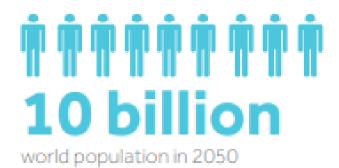
Data Analytics in Precision Agriculture

SARITH DIVAKAR M | GITHUB.COM/SARITHDM

Population growth and Urbanization

POPULATION GROWTH = HIGHER DEMAND FOR FOOD



70%
More food to be produced by farmers

URBANIZATION
DRIVES CHANGE IN
CONSUMPTION
PATTERN

36.4 kg
processed food and meat annual per capita meat consumption

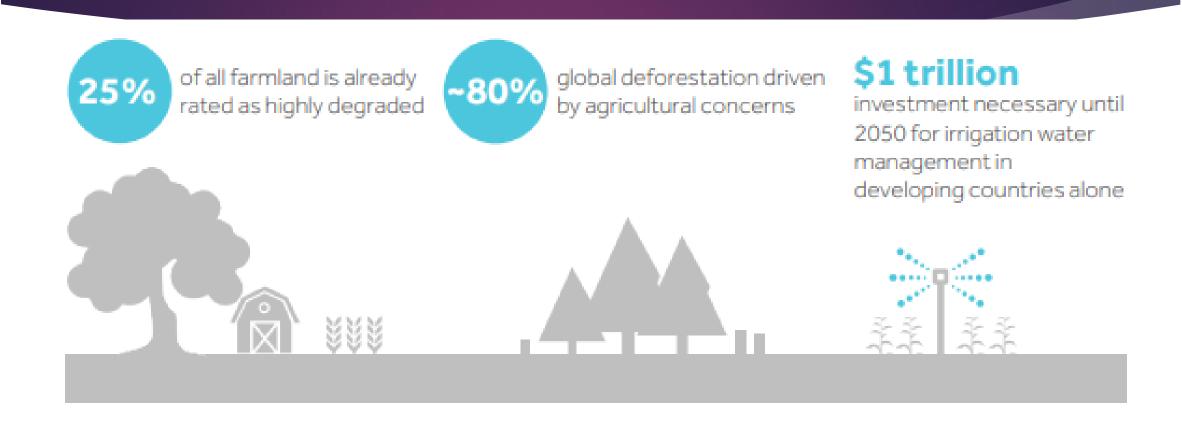
1997-1999



processed food and meat annual per capita meat consumption 2030

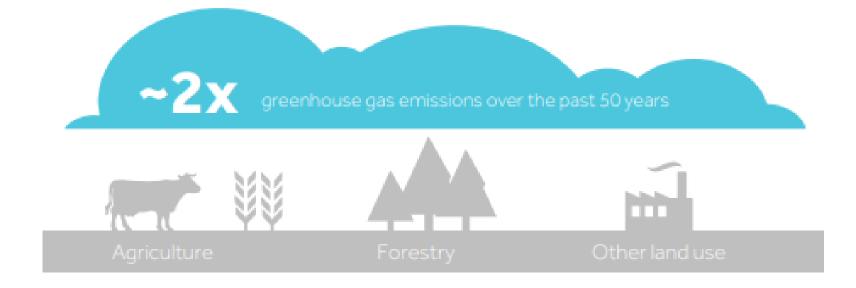
Source: https://www.oliverwyman.com/our-expertise/insights/2018/feb/agriculture-4-0--the-future-of-farming-technology.html

Natural Resources



Climate Change

GREENHOUSE GAS EMISSIONS

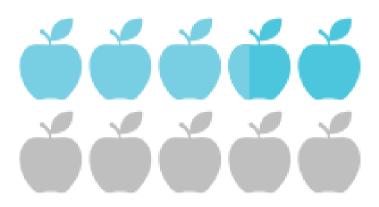


VARIABILITY OF PRECIPITATION REDUCE CROP YIELDS



Rise in the frequency of droughts and floods, all of which tend to reduce crop yields

