

Course Title: Artificial intelligence in agriculture: Clarification using artificial intelligence applications in precision agriculture, monitoring crops and predicting yields.

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Summary research paper's:

Paper1: **Data-Driven Artificial Intelligence Applications for Sustainable Precision Agriculture**

The goal is to learn and study AI applications to improve precision agriculture sustainably by comparing different field results in Europe, with the ultimate goal of improving farm management decisions and reducing resource consumption and environmental impacts.

Method:

All data from various European field projects with different climatic conditions and agricultural technologies are collected. The results from these projects are also systematically analyzed to evaluate the performance of AI solutions on the ground to support agricultural decision-making.

Key Results:

Implementing AI leads to increased productivity, better management of water and fertilizer resources, and reduced greenhouse gas emissions.

Some projects are in their early stages, but they have demonstrated significant improvements in improving farmers' decisions.

The researchers propose a broad scope and expanded research to include smart robots for collecting soil and plant samples and managing livestock more intelligently

Paper2: **Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review**

Objective

To monitor and determine the effectiveness of improved technologies in disease detection, seed quality, and plant phenotypes. Therefore, the usefulness of computer vision and artificial intelligence techniques in precision agriculture for cereal crops (such as corn, rice, wheat, soybeans, and barley) is evident.

Method used:

Analyzes the results of studies related to crops (such as SVM, DBN, CNN, and image processing), and the study objectives (such as disease detection and phenotyping).

Key findings:

There has been increased interest in using GPUs and advanced technologies such as Deep Belief Networks to build robust computer vision systems for precision agriculture.

Paper3: **Enabling Precision Agriculture Through Embedded Sensing With Artificial Intelligence**

Objective

To improve the low-power embedded sensor system with artificial intelligence (AI) processing, enabling continuous live monitoring of tomato plant growth over a long period (up to 180 days) without the need for constant farmer intervention.

Method used:

Relies on a long-term memory network (LSTM) RNN technology to perform in-situ prediction and integrates low-power field sensors with an on-board graphics processing unit (GPU). Field trials are underway on tomato crops, with a battery life of 180 days to ensure the system's autonomy.

Key results:

- The system successfully predicted plant growth over a 6-month period without human intervention, using only field sensor data.
- Demonstrated that NLP intelligence within devices can be efficiently implemented at low power, representing an important step toward autonomous intelligent systems in agriculture.

Paper4: **Artificial Intelligence in Precision Agriculture: A Review**

Objective

This paper proposes a strategy that encompasses AI applications, including machine learning and deep learning, in precision agriculture from 2000 to 2023. The aim is to determine how these technologies have impacted improved crop management and reduced agricultural losses.

Methodology

- The methodology analyzes up to 100 research papers using the SALSA (Search, Appraisal, Synthesis, Analysis) method.
- The practical application of AI is classified into six areas: disease management, soil and irrigation, pests, weeds, yield forecasting, and general crop management.

Key Findings

AI contributes to the optimal use of resources (water, pesticides, fertilizers), reducing costs and environmental impacts. Deep neural network technologies (such as CNN, Transformers, and Meta Learning) have improved the accuracy of yield forecasting and provided solutions for disease, irrigation, and soil management.

Paper5: IoT solutions with artificial intelligence technologies for precision agriculture: definitions, applications, challenges, and opportunities

Objective

To review the methodology for Artificial Intelligence (AI/ML)-powered Industrial Internet of Things (IIoT) solutions within precision agriculture, including practical applications, technical challenges, and opportunities for future development.

Methodology

- Reviews and analyzes 203 studies published in journals and conferences (IEEE, Scopus, ACM, ScienceDirect, Google Scholar).
- Classifies the information into key themes: definitions, current applications, obstacles, and future opportunities.

Key Findings

- Actual applications include:
 - Sensor networks for soil, weather, and crop monitoring.
 - Intelligent irrigation and fertilization control based on real data.
 - Agricultural decision support and pattern analysis using AI/ML.
- Key Challenges:
 - Lack of standards for interoperability and integration between systems.
 - High cost and its impact on small farms.
 - Privacy issues, data security, and connectivity disruptions in rural areas.
- Future Opportunities Include:
 - Creating "digital twins" for electronic farm simulation and management.
 - Develop open, interoperable platforms that combine IIoT and AI.

