Artificial Intelligence Methods for Oil Palm Remote Sensing Applications

Presented by:

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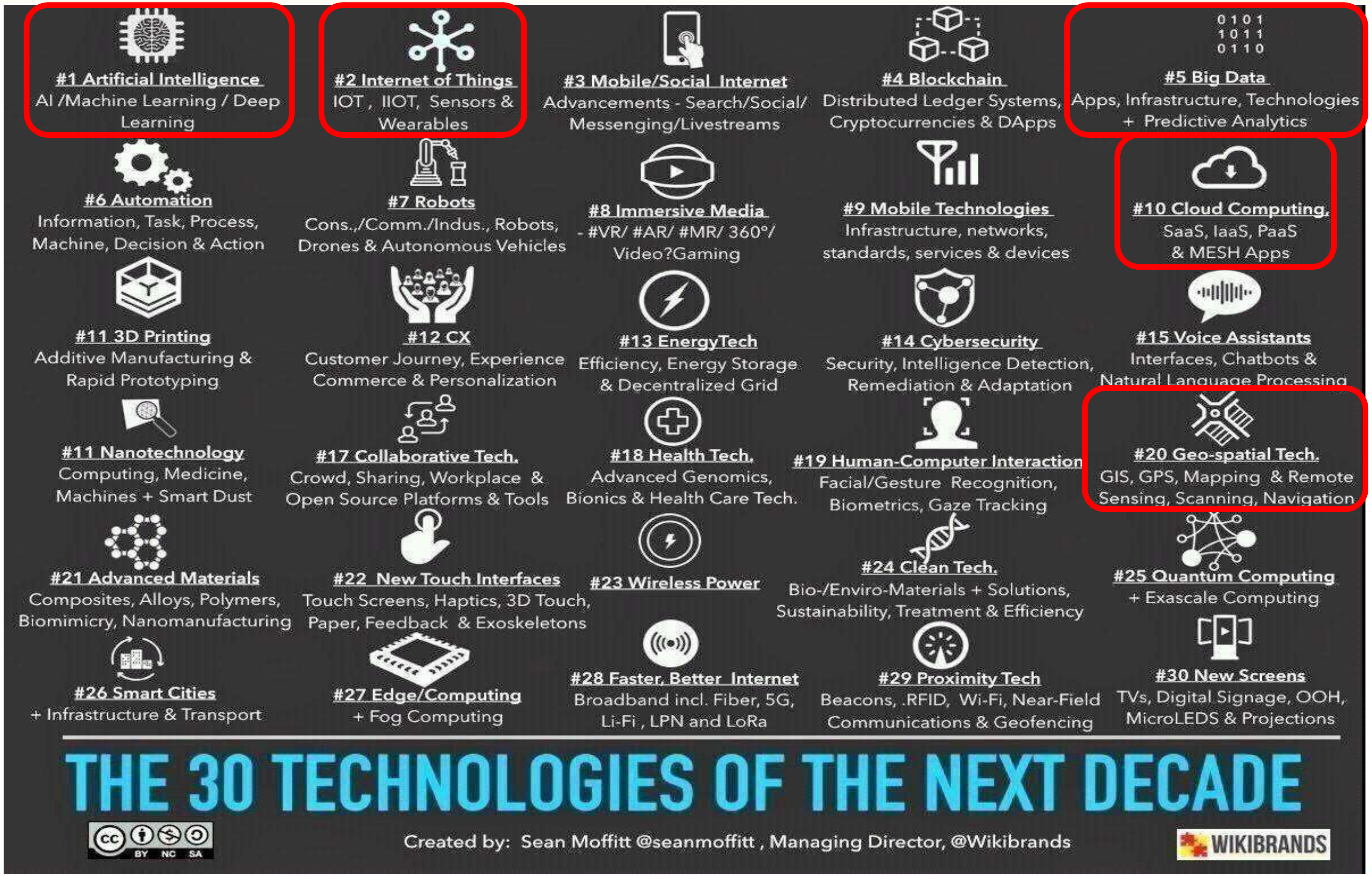
Outline

- ❑ Introduction
- ❑ Industrial Revolution 4.0
- ❑ AI & Machine learning
- ❑ Remote sensing
- ❑ Case Studies
  - Field spectroscopy
  - Airborne
  - Spaceborne
- ❑ Conclusions and Future Outlook

Introduction

- Era of Industrial Revolution 4.0 (IR4.0) and Agriculture 4.0
- Precision agriculture and automation
- Remote sensing as an integral technology to provide data and images.
- Artificial intelligence (AI) is a branch of computer science that aims to create intelligent machines/systems. It has become an essential part of the technology industry.
- Machine Learning (ML) is one of the core areas of AI – provides the brain to the AI (via algorithms).
- AI is blending with remote sensing imagery in different industries to improve efficiency and open new possibilities.
- ML enables computers to learn from data to automatically recognize objects, cluster an image by similarity or classify, among others.
- AI and ML capabilities are embedded inside applications and provide users with functionality such as automation or predictive capabilities
- AI and ML in plantation management using remote sensing will be the focus of this session.


#1 Artificial Intelligence
AI /Machine Learning / Deep Learning
#2 Internet of Things
IOT , IIOT, Sensors & Wearables
#3 Mobile/Social Internet
Advancements - Search/Social/ Messenging/Livestreams
#4 Blockchain
Distributed Ledger Systems, Cryptocurrencies & DApps
0101
1011
0110
#5 Big Data
Apps, Infrastructure, Technologies + Predictive Analytics
#6 Automation
Information, Task, Process, Machine, Decision & Action
#7 Robots
Cons./Comm./Indus., Robots, Drones & Autonomous Vehicles
#8 Immersive Media
- #VR/ #AR/ #MR/ 360°/ Video?Gaming
#9 Mobile Technologies
Infrastructure, networks, standards, services & devices
#10 Cloud Computing,
SaaS, IaaS, PaaS & MESH Apps
#11 3D Printing
Additive Manufacturing & Rapid Prototyping
#12 CX
Customer Journey, Experience Commerce & Personalization
#13 EnergyTech
Efficiency, Energy Storage & Decentralized Grid
#14 Cybersecurity
Security, Intelligence Detection, Remediation & Adaptation
#15 Voice Assistants
Interfaces, Chatbots & Natural Language Processing
#11 Nanotechnology
Computing, Medicine, Machines + Smart Dust
#17 Collaborative Tech.
Crowd, Sharing, Workplace & Open Source Platforms & Tools
#18 Health Tech.
Advanced Genomics, Bionics & Health Care Tech.
#19 Human-Computer Interaction
Facial/Gesture Recognition, Biometrics, Gaze Tracking
#20 Geo-spatial Tech.
GIS, GPS, Mapping & Remote Sensing, Scanning, Navigation
#21 Advanced Materials
Composites, Alloys, Polymers, Biomimicry, Nanomanufacturing
#22 New Touch Interfaces
Touch Screens, Haptics, 3D Touch, Paper, Feedback & Exoskeletons
#23 Wireless Power
#24 Clean Tech.
Bio-/Enviro-Materials + Solutions, Sustainability, Treatment & Efficiency
#25 Quantum Computing
+ Exascale Computing
#26 Smart Cities
+ Infrastructure & Transport
#27 Edge/Computing
+ Fog Computing
#28 Faster, Better Internet
Broadband incl. Fiber, 5G, Li-Fi , LPN and LoRa
#29 Proximity Tech
Beacons, .RFID, Wi-Fi, Near-Field Communications & Geofencing
#30 New Screens
TVs, Digital Signage, OOH, MicroLEDS & Projections
THE 30 TECHNOLOGIES OF THE NEXT DECADE
BY NC SA
Created by: Sean Moffitt @seanmoffitt , Managing Director, @Wikibrands
WIKIBRANDS

INDUSTRIAL REVOLUTION

The industrial revolution begins. Mechanization of manufacturing with the introduction of steam and water power

1st Revolution

Mass production assembly lines using electrical power

2nd Revolution

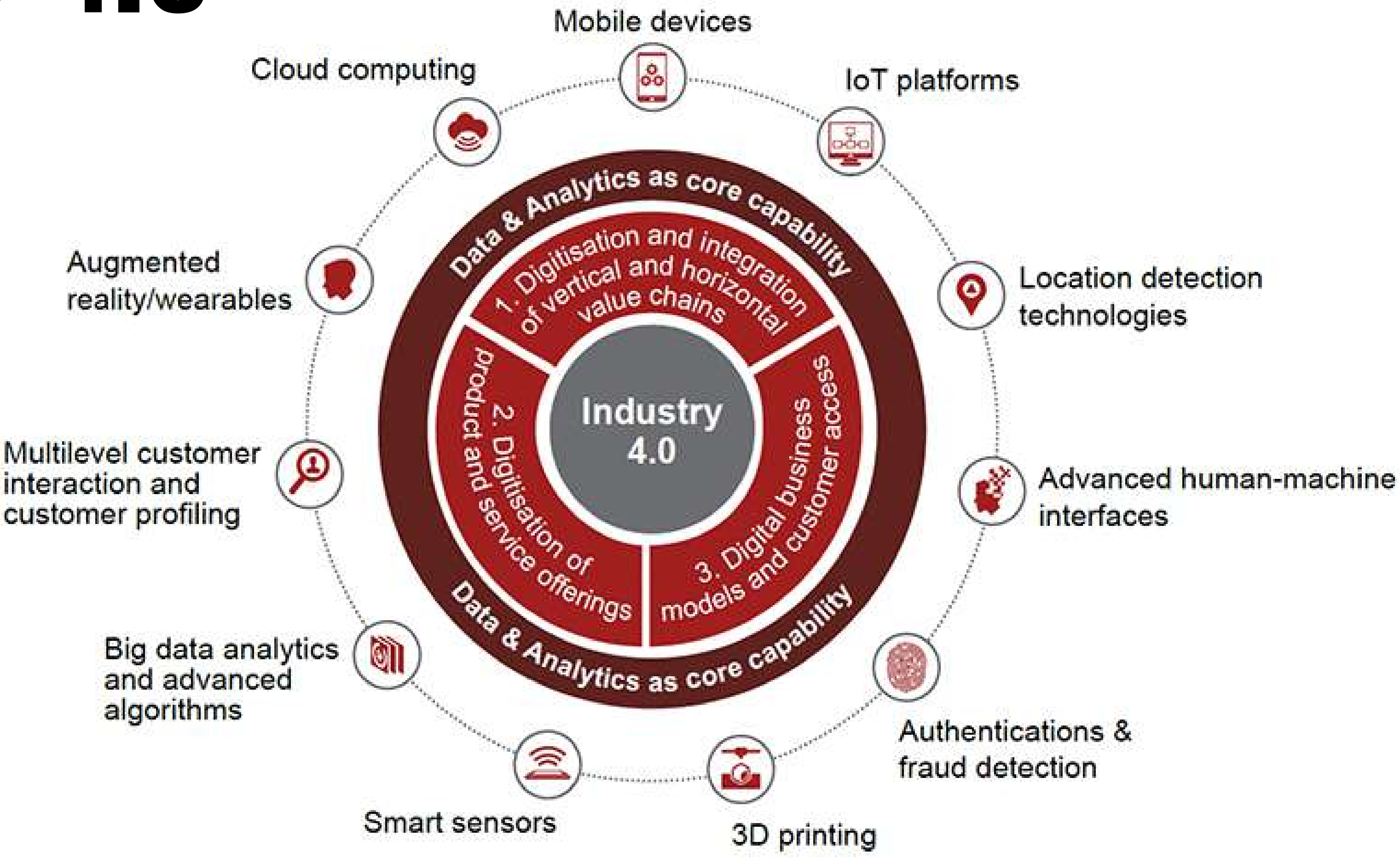
Automated production using electronics, programmable logic controllers (PLC), IT systems and robotics

3rd Revolution

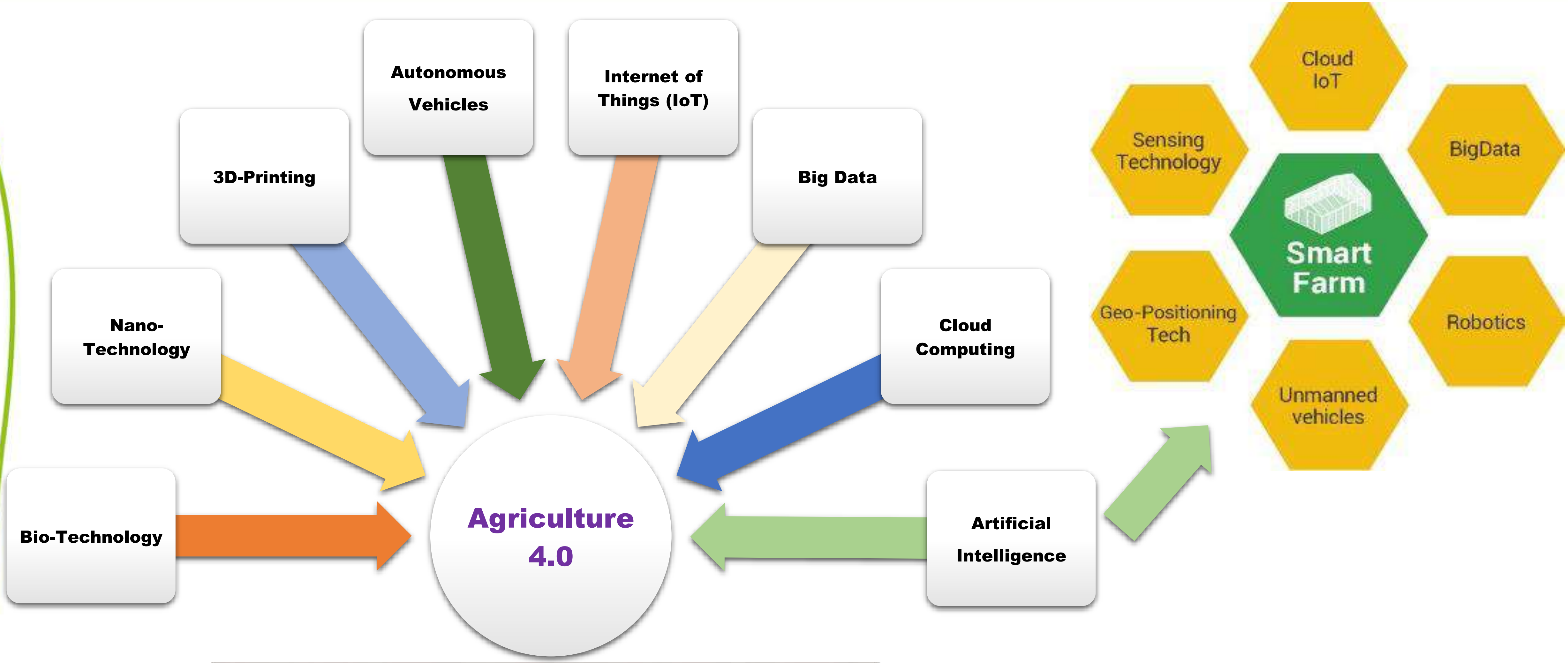
Autonomous decision making of cyber physical systems using machine learning through cloud technology

4th Revolution

Industry 4.0



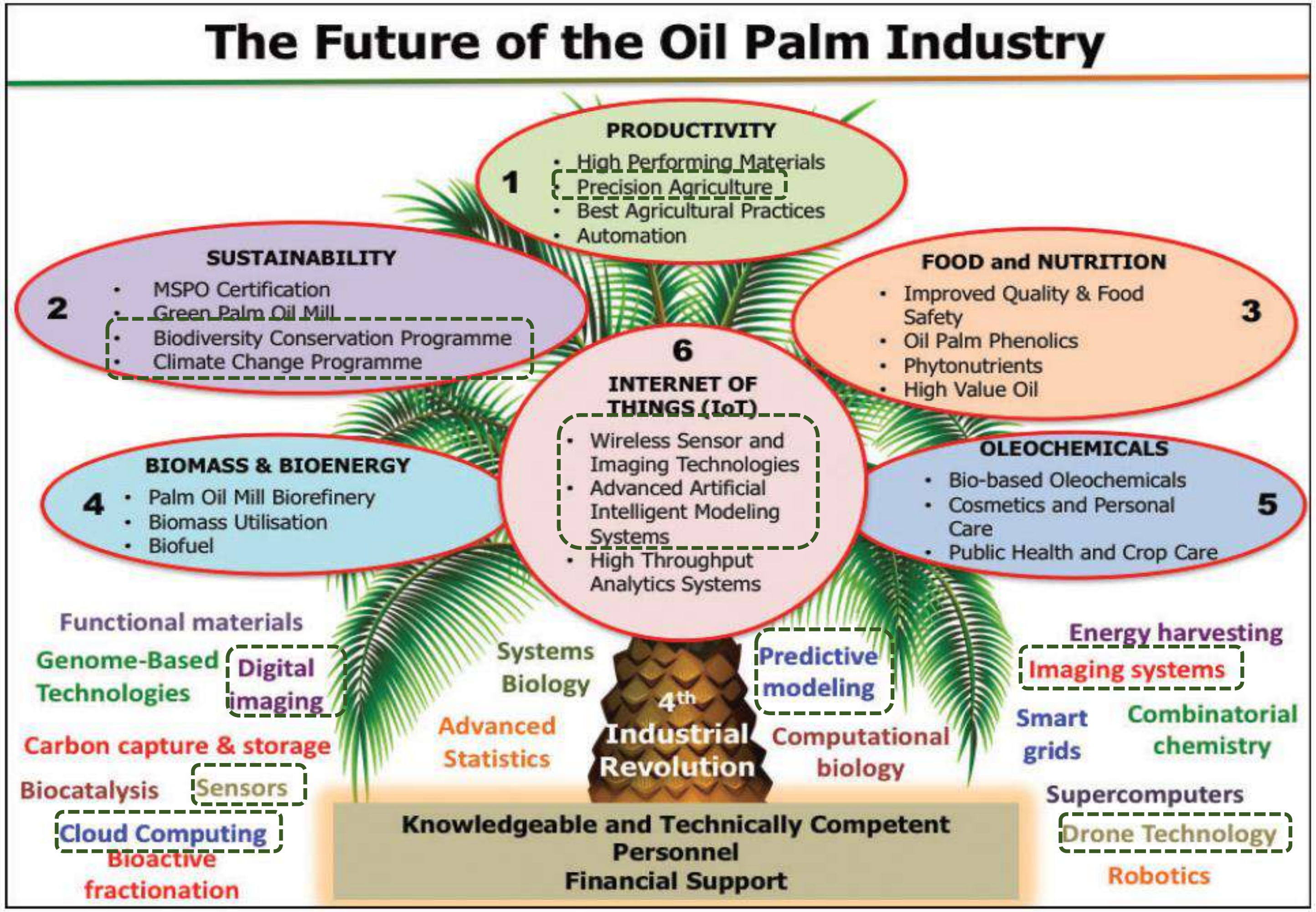
Mobile devices
IoT platforms
Location detection technologies
Advanced human-machine interfaces
Authentications & fraud detection
3D printing
Smart sensors
Big data analytics and advanced algorithms
Multilevel customer interaction and customer profiling
Augmented reality/wearables
Cloud computing
Data & Analytics as core capability
1. Digitisation and integration of vertical and horizontal value chains
2. Digitisation of product and service offerings
3. Digital business models and customer access
Industry 4.0
Data & Analytics as core capability



