Smart Computer Vision Models in Sorghum

Drs. Iván Grijalva and
Brian McCornack

Postdoctoral Researcher in the
Department of Entomology at
Kansas State University
grijalva@ksu.edu

Kansas State University
Department of Entomology

McLab

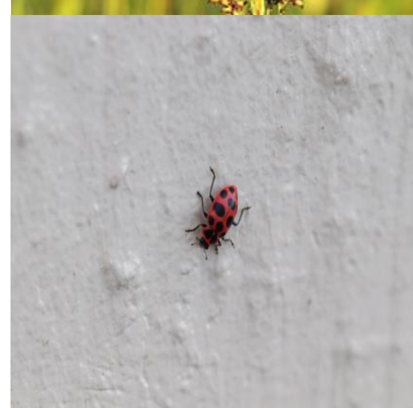
McCornack

Presentation outline

- General introduction
  - Research system:
    - Sorghum
    - Sorghum aphid and Coccinellids

- Project 1:
  - Deep learning: detection of sorghum aphid densities
  - Objectives
  - Results and applications

- Project 2:
  - Deep learning: detection of coccinellids
  - Objectives
  - Results and applications



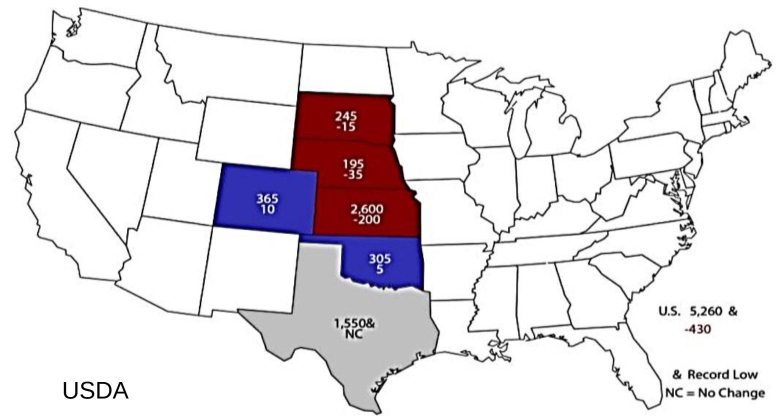
Sorghum economics

- Sorghum [*Sorghum bicolor* (L.) Moench] is the fifth most valuable cereal crop in production worldwide (Hariprasanna et al., 2016)

- This crop in the U.S. had a value of more than $1 billion and was planted on 6.4 million acres in 2022 (NASS, 2022)

- Due to its drought tolerance and relatively low cost of production (i.e., compared with other crops), interest in growing the crop is increasing

Sorghum checkoff



USDA

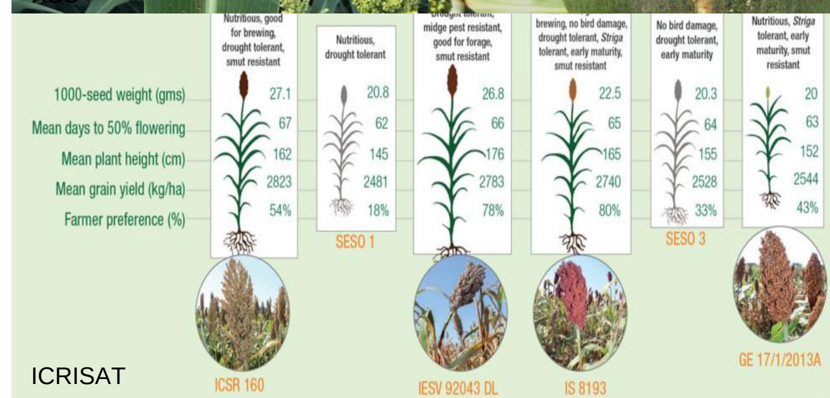
Ocklahoma Ag

Important insect pests in sorghum

- Since 2013, sorghum aphid (SA), *Melanaphis sorghi* (Theobald) has become an important economic pest causing significant yield loss across the sorghum production region in the US (Bowling et al., 2016)

- This damage is resulting in plant stress and reduction of photosynthesis due to honeydew secretion and growth of sooty mold (Bowling et al., 2016; Singh et al., 2004)

- Common management strategies to manage SA include: host plant resistance, early planting, and use of insecticides based on pest monitoring (Bowling et al., 2016)



Common pest management strategies in sorghum

- Pest monitoring consists of tracking the arrival of sorghum aphids by sampling different field areas through space and time:
  - Making estimates about their populations using visual observations for a defined sampling unit (i.e., leaf) (Bowling et al., 2016)

- Usually, sorghum growers in Kansas scout their fields using visual assessments to determine the economic threshold of SA (40 aphids per leaf) (Gordy et al., 2019)

- Also, during pest monitoring an early detection of coccinellids is necessary to avoid unnecessary applications and promote conservation (Brewer et al. 2017). They are good finders of aphids

Issues with aphid management strategies in sorghum

- However, sorghum aphid monitoring is time-consuming and challenging task due to:
  - Aphid exponential growth, requiring an early sampling (Bowling et al., 2016)
  - Consequently, high frequency of sampling, increasing labor costs for monitoring
  - Also, is prone to error in estimates and requires certain level of ID training
  - Because is difficult to distinguish between aphid species (Brewer et al. 2019)

- Also, a complex of natural enemies, primary coccinellids, can help reduce aphid densities and use of costly applications ($15-20/acre + cost of application) (Brewer et al., 2017)