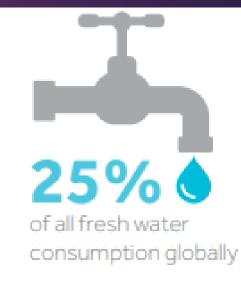
Food Waste



between

33%-50%

of all food produced globally is never eaten





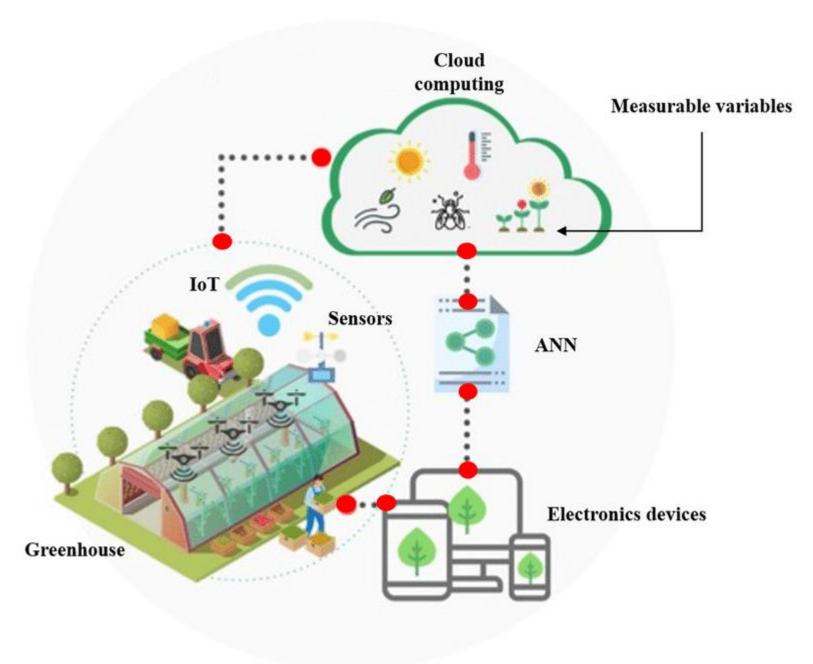
largest emitter of greenhouse gases after China and the US, if food waste were a country

Solution: Agriculture 4.0



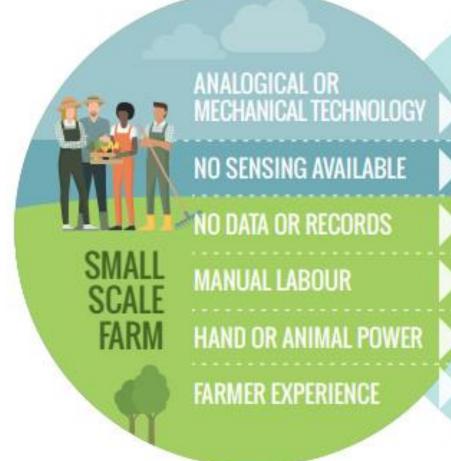
Agriculture 4.0 **Promoting factors** Key features Agriculture 1.0 10,000 BC Manpower and animal forces Usage of simple tools The 1# Industrial Evolution Improvement of steam engines 19th Agriculture 2.0 century Agricultural machinery Invention of computers Usage of chemicals Development of programming Robotic applications 20th and 21st Agriculture 3.0 century Computer programs Deployment of robots Development of Internet of Things, Big Data, Artificial Intelligence, Cloud Computing, etc. Agriculture 4.0 Today Smart systems Smart devices

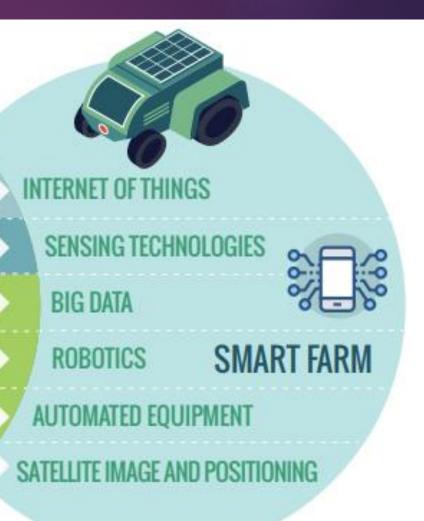
Source: Zhaoyu Z. et al. Decision support systems for agriculture 4.0: Survey and challenges, Computers and Electronics in Agriculture (2020)