Fourth Industrial Revolution (4IR)

Transformative Technologies

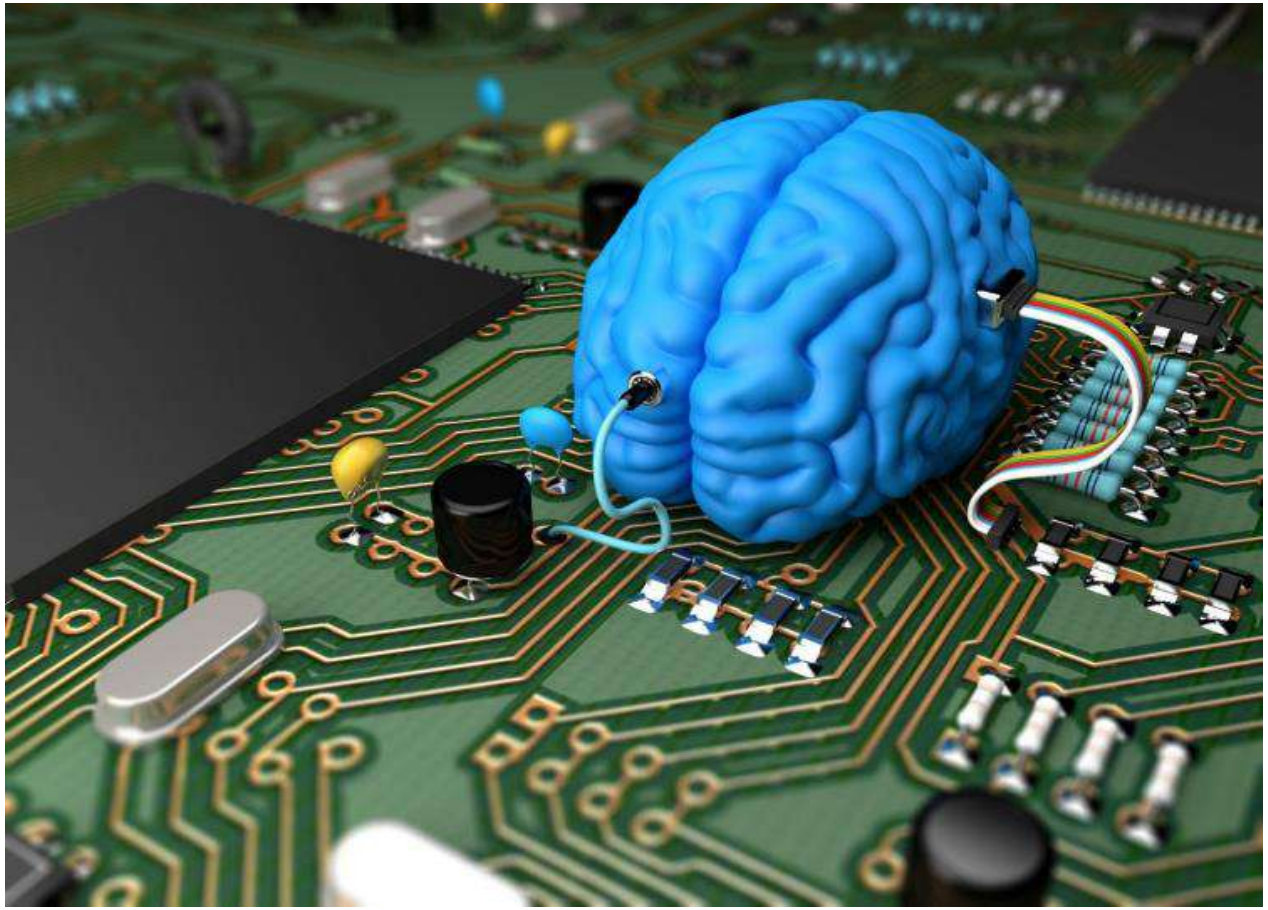
Transformative technologies are crucial for the oil palm industry to remain viable and sustainable Among others include RS, cloud computing, advanced algorithms, big data etc.



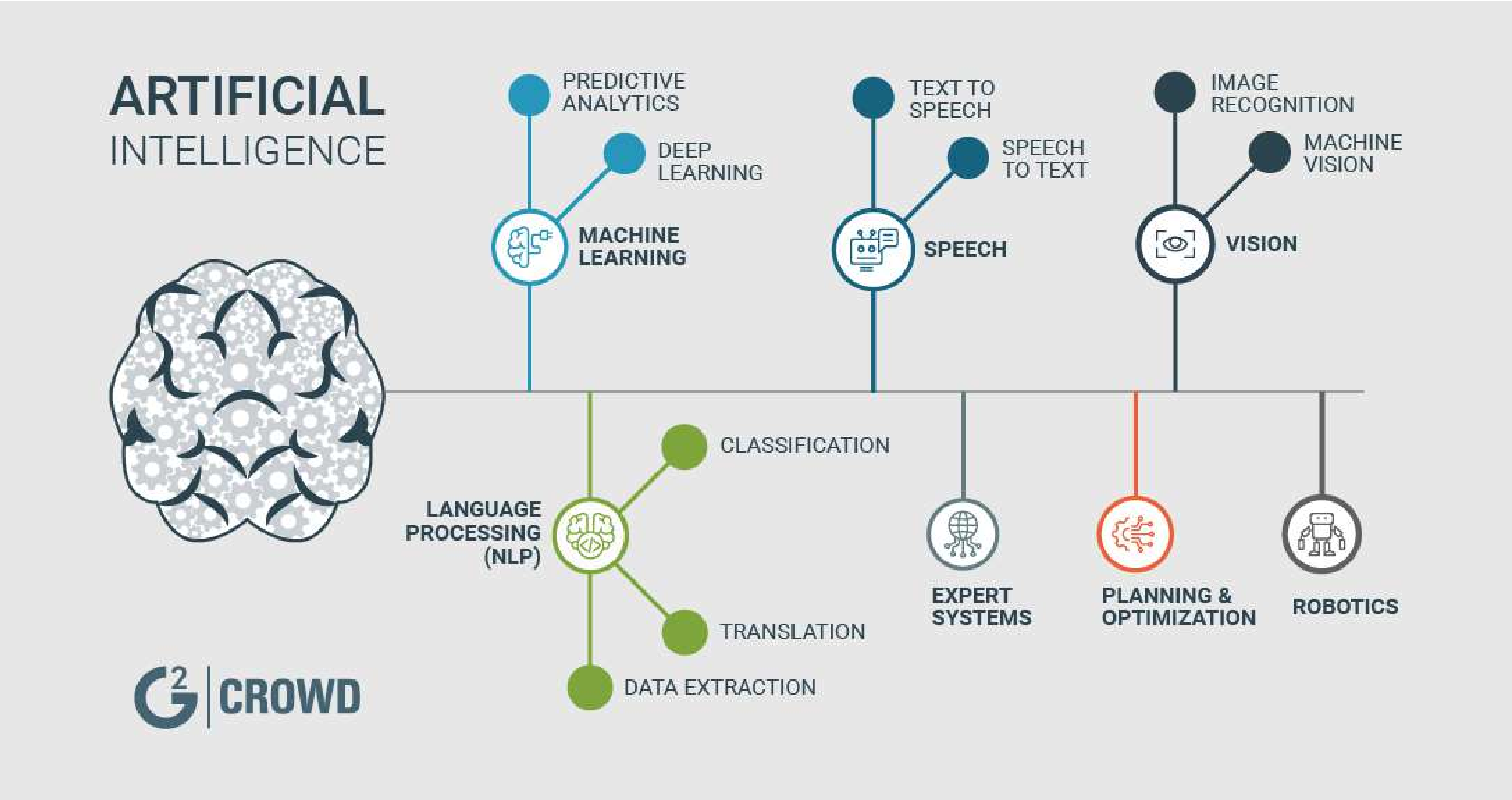
Associated with Remote Sensing Technology

Source: Kushairi et al, 2017

Artificial Intelligence - The Brain behind Industry 4.0

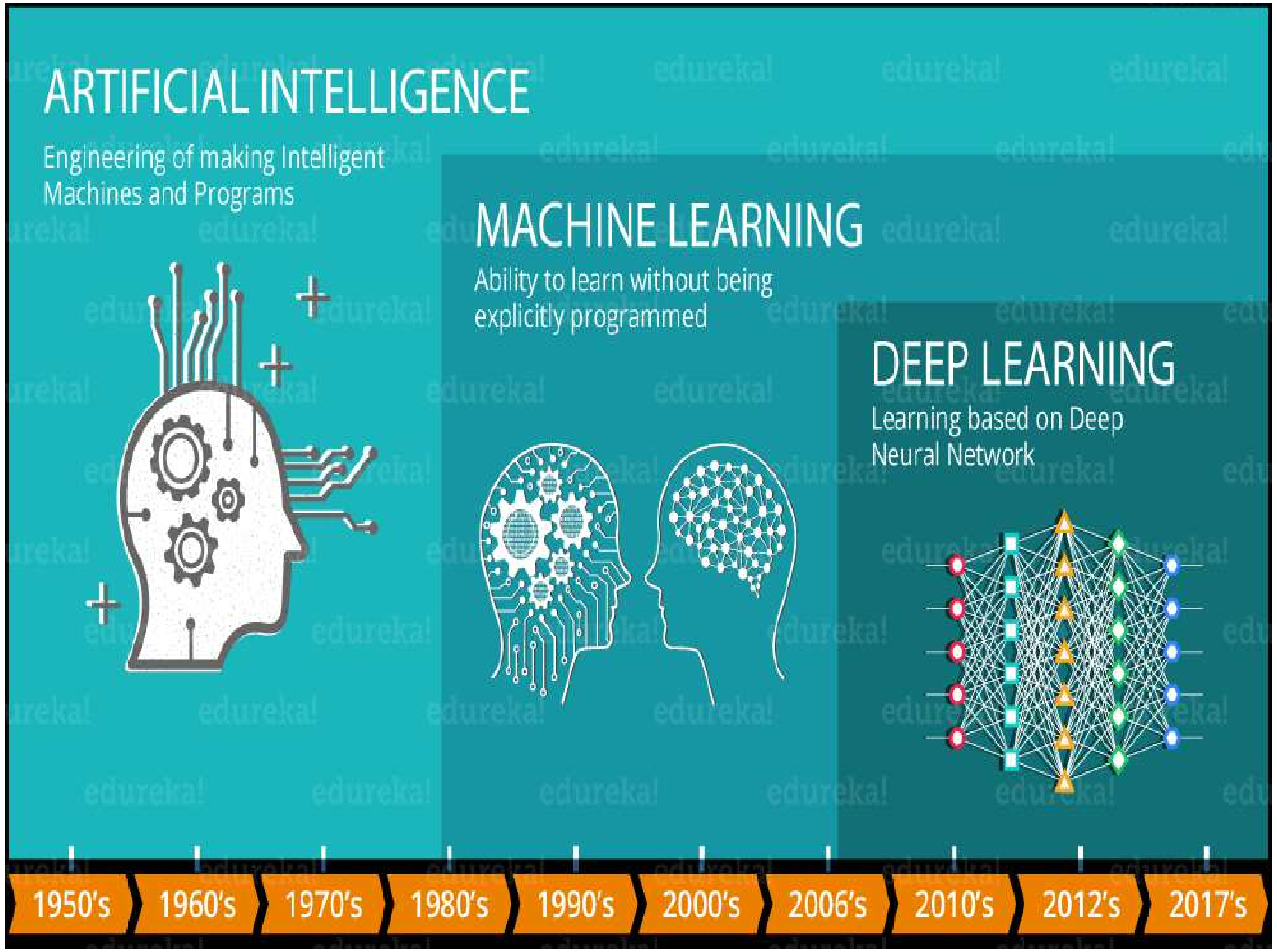


ML is the brain behind AI


ARTIFICIAL
INTELLIGENCE
PREDICTIVE ANALYTICS
DEEP LEARNING
MACHINE LEARNING
TEXT TO SPEECH
SPEECH TO TEXT
SPEECH
IMAGE RECOGNITION
MACHINE VISION
VISION
LANGUAGE PROCESSING (NLP)
CLASSIFICATION
TRANSLATION
DATA EXTRACTION
EXPERT SYSTEMS
PLANNING & OPTIMIZATION
ROBOTICS
G2 CROWD

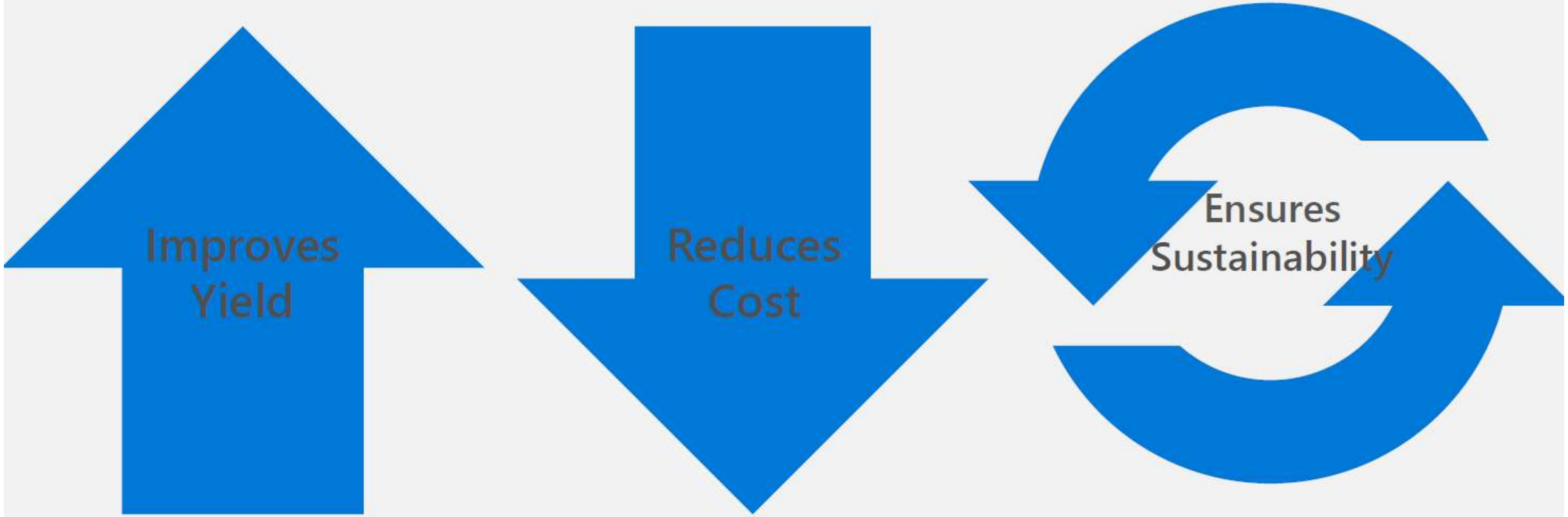
AI and ML

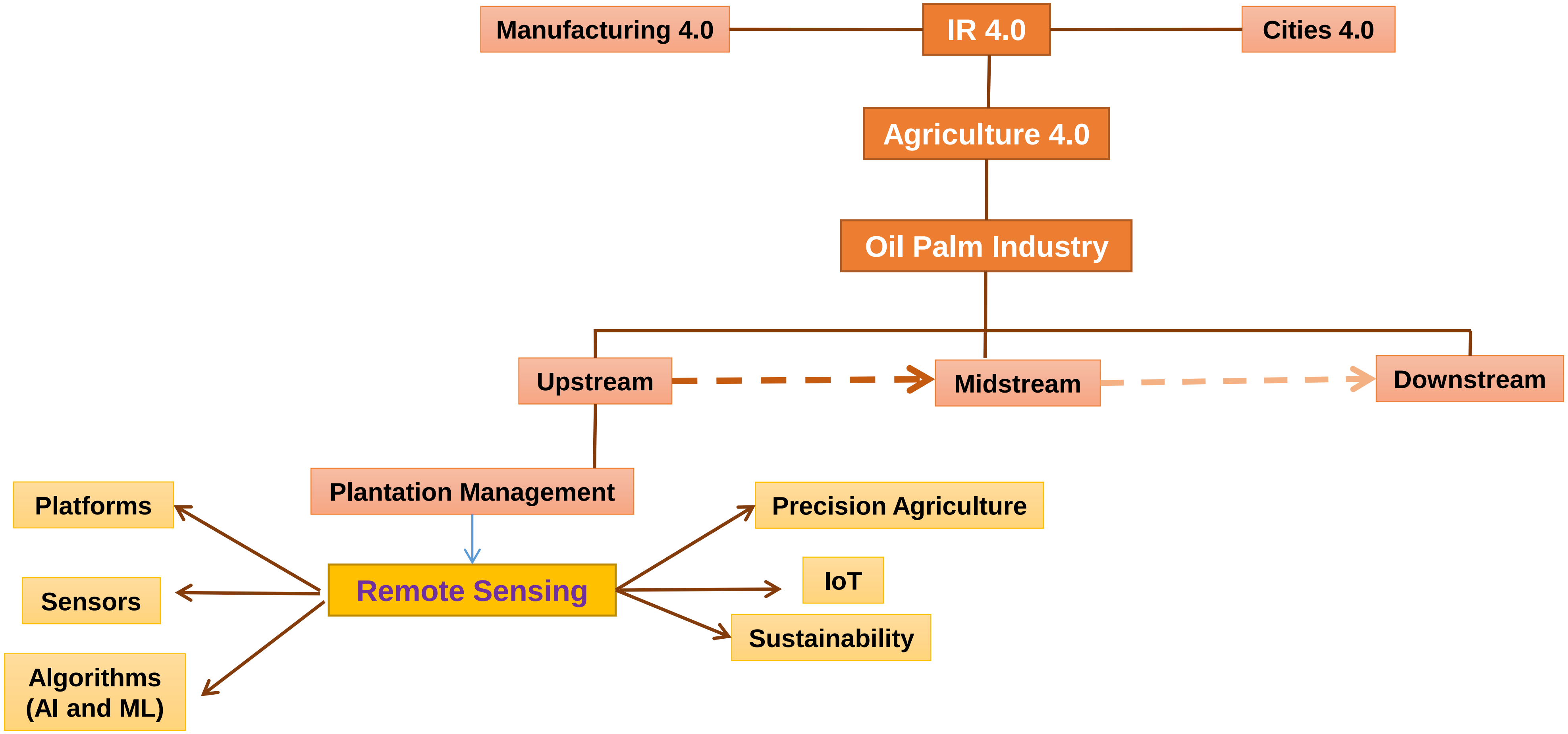
- AI involves machines/software that can perform tasks that are characterise of human intelligence.
- AI was catalyzed by breakthroughs in an area known as machine learning.
- Machine learning is simply a way of achieving AI.



