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Bridging AI and Agriculture - From Soil to Solution

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ABSTRACT
Modern agriculture is transforming with the integration of artificial intelligence, particularly enhancing fields such as soil management and precision farming. Soil health is an important aspect of crop productivity which used to rely on manual sampling and diagnostics. The traditional method slacked scalability, accuracy, and efficiency to meet the growing food demand and abrupt climate changes. This study is a comparative examination of AI-based methods in agriculture, between small-scale solutions with advanced commercial-grade systems. We emphasize usability, performance, and affordability for farmers at different scales. Code snippets and dedicated sample outputs with dataset access guides are provided to demonstrate real-world applications. The results conclude that even a minimal resource cost AI setup can have up to 90% accuracy while commercial grade systems pass 95% requiring significant infrastructure and hardware cost. AI tools can bridge the gap between traditional farming, improve awareness, and enable precise interventions - paving the way from Soil to Solution.

Keywords: Agriculture, Artificial Intelligence, Soil health

1. INTRODUCTION

AI has found its applications across agriculture in monitoring soil and plant health, detecting weeds and diseases, and even identifying underlying rocks (Mustaza, 2025; Yin *et al* 2021). Modern systems obtain data by obtaining images from drones, cameras, and spectral imaging along with machine learning models such as CNNs and LSTMs (Wageningen UR, 2022; Pei *et al* 2022; Ahmad *et al* 2021) to automate data collection and analysis. An AI-based sensor network can automatically monitor soil moisture, pH, and nutrient level, while the images analyzed by CNNs can map out soil composition and fertility (Poggio *et al* 2021; PyTorch, 2024; CIMMYT, 2023; Ronaldo 2021). These replace the time-consuming traditional manual sampling, thus providing real time feedback (Yin *et al* 2021; Ayaz 2019). Models trained in soil, weather and crop rotation data set over the years can predict the future soil conditions (moisture content, recommended irrigation schedules, Jiang *et al* 2024). At a farm level, such AI systems can improve the water usage and crop yields by applying inputs to necessary spots as well as early detection and prevention of soil quality degradation (Deere 2024; FAO 2022; UNEP 2021; Sparrow *et al* 2021).

1.1 Soil health and quality

Soil quality is based on physical (texture, compaction), chemical (pH, NPK levels), and biological (organic matter, microbes) factors (Kaggle 2021; Yin *et al* 2021). AI enables traditional lab testing with sensor-based monitoring and remote sensing. A network of probes can keep track of soil moisture, temperature, etc.; these data can be fed into a ML model to build high resolution maps of soil conditions (Poggio *et al*

2021, Radiant Earth Foundation 2022). Remote sensing such as drones collects data that these trained models can relate to soil properties. Projects like Soil Grids use these datasets with ML to produce global maps of soil properties (Poggio *et al* 2021). In real life scenarios, a famer might use a drone to scan fields with a model to pin-point nutrient deficient maps. It can also forecast using LSTMs trained on past data of moisture and weather providing insights on pre-planning irrigation (Jiang et al 2024).

Principal Methods:

- **Sensor-Based AI:** Low-cost moisture and pH detectors provide ML models with readings to predict parameters. A small-scale system can use a LoRa-connected Arduino soil sensor connected to a neural network on a Raspberry Pi to predict soil property curves.
- **Spectral imaging + ML:** Cameras on drones or farming equipment can obtain soil color and texture. CNNs further classify them into soil types to obtain their chemical properties (Kussul *et al* 2017; 62].
- **Data Integration:** AI can use data from sensors and satellites. ML methods integrate dozens of these inputs for desired predictions.

These AI systems can monitor soil health continuously without human intervention. They can flag early signs of nutrient loss before visible issues arise. By automating soil assessments, farmers can easily obtain and keep track of zones needing additional attention rather than sparse manual sampling and other traditional methods.