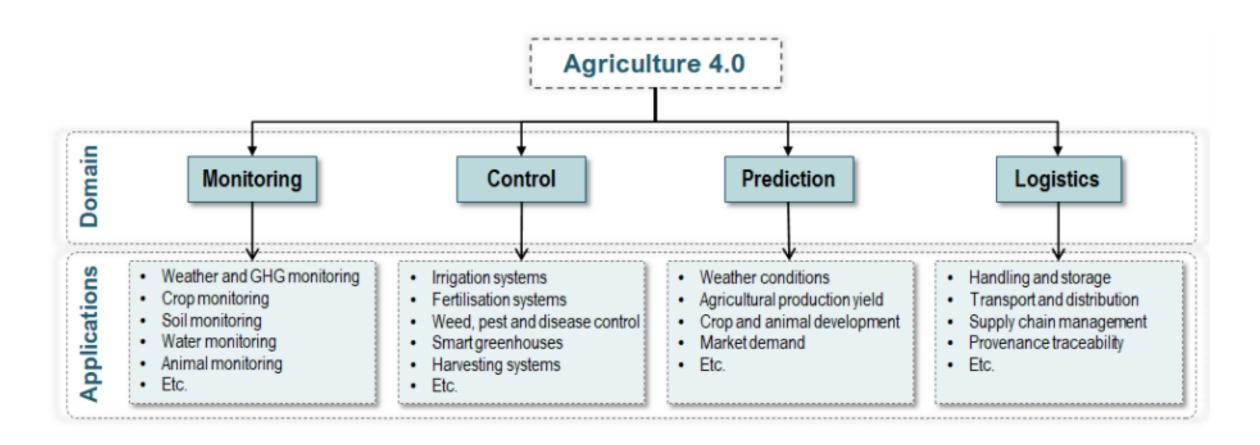
https://www.austrade.gov.au/agriculture40

