Applied Computer Vision in Agriculture

IndabaX - Dodoma

Denis Pastory
PhD. Agricultural Engineering
Tokyo University of Agriculture

Why agriculture

Food security as main focus for **development** and **poverty reduction** (Graef et al 2017)

Agriculture challenges
Abiotic factor – Environment, mineral nutrients, temperature, water
Biotic factors – insects, mites, and disease pathogens

Other
Lack of finance
Poor infrastructure
Lack of market and storage facilities
Technical skills - Lack of expert knowledge

Why care anyway?

Poor infrastructure

No market, late harvest

Early harvest, No market

No market, late harvest

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No market, late harvest

Queleaquelea – E.A. Road, Arusha

Background

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Abiotic factor – Environment, mineral nutrients, temperature, water
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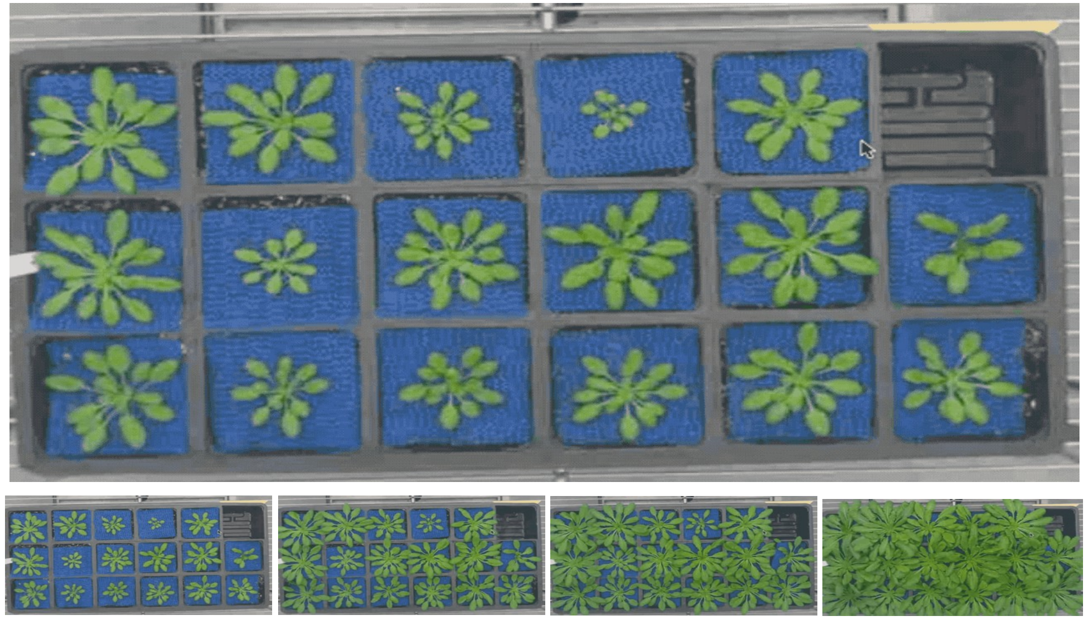
Understanding crop stress effects to crop production (food security and poverty alleviation)
(Munishi et al, 2015)

Growth is dynamic

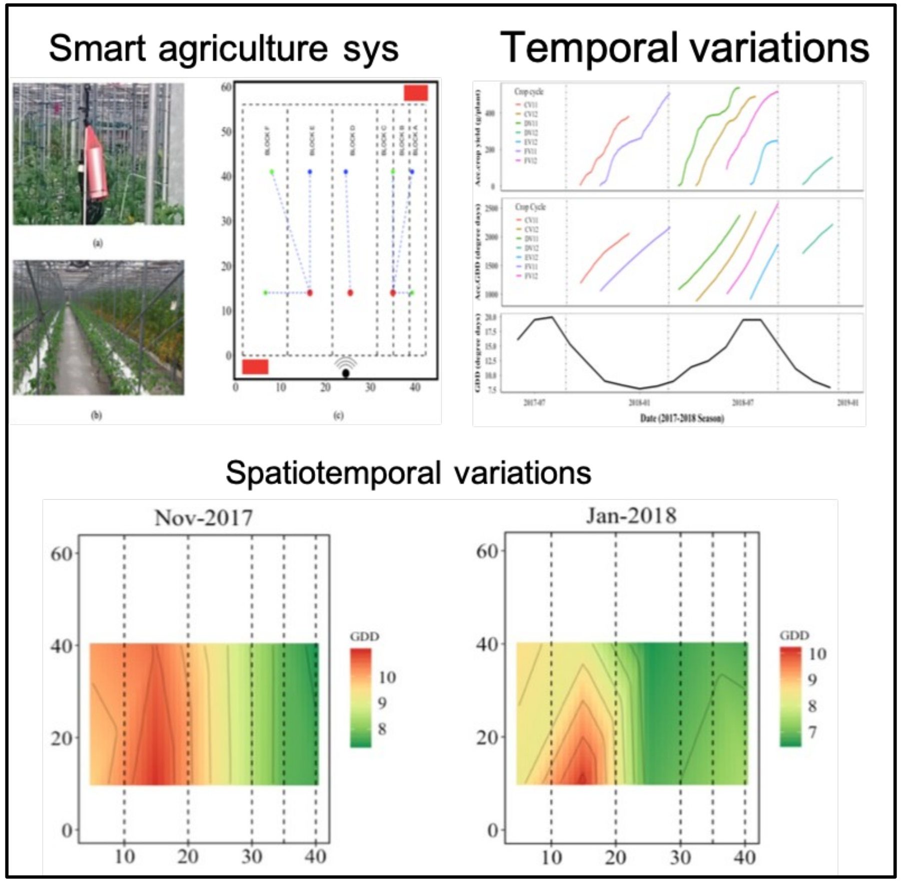


$t_0 \longrightarrow t_n$

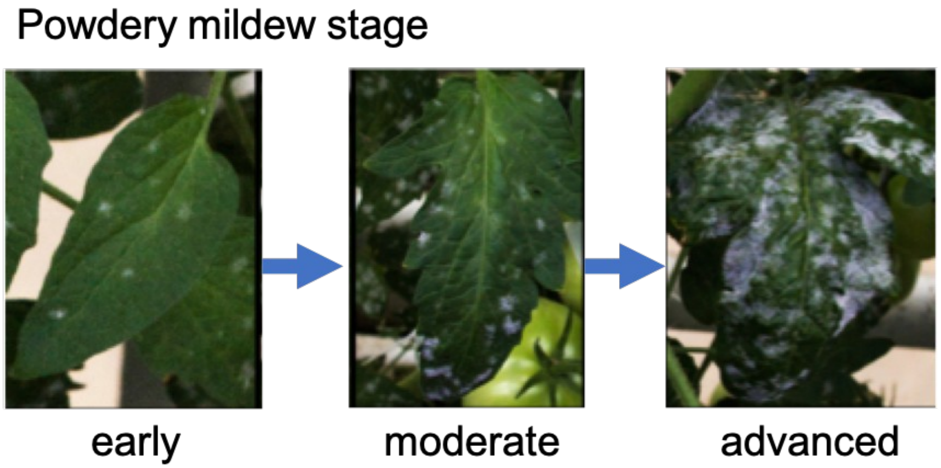
PlantVillage
https://plantcv.danforthcenter.org/

Plant Growth stage

It’s complex…



Source: Denis *et al* (2019)



An **accurate** and **faster detection** of disease and pests in plants could help to develop an **early treatment** technique while substantially reducing **economic loss**.

Information in image

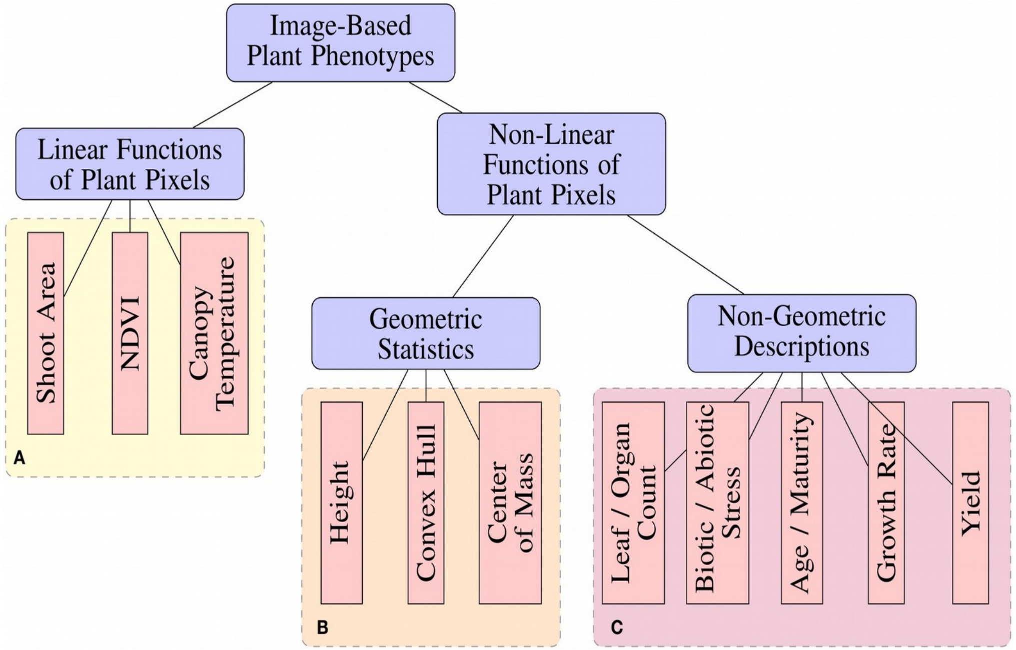
- **Computer Vision** is a branch of computer science concerned with recognizing objects automatically, extraction, analysis and understanding of useful information from a single image or sequence of images

Extract information from images

- Minsky said *“Connect a camera to a computer and do something with it” to* Sussman MIT- Artificial Intelligence Group (**1966)**

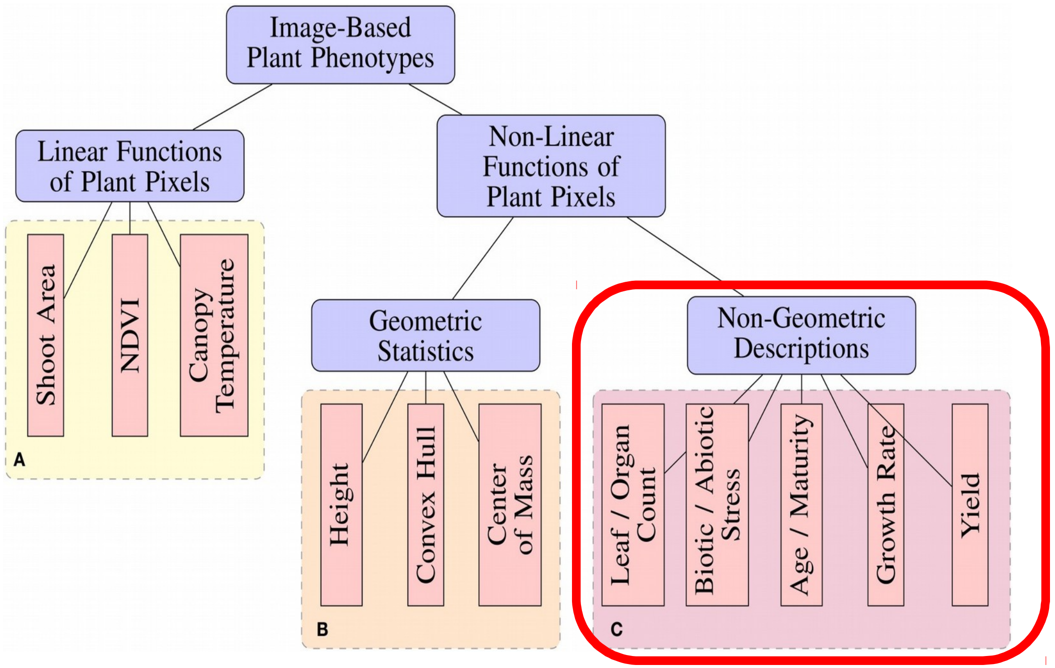
- Breakthrough happened in **2012** in particular **Convolutional Neural Networks** (CNN)

Image-based plant phenotyping tasks



A, B measured accurately using classical image processing techniques.

Image-based plant phenotyping tasks

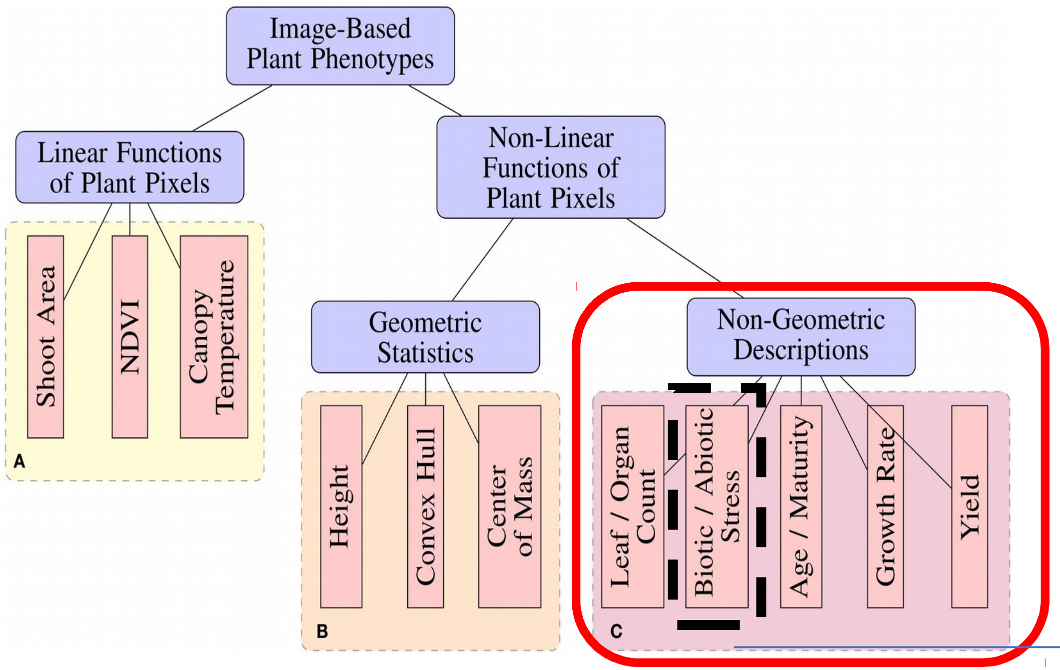


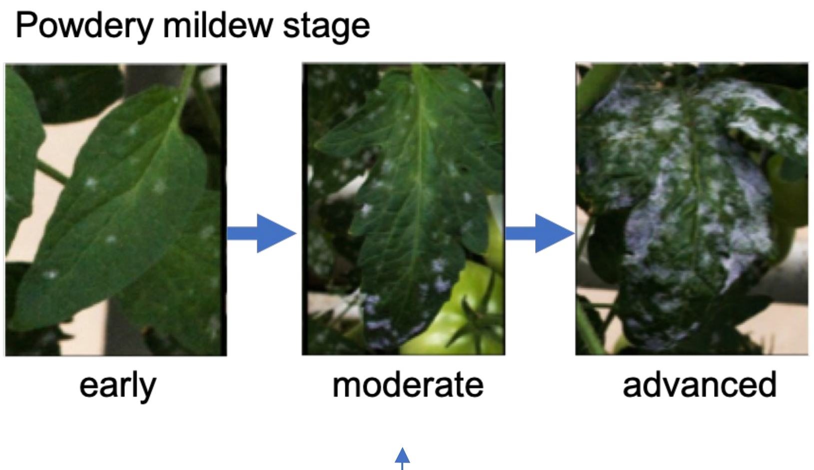
A, B measured accurately using classical image processing techniques.

C complex phenotyping task requiring more sophisticated analysis.

Here is the main challenge

Image-based plant phenotyping tasks.