Alternative for aphid management strategies in sorghum

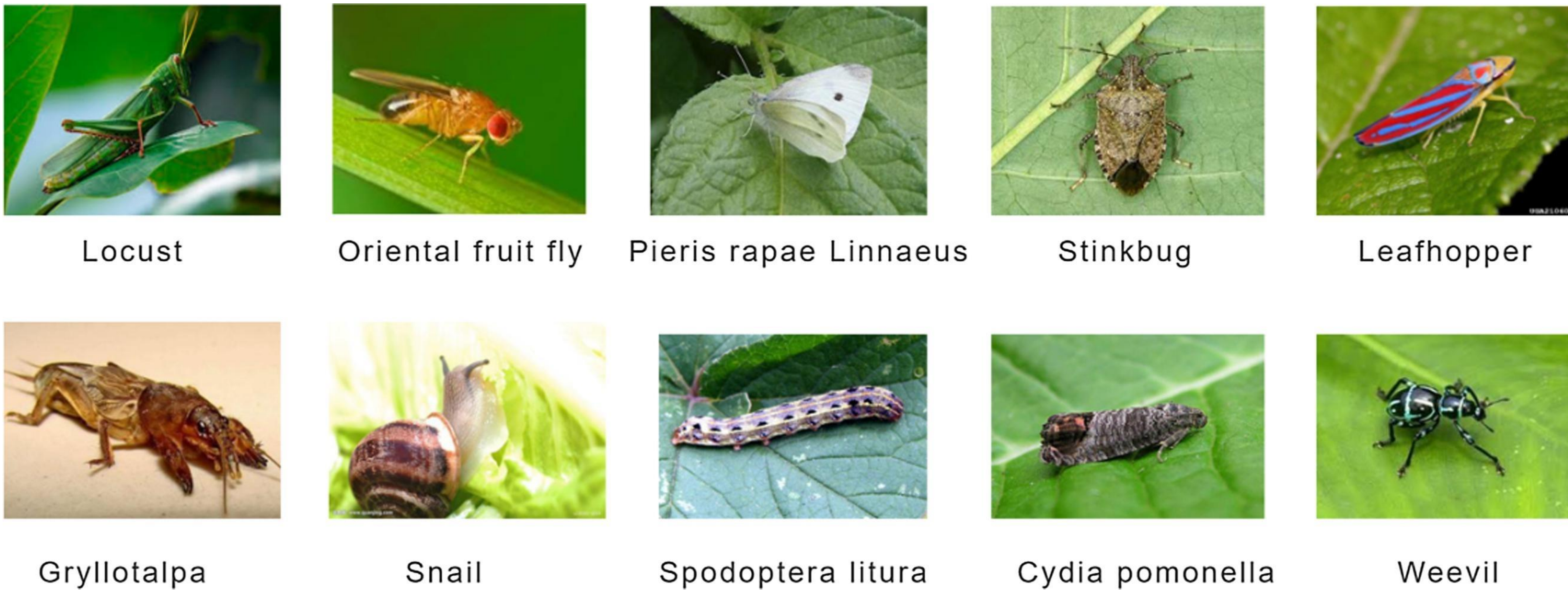
- Therefore, there is one alternative to improve aphid management strategies:

1. The use of automation to detect individual counts of SA and coccinellids in images to reduce the time and cost of aphid monitoring

- Currently, technology such as machine learning can be applied to the field of entomology using deep learning through computer vision models (i.e., CNNs) to perform classification and detection tasks (Høye et al. 2021)

Agricultural tasks using deep learning

- Classification: means that you can assign a category to an object



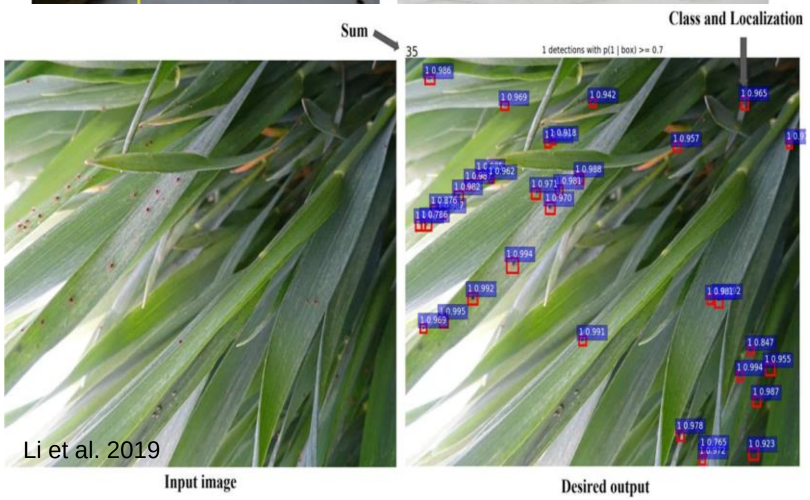
Li et al. 2020

- In deep learning you can automatically classify images based on species name or categories that are useful for management decisions (e.g., classification of arthropod densities)

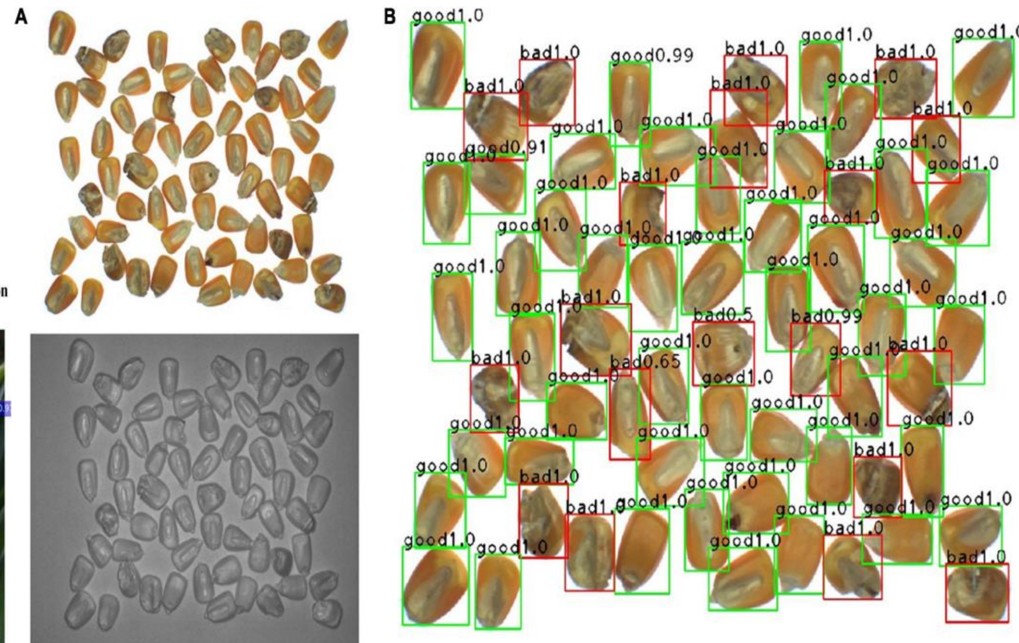
Agricultural tasks using deep learning

- Detection: means that you can assign a category, locate and count the object

Hong et al. 2020



Li et al. 2019



Wang et al. 2022

- In deep learning you can use bounding boxes (i.e., common predictor detector) to locate and count the object automatically

