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AI-Based Crop Health Monitoring and Early Disease Prediction for Precision Agriculture

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Abstract

Changes in crops' health may be gradual in nature, whereas traditional inspections on fields provide rare opportunities to observe it. The paper describes an approach for continuous monitoring and estimation of the probabilityof diseases using environmental sensors and crop images. The IoT (Internet of Things) sensors provide temperature, humidity, and soil moisture readings, whereas the computer-vision models process visible patterns in the crop/leaf images. Both data sets are analyzed independently, and their combination results into a disease-risk estimation based on all inputs. The approach contains explainability mechanisms in order to ensure that the reason of raising the alarm consists of the key observations that affect the prediction result. Recent literature indicates interest in IoT monitoring, lightweight machine learning (deep learning), multi-modal analytics, and edge computing. Explainable AI is increasingly considered a vital part of any AI system applied to agriculture. Nevertheless, issues of dissimilarity of lab-generated data and field environment, lack of diversity of input data, accuracy of sensors, computation costs, and potential for false alarms have to be taken into account. This paper focuses on development and evaluation of field-oriented research framework, in which prediction quality, time of issuing warning, consumption of resources, and usefulness of generated explanation are all evaluated jointly. The goal of the research is a simple decisionsupport tool which allows detecting crop health problems early, but still leaves the final decision up to the farmer or agricultural expert.

Keywords : Artificial intelligence, crop health monitoring, disease prediction, precision agriculture, Internet ofThings, machine learning, computer vision, explainable AI, edge computing.

INTRODUCTION

Decisions make the success of agriculture. Diseases are often recognized by the time when visible changes in the color of the leaves or in other observable properties occur. At that point in time, the number of infected plants is already quite high. Field inspections by experts are an essential part of the process but cannot provide constant attention under constantlychanging weather conditions. This makes crop-monitoring a promising path for precision agriculture.

Recent literature indicates that artificial intelligence, computer vision, remote sensing, and IoT technologies can enable the switch to such crop-monitoring systems. Environmental IoT sensors can collect the

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temperature, relative humidity and soil moisture readings periodically. Imaging solutions may observe crop images and identify visible signs of the disease.

Machine learning (ML) models may learn the relationship between these observations and crop health conditions. Recently published reviews in 2026 also indicate the growing interest in combining these approaches for early warning [1], [2].

The key idea of this paper is thus not about classification of a diseased leaf alone. It should answer another morepractical question – whether the current crop is getting risky, why does the system think so, and how the farmer should monitor the crop next. Thus, this transforms the original image classification problem into crop-health monitoring and risk prediction problem. Such a system can utilize the previous history of the sensor readings, current crop image and output of the ML model to form an estimate.

Another important aspect of developing a good farm monitoring is deployment considerations. Powerful deeplearning systems need quite much memory and computations. Recent research thus started looking into lightweight models, model distillation, quantization and deploying to farm's edge devices [4], [5]. This is important in the cases when farms do not guarantee Internet availability, stable power supply and sufficient computational capacity.

The work in this paper develops the outlined above research direction in the light of the provided abstract – crophealth monitoring based on IoT data, early-stage disease risk prediction, integration of crop images with environment observations and generation of explainable recommendation. This discussion thus concentrates precisely on the outlined research framework without stating the unimplemented yet experimental results.

PROBLEM STATEMENT AND MOTIVATION

Thus, the main problem is the difficulty of detecting the deterioration of the crop health timely to implementpreventive measures. The manual inspections would take too much time and may miss subtle signs of diseases occurring between the field visits. The image-based system will be able to identify some visible symptoms, but the image itself doesn't tell the full story of the environment factors which contribute to the growth of the disease.

At the same time, while IoT sensor could tell about abnormal humidity or soil moisture content, it couldn't identifythe visible signs of disease. The motivation for their combined use is obvious – the IoT signal could provide context and

the image could show visual proof. If both signals identify increased risks, it can result in an even stronger alert than one of these two signals would produce. On the other hand, if they contradict each other, the inconsistency can become a basis for further investigation instead of automatically applied treatment.

Such approach could be motivated by the problem of creating understandable outputs for the farmers. Theyshouldn't decipher complicated probability vector or the name of the used model. A farmer-oriented alert should describe the main observations behind a warning and provide a reasonable next step.

OBJECTIVES

Objectives of this research include the following.

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1) Crop health monitoring continuously: Measure the temperature, humidity, and moisture of crops and soils through the IoT sensors continuously.

