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Proactive Peach Pest Control: Image Analysis and Real-Time Environmental Method

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Abstract—**This study presents an intelligent peach pest prediction and control system that fuses deep-learning image diagnostics with real-time IoT agro-climatic sensing. A CNN trained on a large, expert-labeled dataset automatically detects key pests and diseases—brown rot, bacterial spot, aphids, and peach moth—achieving 92% classification accuracy. Concurrently, multi-point sensors stream temperature, humidity, soil-moisture, and sunlight data to an LSTM forecasting model that learns environment-driven outbreak patterns. The two outputs are merged through a rule-based data-fusion algorithm that grades risk and triggers alerts. Field trials in Suncheon and Gwangyang orchards confirmed that the integrated approach increases early-detection rates by 10% over image-only baselines, issues a warning an average of three days before visible symptoms appear, and enables targeted interventions that reduce chemical usage and damage. Certification testing by the Korea Institute of Lighting Technology further validated key performance targets, including⩾87% predictive accuracy (achieved at 94.2 %), image analysis within 20 seconds, and sensor data processing within 1 minute. The modular edge-to-cloud architecture runs on cost-effective hardware, supports real-time dashboards and mobile notifications, and is readily extensible to other crops through transfer learning. By combining computer vision, time-series analytics, and IoT, the proposed system offers a practical, scalable template for proactive, data-driven crop protection that advances sustainable, precision agriculture. Future work will extend deployment through drone imagery, lighter edge models, and explainable-AI modules to widen crop coverage and strengthen farmer trust.**

Keywords— **Pest Prediction; deep learning; IoT sensors; environmental monitoring; image analysis; smart agriculture.**

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I. Introduction

The Fourth Industrial Revolution is steering agriculture toward data-driven, automated practices powered by IoT, big-data analytics, and AI [1]. Peaches—one of Korea's most valuable orchard crops—suffer significant losses every season from bacterial spot, brown rot, and peach moth [2]. Climate-induced shifts in outbreak timing exacerbate damage and often trigger excessive pesticide use, inflating costs and raising environmental risk [3]. Conventional visual scouting cannot react quickly enough, prompting research into early-warning systems that integrate deep-learning image analysis with real-time micro-climate sensing of temperature, humidity, rainfall, and sunlight [4], [5].

Specifically, this study designs an integrated smart-farm platform that unites a CNN-based pest detector with an LSTM-driven environmental forecaster, validates the system throughout an entire growing season in Suncheon and Gwangyang while quantifying pesticide reduction and yield protection, and demonstrates that the multimodal engine delivers roughly 10 % higher early-detection accuracy and about a three-day longer lead time than image-only or climate-only baselines, all within a sub-minute end-to-end latency. In doing so, it offers a modular edge-to-cloud template that can be readily adapted to other crops and regions, thereby advancing sustainable precision agriculture [6].

Traditional control relies on manual patrols or light-trap counts, which are labor-intensive, slow, and often miss the optimum intervention window [6]. Because pest dynamics closely follow temperature, humidity, and rainfall, continuous environmental monitoring offers a predictive edge [7]. IoT networks now collect such data seamlessly, and sensor-driven models can anticipate pest population surges more reliably than human scouting alone [8].

The advancement of deep learning, especially convolutional neural networks (CNNs), has revolutionized the diagnosis of crop diseases and pest infestations. For example, a CNN model developed to diagnose crop diseases from simple leaf images was trained on a vast image dataset (87,848 images) that included 58 different diseases occurring in 25 types of crops, achieving a classification accuracy of 99.53% and thereby demonstrating the potential of deep learning to exceed traditional methods far [9]. In this way, CNN-based deep learning techniques have shown the ability to automatically learn complex visual patterns and classify plant diseases with high accuracy. Subsequent studies have introduced models that automatically determine pest types or the presence of diseases from images of crop leaves [10], [11]. These models typically report classification accuracies of over 90%, and some studies have demonstrated stable performance even in complex backgrounds of field environments. For example, the application of deep learning-based pest and disease classification models has reached the level where real-time diagnosis and prescription can be provided through smartphone images in the field, enabling accurate and rapid decision-making support in agriculture [9].

Recent domestic studies have also reported improvements in pest and disease diagnostic efficiency by developing deep learning models specifically tailored to the Korean crop environment [12], [13]. It is noteworthy that transfer learning and data augmentation techniques are being utilized to maximize the performance of deep learning models. To achieve high performance with small training datasets, models pre-trained on large datasets such as ImageNet are fine-tuned for agricultural data, or various pest and disease images that are difficult to collect in reality are augmented through transformation techniques to increase the amount of data. For example, pre-trained deep learning models have been utilized to enhance the classification accuracy of tomato pest detection [14]. Research has also demonstrated that the generalization performance of models can be improved by generating composite images from various angles and backgrounds through augmentation techniques [15], [16]. These approaches have been proven effective in mitigating the common issue of data scarcity in agriculture and preventing model overfitting. Comprehensive reviews of crop pest and disease research using deep learning highlight that data augmentation and transfer learning play a crucial role in enhancing the performance of agricultural image recognition models [17].