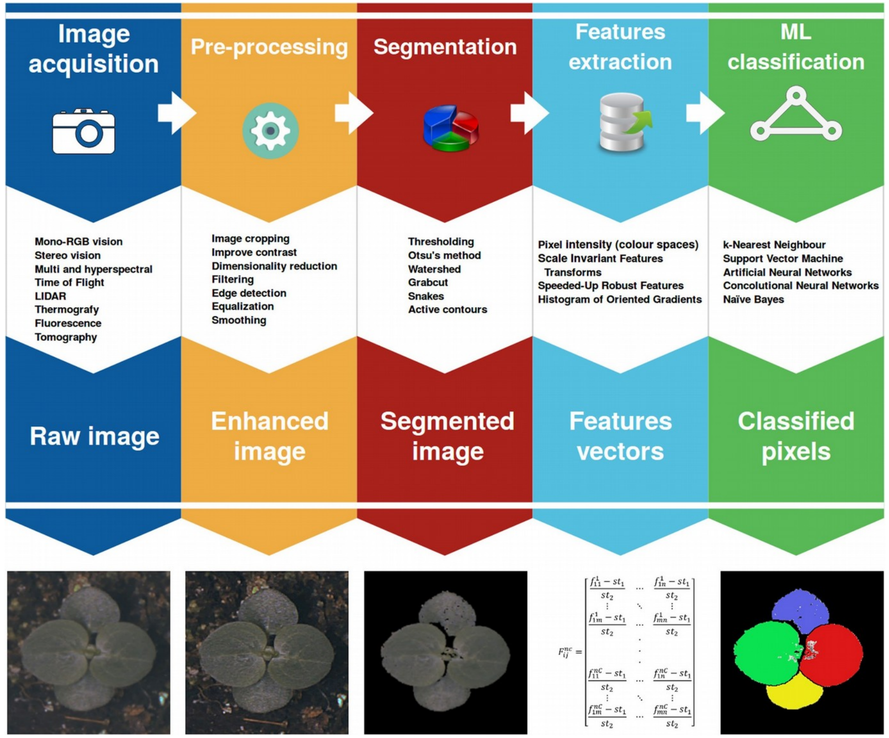


A, B measured accurately using classical image processing techniques.

C complex phenotyping task requiring more sophisticated analysis.

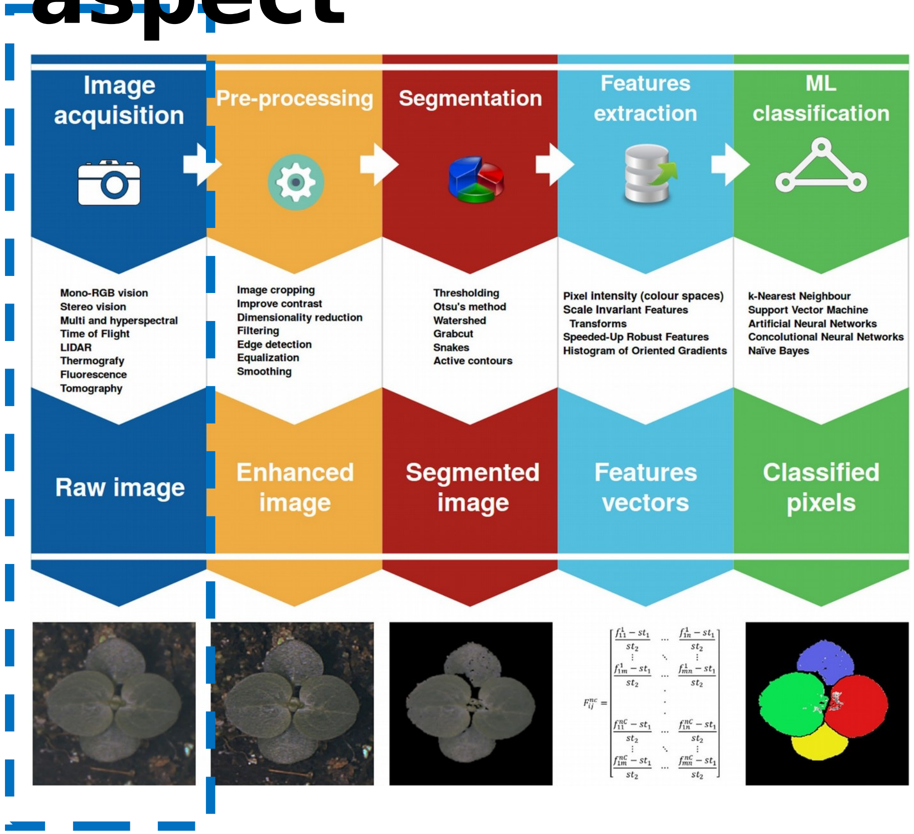
Here is the main challenge

the approach…



Perez-Sanz et al. (2017)

Key aspect



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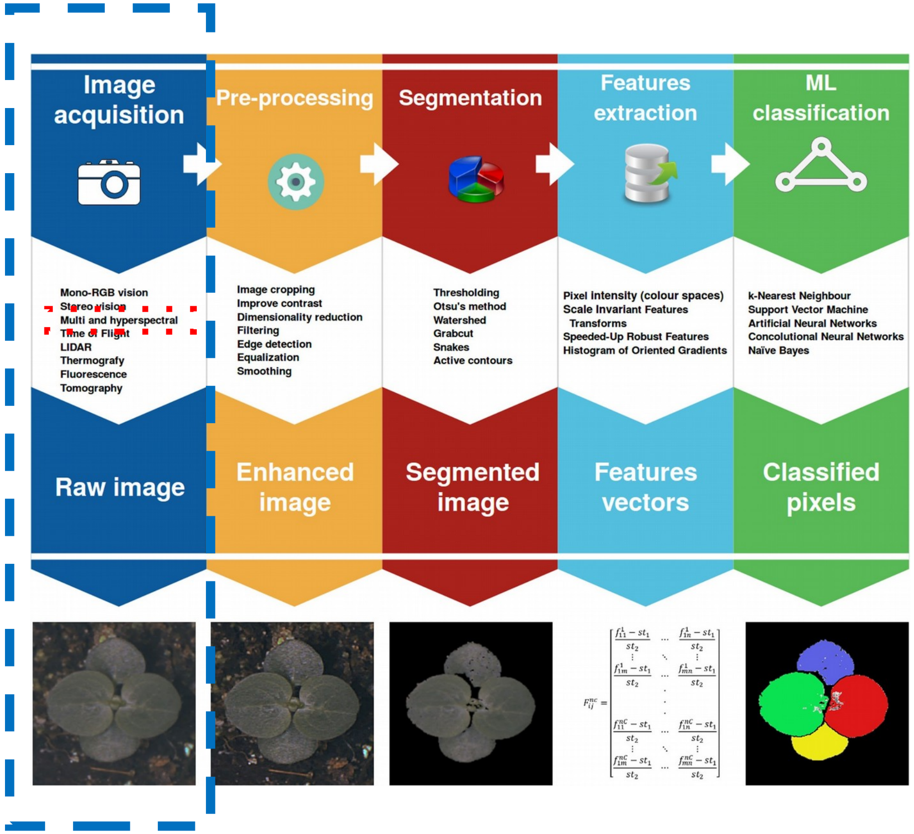
the approach



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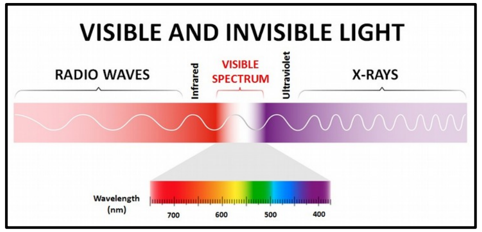

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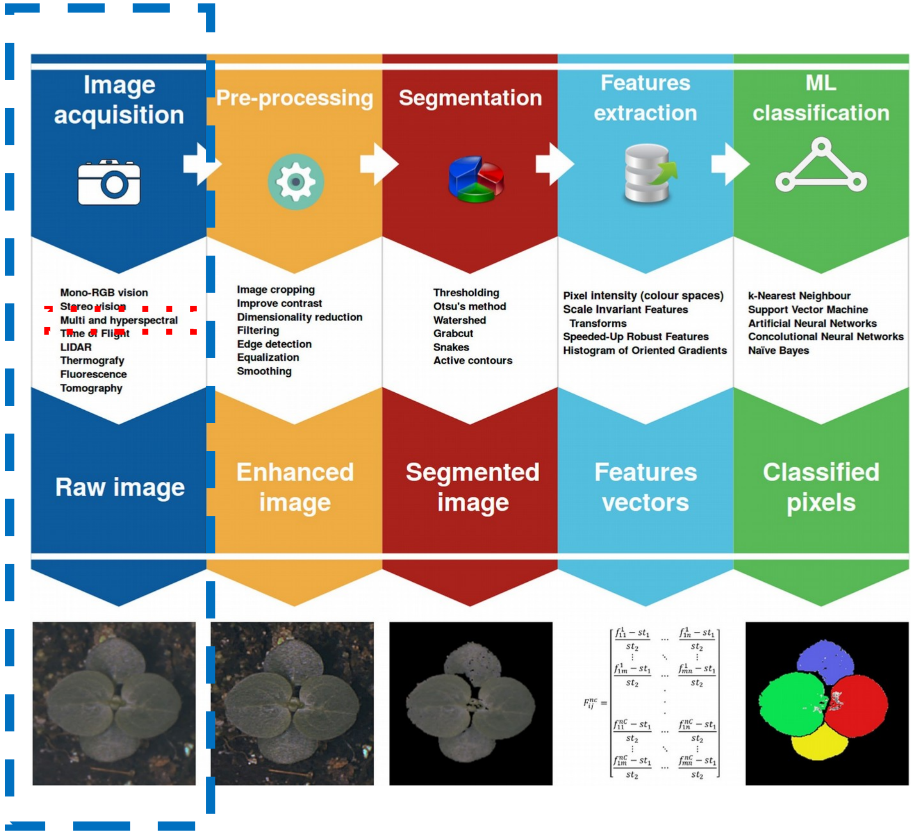

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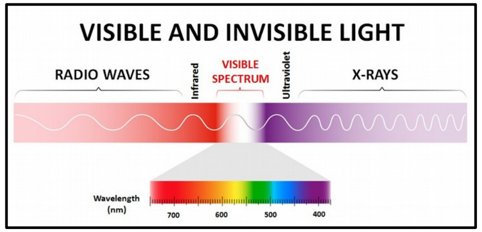
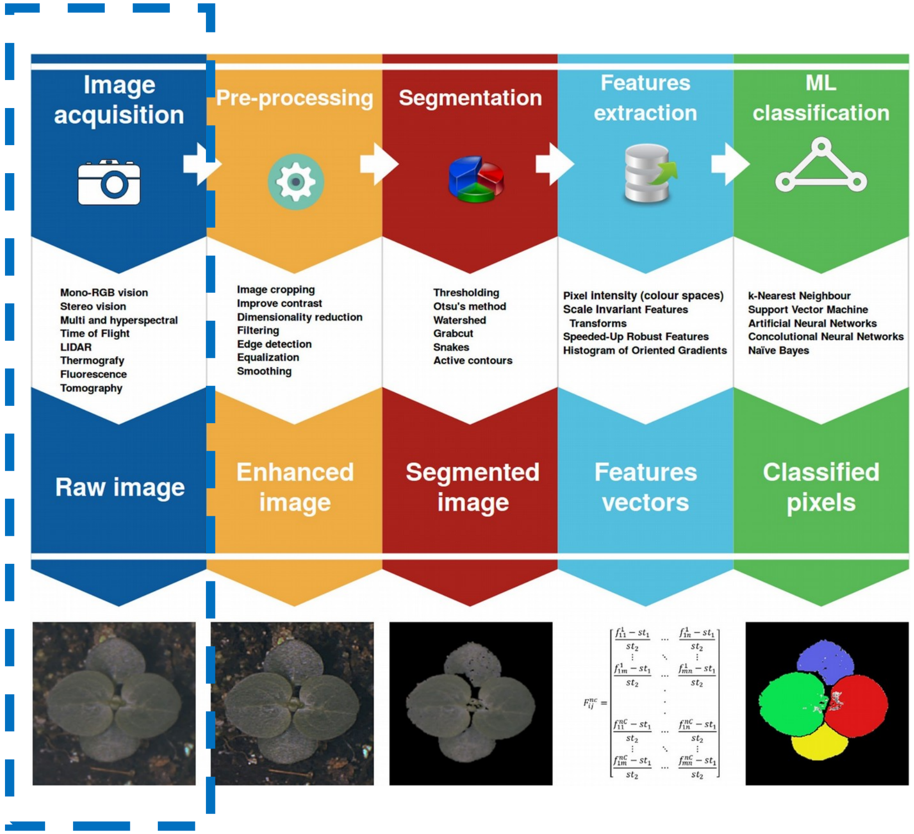


Aspect matters



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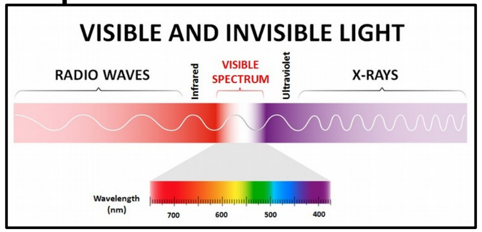
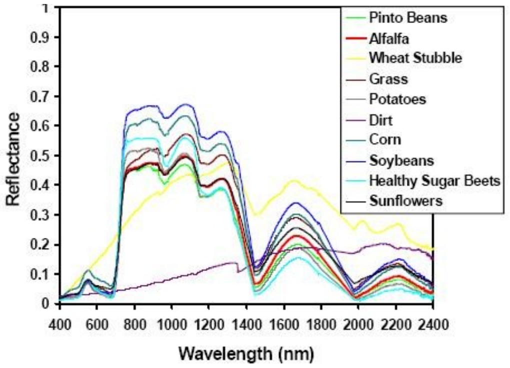
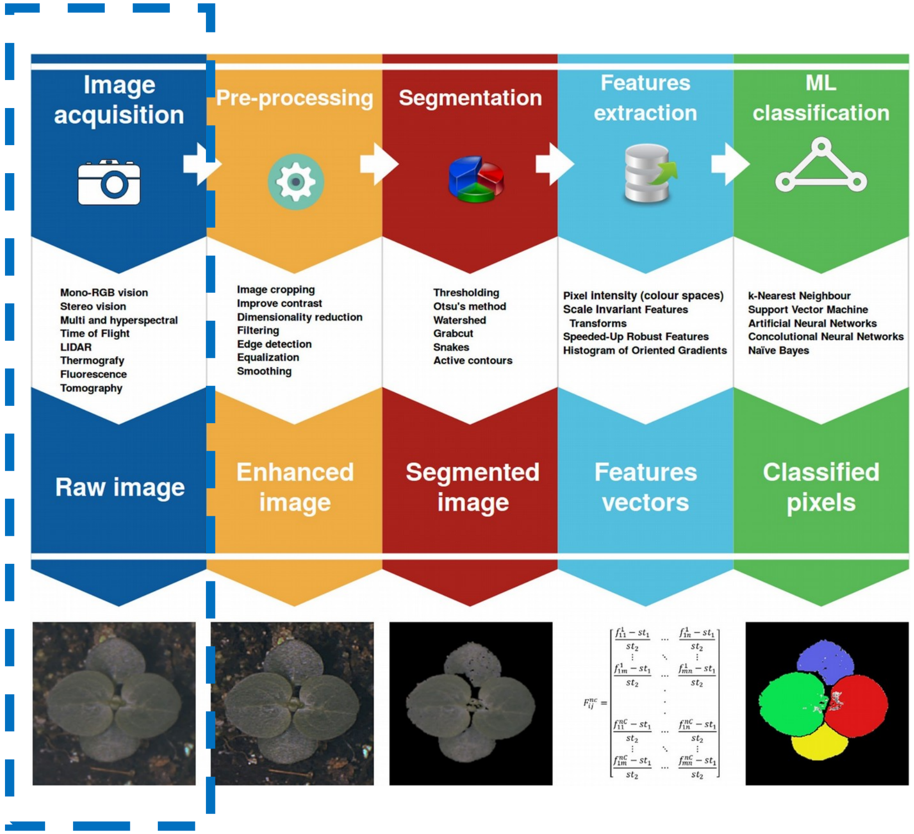


Spectral **signatures** of crops and soil



Kyllo, 2003

It still matters



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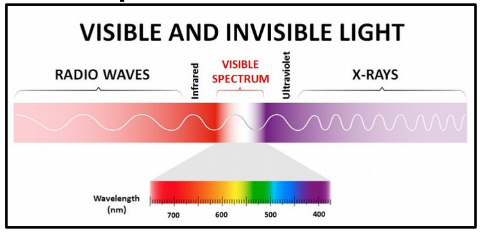

