AI in crop management

1 Pest management[1]

1.1 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.

1.2 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.

1.3 The Application of AI in Pest Management

1.3.1 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. Only affected trees are treated, enabling precision pest control.
- 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, improving effectiveness while reducing chemical usage.

1.3.2 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.

1.3.3 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.

1.3.4 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

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[1] Rahman, Shaik Moizur, and Gollapelly Ravi. "Role of artificial intelligence in pest management." Current Topics in Agricultural Sciences 7 (2022): 64-81.

captured by drones, the system distinguishes between sprayed and non-sprayed areas, achieving an average accuracy of approximately 70% with extremely fast online recognition. This enables real-time autonomous spraying by drones. In the future, if the recognition accuracy improves to over 90%, the system could support remote operations, facilitate precise pesticide application and reduce chemical usage.

1.4 Key Take-Homes

AI transforms pest management by enabling **precision, efficiency, and sustainability**. Its main applications include:

1. **Pest Identification** – Early detection via vibration sensors or image analysis for targeted treatment.
2. **Pest Population Monitoring** – AI-smart traps provide accurate pest counts and distribution, reducing unnecessary pesticide use.
3. **Pest Infestation Alerts** – Early warning systems notify farmers promptly for timely interventions.
4. **Precision Spraying of Pesticides** – drone systems distinguish sprayed and non-sprayed areas for autonomous, accurate pesticide application.

Overall, AI helps farmers apply the **right treatment, at the right place, at the right time**, improving effectiveness while minimizing environmental impact and chemical usage.

2 Disease Identification by drones[2]

2.1 The Problem

Early, accurate, detection of tomato leaf diseases is essential for managing tomato crops, protecting yields, and targeting problem areas before they develop. The paper asks: among the most recent YOLO object-detectors, which provide the best accuracy/speed trade-off for use in real-world agricultural settings?

2.2 Data

The study used the Tomato-Village object-detection dataset, consisting of 14,368 images and 161,223 annotations, captured across three districts in Rajasthan, India. Images capture tomato leaves under different light and growth stages. Disease symptoms are enclosed in bounding boxes and class label annotations are added. Six disease classes are used: late blight, leaf miner, magnesium deficiency, nitrogen deficiency, potassium deficiency, and spotted wilt virus). A healthy leaf has no bounding box. The dataset contains Pascal VOC (XML) and YOLO (text) formats, standard in object detection. The dataset is split 80/10/10 (train/val/test), with augmentations (rotation, brightness/contrast, cropping, flips) randomly added to a percentage to simulate real-world variation.

[2] Ramos, Leo Thomas, and Angel D. Sappa. "A comprehensive analysis of YOLO architectures for tomato leaf disease identification." Scientific Reports 15.1 (2025): 26890.

2.3 The deployment process

A UAV with camera flies in a grid pattern over tomato fields, capturing canopy images. The trained YOLO model scans each frame in real-time, scanning for areas matching the learned bounding-box patterns, and outputs detection instances with class labels. Not all leaves are visible, so the UAV monitoring provides a statistical map of disease incidence rather than a leaf count. A field-level heat map of the area is then built.

2.4 YOLO overview

YOLO (You Only Look Once) is a convolutional neural network (CNN) that was designed for real-time object detection. The model works by dividing an input image into a grid and, in a single forward pass, predicting bounding box coordinates (where disease exists in the image) and class probabilities. Its architecture consists of a "backbone" CNN for feature extraction, a "neck" (intermediate layers) for multi-scale feature refinement and combination, and a detection "head" that outputs predictions (class, locations of disease). The one-stage design avoids the slower two-step region proposal approach used in two-stage models - allowing for high accuracy at real-time speeds for UAV crop monitoring.

2.5 Models compared

Five YOLO versions were benchmarked, versions 8, 9, 10, 11, and 12. Training was standardised (100 epochs, SGD, lr 0.01, batch 64, input 640×640) and run on four A100 GPUs. Metrics included precision, recall, mAP (mean average precision), and training time.

2.6 Key findings

Among the five architectures, YOLOv11 gave the strongest overall performance, balancing high precision and recall with efficient training and inference levels. YOLOv12 followed closely, providing the fastest lightweight option for resource-constrained use. YOLOv10, with its novel NMS-free design, proved reliable and efficient, while YOLOv8 trailed the newer models. In contrast, YOLOv9 underperformed, with longer training times and lower accuracy.

2.7 Implications

These results imply that YOLO architectures are suitable for real-world agricultural deployment. Their speed and small size allow use on UAVs for field scanning, while accuracy supports reliable disease maps that guide targeted spraying.

