Applications and Implications of Artificial Intelligence

Seminar 2 : AI in crop management

Team 8: The_hardest_task_for_a_programmer_NAMING

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- AI in crop management
  - Pest management
  - XAI crop recommendation system
  - Disease Identification by drones
  - Irrigation with AI
  - Advanced Machine Learning for Regional Potato Yield Prediction
  - Advancing crop productivity and sustainability

Pest management

- Why it is Important?

Agricultural pests are responsible for **20%–40%** of global crop production losses each year. Pest infestations cost the global economy around **$220 billion** annually, with invasive insects alone causing approximately **$70 billion** in damages.

Pest management

- Traditional Methods and Their Issues

Farmers use various pesticides to improve both crop quality and storage life. While pesticides mitigate yield losses, **continuous usage of pesticides leads to problems** such as pesticide resistance, secondary pest outbreaks, breakdown of host plant resistance, environmental contamination, and potential health risks to consumers.

Pest management

- The Application of AI in Pest Management

  1. Pests Identification

✓ Installing vibration sensors on trees allows farmers to capture faint vibrations produced by pest larvae. AI analyzes these signals to identify characteristic patterns, determining whether trees are infested.

✓ Integrating IoT and AI, drones or autonomous robotic vehicles can capture orchard imagery. AI processes these images to identify pest presence and species, allowing targeted pesticide application.

Pest management

- The Application of AI in Pest Management

  2. Pest Population Monitoring

Researchers have combined AI with smart traps to identify and count pest species and populations. By analyzing data from traps placed across farmland, AI monitors pest conditions, enabling farmers to apply pesticides only where infestations exceed thresholds, avoiding indiscriminate spraying.

Pest management

- The Application of AI in Pest Management

   3. Pest Infestation Alerts

In India, researchers collaborated with local farmers to establish a cotton pest early warning system. When a field shows infestation, farmers upload photos. AI identifies the pest species and severity, sending alerts to nearby farmers. This provides immediate, localized advice, allowing early pesticide application, increasing effectiveness while reducing chemical use.

Pest management

- The Application of AI in Pest Management

4. Precision Spraying of Pesticides

Researchers have developed a machine learning-based system for drone spraying area recognition in precision agriculture. By classifying farmland and orchard images captured by drones, the system distinguishes between sprayed and non-sprayed areas. This enables real-time autonomous spraying by drones. With further improvements, the system could support remote operations, facilitate precise pesticide application and reduce chemical usage.

Crop diversification using XAI

- Crop diversification is a critical issue to meet the increasing demand for food and to improve food safety and quality.

- This is considered a major issue due to diminishing natural resources, limited arable land and unpredictable climatic conditions.

- XAI, suggests suitable crops for a region based on weather and soil conditions.

AgroXAI: System model

- Models used: K-Nearest Neighbors (KNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine, (SVM), LightGBM (LGBM) and Multilayer Perceptron (MLP) models to classify the crop.

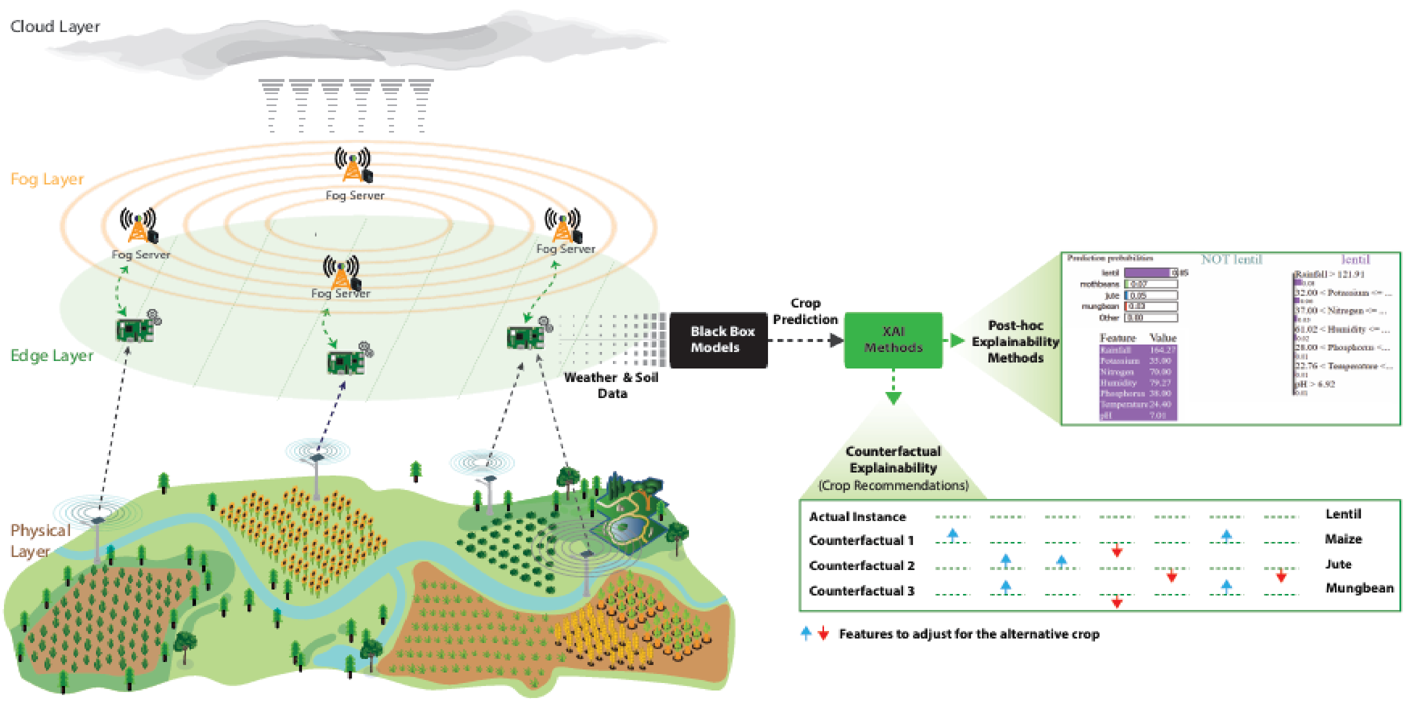


Fig. 1: Proposed Edge Computing-Based Explainable Crop Recommendation System (AgroXAI)

AgroXAI: System model

- Physical Layer: This layer includes sensors that measure the region’s climate, soil structure, water resources, temperature and humidity, and actuators that provide conditions that can be changed in the region.
- EdgeLayer: At this layer, for each geographic region, there are end devices to analyze the locally collected data. These devices are capable of running classicalML and XAImethods.
- Fog Layer: This layer includes hardware clouds that manage data traffic between the edge and the cloudlayer and have the potential to provide network control.
- CloudLayer:This layer includes resource-richnetwork devices that can perform computation and storage tasks that cannot be performed on edge systems in the proposed architecture.