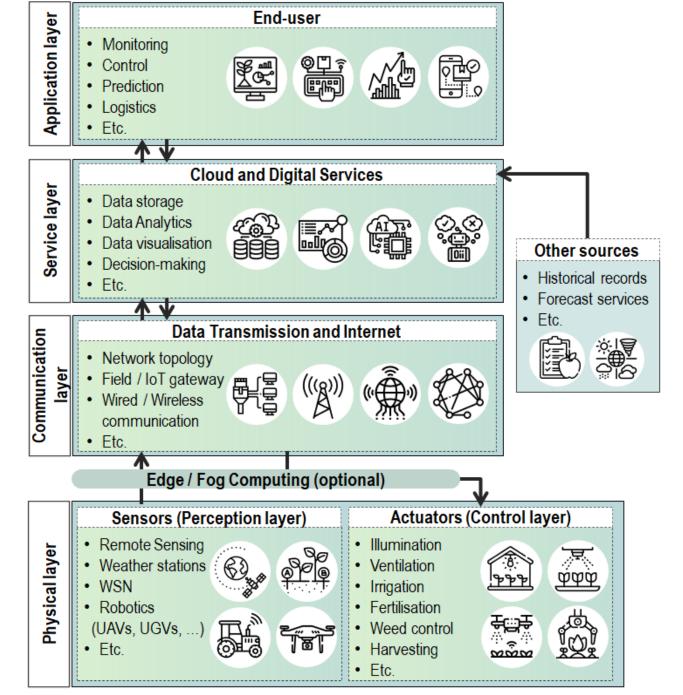
Precision Agriculture/Smart Farming

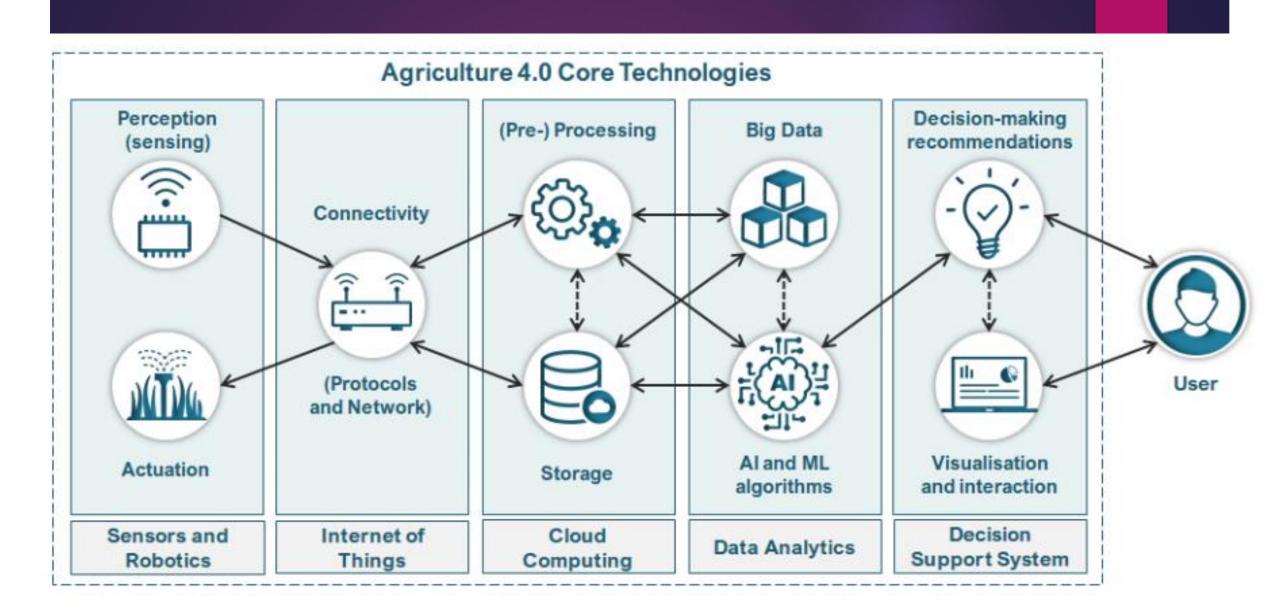


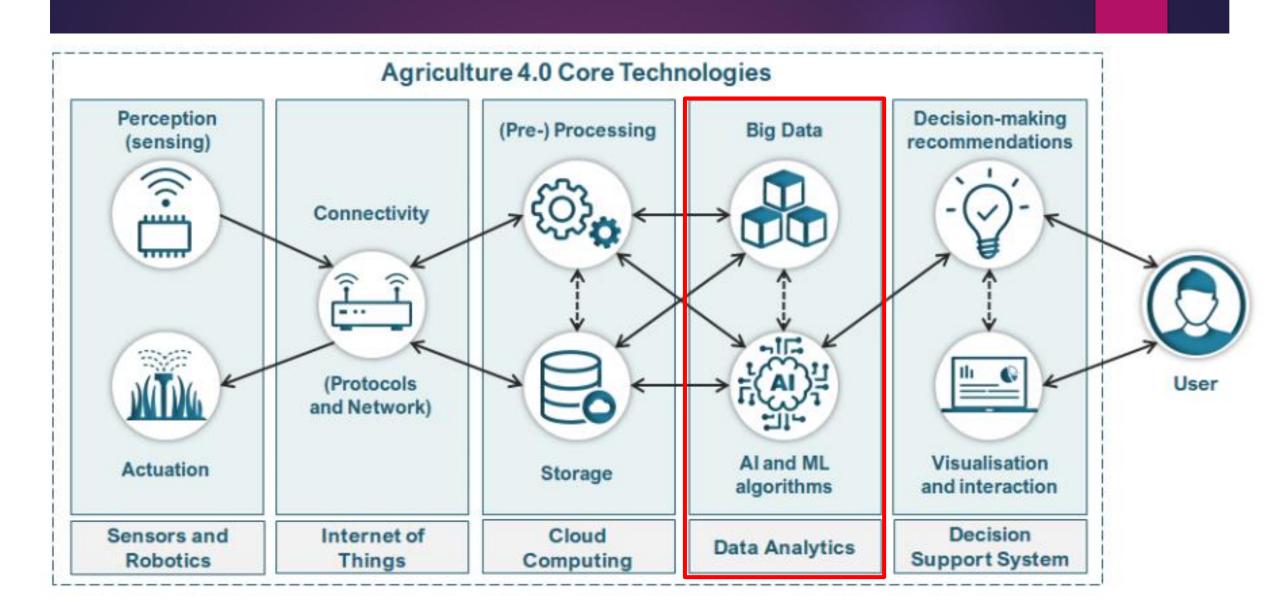


Applications









AI/ML Algorithms

An algorithmic way of **making sense** (learning) from data.

Learning means Improving with Experience at some Task

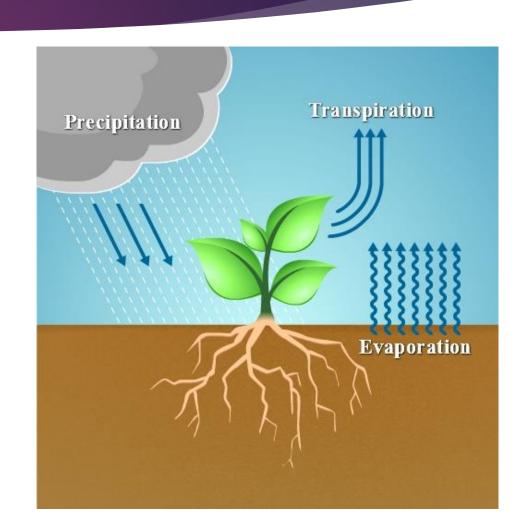
Tom M. Mitchell: A computer program is said to learn from Experience E with respect to some Task T and some Performance measure P, if its performance on T, as measured by P, improves with experience E.