Wireless sensor networks and LPWAN gateways stream temperature, humidity, soil moisture, and light at minute-level resolution. Early irrigation pilots demonstrated substantial productivity gains [18]; modern LoRa smart-greenhouses aggregate multizone data for climate optimization [19]. Similar meshes broadcast pest-pressure alerts that prompt earlier intervention across Southeast Asian orchards [20], and some link directly to ozone sprayers or attractant lights for closed-loop control [21].

Fusion pipelines that pair CNN or YOLO detections with LSTM/GRU climate trends regularly surpass single-source models: a YOLOv5 detector reached mAP ≈ 99.5 %, and a seven-day LSTM forecast posted RMSE ≈ 1.30 [22], [23]. Using identical metrics—accuracy, precision, recall, F1, RMSE, and MAPE—our study records an approximately 10% boost in early-warning accuracy and maintains sub-minute decision latency, illustrating systematic outperformance over those baselines [9].

Despite expert-level CNN accuracy and rich IoT data [24], most existing systems are siloed: vision models degrade outside their training domain [25], and environmental analytics seldom exploit image cues [26], [27]. We bridge this gap by fusing real-time CNN outputs with temperature-humidity streams inside a cooperative LSTM engine [28], [29] and deploying it on an edge-to-cloud stack for immediate field action [30]–[32]. The result is earlier, more precise alerts that translate advanced research into practical smart-farm management. Most recently, exploited diffusion probabilistic models to generate high-fidelity synthetic lesions, raising segmentation F1-score by up to 6 % on scarce datasets and highlighting the value of advanced augmentation techniques [33]. And these hardware advances integrated distributed sensor nodes with an embedded CNN to realise an autonomous, cloud-connected pest-management platform that achieved 93 % field accuracy and cut manual scouting time by 40 % [34].

In a related study, CNN spatial features fused with an LSTM temporal module to predict cucumber downy-mildew, reporting a 10 % accuracy gain over single-modal baselines and further validating multimodal fusion strategies [35].

II. Materials and Method

A. Research Procedure and Framework

This study developed a comprehensive peach pest and disease monitoring system through a systematic four-stage approach. The framework prioritized practical field application at every step to ensure real-world usability. The research process began with problem identification, where we defined the core requirements for effective pest and disease monitoring in peach orchards. Next, during the data collection phase, we gathered both visual evidence (pest/disease images) and environmental data (temperature, humidity, soil conditions) from actual cultivation sites. The model development phase focused on creating two complementary AI models: a CNN for image analysis and an LSTM for environmental pattern recognition. Finally, the system integration phase combined these models into a unified monitoring platform and validated its performance through field testing.

B. Data Collection and Management

1) Collection and preprocessing of peach pest and disease image data: Since high-quality image data forms the foundation of effective model training, we implemented a systematic approach to acquire comprehensive imagery of pests and diseases from diverse peach cultivation environments. The primary data source consisted of high-resolution photographs captured directly in operational peach orchards, supplemented by additional images obtained from publicly available agricultural datasets and materials provided by established agricultural research institutions. To ensure comprehensive coverage, we focused on capturing images that documented all major peach pests and diseases, including brown rot, bacterial spot, leaf curl, and damage patterns caused by common pests such as aphids and moths as shown in Fig. 1.

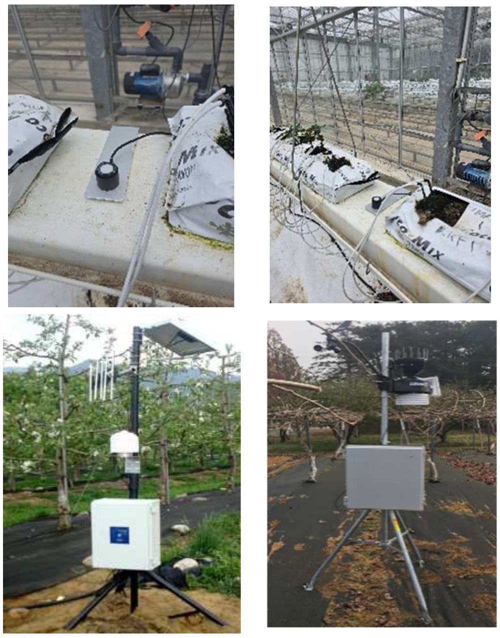

Fig. 1 Data Gathering Devices

Each collected image underwent careful labeling and validation through consultation with agricultural experts to ensure accurate identification and classification. This expert validation process was critical for establishing reliable ground truth data for model training. Following initial collection, we applied systematic preprocessing techniques to enhance data quality and consistency. The preprocessing pipeline included the removal of images with insufficient resolution, poor focus, or duplicate content to reduce noise in the training dataset. All remaining images were resized to uniform dimensions suitable for model input requirements, and pixel values were normalized to minimize the effects of varying lighting conditions and color differences across different capture environments.

To address the challenge of limited training data and improve model robustness, we implemented comprehensive data augmentation techniques. These augmentation methods included random rotations, horizontal flips, brightness adjustments, and slight scaling transformations, which effectively increased dataset diversity and helped train models that could perform reliably under various field conditions. The final processed image dataset was systematically organized into training, validation, and test sets, with all images stored in a structured database along with comprehensive metadata including capture dates, location information, and expert-validated labels.