Data used and Model results

- Data used: https://www.kaggle.com/datasets/chitrakumari25/smart-agricultural-production-optimizing-engine
- 22 different crop types as target labels.

TABLE II: Dataset Features and Descriptions

Features	Descriptions
Nitrogen	Amount of Nitrogen in soil
Phosphorus	Amount of Phosphorus in soil
Potassium	Amount of Potassium in soil
Temperature	The average soil temperatures
Humidity	Amount of humidity
ph	pH level of the soil
Rainfall	Amount of rainfall
Target	Types of crop

- Classification results of ML models

TABLE III: Classification Results of ML Models

	Precision	Recall	F1-Score	Accuracy
KNN	97.1071	96.6667	96.6198	96.6667
RF	99.3395	99.2424	**99.2312**	**99.2424**
DT	98.5620	98.4848	**98.4742**	**98.4848**
SVM	97.7694	97.4242	97.4163	97.4242
LGBM	97.7930	97.5758	**97.5527**	**97.5758**
MLP	95.7698	95.6061	95.5945	95.6061

XAI methods and results

XAI methods

- Explain Like I'm 5 (ELI5):It provides both global and local explainability. ELI5 uses tree models for calculating feature weights. The contribution of the feature to the decision is based on how much the score has changed from parent to child at each node of the tree.
- SHapley Additive exPlanations (SHAP): SHAP is an explainability method based on game theory. In this method, a value called Shapley value is calculated for each feature, which expresses the contribution of the feature to the outcome.
- Local Interpretable Model-agnostic Explanations (LIME): LIME method examines how the model works by changing the inputs and observing how the predictions vary. LIME is model-agnostic and provides local explanations.
- Counterfactual: Counterfactual is a human-friendly explainability method that explains the smallest change in feature values and transforms the prediction into a predefined output.

Weight	Feature
0.2276 ± 0.1840	Humidity
0.1953 ± 0.1636	Rainfall
0.1934 ± 0.1850	Potassium
0.1459 ± 0.1340	Phosphorus
0.1382 ± 0.1366	Nitrogen
0.0633 ± 0.0769	Temperature
0.0362 ± 0.0369	pH

Weight	Feature
0.2404	Humidity
0.2361	Rainfall
0.1712	Phosphorus
0.1431	Nitrogen
0.1330	Potassium
0.0550	Temperature
0.0212	pH

Fig. 2: ELI5 global explanations for RF (Left) and LGBM (Right)

ELI5 and SHAP results

y=papaya (probability 0.955) top features			y=grapes (probability 0.022) top features			y=maize (probability 0.011) top features		
Contribution?	Feature	Value	Contribution?	Feature	Value	Contribution?	Feature	Value
+0.226	Potassium	55.000	+0.044	<BIAS>	1.000	+0.055	Potassium	55.000
+0.164	Phosphorus	60.000	+0.032	Rainfall	98.540	+0.050	Rainfall	98.540
+0.161	Humidity	90.556	+0.017	Temperature	34.280	+0.048	<BIAS>	1.000
+0.125	Nitrogen	44.000	+0.008	Nitrogen	44.000	+0.017	Phosphorus	60.000
+0.119	Temperature	34.280	-0.001	pH	6.825	+0.001	Temperature	34.280
+0.100	pH	6.825	-0.006	Potassium	55.000	-0.037	Humidity	90.556
+0.041	<BIAS>	1.000	-0.026	Phosphorus	60.000	-0.055	pH	6.825
+0.021	Rainfall	98.540	-0.045	Humidity	90.556	-0.066	Nitrogen	44.000

Fig. 3: ELI5 local explanations for RF (Randomly selected sample test data: Nitrogen = 44, Phosphorus = 60, Potassium = 55, Temperature = 34.28046, Humidity = 90.555618, pH = 6.825371, Rainfall = 98.540474)

y=papaya (probability 1.000, score 4.128) top features			y=chickpea (probability 0.000, score -6.353) top features			y=lentil (probability 0.000, score -6.521) top features		
Contribution?	Feature	Value	Contribution?	Feature	Value	Contribution?	Feature	Value
+6.715	Phosphorus	60.000	+0.274	pH	6.825	+0.138	pH	6.825
+2.589	pH	6.825	+0.247	Phosphorus	60.000	+0.126	Potassium	55.000
+1.658	Humidity	90.556	+0.152	Temperature	34.280	+0.118	Phosphorus	60.000
+0.446	Temperature	34.280	-0.103	Potassium	55.000	-0.056	Temperature	34.280
-0.000	Nitrogen	44.000	-0.284	Rainfall	98.540	-0.159	Nitrogen	44.000
-0.502	Potassium	55.000	-0.384	Humidity	90.556	-0.182	Humidity	90.556
-6.777	<BIAS>	1.000	-6.255	<BIAS>	1.000	-0.478	Rainfall	98.540
						-6.029	<BIAS>	1.000

Fig. 4: ELI5 local explanations for LGBM (Randomly selected sample test data: Nitrogen = 44, Phosphorus = 60, Potassium = 55, Temperature = 34.28046, Humidity = 90.555618, pH = 6.825371, Rainfall = 98.540474)

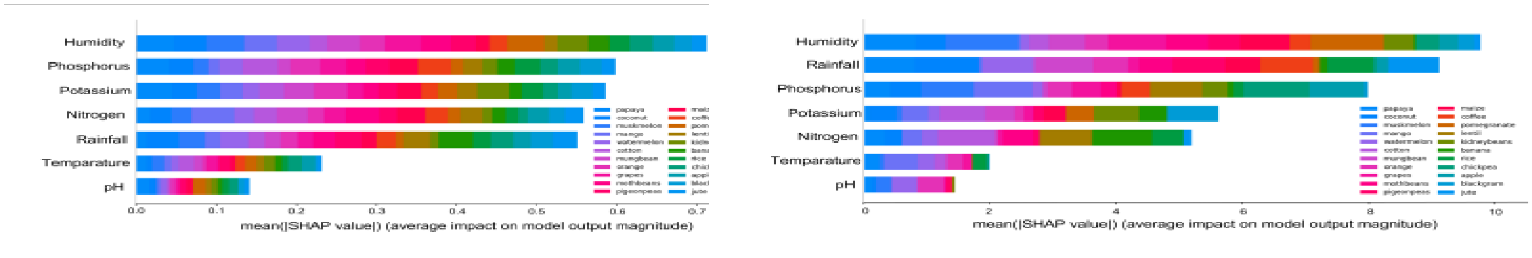


Fig. 5: SHAP global explanations for RF (Left) and LGBM (Right)

SHAP local and LIME explanations

- Feature taking larger area contributes the highest. Features in red have positive contribution and blue have negative.