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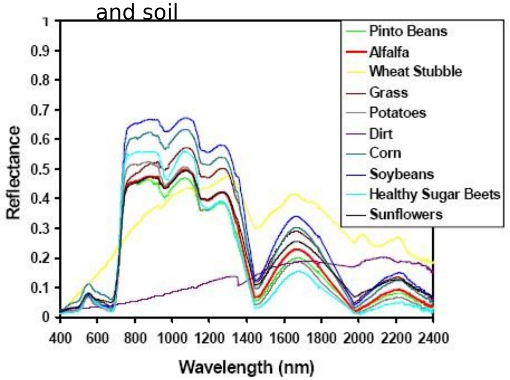
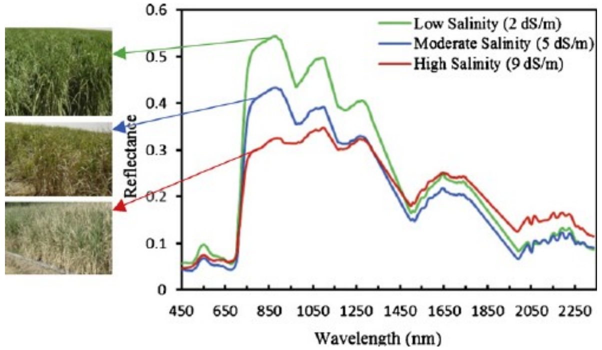
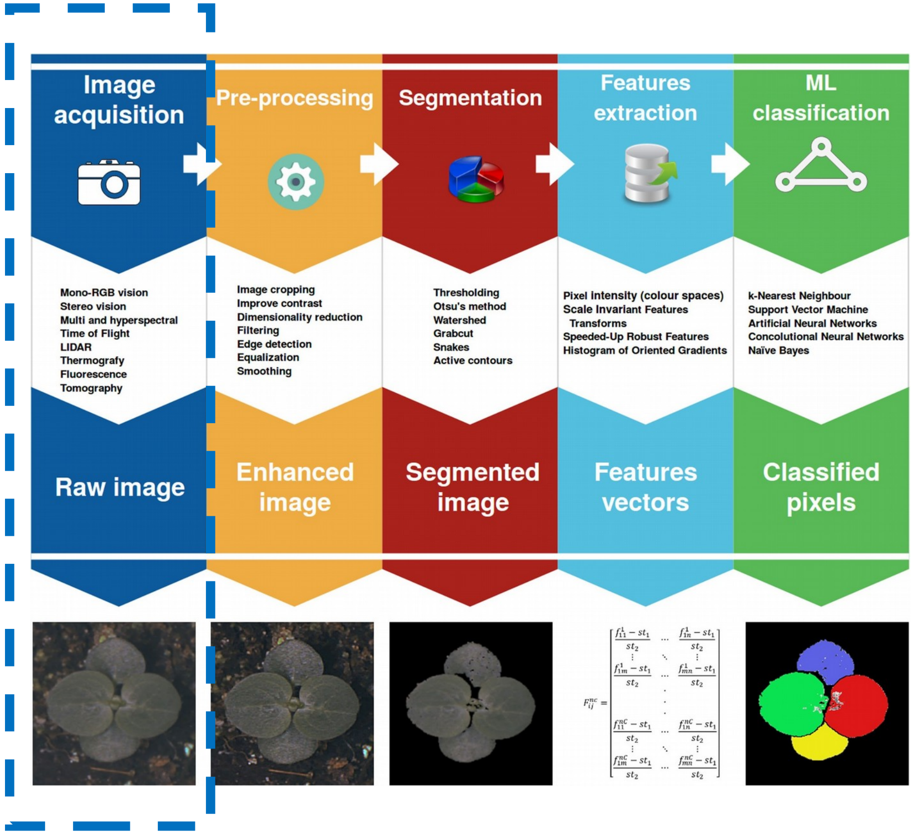


Kyllo, 2003

Further …





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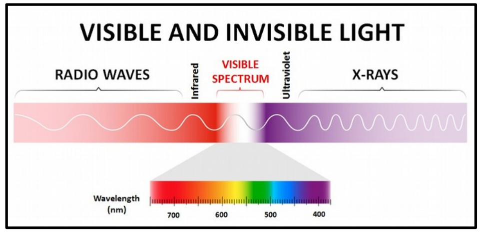

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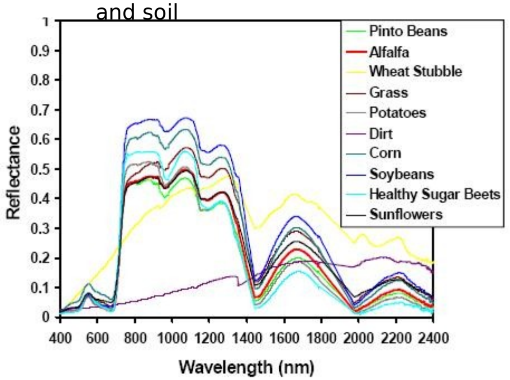
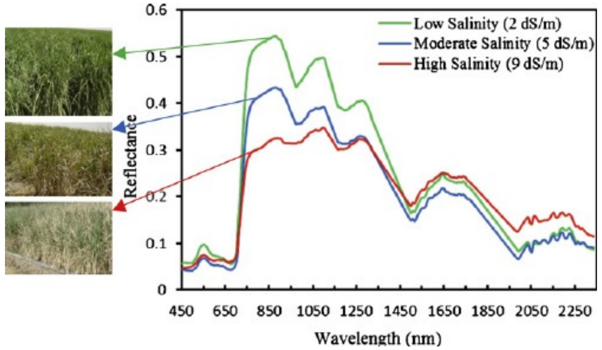


Kyllo, 2003

Further …

Image of large irrigation scheme

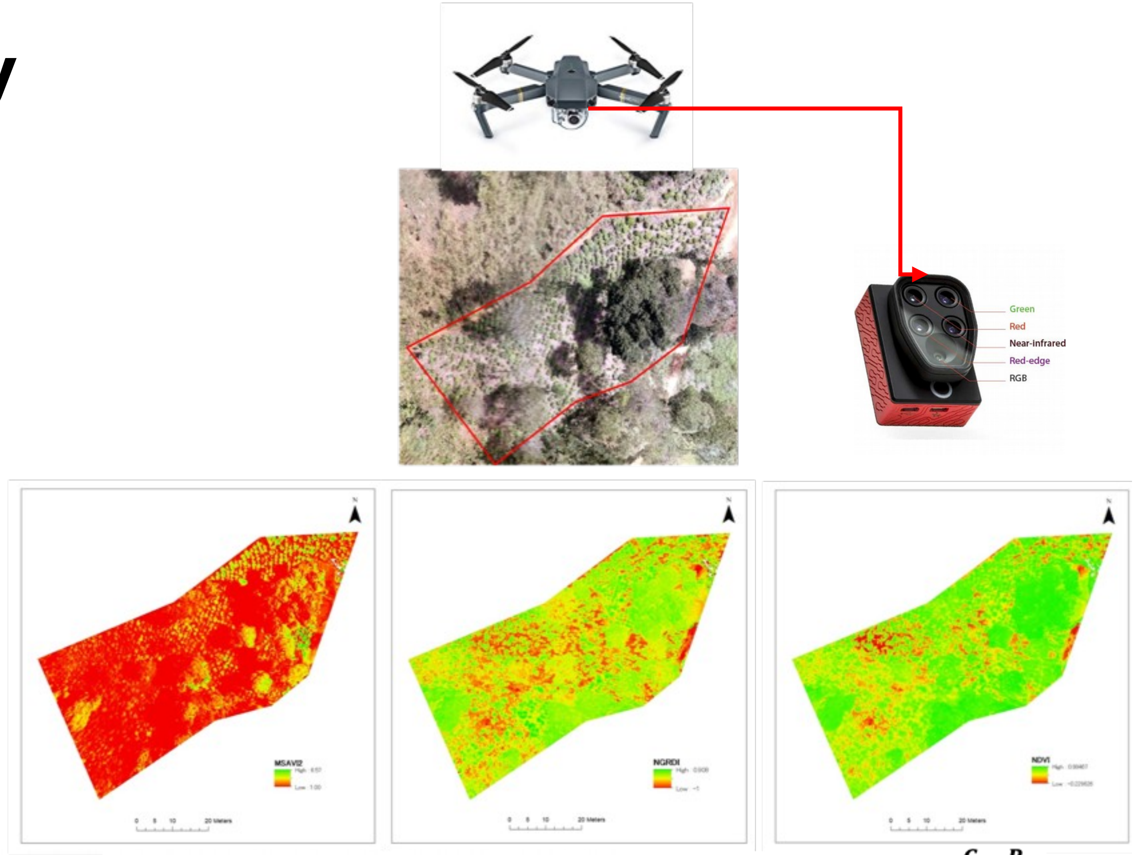


the power in image

Monitoring Photosynthetically Active Biomass of Tea Plant canopies, korogwe-Tanga

Tools
UAV- Mavic Pro (DJI)
Multispectral camera – Parrot Sequoia

Results showed 40% of active biomass

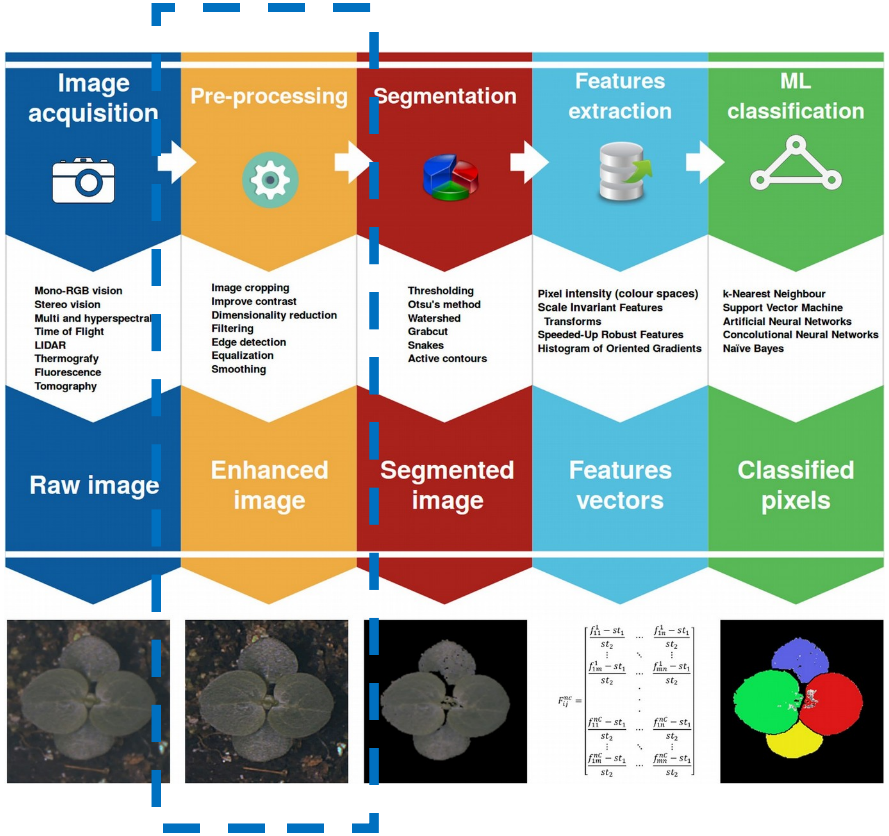


$$MSAVI2 = \frac{(2NIR + 1) - \sqrt{(2NIR + 1)^2 - 8(NIR - R)}}{2}$$

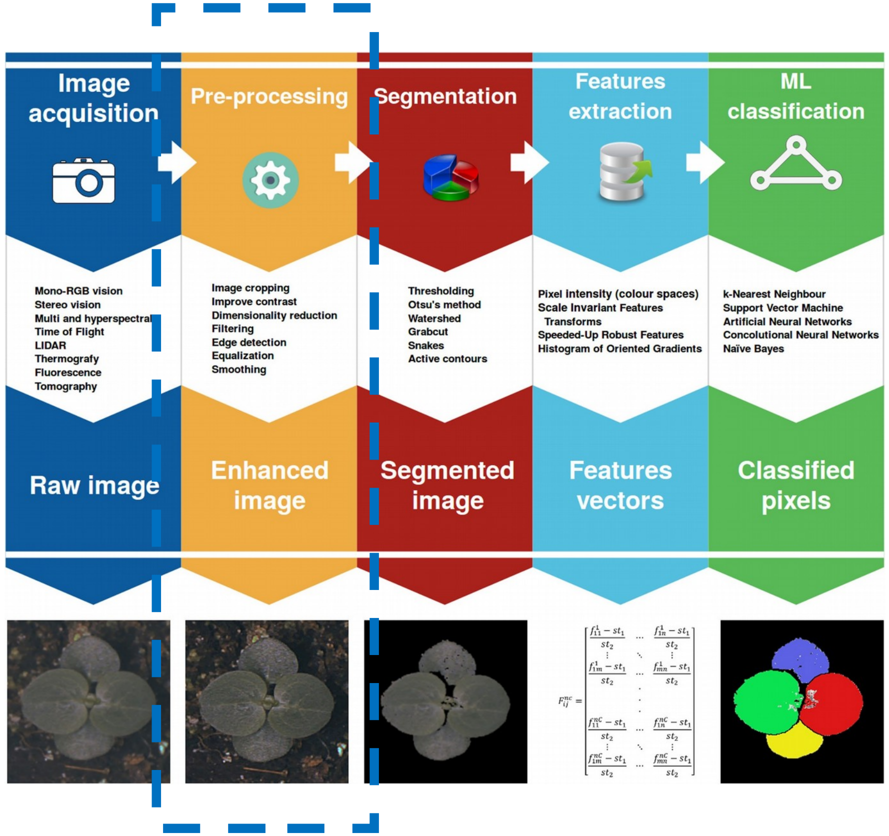
$$NDVI = \frac{NIR - R}{NIR + R}$$

$$NGRDI = \frac{G - R}{G + R}$$

Enhance image



use a tool



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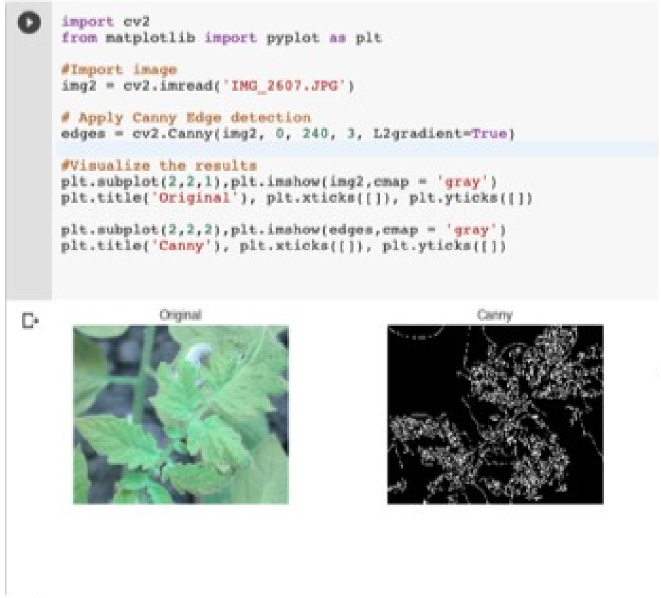
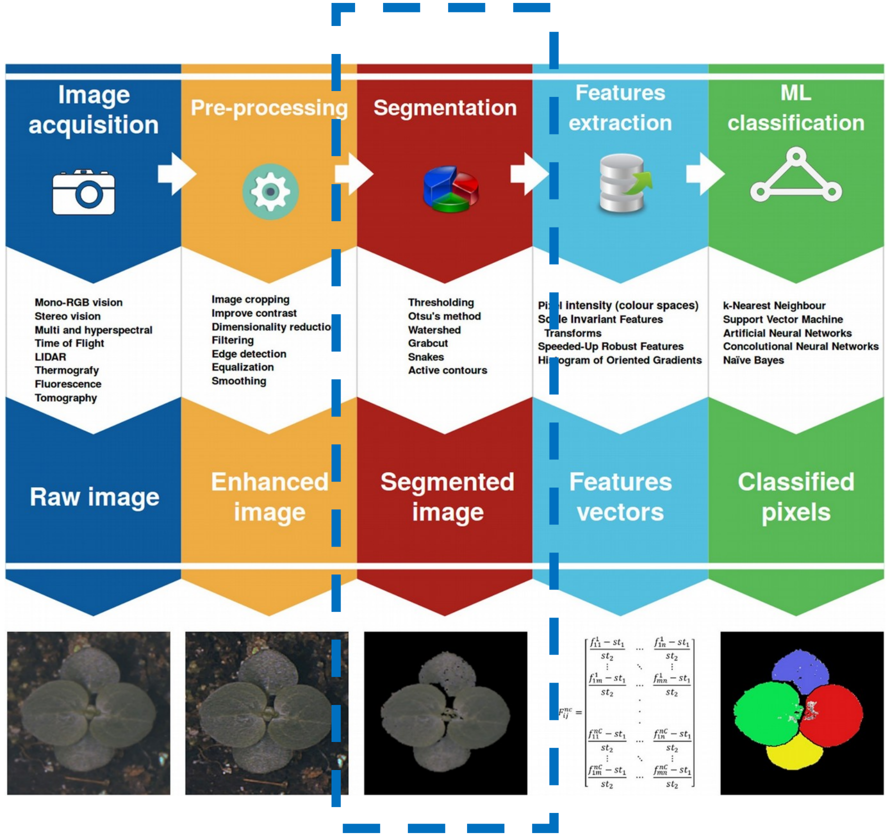
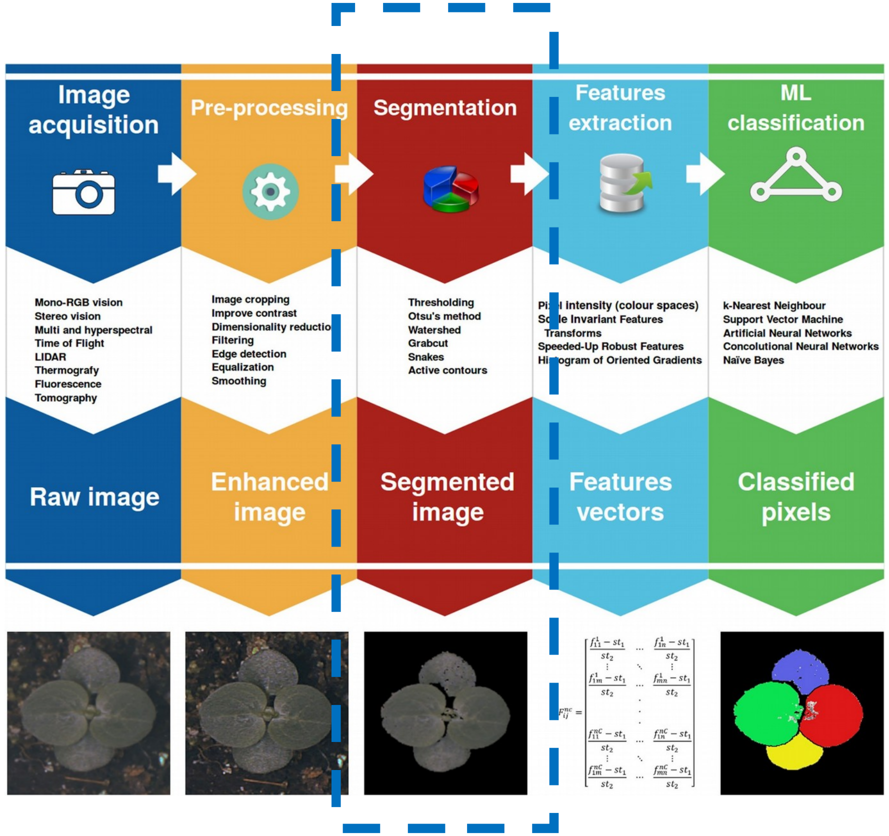


