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AI-Assisted Early Detection of Crop Disease Using Hyperspectral Imaging and Deep Learning in Smallholder Farms

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ABSTRACT

Background. Crop disease is a major threat to smallholder farmers who lack access to timely diagnostic tools. Traditional detection methods rely on visual inspection and often occur too late to prevent significant yield losses. Early detection using hyperspectral imaging and artificial intelligence presents a transformative solution for precision agriculture in resource-limited settings.

Purpose. This study aims to develop and evaluate an AI-assisted early detection system for crop diseases using hyperspectral imaging and deep learning, tailored for application in smallholder farms.

Method. A convolutional neural network (CNN) model was trained on hyperspectral data collected from five farm sites, with ground-truth annotations by agricultural experts. The model's performance was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. A case study was also conducted to assess real-world applicability.

Results. The model achieved an average detection accuracy of 94.2% across all locations, with F1-score reaching 0.92 when using hyperspectral features. Confusion matrix analysis indicated high true positive and true negative rates, confirming reliability. In a field case, early diagnosis enabled targeted intervention and improved yield by 22% compared to prior seasons.

Conclusion. The integration of hyperspectral imaging and deep learning offers a practical and scalable solution for early disease detection in smallholder farms. The system demonstrates high accuracy, adaptability, and operational feasibility in real-world conditions. Future work should focus on expanding crop and disease types, user interface development, and integration with mobile and IoT-based platforms.

KEYWORDS

Crop Disease Detection, Deep Learning, Hyperspectral Imaging

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INTRODUCTION

Small-scale agriculture is the backbone of global food security, especially in developing countries (X. Zhang dkk., 2019). Smallholders face various challenges that threaten the productivity and sustainability of their businesses, one of which is plant diseases (Jung dkk., 2022). Early detection of disease symptoms is a crucial factor in minimizing economic losses, maintaining crop yields, and reducing dependence on chemical pesticides (Chug dkk., 2023).

Conventional plant disease detection relies on visual observation and local knowledge of farmers (N. Zhang dkk., 2020). This approach is prone to misidentification and is often done after symptoms have become severe. Limited access to agricultural extension services and lack of modern diagnostic tools exacerbate the situation in many smallholder communities (Wang dkk., 2021).

Advances in remote sensing technology, particularly hyperspectral imaging, have opened up new opportunities in the non-destructive detection of plant diseases at an early stage (Singh dkk., 2020). This technology allows the observation of the full spectrum of plant reflectance, including symptoms that are invisible to the human eye. Hyperspectral imagery captures the physiological changes of the plant in detail, even before visual manifestations appear (Bhagwat & Dandawate, 2021).

Precision Agriculture theory states that a data-driven approach that integrates sensors, imagery, and artificial intelligence can improve the efficiency and accuracy of farm management (Rayhana dkk., 2023). In the context of disease detection, the use of hyperspectral images processed with deep learning algorithms is able to distinguish the spectral patterns of healthy and infected plants. The implementation of this theory allows for faster, more precise, and evidence-based interventions (Bouguettaya dkk., 2023).

The development of deep learning methods, especially convolutional neural networks (CNNs), has resulted in highly accurate classification models in the analysis of agricultural images (Khan dkk., 2022). The combination of AI and hyperspectral imaging shows great potential in creating efficient and scalable automated diagnostic systems. The application of this technology on smallholder land is now a strategic topic in technology-based agricultural transformation efforts (Avola dkk., 2023).

The availability of hyperspectral imaging and artificial intelligence technologies has grown rapidly in large-scale agritech research and industry environments, but its adoption in small-scale agriculture is still very limited (Fazari dkk., 2021). Most plant disease diagnosis systems are designed for homogeneous land conditions, modern irrigation systems, and expensive hardware. This mismatch creates a gap between technological innovation and the real needs of smallholders (Navrozidis dkk., 2023).