2.8 Conclusion

For tomato leaf disease detection, YOLOv11 is the most effective overall, and YOLOv12 excels under limited resources. Their deployment in UAVs and field systems can improve detection, reduce chemical use, and support more sustainable farming.

3 Crop diversification using XAI

Global climate change, population growth and land depletion possess a serious threat in food industry. Crop diversity is adding a new variety of the crops in the existing conditions. This not only mitigates soil degradation, pest infestation but also fosters income growth, more variety and improves soil health.

IoT offers innovative digital solutions in many areas based on low-cost, low-latency approaches such as edge and fog computing that respond to end-user needs on-site. But there is also a growing need for interpretability and explainability for the effective use of these technologies. In this regard, Explainable Artificial Intelligence (XAI) plays a crucial role in agriculture by enhancing the transparency of AI-driven recommendations, such as those for crop selection, soil health, and pest management.

3.1 AgroXAI

Paper proposes and introduces an edge-based computing system, AgroXAI, which collects real time data using IOT and sends it to edge layer for model calculation, fog layer which is an intermediate networking layer between edge layer and cloud layer. Cloud layer can be used for additional compute and storage if needed.

3.2 Dataset

Dataset is available at:https://www.kaggle.com/datasets/chitrakumari25/smart-agricultural-production-optimizing-engine.

And it contains 2200 rows and has data for 22 different crops.

3.3 Features used: Below is the set of features used:

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

3.4 Models used

Models used to determine XAI results:

- KNN, Random Forest, SVM, DT, Light Gradient Boosting Machine (LGBM) and Multi-layer perception (MLP).

3.5 XAI methods

Below XAI methods to determine XAI results:

1) Explain Like I'm 5 (ELI5): provides both global and local explanations.
2) SHapley Additive exPlanations (SHAP): provides both global and local

explanations.
3) Local Interpretable Model-agnostic Explanations (LIME): provides local explanations.
4) Counterfactual: Give alternate crop recommendations, which can be grown by altering current soil, environmental conditions.

3.6 Results

Results of the paper look very promising as they not only provide global and local explanations, but counterfactual as well which provides alternate crop recommendations which can be grown.

- ELI5 and SHAPely provided both local and global explanations whereas LIME provided local explanations.
  a) global explanations: how current set of features (table II above) impact all the crops on the dataset, we have 22 crops in the dataset. Report on the feature level across for all the crops.
  b) Local explanations: Crop wise detail on what features impact the individual crop growth.
- Whereas Counterfactual provided alternative crop options that can be planted by varying the existing conditions like increasing the Nitrogen content or decreasing potassium content, we can also produce mangoes in current conditions.

3.7 Conclusion

XAI makes things easy to interpret and understand, it not only tells what features affect most in the given soil, atmosphere and weather conditions but also recommends which new crops can be grown with slight changes in conditions.

Currently, farmers encounter numerous challenges in adopting AI for crop diversification. Like limited knowledge and skills, infrastructure barriers and environmental constraints. Knowledge with proper guidance, AI can uplift farmers of any country, agriculture still being one of the major economic drivers of any nation can not only make any country self-sustainable but also exporter of the crops.

4 AI in Irrigation Management

4.1 The Problem

Irrigation is very important for improving crop yields and saving water. However, traditional irrigation still has many difficulties, such as low efficiency of water use, high labour cost, lack of real-time data, and increasing expenses. For small farmers especially, it is not easy to adopt advanced systems because of problems like affordability, usability, and data privacy.

4.2 Data and Methods

This review paper introduces different AI methods applied to irrigation. Common techniques include support vector machines, decision trees, artificial neural networks, reinforcement learning, and hybrid approaches. It also covers expert systems, image processing with remote sensing, decision support systems (DSS), and multi-agent systems. The data usually comes from soil moisture, weather and climate records, crop growth, satellite images, and IoT sensors. The paper also discusses how to evaluate these systems, for example accuracy, scalability, interpretability, cost-effectiveness, and social or ethical influence.

4.3 Key Findings

AI can help farmers make better irrigation schedules, predict soil moisture and crop water needs, and reduce both water use and labour cost. For example, remote sensing with ML can create moisture maps, and DSS can provide useful scenarios for farmers to choose. Reinforcement learning can design adaptive strategies in changing environments. Human-centred AI and explainable AI are considered very important to increase farmers' trust and adoption. But the review also points out many problems, such as poor quality of data, high cost for small farms, lack of technical skills, and difficulty of integrating AI systems with existing infrastructure.

4.4 Implications

The paper shows that AI irrigation is not only a technical issue but also a human and social one. Farmers want affordable and easy-to-use systems, policymakers care more about sustainability and regulations, while scientists need systems that can integrate with other research tools. If these requirements are satisfied, AI has the potential to improve food security, save water resources, and reduce negative environmental impacts.