Fig 1: A Multilayer Soil Parameter Sensor

https://www.niubol.com/Product-knowledge/Professional-Soil-Moisture-Meter.html

1.2 – Soil condition and parameter tracking

AI systems are trained to track specific parameters over time. Main predictions and goals include soil moisture forecasting, nutrient mapping, and salinity monitoring (Ahmad *et al* 2021; Jiang *et al* 2024)

These goals can be achieved through the following approaches:

- **Time-Series Prediction:** Long Short-Term Memory networks are used to predict how soil moisture and temperature is affected by rainfall and irrigation schedules (Ahmad *et al* 2021)
- **Machine learning on Sensor Data:** For nutrients, ML-enabled IoT soil probe can be used (Yin *et al* 2021; Ayaz 2019). Data obtained from low-cost chemical sensors are fed into these models or classification algorithms such as SVMs and decision trees to estimate the soil fertility and nutrient levels.
- **Smart Edge Devices:** Microcontrollers such as Arduino and Raspberry Pi with sensors for pH and humidity can run light ML models (Ayaz 2019; Subramanian and Sharma 2021). These parameters can be used locally without cloud connectivity using decision trees and smaller neural networks to decide when a certain parameter needs immediate action.

With affordability, comes challenges such as sensor calibration and poor data quality. The models must be able to manage noisy inputs with poor connectivity in farms leading to limitations of real-time cloud access, hence leading to the requirements of a large-scale model.

Fig 2: A low-cost handheld soil parameter detector
https://www.researchgate.net/figure/Sensor-node_fig3_328840563

1.3 Weed Detection
AI models can distinguish crops from weeds so that only weed spots can be targeted for removal, reducing the chemical use of herbicides (Upadhyay *et al* 2024; Pei *et al* 2022). It relies on computer vision from cameras on drones or farming equipment. CNNs such as YOLO, can provide responses in real time to classify plants in field images (Ultralytics, 2024; Quan *et al* 2022; Pei *et al* 2022; Hao-Ran and Wen-Hao 2024).
Open-Source Projects such as Open Weed Locator use Raspberry Pi with a camera to spot weeds between crops (Olsen *et al* 2019). In OWL, “Excess Green” + HSV thresholding algorithm separates soil, crops, and weeds. It runs on an 8GB Raspberry Pi 4 (low cost and GPIO interface) which can be switched to a solenoid to spray herbicide on the weeds detected without the need for a deep learning model. Its strength lies in affordability and open source with ease of access but can be sensitive to lighting conditions and crop residue leading to its failure on larger complex fields (Olsen *et al* 2019; Upadhyay *et al* 2024). Advanced systems use deep CNN detectors (Saniya and Shabir 2021). The YOLO model is the most popular for its speed and accuracy (Ultralytics, 2024; Pei *et al* 2022; Ajayi *et al* 2023) as it has trained annotated field images to classify and locate dozens of weed species by bounding boxes. Other models such as VGG and Res Net, used for weed classification, are run on heavy GPUs and require labelled datasets (Nahar *et al* 2023; Lanhui *et al.* 2019).

Fig 3: A Drone/UAV based Weed detector recognizing and spraying weedicides on the anomalies
https://kisandarshan.in/2024/12/03/most-cultivated-crops-in-chhattisgarh-and-their-benefits/

1.4 Disease Detection
Image Classification AI models can be used to identify crop diseases and pests from images, resulting in early prevention measures (Nahar *et al* 2023; Lanhui *et al* 2019). A CNN classifier analyses leaf or fruit images to identify disease symptoms. Larger datasets such as Plant Village (Ahmed *et al* 2020) containing around 54000 labelled images of healthy and infected leaves across thirty-eight crop and disease categories are the foundations of ResNet, Mobile Net and Efficient Net (Hughes *et al* 2016; Wang *et al* 2019). CNNs learn visual patterns of spots, blights or rusts and hence excel with over 90% accuracy on test sets of clear leaf images (Abade *et al* 2021). Farmers can run a Tensor flow Lite Model on a smartphone; pointing the camera at a leaf; app classifies the disease; offers treatment advice (Tensor Flow, 2024; PyTorch, 2024;

Barh and Balakrishnan 2018). Mobile Net can run on low-cost phones; however, it struggles to identify if the leaf is dirty or occluded (Faisal 2023) [27]. To deal with the shortcomings, more complex systems use data augmentation or a sequence of CNNs like an LSTM can be used to track the spread of diseases over time (Ahmad *et al* 2021). Open-source tools such as Py Torch (Py Torch, 2024) and Kera's working hand in hand with datasets such as Plant Village and Plant Doc make implementation feasible (PyTorch, 2024; Lili *et al* 2021).