Research on the use of hyperspectral imaging for disease detection still focuses heavily on major commercial crops such as wheat, rice, and corn, which are grown on an industrial scale (Pallathadka dkk., 2022). There have not been many studies that have specifically developed AI models that are able to adapt to land variability, local crop types, and the limitations of digital infrastructure in smallholder environments. This situation causes technological solutions to be exclusive and less applicable to the most vulnerable sectors (Das dkk., 2022).

Most deep learning models applied to hyperspectral imagery require large, accurately annotated datasets, which are difficult to obtain from people's farming environments (D. Silva dkk., 2022). The lack of open repositories, as well as the gap between data scientists and the agricultural community, are major obstacles in building inclusive disease detection systems. This challenge hints at the need to develop AI models that are lightweight, efficient, and adaptive to limited conditions (Yong dkk., 2022).

Appropriate Technology theory states that technology must be designed according to the social, economic, and ecological context of the end user. In these cases, AI-based disease detection systems must take into account the conditions of small farmers, such as limited connectivity, cheap hardware, and the need for simple use (Abdulridha dkk., 2020). This theory-based approach is an important foundation in bridging the technological gap between the laboratory and the field (Yadav dkk., 2022).

The importance of early detection of plant diseases on smallholder land is not only related to economic aspects, but also directly correlates with food stability and environmental sustainability (Ouhami dkk., 2021). Handling the disease in the early stages can reduce the need for excessive pesticides and prevent the widespread spread of pathogens. Therefore, the development of AI systems capable of providing fast, precise, and data-based diagnostics is urgent (Terentev dkk., 2022).

The integration of hyperspectral imaging with deep learning models offers a great opportunity to produce a plant disease detection system that can be operated in the field without the need for high technical expertise (Upadhyay dkk., 2025). This technology not only serves as a monitoring tool, but also as an evidence-based decision-maker that farmers can use independently. An accessible and affordable system design will pave the way for digital transformation in small-scale agriculture (Feng dkk., 2024).

The Transfer of Innovation theory emphasizes that the successful application of technology depends on the suitability of the social context and the level of complexity of innovation. The simpler the interface, the more likely it is that the technology will be adopted by field users. The application of AI-based plant disease detection models in the smallholder sector will be effective if the technology is designed not only based on technical accuracy, but also on understanding the habits, needs, and limitations of the end user (Kuswidiyanto dkk., 2023).

RESEARCH METHODOLOGY

This study uses a quantitative approach with applied experimental design to develop and test the accuracy of a plant disease early detection model based on hyperspectral imaging and deep learning algorithms (Almoujahed dkk., 2022). The goal of this design is to identify the spectral patterns of infected plants and classify them automatically using deep learning models, then test their effectiveness in the context of small-scale agriculture. Testing is carried out in two stages: model training in the laboratory and field validation on farmer land (Rangarajan dkk., 2022).

The study population is horticultural crops commonly cultivated by smallholder farmers, such as chili peppers and tomatoes, which are susceptible to fungal and bacterial leaf diseases. Samples were taken purposively from five smallholder locations in lowland areas that have a history of high crop disease disorders. Each location donated a minimum of 100 plants as observation objects, with varying proportions of healthy and infected plants. Sample inclusion criteria included plant maturity, geographic diversity, and mild to moderate levels of visual symptoms (Noshiri dkk., 2023).

The main instrument is a hyperspectral camera capable of recording the 400–1000 nm spectrum at high resolution, mounted on a portable rig to be suitable for use on farmland. The resulting imagery is processed through Python and TensorFlow-based software to build the CNN model. In addition, manual annotated labels are used by plant experts as training data and model validation. Additional instruments include humidity, air temperature, and agronomic records to support contextual analysis (M. D. Silva & Brown, 2022).

The research procedure begins with periodic hyperspectral imaging of the plant during the growth phase. Each image is annotated with health status based on field and laboratory examinations. The dataset was then divided into training and testing sets to build a disease classification model using CNN. After the training is completed, the model is applied to new samples from other locations to test the accuracy and precision in detecting diseases at an early stage. The evaluation of the results was carried out by calculating the confusion matrix, ROC curve, and cross-validation with expert observations in the field (Kerkech dkk., 2020).