T: Estimate Evapotranspiration rate

E: Learning from Evapotranspiration dataset

P: Accuracy of the Evapotranspiration rate

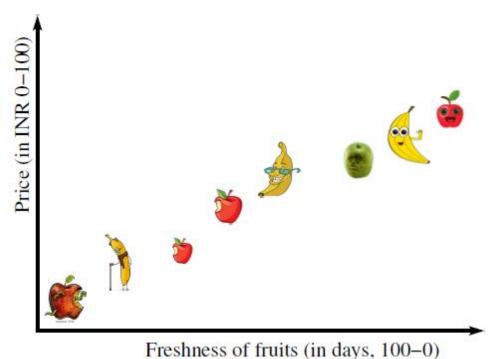
Decision: Irrigation Scheduling

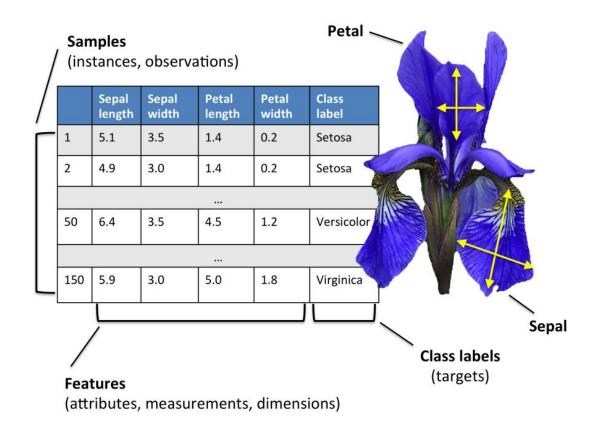


Predictive Analytics/ Supervised learning

Build an analytical model predicting a target measure of interest

Example: Predict Price based on freshness

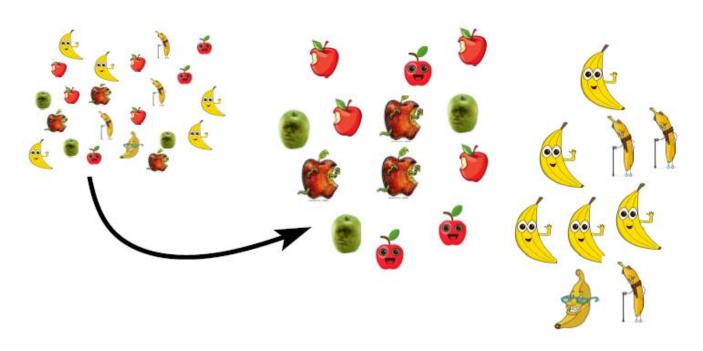


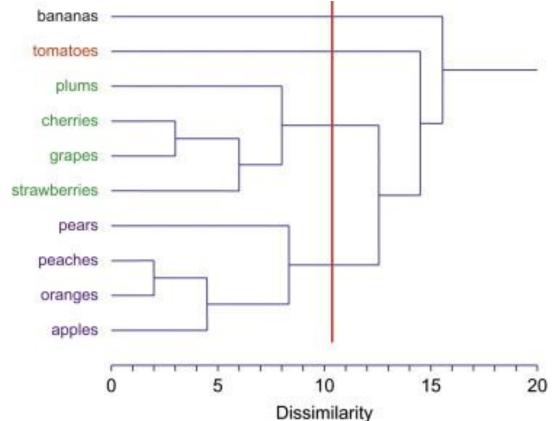


Descriptive Analytics/Unsupervised learning

Describe patterns from the data

Example: Group fruits into two groups





Deep Learning

Neural Networks are considered universal function approximators

They can compute and learn any function

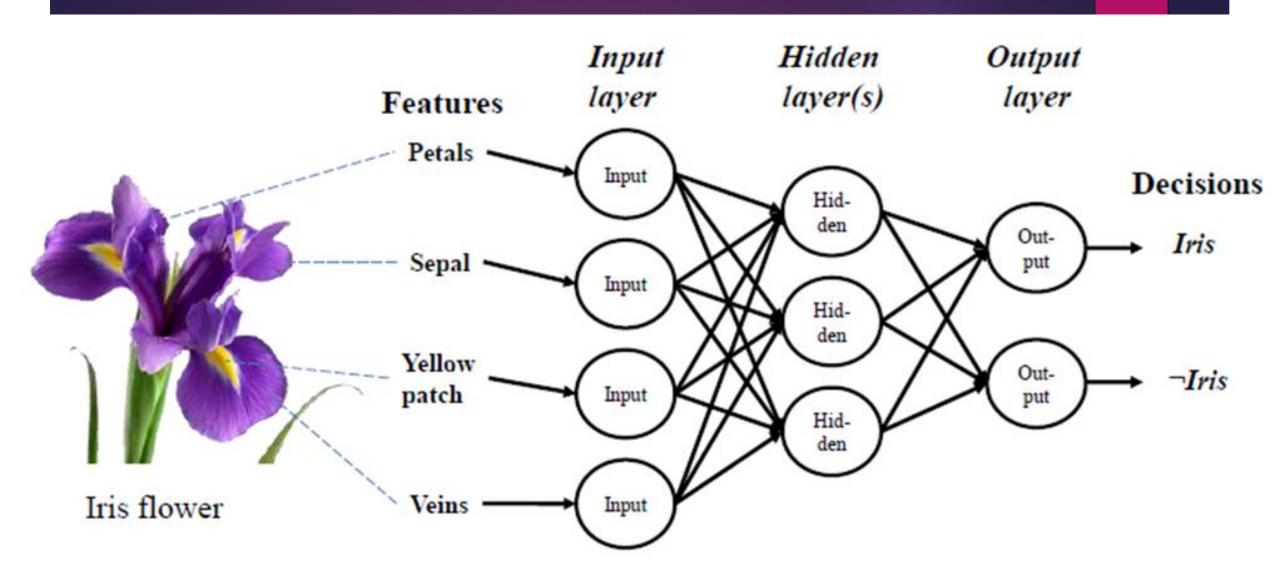
The neuron count has risen over the years to express more complex models.