import cv2
from matplotlib import pyplot as plt
#Import image
img2 = cv2.imread('IMG_2607.JPG')
# Apply Canny Edge detection
edges = cv2.Canny(img2, 0, 240, 3, L2gradient=True)
#Visualize the results
plt.subplot(2,2,1),plt.imshow(img2,cmap = 'gray')
plt.title('Original'), plt.xticks([]), plt.yticks([])
plt.subplot(2,2,2),plt.imshow(edges,cmap = 'gray')
plt.title('Canny'), plt.xticks([]), plt.yticks([])
Original
Canny

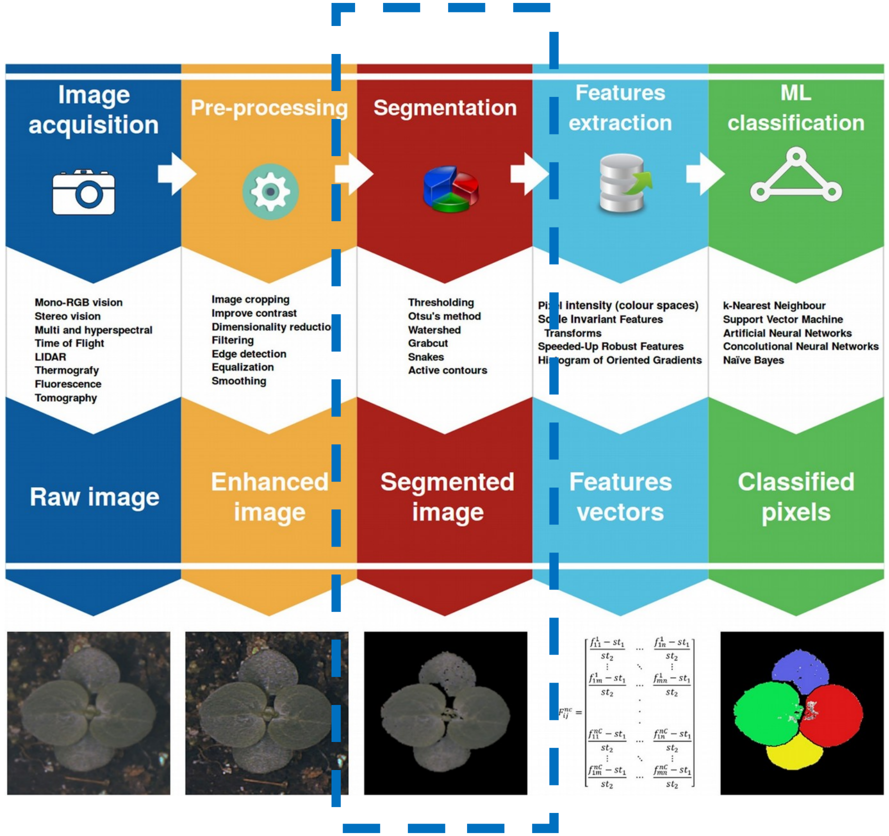
Segmented image



Segmented image



3
channel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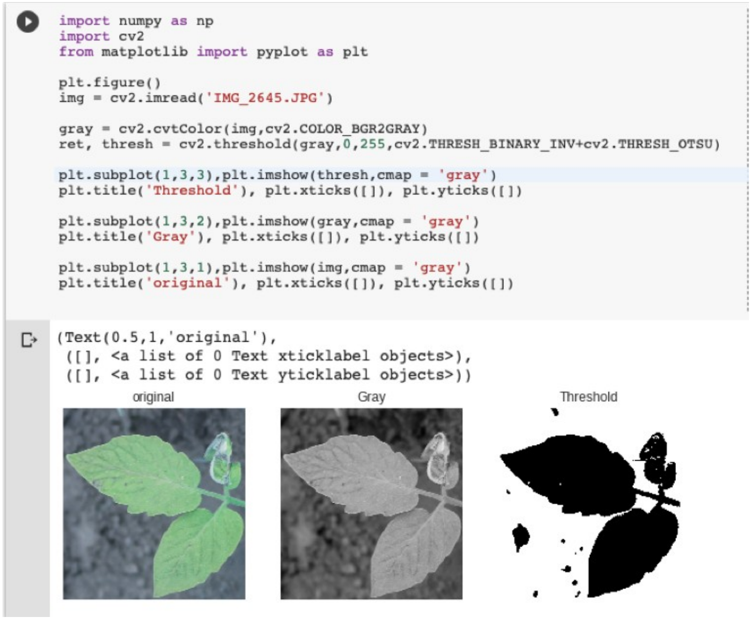
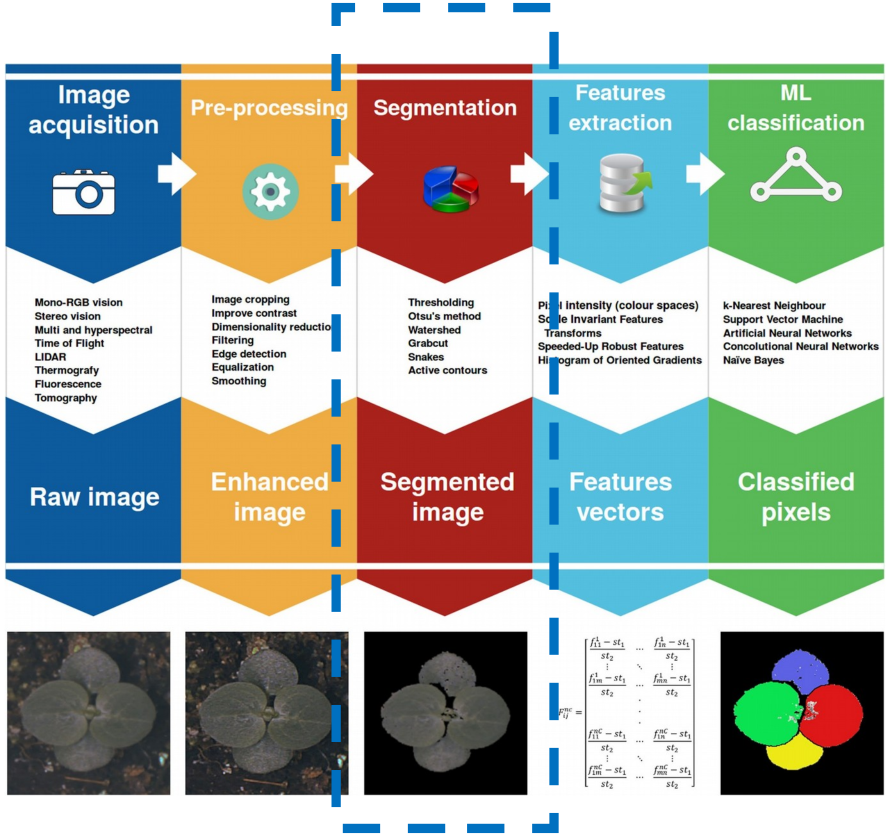
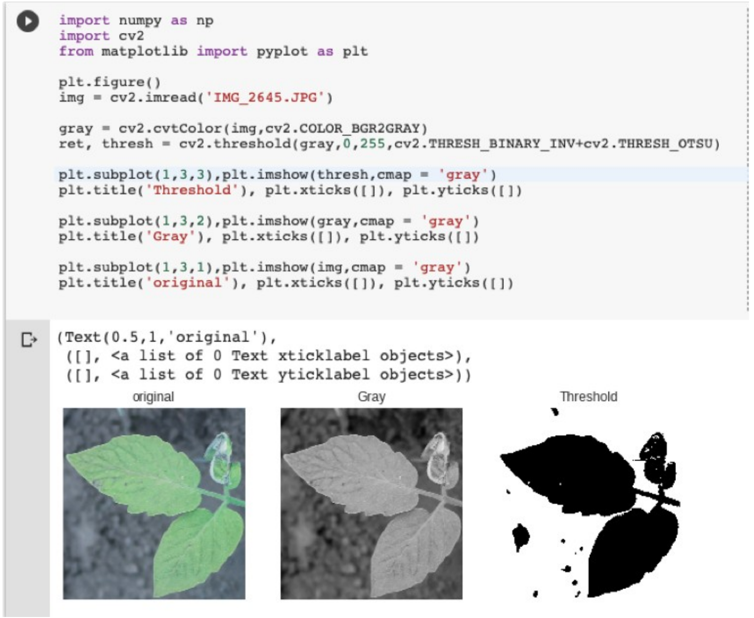

import numpy as np
import cv2
from matplotlib import pyplot as plt
plt.figure()
img = cv2.imread('IMG_2645.JPG')
gray = cv2.cvtColor(img,cv2.COLOR_BGR2GRAY)
ret, thresh = cv2.threshold(gray,0,255,cv2.THRESH_BINARY_INV+cv2.THRESH_OTSU)
plt.subplot(1,3,3),plt.imshow(thresh,cmap = 'gray')
plt.title('Threshold'), plt.xticks([]), plt.yticks([])
plt.subplot(1,3,2),plt.imshow(gray,cmap = 'gray')
plt.title('Gray'), plt.xticks([]), plt.yticks([])
plt.subplot(1,3,1),plt.imshow(img,cmap = 'gray')
plt.title('original'), plt.xticks([]), plt.yticks([])
(Text(0.5,1,'original'),
([], <a list of 0 Text xticklabel objects>),
([], <a list of 0 Text yticklabel objects>))
original
Gray
Threshold





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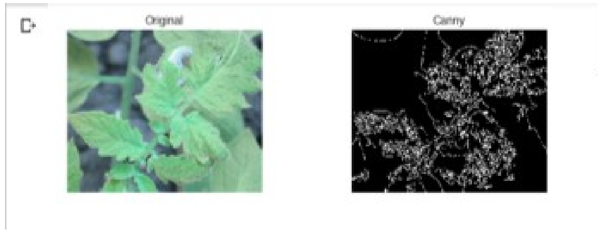
plt.subplot(1,3,3),plt.imshow(thresh,cmap = 'gray')
plt.title('Threshold'), plt.xticks([]), plt.yticks([])

plt.subplot(1,3,2),plt.imshow(gray,cmap = 'gray')
plt.title('Gray'), plt.xticks([]), plt.yticks([])