4.5 Conclusion

AI has strong potential to make irrigation management more precise, efficient, and sustainable. But these benefits will only come true if we solve problems about data, cost, usability, and ethics. In the future, human-centred, explainable, and adaptive AI systems will be more useful, because they can support farmers' decisions instead of simply replacing them.

4.6 Limitations of the Paper

Although this review provides a wide overview of AI techniques for irrigation, it still has some limitations. The paper mainly introduces different methods and application cases, but it does not give a clear summary of what a typical AI-assisted irrigation system looks like. For example, there is no explicit framework that shows how sensors, data processing, machine learning models, and decision support should be connected as one complete system. Because of this, readers who want to design or implement a system still need to check many other papers and combine the information by themselves. This makes the review less practical for people who expect a ready-to-use architecture or guidelines.

5 Advanced Machine Learning for Regional Potato Yield Prediction

5.1 Introduction

Potatoes are a staple crop and a key economic driver in Prince Edward Island (PEI), Canada. Since production in this region depends almost entirely on rainfall rather than irrigation, yields are highly sensitive to climatic variation. Traditional regression and process-based models have limited ability to capture nonlinear and multi-factor interactions between weather, soil, and crop development. This study applies machine learning (ML) methods to predict potato yields at the postal-code level and to identify the most influential environmental drivers.

5.2 Data and Preprocessing

The dataset spans 1982–2016 and integrates three main categories of variables: (1) agroclimatic indicators such as temperature and precipitation, (2) soil parameters including water retention capacity, and (3) remote sensing measures, particularly the Normalized Difference Vegetation Index (NDVI). To address noise and skewed distributions, polynomial and power transformations were applied. This preprocessing step ensured that the models could better capture relationships between features and yields.

5.3 Methodology

Multiple ML models were tested, ranging from linear approaches (ridge and lasso regression) to decision trees and ensemble models. Random Forest, Gradient Boosting, AdaBoost, and stacking ensembles were of particular interest. The evaluation used time-series cross-validation: earlier years were used for training while later years tested predictive performance. Metrics included mean squared error (MSE), root mean squared error (RMSE), and the coefficient of determination (R^2).

5.4 Results

Tree-based ensemble methods achieved the highest predictive accuracy. Random Forest performed best, with MSE = 0.014 $(t/ac)^2$, RMSE ≈ 0.119 t/ac, and $R^2 \approx 0.99$. Gradient Boosting also delivered strong results, though slightly weaker. By contrast, linear models showed higher error and lower R^2, reflecting their inability to capture nonlinear crop–environment dynamics. Feature importance analysis, conducted with SHAP values, highlighted temperature variables and NDVI as the dominant predictors, with precipitation and soil water retention also exerting significant influence.

5.5 Discussion

The findings underscore the effectiveness of ensemble ML models in modeling complex agricultural systems. The identification of essential drivers provides not only predictive capacity but also agronomic insight. Importantly, the study estimates that improved prediction could generate annual economic benefits of around 81,600 CAD per farm in PEI by enhancing planning and reducing uncertainty. However, limitations include weaker performance in sparsely farmed areas and potential over- or under-estimation in extreme yield cases. The models' generalizability to other regions remains uncertain and may require retraining.

5.6 Conclusion and Future Work

This research demonstrates that advanced ML, particularly Random Forest, is highly effective for regional yield prediction. Integrating climate, soil, and remote sensing data enables both accurate forecasts and improved understanding of yield drivers. Future directions include incorporating additional Earth observation indices (e.g., Leaf Area Index), extending analysis to multiple crops and climates, and adding socio-economic factors to broaden the models' applicability in sustainable agriculture.

6 Artificial intelligence in agriculture: Advancing crop productivity and sustainability

6.1 Background

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.

6.2 AI in agriculture

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

6.2.1 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.

6.2.2 machine learning

These models can help 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.

6.2.3 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.

6.3 Enhancing crop productivity with AI

AI is a key factor that influences future agricultural productivity is AI. This can significantly improve farming efficiency.

6.3.1 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.

6.3.2 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.

6.4 Barriers to adoption

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

6.4.1 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.

6.4.2 Sociocultural barriers

Farmers require considerable knowledge and training to acquire the skills necessary to efficiently employ AI.

6.4.3 Regulatory and ethical concerns

Ethical concerns linked to the use of AI in genetic engineering and breeding might even result in new regulations.

6.5 Future perspectives

The potential of AI in agriculture is very large; it not only has the capability of changing the face of agriculture, but also increasing crop output. AI-powered solutions are envisioned to further infiltrate with the advancement of technology and its affordability, bringing about radical changes in food production, processing, and delivery.