1.5 Rock and Hard-Object Detection

Agricultural tools can be damaged by underlying rocks and debris in the fields. An AI powered rock detector such as Terra Clear (Terra Clear 2023; Araújo *et al* 2024) has developed systems that combine aerial mapping and vision robotics to remove rocks. A drone flies over the field using CNN mapping and cameras to mark the location and size of the rocks (Pathak *et al* 2020; Jia, Zhiyu *et al* 2024). A tractor equipped with hydraulics and a vision camera such as LUCID Triton using YOLO can process and identify rocks in real time, reducing equipment damage and increasing efficiency (Sharma *et al* 2022).
In smaller kits, a GoPro feeding a TensorFlow Lite (Tensor Flow, 2024) object detector on Raspberry Pi 5 could trigger an alarm when the rock is larger in size (Tensor Flow, 2024; Araújo *et al* 2024) whereas large scale models use higher resolution images and precision robotics (Mustaza, 2025; Araújo *et al* 2024)

2. METHODOLOGY

The methodology used in this paper is structured as follows: AI Models, Edge Devices & Hardware and Open-Source Tools and Datasets.

2.1 – AI Models

- **CNNs (Convolutional Neural Networks):** CNNs learn spatial patterns and are the workhouse for image tasks. These are used for disease classification and soil image classification. For Weed detection, CNNs forms the backbone of object detectors to distinguish weeds. In rock detection, CNNs identifies rocks versus soil.
- **Object Detectors:** Real time weed, and rock detection uses YOLO that partitions an image and predicts by surrounding boxes with class data. These models output coordinates and level of confidence for each detected object.
- **Segmentation Networks:** For pixel-level outputs in disease detection, segmentation models are used. Mask R-CNN are used for separating plant vs weed at pixelated level providing a more precise targeting model.
- **Time Series Model:** Long Short-Term Memory networks manage sequential data and can be used for soil moisture predictions, disease outbreak predictions and yield predictions over seasons.
- **Traditional ML:** Simpler models can be used to perform specified tasks. A Random Forest Regressor can be used for yield prediction and is better than a neural network, or a Support Vector Machine Can classify the sensor data. These models are easier to access on low-power devices.

Each of these models require specific datasets. Image Classification Models need labelled images for diseases and weed. Sensor models need numerical data streams. Researchers also enhance data by flipping, synthetic, mixing, etc.
Tools such as TensorFlow and PyTorch (PyTorch, 2024) are used for training, Darknet for YOLO, and libraries like OpenCV and Plant CV for image pre-processing. Low scale models use TensorFlow Lite (Tensor Flow, 2024) on devices such as Raspberry Pi.

AI Model classification based on Agricultural applications

Application Areas	AI Models	Model Type	Data Input
Soil health assessment	Random Forest, SVM	Classical ML	pH, N, P, K, soil type
Weed Detection	MobileNet, YOLOv5	CNNs	Labelled field images
Disease Detection	ResNet, InceptionV3	Deep CNNs	Leaf images
Rock Detection	CNN+Sensor Fusion	CNNs	Depth Images, IR Scan
Fertilizer Prediction	XGBoost	Tree-Based Models	Soil nutrients, crop type