plt.subplot(1,3,1),plt.imshow(img,cmap = 'gray')
plt.title('original'), plt.xticks([]), plt.yticks([])
```

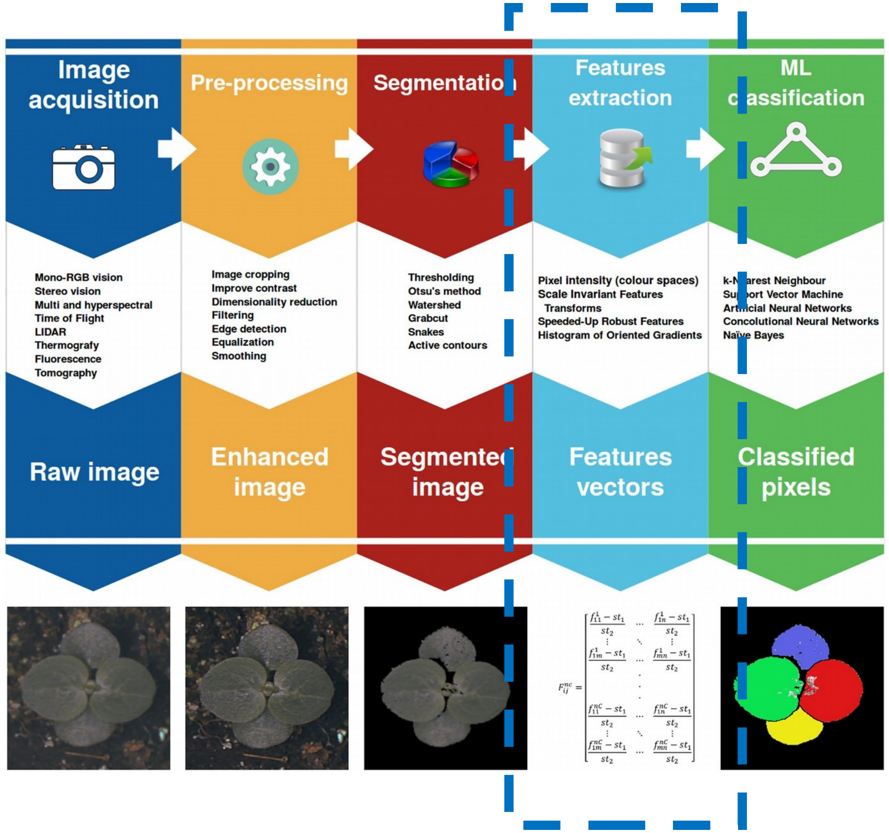
```
(Text(0.5,1,'original'),
 ([], <a list of 0 Text xticklabel objects>),
 ([], <a list of 0 Text yticklabel objects>))
```


Not **confuse** with previous



Detect **edge suppress** noise

Features are the bottom line



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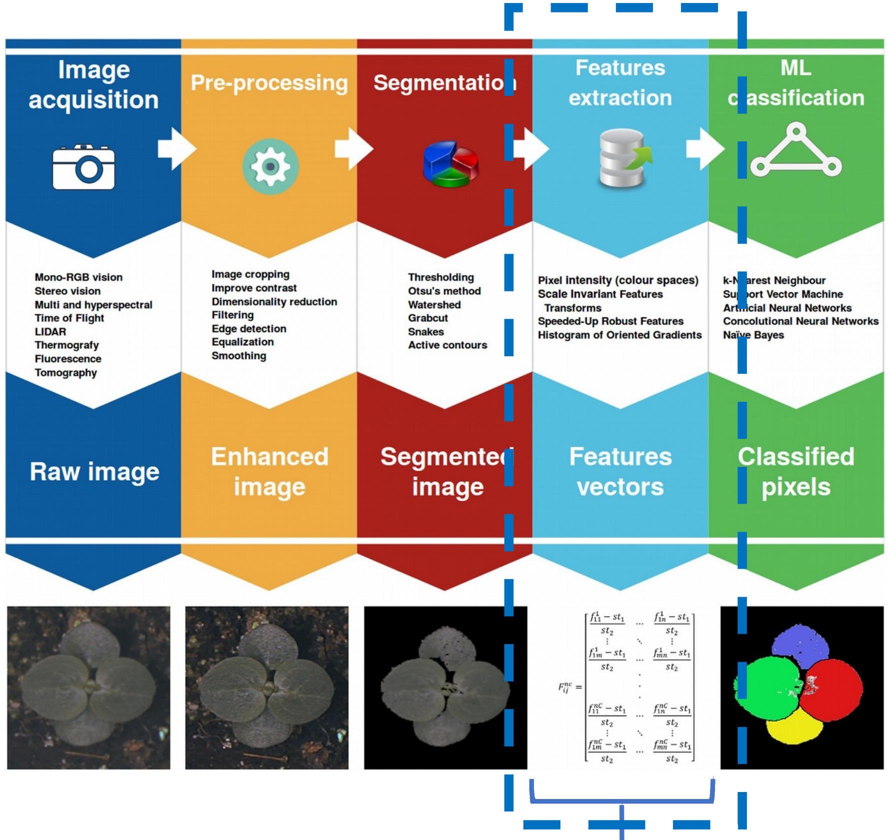
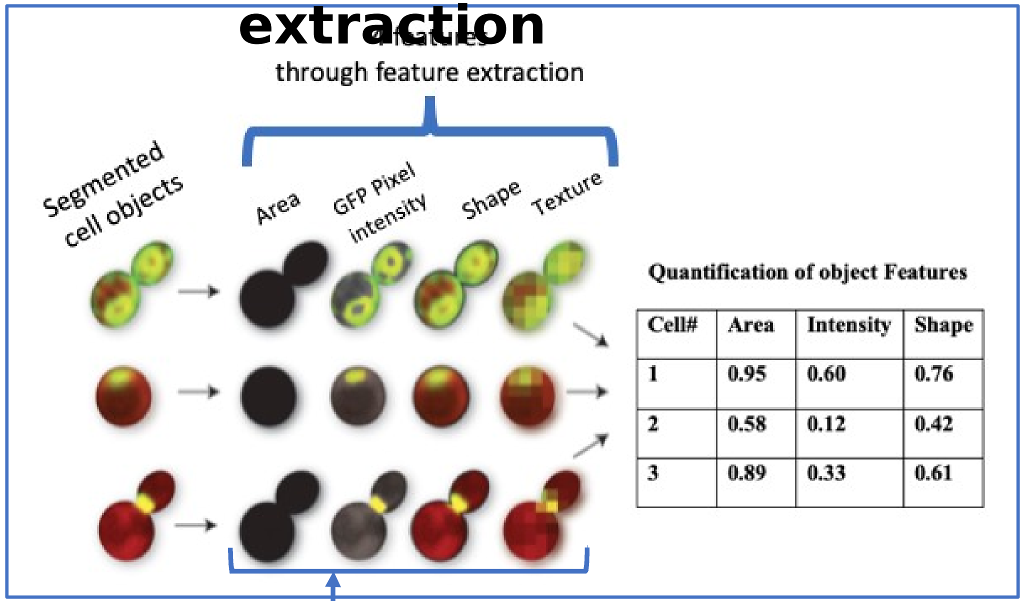
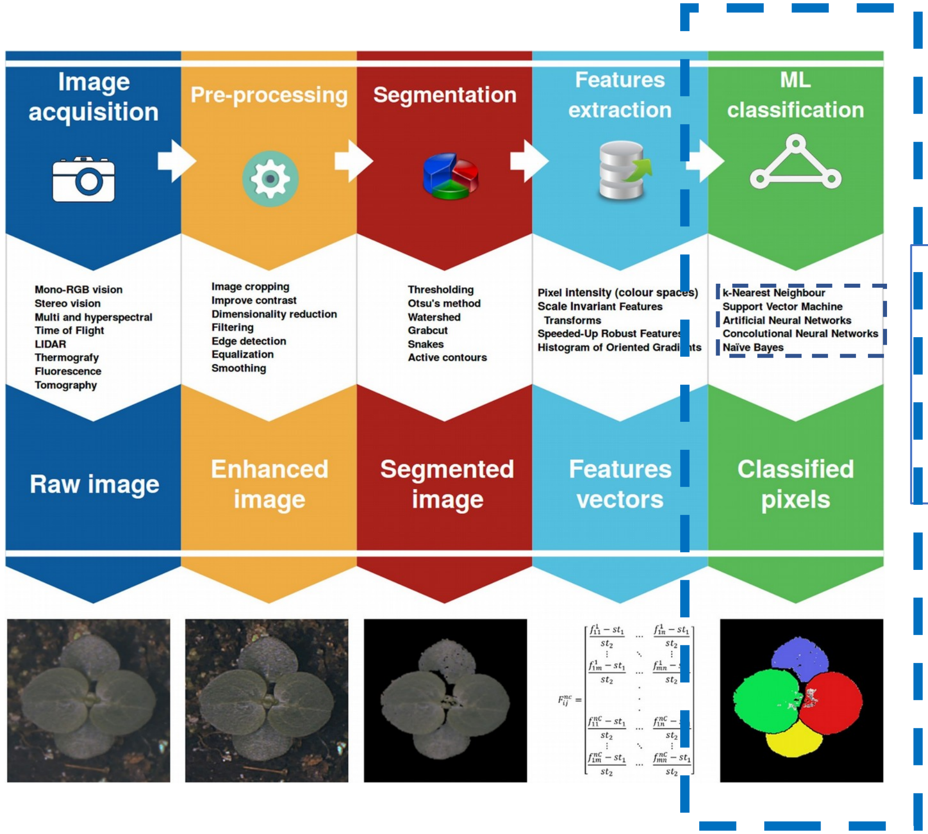


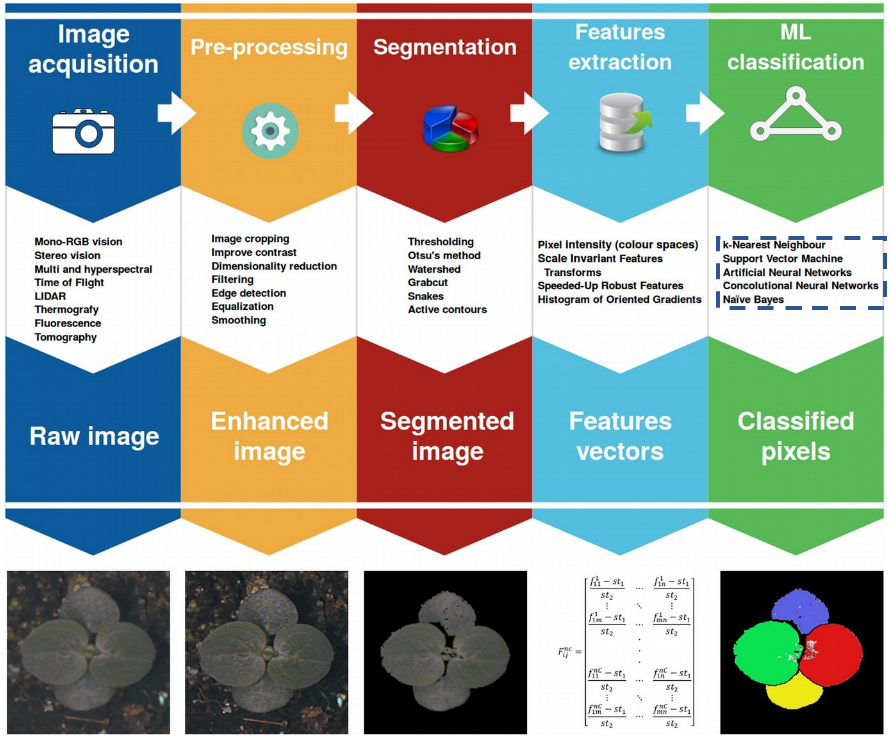
Feature extraction



Morphology- size, shape
Texture features- quantify spatial statistics of pixel intensities



K-Nearest Neighbor
SVM
ANN
CNN
Naïve Bayes



K-Nearest Neighbor
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CNN powerful machine learning algorithms for processing images

Agriculture challenges

Abiotic factor – Environment, mineral nutrients, temperature, water

Biotic factors – insects, mites, and disease pathogens

Understanding crop stress effects to crop production (food security and poverty alleviation)

A case study

Tomato Leaf Miner (T. *absoluta)*
case study

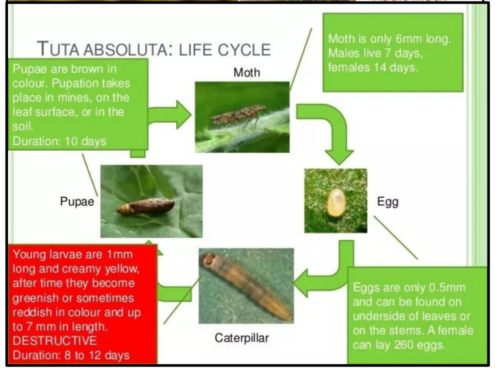
- Invasive tomato pest a major **threat** to tomato production
- Origin – Peru (Central America, Europe, Africa, Middle East and Asia)

(Biondi, A. et al. 2018)

- First occurance report Ngare nanyuki in **2014** Already in 13 regions.

(Zekaya)

- High yield loss **50 – 100%** sub-sahara
(Tonnang HE et al. 2015)



T.*Absoluta* life cycle

Low
damage

moderate
damage

Very severe
damage

Low
damage

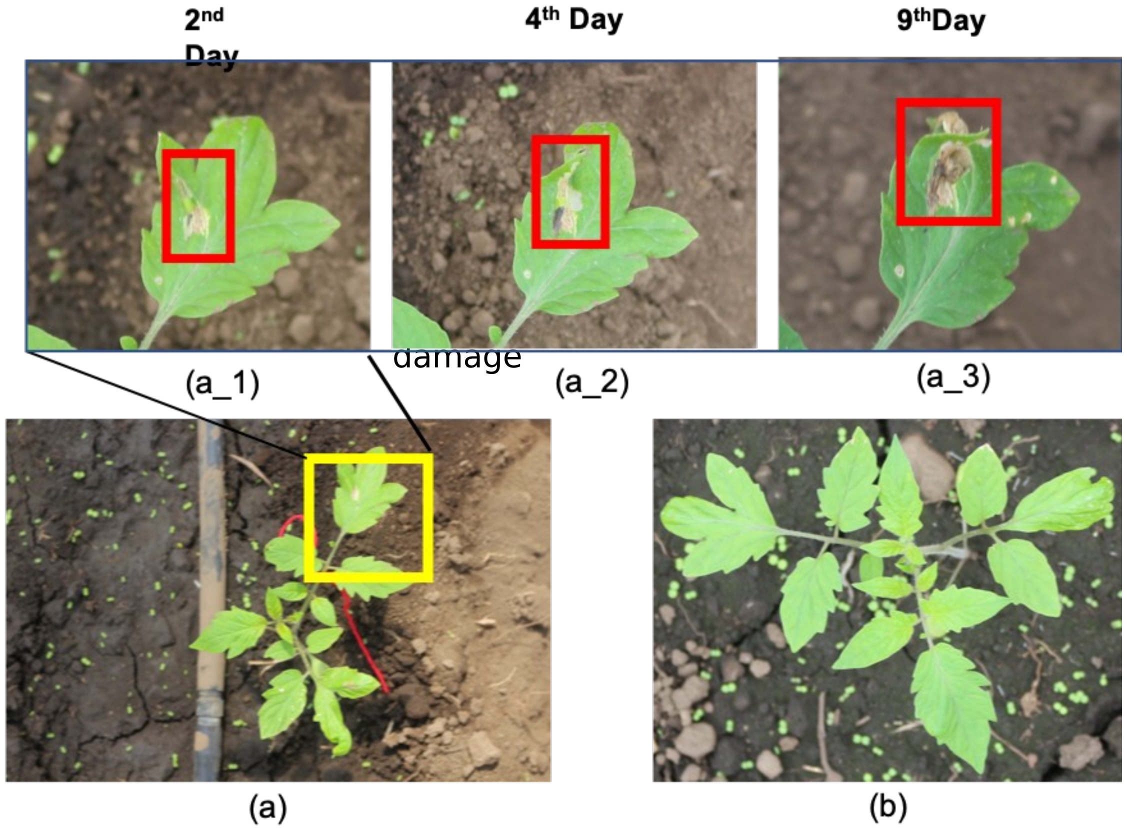