2) Disease risk early prediction: Analyse and process current and past records of crops to estimate if there is any risk associated with developing the diseases.

3) Image based disease detection: Classify crop images using computer vision models and deep learning technology in order to detect the diseases through their patterns orvisible changes.

4) Information integration: Integrate all collected infor mation into an assessment so that the final outcome will not rely on just one type of information.

5) Explanation of the alarm in understandable terms: Construct a mechanism to present the reasons of the alarm in an easy way to understand for farmers.

6) Lightweight model and execution: Make the system to consider execution in case of limited computing and network resources.

PROPOSED SYSTEM ARCHITECTURE

The proposed architecture will implement a simple sensorto-decision process where the field sensors and camera are used to collect the environmental data and the images of the crops respectively. Preprocessing of both datasets will help to filter out noisy elements.

An AI layer will include both models: the environmental risk model and the image model. Both will contribute their output to a fusion layer where the final alarm will be constructed.

Proposed architecture explicitly separates disease risk and confirmation. High disease risk does not have to mean a definite presence of the disease. On the other hand, image classification must not ignore uncertainty if the image is blurry, poorly illuminated or falls outside of the distribution the model knows about.

METHODOLOGY

A. Data Acquisition

The first layer collects environmental factors such as temperature, relative humidity, and soil moisture. Sensor observations can be timestamped and acquired on periodic basis.

Images of crops can be obtained either manually through mobile devices or automatically using a camera module. Eachof the images should have a possibility to be connected, wherever possible, with a timestamp and location of the sensorobservations.

B. Data Preprocessing

The sensor data may contain missing values, sharp spikes, or multiple samples caused by poor communications.The preprocessing step should address issues related to missing values and sensor error detection as well as normalization of numeric attributes. Image preprocessing can involve resizing, normalization, and careful augmentations. One needs to be careful not to generate augmented images which would be impossible in real conditions of the fields.

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C. Disease-Risk Model

The baseline model can be built using traditional machinelearning algorithms such as logistic regression, randomforests, and gradient boosting. This stage will help to understand whether environmental features have some value for predicting diseases. Next, one can use historical observations in short windows and treat them as sequential, thus making them dependent.

A simple model for disease risk can be Re = f (T, H, M, □T, □H, □M), (1)

where T , H, and M are temperature, humidity, and soil moisture, respectively, while □ terms denote the changes of the corresponding quantities. The function f (·) is estimated through labeled data and should provide probabilities or risk categories instead of numeric values without explanation.

D. Image-Based Detection

The image branch can employ a CNN or a compact transfer learning architecture. The recent research proves the power of deep learning for plant disease recognition, but highlights at the same time a lack of realistic conditions in the available datasets [7], [9]. It is important to include the pictures with variable lighting, background, growth conditions andcamera quality in training and test sets.

E. Multimodal Fusion

Both branches can produce their intermediate outputs and can be combined further in a simple late fusion manner: R = □Re + (1 □ □)Ri, (2)

where Re is the environmental disease risk, Ri is the imagebased risk, and □ is a weighting factor. The value of □ must be learned or validated and cannot be simply chosen for convenience.

This approach is valuable since the image-based detection is capable of making the decision about the risk when visible symptoms are present, while environmental signals can provide additional context. Work regarding crop monitoring from recent literature emphasizes the same two areas as major research trends [1].

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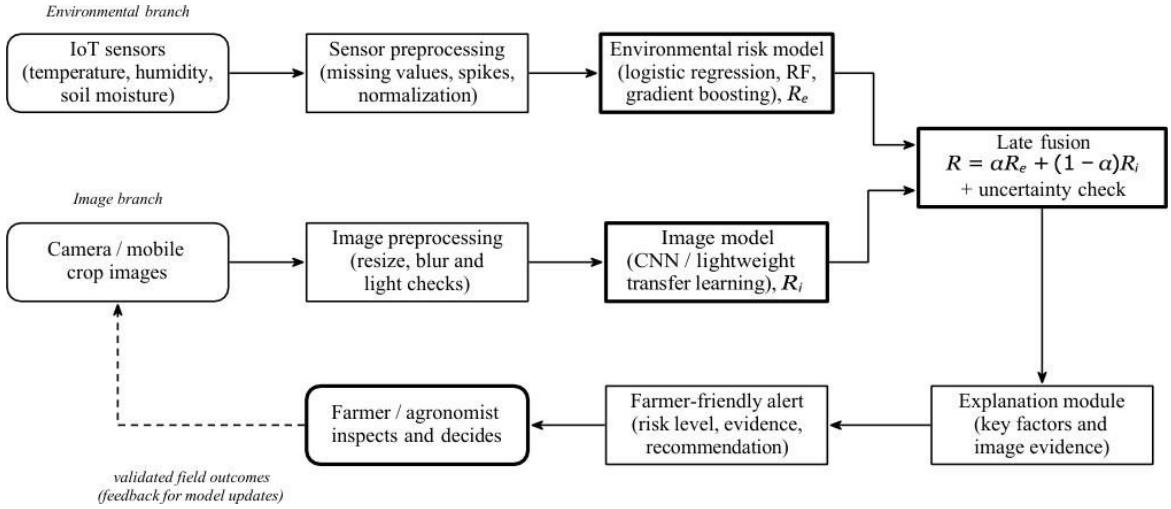