Data-Driven Agriculture

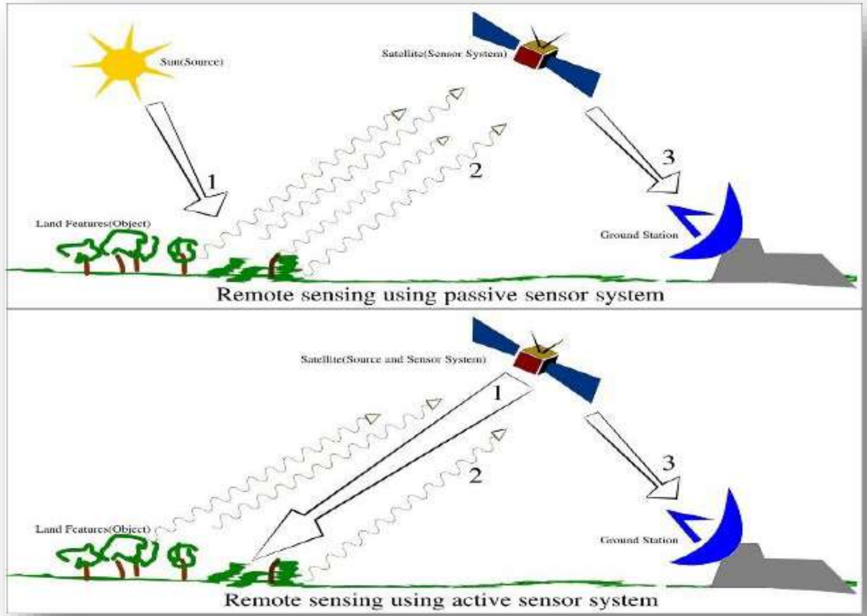
Ag researchers have shown that data-driven agriculture:

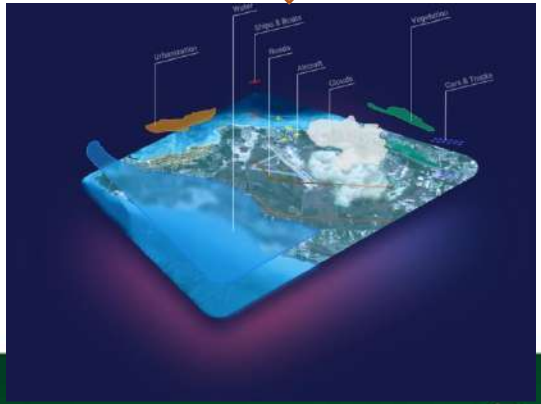


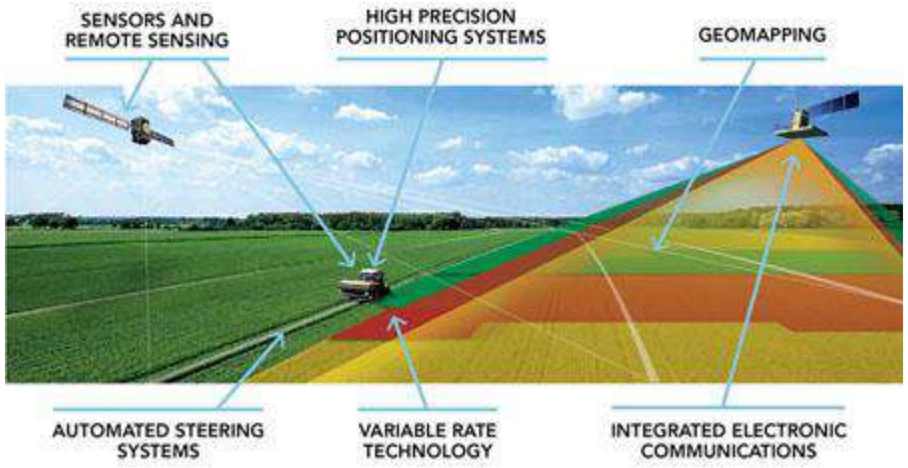

Manufacturing 4.0
IR 4.0
Cities 4.0
Agriculture 4.0
Oil Palm Industry
Upstream
Midstream
Downstream
Plantation Management
Platforms
Sensors
Algorithms (AI and ML)
Remote Sensing
Precision Agriculture
IoT
Sustainability

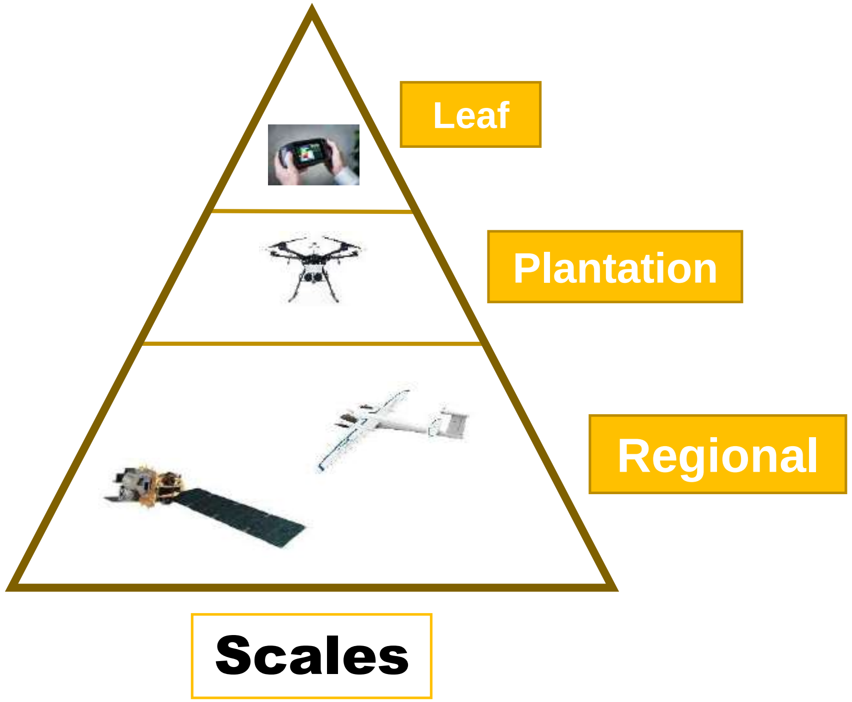
Remote Sensing

- Remote sensing is generally defined as the technology of measuring the characteristics of an object or surface from a distance.
- Divided into active and passive systems.
- Active – Lidar, Radar
- Passive – Multispectral, Hyperspectral









Remote Sensing

AI/ML

Field Spectroscopy

Airborne

Scapeborne

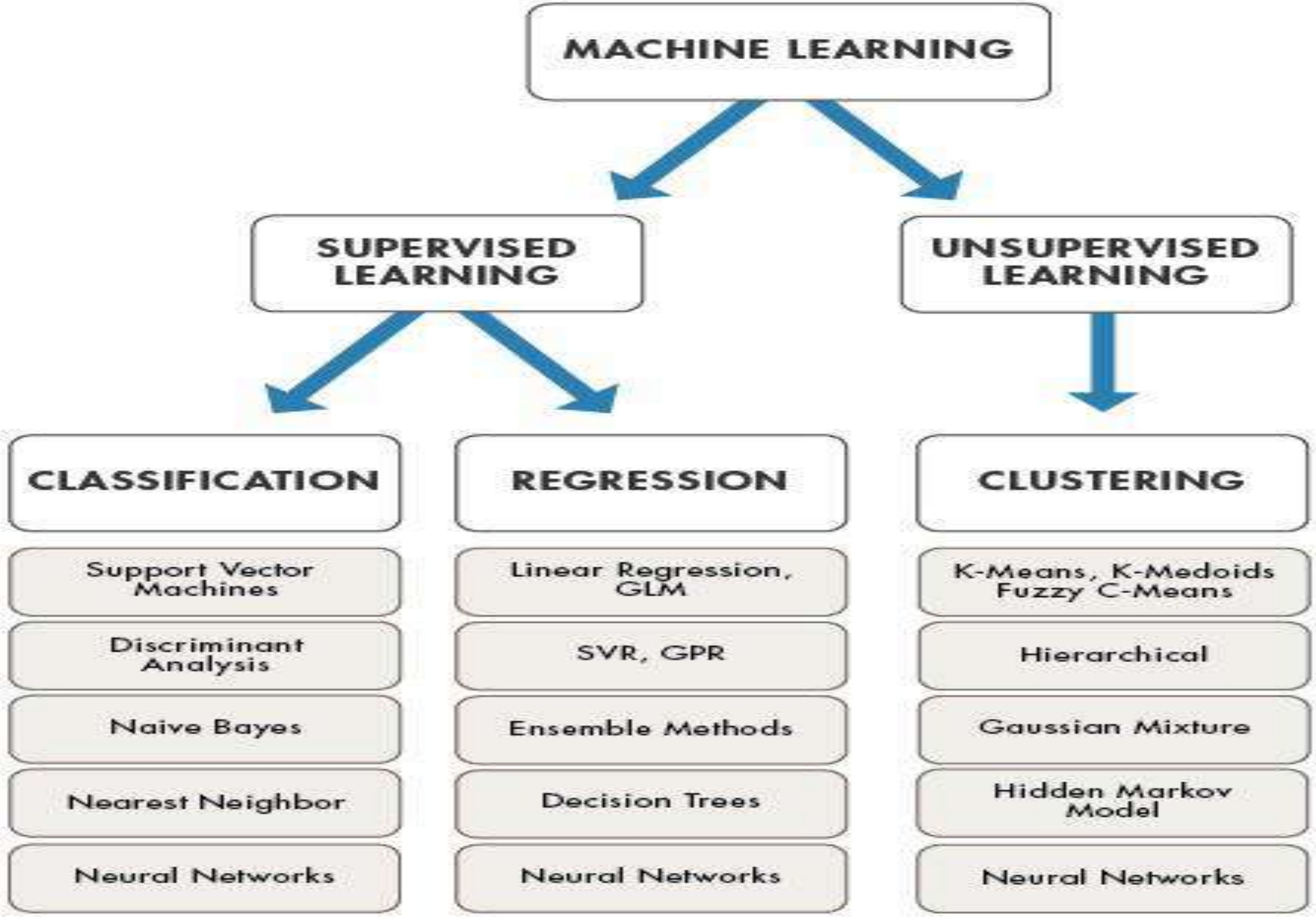
Machine Learning in Remote Sensing

What is Machine Learning?

- ❑Machine learning is a subdivision of Artificial Intelligence (AI) and also covers data mining/classification approaches.

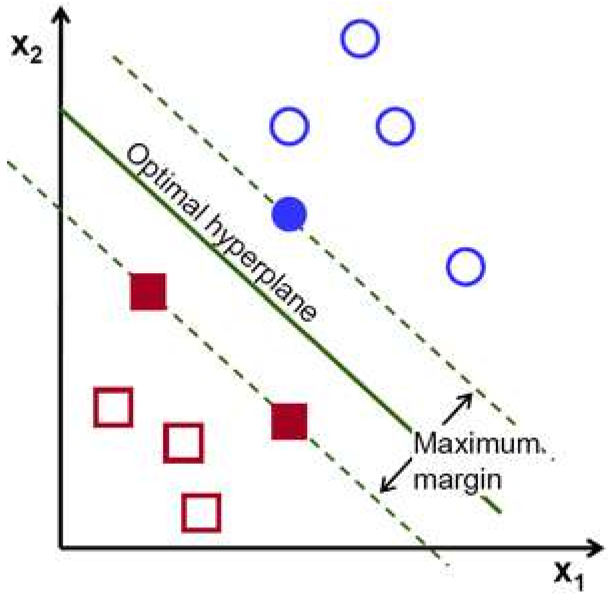
- ❑Example of machine learning algorithms that have been widely utilized in remote sensing applications:
  - Random Forest (RF)
  - Support Vector machines (SVM)
  - Artificial Neural Network (ANN)

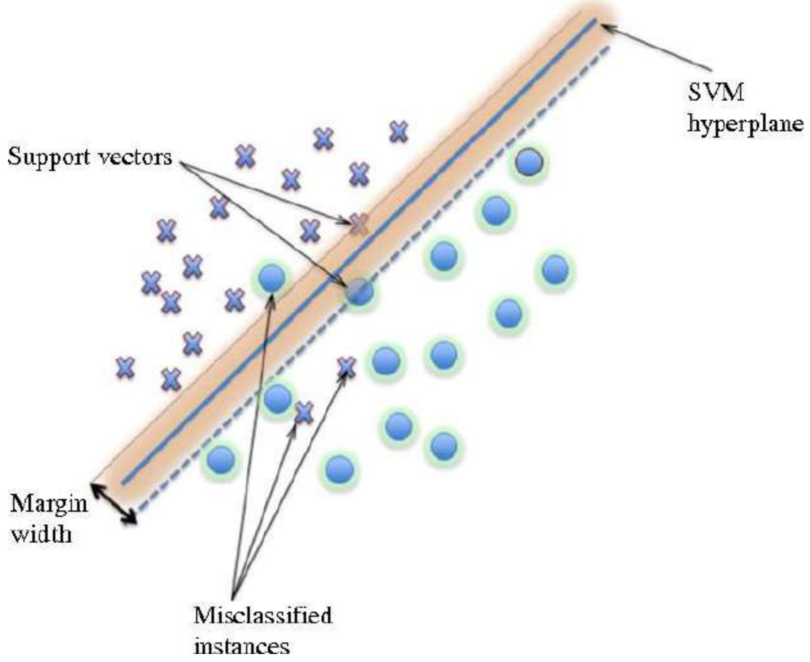
- ❑These algorithms do not assume specific class distributions and well suited for complex environments or approaches using fused data sets.


MACHINE LEARNING
SUPERVISED LEARNING
UNSUPERVISED LEARNING
CLASSIFICATION
REGRESSION
CLUSTERING
Support Vector Machines
Discriminant Analysis
Naive Bayes
Nearest Neighbor
Neural Networks
Linear Regression, GLM
SVR, GPR
Ensemble Methods
Decision Trees
Neural Networks
K-Means, K-Medoids Fuzzy C-Means
Hierarchical
Gaussian Mixture
Hidden Markov Model
Neural Networks

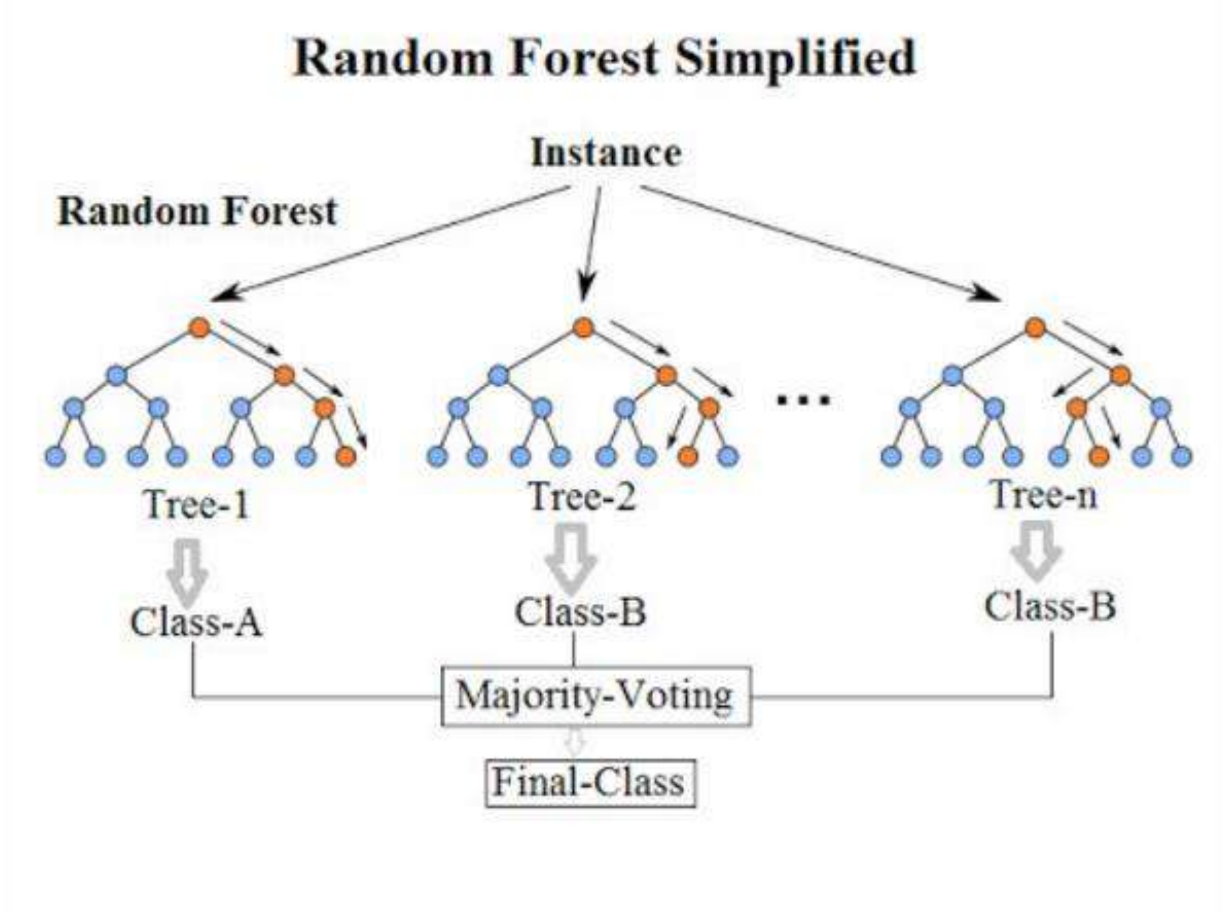
Support Vector Machine (SVM)

- supervised learning models with associated learning algorithms that analyze data used for classification and regression.