moderate
damage

Very severe
damage

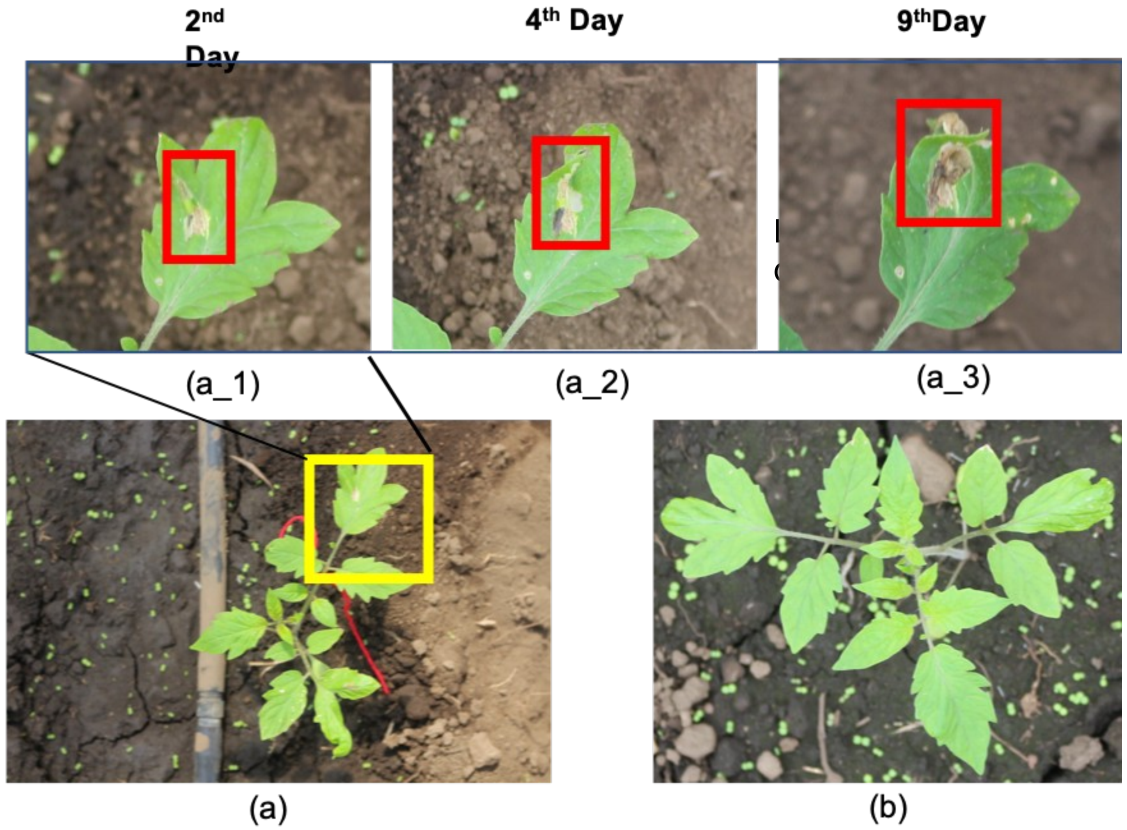
…..Possible solution..

An **accurate** and **faster detection** of disease and pests in plants could help to develop an **early treatment** technique while substantially reducing **economic loss**.

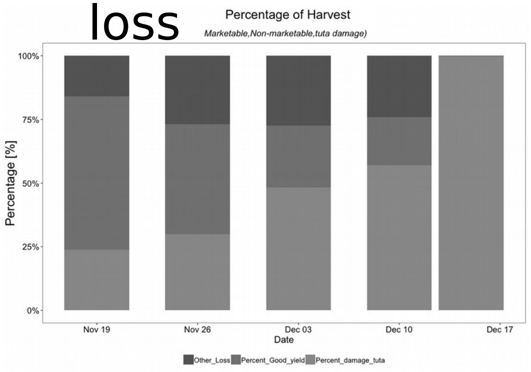
Early detection for early management and control of T.*absoluta*

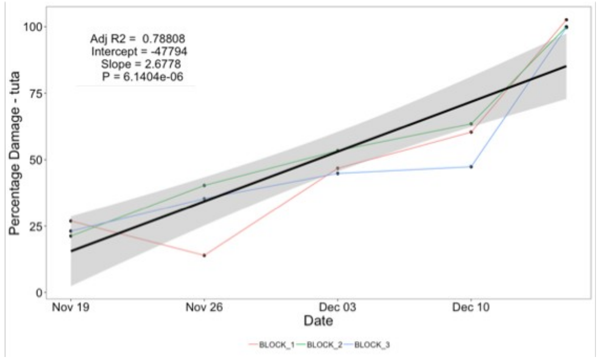


Early detection for early management and control of T.*absoluta*



Extreme yield loss





a view of CNN application

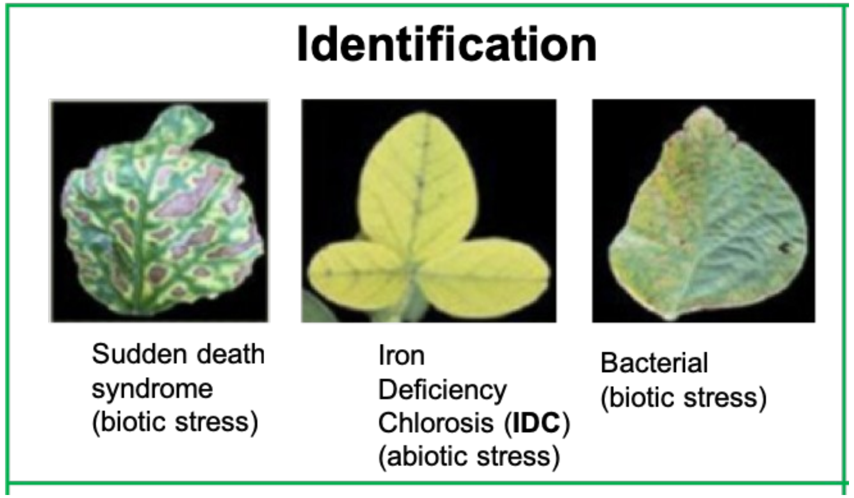
General architecture of DL classification system
Depends on main three phases

- **Image pre-processing** e.g color space conversion from RGB to grey
- **Feature extraction** e.g. features proposed by experts are extracted from the image for constructing feature vectors
- **Classification/Clustering**

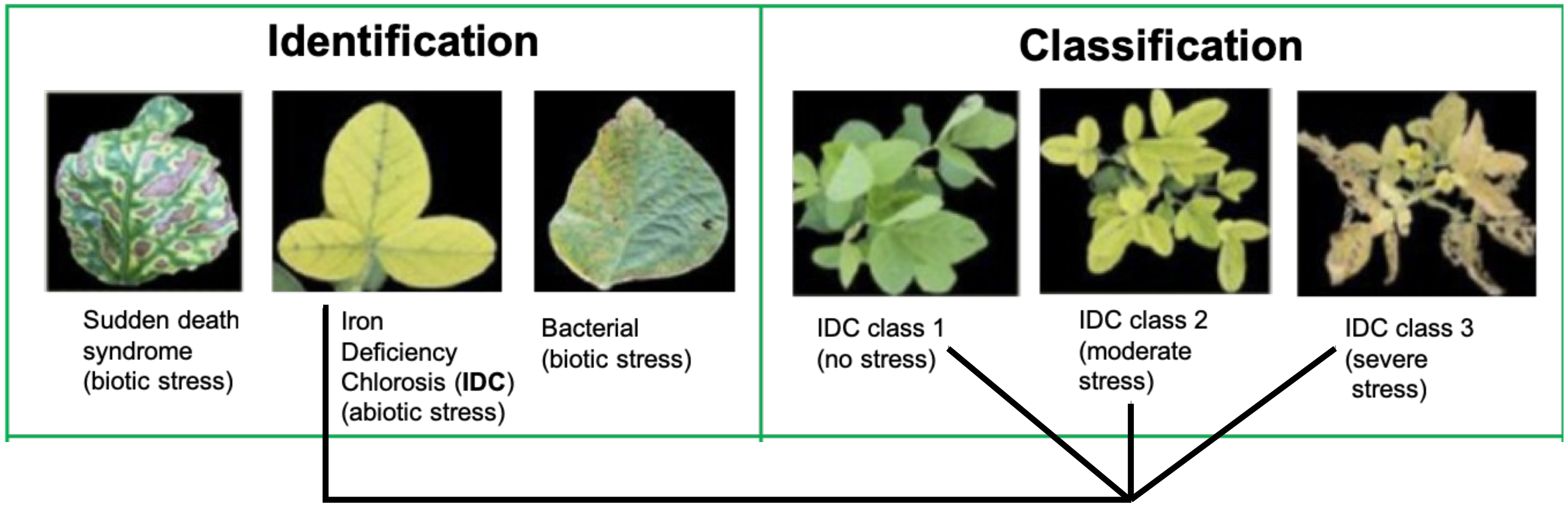
Approach..

- Plant detection and localization (multi-instance detection/localization)
- Plant segmentation (foreground to background segmentation)
- Leaf detection, localization, and counting (multi-instance detection, object counting
- Leaf segmentation (multi-instance segmentation)
- Leaf tracking (multi-instance segmentation)
- Boundary estimation for multi-instance segmentation (boundary detectors)

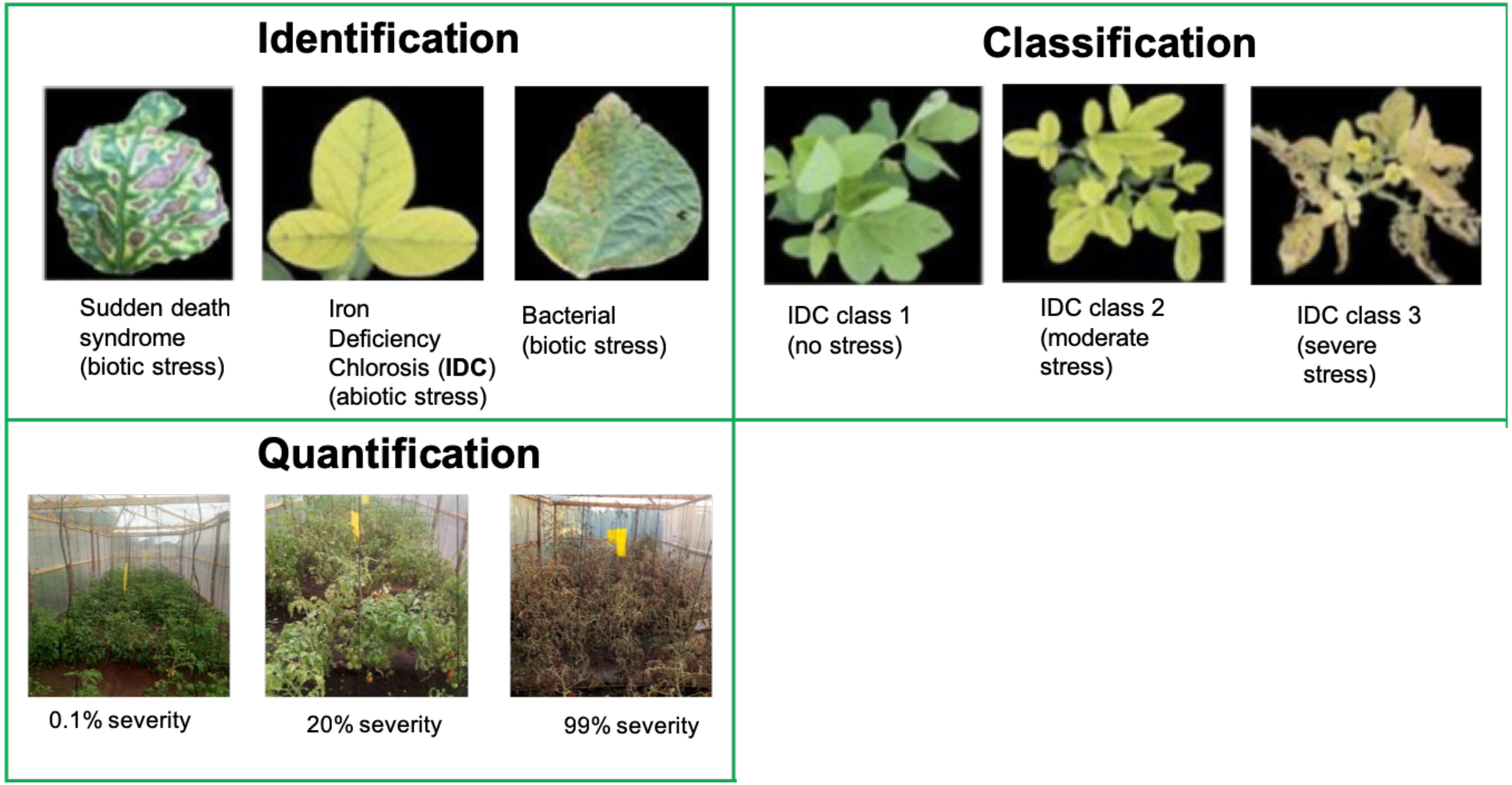
where it’s useful



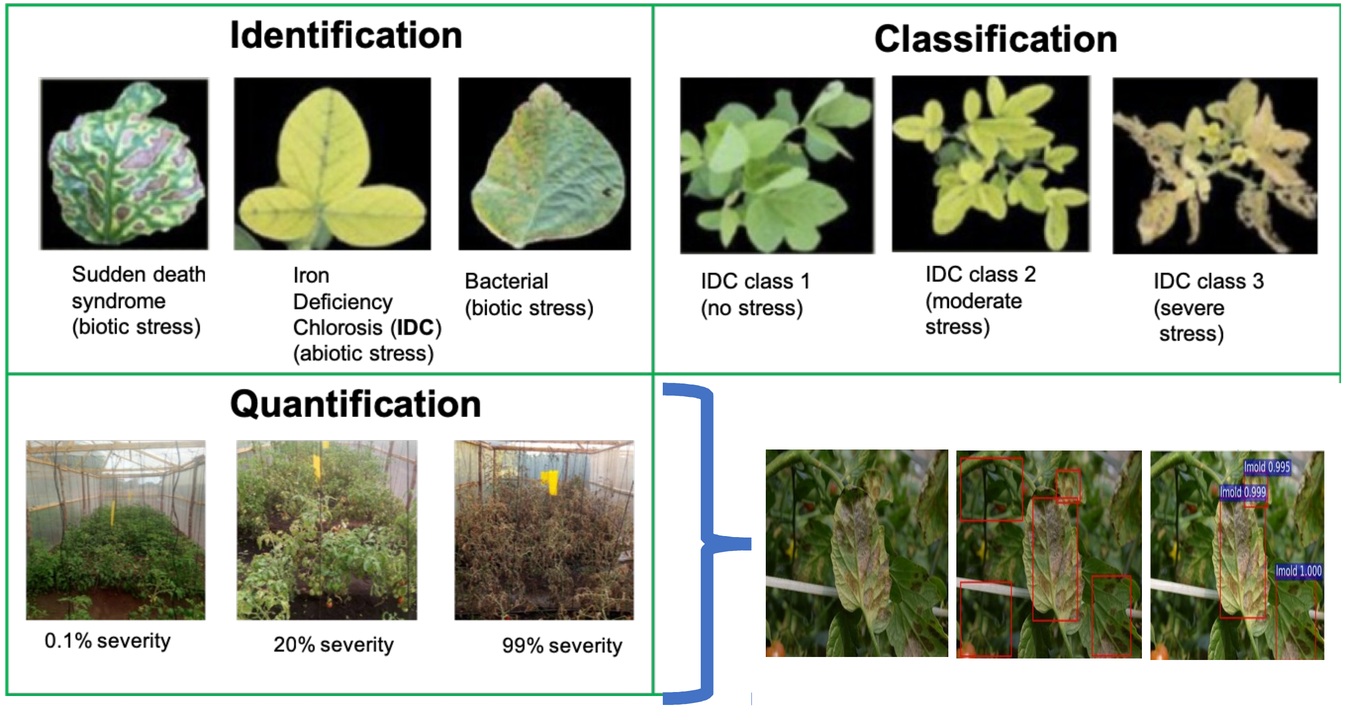
where it’s useful



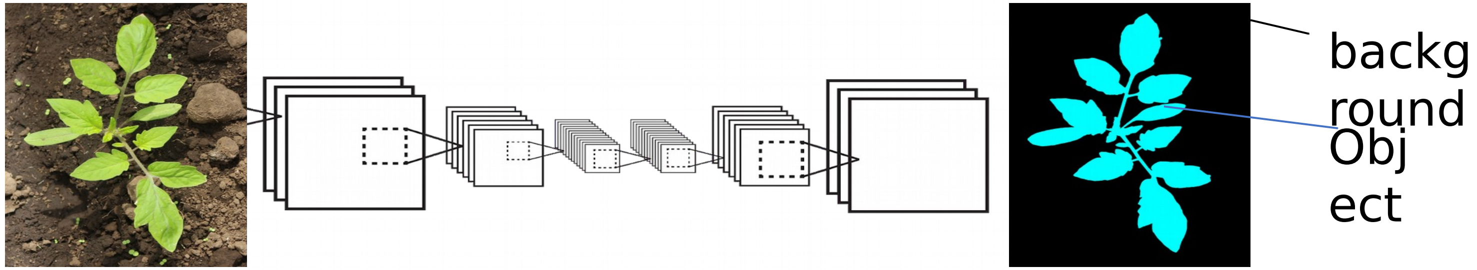
where it's useful

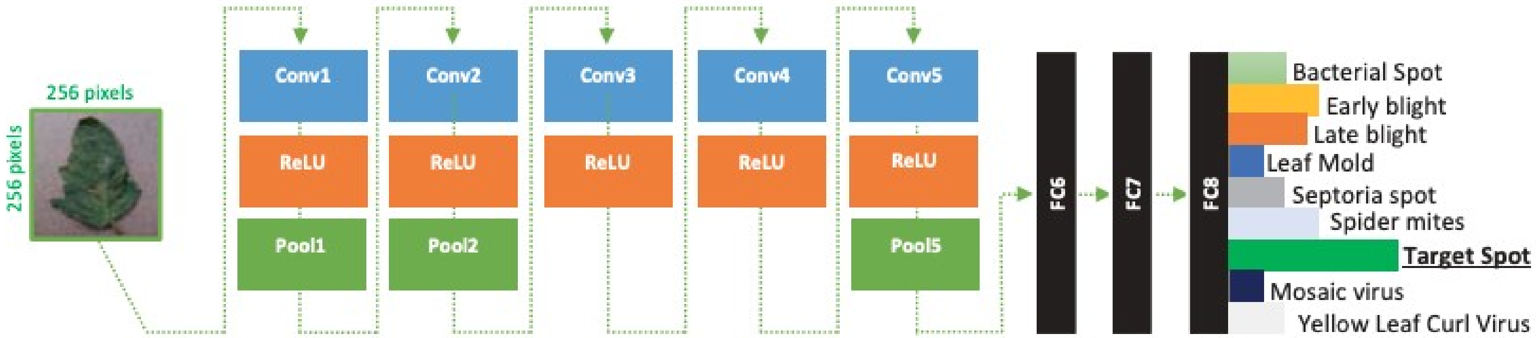


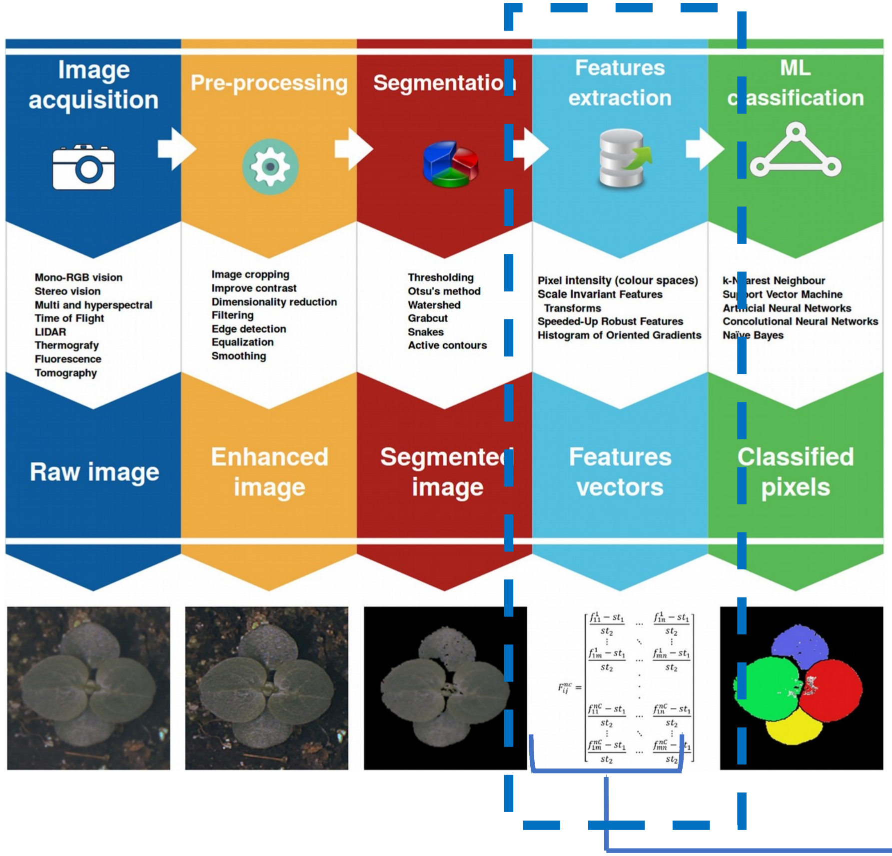
where it’s useful



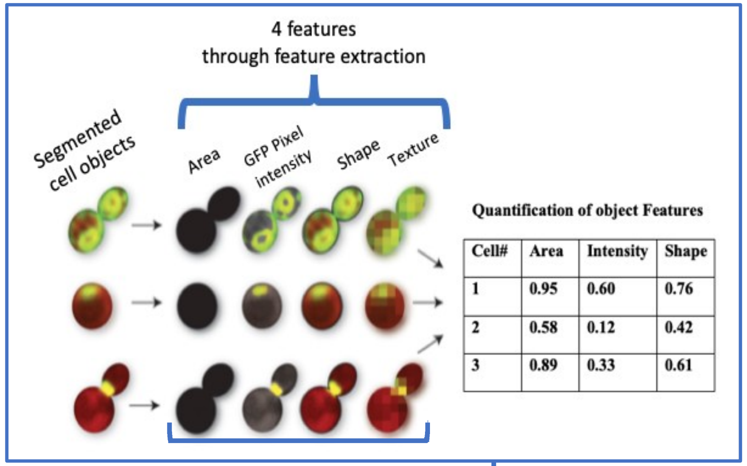