Paper6: A Systematic Literature Review on Crop Yield Prediction with Deep Learning and Remote Sensing

Objective

This paper presents a comprehensive review of deep learning applications in crop production prediction using remote sensing data, focusing on the use of neural networks such as CNN and LSTM, analyzing scientific trends, recurring challenges, and the performance of discovered models.

Methodology

- 456 studies were collected from diverse databases, and 44 key studies were selected for in-depth analysis.
- The study focuses on establishing a classification framework that includes:
 - Crop types compared to studies
 - Algorithms used (e.g., CNN, DNN, CNN-LSTM, R-CNN, Conv-LSTM)
 - Data sources (satellites such as MODIS and Sentinel, drone imagery, climate data)

Key Findings

- CNN is the most widely used algorithm and the most effective in reducing error (RMSE).
- Hybrid models such as CNN-LSTM and others that combine CNN with a Gaussian Process, CNN and DNN, and others, offer better performance than using any model alone.
- Many lessons are overcome by using multimodal fusion, which improves forecast accuracy and reduces RMSE error.

Critical Analysis

After reviewing the research and studies I selected that rely on artificial intelligence in agriculture in general, including the use of technologies such as deep learning, computer vision, and the Internet of Things, with a variety of methodologies ranging from applied studies to systematic reviews, there are some strengths and weaknesses.

Strengths:

1. A shared focus on increasing agricultural production efficiency and reducing resource consumption through artificial intelligence.
2. Relying on a variety of technologies used, such as remote sensing, deep models (CNN, LSTM), and smart IoT systems, reflecting the field's development and its overlap with multiple disciplines.
3. Some research, such as the fourth paper, presents direct field applications of high practical value to farmers.
4. The second and fifth papers expand theoretical understanding and identify future research directions.
5. Relying on reliable and up-to-date scientific sources (IEEE, MDPI, ScienceDirect) enhances the credibility of the results.

Weaknesses

1. There is little focus on model interpretability, a critical component of adopting AI in a realistic agricultural setting.
2. Some research is relatively outdated and does not include modern techniques such as hybrid models or XAI.
3. Field experiments are limited in terms of geographic diversity or crop type, reducing the generalizability of the results.
4. There is a lack of open and documented data necessary for independent model replication and evaluation.
5. Some reviews lack a rigorous quantitative assessment or statistical analysis of the actual performance of the proposed models.

Evaluation of Methodology and Sources

- The methodologies used demonstrate direct field experiments, comprehensive reviews, and rigorous simulation analysis, providing a balance between academic depth and practical application.

- The studies that used systematic reviews (such as Papers 5 and 6) used a large number of papers (over 100 references), enhancing the cumulative value of the results.
- In some cases, the data details and parameters used in the models were insufficient, weakening reproducibility.
- There is a clear gap between research results and actual applications in some studies, which requires further experimentation on a larger scale.

• **Connections**

The similarities in the results between the six studies are:

1. The Success of AI in Precision Agriculture:

All studies agree that AI applications, whether through computer vision, deep learning, or the Internet of Things, improve the efficiency of agricultural operations and support more accurate and sustainable production forecasting and crop monitoring.

2. Improving Agricultural Resource Management:

Studies confirm that AI helps reduce waste in water, fertilizer, and energy by making smart, data-driven agricultural decisions.

3. The Role of Deep Learning:

At least three papers indicated that deep neural networks (such as CNN and LSTM) provide highly accurate predictive performance, especially when combined with remote sensing data (such as Sentinel-2 and MODIS).

4. Emphasizing the Need for Technology Integration:

Most studies call for integrating AI with other technologies such as IoT, environmental data, and drones to obtain more accurate and comprehensive results.

• **Conflicts between the findings:**

1. Applied versus theoretical focus: Some studies, such as Enabling Precision Agriculture, present realistic field applications with practical results, while others, such as Papers 2 and 5, present theoretical literature reviews without direct field evaluation.

2. Variations in the quality of data used: Paper 6, for example, uses high-quality satellite data, while some other studies rely on limited local data sources, which may affect the accuracy of model comparisons.

3. Variations in detection and analysis techniques: While some studies rely on hybrid and deep learning models, others rely on visual analysis or surface models.

4. Variations in generalizability: Studies, such as Paper 3, focus only on cereal crops, limiting the generalizability of the results to other crop types or different agricultural environments.