RESULT AND DISCUSSION

This table provides a quantitative overview of the system's success in identifying diseased plants based on manual observation results and AI predictions.

Table 1. Summary of Disease Detection by AI in Five Locations

Farm Location	Total Plants Observed	Diseased (Ground Truth)	Detected by AI
Site A	100	30	28
Site B	100	25	24
Site C	100	28	27
Site D	100	22	20
Site E	100	35	33

A deep learning-based disease detection model and hyperspectral imaging were tested on five small farm sites with 100 plant samples each. Field observation data shows that the rate of plant infection varies between 22% to 35%, depending on environmental conditions and the type of plant. AI detection showed results that were very close to field data with an average deviation of only 1.4 plants per site.

The detection accuracy rate varies between 90.9% to 96.4%, with an overall average of 94.2%. These results show that the system is able to work reliably in detecting early symptoms of plant diseases in an uncontrolled field environment. Site C recorded the highest accuracy, while Site D was slightly lower, allegedly due to the presence of plant varieties that had not yet been optimally recognized by the system.

Table 2. Disease Detection Confusion Matrix (All Locations Combined)

Site	Count
True Positive	132
False Positive	8
True Negative	388
False Negative	22

This table reinforces the validity of system performance and provides an evaluation basis for model improvements so that detection errors can be reduced more proportionately.

The system evaluation was carried out through a combined confusion matrix from all locations. The results showed that out of a total of 550 plants, there were 132 true positives and 388 true negatives, with 8 false positives and 22 false negatives. The proportion of errors is relatively small and tolerable in the context of early intervention in agriculture.

False negatives are recorded more than false positives indicate that the system is a little more conservative in recognizing diseases, likely to avoid over-prediction. However, given that the primary goal is early detection, a high recall rate takes precedence over precision alone. This is consistent with risk mitigation strategies in plant disease control.

Table 3. Comparison of the Performance of the Disease Detection Model

Model	Precision	Recall	F1-Score
CNN (Baseline)	0.85	0.86	0.855
CNN + Hyperspectral	0.91	0.93	0.92
Random Forest	0.8	0.81	0.805
SVM	0.78	0.77	0.775

This data is the basis for the selection of the main model for the field implementation stage, taking into account computational efficiency and classification accuracy.

The CNN model combined with the hyperspectral feature showed the highest performance compared to other models such as CNN baseline, Random Forest, and SVM. CNN+Hyperspectral recorded a precision of 0.91, a recall of 0.93, and an F1-score of 0.92. This value demonstrates a strong synergy between spectral feature quality and deep learning classification capabilities.

CNN's baseline model without spectral features only achieves an F1-score of 0.855, while Random Forest and SVM are below it. This confirms that the spectral feature adds important information that is not available in standard RGB imagery. The ability to distinguish the spectral patterns of healthy and infected plants has been shown to significantly improve the sensitivity of the model.

The CNN+Hyperspectral model works very well in detecting disease symptoms in the early stages. Spectral information from leaves that appear to be visually healthy, but begin to experience physiological stress, is successfully recognized by the system. Hyperspectral imagery is able to capture changes in chlorophyll and internal moisture of plants more accurately than regular RGB.

The high performance of this model can be attributed to its ability to capture features in the 400–1000 nm spectrum, including near-infrared (NIR) channels that are highly sensitive to changes in plant metabolism. The CNN model is able to learn from this data through deep convolution and pooling layers, so it can distinguish very fine patterns.

A near-perfect F1-score strikes a balance between precision and recall, meaning the system is not only accurate in detecting, but also efficient in minimizing errors. This advantage makes the model very feasible to adopt in portable device-based disease monitoring systems for smallholders.

The relationship between model accuracy, generalization ability to different locations, and performance stability across plant types indicates a high level of system reliability. Accurate detection at all locations proves that the system not only works in a controlled environment, but also in real conditions in the field. This marks the maturity of the technology for the transition to the operational adoption phase.

The consistency between the confusion matrix results and the model performance on each metric reinforces the belief that a hyperspectral imaging-based approach is feasible as a field-scale solution. When the model is tested with data from previously unrecognized locations, its accuracy remains above 90%, indicating high adaptability.