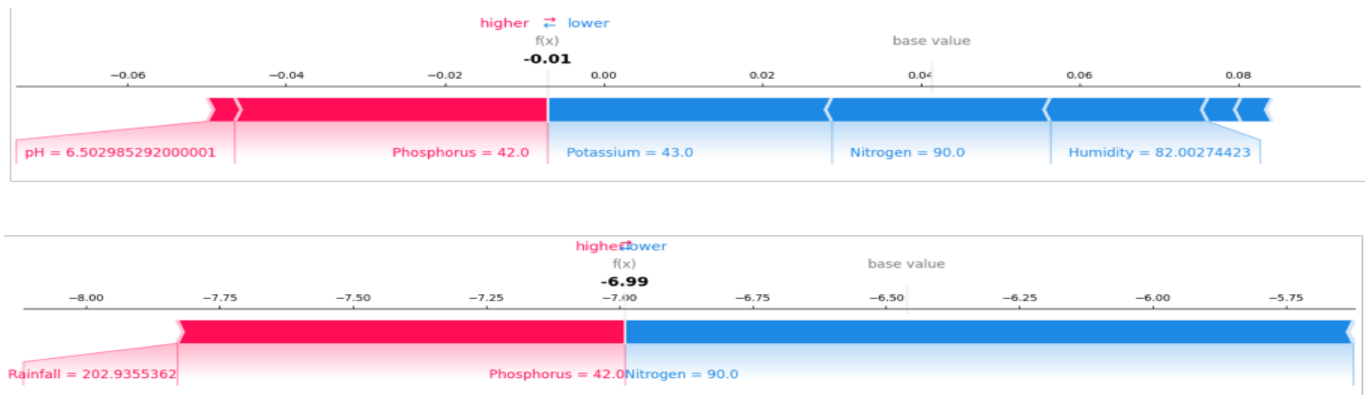


Fig. 6: SHAP local explanations for RF (Top) and LGBM (Bottom)- Randomly selected sample data: Nitrogen = 39, Phosphorus = 77, Potassium = 21, Temperature = 22.997744, Humidity = 60.242188, pH = 4.603563, Rainfall = 159.689346

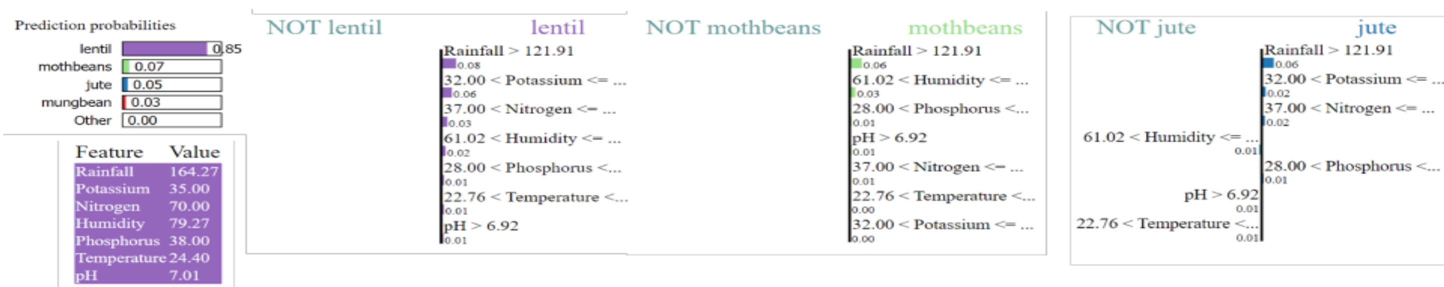


Fig. 7: LIME local explanations for RF (Used sample data: Nitrogen = 70, Phosphorus = 38, Potassium = 35, Temperature = 24.397362, Humidity = 79.268616, pH = 7.014064, Rainfall = 164.269699)

Counterfactuals results

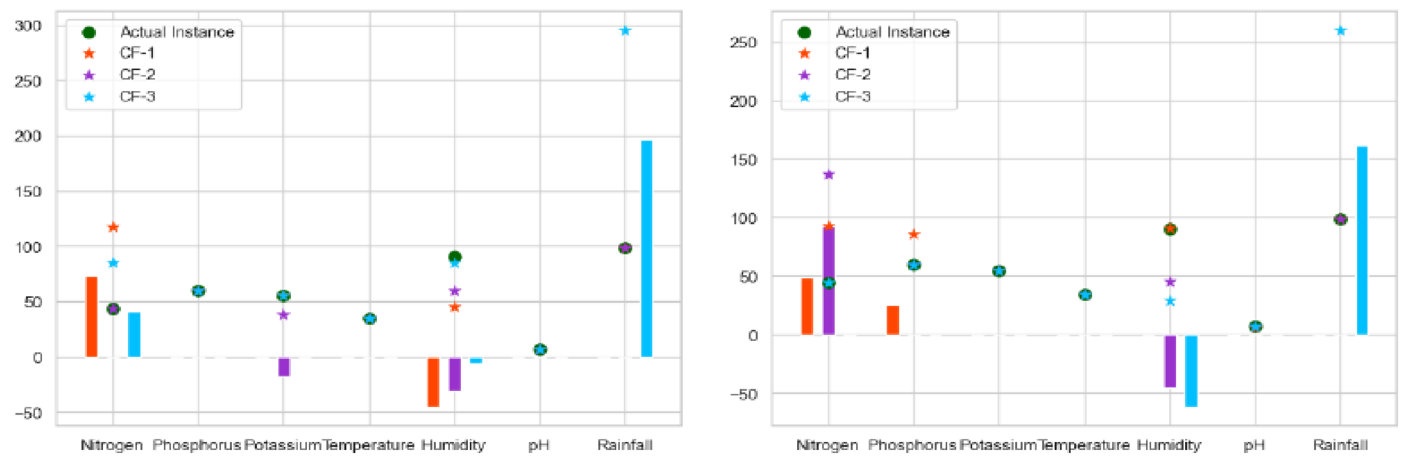
- In counterfactual explainability, each selected data sample is referred to as the "actual instance," and the class for selected data is predicted. In addition to this result, alternative counterfactual suggestions are provided for the output.

