNet50	98	74.9%	92.1%	25.6M	107	58.2	4.6
EfficientNetB0	29	77.1%	93.3%	5.3M	132	46.0	4.9
EfficientNetB1	31	79.1%	94.4%	7.9M	186	60.2	5.6
EfficientNetB2	36	80.1%	94.9%	9.2M	186	80.8	6.5
EfficientNetB3	48	81.6%	95.7%	12.3M	210	140.0	8.8
EfficientNetB4	75	82.9%	96.4%	19.5M	258	308.3	15.1
EfficientNetB5	118	83.6%	96.7%	30.6M	312	579.2	25.3
EfficientNetB6	166	84.0%	96.8%	43.3M	360	958.1	40.4
EfficientNetB7	256	84.3%	97.0%	66.7M	438	1578.9	61.6

\* Pre-trained models are from Keras and TensorFlow

### **Neural Network Model Architecture**

•••	AI4EVER		AI4EVE	2
Pre-trained model	Name: input_1 Class: InputLayer Input:			Name: input_1 Class: InputLayer Input:
	Name: flatten Class: Flatten	Pre-trained model		Name: conv1_bn Class: BatchNormalization Input: conv1_conv
Customize model New Model	Input: input_1			Name: conv1_conv Class: Conv2D Input: conv1_pad
Add node class:		Customize model		
Conv2D 🔽 Gnerate ML Model	Name: predictions Class: Dense Input: flatten	New Model Add node class: Conv2D	Layer configuration Name conv1_conv filters 64	Name: flatten Class: Flatten
Training Strategy		Gnerate ML Model	strides 2 × 2 dilation_rate 1 × 1	Input: input_1
Strategy Config		Strategy Config	kernel_size     7     x     7       trainable     true     Incar     Incar       activation     linear     Incar     Incar       padding     valid     Valid       Input     conv1_pad       Update Layer       Remove Layer	Name: predictions Class: Dense Input: flatten
	Input Model Label 💿 Train 🕜 Result Output		Input	Model Label 💿 Train 🔍 Result Output

Click "New Model"

Default three layers: input, flatten, dense(output)

Select neural-network layers from "Add node class" Click on layer component to trigger layer editor \*Drag layer component to change their positions \* Need to type layer names for input and output

### Training

AMAYER  Mark 1991.3  Gata Rend.aw  Rept  Gata Rend.aw  Gata Cond.aw  Gata Cond.aw  Gata Cond.aw  Gata Cond.aw  Cond	AI4	AI4	AI4
	EVER	EVER	EVER
	Training Strategy Panel	Training Strategy Panel	Training Strategy Panel
<form></form>	Test   data   Training   data   Training   doc   Weights     Batch   4   Training   3   Optimizer   Adam   Loss   Function   mean_squared_error   Adjust Training & Validation Ratio   Start!   Script!   Cancel	Irain Ratio Colored Colored Co	Image Rotate in degrees x 1            Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate in degrees x 1           Area Rotate Rota

- Start: To train at the background
- Script: To generate command line script and all files to run on server or other computer

# **Collaborators and funding**



Arron Carter



Mike Pumphrey



Karen Sanguinet



Kawamu Tanaka



Sindhuja Sankaran



Longxi Yu



Jack Brown



Ananth Kalyanaraman



Kim Campbell



Deven See



**Camille Steber** 



Mike Peel









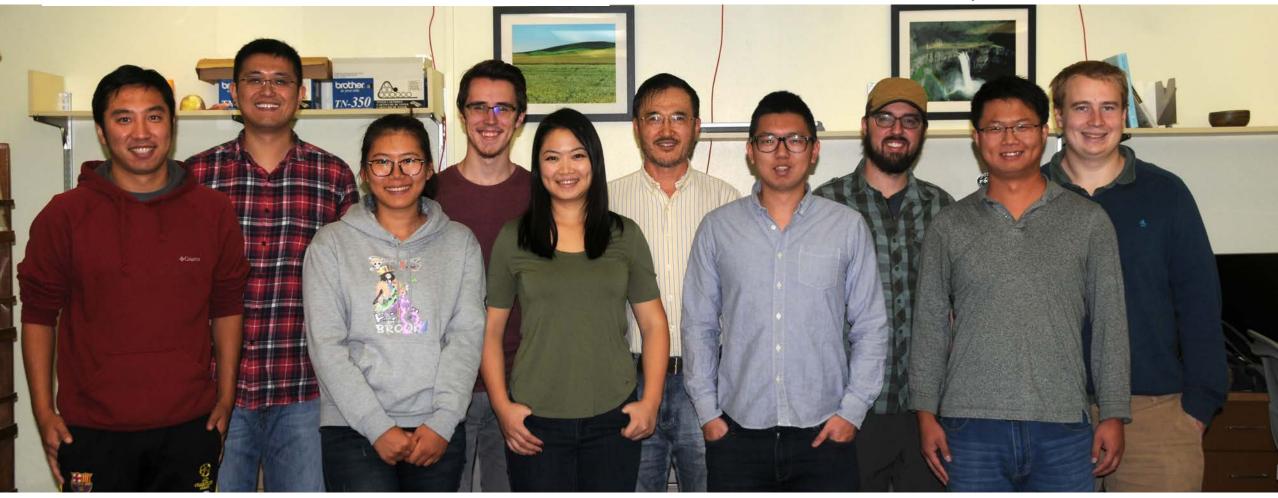
















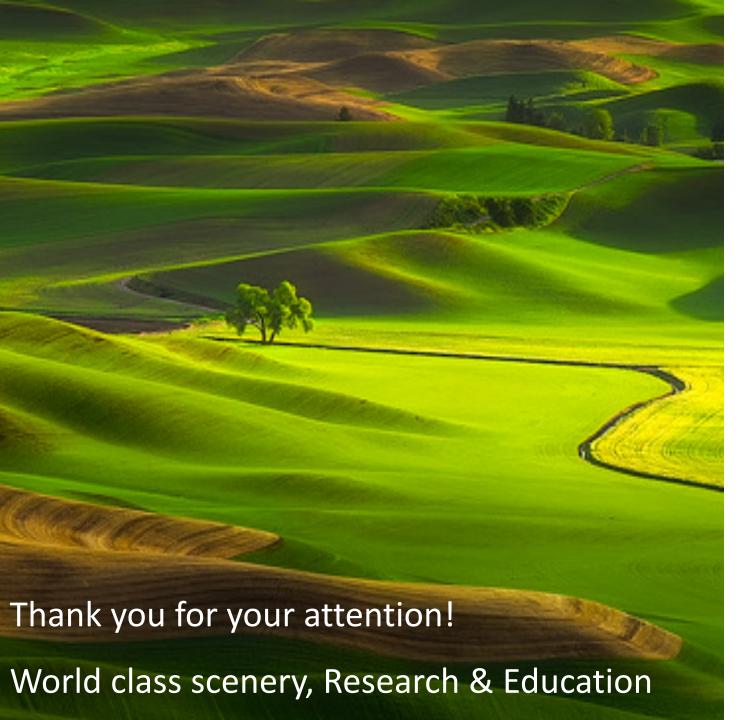












#### WASHINGTON STATE

Department of Crop and Soil Sciences



#### 张志武教授在中国定向招收博士研究生数名

美国华盛顿州立大学, Pullman, WA, USA
国家留学基金委(CSC)奖学金(四年)获得者
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