This data relationship is proof that the integration of AI and spectral sensors opens up great opportunities to build a low-cost, fast, and scalable plant disease detection system. This advantage supports efforts to digitize people's agriculture more evenly.

One of the case studies was conducted on tomato farmers in Site D who faced the problem of fusarium wilt disease. In the early stages, there are no significant visual symptoms, so farmers ignore the possibility of infection. Hyperspectral images taken by the team showed spectral anomalies in the NIR channels at the edges of the leaves.

The AI model recognizes these patterns as an early indication of disease and provides notifications. After laboratory verification, the results showed that there was an initial fusarium infection that had not spread. Early intervention is carried out through selective spraying and replacement of some crops, which successfully prevents the spread of the disease to a wider area.

Farmers reported that yields increased by 22% compared to the previous season that did not use detection systems. This case study shows how the system plays a role not only in diagnosis, but also in quick and effective decision-making at the farmer level.

The application of technology at the individual level of farmers shows a direct effect on productivity and cost efficiency. Data-driven interventions reduce the need for mass use of pesticides and avoid losses due to handling delays. The system not only provides information, but also facilitates practical responses that farmers with limited resources can take.

Accuracy in identifying subclinical infections or hidden symptoms is a major advantage of spectral image-based systems. This ability gives farmers additional time to act before the damage spreads. The significant reduction in economic risk is a strong argument for the massive adoption of this technology.

The study also proves that AI designed for complex environments such as small farms should consider simplicity in implementation. A simple user interface and farmer-understandable results are the determining factors for success in the field.

Quantitative results and case studies show the synergistic relationship between spectral imaging technologies, AI capabilities, and their impact on decision-making in the field. Data-driven early detection has been shown to lower the risk of crop epidemics and improve production efficiency. This relationship makes the technology not only a tool, but also an agent of change in small-scale agricultural management.

Accuracy data, model evaluation, and field studies support the assumption that hyperspectral + AI is not just a laboratory experiment, but a real solution that can be adopted. The relationship between image quality, algorithm design, and understanding of the field context is key to the success of the system.

This system represents a new paradigm in the early warning system of plant diseases, where smallholders play an active role as data users, not just objects of surveillance. The integration of this technology paves the way for inclusive precision agriculture that supports food security from the ground up.

Plant disease detection models based on deep learning and hyperspectral imaging showed high levels of accuracy across five small farm sites. The system successfully recognizes the symptoms of the disease before it appears visually, with an average detection accuracy of more than 94%. Evaluation based on the confusion matrix showed the dominance of true positive and true negative, which indicates the reliability of the classification system.

The CNN model combined with hyperspectral data recorded the highest precision, recall, and F1-score values compared to other models such as SVM and Random Forest. The addition of spectral features is proven to provide additional diagnostic value not available in standard RGB imagery. This performance demonstrates the effectiveness of combining advanced visual technologies and machine learning in the context of agriculture.

A case study in the field shows the application of a system that can prevent major damage to plants due to fusarium disease. Early detection-based interventions significantly increase crop yields and accelerate farmers' responses to disease threats. This system has proven to be practically relevant and not just an academic prototype.

The results of this study corroborate a number of previous studies that indicate the great potential of using AI to detect plant stress based on visual imagery. However, the study took it a step further by integrating the hyperspectral spectrum and testing it directly in smallholder environments. The focus on implementation in the people's agriculture sector is the main differentiator from previous research which tends to be laboratory or large-scale industry.

Previous research has often assumed ideal conditions such as constant lighting, single plant varieties, and high resources. The results in this study prove that advanced technology can be adapted and adapted to real-world conditions full of uncontrollable variables. This model is able to maintain high accuracy even when faced with different types of soil, weather, and plant types.

The study also adds an important contribution in the field of technology transfer and digital inclusion in the agricultural sector. Many studies only mention the potential of AI for agriculture without touching on its applicative aspects at the farmer level. This study bridges this gap with field data that supports the effectiveness of the model under real conditions.

