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AI-Based Crop Health and Yield Prediction in Smart Farming: Integrating IoT, Remote Sensing and Farmer Decision-Making

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Abstract
The integration of Artificial Intelligence (AI), Internet of Things (IoT), and remote sensing is transforming crop management from largely reactive practices toward data-driven and predictive decision-making. This paper proposes an integrated framework for crop-health assessment and yield prediction using IoT-generated environmental data, remote-sensing observations, crop-growth information and historical agricultural records. The framework considers soil moisture, temperature, relative humidity, rainfall, soil characteristics, vegetation indices, crop-growth parameters and remotely sensed imagery as potential predictors of crop performance. Machine-learning techniques including Random Forest, Support Vector Machine and Artificial Neural Networks, together with deep-learning approaches such as Convolutional Neural Networks and Long Short-Term Memory networks, can be evaluated according to the nature of the prediction task and available data. Crop-health analysis can incorporate image-based disease identification and stress detection, whereas yield prediction can integrate temporal environmental variables with remote-sensing features. Model performance should be evaluated using appropriate metrics such as accuracy, precision, recall and F1-score for classification and MAE, RMSE and R^2 for continuous yield prediction. Beyond technical accuracy, the paper emphasizes the importance of farmer decision-making, perceived usefulness, ease of use, trust, technology cost and access to digital infrastructure. Existing literature indicates substantial potential for machine learning and remote sensing in crop-yield prediction, but also identifies challenges involving data quality, geographical transferability, ground-truth availability, model interpretability and field validation. The proposed framework therefore combines technological performance with practical farmer-oriented considerations and is particularly relevant to small and medium-scale agricultural systems.

Keywords: Artificial Intelligence, Machine Learning, IoT, Remote Sensing, Crop Yield Prediction, Disease Detection, Smart Farming, Precision Agriculture, Farmer Adoption.

1. Introduction

Agricultural decision-making is increasingly influenced by the availability of digital data. Conventional crop management often relies on farmer experience, periodic field inspection and generalized recommendations. Although experiential knowledge remains important, the

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increasing variability of weather, soil conditions, pest and disease pressure and crop development creates a need for more timely and spatially specific information.

Artificial Intelligence provides analytical capabilities that can transform large agricultural datasets into predictions and classifications. When AI is integrated with IoT sensors and remote sensing, the resulting system can observe field conditions, identify crop-health abnormalities and estimate likely crop performance.

The importance of this integration is reflected in recent research. Systematic reviews identify temperature, soil characteristics, vegetation variables, rainfall and remotely sensed indices among frequently used predictors of crop yield, while Random Forest, Gradient Boosting, Support Vector Machines, CNNs and LSTMs are among commonly applied algorithms.

The proposed research consequently considers smart farming as a connected information system:

IoT Sensors + Remote Sensing → Data Integration → AI/ML Analysis → Crop-Health Assessment → Yield Prediction → Farmer Decision Support

The central premise is that the value of AI does not arise merely from selecting a sophisticated algorithm. Its practical value depends on the quality of input data, appropriate validation, interpretability and the ability of farmers to use the resulting information.

2. Review of Related Literature

2.1 AI in Agriculture

AI refers broadly to computational approaches capable of performing tasks involving learning, prediction, classification, pattern recognition or decision support. Machine learning is particularly relevant because agricultural relationships are frequently nonlinear.

Supervised learning can be used when historical observations have known outcomes. For example, historical crop data containing environmental variables and final yield can be used to develop a yield-prediction model. Similarly, labelled leaf images can be used for disease classification.

Unsupervised learning may be useful when labelled agricultural data are limited. It can help identify clusters or patterns within field observations, although such clusters require agronomic interpretation.

2.2 Machine Learning for Crop-Yield Prediction

Crop yield depends on numerous interacting variables. These can include:

- Temperature
- Rainfall
- Soil characteristics
- Soil moisture
- Relative humidity
- Crop variety
- Sowing date
- Crop-growth stage

- Vegetation indices
- Historical yield
- Irrigation
- Fertiliser application

Recent systematic evidence shows that machine-learning crop-yield studies frequently use temperature, soil type, vegetation measures, NDVI, rainfall and imagery as predictors.

Random Forest is useful because it can capture nonlinear relationships and interactions among predictors. Support Vector Regression can perform well in high-dimensional feature spaces when appropriately configured. Neural networks can model complex nonlinear relationships but generally require careful tuning and sufficient training data.

3. Remote Sensing for Crop Monitoring

Remote sensing provides observations without requiring physical inspection of every portion of a field. Satellite imagery, UAV/drone imagery and other sensing platforms can provide spatial information about crop development.

Important data sources include:

Data source	Examples	Potential application
RGB imagery	Red, green, blue bands	Crop canopy and visible disease symptoms
Multispectral imagery	NIR, red, green, etc.	Vegetation and crop-stress assessment
Thermal imagery	Surface temperature	Water-stress assessment
Satellite imagery	Sentinel-type observations	Large-scale monitoring
UAV imagery	Drone-based high-resolution images	Field-level crop assessment

Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) can provide indicators related to vegetation condition. However, an index should not automatically be interpreted as a direct measurement of a specific physiological variable. NDVI responses can be influenced by crop structure, canopy density, atmospheric conditions and other factors.

4. AI-Based Crop Disease Detection

Disease detection represents a second major application of AI. Conventional disease identification depends substantially on visual inspection and expert knowledge. AI-based computer vision can potentially assist by analysing digital images of leaves, stems or crop canopies.