More parameters efficiently learned using high computing powers.

More connections means that our networks have more parameters to optimize, and this required the explosion in computing power that occurred over the past 20 years.

Core components

- Parameters
- Layers
- Activation functions
- Loss functions
- Optimization methods
- Hyperparameters



ML/DL is an iterative process: Don't expect it to work first time

Andrew Ng (Co-Founder of Coursera and a former head of Google Brain) states that his approach to building machine learning/deep learning software is threefold:

1. Idea

3. Experiment

Code

- Start off with an idea
- 2. Implement the idea in code
- 3. Carry out an experiment to conclude how well the idea worked

The faster you can go around this loop, the quicker progress will be made!

How to solve an agricultural problem?

Is it a ML task? Are you sure ML is the best solution?

- ➤ Hard: X is independent of Y: X , Y=?
- ➤ Easy: X is a set with limited variations. Configure Y=F(X)

Appropriate ML scenario?

- Supervised learning
- Unsupervised learning

Appropriate model?

- Data size (small data -> linear model, large data -> consider non-linear)
- > Imbalanced data (special treatment of the minority class required)

Enough training data?

> Investigate how precision improves with more data

Model overly complicated?

- > Start simple first, increase complexity and evaluate performance
- Avoid overfitting to training set

Feature quality

- ➤ Have you identified all useful features?
- > Use domain knowledge of an expert to start
- > Include any feature that could be found and investigate model performance

Feature engineering

- > The best strategy to improve performance and reveal important input
- ➤ Encode features, normalize [0:1], combine features

Combine models

- > If multiple models have similar performance there is a chance of improvement
- > Use one model for one subset of data and another model for the other

Model Validation

- Use appropriate performance indicator (Accuracy, Precision, Recall, F1, RMSE, MSE, etc.)
- How well does the model describe data? (AUC)
- Data typically divided into Training and Validation
- Evaluated accuracy on disjoint dataset (other than training dataset)
- > Tune model hyper parameters (i.e. number of iterations)

Use Cases



Health assessment, irrigation, crop monitoring, crop spraying, planting, and soil and field analysis The Smart
Agriculture market
is expected to
reach \$18.45
Billion in 2022, at
a CAGR of 13.8%