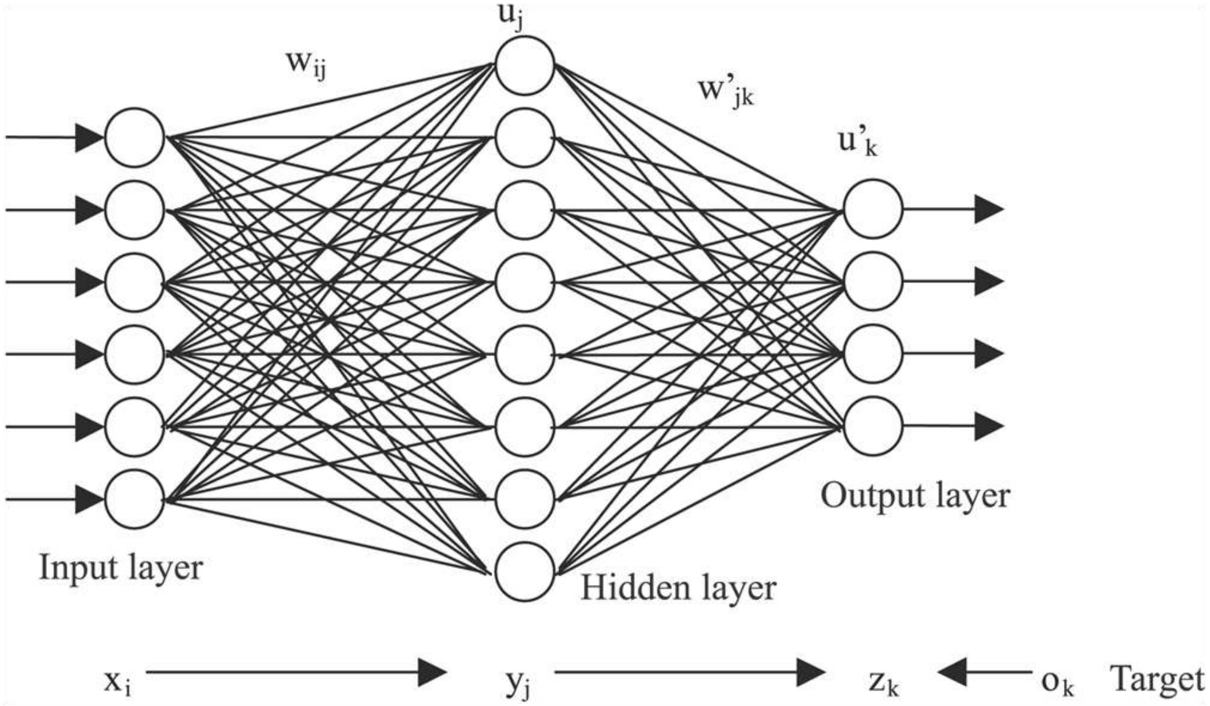




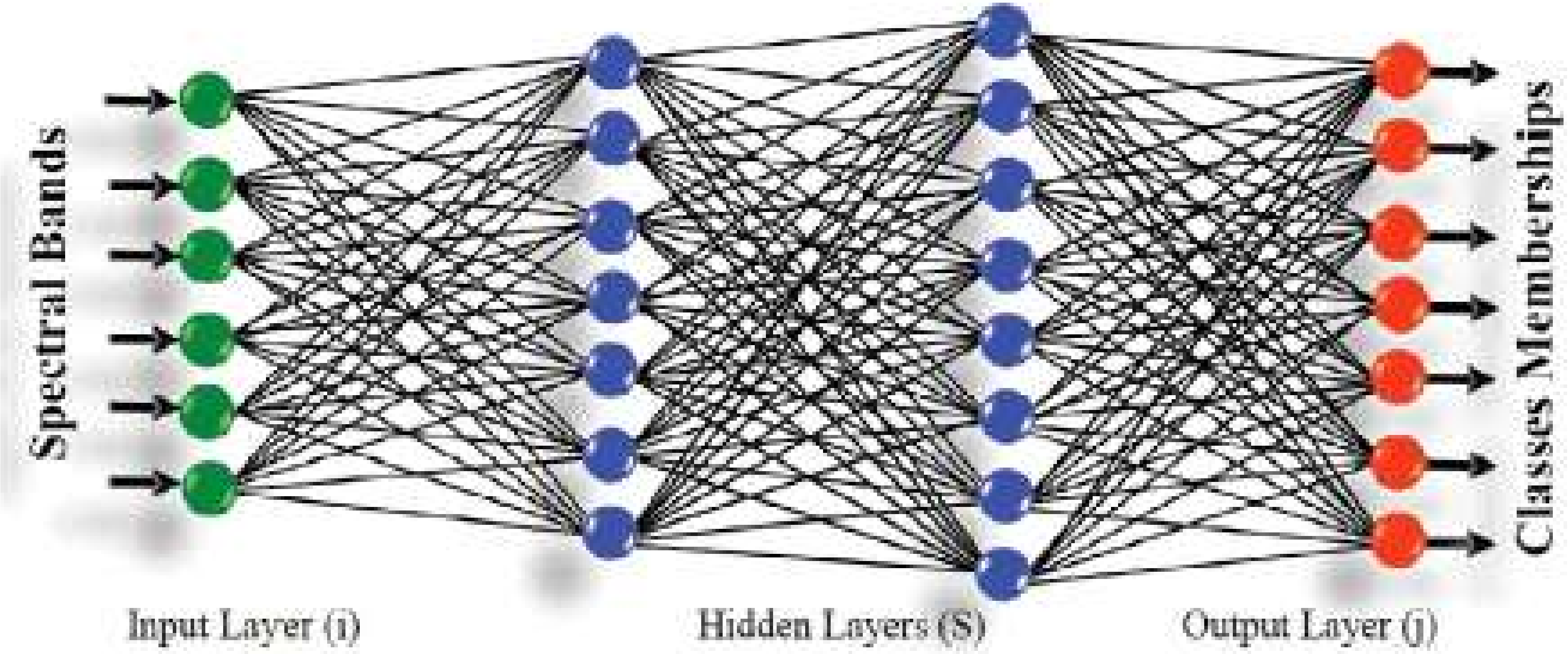
Random Forest



Artificial Neural Network (ANN)



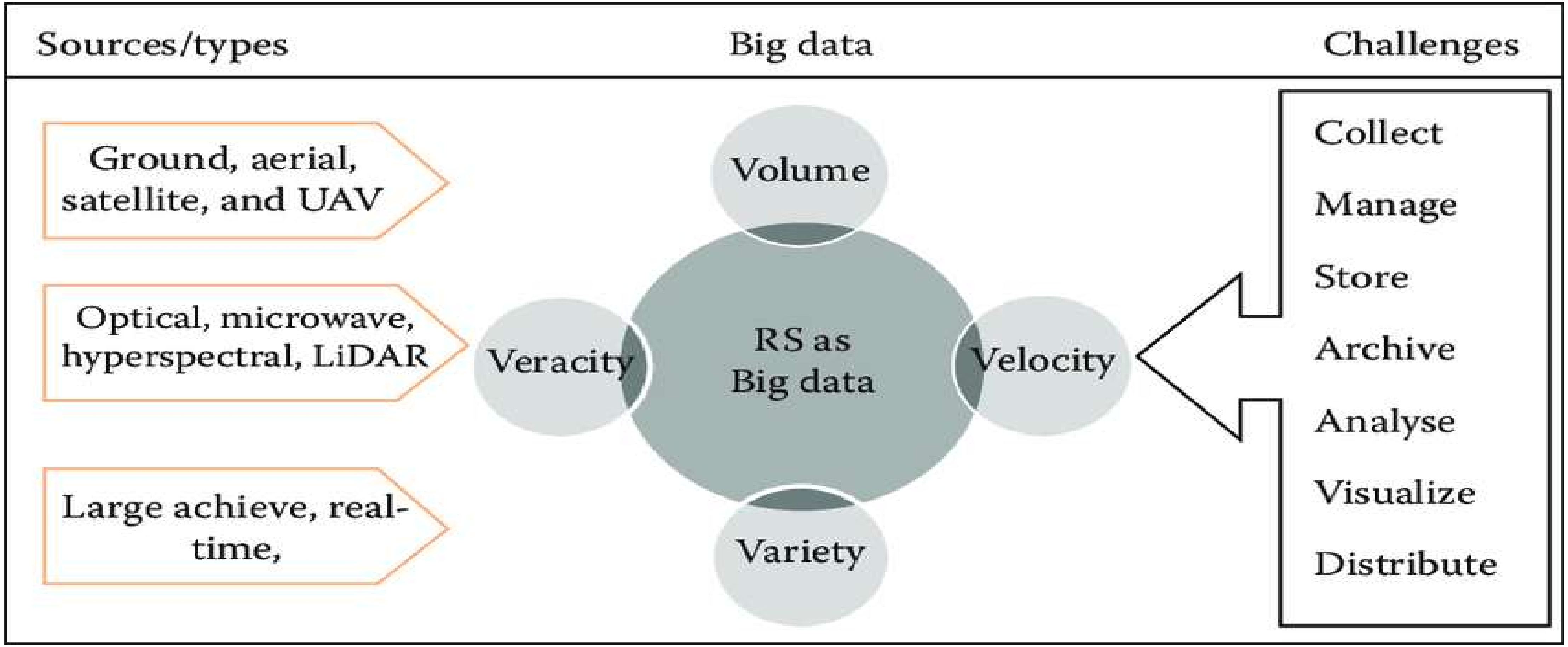
Deep Learning (DL)



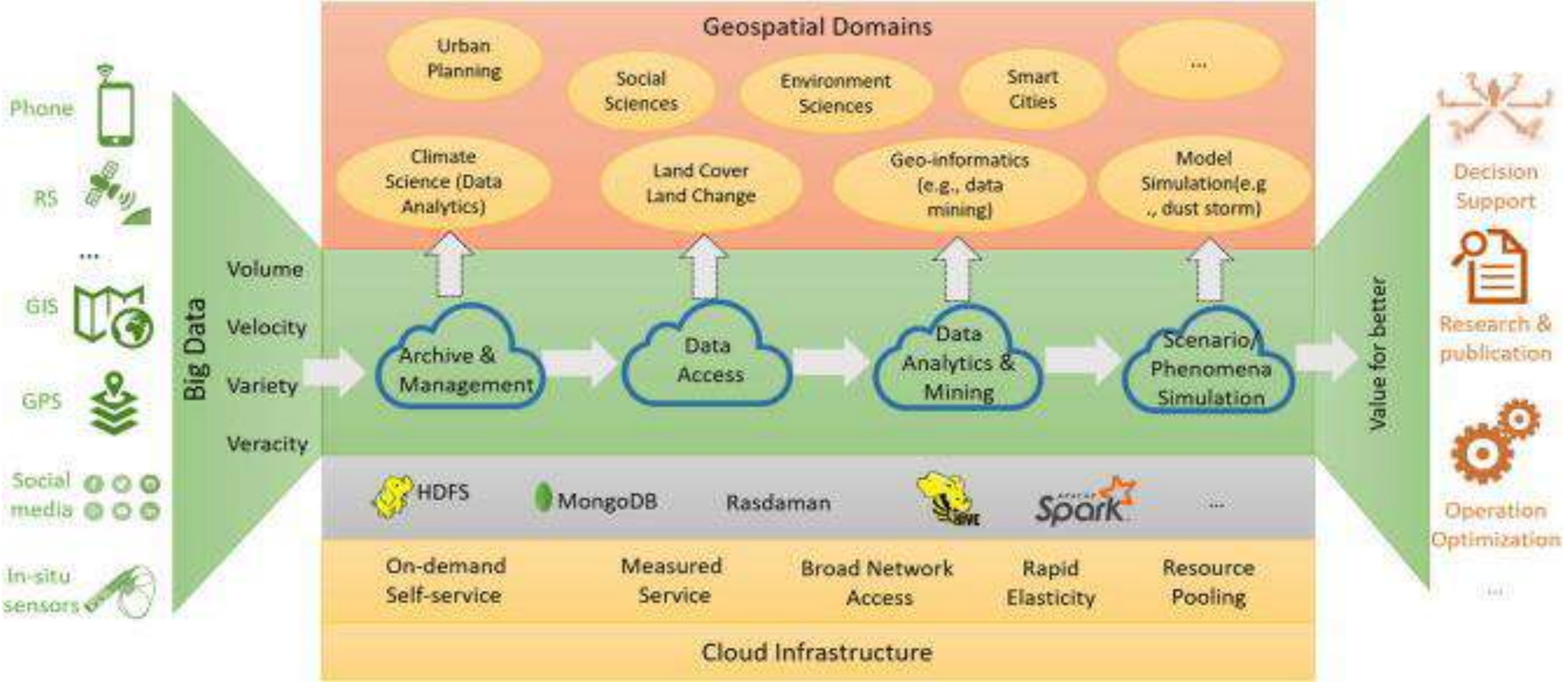
ML + Big Data + Cloud Computing

Machine Learning is an approach to make algorithms "**smarter**" as they "**learn**" from more examples. That's one of the reasons why **Big Data and AI** seem to be evolving together. Cloud computing enables an infrastructure for big data storage and analysis more effectively.

RS Big Data


Sources/types
Big data
Challenges
Ground, aerial, satellite, and UAV
Optical, microwave, hyperspectral, LiDAR
Large achieve, real-time,
Volume
Veracity
RS as Big data
Velocity
Variety
Collect
Manage
Store
Archive
Analyse
Visualize
Distribute

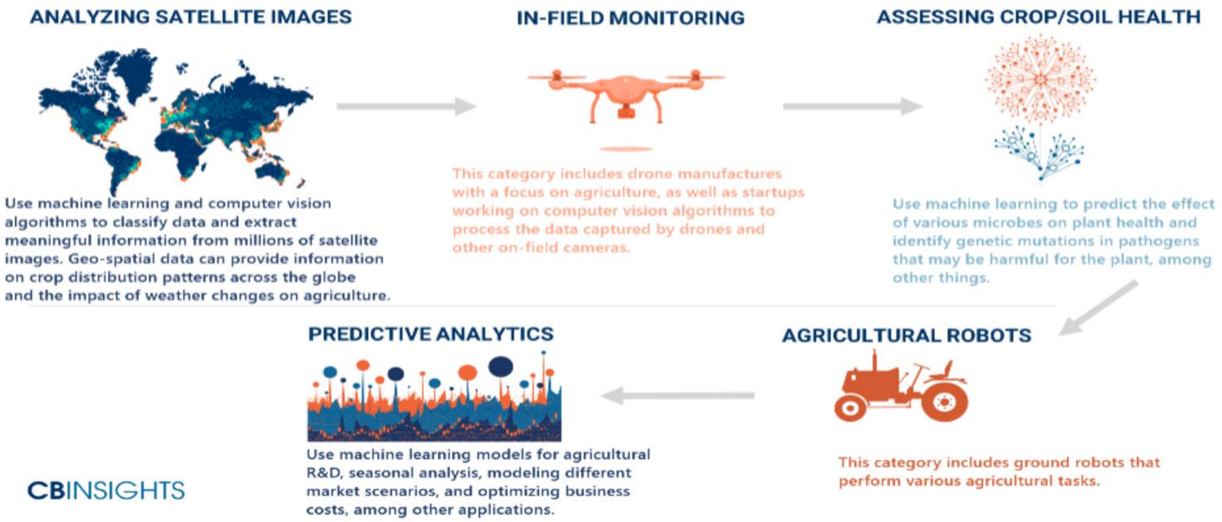
Cloud Computing



Source: https://www.sciencedirect.com/science/article/pii/S0198971516303106

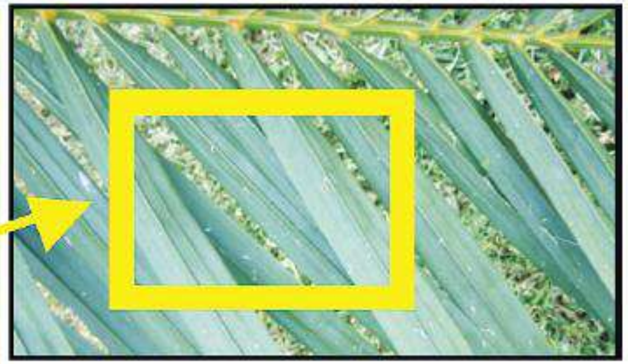
CASE STUDIES

- Field/Lab Spectroscopy
- Airborne
- Satellite

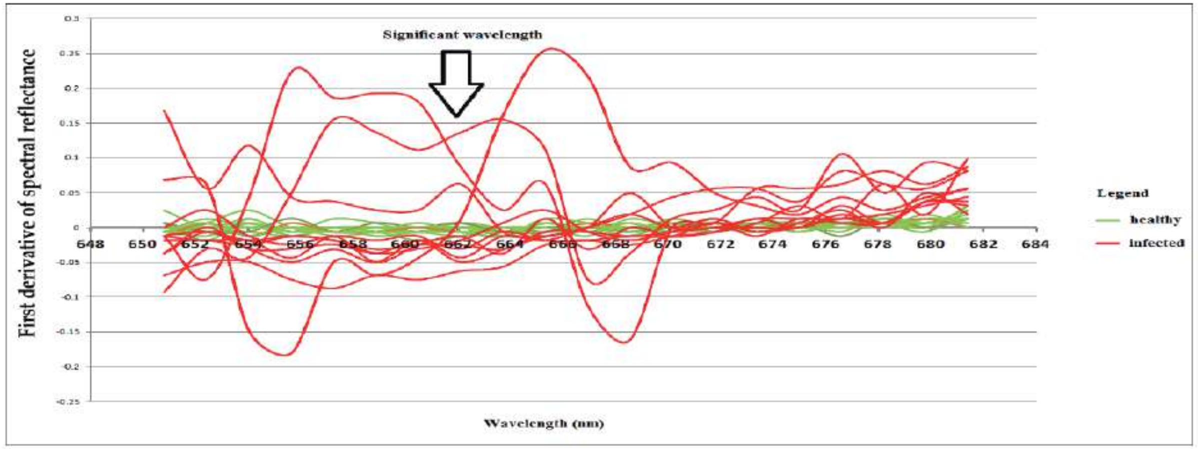


Field Spectroscopy

- Important to study the fundamental response towards disease severity and nutrient deficiency.
- Also for the development of spectral library.
- Studies have indicated some success (Shafri et al., 2011; Liaghat et al., 2014; Izzuddin et al., 2017; Ahmadi et al., 2017) but further improvements are needed.