TABLE IV: Counterfactuals for RF

Type of Instance	Nitrogen	Phosphorus	Potassium	Temperature	Humidity	pH	Rainfall	Label
Actual Instance	44	60	55	34.28046	90.555618	6.825371	98.540474	Papaya
Counterfactual-1	117	60	55	34.281461	45.50041	6.825371	98.550477	Banana
Counterfactual-2	44	60	38	34.281461	60.18227	6.825371	98.550477	Mango
Counterfactual-3	**85**	60	55	34.281461	**85.29596**	6.825371	**295.154486**	Rice

TABLE V: Counterfactual Explainability for LGBM

Type of Instance	Nitrogen	Phosphorus	Potassium	Temperature	Humidity	pH	Rainfall	Label
Actual Instance	44	60	55	34.28046	90.555618	6.825371	98.540474	Papaya
Counterfactual-1	93	86	55	34.281461	90.655616	5.916632	98.550477	Banana
Counterfactual-2	137	60	55	34.281461	45.35615	6.825371	98.550477	Mango
Counterfactual-3	44	60	55	34.281461	29.08982	6.825371	259.863518	Rice



(a) Counterfactuals for RF (b) Counterfactuals for LGBM

Fig. 9: Counterfactual Explainability of RF and LGBM models

XAI Summary

- Choose the model wisely, there is generally a trade-off between accuracy and interpretability.
- Balance between optimizing the accuracy and ensuring transparency for users.
- If sensor security is not adequately ensured, malicious actors could create privacy and security risks.
- If the recommended crops are not suitable for local climate conditions or soil characteristics, crop failure may occur, leading to a significant decline in farmers’ income

Disease Identification by drones

A comprehensive analysis of YOLO architectures for tomato leaf disease identification (Ramos & Sappa, Scientific Reports, 2025)

- Tomatoes are a major global crop, important for nutrition and rural economies.
- Leaf diseases and nutrient deficiencies cause major yield and quality losses.
- Farmers usually rely on visual inspection, which is slow, error-prone and unreliable at scale.
- UAV drones with cameras and AI vision models can monitor fields quickly and consistently.
- **Aim:** Benchmark recent YOLO models (v8–v12) for tomato leaf disease detection.

Disease Identification by drones

Methods and dataset

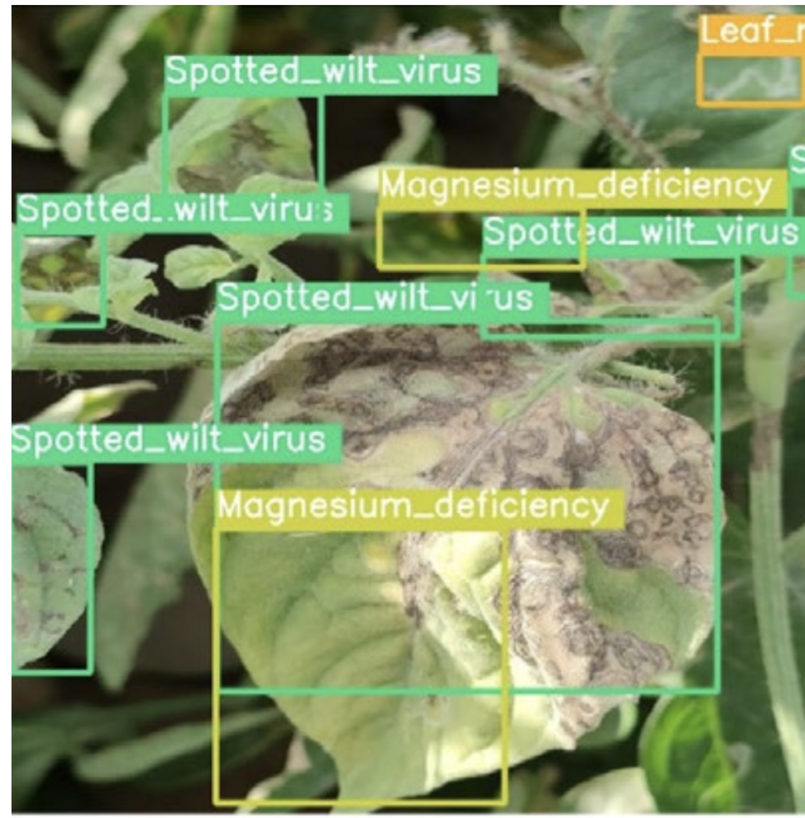
- Dataset: Tomato-Village (14,368 field images, ~161k annotations)
- Six conditions: late blight, leaf miner, magnesium, nitrogen, potassium deficiencies, spotted wilt virus
- Images captured under varied conditions (lighting, time of day, plant ages) in Rajasthan, India
- Augmentations (rotation, cropping, brightness/contrast, flips) used to expand training diversity
- YOLO (You Only Look Once): a fast, single-pass CNN-based object detector that learns to draw boxes around diseased leaf areas and classify the condition
- All YOLO versions (v8–v12) trained identically for fair comparison; evaluated on precision, recall, mAP, training time, and inference speed

Disease Identification by drones

Results & Implications

YOLOv11 = most accurate and balanced (best for deployment)
YOLOv12 = strong alternative, fastest lightweight variant for drones
YOLOv10 = efficient, reliable, good mid-tier choice
YOLOv8 = solid baseline, slightly behind newer versions
YOLOv9 = weakest, slower and less accurate

Overall finding: modern YOLO enables reliable, real-time crop monitoring
Implication: advanced YOLO models enable early disease detection, scalable UAV monitoring, and reduced chemical use

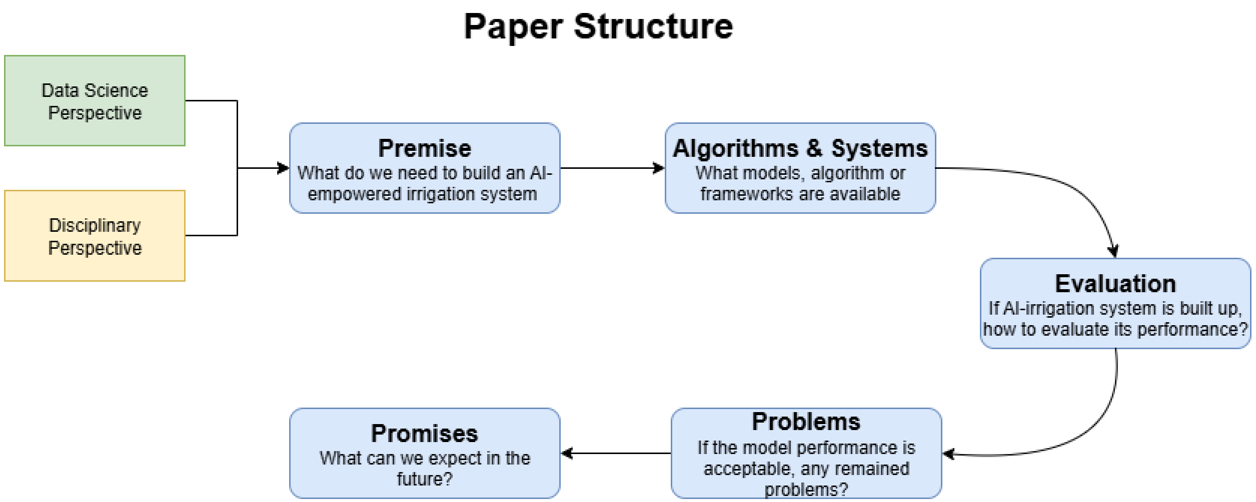


Irrigation with AI

- **Key Point**: Irrigation conditions are **not homogeneous**
  - Rainfall is uneven, groundwater availability varies, crops have different water needs
- **Why it matters**
  - Traditional “one-size-fits-all” irrigation wastes resources
  - Leads to inefficiency and environmental risks
- **AI Potential**
  - Analyse big data (sensors, remote sensing, weather)
  - Predict crop water requirements
  - Support smart scheduling & resource allocation
  - Enable **human-in-the-loop** and **explainable AI**
- **Paper’s Aim**
  - Review premises, evaluation metrics, problems, and promises of AI in irrigation management
  - Highlight both **technical potential** and **social/ethical dimensions**