Fig. 1. Conceptual architecture for AI-based crop-health monitoring and early disease-risk prediction. Environmental and image branches are processed independently and combined by a late-fusion layer; an explanation module and a farmer-friendly alert keep the final action withthe human decision maker. The dashed line shows validated field outcomes feeding back into future model updates.

DATA PREPARATION AND AI MODEL DEVELOPMENT

The performance of the AI system largely hinges on the way its training data are pre-processed. In order to use the proposed technique, the sensor measurements need to be tagged by time stamp and the identifier of the plot that isbeing observed in case there is more than one. The images of the crops will be tagged with similar information, as this is needed in order to relate the image to the environmental state when the picture was made. This is essential because disease development is a process.

Before the model training, the sensor readings must be checked for missing values, impossible values, repeat time stamps, and sudden jumps caused by malfunctioning sensors. Short-term missing values must be restored using proper interpolation, whereas long missing data intervals should be left as they are, with no values invented for them. Pre-processing of the images can comprise resizing, normalization, testing for blurring and low illumination. Some of the data augmentation procedures can be used to provide some variations of rotations, scaling and lighting to the vision model.

Confidence or uncertainty should be implemented in the system too. Low-confidence predictions can be selectedfor manual review and not used to make an automated highconfidence recommendation. This will be essential especially for the cases when the crop condition seen on the image or sensor data is novel, or sensor readings are incomplete. The goal is to build an assistance rather than guarantee that each prediction will be sure.

ALERT LOGIC AND FARMER-FRIENDLY OUTPUT

The output should be designed specifically simple. One form of the alert can be the risk level, the primary evidence and recommendations. As an example, medium risk alert can state that humidity stayed at high

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levels, the state of soil moisture changed from its recent range, and there is a suspicious pattern detected by the image model. The recommendation wouldbe for farmers to investigate that area, not making treatment automatically.

This approach makes the division between risk detection and action. The risk is calculated with the help of theartificial intelligence model, and decision on how to act should be made either by farmers or agronomists. That division will be useful since symptoms of diseases can appear due to the different causes, and sometimes the same visual symptom can occur under different field conditions.

The system's warning history can also be used to compare alerts with later field observations, including timely warnings and whether there are recurrent patterns in the environmental data preceding confirmed instances of disease. Thisinformation can be added to the process of improving the future models, under the condition of validation of such updates.

LITERATURE REVIEW

Selected publications cover the recent work which reflects major directions of research that are important for thisproject. There are ten publications from 2026 to 2025 arranged according to a compact format of a conventional literature survey matrix (Table I).

It is obvious that all the reviewed publications reflect the trend towards integrated sensing, explanation, deployment of models on the edge, as well as monitoring the phenomena continuously. The proposed research continues this trend,focused specifically on early risk prediction, multimodality, and conciseness of warnings to farmers.