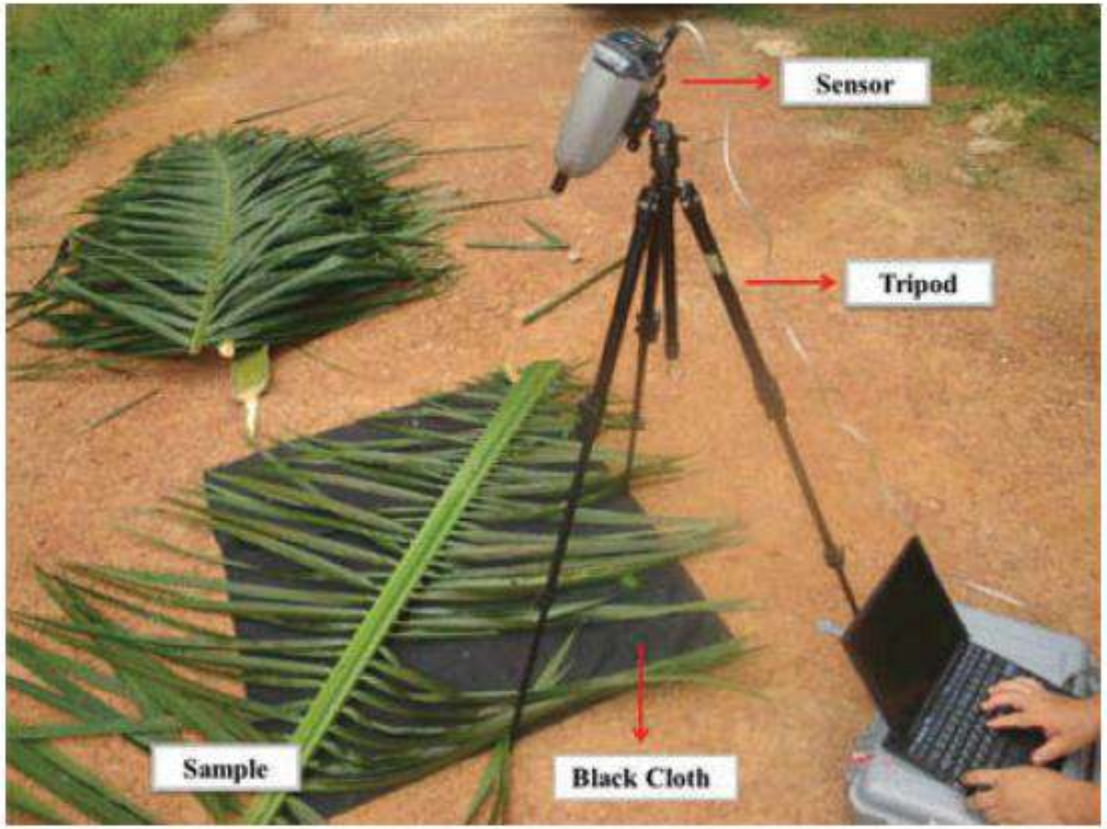


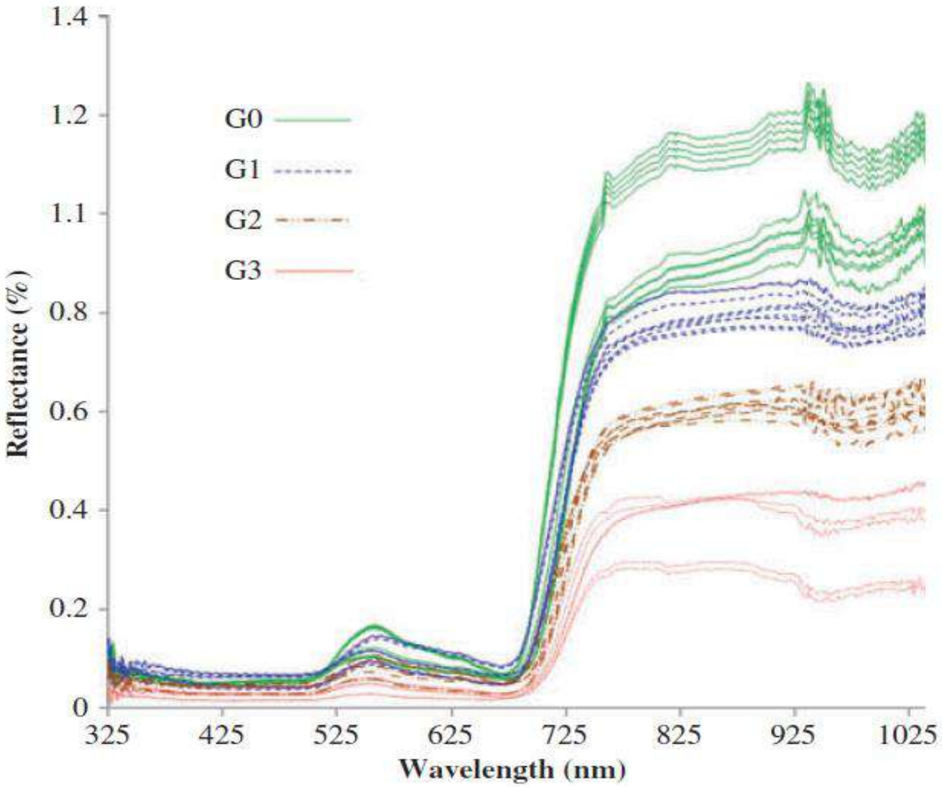
Spectral measurement on leaves (yellow box)



Source: (Izzuddin et al., 2013)

ML on field data





Healthy (G0) and Ganoderma-infected (G1, G2, and G3)

Liaghat, S., Ehsani, R., Mansor, S., Shafri, H. Z., Meon, S., Sankaran, S., & Azam, S. H. (2014). Early detection of basal stem rot disease (Ganoderma) in oil palms based on hyperspectral reflectance data using pattern recognition algorithms. International journal of remote sensing, 35(10), 3427-3439.

- Linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), vs k-nearest neighbour (kNN), and Naïve–Bayes (NB) ML classifiers
- Analysis of variance (ANOVA) with a 5% level of significance ($\alpha = 0.05$) was performed to study the effect of different classification models (LDA, QDA, kNN, and NB) and different datasets (raw, first, and second derivatives) on classification accuracies
- Overall accuracy rate of 97% (without false-negatives) when the kNN-based classification model was used

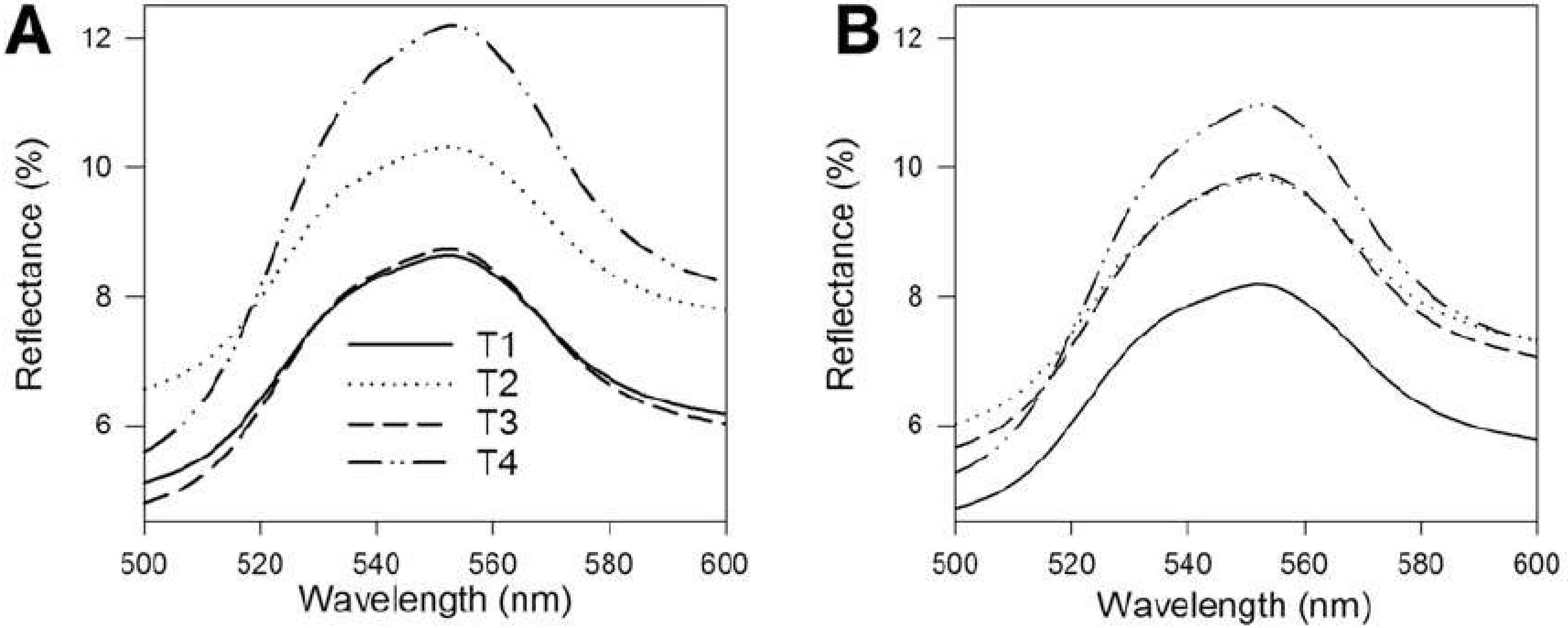
Table 2. Average overall and individual class classification accuracies obtained from preprocessed data sets using LDA-, QDA-, kNN-, and NB-based models.

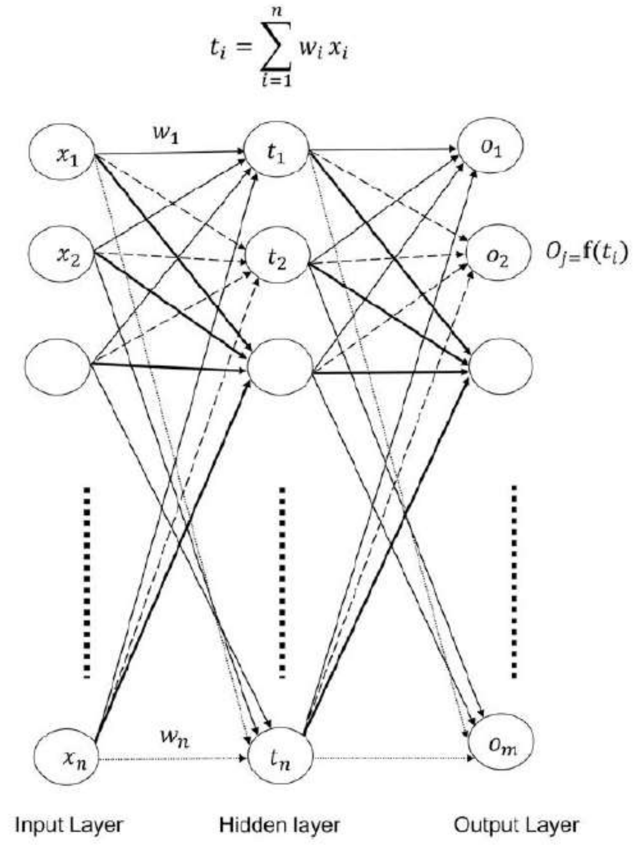
	No. of PCs	Average classification accuracies (%)					k	SD (%)
		Overall	G0	G1	G2	G3		
LDA								3.5
Raw	6	95.6	96.8	95.5	96.9	94.8		0.9
First D	15	93.1	96.8	89.6	93.7	92.6		2.6
Second D	23	89.3	86.4	90.9	87.0	93.1		2.8
QDA								8.5
Raw	6	85.0	86.3	84.9	83.9	83.5		1.1
First D	15	92.3	96.9	91.0	93.6	87.1		3.6
Second D	23	86.8	98.5	95.5	87.4	62.6		14.1
kNN								5.6
Raw	6	86.5	84.5	91.2	88.7	81.2	1, 2	3.8
First D	15	96.4	96.8	97.1	95.3	96.8	1, 2	0.7
Second D	23	97.3	98.5	95.6	96.9	98.5	1, 2	1.2
NB								10.5
Raw	6	96.0	96.9	98.5	91.9	96.6		2.5
First D	15	83.5	84.2	94.0	81.1	71.4		8.1
Second D	23	78.9	76.5	91.0	82.1	62.7		10.3

Note: D – derivative: SD – standard deviation.

• Ahmadi et al (2017) used ANN to investigate the hyperspectral capability to discriminate severity levels

Severity level	Symptoms
T1 (healthy)	Negative GSM[a] test Healthy leaves and normal palm canopy
T2 (mild)	Positive GSM test Presence of mycelium in the stem bark, or brittle wood Healthy leaves and normal palm canopy
T3 (moderate)	Positive GSM test Presence of mycelium in the stem bark, and fruiting body Less than 50% foliar symptoms
T4 (severe)	Presence of fruiting body at the bottom of the rotten stem More than 50% foliar symptoms





		Discrimination accuracy[a] (%)					
		Frond 9			Frond 17		
Dataset	**Wavelengths (nm)**	**Healthy (T1)**	**Mildly infected (T2)**	**Overall**	**Healthy (T1)**	**Mildly infected (T2)**	**Overall**
RAW	553, 557, 562	100.0	100.0	100.0	80.0	85.0	82.8
RAW	550 to 560	66.7	100.0	83.3	66.7	100.0	83.3
FDR	550 to 560	100.0	100.0	100.0	100.0	66.7	83.3
SDR	540 to 550	66.7	66.7	66.7	100.0	100.0	100.0

[a] The accuracies were derived for 46 spectral leaf measurements of T1 and 46 spectral leaf measurements of T2 for each frond number.

Airborne/UAV RS

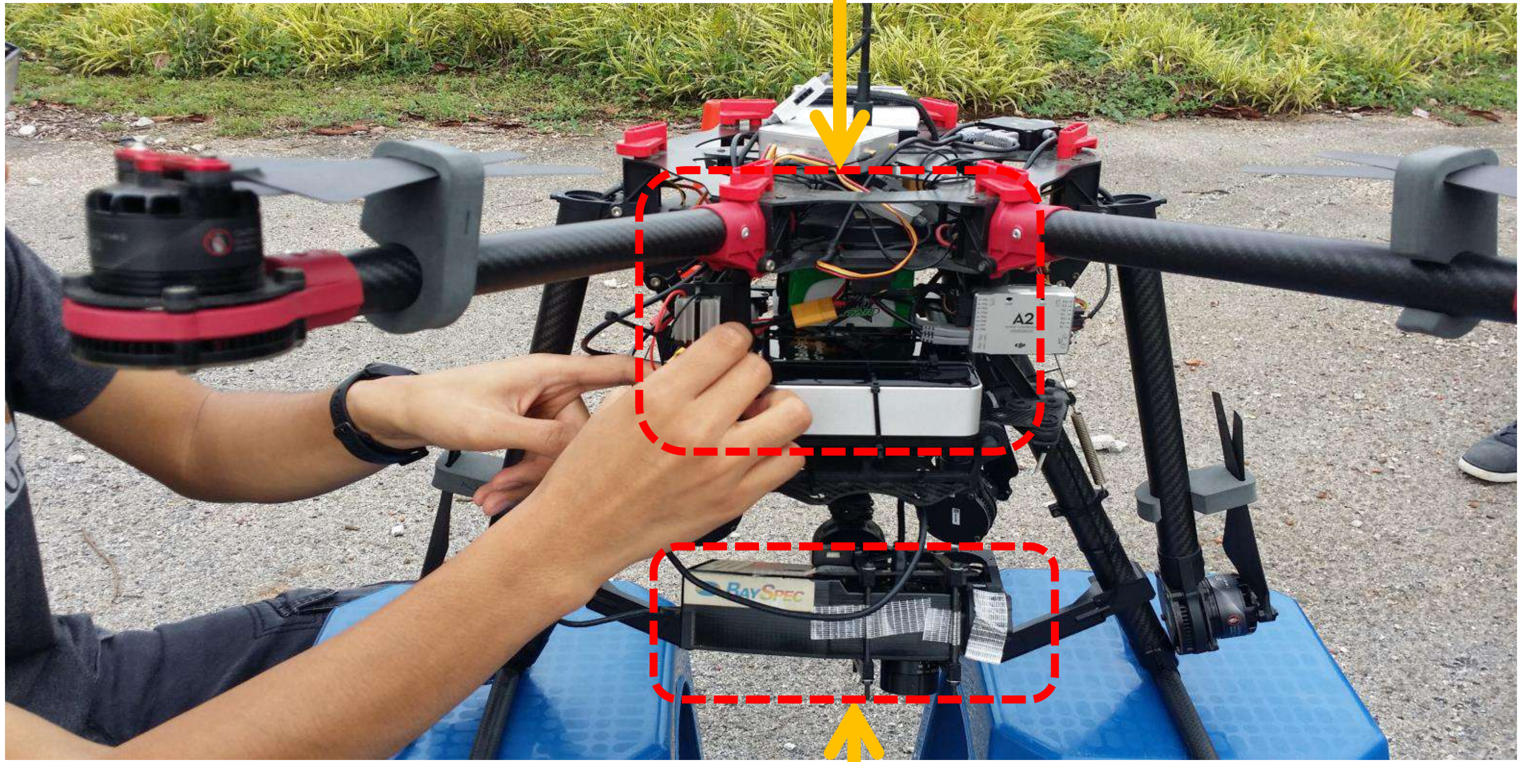
- Acquired data using piloted aircraft and UAV for oil palm plantation analysis.
- Previous campaigns were flown using AISA sensors
- Utilised spectral indices developed from field studies.
- Current research going towards UAV utilisation due to piloted aircraft limitations (cost, maintenance, schedule etc).