Inter- and extra-class variations i.e.
infection status and location in the plant


backg
round
Obj
ect

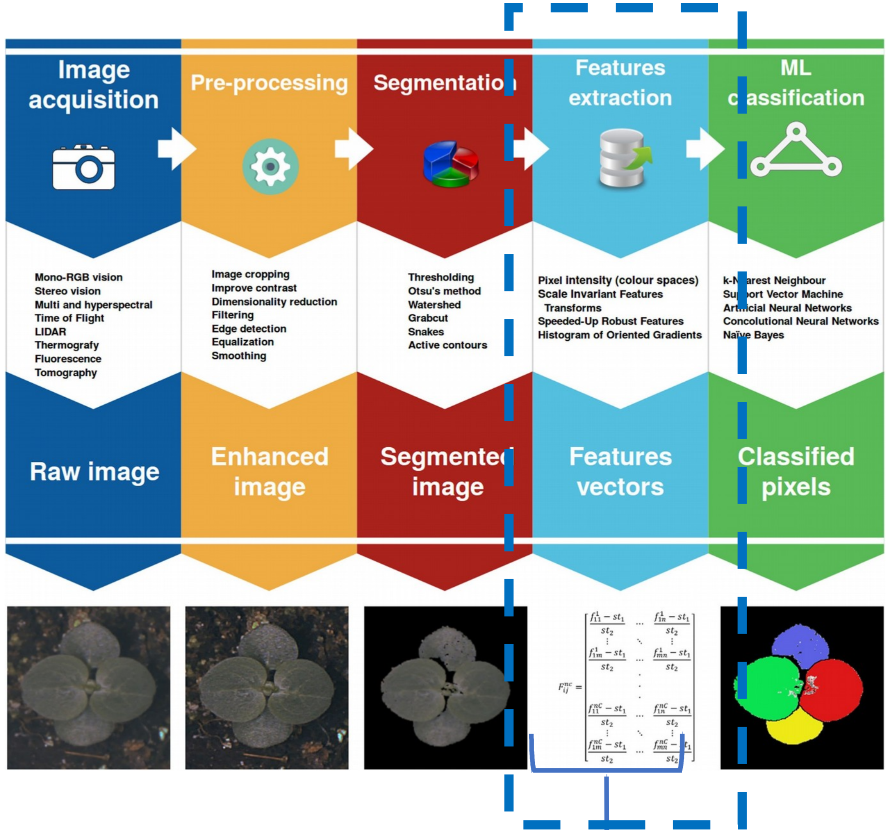

256 pixels
256 pixels
Conv1
Conv2
Conv3
Conv4
Conv5
ReLU
ReLU
ReLU
ReLU
ReLU
Pool1
Pool2
Pool5
FC6
FC7
FC8
Bacterial Spot
Early blight
Late blight
Leaf Mold
Septoria spot
Spider mites
Target Spot
Mosaic virus
Yellow Leaf Curl Virus



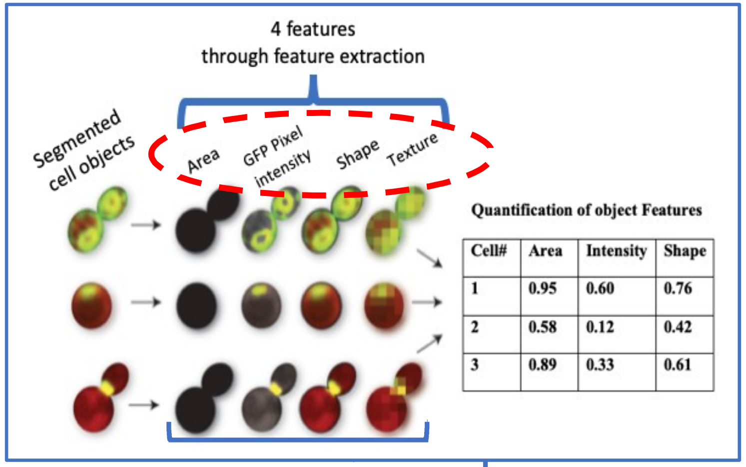
Feature extraction



Morphology- size, shape
Texture features-
quantify spatial statistics of pixel intensities

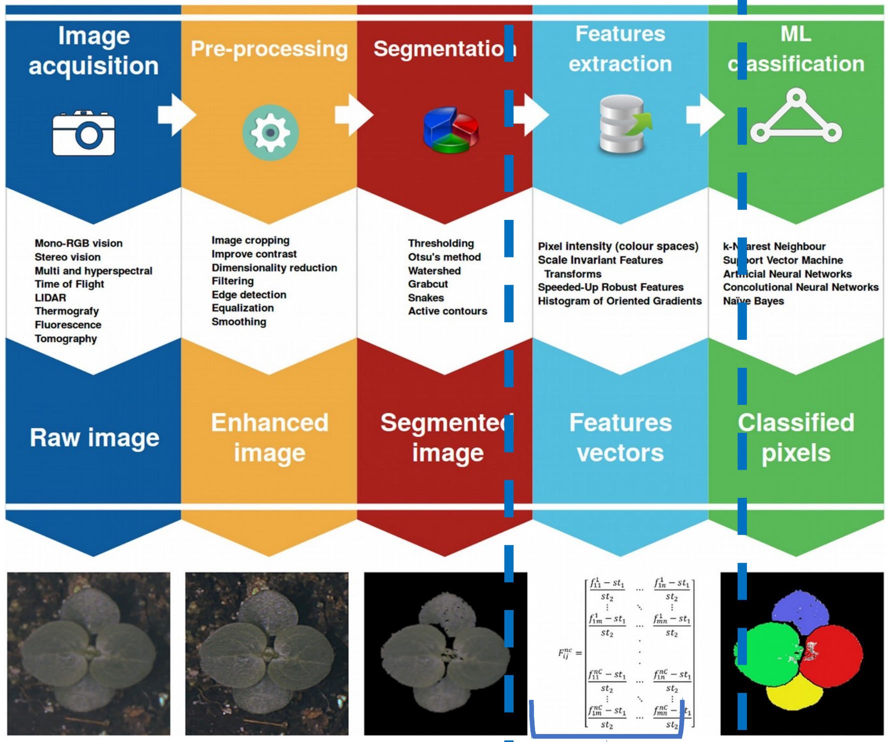


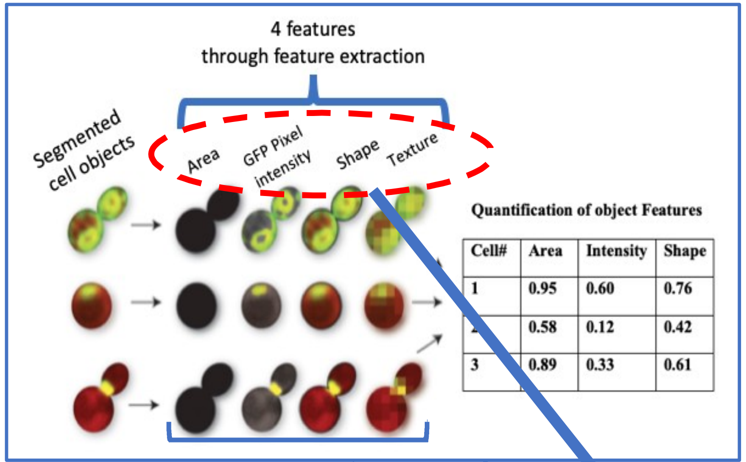
Feature



Morphology- size, shape
Texture features-
quantify spatial statistics of pixel intensities

Feature





Morphology- size, shape
Texture features-
quantify spatial statistics of pixel intensities

Quantifying damage

(a) (b) (c) (d)

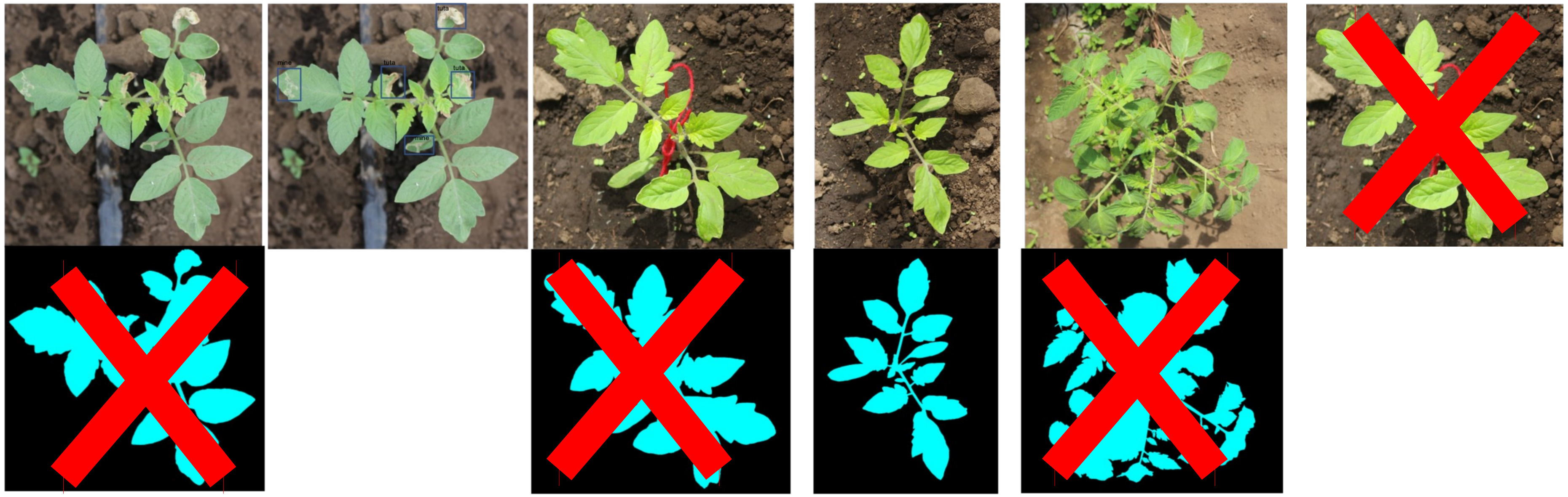
Leaf damage: (a) damage 5%, (b) damage 10%, (c) damage 15%, and (d) damage 30%

Wang-Su *et al* (2017)

Impact of input

(a) (b) (c) (d) (e) (f)

Impact of input



(a) (b) (c) (d) (e) (f)

Data augmentation

To increase data
To increase performance of CNN models,
Purpose: To make learning algorithms invariant to some transformed images

Transformation-translations, rotations
Increasing dataset to make learning algorithms invariant to translations

Data augmentation

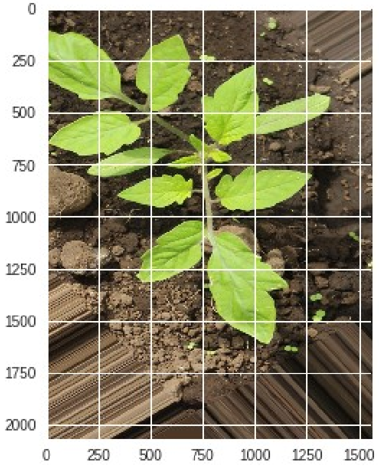
To increase data
To increase performance of CNN models,
Purpose: To make learning algorithms invariant to some transformed images

Transformation-translations, rotations
Increasing dataset to make learning algorithms invariant to translations