A typical pipeline is:

Image Acquisition → Image Preprocessing → Segmentation → Feature Extraction → CNN Classification → Disease Prediction

CNNs are particularly suitable because they can automatically learn spatial image features. Depending on the dataset, classification can involve categories such as:

- Healthy crop
- Fungal disease
- Bacterial disease
- Viral disease
- Other stress symptoms

However, laboratory image performance should not automatically be generalized to real field conditions. Lighting, background vegetation, leaf orientation, disease severity and multiple simultaneous stresses can affect prediction. Recent systematic evidence similarly identifies external validation, data variability and transferability as continuing challenges in operational AI-based crop-health monitoring.

5. Nutrient and Crop-Stress Detection

AI can also assist in identifying potential nutrient or environmental stress. Nitrogen deficiency may influence canopy colour and vegetation indices, while water, heat and salinity stress can alter crop growth and spectral responses.

Potential indicators include:

Stress	Potential observations
Nitrogen deficiency	Leaf colour, canopy characteristics, spectral response
Water stress	Soil moisture, canopy temperature, vegetation indices
Heat stress	Air/canopy temperature, crop-growth changes
Salinity stress	Soil electrical properties, vegetation response
Phosphorus/potassium deficiency	Growth and spectral characteristics

A critical consideration is that similar visual or spectral symptoms can arise from different causes. Therefore, AI predictions should ideally combine multiple data sources rather than relying on a single image or vegetation index.

6. Integrated IoT–Remote Sensing–AI Framework

The proposed architecture consists of six major layers.

Layer 1: Data Acquisition

IoT sensors collect:

- Soil moisture
- Soil temperature
- Air temperature
- Relative humidity
- Rainfall
- Soil parameters

Remote-sensing systems provide:

- RGB images
- Multispectral imagery

- Vegetation indices
- Crop-canopy information

Layer 2: Data Communication

Data may be transferred through:

- Wi-Fi
- Cellular networks
- LoRa/LoRaWAN
- Gateway-based communication

Layer 3: Data Storage and Management

Data are organized into a structured agricultural database containing sensor observations, imagery, crop-growth records, management practices and historical yield.

Layer 4: Analytical Layer

The data undergo:

Cleaning → Missing-value treatment → Normalisation → Feature extraction → Feature selection → Model training

Layer 5: AI Prediction

Two principal analytical streams are proposed:

Crop health:

Image → CNN/ML model → Health/disease/stress classification

Yield:

IoT + Remote Sensing + Historical Data → ML/DL model → Yield prediction

Layer 6: Decision Support

The outputs are presented to farmers in understandable forms, such as:

- Expected yield
- Crop-health status
- Disease warning
- Stress warning
- Recommended inspection
- Recommended intervention

7. Proposed Research Methodology

7.1 Research Design

A mixed-method design is appropriate because the study involves both technological evaluation and farmer perceptions.

The quantitative component includes:

- IoT measurements
- Remote-sensing observations
- AI model performance
- Crop yield
- Crop-health indicators

The qualitative component examines:

- Farmer experiences
- Technology awareness
- Trust in AI
- Perceived usefulness
- Adoption barriers
- Training requirements

7.2 Data Preparation

Agricultural datasets should be checked for:

1. Missing observations.
2. Sensor anomalies.
3. Duplicate records.
4. Outliers.
5. Inconsistent units.
6. Temporal mismatches.
7. Incorrect geographical associations.

Data normalization may be required for algorithms sensitive to feature scale.

For image data, preprocessing can include:

- Resizing
- Quality screening
- Background handling
- Image normalization
- Data augmentation where justified

8. AI Model Development

The study may compare several models rather than assuming that one algorithm will always perform best.

Model	Potential application	Main advantage
Linear Regression	Yield prediction	Simple and interpretable
Random Forest	Yield/stress prediction	Handles nonlinear relationships
SVM/SVR	Classification/regression	Effective in suitable high-dimensional datasets
ANN	Yield prediction	Models nonlinear relationships
CNN	Image classification	Learns spatial image features
LSTM	Time-series yield prediction	Captures temporal relationships

The choice of model should be determined empirically through validation.

9. Model Evaluation

Farmer Decision-Making and Technology Adoption

Technological accuracy alone does not guarantee agricultural adoption. Farmers may reject technically effective systems if they are expensive, difficult to operate or poorly aligned with existing practices.

The proposed adoption framework incorporates:

Perceived usefulness + Ease of use + Technology affordability + Digital literacy + Infrastructure + Trust → Adoption intention

Farmer interviews can investigate:

- Awareness of AI and IoT
- Perceived usefulness
- Ease of operation
- Trust in predictions
- Cost concerns
- Training requirements
- Internet availability
- Technical support
- Willingness to adopt

This is particularly relevant because recent research continues to identify data availability, cost, transferability and operational deployment as major barriers to agricultural AI adoption.

Expected Research Contribution

The proposed paper contributes at three interconnected levels.

Technological contribution: integration of IoT, remote sensing and AI into one analytical architecture.

Agricultural contribution: early crop-health assessment and yield forecasting can potentially support better timing of field interventions.

Socio-economic contribution: evaluation of farmer perceptions ensures that technological recommendations are assessed in relation to affordability, usability and adoption.

The approach is particularly relevant because recent literature increasingly emphasizes multimodal data integration, contextual calibration, external validation and interpretable models rather than relying exclusively on highly complex algorithms.

10. Conclusion

AI-based crop-health and yield prediction represents an important component of smart farming because it transforms agricultural observations into predictive information. IoT sensors provide continuous environmental measurements, remote sensing contributes spatially detailed crop observations, and AI provides analytical capabilities for classification and prediction.

Nevertheless, technological sophistication should not be confused with practical effectiveness. Models trained under controlled or highly specific conditions may not necessarily generalize to different crops, regions, seasons or management systems. Ground-truth data, external validation, sensor reliability and model interpretability are therefore essential.

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