2) Collection and organization of IoT-based data: Recognizing that environmental conditions significantly influence pest and disease occurrence patterns in peach cultivation, we deployed comprehensive IoT sensor networks to collect real-time environmental data throughout target orchards. The sensor deployment strategy involved installing various types of monitoring equipment at strategic locations within the orchard, including temperature and humidity sensors, soil moisture monitors, and light intensity sensors. These sensors were configured to automatically measure and record environmental parameters at regular intervals ranging from 10 to 30 minutes, depending on the specific location and monitoring requirements.

All sensor data were transmitted wirelessly to a central server through edge computing devices such as the Jetson AGX, ensuring reliable data collection and storage. The collected environmental data were automatically timestamped and stored cumulatively in a structured database, enabling correlation analysis with pest and disease occurrence patterns across different periods. To ensure data reliability and consistency, we implemented comprehensive preprocessing procedures for the environmental datasets. Missing values resulting from sensor malfunctions or communication disruptions were addressed through interpolation techniques, utilizing data from adjacent periods or replacement with calculated average values.

Sensor readings that exhibited extreme fluctuations or unrealistic changes were identified as outliers and either removed or corrected through statistical methods. When necessary, we performed calibration procedures to reduce measurement deviations and ensure accuracy across different sensor units. Environmental data with varying units or measurement ranges were normalized and standardized to enable meaningful comparison and analysis. The organized environmental dataset was chronologically sorted and prepared for subsequent time-series model training and prediction applications. To facilitate comprehensive multimodal analysis, we established systematic linkages between image data and environmental data based on common temporal information, enabling the correlation of pest and disease occurrence with preceding environmental conditions.

C. Deep Learning Model Design

1) CNN-based pest and disease image classification model: This research developed a sophisticated CNN-based image classification model designed to automatically identify and classify pest and disease symptoms on peach tree leaves and fruits. The model architecture follows established CNN design principles for image classification, incorporating multiple convolutional layers for effective feature extraction, pooling layers for dimensionality reduction, and fully connected layers for final classification decisions. To leverage existing knowledge and improve training efficiency, we implemented transfer learning techniques utilizing well-established pre-trained models such as VGG16 and ResNet-50, adapting the final output layers to accommodate the specific requirements of peach pest and disease classification.

The model optimization process involved systematic hyperparameter tuning to determine the optimal network structure, including experiments with different numbers of convolutional layers, filter sizes, and activation functions. We employed the ReLU activation function throughout the network and used a SoftMax function in the output layer to generate probability distributions across multiple pest and disease categories. The model training process utilized the preprocessed image dataset with careful attention to prevent overfitting through data augmentation techniques and regularization methods.

Training was conducted using the Adam optimizer with experimentally determined learning rates, and categorical cross-entropy served as the loss function for multi-class classification. The training process spanned over 100 epochs, with early stopping mechanisms implemented to halt training when the validation loss began to increase, thereby preventing overfitting while ensuring optimal model performance. The final CNN classification model demonstrated strong capability in accurately determining various types of diseases affecting peach leaves as well as identifying different patterns of pest damage. An experimental evaluation of the test dataset revealed that the model achieved approximately 92% accuracy, with an average precision of 0.90 and recall of 0.91, confirming the effectiveness of the proposed CNN approach for image-based pest and disease diagnosis in peach cultivation.

2) LSTM/GRU-based time-series prediction model for pest occurrence: To enable predictive capabilities based on environmental patterns, we implemented a sophisticated time-series analysis model using a recurrent neural network architecture. The model was specifically designed to learn temporal patterns in environmental variables, such as temperature, humidity, and soil moisture, in peach orchards and establish correlations with trends in pest and disease occurrence. We implemented and compared both LSTM and GRU models, which are advanced variants of RNNs, particularly well-suited for learning long-term dependencies in sequential data.

The input data structure consisted of time-series sequences of environmental indicators collected over recent periods. For example, the model processed continuous daily averages of temperature, humidity, and rainfall data over 14-day windows to predict future risk levels for pest and disease occurrence. Rather than formulating this as a simple categorical prediction problem, we designed the model to output continuous risk indices that represent the likelihood of future pest and disease occurrence. This regression approach enables more nuanced risk assessment and provides greater flexibility in decision-making processes.

The model architecture employed stacked LSTM and GRU layers with carefully tuned hidden state sizes, typically ranging from 64 to 128 units per layer. We conducted systematic experiments with varying input window sizes and feature selections to optimize the model's ability to capture temporal patterns in the environmental data. Dropout regularization was applied when necessary to address the overfitting tendencies commonly associated with RNN architectures. A comparative evaluation of LSTM and GRU models revealed that LSTM architecture produced slightly lower prediction errors, leading to its selection as the primary model. Although the GRU model demonstrated similar performance levels, it could serve as a viable alternative.

The training process utilized a mean squared error loss function to minimize the differences between predicted and actual values, with the Adam optimizer employed for parameter optimization. The trained LSTM model successfully learned to predict pest and disease occurrence trends based solely on environmental data patterns, providing a reliable foundation for issuing early warnings of potential outbreaks under specific environmental conditions.