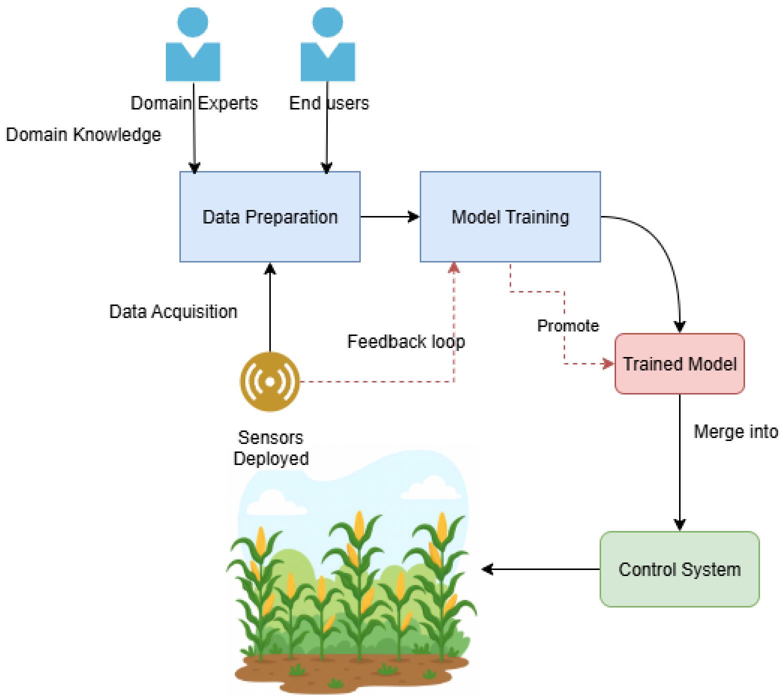
Irrigation with AI

Paper: Wei H, Xu W, Kang B, et al. Irrigation with artificial intelligence: problems, premises, promises



Irrigation with AI

Typical AI-Assisted Irrigation System



Key workflow:

- Data acquisition from sensors / IoT
- Data preparation & feature engineering with domain knowledge & user input
- AI model training, validation & deployment
- Control system executes irrigation decisions
- Feedback loop for continuous improvement

Note:
The original paper did **not** provide a system architecture.
→ This diagram is **my own synthesis** based on related literature.

Irrigation with AI

Premises – Disciplinary & Data Science Perspectives

Disciplinary Perspective

- Farmers: focus on water efficiency, scheduling, cost, training, and data privacy
- Scientists: need advanced analytics, integration, extensibility
- Policymakers: require compliance, scalability, environmental & social benefits

Data Science Perspective

- Data requirements: soil moisture, weather, crop status, remote sensing, IoT
- Methods: ML/DL (prediction & scheduling), expert systems, DSS, hybrid approaches
- Emphasis on pre-processing, integration, and model robustness

Irrigation with AI

Algorithms & Systems for AI Irrigation

What algorithmic options do we have for building AI irrigation systems?
From data-driven models to decision support, multiple approaches exist.

Type	Application
Machine Learning / DL	Prediction, scheduling
Expert Systems	Rule-based decisions
Remote Sensing	Crop & soil monitoring
Hybrid Approaches	Combine methods, improve accuracy
DSS	Scenario support, scheduling
Multi-Agent / Crowd	Feedback, adaptive solutions

Each option has strengths and limitations — no single method is sufficient alone.
The original paper lists methods, but does not unify them into a system framework.

Irrigation with AI

Evaluation of AI Irrigation Systems

Once we build an AI irrigation system, how do we evaluate it?

Type	Application
Reliability	Robustness, stability, error rates
Performance	Accuracy, speed, scalability
Interpretability	Transparency, explainable decisions
Ethics & Morality	Data privacy, fairness, user autonomy
Social Impact	Jobs, equity, sustainability
Cost-Effectiveness	Feasibility, ROI, affordability

Evaluation goes beyond accuracy — it must consider reliability, ethics, and social value.

Irrigation with AI

Problems with AI in Irrigation

Data perspective
- Limited availability and variable quality
- Weak pre-processing and poor integration of diverse sources

User perspective
- Lack of technical skills and training
- High costs, limited access for smallholders
- Trust, privacy, and security concerns

Integration perspective
- Difficulty fitting into existing farm systems
- Resistance to new technologies
- Incomplete modelling of complex environments (e.g. microclimates)

These problems show that AI in irrigation is not just a technical challenge, but also social and systemic

Irrigation with AI

Promises of AI in Irrigation

Better data use
- Fusion of sensors, remote sensing, weather, and IoT
- Improved scheduling, resource allocation, and sustainability