TABLE I
RECENT LITERATURE ON AI-BASED CROP HEALTH MONITORING AND DISEASE PREDICTION

Work	Method / focus	Main contribution	Limitation / gap
Yan et al., 2026 [1]	Disease prediction and early-warning review	Provides an overview on the approaches to sensing, AI-based prediction, and early warning of crop diseases.	Field-level early warning and robust implementation still remain open.
Elngar et al., 2026 [2]	AI–IoT integration review	Analyses AI–IoT integration methods for detecting plant disease.	More wide testing of the solution over crops and environment is required.
Shawon et al., 2026 [3]	Federated learning and XAI	Investigates privacy-sensitive learning and XAI methods for detecting diseases in order to support precision agriculture.	Generalization, imbalanced and edge efficient problem are not investigated yet.
Pal et al., 2026 [4]	Multimodal deep learning	Integrates remote-sensing, drone and IoT data into crop health diagnostics.	Multi-source data lead to increased computational burden.
Das et al., 2026 [5]	Quantized DL, IoT, and XAI	Integrates light-weight disease detection with soil and visual explanation for edge deployment.	The validation is mainly based on rice diseases.
Shakib et al., 2026 [6]	Smartphone, CNN, and IoT	Suggests a farmers' friendly crop disease detection and electronic reporting system.	Coverage of the crops and diseases is not wide enough.
Chihaoui et al., 2026 [7]	Leaf-image AI and XAI review	Compares modern vision approaches and gives emphasize on explainability and field-imaging problems.	Data-bias and domain-shift can decrease field performance.
Saini et al., 2025 [8]	IoT and optimized deep residual network	Proposes an approach to crop disease monitoring using IoT devices and optimizing deep learning.	Broader validation over crops and fields is needed.
Verma et al., 2025 [9]	IoT-integrated CNN	Applies image analysis in combination with IoT for automated disease detection of rice and potato.	Robustness under non-controlled conditions is very important.
Njoroge et al., 2025 [10]	Edge-optimized DL and IoT	Employs light-weighted deep learning and IoT sensing to monitor crop health.	Hardware limitation and field testing over time influence scalability.

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RESEARCH GAP

Gaps revealed by reviewing relevant literature motivate the proposed framework.

1) Early risk rather than only visible symptoms. Quite often the visual symptoms of a disease are too weak, and image classification-based systems are able to recognize them only if the disease has advanced. 2) Multimodal integration. Crop images and sensor read ings are usually investigated independently. In a joint framework, a potential way to improve on either could emerge; the combination should, however, be validated, as one cannot assume that more data always gives better results. 3) Explainability. A farmer needs to understand the basis for a warning. Explainable AI research has recently shown the possibility of finding the most influential environmental factors; yet, the explanations should still be validated for consistency and applicability, not merely provided as a technical visual [5]. 4) Field deployment. A model trained on clear datasets may behave differently in presence of natural lighting, occlusions, backgrounds diversity, different cameras, and crop growth. Generalization and deployment challenges were repeatedly addressed by 2025–2026 reviews [1], [7]. 5)Resource constraints. One cannot evaluate the per formance of a model that would operate in a farm environment in terms of classification accuracy alone. Inference latency, memory, energy usage, dependence on the network, sensor maintenance, and costs are to be considered too. Therefore, approaches addressing these aspects are relevant to the research problem.

PROPOSED EVALUATION FRAMEWORK

The proposed system can be evaluated at multiple levels. First, the image classifier can be validated with the accuracy measure, precision, recall, F1 score, and a confusion matrix. Just the accuracy may be misleading in case of classes containing substantially fewer samples of the disease.

To assess the early-warning capability, one should measure whether the system gives the alert at a sufficient time in advance before a disease is confirmed. Useful measures include warning lead time, false alarm rate, missed alarm rate, and the probability calibration of the predicted risk. If a model issues the alarm frequently, it might look sensitive, yet will cease being applicable if the farmer starts doubting its accuracy. Additionally, the sensors component should also be evaluated independently with a record of missing readings, connectivity problems, the drift of the values, and anomalies. The full model should be tested for multimodal capabilities of processing an image-only, sensor-only, and image + sensor readings cases.

Deployment should also be evaluated with latency and consumption of resources. Should the edge device be involved, the time for inference per image, model's size, and energy consumption should be estimated across the model variations. Recent works dedicated to knowledge distillation and quantization prove the relevance of the mentioned evaluation measures [4], [5].

In conclusion, explainability needs to consider both the technical and user perspectives. From the technical perspective, explainability could evaluate the stability of the emphasized factors with small variations in the input. On the user-side perspective, a study can investigate the understanding of the alert cause and actionability of the recommendation. Not only making the model explainable but its explanation must have utility.

CHALLENGES AND PRACTICAL CONSIDERATIONS

Some challenges might arise during the development of the proposed system. First, there are data quality issues. Sensors require proper installation and maintenance, and cameras are impacted by the light,

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movement, distance, andbackground noise. Also, a model can learn unwanted artifacts if the training data is too homogeneous.

The second challenge is the diversity of the training data. A disease could look different depending on the cultivar, plant stage, or growing condition. Therefore, training data coming from a certain area cannot be extrapolated onto other farms. Validation with external data points is especially important before such a generalization is made.