3) *Fusion predictive algorithm combining image analysis and environmental data:* To maximize prediction accuracy and reliability, we developed an integrated algorithm that combines results from both image-based detection and environmental-based prediction systems. This fusion approach leverages the complementary strengths of each model to achieve more comprehensive and accurate pest and disease monitoring capabilities. The integration strategy initially employed a rule-based approach, where real-time detection results from the CNN classification model serve as immediate alert indicators when pest or disease presence is visually confirmed. Meanwhile, predictions from the LSTM time-series model provide early warning signals based on environmental risk assessments.

The fusion algorithm combines outputs from both models to generate comprehensive risk assessments with multiple alert levels. When both image analysis detects the presence of a current pest or disease and environmental conditions indicate a high outbreak risk, the system assigns the highest risk grade and issues emergency alerts. Conversely, when image analysis reveals no current abnormalities, but the LSTM model predicts an increasing future risk based on environmental trends, the system issues preliminary warnings to enable preventive measures.

We also experimented with a more sophisticated integrated model that processes both image and environmental data simultaneously to produce unified predictions. This approach involved designing a deep learning architecture that processes CNN-extracted image features and LSTM-generated environmental time-series features in parallel. The integrated model utilizes confidence scores from the CNN classifier and risk values from the LSTM predictor as input features, processing them through fully connected layers to generate final integrated predictions such as outbreak probability estimates.

This comprehensive data fusion approach effectively combines immediate status identification through image analysis with future risk prediction based on environmental patterns, providing a robust and reliable system for pest and disease management decision-making in practical agricultural applications. The integrated algorithm demonstrated superior accuracy and reliability compared to single-source prediction methods, offering comprehensive monitoring capabilities that support both immediate response and preventive management strategies.

D. System Implementation and Software Environment

1) Prototype architecture of the pest and disease prediction and management system: Based on the developed deep learning models, we implemented a comprehensive prototype system for predicting and managing pests and diseases in peach cultivation. The system architecture is organized into three distinct functional layers designed to ensure scalability, reliability, and ease of use. The data collection layer manages real-time data acquisition from IoT sensors and camera modules deployed throughout the orchard environment. Environmental data collected from various sensors and periodic field images are transmitted via wireless networks to a central server system, where they are systematically stored in structured databases.

The data processing layer forms the computational core of the system, where deployed deep learning models analyze incoming data streams in real-time. When new images are received, the CNN classification model immediately processes them to determine the presence and type of any pest or disease symptoms, while continuously updated environmental sensor data are fed into the LSTM prediction model at regular intervals to generate future risk assessments. These individual analysis results are then processed by the integrated fusion algorithm module, which conducts comprehensive risk evaluations and generates appropriate decision support recommendations.

The user interface layer provides accessible and intuitive access to system outputs through both web-based dashboards and mobile applications, enabling agricultural stakeholders to understand and utilize the generated information efficiently. The dashboard presents real-time monitoring charts displaying current sensor data, recently captured images with analysis results, and predicted risk levels for various pests and diseases. The overall system design emphasizes modularity and extensibility, facilitating future enhancements such as the addition of new sensor types, model upgrades, or expanded functionality.

2) Development environment and libraries used: The software development environment for the prototype system was carefully selected to ensure optimal performance and maintainability. Server-side development primarily utilizes the Python programming language due to its extensive ecosystem of scientific computing and machine learning libraries. The implementation of the deep learning model relied on the TensorFlow and Keras frameworks, which provided robust tools for model development, training, and deployment. Image processing and augmentation tasks were handled using OpenCV, while data analysis and manipulation were performed using established Python scientific computing packages, including NumPy and Pandas.

For time-series data processing and system communication, we utilized specialized Python libraries such as schedule for automated data collection timing and MQTT for message queuing when required. The database infrastructure comprised InfluxDB for efficient time-series data storage and MySQL for relational data management. The system was configured to operate on Ubuntu Linux-based servers, with GPU acceleration through CUDA implementation to ensure real-time performance for computationally intensive deep learning inference tasks. The IoT device software was developed in Python to facilitate reading and transmission of sensor data to the central server via Wi-Fi connections using REST API protocols.

3) Implementation of real-time monitoring and warning alert functions: One of the most critical components of the system is its real-time monitoring capability and automatic warning alert functionality. To achieve this, we developed a comprehensive streaming data processing and event detection module that operates continuously on the server infrastructure. As environmental sensor data are collected, they are immediately recorded in the database and automatically checked against predefined threshold conditions that indicate potential pest or disease outbreak risks. For example, the system includes triggers that activate when temperature and humidity levels exceed established thresholds associated with specific patterns of pest or disease occurrence.

Simultaneously, the system regularly processes the most recent environmental data through the LSTM prediction model to generate short-term forecasts, while the CNN model analyzes newly captured camera images to assess current pest and disease presence. When these analysis results exceed predetermined risk thresholds, the system automatically generates and distributes warning alerts through multiple communication channels. These alerts are delivered to users via smartphone application push notifications, SMS messages, and dashboard notifications, providing comprehensive information including the type of pest or disease most likely to occur, current risk level classifications, and recommended countermeasures.