Agricultural tasks using deep learning

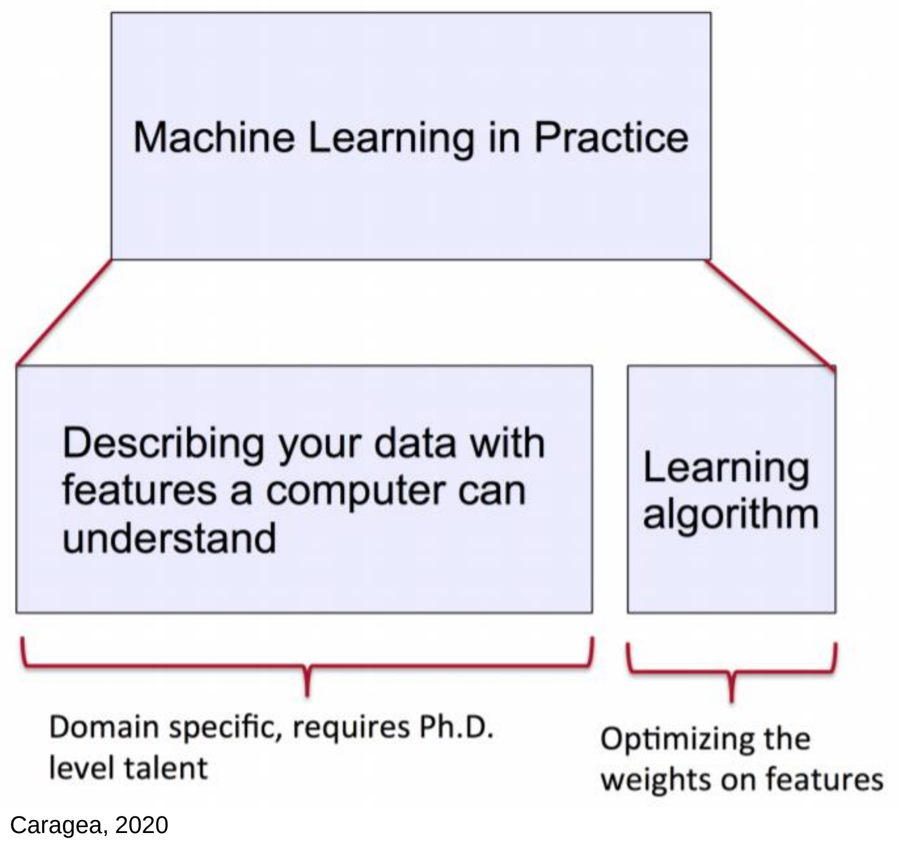
- Segmentation: means that you divide into separate parts

Liu et al. 2021

- In deep learning you can use polygons to locate and segment the object automatically

What is machine learning in practice?

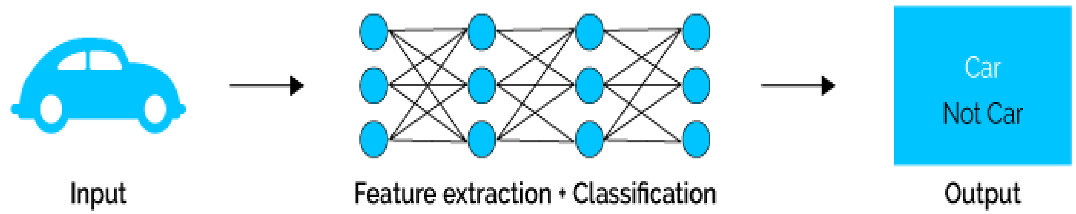
- Process of teaching a computer system how to make accurate predictions when fed data
- Machine learning uses "deep learning" as a modern technique for image processing and data analysis

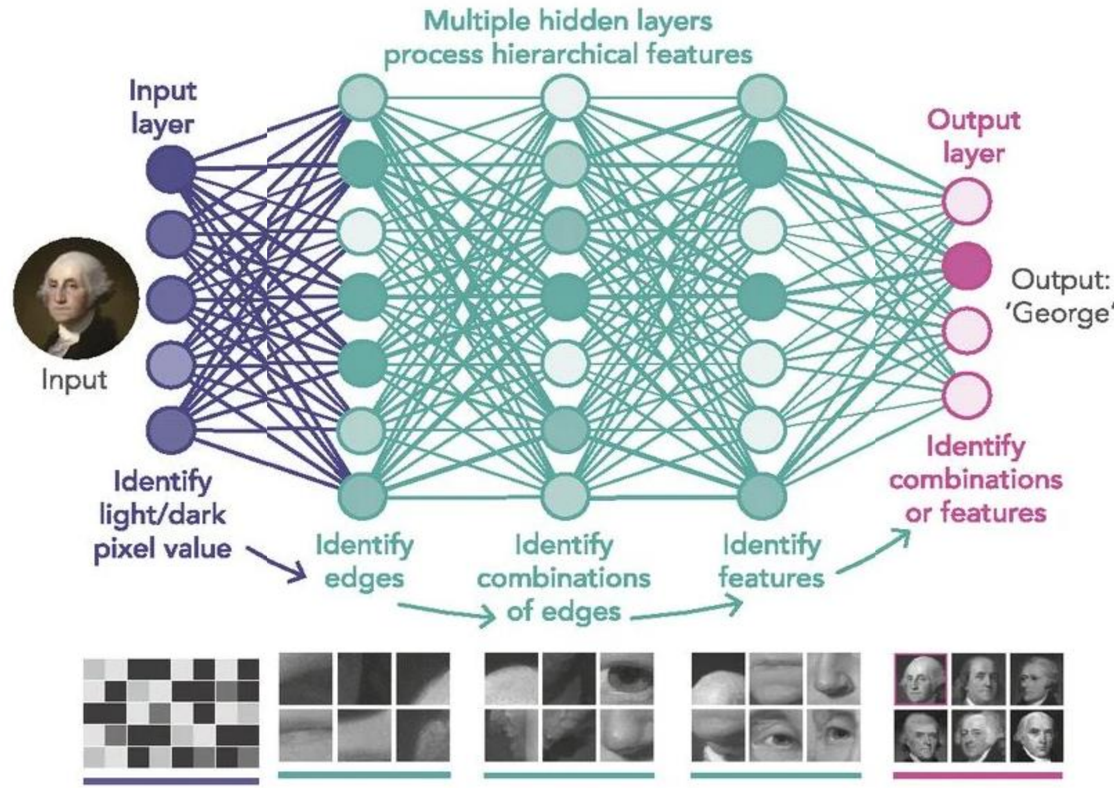


Caragea, 2020

What is deep learning?