Data Acquisition and Equipment

Piloted aircraft with
AISA sensor

Hexacopter UAV

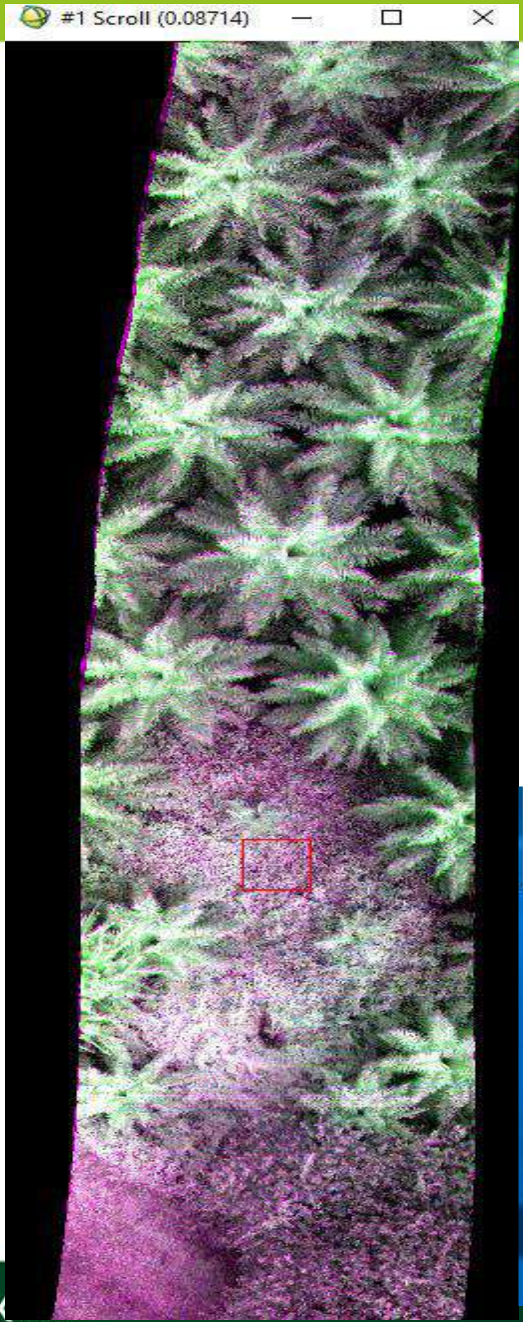
On-board Computer



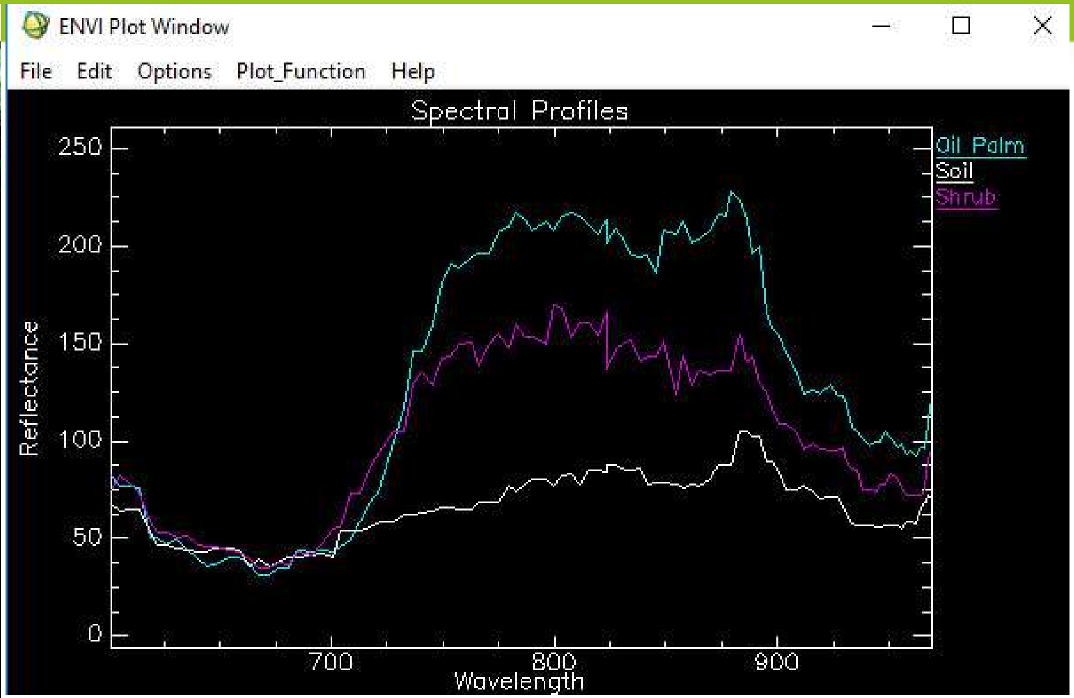
Bayspec Hyperspectral OCI UAV

UAV with OCI hyperspectral sensor

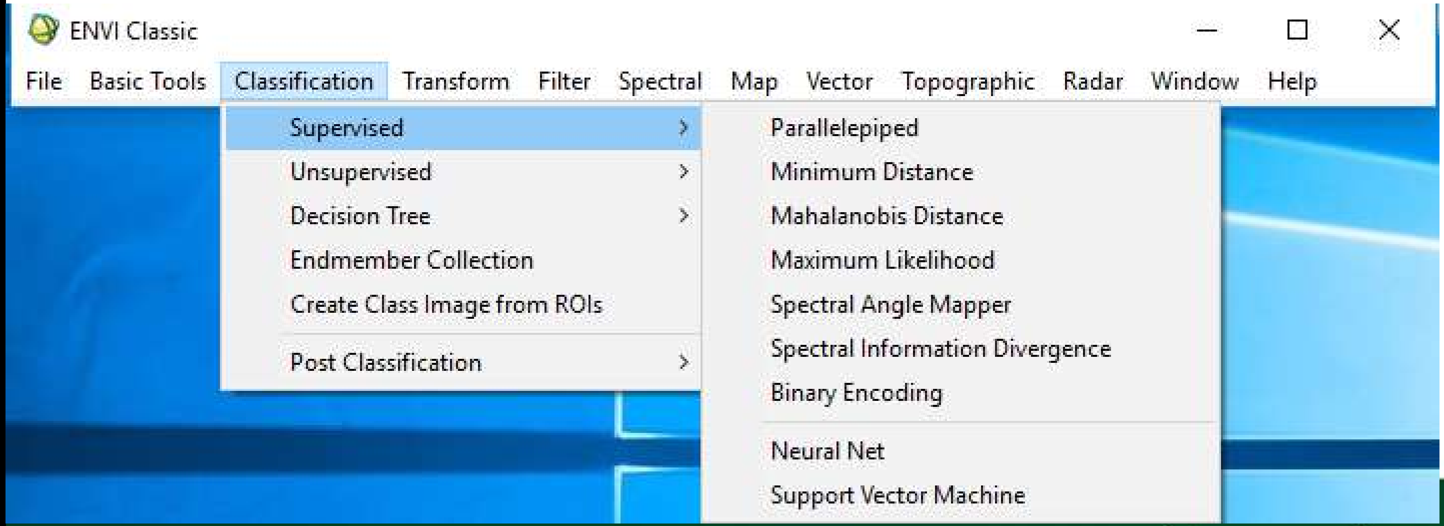
OCI-UAV-1000



UPM Test site

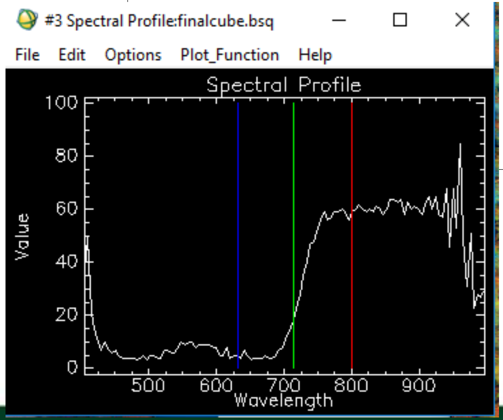


Wavelength range: 600-1000 nm, 103 bands



Challenges with UAV-based hyperspectral systems

- Risk
- Complexity of device integration
- Stability of platform
- Data distortion
- Data processing complexity

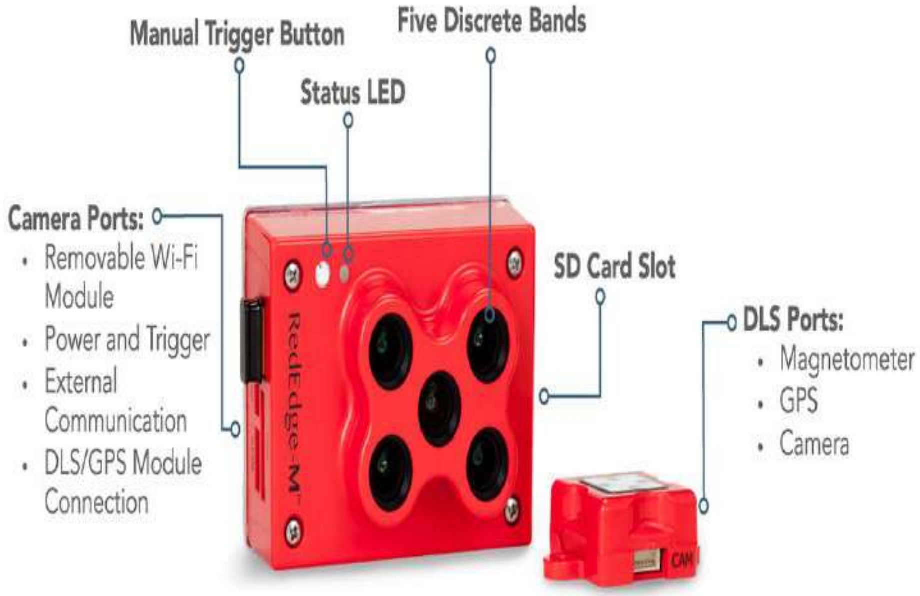


Bayspec OCI-F-1000

Multispectral UAV

- Model:-
  - MicaSense RedEdge
- Benefits:-
  - Easier to handle
  - Cheaper
  - 5 bands

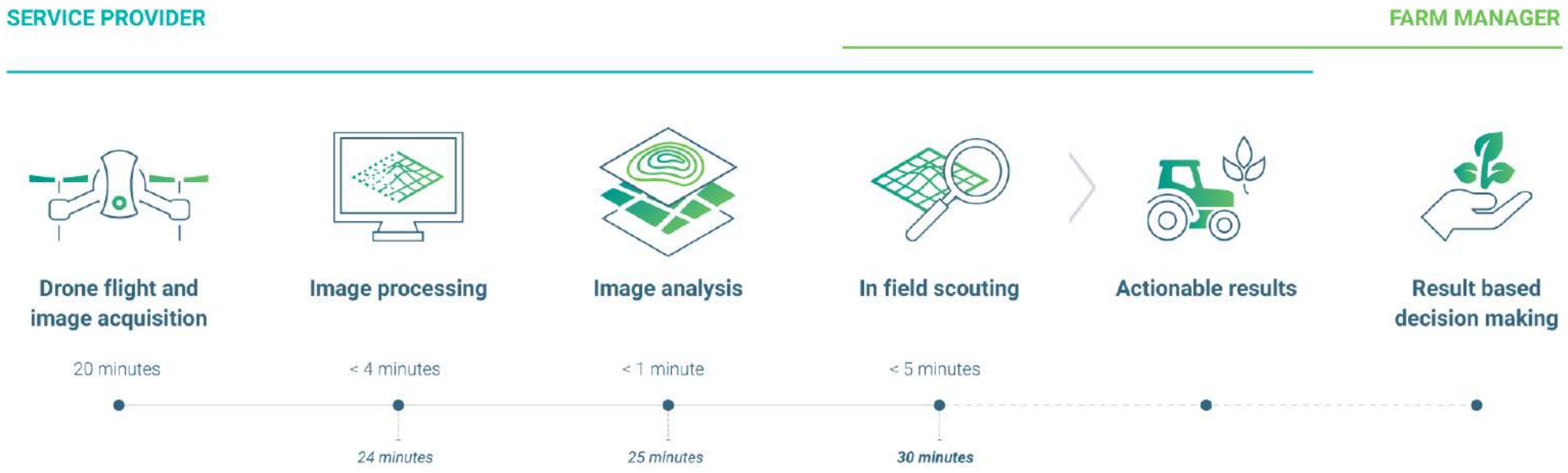
RedEdge-M™



Specifications

Weight:	170 grams (6 oz) (includes DLS and cables)
Dimensions:	9.4 cm x 6.3 cm x 4.6 cm (3.7 in x 2.5 in x 1.8 in)
External Power:	4.2 V DC - 15.6 V DC 4 W nominal, 8 W peak
Spectral Bands:	Blue, green, red, red edge, near-IR (global shutter, narrowband)
RGB Color Output:	Global shutter, aligned with all bands
Ground Sample Distance (GSD):	8 cm per pixel (per band) at 120 m (~400 ft) AGL
Capture Rate:	1 capture per second (all bands), 12-bit RAW
Interfaces:	Serial, 10/100/1000 ethernet, removable Wi-Fi, external trigger, GPS, SDHC
Field of View:	47.2° HFOV
Triggering Options:	Timer mode, overlap mode, external trigger mode (PWM, GPIO, serial, and Ethernet options), manual capture mode