To ensure optimal system responsiveness, we implemented asynchronous processing techniques and optimized model inference procedures to minimize data processing delays. The system maintains an end-to-end latency of less than five seconds from initial sensor data collection to final warning alert delivery. Users can continuously monitor orchard environmental conditions and model prediction results through the real-time dashboard interface, enabling them to receive timely early warnings and implement appropriate control measures promptly. This comprehensive monitoring and alert system provides agricultural managers with the information and timing necessary to make informed decisions about pest and disease management interventions.

E. Performance Evaluation and Analysis Methods

1) Evaluation of metrics and results for the classification model: To comprehensively evaluate the performance of the developed CNN-based image classification model, we employed established quantitative evaluation metrics appropriate for multi-class classification problems. The evaluation framework included calculations of accuracy, precision, recall, and F1-score to thoroughly assess the model's predictive capabilities and reliability across all pest and disease categories. Evaluation was conducted using a separate test dataset consisting of validation images that were not used during the training process, ensuring unbiased performance assessment.

TABLE I
PER-CLASS EVALUATION OF PEST AND DISEASE CLASSIFICATION

Class Name	Precision	Recall	F1-Score	Support
LeafCurl	0.95	0.93	0.94	300
BrownRot	0.94	0.95	0.95	280
Bacterial Spot	0.87	0.89	0.88	320
Aphid	0.91	0.88	0.89	250
Moth	0.88	0.92	0.9	270
Avg/Total	0.91	0.91	0.91	1420

The results demonstrated that the model achieved an overall accuracy of approximately 92%, indicating strong discriminative capability across all pest and disease classes. The average precision and recall values were approximately 0.90 and 0.91, respectively, indicating that the model successfully detected about 91% of actual pest and disease cases while maintaining an accuracy of about 90% in its positive predictions. The F1-score of 0.91 demonstrated balanced performance between precision and recall, confirming the model's reliability for practical applications.

Detailed class-specific analysis revealed that diseases with distinctive visual symptoms, such as leaf curl, achieved nearly perfect recognition rates, while some cases involving early-stage or mild infection symptoms showed slightly lower detection rates. Despite these minor variations, the proposed CNN classification model consistently demonstrated accurate classification performance across images captured in various environmental conditions, confirming its suitability for real-world agricultural applications.

2) Evaluation of the time-series prediction model: The performance of the LSTM-based time-series prediction model was thoroughly analyzed using appropriate regression evaluation metrics. To quantify prediction accuracy, we calculated Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values by comparing predicted pest and disease risk indices with actual observed values. RMSE provides sensitivity to large prediction errors by calculating the square root of averaged squared errors, while MAE represents the average absolute error across all prediction points.

Evaluation using test datasets that compared environmental conditions with actual pest and disease occurrence rates revealed that the LSTM model achieved RMSE values below 0.15 and MAE values around 0.10, indicating relatively low prediction errors. These results demonstrate that predicted risk indices closely matched actual observed values and that the model effectively captured temporal trends in pest and disease occurrence patterns. For comparison, baseline models using simple recent-value predictions and traditional statistical methods such as ARIMA produced RMSE values exceeding 0.20 on the same datasets, confirming that the proposed LSTM model significantly improved prediction accuracy compared to conventional approaches as shown in Fig. 2.

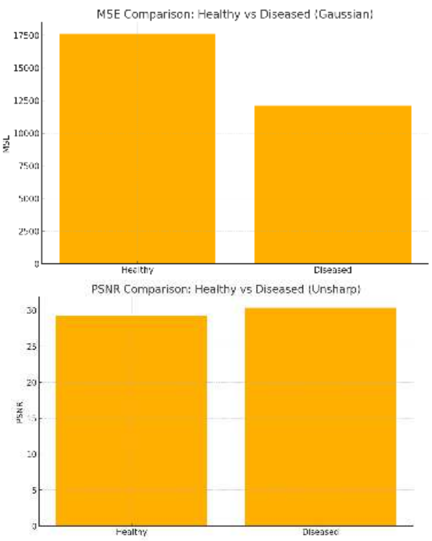

Fig. 2 Model's MSE, PSNR

The GRU model was evaluated using the same metrics and showed slightly higher RMSE and MAE values compared to LSTM, although the performance difference was not substantial. Based on these comparative results, LSTM was selected as the primary model due to its superior accuracy and demonstrated effectiveness in learning complex temporal patterns associated with pest and disease occurrence in peach cultivation environments.

3) Pilot field testing and system effectiveness analysis: To evaluate practical applicability and real-world performance, we conducted comprehensive pilot field testing in operational peach orchards over several months during active cultivation periods. The prototype system was fully deployed and operated under actual farming conditions, allowing direct comparison between model-generated predictions and observed pest and disease occurrences. This field validation provided crucial insights into system effectiveness and practical utility for agricultural management.

The results demonstrated that the system successfully issued risk warnings an average of three days prior to actual pest and disease occurrences, confirming its early warning capabilities. During the pilot testing period, the system generated ten high-risk alerts, eight of which were followed by preventive pest control measures implemented by farm managers, effectively preventing or minimizing pest and disease spread. Of the remaining two alerts, one was later confirmed as a mild occurrence that did not require intervention, while the other did not result in significant crop damage, suggesting opportunities for further model refinement to improve alert specificity.