```
datagen = ImageDataGenerator(
    rotation_range=60,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest')
```

Sensitivity to data augmentation

augmented



Original

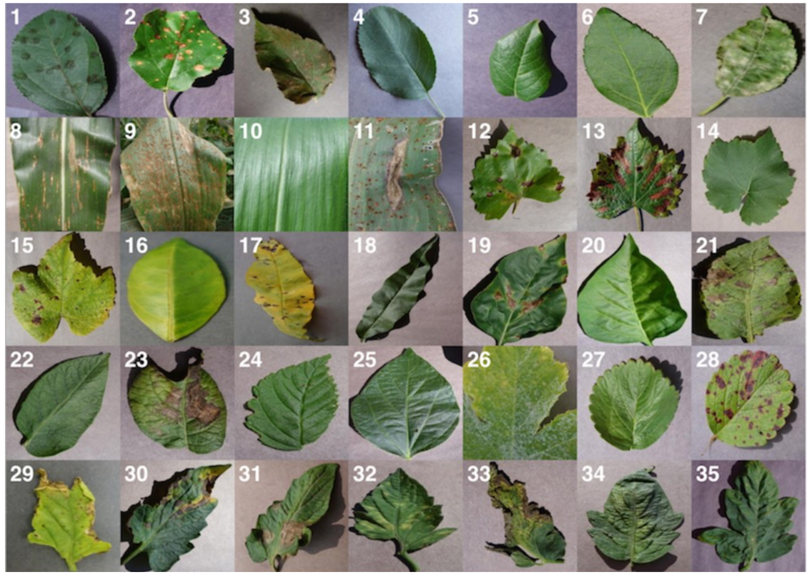
Challenges in CV

Illumination variation

Other
Scale variation
Viewpoint variation

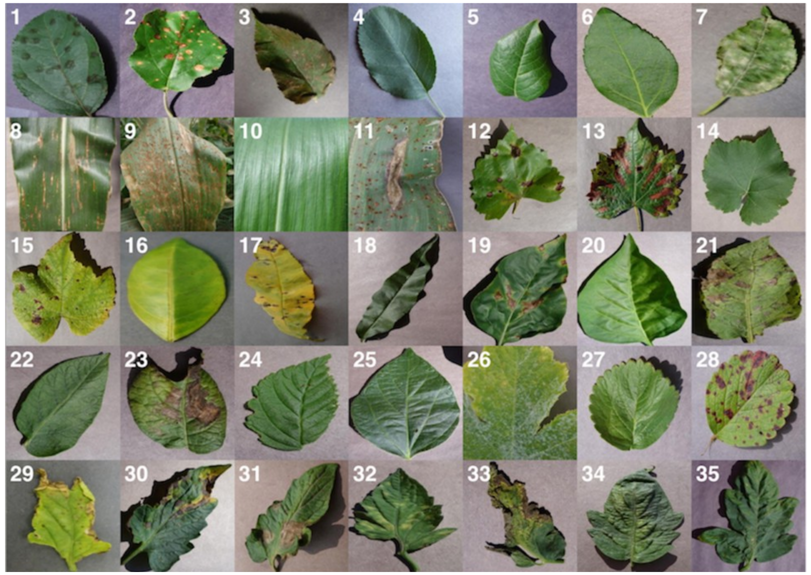
Poor annotation

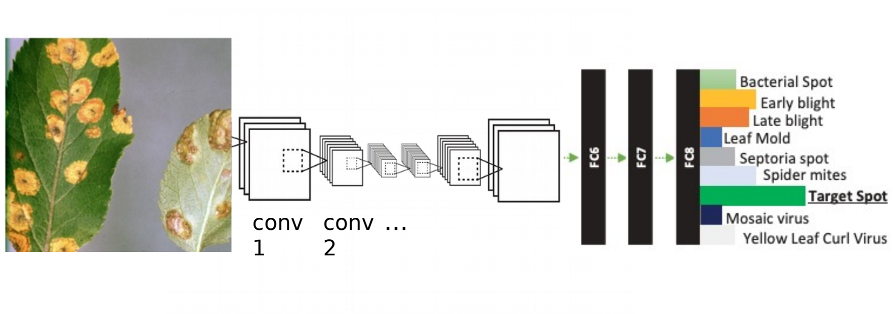
Visualization



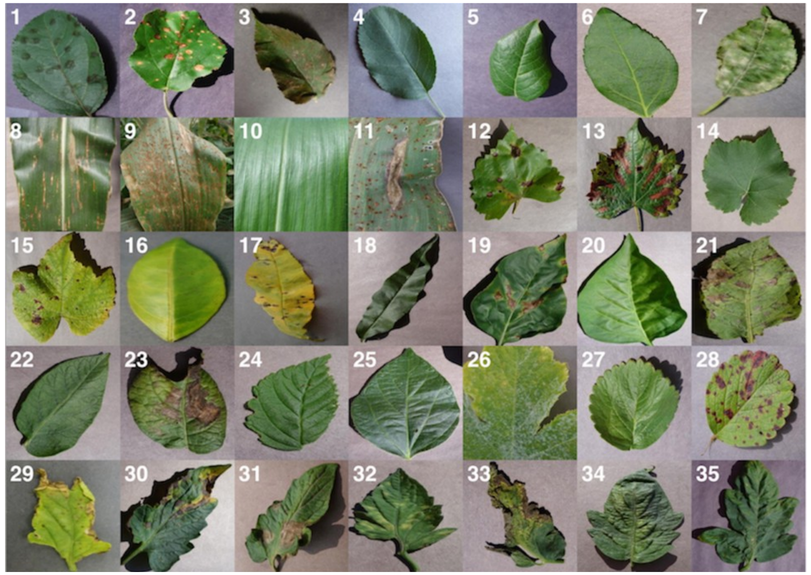
Sharada *et al*
(2016)

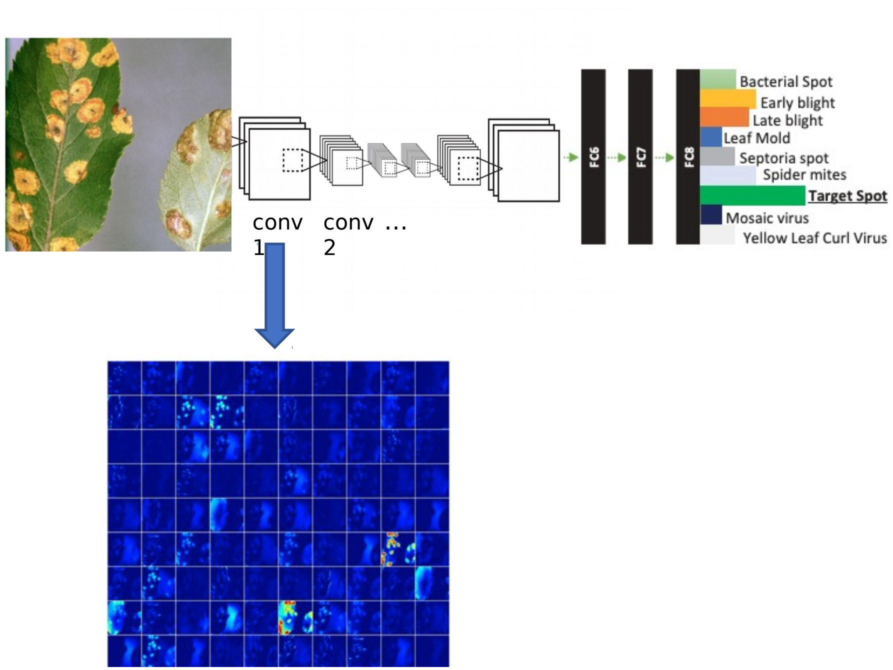
Visualization





Visualization

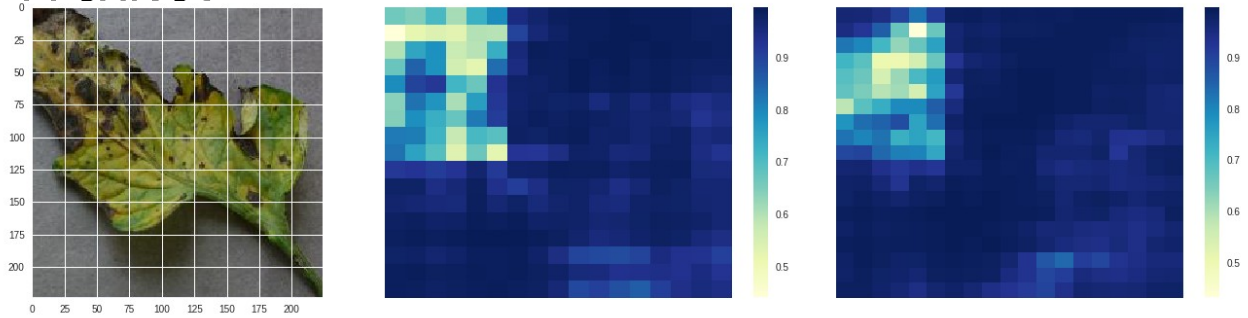




Activation in conv1
forward pass
of AlexNet from scratch

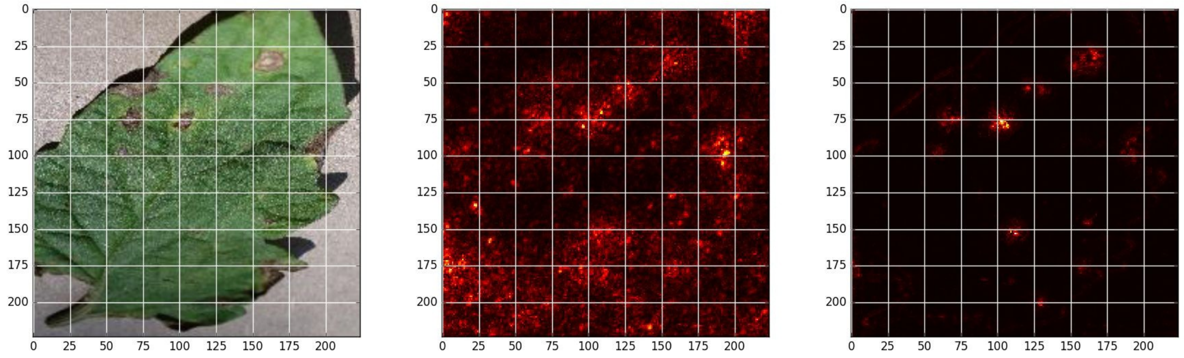
Visualization

Heat maps - AlexNet



Improves the
Lack of **interpretability** and **transparency** of classifiers

Saliency

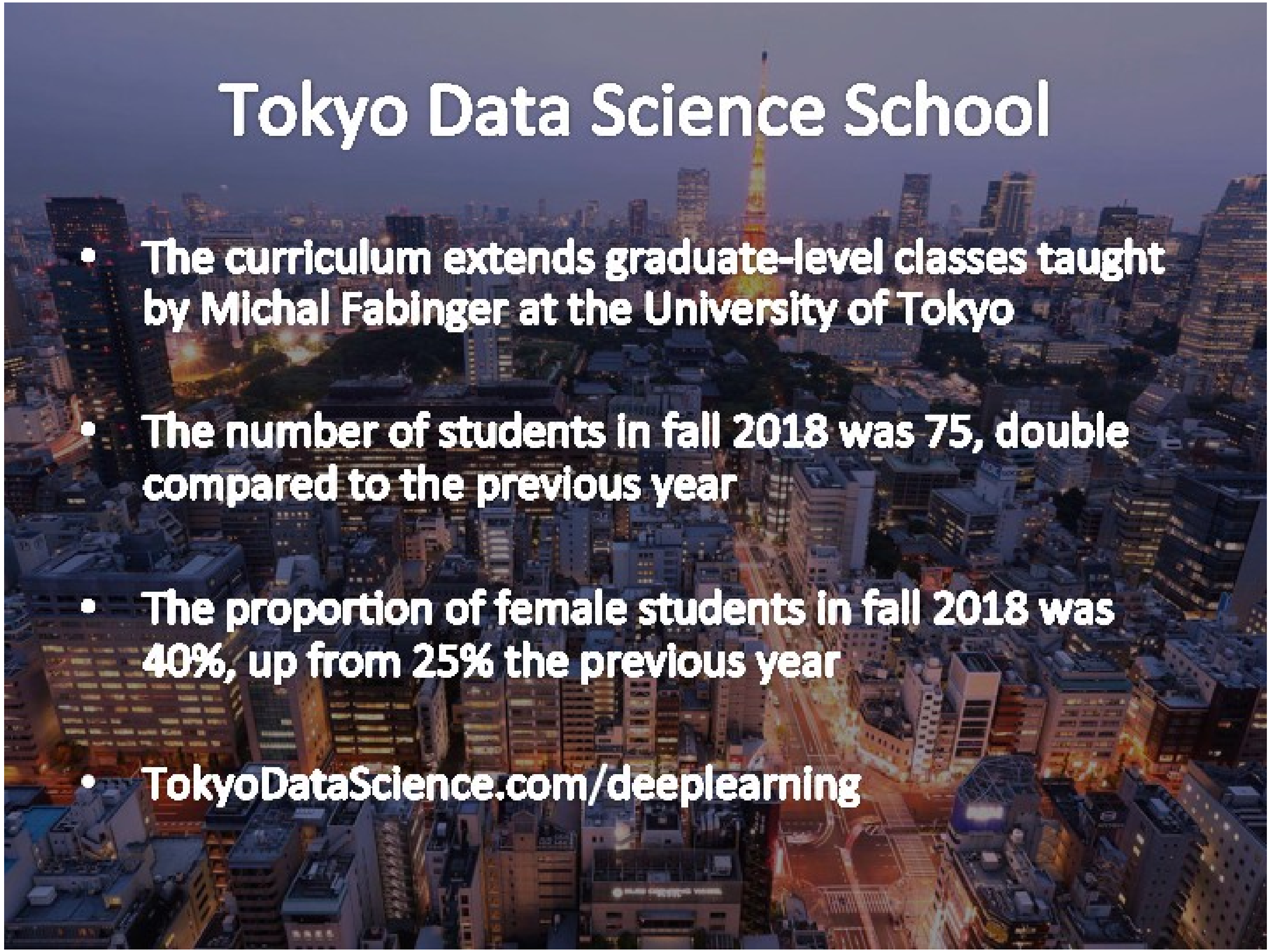


...and gives more insights into the
symptoms of plant disease

Studies in plant disease classification

Data set Description Image number	Dataset Source (on-site, Lab)	Task (Identification, classification, Detection)	Plant parts/ Leaves	Classifier/Architecture	Author
57 trees 5404 leaf images	PlantNet, Flavia, LeafSnap + author	Leaf-based plant classification	Leaves	SVM + CNN	Ilke Cugu et all (2017)
3700 images 1643-healthy 240 black sigatoka 1817 black speckle	PlantVillage project	Classifying healthy and diseases (3) banana leaves	leaves	CNN-based LeNet	Amara Jihen et al (2017)
87848 images 25 plants 58 classes(plant, disease)	Open data set (33% field, 67 % lab)	Plant disease detection and diagnosis leaves	Plant, leaves	AlexNet, AlexnetOWTBn, GoogleNet, Overfeat, VGG	Konstantinos P. Forentinos (2018)
7520 good and bad condition images 7 types of disease	On site	Leaves of cucumber	cucumber leaves	4-layer CNN	Fujita et al (2016)
PlantVillage 54323 of 14 crops 38 classes diseases and healthy plants + 715 (background)	Open	Leaves Cropped in field, captured in lab	multiple	Alexnet, DenseNet-169, Inception v3, ResNet-34, Squeeze-1.1, VGG13	Brahimi et al (2018)
Tomato diseases and pest disease	Author On site	Plant parts and leaves tomatoes	Tomato Plant, leaves	Fater R-CNN, SDD R-FCN, VGG, ResNet	Alvaro et al (2017)
4483 images .13 classes plant disease One class healthy One class background	Open	Plant disease Classification	leaves	CaffeNet (modified version of AlexNet)	Sladojevic et al (2016)

Crop & Disease/ Pest	On-site, Lab	Dataset source	Task (Identification, classification	Feature	Approach, Methods	Future work	Author
Banana	lab	520 images of HS (16cmX 16cm 0.5mm resolution), **RGB**	**Detection** of image regions associated with leaf structure	Leaf structure **Physiological** changes	**Morphological** Image analysis using Morphological fusion (Spectral profiles of **Dead**, spot, midrib, bent, flat, flying leaf) Pixel reflectance	Future: Using large UAV dataset collected from field.	Gladys Villega et al (2017)
Spider damage cotton	Field early season of symptom started	**Multispectral** NIR, R, G	Pixel **classification** (shadow, cotton and others) ortho-photos	**Severity** (normal, light, medium & heavy)	SVM: for **Scene classification** Transfer CNN: mite-infestation identification (AlexNet,8C, softmax) NDVI, GNDVI, DVI, RGI, MACRI, GRVI. Local Binary Pattern Histogram		Huasheng Huang et al. (2018)
Potato beetle damage	UAV 10 flights in 15 days (60 and 30m)	Orthophotos, **multispectral**	Object-based image analysis- for **detecting** the relative amount of damage	Leaf, **canopy**	**Canopy surface** elevation from **SfM** point clouds NDVI	Pixel classification using NDVI was not important. **No studies done to show cost effectiveness**. Digital surface model. With insect pests, pattern of damage is unpredictable	E. Raymond et al (2017)
vineyard	field	Orthophotos, hyperspectral, **multispectral**	**Detection** of early incursions of pest species	Tree canopy averaging of pixels	Digital vigor model. Several VI e.g. MCARI, TACRI, NDRE, NDVI	Spectral signatures	S.F. Di Gennaro et al.


Tokyo Data Science School
The curriculum extends graduate-level classes taught by Michal Fabinger at the University of Tokyo
The number of students in fall 2018 was 75, double compared to the previous year
The proportion of female students in fall 2018 was 40%, up from 25% the previous year
TokyoDataScience.com/deeplearning

“Return man to the Farm”

YOKOI Tokiyoshi (1891)
Advocated

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Thanks for your attention

https://denispastory.com/

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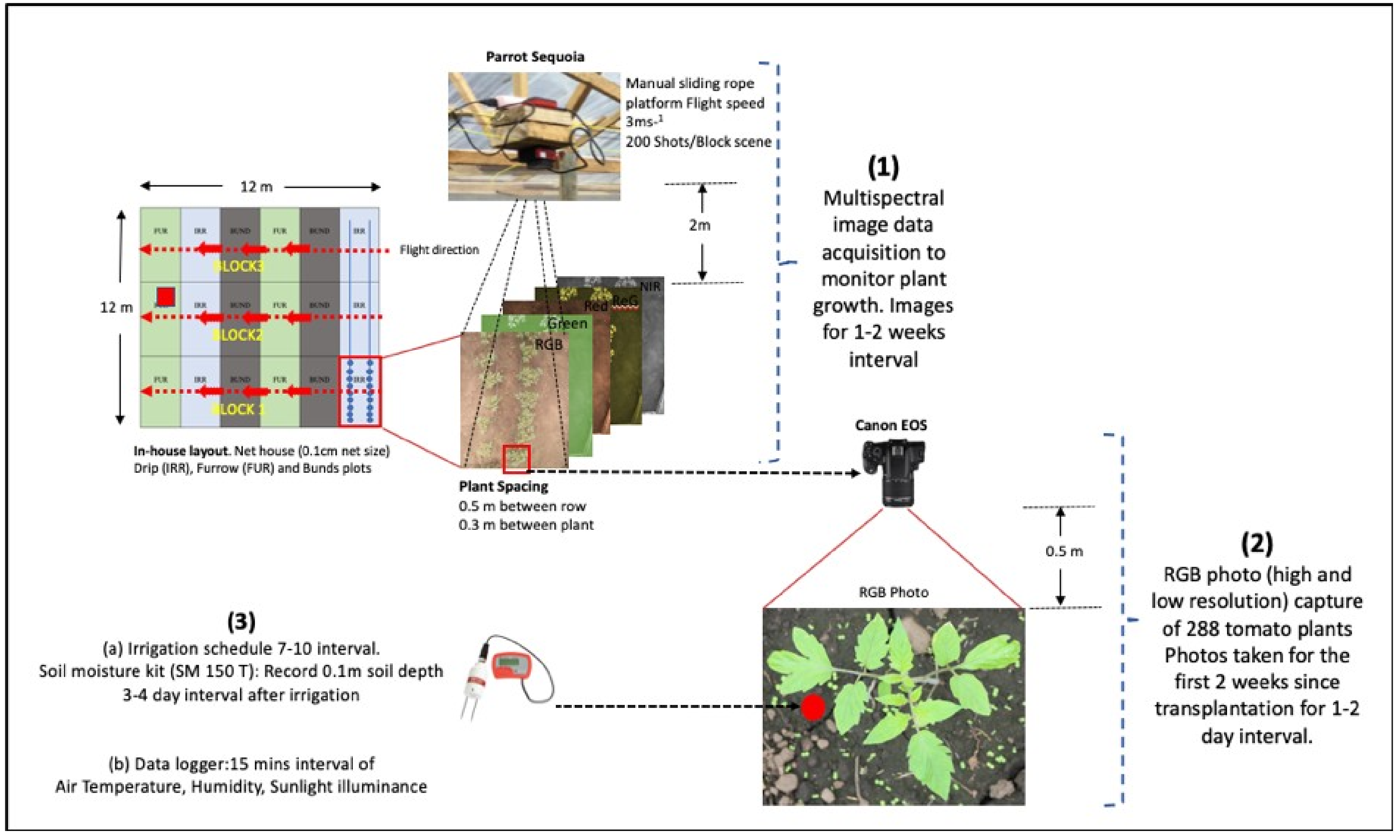
DenisPastoty



Schematic diagram for data collection