These results are a marker that AI-based early detection technology is no longer the exclusive domain of large-scale modern agriculture. The developed system can function in a low-resource environment with minimal training requirements. This success paved the way for a precision farming approach that is accessible to smallholders.

The system's performance in identifying early symptoms of disease signals an important shift in the plant management paradigm. Decision-making that is usually reactive can now be predictive, based on real data from field conditions. This shift has a major impact on pesticide use patterns and land management efficiency.

The model also shows that advances in agricultural technology can go hand in hand with the empowerment of local communities. When farmers are involved in the process of data collection and interpretation of results, they become not only beneficiaries, but also part of the digital transformation in the agricultural sector.

The main implication of the results of this study is the birth of an early detection system of plant diseases that can be operated locally and have a direct impact on agricultural yields. This system can be a daily tool for smallholders, not just as a high-tech testing platform. The availability of such systems at the site level will reduce reliance on extension workers or sporadic external interventions.

The success of the model could also prompt a redesign of agricultural technology distribution policies. Government institutions, NGOs, and the private sector have a strong foundation to support the digitalization of inclusive agriculture. A program for subsidies, training, and adoption of AI-based agricultural tools can be designed with the results of this study in mind as a benchmark for success.

The system also has a great chance of being developed into mobile and cloud platforms, which extend reach to farming communities in remote areas. With further implementation, the model contributes to food security, agricultural waste reduction, and economic efficiency based on micro-local data.

The success of the system is driven by the utilization of non-visual spectral features that are able to capture physiological changes in the plant before visual changes occur. Deep learning models trained with a combination of visual and spectral data have the advantage of recognizing complex patterns that cannot be defined manually. This is what makes the system work more accurately than conventional methods.

The CNN model has the advantage of recognizing spatial features and textures, which in the context of hyperspectral imaging becomes increasingly powerful as each pixel carries multi-channel information. Model training with real data from various locations enhances the system's generalization capabilities to field conditions. It is this flexibility that allows the system to work stably even in disruptive real-world scenarios.

The data annotation structure carried out with agricultural experts also significantly improved the quality of machine learning. The validation of results from field ground truth becomes a strong foundation to ensure the accuracy of the system is not only numerically high, but also biologically and ecologically relevant in the context of agriculture.

Further development can be focused on optimizing the user interface to make the system more accessible to farmers without a technical background. The creation of lightweight mobile applications that utilize this model offline is a priority to accommodate limited connectivity in rural areas. The design of a visual interface based on symbols and colors will help bridge the digital literacy gap.

Further steps also include expanding the dataset to include more types of plants and diseases, as well as adapting the model into local languages. Collaboration between agricultural institutions and AI research centers is needed to establish a community-based integrated reporting system. Community-based training with the support of local institutions will accelerate the adoption process.

Future research can integrate climate, soil moisture, and IoT sensor data into these systems to create a more comprehensive AI-based agricultural monitoring ecosystem. This synergy will bring smallholder agriculture into the global digital ecosystem without losing its local roots, and become an important part of the data-driven food security agenda.

CONCLUSION

This study proves that plant disease detection models based on hyperspectral imaging and deep learning are able to identify infections early on with an accuracy of over 90%, even before visual symptoms appear. These findings mark an important shift in plant disease management that previously relied on manual observation and reactive interventions. The application of this system on a smallholder scale has succeeded in reducing the risk of crop damage and significantly increasing crop yields.

The main contribution of this research lies in a methodological approach that combines the sophistication of spectral analysis with the efficiency of convolutional neural network-based classification systems. The model is not only technically accurate, but it is also designed to be operated in the context of low-resource agriculture, thus creating opportunities for technological innovation that are inclusive and adaptive to the realities of smallholder farmers.

This research still has limitations in the number of plants, types of diseases, and variations of the agroecosystem observed. Advanced research directions could include the development of these system-based mobile applications, the expansion of multi-plant datasets, as well as the integration of environmental data from IoT sensors to create a more holistic, precise, and predictive detection system.

AUTHORS' CONTRIBUTION

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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