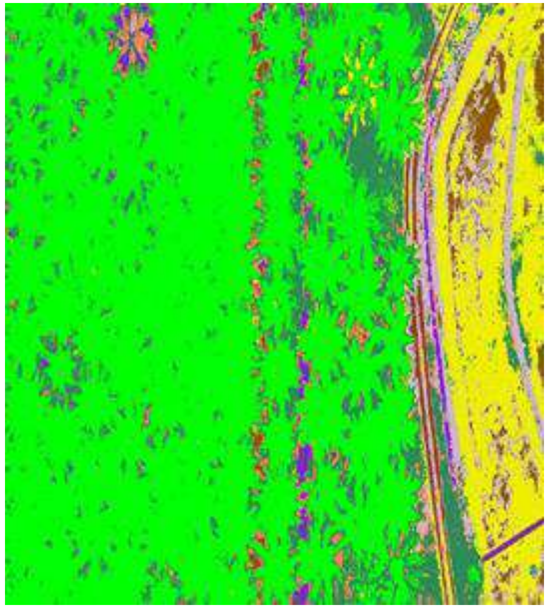
Near Real-time Data Analysis



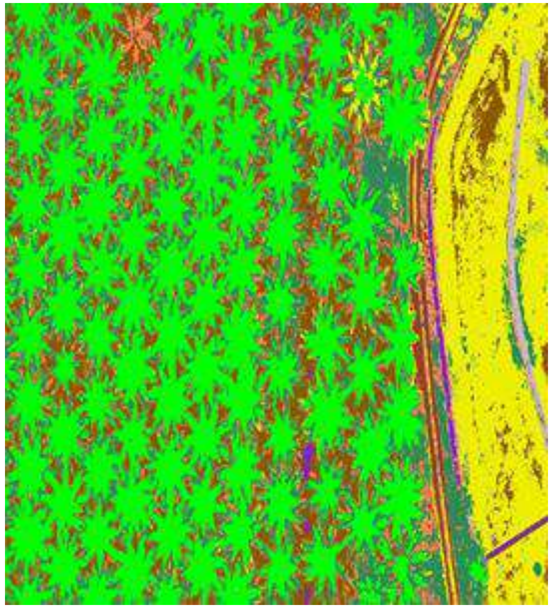
ML Application for UAV Data Analysis

Classification of plantation land cover (1st level):- Original 5 bands

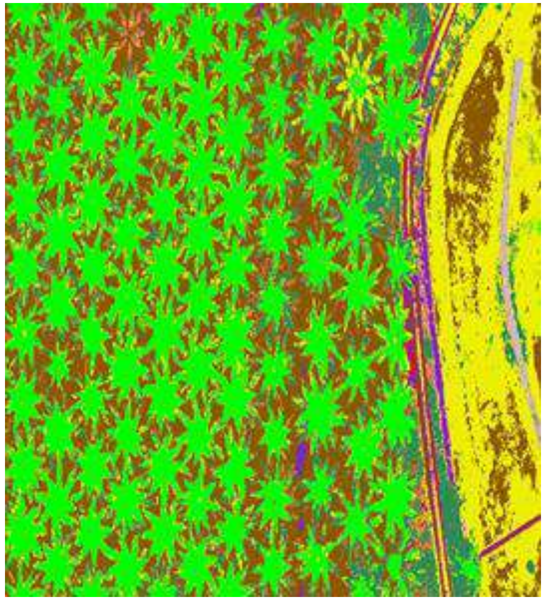
Original image



Maximum Likelihood – 85%

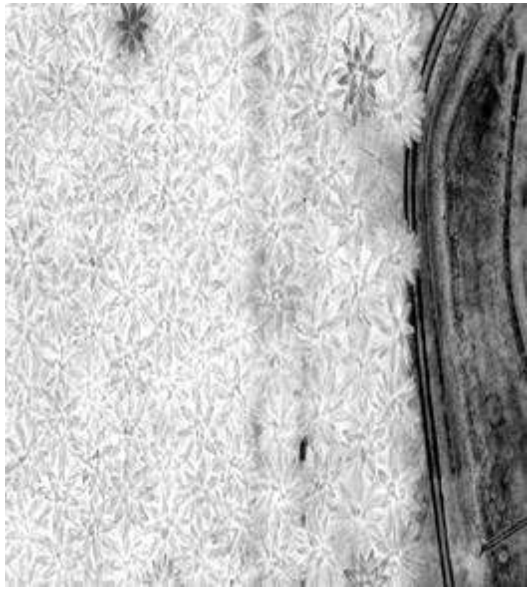


SVM – 89%

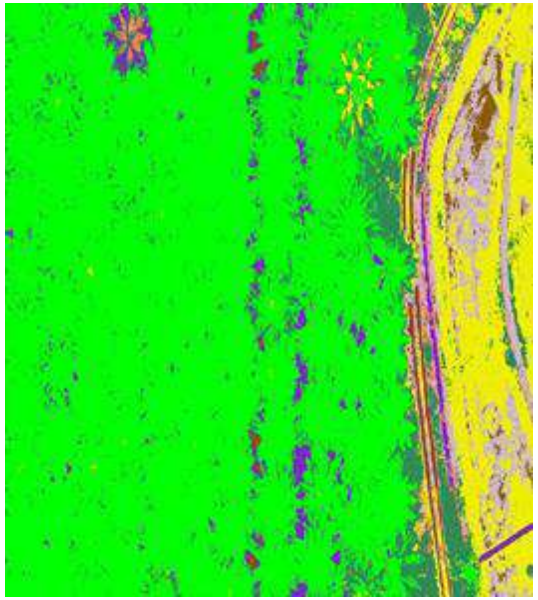


ANN- 85%

Using the Normalized Difference Red Edge Index (NDRE) and ML



NDRE



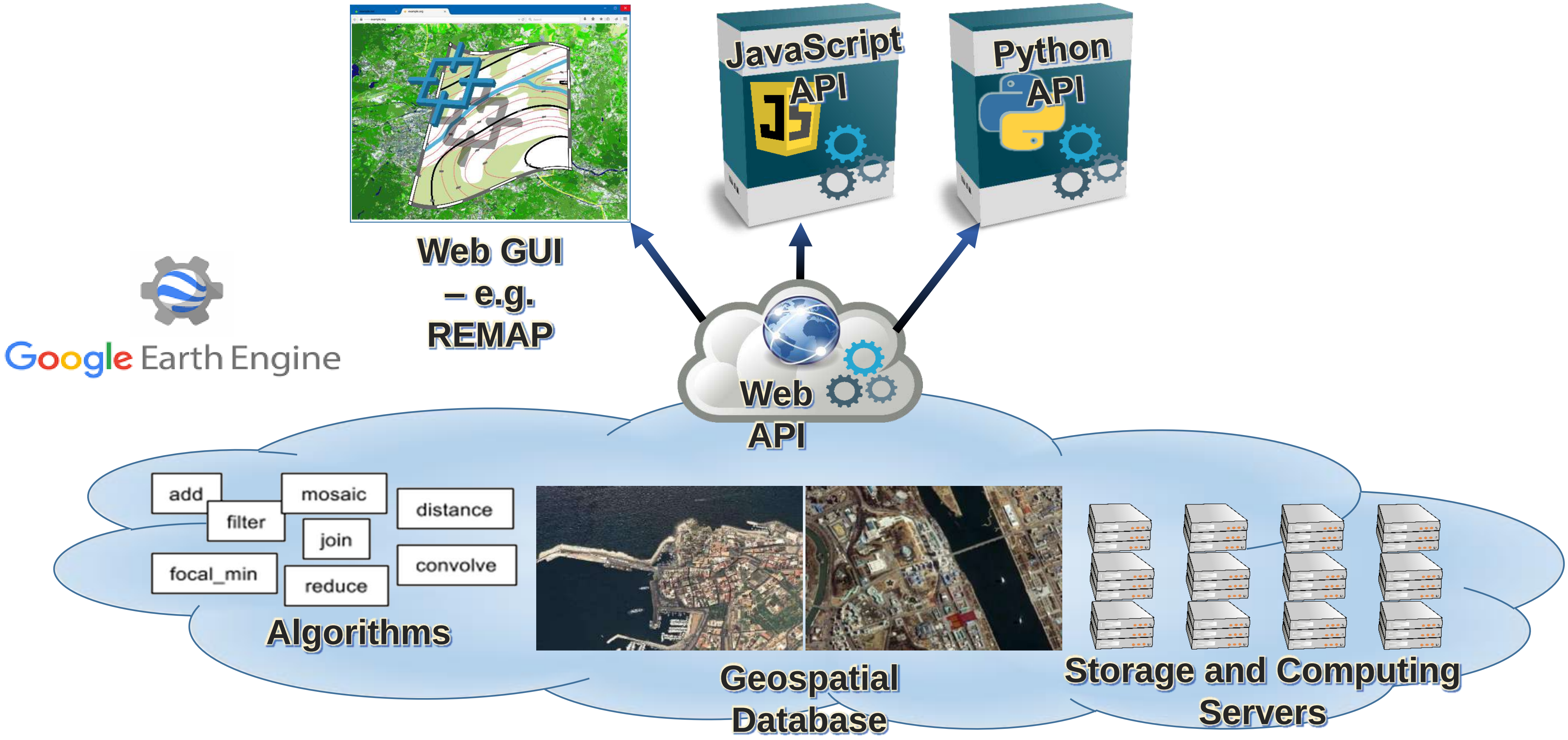
Maximum Likelihood – 83%

SVM– 90%

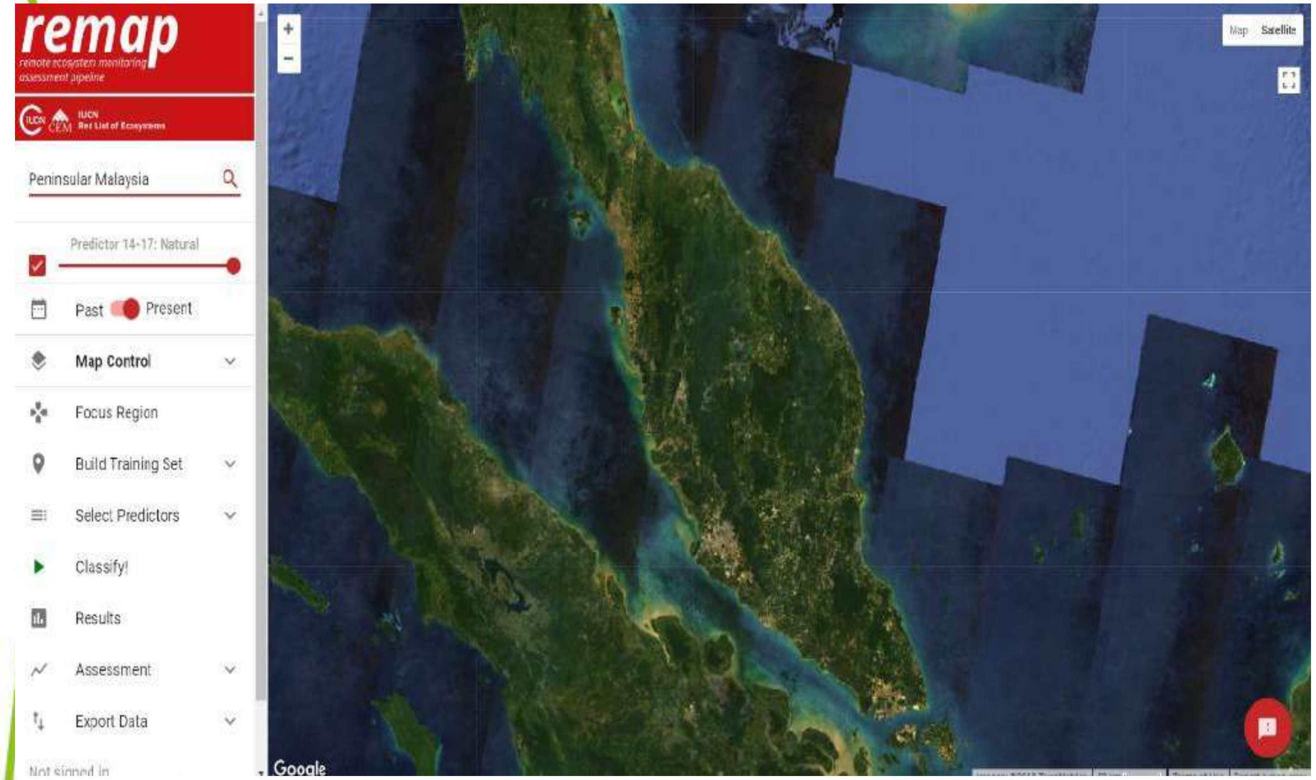
ANN– 86%

Spaceborne (Satellite)

- Issues such as biodiversity loss, deforestation, protection of high conservation value areas.
- Satellite remote sensing plays an important role in monitoring oil palm plantations.
- Traditional methods require storage of huge amount of data and in-house processing capabilities.
- Recent trend has been to perform image processing using cloud computing such as Google Earth Engine (GEE).
- The advantages of cloud computing include the availability of a large volume of satellite data already stored in the cloud. This will avoid the need of an external hard disk and facilitate easy data access.
- Using parallel computing, users will have unlimited computer processing capabilities. Moreover, code and classification algorithms can be shared and discussed in the shared platform.


Web GUI
– e.g.
REMAP
JavaScript
API
Python
API
Google Earth Engine
Web
API
add
filter
mosaic
join
distance
focal_min
reduce
convolve
Algorithms
Geospatial
Database
Storage and Computing
Servers

REMAP (Remote Ecosystem Assessment & Monitoring Pipeline)

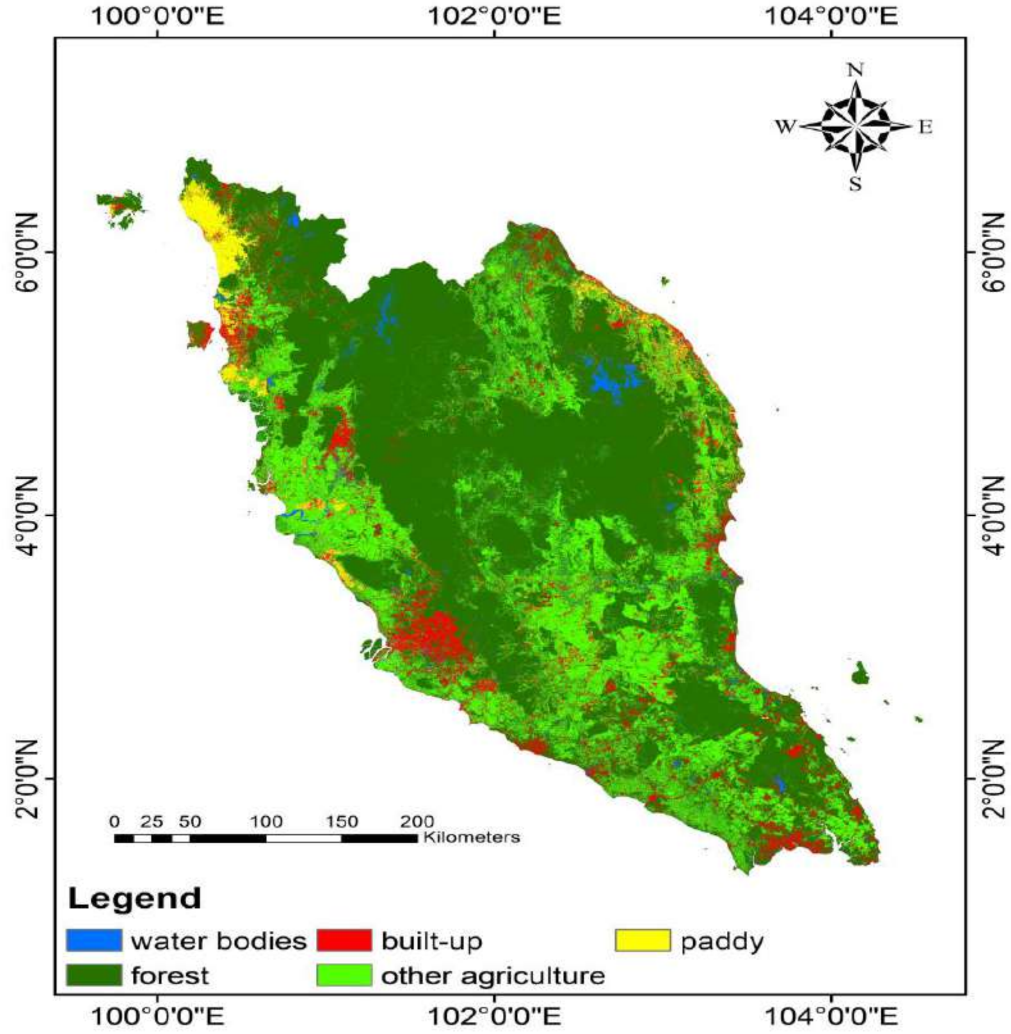


-A free **online mapmaking tool** that allows users to detect environmental change over time using satellite images.

-National level cloud computing with REMAP powered by Google Earth Engine.

-Years of desktop computing = Days of cloud computing

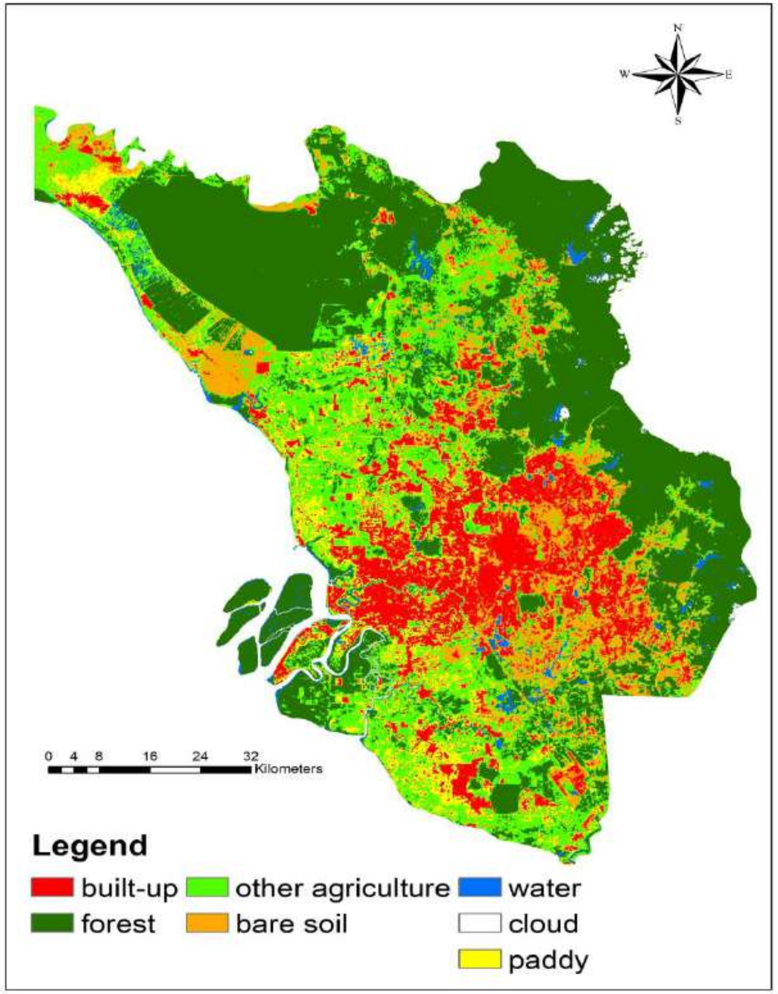
Land Cover Map Generated by REMAP 2017



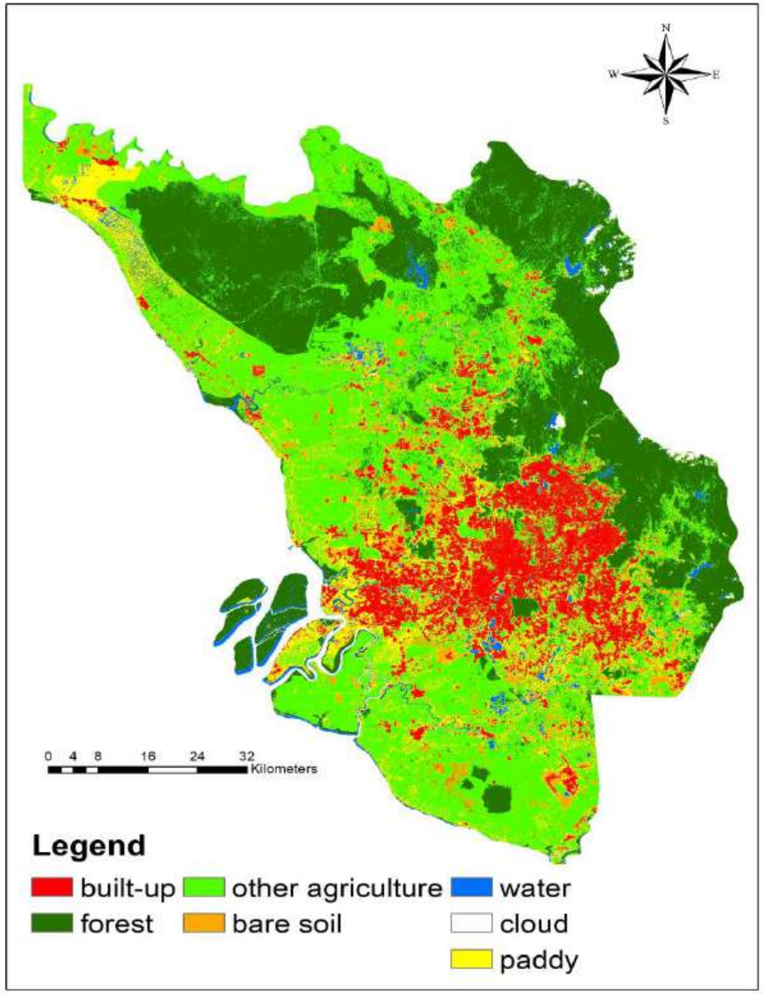
- Accuracy = 90%

Peninsular Malaysia -132,156 square kilometres

Google Earth Engine (GEE) for Selangor



SVM = 93%



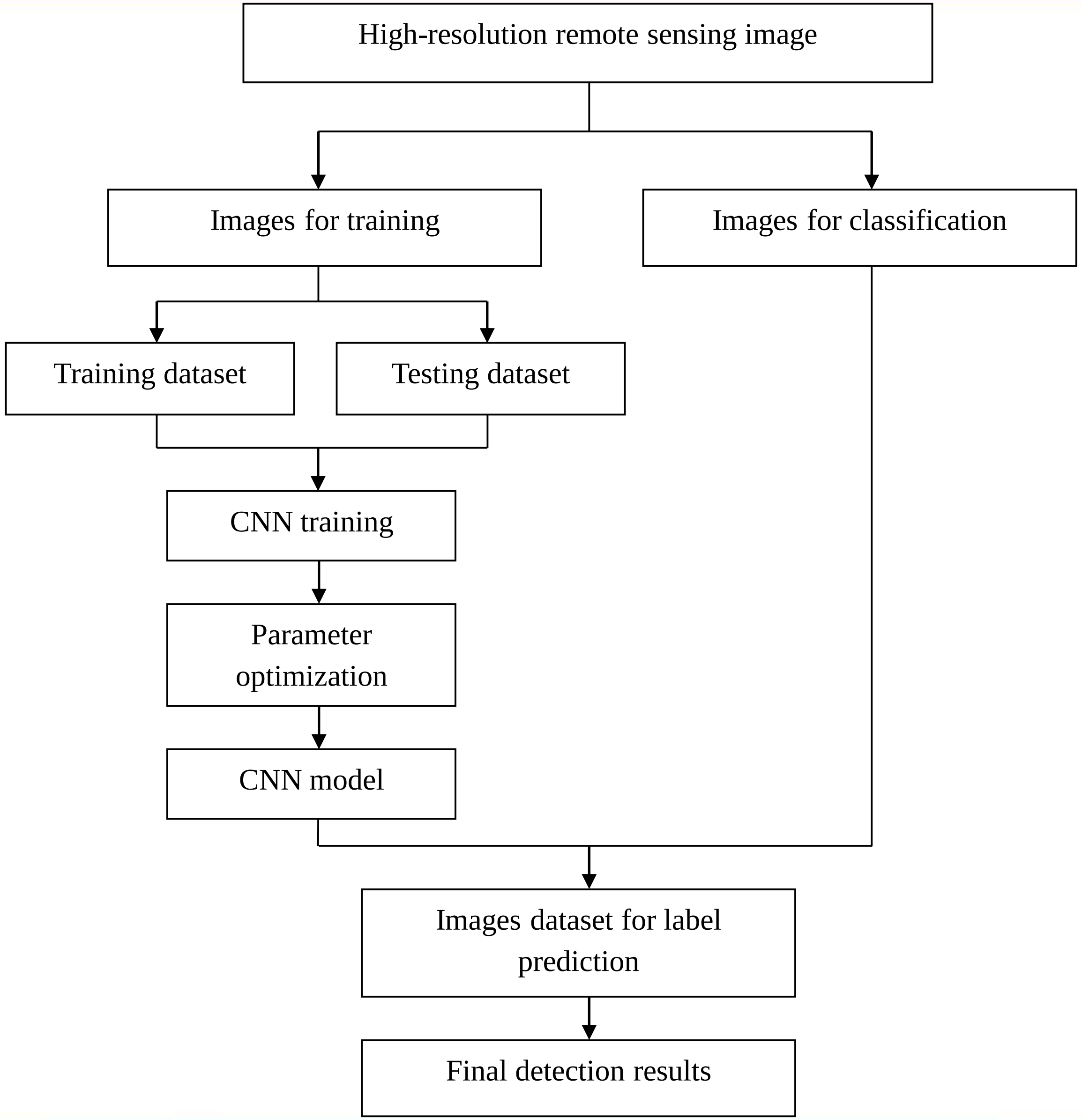
RF = 95%

Discussions

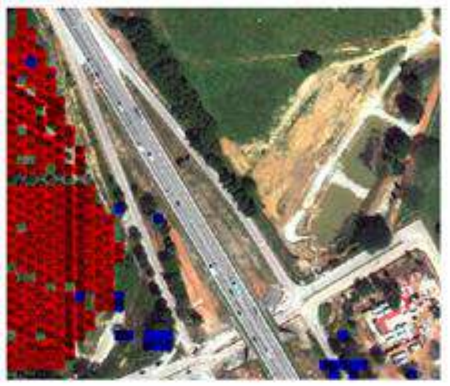
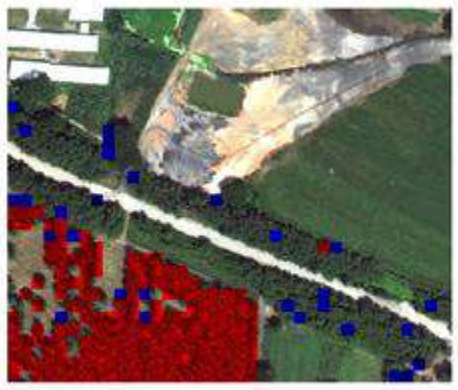
- REMAP allows **quick and accurate** way of mapping over wide area.
- GEE allows more control over the **algorithms** and **tuning**.
- Both methods are making large scale mapping more manageable as users are not required to store/download **big data**/perform **complex algorithm** development.