- Representation learning attempts to automatically learn good features or representations (Caragea, 2020)
- Deep learning algorithms rely on layers of neural networks (CNN) to attempt to learn representations and an output (Caragea, 2020; Li et al. 2021)
- Neural networks is running several logistic regressions at the same time (Caragea, 2020)

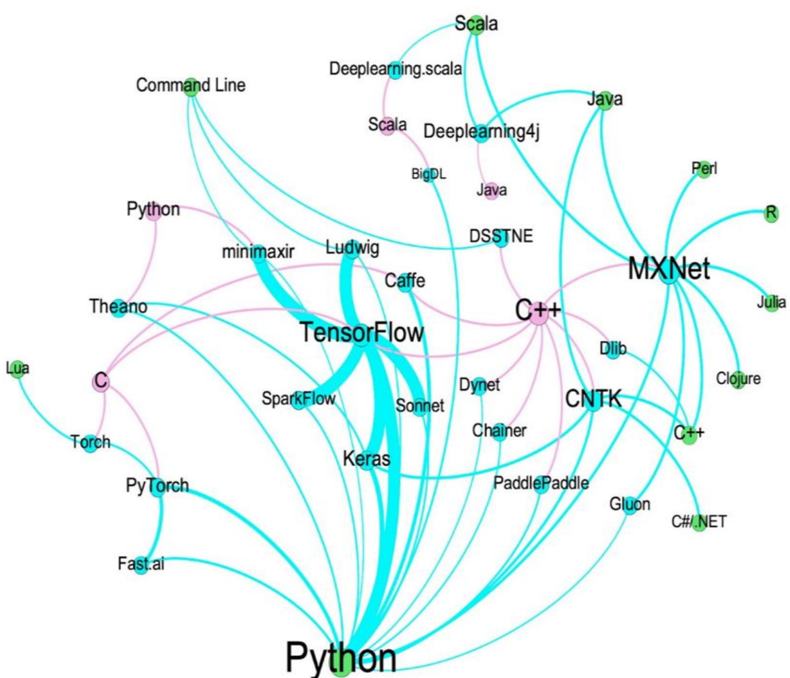




Waldrop, 2019

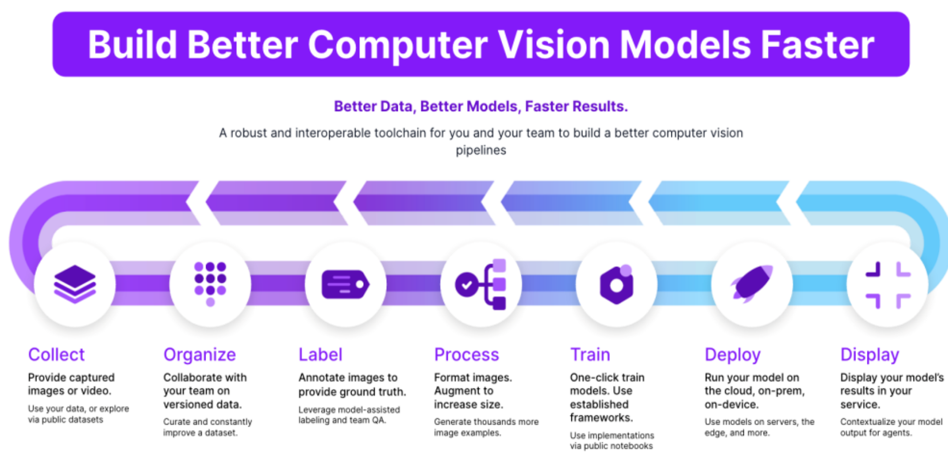
Deep learning frameworks

- To use deep learning models we need frameworks to function
- We can find open-source models to use
- They require an algorithm written in programming language
- Labeling interfaces and machine learning platforms