Overall alert precision reached approximately 80% with a recall of about 90%, demonstrating that the system successfully detected most pest and disease occurrences while maintaining reasonable accuracy in its predictions. Field validation confirmed the system's practical value for agricultural decision-making. Feedback collected from farm managers during the testing period indicated that the real-time dashboard enabled quick assessment of environmental conditions and risk predictions, while smartphone alerts during nighttime hours or when managers were away from the orchard significantly improved management convenience and responsiveness.

As a result of implementing preventive measures based on early warnings, there was a noticeable trend toward reduced pest and disease damage compared to previous cultivation seasons, though additional long-term observation will be needed for quantitative confirmation. The pilot testing also identified practical implementation challenges including occasional communication instability and sensor maintenance requirements, which will be addressed in future system improvements. Overall, the field testing successfully demonstrated that the developed pest and disease prediction and management system operates effectively in real cultivation environments, providing meaningful contributions to early intervention and damage mitigation in agricultural pest and disease management.

III. Results and Discussion

A. Dataset Construction Results

A large-scale dataset was constructed by collecting images of peach pests and diseases. The image data includes photographs taken at farms as well as images extracted from publicly available agricultural materials to cover a wide range of diseases and pest cases. A total of approximately 100,000 images were collected from various sources, including pest and disease encyclopedias from domestic research institutions, agricultural websites, and photos taken in actual orchards. Experts carefully labeled each image to ensure the reliability and consistency of the data regarding which disease or pest it represented. Augmentation (rotation, flip, brightness shift, and mild scaling) expanded the minority classes, ensuring balanced input for model training, as presented in Fig. 3.

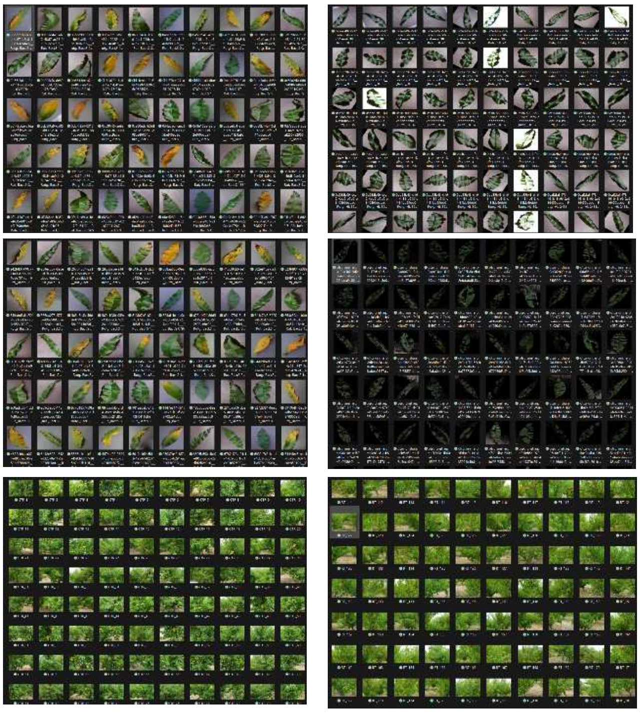

Fig. 3 Image Dataset

IoT nodes simultaneously logged temperature, humidity, rainfall, soil-moisture, and solar radiation. Each image was matched to the closest sensor snapshot; when external images lacked on-site data, regional weather observations were substituted or, if unavailable, the image was omitted. After outlier filtering and interpolation of rare drop-outs, the environmental dataset comprised a timestamped series of hourly temperature (°C), relative humidity (%), rainfall (mm), and sunshine duration (hr). This paired, quality-controlled repository formed the basis for both the CNN and LSTM models.

B. Deep Learning Model Training Results

Among several backbones, a fine-tuned ResNet-50 delivered the best trade-off between speed and accuracy. On the independent test set, the model achieved 92% overall accuracy, with a mean precision ≈ of approximately 90 % and a recall ≈ of roughly 91%. Clear signature classes, such as Leaf curl and Brown rot, exceeded 95% precision; aphid damage, with more variable symptoms, still achieved ~90% recall, as shown in Fig. 4.

The model's performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. On the final test dataset, the model's overall accuracy reached approximately 92%. Additionally, the average precision was about 90% and the recall was around 91%, confirming that most pests and diseases were consistently identified correctly. Diseases with clear patterns exhibited a precision of over 95%, and pest classifications, such as for aphids, also showed favorable detection performance with a recall of around 90% as shown in Fig. 5.