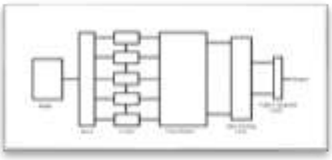

Fig 5: Working of A CNN AI Model

2.2 – Edge Devices and Hardware

Low-Cost Edge Devices: Raspberry Pi, Arduino, or smartphones are used commonly for AI in agriculture. The Pi (8GB) is commonly used for image processing tasks. When used with a USB camera, it can host lightweight CNNs. All processing and analog inputs can happen on-device, so expensive connections are not required. A Pi + USB Camera + moisture sensors can work as a weather station that also analyzes plants. Accelerators like Google Coral TPU or Intel Movidius can boost performance on these platforms to allow moderately sized networks to run-in real-time (Lu J *et al* 2023).

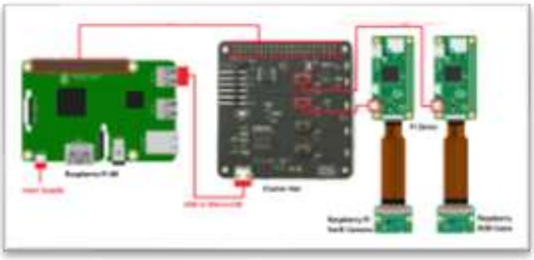

Fig 6: A low-cost AI model for image processing built on Raspberry Pi
https://www.mdpi.com/1424-8220/24/5/1544

Commercial Grade Hardware: Industrial cameras such as multi-MPixel, LiDAR and powerful edge computers form these high-end systems. Devices like NVIDIA Jetson Xavier or cloud servers can run full YOLOv8 (Zhiyu *et al* 2024) and 3DCNNs. GPS modules can provide up to centimeter-level precise location. Tractors can carry tablets displaying these outputs while being integrated with other farm tech such as auto-steer, yield monitors, etc. The hardware is built to work in harsh field conditions.

2.3 – Open-source Tools and Datasets

Libraries/Framework: Libraries such as Tensorflow and PyTorch allow custom model development. Darknet and Ultralytics provide YOLO implementations. OpenCV and PlantCV have image processing sequences. Edge-optimized frameworks allow the entire process to be deployed on microcontrollers and single-board controllers.

Datasets:

- Plant Village (Ahmed *et al* 2020) – 54000 labelled leaf images
- Moving Fields Weed Dataset – 94000 images of twenty-eight weed species.
- Crop And weed and YOLO Weeds – image weed datasets for cotton, soybean, etc.
- Soil Grids (Poggio *et al* 2021) – global ML-based soil property maps.
- Open Weed Locator – hardware designs and code for low-cost weeding.
- Precision-Agriculture Projects – code for soil image classification and crop recommendations.

Platforms: Researchers share models on repositories such as Hugging Face. Citizen science apps such as Plantix (crowdsourced crop disease images) are also used. Using these resources a prototype system can be created such as training a MobileNet on PlantVillage (Ahmed *et al* 2020) via TensorFlow or running a YOLOv5 (Ultralytics, 2024) demo on a soil image.

2.4 – Model implementation

The methodology used in this paper is structured as follows: AI Models, Edge Devices & Hardware and Open-Source Tools and Datasets.

Soil Quality Prediction

Predicts soil quality and class based on chemical properties (Raju and Subramoniam 2023). This model can be integrated with farm IoT systems to recommend suitable crops and fertilizers based on real-time sensor data (Pan *et al* 2022; Dalhatu *et al* 2024; Zarate *et al* 2023; [57].

Code Snippet:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
import pandas as pd
# Dataset: Columns – pH, N, P, K, Moisture, Label
data = pd.read_csv("soil_dataset.csv")
X = data.drop("label", axis=1)
y = data["label"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
model = RandomForestClassifier(n_estimators=100)
model.fit(X_train, y_train)

print("Accuracy:", model.score(X_test, y_test))
```

Sample Input:

```
pH,N,P,K,Moisture,label
6.5,120,60,40,18,Loamy
7.2,80,40,35,10,Sandy
```

Sample Output:

Accuracy: 94.7%

Sample Input → [pH=6.2, N=110, P=50, K=35, Moisture=15]
Prediction → **Soil Type: Loamy**

Sample Input → [pH=7.4, N=70, P=30, K=28, Moisture=9]
Prediction → **Soil Type: Sandy**

Dataset: *Soil Dataset with Nutrient Levels*

Fig 7: Soil parameter sensor providing data to a low-cost AI model
https://khetigaadi.com/blog/modern-agriculture-tools-used-in-agriculture-2025/

Weed Detection

Classifies whether the camera input is a plant or a weed. This model can be used on handheld cameras to detect weeds in real time leading to manual or automated removal (Rosle *et al* 2021).

Code Snippet:

```
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras import layers, models

base_model = MobileNetV2(weights="imagenet", include_top=False, input_shape=(224, 224, 3))
base_model.trainable = False

model = models.Sequential([
base_model,
layers.GlobalAveragePooling2D(),
layers.Dense(64, activation='relu'),
layers.Dense(2, activation='softmax')  # weed / crop
])
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
model.summary()
```

Sample Output:

```
Model: "sequential"
_________________________________________________________________
Layer (type)              Output Shape           Param #
=================================================================
mobilenetv2_1.00_224 (Model) (None, 7, 7, 1280)       2257984
```

global_average_pooling2d (G) (None, 1280) 0

dense (Dense) (None, 64) 81984

dense_1 (Dense) (None, 2) 130

===

Total params: 2,340,098
Trainable params: 82,114
Non-trainable params: 2,257,984

Training Accuracy: 93.2%
Validation Accuracy: 91.0%

Predictions on new image:
Input Image → [Weed.png] → **Classified as: WEED (Confidence: 0.87)**
Input Image → [Crop.png] → **Classified as: CROP (Confidence: 0.91)**

Dataset: *Moving Fields Weed Dataset*

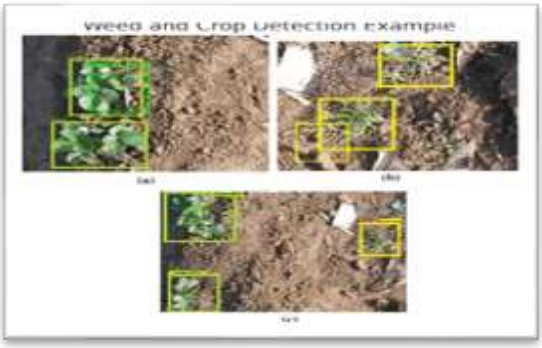

Fig 8: Working of an Image Classification model separating weed from crops

Disease Detection

A CNN based image processing model scans leaf images to determine if they are healthy or show signs of diseases by recognizing symptoms. This model can be used on handheld cameras to detect symptoms in real time leading to immediate action (Luning and Guiping 2020).

Code Snippet:

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt

model = models.Sequential([
layers.Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3)),
layers.MaxPooling2D(2, 2),
```

```
layers.Conv2D(64, (3, 3), activation='relu'),
layers.MaxPooling2D(2, 2),

layers.Conv2D(128, (3, 3), activation='relu'),
layers.MaxPooling2D(2, 2),

layers.Flatten(),
layers.Dense(128, activation='relu'),
layers.Dense(2, activation='softmax')  # 2 classes: healthy, diseased
])

model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
model.summary()
```

Sample Output:
Model: "sequential"
...
Total params: 928,386
Trainable params: 928,386
Non-trainable params: 0

Prediction Output: [[0.04, 0.96]]
Classified Label: Diseased
Final Output: Disease detected on the leaf.