Very High Resolution Satellite Data

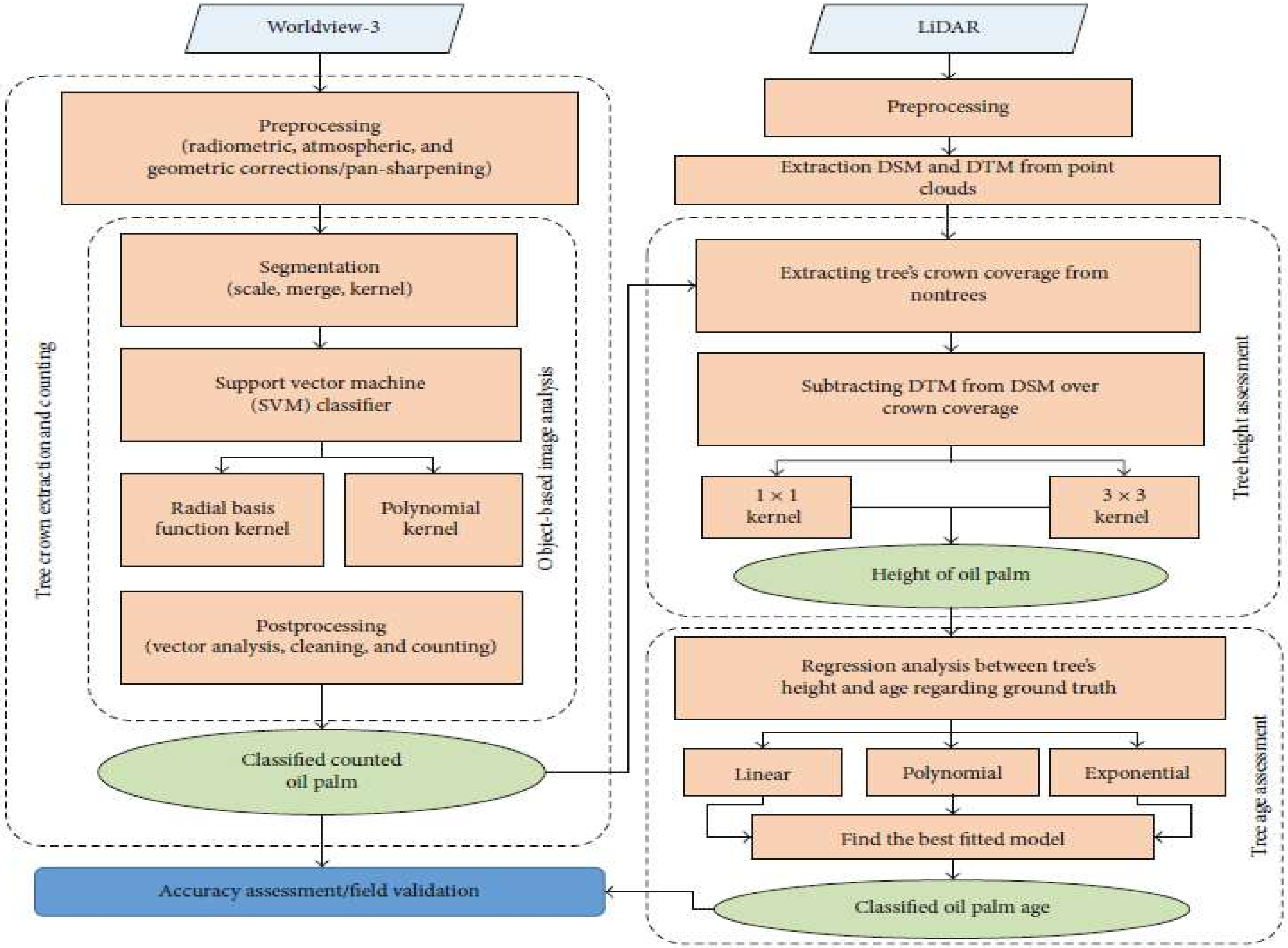
- Tree detection and counting relies on high resolution datasets.
- Deep learning can effectively perform this repetitive task.
- More efficient than the use of Object-based Image Analysis (OBIA) (Guirado et al., 2017) for vegetation crown detection.
- DL-based approach is based on open-source software (Python).



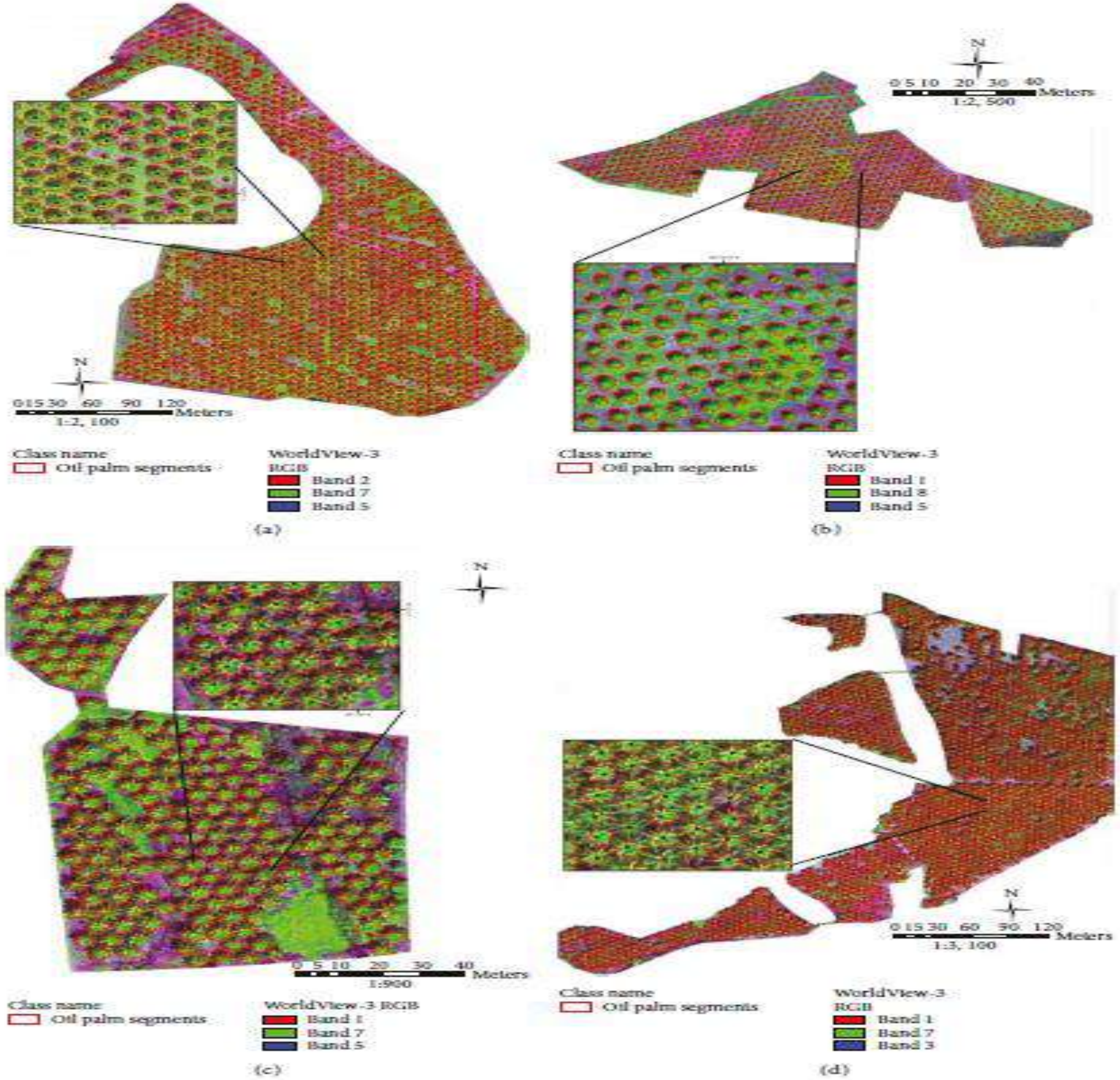
Nurulain Abd Mubin, Eiswary Nadarajoo, Helmi Z.M. Shafri , and Alireza Hamedianfar (2018). Young and Mature Oil Palm Tree Detection and Counting Using Convolutional Neural Network (CNN) Deep Learning Method. Submitted to the International Journal of Remote Sensing (under review).

Types of Oil Palm	Classification of Oil Palm Detection and Background	Accuracy (%)
Young		94
Matured		88

Fusion of VHR and LiDAR Data for Counting and Age Estimation

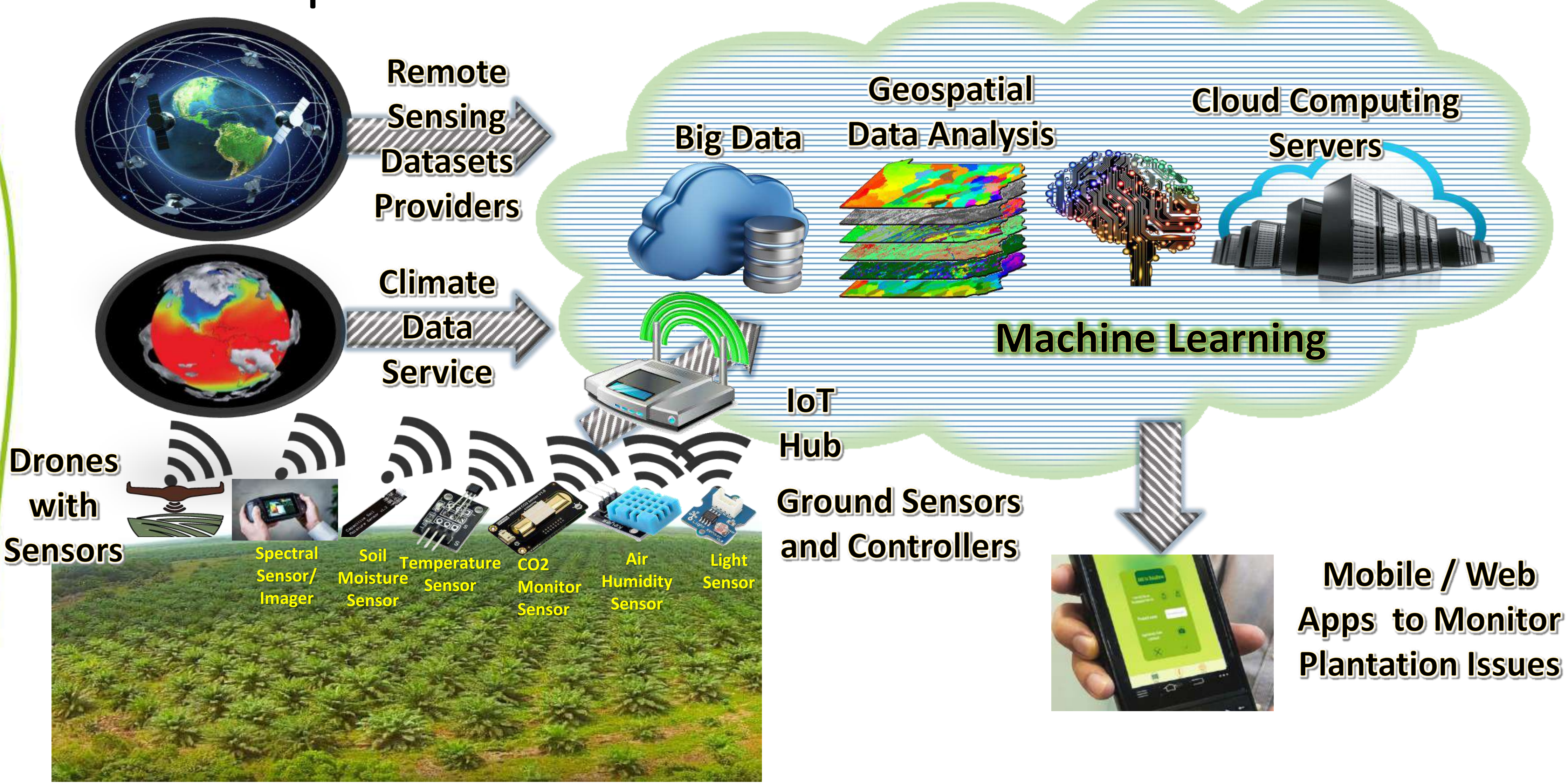


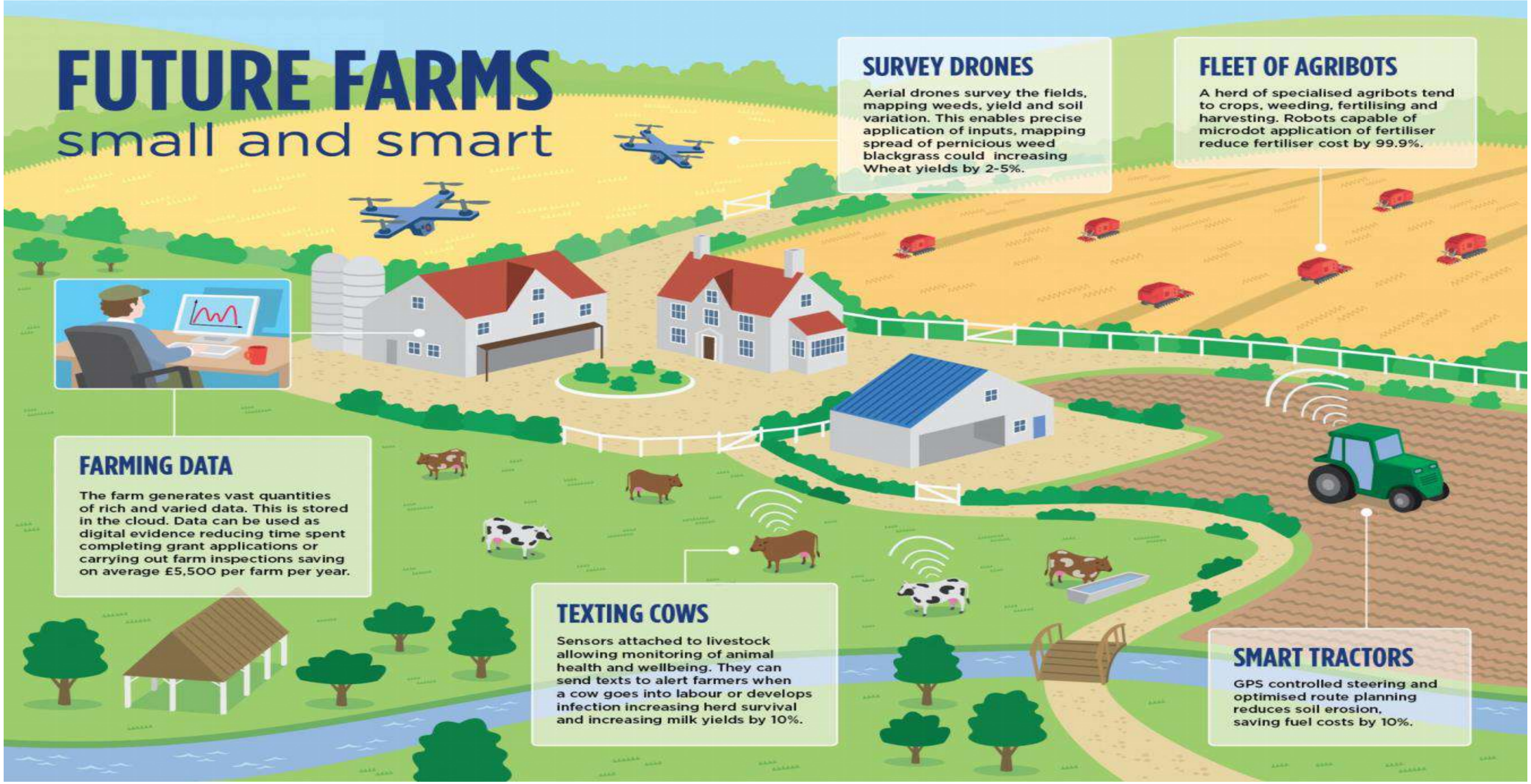
Rizeei, H. M., Shafri, H. Z. M., Mohamoud, M. A., Pradhan, B., & Kalantar, B. (2018). Oil palm counting and age estimation from WorldView-3 imagery and LiDAR data using an integrated OBIA height model and regression analysis. Journal of Sensors, 2018.


N
0 15 30 60 90 120
Meters
1:2, 100
Class name
Oil palm segments
WorldView-3
RGB
Band 2
Band 7
Band 5
(a)
N
0 5 10 20 30 40
Meters
1:2, 500
Class name
Oil palm segments
WorldView-3
RGB
Band 1
Band 8
Band 5
(b)
N
0 5 10 20 30 40
Meters
1:900
Class name
Oil palm segments
WorldView-3 RGB
Band 1
Band 7
Band 5
(c)
N
0 15 30 60 90 120
Meters
1:3, 100
Class name
Oil palm segments
WorldView-3
RGB
Band 1
Band 7
Band 3
(d)

No	Methods of data acquisition	ML algorithms	Summary
1	Field spectroscopy – ASD (Liagath et al, 2014)	KNN, Bayes	High level of discrimination
2	Field spectroscopy – GER (Ahmadi et al 2017)	ANN	High level of discrimination
3	Airborne (Piloted) - on going	SVM, ANN, RF	Most studies applied spectral indices with no comparisons with ML
4	Airborne – RGB UAV (Kalantar et al 2017)	SVM OBIA	Oil palm tree counting
5	Airborne - Multispectral UAV – on going	ANN, SVM combined with NDREi	Good accuracy for diseased oil palm detection
6	Satellite – Quickbird (Santoso et al 2017)	RF, SVM, CART	ML classified healthy vs unhealthy palms better than spectral index but no early detection
7	Satellite - Quickbird (Li et al 2017)	Deep Learning	High accuracy for tree counting
8	Satellite – WorldView-3 (Rizaeei et al 2018)	SVM	High accuracy for counting and age estimation
9	Satellite – Landsat (on-going, under review)	REMAP/GEE cloud computing	High accuracy and efficiency for large scale mapping (national)

Proposed Framework for Oil Palm Plantation




FUTURE FARMS
small and smart
SURVEY DRONES
Aerial drones survey the fields, mapping weeds, yield and soil variation. This enables precise application of inputs, mapping spread of pernicious weed blackgrass could increasing Wheat yields by 2-5%.
FLEET OF AGRIBOTS
A herd of specialised agribots tend to crops, weeding, fertilising and harvesting. Robots capable of microdot application of fertiliser reduce fertiliser cost by 99.9%.
FARMING DATA
The farm generates vast quantities of rich and varied data. This is stored in the cloud. Data can be used as digital evidence reducing time spent completing grant applications or carrying out farm inspections saving on average £5,500 per farm per year.
TEXTING COWS
Sensors attached to livestock allowing monitoring of animal health and wellbeing. They can send texts to alert farmers when a cow goes into labour or develops infection increasing herd survival and increasing milk yields by 10%.
SMART TRACTORS
GPS controlled steering and optimised route planning reduces soil erosion, saving fuel costs by 10%.

Conclusions

- Remote sensing is a useful tool for oil palm plantation management.
- AI and ML have important roles in remote sensing of oil palm plantation management.
- AI + RS formed core components of modern agriculture.
- Applicable at different spatial scales – field, airborne, spaceborne and used to complement each other.
- Input and interpretation from experts in the field produce the best decision making process.

Future work

- AI/ML algorithms are advancing and further testing required in order to increase accuracy, robustness and automation.

- More integration with cloud computing, IoT, new generation platforms and sensors will be interesting to explore.

- Data fusion (optical/radar/lidar etc).

AI Technology to make a crucial impact on Agritech

Deep learning application to identify potential defects and nutrient deficiencies in the soil

AI Sowing App which sends sowing advisories to participating farmers on the optimal date to sow

Machine learning technology enabling farmers to reduce the use of herbicides by spraying only where weeds are present

AI for Precision Farming to develop a crop yield prediction model using AI to provide real time advisory to farmers

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Thank you!!

Muchas Gracias!!