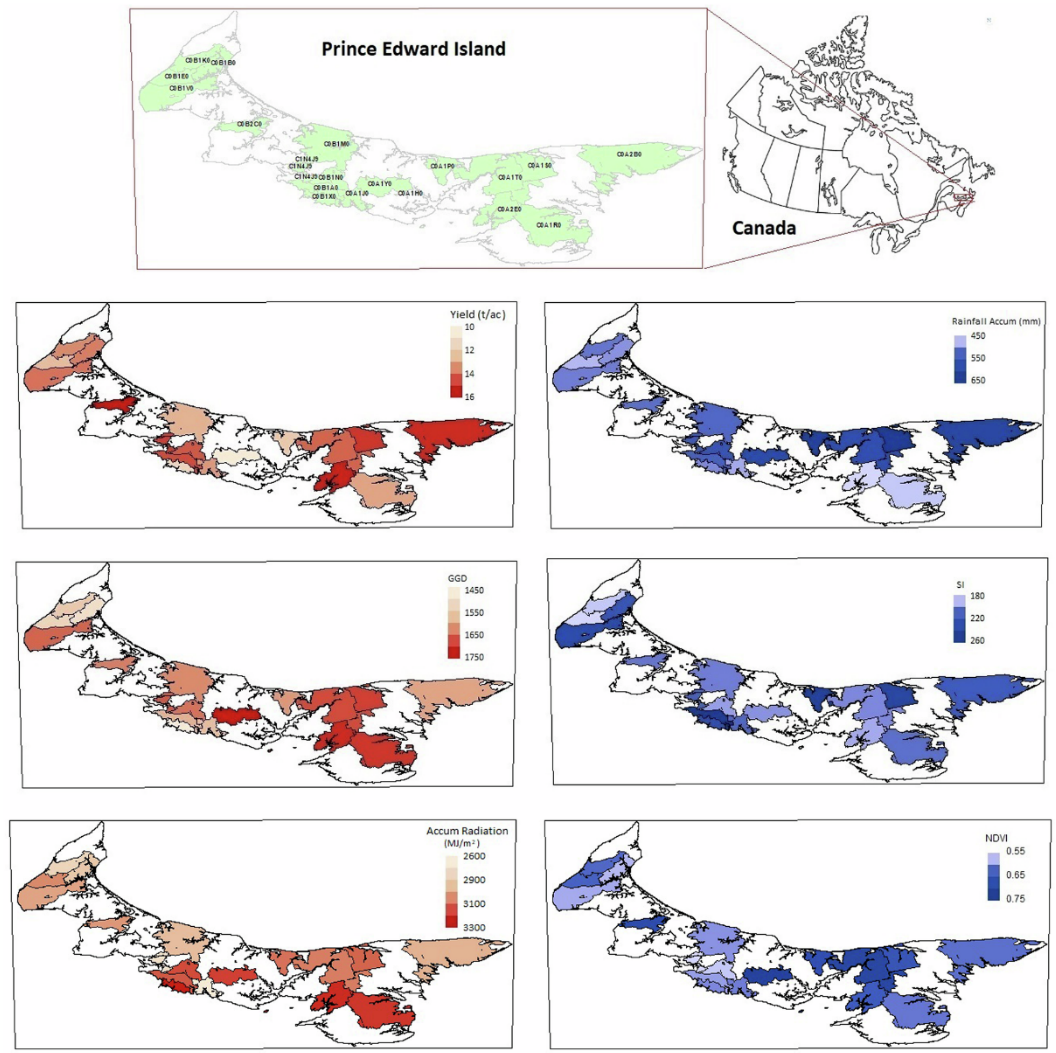
Human-centred AI
- Human-in-the-loop for feedback and trust
- Explainable AI for comprehensible, tailored outputs

Advanced methods
- Transfer learning & domain adaptation to new regions/crops
- Federated learning, differential privacy for secure collaboration

Emerging technologies
- Robotics & embodied intelligence for field operations

The future is not just smarter algorithms, but systems that are human-centred, secure, and sustainable.

Advanced Machine Learning for Regional Potato Yield Prediction



Introduction

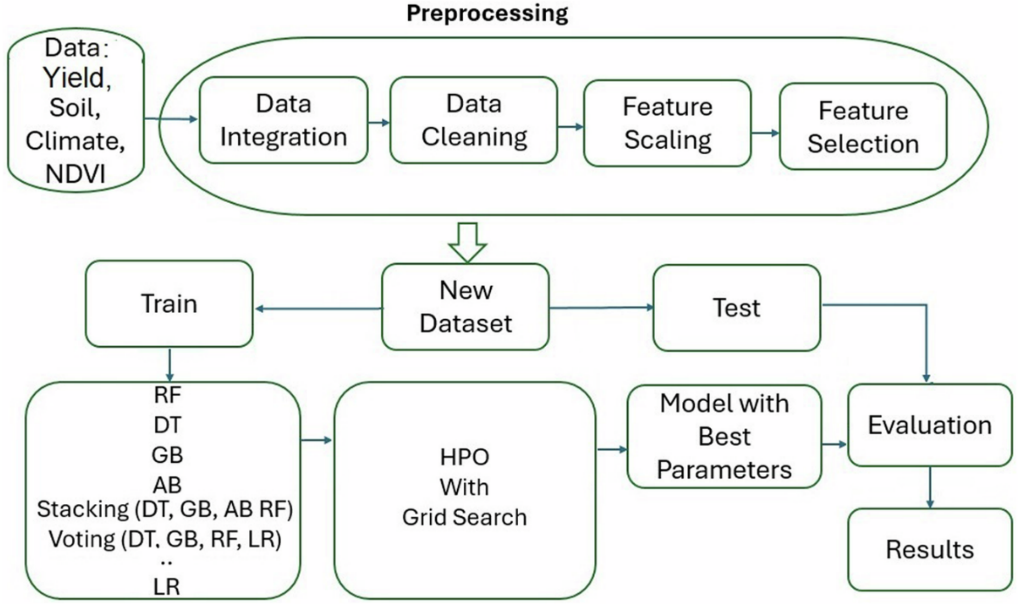
- Potatoes: key crop in Prince Edward Island (PEI), Canada
- Rain-fed farming → high sensitivity to climate variation
- Traditional regression models insufficient
- Research aim: apply ML to predict yield and analyze key drivers

Data and Features

- Time span:1982-2016, postal code-level data
- Variables:
  - Climate: temperature, precipitation, agroclimatic indices
  - Soil: water retention capacity
  - Remote sensing: NDVI(vegetation index)
- Preprocessing: polynomial & power transformations