Geeks

roboflow



Roboflow

Labelbox

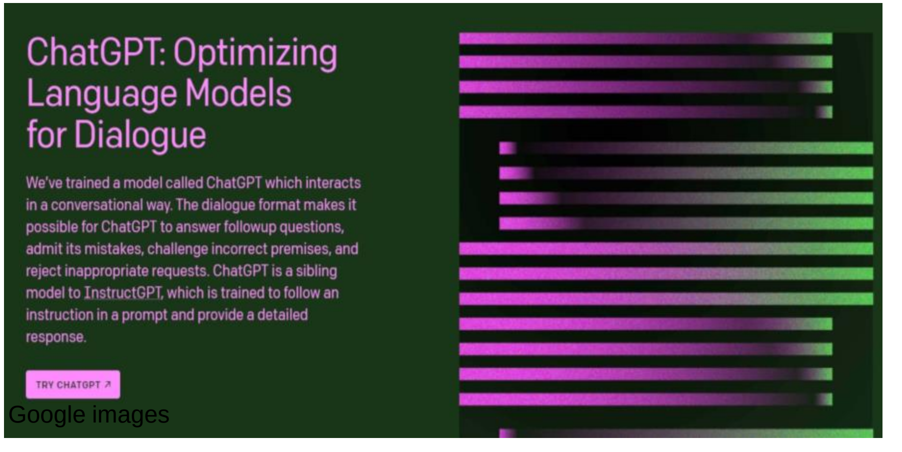
Labelbox

Common examples using deep learning

- Speech recognition on smart phones or Alexa

- Self-driving cars

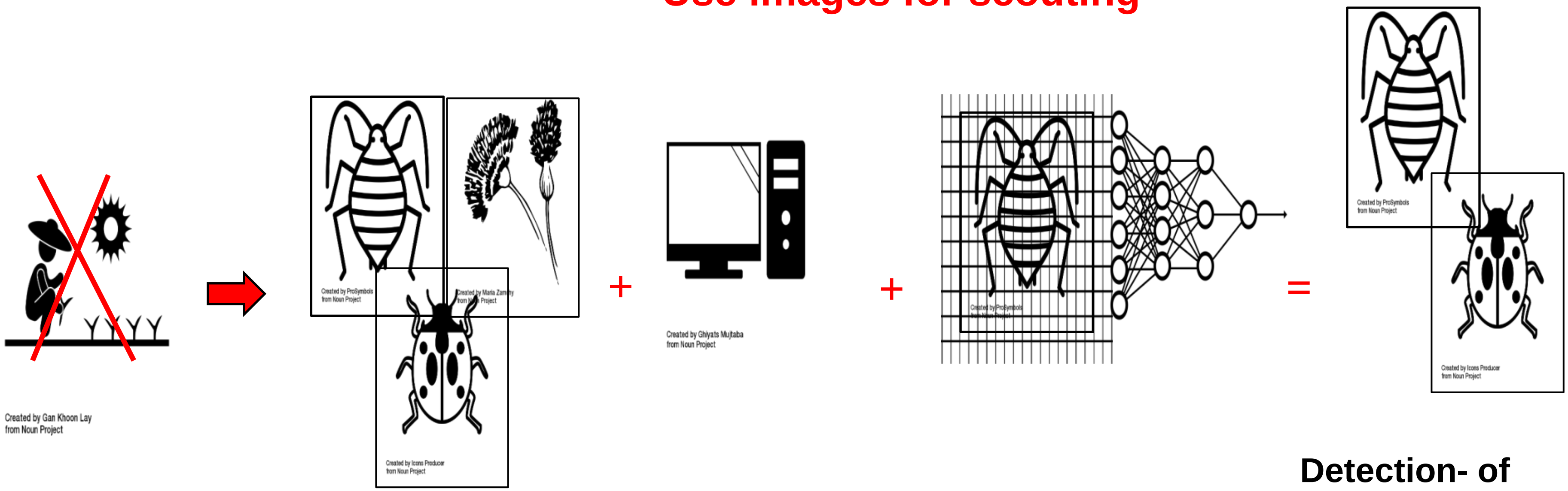
- ChatGPT



Google images

Project overview: Machine learning

Use images for scouting



Traditional scouting use visual assessments

Images from field scouting events

Algorithm programming

Deep learning models

Detection- of sorghum aphids and coccinellids to perform further management decisions

Computer vision model for sorghum aphid detection using deep learning

Grijalva et al. 2023 https://doi.org/10.1016/j.jafr.2023.100652

Material & Methods

1. Data generation and imagery preprocessing

- Images consisted of a section of the leaf with SA (>1100 images) collected during field scouting

2. Manual labeling based on standard threshold levels for spraying (1-125 sorghum aphids/leaf)

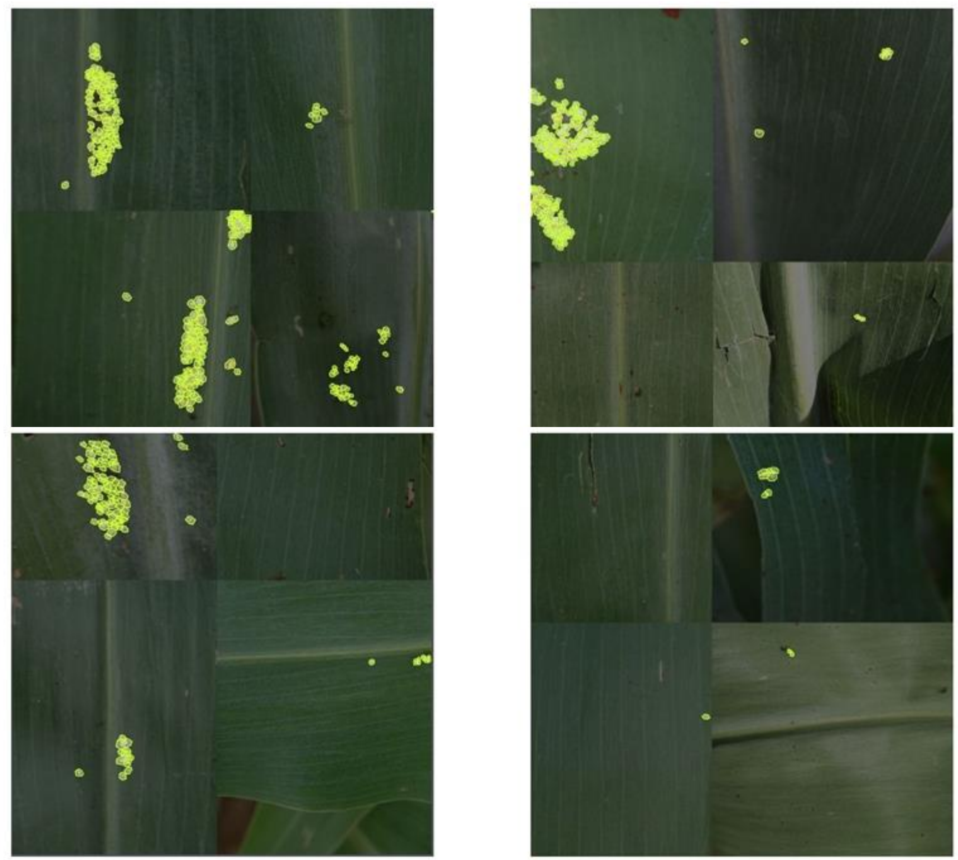
Material & Methods

3. Creation and testing models by computer programming with image augmentations

- Images downscaled:
  - 416 × 416 pixels
  - 640 × 640 pixels
  - 1280 × 1280 pixels
- Data split/ratio: 80% Train; 10% Validation; and 10% Testing
- Augmentation: Mosaic generated 6 different variants of training images
- Evaluated the performance of 3 models found on Pytorch:
  - YOLOv5n
  - YOLOv5s
  - YOLOv5m

4. Model metric performances

- Metrics evaluated:
  - Precision (%)
  - Recall (%)
  - mAP@0.5 (%)
  - Mean error of misdetection (%)



Results

Overall precision, recall, and mAP@0.5 scores of the three detection models tested at different image pixel input resolutions

Model type	Image pixel input resolutions (pixel × pixel)	Precision (%)	Recall (%)	mAP@0.5 (%)
YOLOv5n	416 × 416	46.80	35.00	31.70
	640 × 640	69.70	54.40	59.10
	1280 × 1280	89.00	82.60	89.20
YOLOv5s	416 × 416	56.10	38.10	38.70
	640 × 640	75.30	58.40	64.50
	1280 × 1280	92.40	82.60	90.40
YOLOv5m	416 × 416	59.90	41.40	43.20
	640 × 640	77.70	59.10	65.40
	1280 × 1280	92.00	84.50	90.60

Results

Detection results using testing images at 1280 × 1280-pixels input resolution without (A) or with aphid detections (B) performed by YOLOv5m model

A)