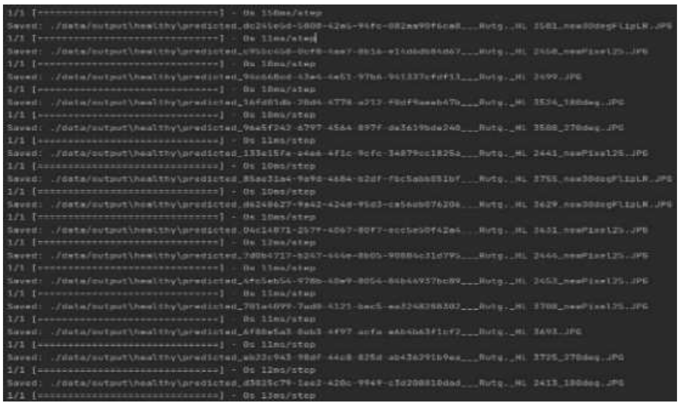

Fig. 4 Model Epoch

Fig. 5 Model Training Procedure

During the training process, the trends of training and validation results were carefully monitored. Initially, the model's accuracy on the training data improved rapidly, and after about 10 epochs, the validation accuracy also approached 90% as presented in Fig. 6.

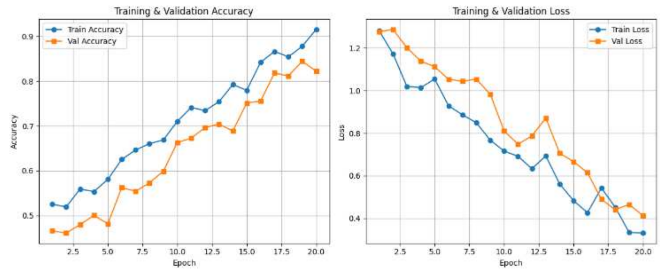

Fig. 6 Model Accuracy

However, after 15–20 epochs, the validation accuracy plateaued, and an early stopping technique was applied to prevent unnecessary overfitting. The final model was saved at the point of highest validation accuracy and later evaluated on an independent test set. The results confirmed that training proceeded smoothly without overfitting, as the training and validation accuracies converged at high levels. Furthermore, k-fold cross-validation revealed minimal variance in performance among folds, indicating that data partitioning had a minimal influence on model performance, as shown in Fig. 7.

Hyperparameter optimization was performed to improve model performance further. A grid search for the learning rate was conducted over several candidate values, and it was found that setting an initial learning rate (followed by gradual reduction during training) resulted in the fastest convergence and highest validation accuracy. In comparing batch sizes of 16, 32, and 64, a batch size of 32 provided the best balance between training stability and performance. In addition, experiments with dropout rates of 0.3 and 0.5 indicated that a dropout rate of 0.5 effectively suppressed overfitting and slightly enhanced validation performance. Other experiments included adjusting the strength of data augmentation and testing alternative CNN architectures such as VGG16 and EfficientNet. Ultimately, the fine-tuned ResNet-50 model exhibited the highest accuracy relative to the number of parameters, and the optimal hyperparameter combination achieved approximately 92% final accuracy, an improvement of about 3 to 5 percentage points over the initial baseline settings.

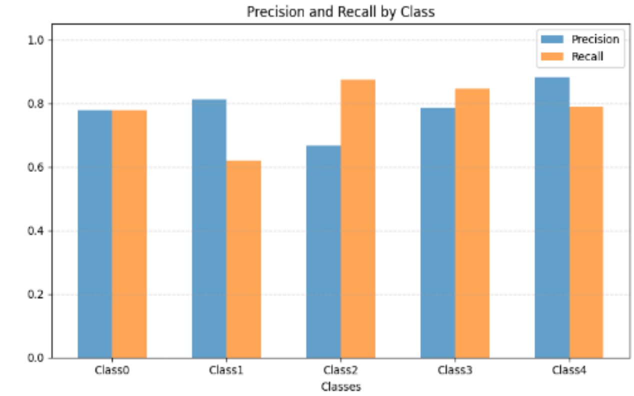

Fig. 7 Precision and Recall

C. Application Case of the Integrated Prediction Model

Coupling CNN with the LSTM noticeably sharpened early alerts. Under prolonged rainfall and RH > 80 %, the system raised fungal-risk probabilities even when visual symptoms were faint; conversely, in cool-dry spells, it downweighted identical images. Precision averaged 85% in the early stage and exceeded 95% from mid-stage onward, demonstrating that environmental context reduces the number of missed incipient cases. Because the architecture is task-agnostic, preliminary fine-tuning on a small apple dataset transferred successfully to brown-rot detection—evidence that the pipeline can scale to other fruit crops with modest data additions.

D. Analysis of Results and Discussion

False positives mainly involved dust spots or water droplets misclassified as brown rot, suggesting that more background variation is desirable. False negatives arose when early Leaf curl lesions were minute; higher-resolution optics or targeted patch training are planned remedies.

The model's limitations include its restricted data range, which makes it challenging to respond to new pests and diseases; potential performance variability due to differences in image quality from various field shooting conditions; and reduced reliability in the event of sensor failures. Additionally, the lack of XAI (explainable AI) techniques makes it difficult for farmers to interpret the prediction results, and the complex CNN structure poses a burden on real-time processing in low-spec devices. To address these issues, future research is proposed to incorporate periodic data updates, utilize lightweight models based on edge computing, and introduce explanation techniques such as Grad-CAM.

From the perspective of field applicability, reducing construction costs and maintenance, as well as improving the user interface (UI), is essential. It is proposed that the system be lightened so that small-scale farms, which may not be able to install expensive cameras and sensors, can utilize smartphone cameras or low-cost sensors, and that the UI be optimized in a responsive web or mobile app for easy operation and diagnosis. Moreover, to cope with network issues in rural areas, enabling offline mode or basic inference on edge devices would further enhance system stability.