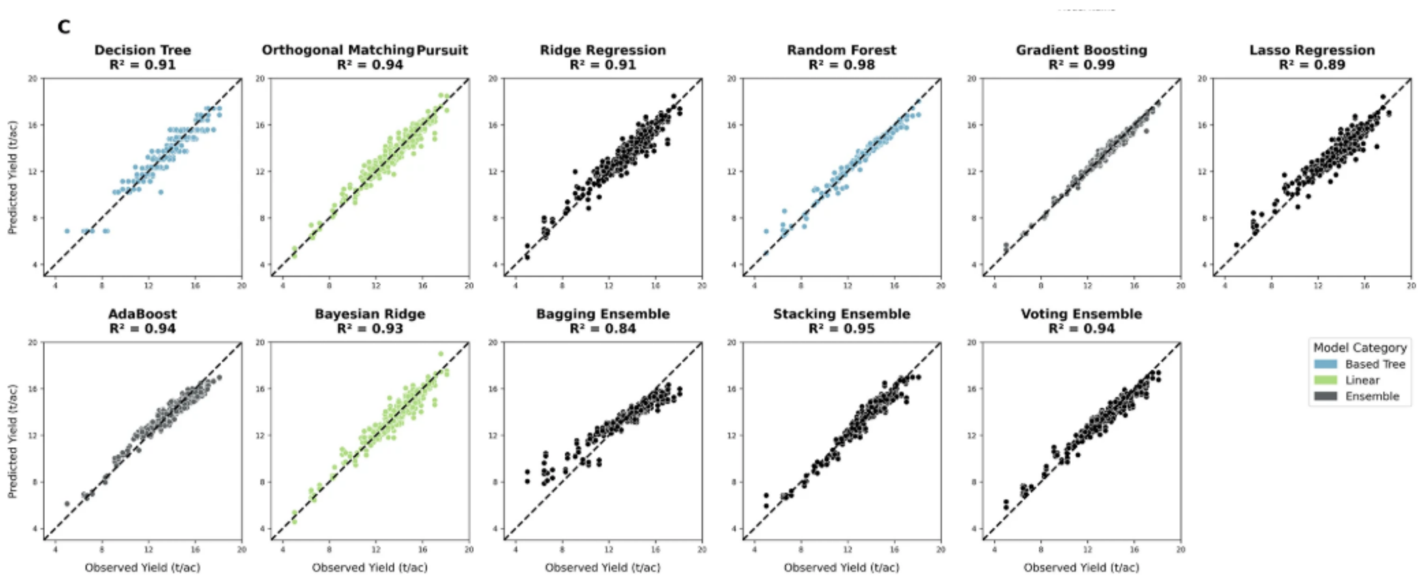
Methodology

- Models tested:
  - Linear(ridge, lasso regression)
  - Decision Tree
  - Ensembles: random forest, gradient boosting, adaboost, stacking
- Validation: time-series cross-validation
- Metrics: MSE, RMSE, R^2



Results

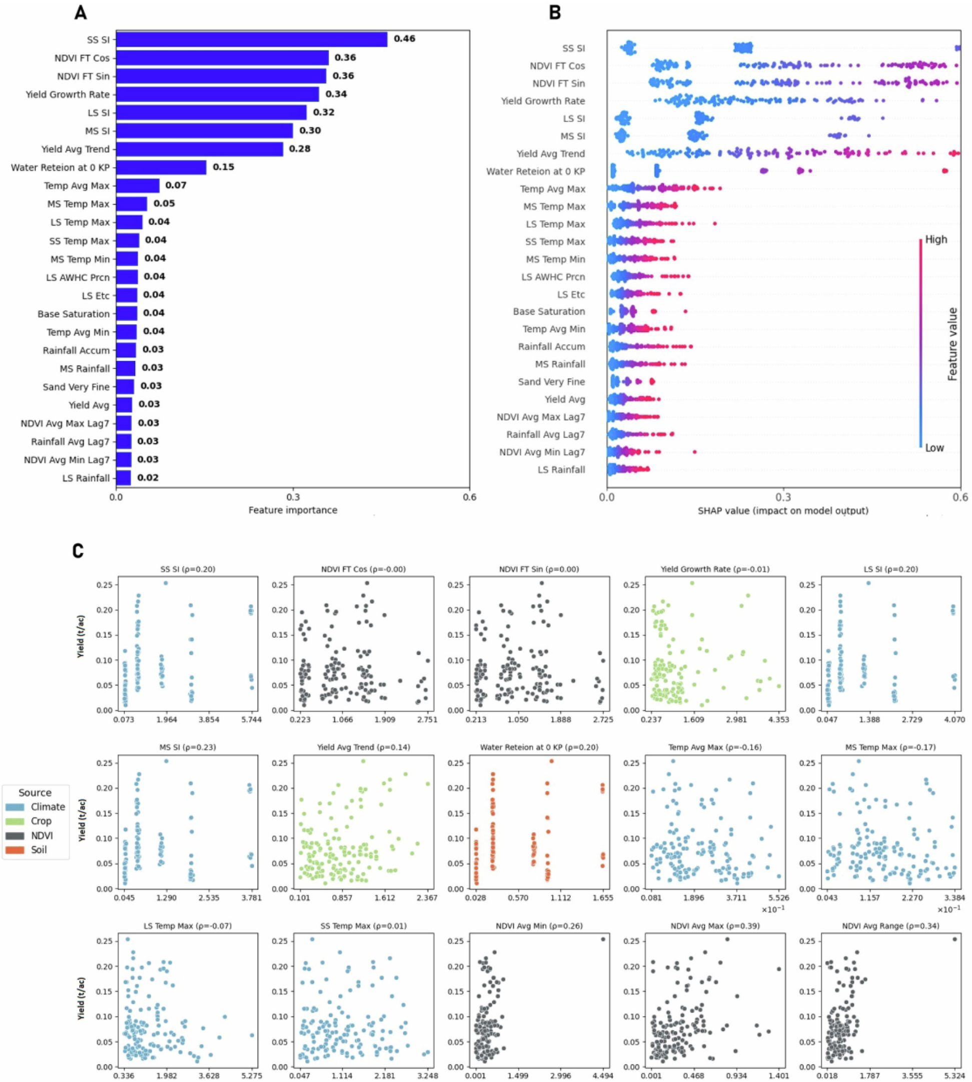
- **Random Forest**: best performance (MSE = 0.014, RMSE ≈ 0.119, $R^2 \approx 0.99$)
- Gradient Boosting also strong
- Linear models → weaker results



Results

- SHAP values used for feature importance
- **Top drivers:** NDVI (vegetation index), Soil salinity
- **Temperature-related features** also significant:
  - Temp Avg Max, Temp Avg Min
  - MS / SS / LS Temp Max/Min

- Precipitation and soil water retention: moderate influence
- Key insight: yield depends on vegetation health + soil + climate factors



Discussion

- Ensemble ML models capture complex crop–environment relations
- Economic value: ~81,600 CAD benefit per farm annually
- Limitations:
  - Sparse-farming areas → less accurate
  - Extreme yield values harder to predict
  - Limited generalization to other regions/crops

Conclusion and Future Work

- ML, especially Random Forest, effective for yield prediction
- Integration of climate, soil, and remote sensing data boosts accuracy
- Future directions:
  - Add Earth observation indices (e.g., Leaf Area Index)
  - Extend to multiple crops/regions
  - Include socio-economic variables

Advancing crop productivity and sustainability

The rapid growth of the global population, expected to reach 10 billion by 2050, presents unprecedented pressure on agriculture to sustainably increase production.

With the added challenges of dwindling water resources, shifting climate patterns, and the loss of agricultural land, there is an urgent need for innovative solutions to boost farm productivity and efficiency. Among the most promising of these solutions is Artificial Intelligence (AI), which has the potential to revolutionize agricultural practices worldwide.