- Business Intelligence



With IoT, all data from

different sensors is accessible to the agriculturist on their mobile phones



Soil Management

Analyze soil status, temperature and humidity



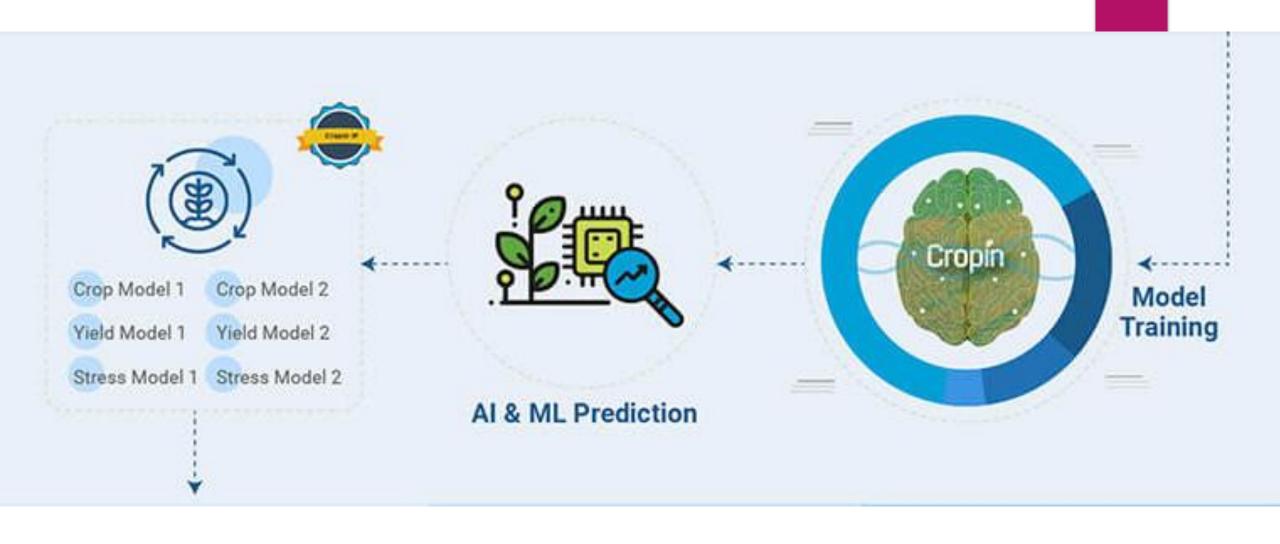
Livestock Management

Monitor livestock productivity and health

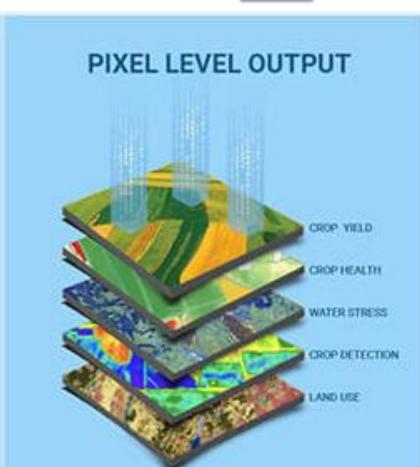
Water Management with Automated Irrigation





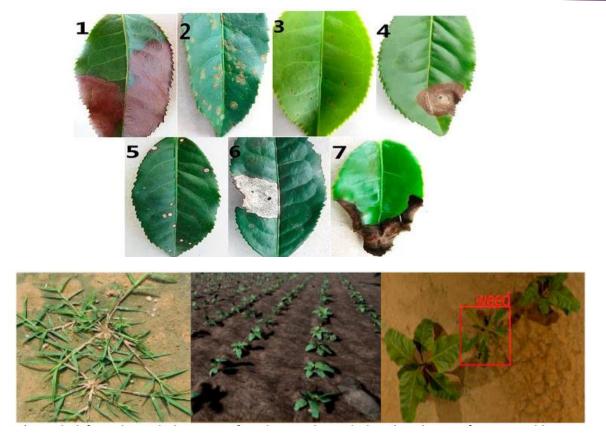


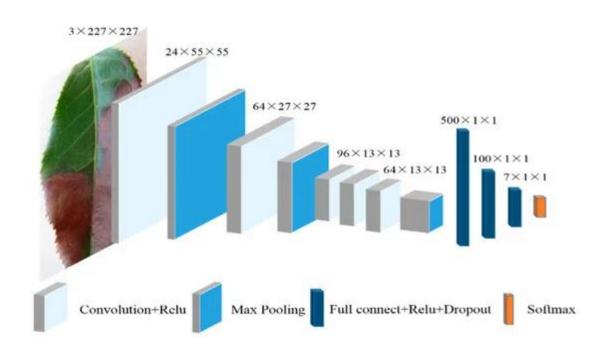




Case Studies

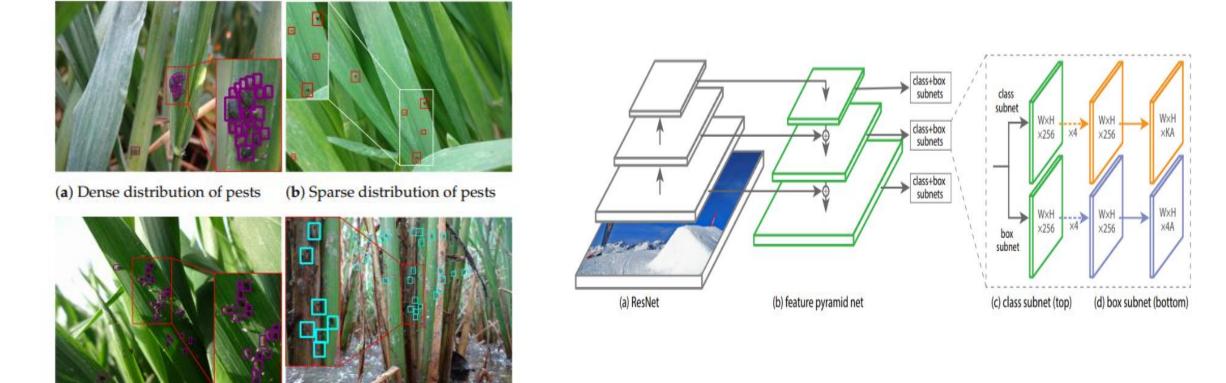
Leaf disease detection/Identification of weeds - CNN