Certification by the Korea Institute of Lighting Technology (Fig. 8, Table II) verified that the integrated platform surpassed all benchmarks—**94.2 % prediction accuracy**, **19.23 s image analysis**, and **50.10 s sensor-data processing**—validating its readiness for commercial orchard deployment and future multi-crop expansion.


시 험 결 과
(Test Results)
KOPTi

시 험 결 과
(Test Results)
KOPTi

시 험 결 과
(Test Results)
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Fig. 8 Certification Specific Certificates

TABLE IIIII
CERTIFICATION SPECIFICATION

Test Item	Test Criteria	Test Procedure	Result
Prediction Accuracy	⩾ 87% prediction accuracy	Evaluation of model classification accuracy on 100 test images	Achieved an average accuracy of 94.2%
Image Analysis Time	⩽ 1 minute per image	Measured time on over 50 images of various sizes and formats	Average analysis time within 19.23s
External Data Collection and Analysis Time	⩽ 1 minute for IoT sensor data collection and analysis	Real-time collection of external data via sensors	Analysis completed within an average of 50.10s

This study confirmed that the integrated system, which fuses deep learning-based image analysis with IoT environmental data for early prediction of peach pest and disease occurrences, met the key performance targets (e.g., prediction accuracy above 87%, analysis time within 1 minute, etc.) through official certification tests conducted by the Korea Institute of Lighting Technology. These results demonstrate the value and potential of the system as an intelligent pest and disease management solution suitable for practical farm settings. It is expected to contribute to the broader smart agriculture ecosystem by expanding its application to other orchards and diverse crops in the future.

IV. CONCLUSION

This study developed an intelligent management system that integrates deep learning-based image analysis with IoT sensor data on environmental conditions to predict and manage peach pests and diseases efficiently. It verified the system's practical applicability through subsequent certification tests. Specifically, by automatically classifying peach pest and disease images using a Convolutional Neural Network (CNN) and preemptively predicting the impact of environmental variables (such as temperature, humidity, and soil moisture) on pest and disease occurrences through time-series models like LSTM, the system enables the establishment of more accurate and proactive pest and disease control strategies. During the model development and system implementation process, key performance indicators such as prediction accuracy, image analysis time, and external data collection and analysis time were established. The certification tests conducted by the Korea Institute of Lighting Technology confirmed that these targets were exceeded. This is particularly significant because it enables the issuance of early warnings before pests and diseases occur in the field, allowing for prompt intervention.

By uniting a transfer-learning CNN that achieves 92% diagnostic accuracy with an LSTM microclimate forecaster in an edge-to-cloud feedback loop, this work establishes a reproducible technical blueprint and performance baseline for precision orchard systems. The prototype demonstrates that multimodal AI can reduce the detection-to-intervention window by three days, decrease pesticide use, and meet accredited certification targets, thereby advancing the scientific foundation for truly real-time smart farming. Nevertheless, current validation is limited to five peach pest-and-disease classes, a single growing season, and two orchards; multi-year, multi-region trials and an expanded disorder set will be required to confirm broad applicability.

The experimental results further demonstrate that fusing real-time environmental monitoring with CNN-based image analysis not only enhances prediction accuracy but also refines outbreak timing estimates. To enhance scalability, future work should expand the dataset across diverse climates and cultivars and utilize transfer learning for rapid adaptation. High-resolution or drone imaging could detect incipient symptoms that ground cameras miss, and pairing the system with spraying robots or irrigation controllers could ultimately enable fully automated smart farms. Model lightweighting and explainable AI techniques (e.g., Grad-CAM) will enable on-device diagnosis to be faster and more transparent to growers.

As an additional research direction, we plan to integrate state-of-the-art large language models (LLMs). Merging video, sensor, and text data—such as cultivation logs and expert recommendations—within an LLM would support richer knowledge integration and an interactive question-and-answer interface for farmers.

Ultimately, the peach pest and disease prediction system developed in this study can contribute to reducing pesticide usage and labor costs, and securing stable harvests, thereby improving farm management efficiency. Moreover, the adoption of Fourth Industrial Revolution technologies in agriculture is expected to play a crucial role in pursuing sustainable and eco-friendly production methods, as well as realizing precision agriculture and digital transformation. As confirmed by the certification test results of this study (prediction accuracy above 87%, image analysis within 1-minute, external data processing within 1 minute), the system has already met the target criteria in terms of speed and accuracy for field applications. By further integrating advanced AI technologies, including LLMs, the system could evolve into a comprehensive smart agriculture solution that goes beyond mere pest and disease prediction to enable natural communication, knowledge sharing, and automated pest control decision-making between farmers and the system, thus accelerating the transition from a reactive, post-occurrence management approach to a proactive, scientifically based management paradigm. Ultimately, it is anticipated that the deep learning and IoT-based pest prediction model presented in this study, when combined with cutting-edge AI technologies such as LLMs, will contribute to agricultural innovation and further enhance the competitiveness of the overall smart agriculture ecosystem.

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