Manual counting

- 58 SA/leaf

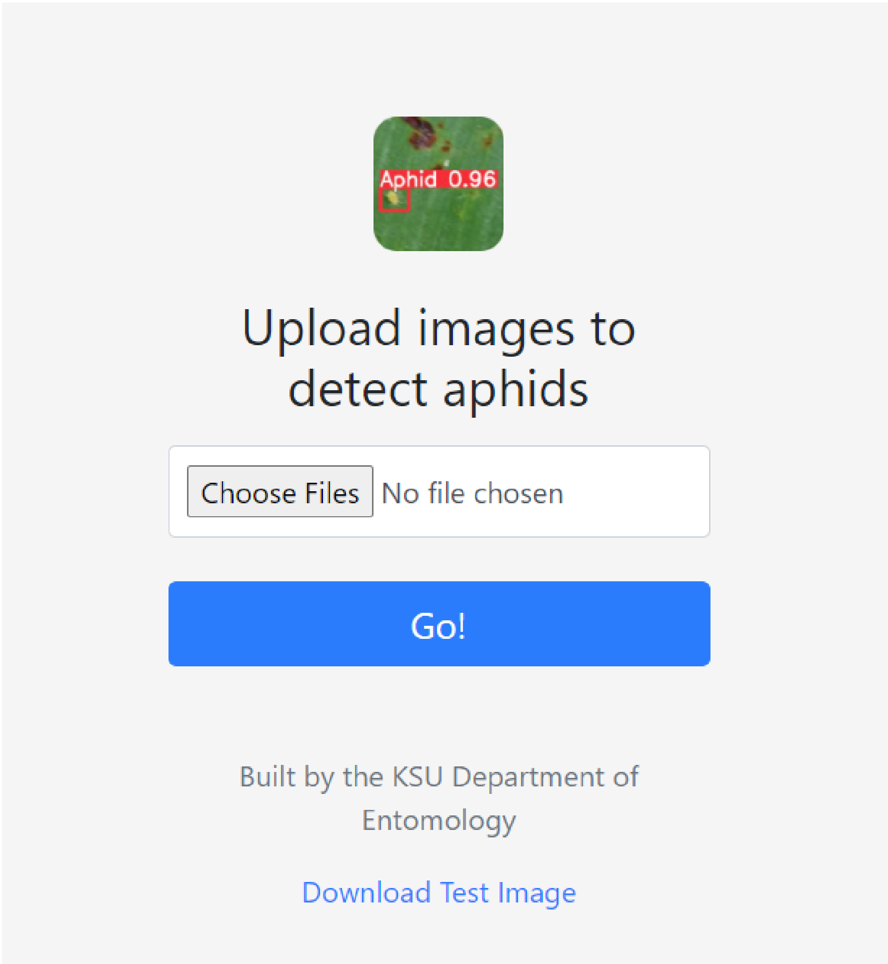
B)