Third, there is a problem of false confidence. A system needs to express uncertainty in case the input data is outside the normal range of observations. For example, a picture which is significantly different from the training data set must preferthe "inspection required" response to a very precise recommendation.

The last challenge is the cost. Sensors, cameras, edge computing nodes, connectivity, installation, and maintenance are the components of the overall system cost. A very technically complex system is useless if it costs too much to deploy on the farm or to maintain. The recent literature on precision agriculture keeps pointing out the cost, interoperability, and resource limitations as major obstacles to implementation [2], [3].

EXPERIMENTAL SETUP AND EVALUATION PROTOCOL

A replicable evaluation protocol is a mandatory step before considering deployment of the proposed system. The experiment setup should include paired observations in each modality (environmental and image) to refer to the samecrop state as close as possible. The sensor record should include timestamps and, preferably, plot identifiers. Images should be retained with their capture time and crop or disease label. The records affected by sensor errors or low-quality images have to be annotated but not silently deleted.

Three equally comparable models have to be evaluated in order to compare: sensor-only model, image-only model and the proposed multimodal one. The sensor branch can utilize current readings along with historical window, while theimage branch could be implemented either with CNN or transferlearning-based light-weight model. Multimodal approach requires combination of both learned risk representations. All train, validation and testing should be conducted separately at plant level if possible in order not to have near-duplicate images/measurements present in different subsets.

Image classification evaluation will include accuracy, precision, recall, F1 score and confusion matrix. Besides,since warning as soon as possible is the key goal here, the following metrics should be measured and reported in the study: warning lead time, false alarm frequency, missed alarm frequency and risk estimate calibration.

Comparison between performance of sensor-only, imageonly and multimodal methods will reveal whether or notany benefit was gained due to combination of these two sources of information.

Deployment-oriented evaluation should focus on measuring latency, memory usage, network dependence andsensor reliability. In case of using some edge device for inference the same set of tests should be performed on the edge device itself and not just a desktop PC. Explanation quality evaluation should also take place: technical part could check the stability of highlighted factors while user study of limited number of users will help to find out if domain experts and farmers can interpret the reason behind the warning and the next step they need to take.

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In this paper there are no actual numbers regarding accuracy and performance since their calculation is part of thenext research stage along with the development and collection of real dataset. This is an intentional decision: presenting invented values would give wrong impression about the work done. Instead of this the protocol describes which measurements have to be done prior to reporting some experimental results.

RESEARCH CONTRIBUTION

Main contribution of this study is a field-oriented architecture that connects continuous sensing of the environment, image analysis and disease evidence and creation of farmerfriendly explanation.

The second contribution is the multimodal evaluation strategy. As opposed to assuming that more sensors lead to better performance, this paper tests sensor-only, image-only, and multimodal models under similar conditions and shows whether the contribution can be quantified to justify the extra costs. The third contribution is considering deployment and explanation requirements along with traditional classification criteria. Such metrics as accuracy, precision, recall, and F1 score are essential but not enough for the real-world problem, and thus they are considered as part of the research problem.

Use of new field data, along with methods of validating the process, can aid in preserving the accuracy of the models.

Another method that could be considered is that of federated learning, where the goal would be to improve acommon model without sharing any of the data [3].

This system could be later extended beyond the application in disease prediction to a wider range of applications such as assessment of water stress, nutrition deficiency, and weatherbased stress on the crops. Any such addition must be done cautiously and only after acquiring enough labeled data for them.

CONCLUSION

In this paper, a framework for researching AI crop health monitoring and early disease prediction for precision agriculture has been provided. The proposed approach involves IoT sensing, crop imaging, machine learning, computervision, multimodal fusion, and explainable alerts. The current state-ofthe-art literature from 2025 and 2026 shows fast development of these technologies in such directions as lightweight edge inferring, IoT sensing, explainability, and early warning system. Simultaneously, it is clear from the state-of-the-art literature that good results in laboratory conditions do not necessarily mean field applicability.

The primary research problem being solved by this work is the lack of a way to correlate the early stage environmental risk with visible proof of its presence and then display it in such a manner that the farmer could comprehend it. In that case, the evaluation criteria include not only classification ability but also early warning efficiency, false positive warnings, robustness, delay, resource consumption and explanatory power of the system. Next step in the process of development is choosing proper datasets, setting up baselines, experimenting with the multimodal approach and validation of the system on-field.

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