Chen, Jing, Qi Liu, and Lingwang Gao. 2019. "Visual Tea Leaf Disease Recognition Using a Convolutional Neural Network Model" Symmetry 11, no. 3: 343. https://doi.org/10.3390/sym11030343 Fenil D.et al. Analysis of robust weed detection techniques based on the Internet of Things (IoT), Procedia Computer Science, Volume 160,2019, https://doi.org/10.1016/j.procs.2019.11.025.

Pest Population Counting-RetinaNet



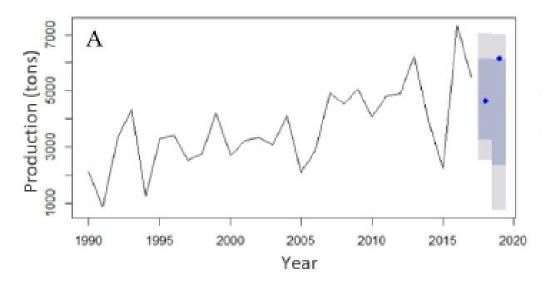
Wang, R.et al. AgriPest: A Large-Scale Domain-Specific Benchmark Dataset for Practical Agricultural Pest Detection in the Wild. Sensors 2021, 21, 1601. https://doi.org/10.3390/s21051601

(d) Background clutter

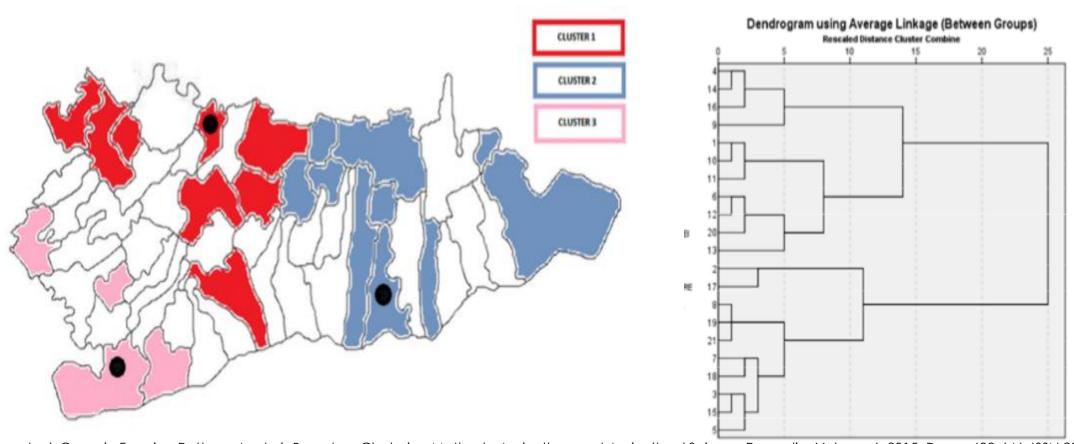
(c) Illumination variations

Crop Yield Prediction

Data Names	Abbreviation	Sources
Normalized Difference Vegetation Index	NDVI	MODIS (MOD13Q1)
Potential Evapotranspiration	PET	Climate Research Unit
Precipitation	PRE	Climate Research Unit
Minimum Temperature	TMN	Climate Research Unit
Maximum Temperature	TMX	Climate Research Unit
Soil Moisture	SM	European Space Agency
Size of land cultivated for maize production	Land	Department of Agriculture, Forestry and Fisheries



Organic Farming Patterns Analysis Based on Clustering Methods



A-V Bălan et. al. Organic Farming Patterns Analysis Based on Clustering Methods, Agriculture and Agricultural Science Procedia, Volume 6, 2015, Pages 639-646, ISSN 2210-7843, https://doi.org/10.1016/j.aaspro.2015.08.110.

Hands-on Session

Plant disease detection

Dataset:

https://www.kaggle.com/emmarex/plantdisease

Code:

https://www.kaggle.com/sarithdivakar/plant-disease-detection-using-keras