Model counting

- 41 SA/leaf

Application

We deployed our best trained model to a web application

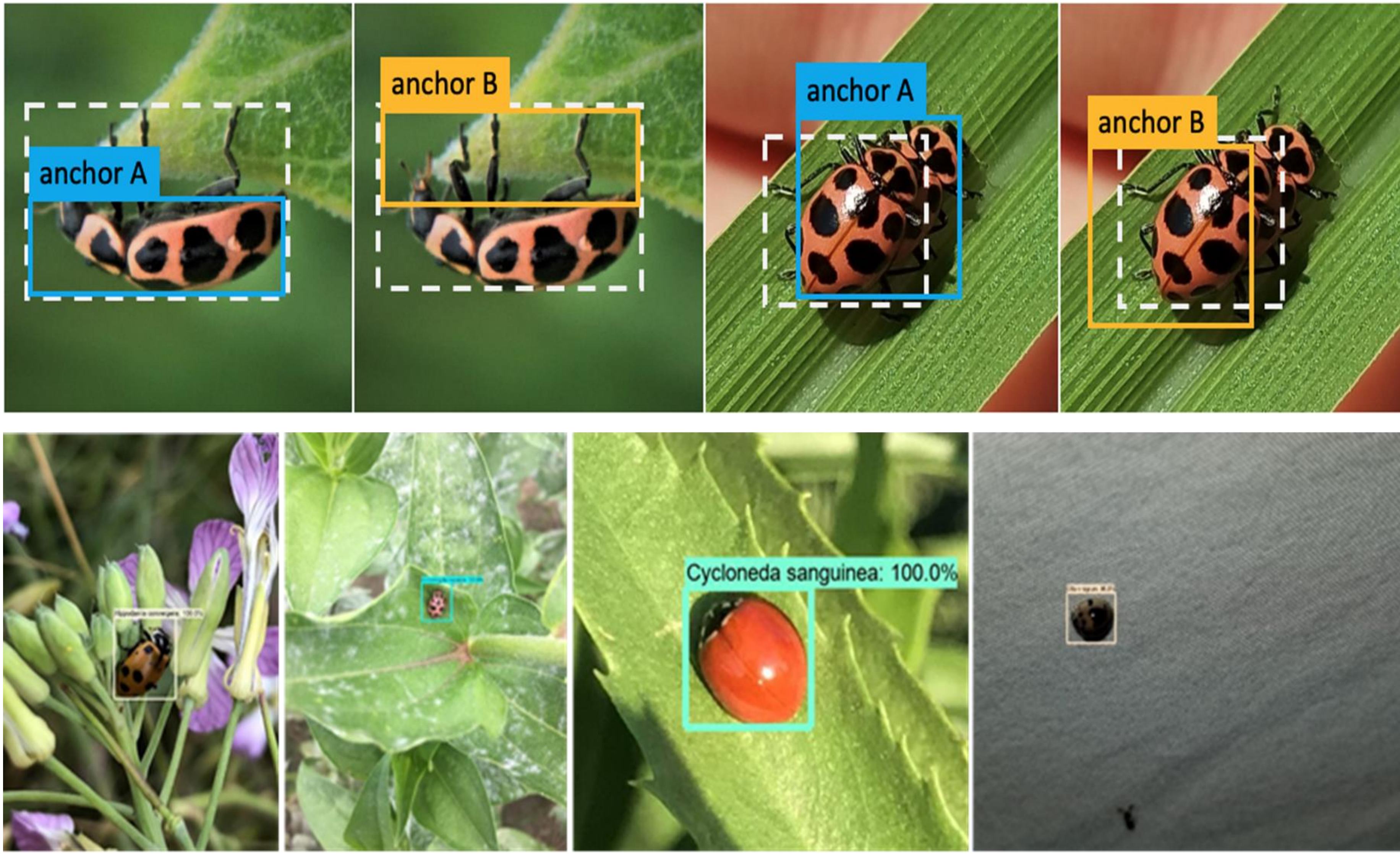


Average aphid count = 674.0

Image #	Aphid Count	Image
1	348	
2	1000	

https://bit.ly/ksuaphidalatedetection

Detecting common coccinellids found in sorghum using deep learning models



Wang et al. 2023 https://doi.org/10.1038/s41598-023-36738-5

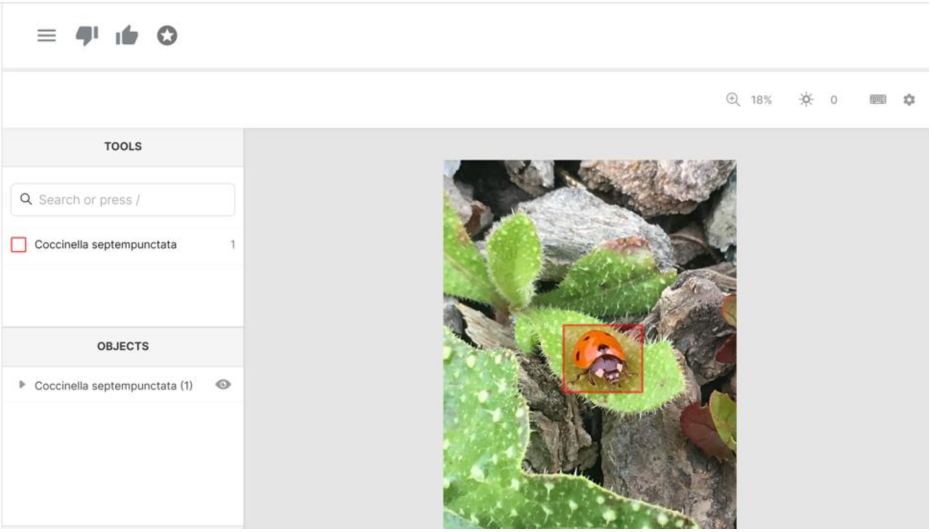
Material & Methods

1. Data generation and imagery preprocessing

- Downloaded images from iNaturalist project (approx 700 images/per category) for a total dataset of 4865 images




2. Manually labeling using bounding boxes and categorizing based on species and subfamily



- 6 species of coccinellids and one subfamily category
  - *Coccinella septempunctata*
  - *Coleomegilla maculata*
  - *Cycloneda sanguinea*
  - *Harmonia axyridis*
  - *Hippodamia convergens*
  - *Olla v-nigrum*
  - Scymninae

Material & Methods

3. Creation and testing models by computer programming

- Data split/ratio: (3053 images) Train; (1113 images) Validation; and (699 images) Testing
  - Classified by beetle instances per image and according to their size: small, medium or large

- Evaluated the performance of 3 models found on Pytorch:
  - Faster R-CNN with FPN
  - YOLOv5 family
  - YOLOv7 family

4. Model metric performances

- Metrics evaluated:
  - Average-Precision (%)
  - AP@0.5 (%)
  - AP@0.75 (%)
  - Model architectures

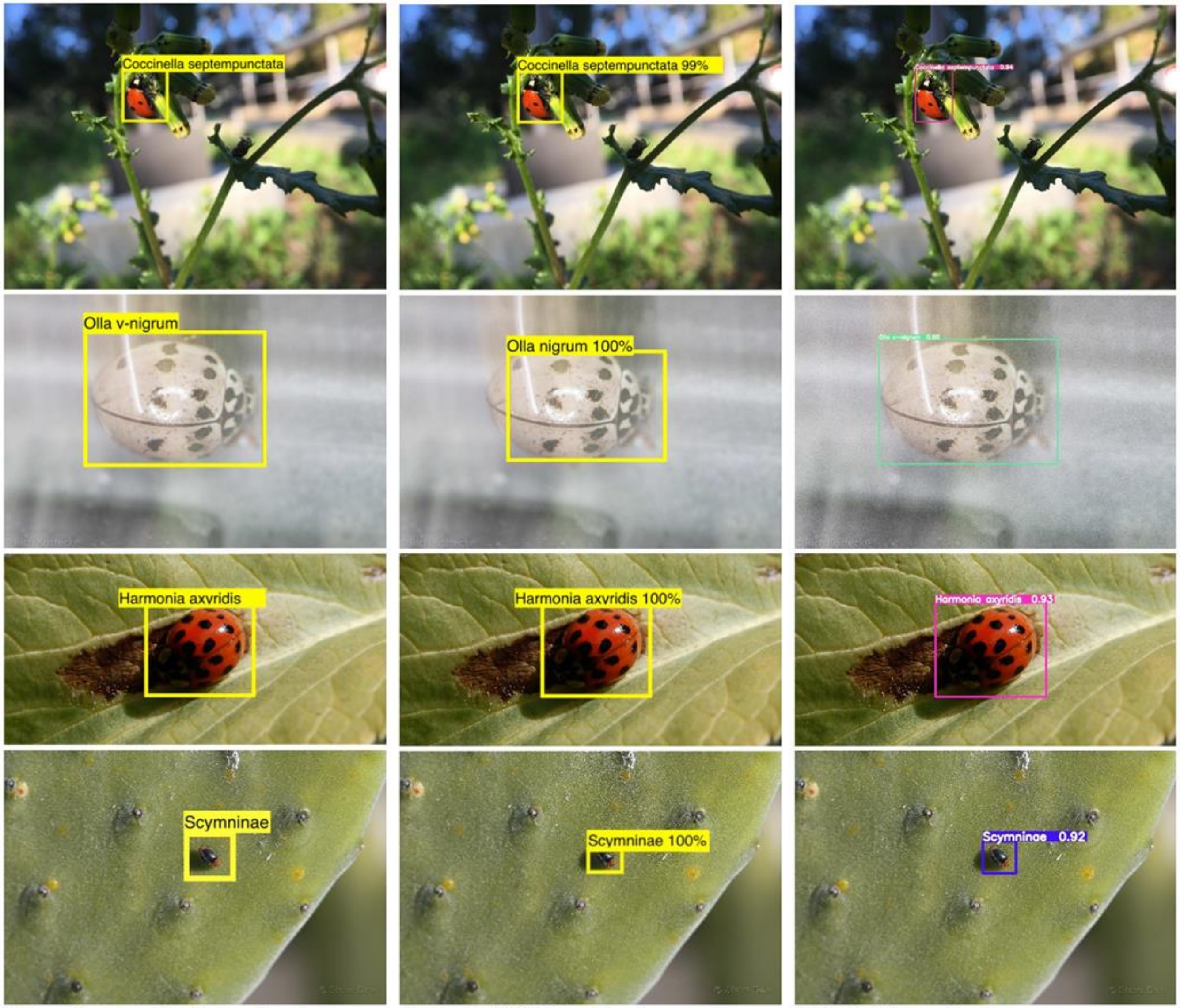
Results

Overall average-precision (AP), AP@0.5, AP@0.75 scores, and different model architectures of the three detection models tested