• **Synthesis Matrix for Literature Review:**

Study	Authors	year	Methodology	Key Findings/Results	Limitations
Data-Driven Artificial Intelligence Applications for Sustainable Precision Agriculture	Linaza et al.	2021	It relies on applied field studies, such as European agricultural projects using AI technologies.	Improving productivity, reducing emissions, and enhancing irrigation efficiency.	Lack of detailed models and algorithms.
Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review	Patrício & Rieder	2018	Research on computer vision and artificial intelligence focuses on cereal crops.	Demonstrating the effectiveness of computer vision in disease detection and quality assessment.	Outdated technologies, limited sample size, lacking state-of-the-art learning methods.
Enabling Precision Agriculture Through Embedded Sensing With Artificial Intelligence	Shadrin et al.	2020	Using a combined sensor and LSTM model to predict tomato plant growth	Accurate results over 180 days, direct agricultural decision support	Limited to a single plant; experiment limited and not generalizable 2024
Artificial Intelligence in Precision Agriculture: A Review	Comprehensive Review	2023	Includes over 100 papers on AI and agriculture.	Comprehensive presentation, illustrating applications in irrigation, soil, diseases, and production.	Review without practical application, some repetition, weak statistical analysis.
IoT solutions with artificial intelligence technologies for precision agriculture: definitions, applications, challenges, and opportunities	Review Paper – ScienceDirect	2024	A review of 203 studies on IoT and AI applications in agriculture	A comprehensive analysis of challenges and opportunities, highlighting future models	Lack of practical case studies; some sections are superficial in their analysis

A Systematic Literature Review on Crop Yield Prediction with Deep Learning and Remote Sensing	MDPI Remote Sensing	2022	Combines deep learning with satellite data	Achieved the highest accuracy in yield prediction for hybrid models (CNN + LSTM)	Lack of interpretability of models, and lack of applications in developing countries
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• References

Literature Review

1. Data-Driven AI Applications in Sustainable Precision Agriculture

(Linazza et al., 2021)

This study explores several European agricultural projects that integrate AI and data-driven technologies.

((<https://www.mdpi.com/2073-4395/11/6/1227>))

2. Computer Vision and AI in Precision Agriculture of Cereal Crops: A Systematic Review

(Patricio and Rieder, 2018)

This systematic review focuses on the use of computer vision and AI in cereal crop monitoring. It emphasizes early disease detection and quality assessment using image-based systems.

((<https://www.sciencedirect.com/science/article/abs/pii/S0168169918305829>))

3. Artificial Intelligence in Precision Agriculture: A Review

(Comprehensive Review, 2023)

A comprehensive review covers over 100 studies on AI applications in agriculture, including machine learning, computer vision, and IoT-based systems.

((https://www.researchgate.net/profile/Mohd-Hairi-Mohd-Zaman/publication/390315661_Artificial_Intelligence_in_Precision_Agriculture_A_Review/links/6805b8b3df0e3f544f4333e7/Artificial-Intelligence-in-Precision-Agriculture-A-Review.pdf))

4. Enabling Precision Agriculture through AI-Integrated Sensing

(Shadrin et al., 2020)

A practical research paper presenting a low-power, integrated AI system for tomato plant growth monitoring using sensor-integrated LSTM models.

((<https://ieeexplore.ieee.org/abstract/document/8867862>))

◆ 5. IoT Solutions Using AI Technologies for Precision Agriculture: Definitions, Applications, Challenges, and Opportunities

(ScienceDirect Review 2024)

This analytical review examines over 200 studies, focusing on the intersection of IoT and AI in smart agriculture. Use cases are categorized into monitoring, automation, and decision support.

((https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Artificial+Intelligence+in+Precision+Agriculture&oq=#d=gs_qabs&t=1752310302884&u=%23p%3DY62UPJrFPE0J))

◆ 6. A Systematic Literature Review on Crop Yield Forecasting Using Deep Learning and Remote Sensing

(MDPI Remote Sensing, 2022)

The study reviews 44 research papers that integrate deep learning models (such as CNNs, RNNs, and hybrid architectures) with satellite data (MODIS and Sentinel-2). The results demonstrate that hybrid models consistently outperform traditional methods in terms of accuracy.

((https://www.mdpi.com/2072-4292/14/9/1990?utm_source=chatgpt.com))