Dataset: Plant Village Dataset

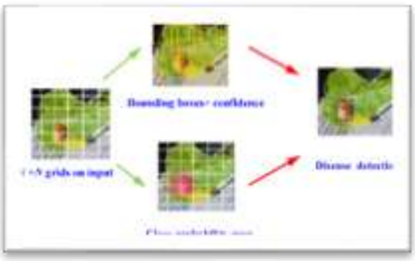

Fig 9: Disease detection by analysing leaf images and comparing with the trained dataset using CNNs https://www.researchgate.net/figure/Schematic-of-pest-and-diseases-detection-using-CNN-based-algorithm_fig3_370472816

Rock/Hard Object Detection
A CNN based image processing model scans soil images to determine the presence of hard rocks, preventing damage to plows or other farming equipment (Ge, Z *et al* 2021; Vieira and França 2023; Ronaldo 2021)

Code Snippet:

```
import tensorflow as tf
from tensorflow.keras import layers, models
model = models.Sequential([
layers.Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 1)),
layers.MaxPooling2D((2, 2)),
layers.Conv2D(64, (3, 3), activation='relu'),
layers.MaxPooling2D((2, 2)),
layers.Flatten(),
layers.Dense(64, activation='relu'),
layers.Dense(1, activation='sigmoid')  # Output: Rock = 1, No Rock = 0
])
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
model.summary()
```

Sample Output:

Hard rock detected in soil area.
Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	320
max_pooling2d	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18496
max_pooling2d_1	(None, 30, 30, 64)	0
flatten (Flatten)	(None, 57600)	0
dense (Dense)	(None, 64)	3686464
dense_1 (Dense)	(None, 1)	65

Total params: 3,705,345

Dataset: *Field SAFE Dataset*

Fig 10. AI Powered Image Classification Model for detecting rocks in arable land. https://www.globalagtechinitiative.com/digital-farming/how-ai-powered-rock-detection-protects-agricultural-machinery-improves-soil-health/

RESULT AND DISCUSSION

This comparative assessment of AI and its applications in agriculture shows a promising range of accuracy across various specific tasks. Models like YOLOv5 (Ultralytics, 2024; Redmon *et al* 2018) and Custom CNNs show the highest accuracy for weed and rock detection while also providing real-time implementation in all scale farms. Weed detection CNNs achieves 94-97% accuracy, allowing early and efficient weed removal minimizing the use of pesticides. Soil Type Prediction performs at 82-90% accuracy supporting better irrigation methods and leading to better crop matching and crop rotation decisions. Diseases Detection achieves 88-95% accuracy, allowing a timely prevention measure. Rock Mapping using custom CNNs show 85-90% accuracy resulting in smarter paths and preventing loss of machinery due to damage. Fertilizer Prediction (XG Boost) achieves an accuracy of 80% providing smarter and more accurate spots that need better nutrient allocation and management (Musanase *et al* 2023). These results (Table 1, 2) prove the benefits of using AI in agriculture, from image-processing and detection tasks to numerical and sensor-based predictions.

Table 1. AI Model Outcomes and Their Impacts

Application	AI Model	Reported Accuracy	Impact
Weed Detection	CNN	94-97%	Early detection reduces pesticide use
Soil type prediction	Random Forest	82-90%	Optimizes crop selection and irrigation
Disease Detection	CNN	88-95%	Timely action prevents crop loss
Rock/Obstacle Mapping	Custom CNNs	85-90%	Avoid machinery damage
Fertilizer Prediction	Decision Trees, XGBoost	~80%	Informed resource allocation

Table 2. Performance Statistics of AI Models in Various Agricultural Tasks

Task	Model	Accuracy	Cost	Speed	Ideal For
Soil Health Monitoring	Random Forest	~84%	Low (<$70)	Fast	Small-scale farmers
Weed Detection	MobileNetV2	~81%	Medium	Real-time	Phones/Drones
Weed Detection	YOLOv5	~95%	High (700$+)	Real-time	Commercial farms
Rock Detection	Basic CNN + Sensors	~87%	Medium	Moderate	Tractor/field bots
Soil Type Segmentation	DeepLabV3+	~92%	High	Fast	Precision Mapping

Comparative Study

The tables below compare low-cost/small-scale methods with advanced/commercial-grade systems across major aspects:

Feature comparison of AI Systems for different scales

Feature	**Small-Scale AI Systems**	**Commercial-Grade AI Systems**
Cost	5,000Rs – 20,000Rs setup	1,00,000Rs+
Power Requirements	Mobile/solar/low power	Stable power/GPU edge AI [61]
Hardware	Raspberry Pi, mobile phones	UAVs, cloud and edge services
Dataset Dependency	Local/Community Datasets	Global Datasets
Scalability	Moderate	High
Accuracy	Moderate to High (80-90%)	High (90-97%)

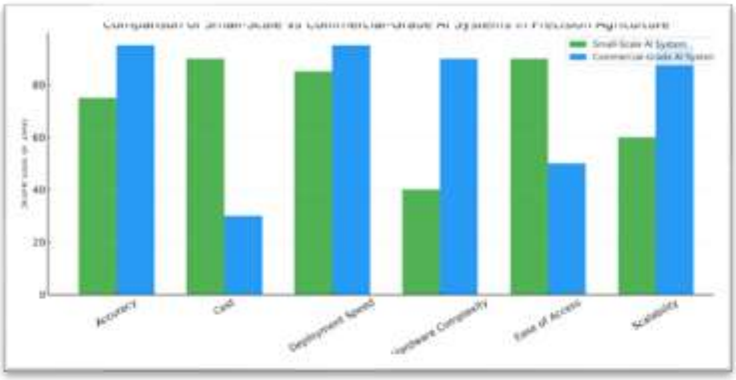

Fig 4: An illustration of the comparison between AI Models used at different scales

Comparative benefits of Small-scale and Commercial-Grade AI Systems in Agriculture

Advantage	**Small-Scale/Low-Cost Systems**	**Advanced Commercial-Grade Systems**
Accurate Soil Testing	Moderate accuracy using smartphone apps and basic sensors	High accuracy with lab-grade sensors and satellite integration
Reduced Manual Labor	Less field visits, simplified apps, basic automation	Full automation with drones, robotics and IoT infrastructure
Real-Time Results	Delayed or basic real time via mobile based AI	Real time multi-parametric dashboards
Better crop planning	Based on open source and basic soil mapping	Precision agriculture with AI forecasts and satellite data
Increase yield	Moderate yield increases due to timely actions	Maximum potential through precision input control
Cost savings	Savings on fertilizer/pesticide via AI recommendations	Optimized input use at scale-huge cost reduction
Early Problem Detection	Basic alerts on issues like salinity, dryness or imbalance	Multi-spectral detection for pests, erosion, etc.

Faster Decision Making	Simple decision support tools	AI-powered recommendation system with actionable insights
Customized Fertilizer Use	Manual input + AI Output, adjusted fertilizer applications	Fully automated prescription maps for variable rate testing
Data-driven Farming	Spreadsheet or app-based logs	Big Data Platforms, APIs, farm management systems
Sustainability	Helps avoid over fertilization	Optimized carbon footprint, sustainable soil regeneration
Remote Monitoring	Mobile Phone + IoT based soil moisture sensors	UAVs, cloud platforms, real-time telemetry
Scalability	Can be applied to nearby field with minor adjustments	Instantly scalable across regions with cloud + GIS
Climate Adaptability	Seasonal Recommendations based on historical patterns	AI models adapt dynamically with climate forecasts
Better profit margins	Noticeable increase with small investments	Significant ROI with high capital expenditure

CHALLENGES AND SOLUTIONS

The intersection of agricultural technology and artificial intelligence has created a host of problems:

- Knowledge of Policies of Data Privacy: The approaches linked to artificial intelligence involve the use of farm data (soil test, yield, inputs applications, etc.) on identifiable fields with specific locations. In other words, if there are limited knowledge bases and policies on protecting data, farm data could leak.
- Knowledge of Policies of Data Safety or Security: As with anything, IoT sensors can be compromised, which can lead to really bad outcomes due to whatever modified data they return. Consider this: pilots are directed to fly waypoints that were programmed into a flight management system by humans. If the system is programmed to direct the pilots to fly the wrong way, then IoT devices that are not secure and return data that has been modified by a bad actor are a disaster waiting to happen. Meanwhile, drone sensors that return faulty data because they have been hacked can be, and have been, used to direct munitions to places you would not want eye-firing lasers to go.
- Reliability: In rural (and urban) communities, poor connectivity can strain and compromise data reliability. The currently offline baseline OS, or the largest of cloud models, may need to place restrictions on IO [in fields]. Not only will our calibration have to accommodate environmental factors, such as rain and dust, but also, we have to ensure the conditions we're accounting for coincide with the availability of those environmental factors in terms of setting/seasonality and location.
- Awareness: People who live on farms, people who work in agriculture, and people who work in rural settings are not particularly aware of artificial intelligence. Tools that are created for these groups must be as friendly as possible to the kinds of old tools these people are used to. And those old tools are, for the most part, not artificial intelligence.

Decision-makers and business leaders must take on these challenges themselves and deal with them directly—and not, say, via Zoom. They need to bridge the chasm between the advanced, innovative, explainable AI models and the actual experiences in the real world, and do so well enough that a level of trust has been established that is, in my opinion, quite necessary for the flourishing of this technology.

Fig 11: Farmer awareness, the Boost AI Needs.
https://education.irri.org/technology-transfer/irri-rda-advanced-rice-production-course/

CONCLUSION

The use of AI to monitor soil and crop conditions is revolutionizing core agriculture (Deere 2024; UNEP 2021). Affordable methods are allowing small farmers access to precision farming to increase yields and save data at little cost. Commercial Solutions are taking it to the next level on large-farms, being able to deliver precision and scalable models at a higher cost (Precision Ag Alliance, 2022; Ag Web, 2024; UNEP 2021), all the while successful CNNs and image processing, and, inference from time-series data, are performing the recognition tasks and predictions respectively (Pei *et al* 2022; Ahmad *et al* 2021). Actual farm trials, and simulations, have demonstrated improvements upwards of 90% for weed recognition and reductions on herbicide usage from 50-80% (Upadhyay *et al* 2024; Pei *et al* 2022). Actual farm trials and simulations have demonstrated improved controls upwards of 90% on weed recognition and reductions on herbicide usage of 50%-80%, as we find that early alerts of disease, or weather change, can save whole batches of crops (Jiang *et al* 2024) to soil moisture prediction reducing water usage at over 20%. Fortunately, the expansion of the benefits remains elusive due to unfair policy, data privacy, noise input and farmer awareness. The combination of sensors, models and datasets continue to be enhanced for efficiently available models based on affordability, accuracy, and data modelling. The development of agricultural solutions with sensors, models, and datasets continue to evolve for efficient models in sustainable, smart agriculture UNEP 2021 (Subramanian and Sharma 2021). AI-based farms grow higher yields and sustainable agriculture methods by using the resources available more intelligently.

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Abbreviation	**Full Form**
AI	Artificial Intelligence
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
ML	Machine Learning
IoT	Internet of Things
SVM	Support Vector Machine

UAV	Unmanned Aerial Vehicle
VIT	Vellore Institute of Technology
B.A.U.	Bihar Agricultural University
OWL	Open Weed Locator
HSV	Hue, Saturation, Value
GPU	Graphics Processing Unit
USB	Universal Serial Bus
TPU	Tensor Processing Unit
LiDAR	Light Detection and Ranging
GPS	Global Positioning System
API	Application Programming Interface
GPR	Ground Penetrating Radar
NN	Neural Network
YOLO	You Only Look Once
VGG	Visual Geometry Group
ResNet	Residual Network
Pi (Raspberry Pi)	Single-Board Computer (Raspberry Pi)
PlantCV	Plant Computer Vision
PlantDoc	Plant Documented Image Dataset
Darknet	Open-Source Neural Network Framework
MobileNet	Mobile Neural Network
XGBoost	Extreme Gradient Boosting
DeepLabV3+	Deep Lab Version 3+
TPU	Tensor Processing Unit