Model type	AP (%)	AP@0.50 (%)	AP@0.75 (%)	Layer numbers	Parameter numbers	Inference time (ms)	Size (MB)
Faster-R50-IoU	62.9	94.1	74.2	50	42,000,000	130.2	165.8
Faster-R101-IoU	64.7	93.4	74.5	101	60,000,000	141.6	242.1
Faster-R50-GIoU	63.5	94.3	73.9	50	42,000,000	127.4	165.8
Faster-R101-GIoU	65.6	93.7	75.6	101	60,000,000	138.5	242.1
YOLOv5n	67.6	93.1	79.9	157	1,768,636	4.8	3.8
YOLOv5s	70.8	94.5	83.2	191	7,468,160	3.3	14.4
YOLOv5m	73	96	85.1	212	20,877,180	11.6	44.2
YOLOv5l	73.2	95.3	84.7	267	46,140,588	17.7	92.8
YOLOv5x	73.8	95.9	85.6	322	86,213,788	28	173.1
YOLOv7	74.6	97.3	86.2	314	36,514,136	19.2	74.8
YOLOv7-tiny	68.3	94.7	81.1	208	6,023,832	5.7	12.3
YOLOv7-x	68.3	94.1	79.7	362	70,822,872	28.3	142.1
YOLOv7-d6	65.3	90.6	75.2	566	152,967,984	41.8	1200

Results

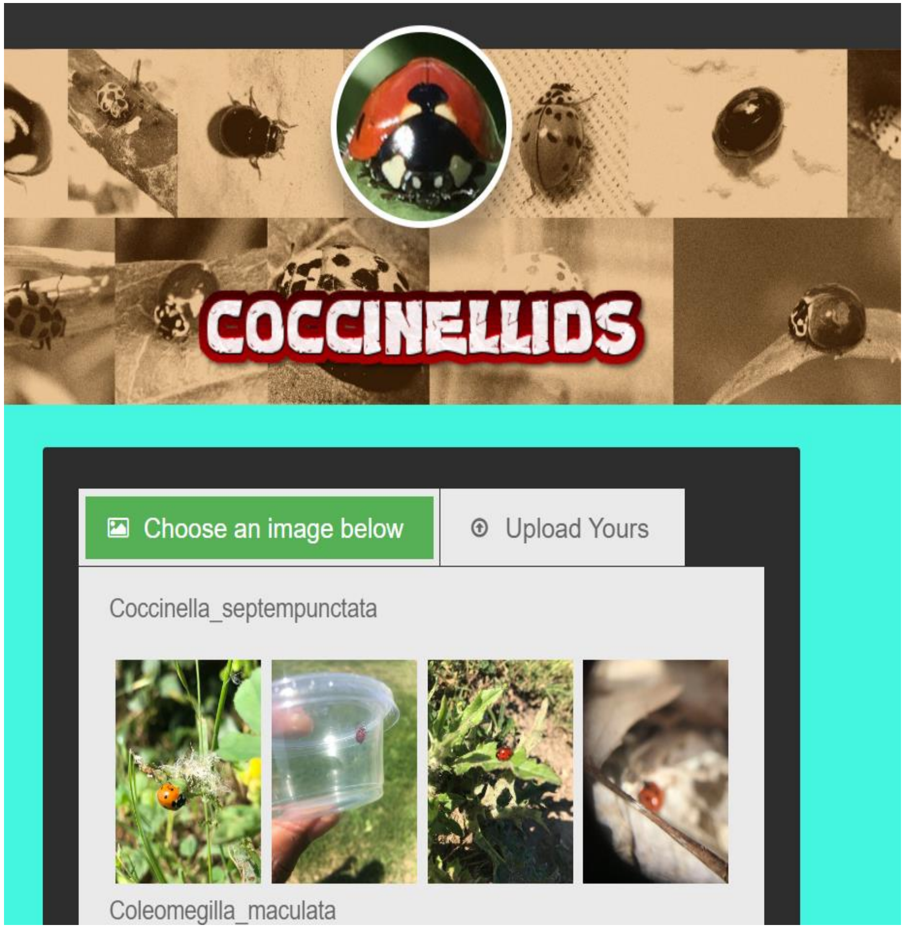
Detection results using testing images performed by Faster R-CNN and YOLOv7 model



Manually annotated bounding box   Faster R-CNN bounding box   YOLOv7 bounding box

Application

We deployed our best trained model to a web application



https://coccinellids.cs.ksu.edu/

Future directions

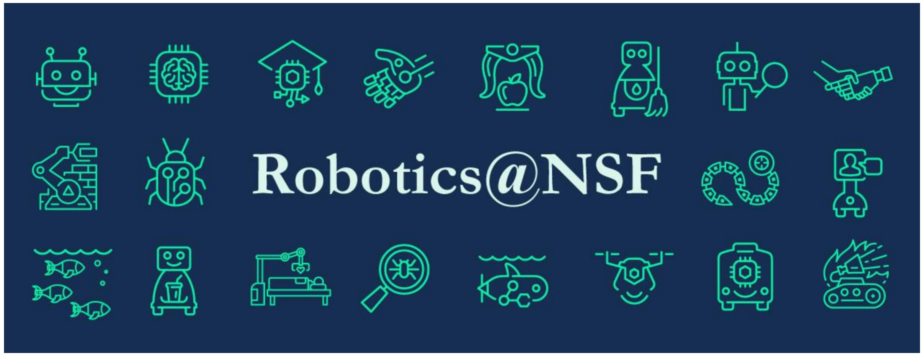
Previous developed technology, using deep learning, can be implemented in sampling protocols for management decisions of sorghum aphids and by further developing mobile applications and unmanned vehicles with sensor systems

Witt, 2022

Acknowledgments

- Special thanks to the McLab members:
  - Kent Hampton
  - Nick Clark
  - Max Dunlap
  - Trevor Witt
  - Anna Keenan
  - Amanda Drouhard
  - Luke Carney

- National Robotics Initative (NRI) grant no 2019-67021-28995



Questions

?