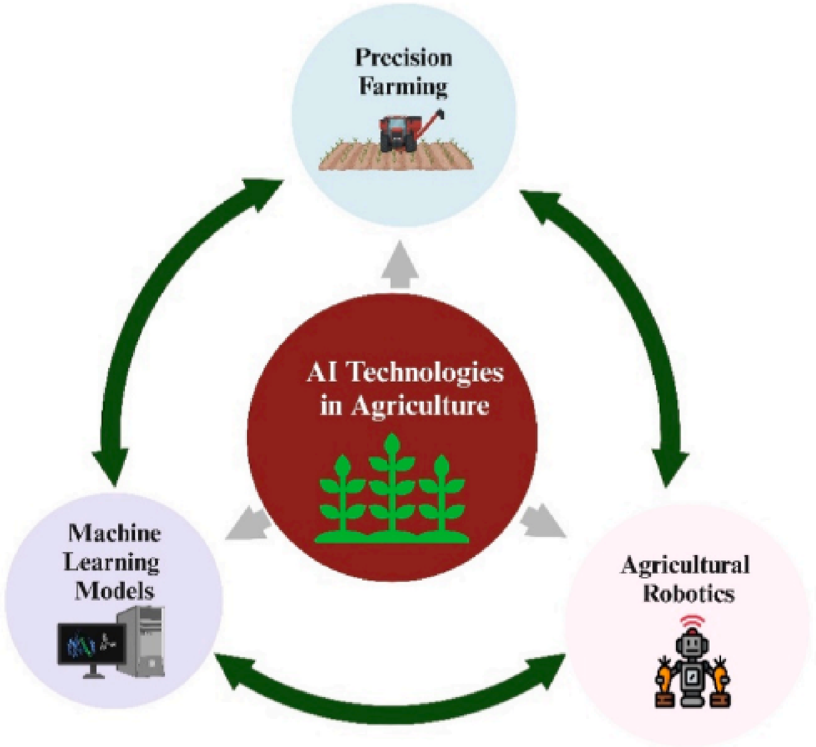
Advancing crop productivity and sustainability

AI in agriculture

AI is changing the face of agriculture from environmental effect forecasts to efficient resource use and crop management.

Here’s three critical AI applications in agriculture for enhancing production and sustainability:

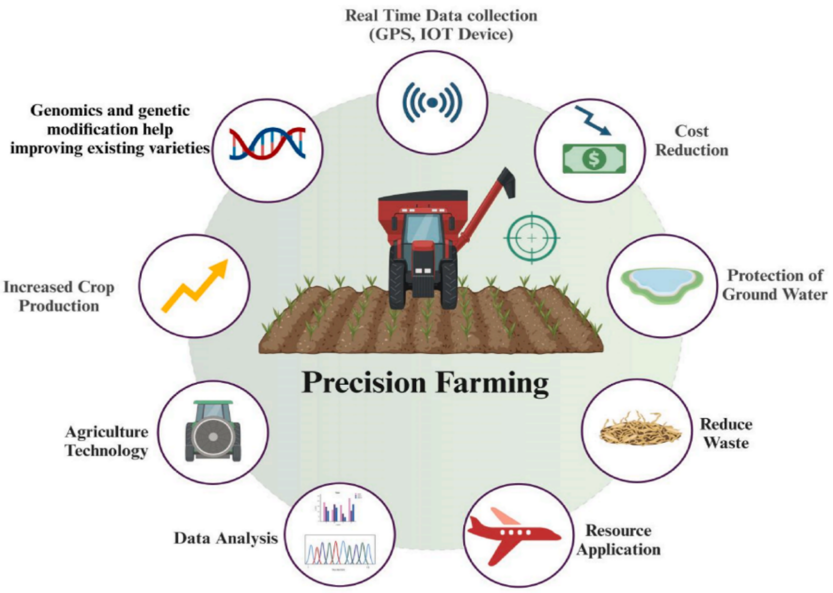
- precision farming
- machine learning
- agricultural robotics



Advancing crop productivity and sustainability

Precision farming

Abundant data have been collected from agricultural environments using GPS and IoT devices for precision farming. This dataset was used to obtain the temperature, crop health, fertilizer availability, and soil moisture levels. AI algorithms assess these data to provide relevant and helpful recommendations to farmers regarding the sowing, irrigation, and harvesting of crops. AI-powered systems can recommend the optimum quantity of water and fertilizer to be treated on each field, reduce waste, and ensure proper crop development.



machine learning

These models can predict agricultural output through the analysis of both historical and contemporary datasets. This analysis helps farmers to enhance their planning strategies and risk profiling associated with unpredictable weather conditions. Moreover, machine learning algorithms can detect trends indicative of illness or vermin, thereby triggering early intervention measures.
(eg.Image recognition software might look for anomalies in photographs of crops taken either from in-field cameras or drones to identify nutritional deficits or diseases.)

agricultural robotics

Besides speeding up agricultural processes, robotics also minimizes human error and increases the overall quality standards of agricultural produce.
For example, robotic harvesters may be programmed to pick ripe fruits only, guaranteeing homogeneous product quality and simultaneously reducing waste.

Advancing crop productivity and sustainability

Enhancing crop productivity with AI

AI is a key factor that influences future agricultural productivity is AI.

This can significantly improve farming efficiency.

In this regard, the mechanisms through which AI results in：

1.genetic improvement

2.efficient use of resources

3.practical applications

help to increase crop yields and further enhance resistance.

Advancing crop productivity and sustainability

1.genetic improvement

Analysis of large databases of genetic information and interactions with the environment will enable AI systems to predict the likeliest changes to succeed in crop production. This will hasten the breeding process and enhance the possibility of viable crops,thereby improving agricultural productivity.

2.efficient use of resources

It is through such a meticulous approach to farming that crop health and yield are maximized at the same time as the minimization of waste and environmental impacts.

3.practical applications

One experiment conducted in California that used AI to manage nitrogen and irrigation applications in growing grapes.
The move resulted in a 25 % increase in production while using 20 % fewer water resources.

Another example in India has been in predicting the best planting times and crops to grow based on market demand and weather patterns, which has significantly improved crop yields and farmers’ incomes.

Such tangible examples demonstrate the power of AI in promoting agriculture and further prove its potential to transform traditional farming methods into more profitable, sustainable, and effective operations.

Advancing crop productivity and sustainability

Barriers to adoption

The implementation of AI-integrated agricultural systems encounters several obstacles, notwithstanding the significant opportunities that AI presents to the farming sector.

To maximize the capacity of AI to enhance crop yields, these challenges can be classified into three main categories:

- **Technological challenges**(Given that AI systems are complex, they require data processing power and reliable access to the Internet, which are not always available in rural areas or places far from cities.)
- **Sociocultural barriers**(Farmers require considerable knowledge and training to acquire the skills necessary to efficiently employ AI.)
- **Regulatory and ethical concerns**(Ethical concerns linked to the use of AI in genetic engineering and breeding might even result in new regulations.)

Advancing crop productivity and sustainability

Future perspectives