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Smart Apple Guardian(SAG): Predicting and Controlling Apple Diseases Using IoT Data and AI

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Abstract: *This study proposes a 'Smart Apple Guardian (SAG)' architecture for apple diseases, leveraging Internet of Things (IoT) sensors and artificial intelligence (AI) technologies. Specifically, the proposed architecture employs a deep learning model—incorporating CNNs, RNNs, and LSTMs—to target anthracnose and Marssonina blotch and predict disease outbreaks using environmental data (e.g., temperature, humidity, precipitation, and wind speed) collected through weather and soil IoT sensors. The training dataset was constructed based on disease occurrence history data from 2013 to 2024 from the Rural Development Administration (RDA). A key contribution of this study is the proposal of an Optimal Input Data Window for AI that integrates the existing disease-specific incubation periods (11 days for anthracnose and 21 days for Marssonina blotch) into a 15-day model. Experimental results show that the training dataset with the proposed 15-day incubation period showed higher prediction accuracy than the datasets with existing disease-specific incubation periods. Specifically, the RNN model achieved the best performance in Anthracnose prediction, with an accuracy of 0.9727, a specificity of 0.9455, and a sensitivity of 1.0000. In contrast, the LSTM model achieved superior performance in Marssonina blotch prediction, with an accuracy of 0.9200, a specificity of 0.8982, and a sensitivity of 0.9418. In conclusion, this study demonstrates that applying a unified incubation period can improve both the predictive accuracy and data efficiency of AI models, providing a robust framework for precision agriculture.*

Keywords: SAG; Smart Agriculture; IoT; Artificial Intelligence; Apple Disease Prediction; Pest Control

1. Introduction

Agriculture is the oldest industry in human history [1]. The global population is projected to increase by 1.2 times, from approximately 8 billion in 2022 to 9.7 billion by 2050, while the total area of arable land is expected to continue declining [2]. Agricultural productivity has been decreasing due to climate change factors such as rising temperatures and changes in precipitation, and it is predicted that by around 2030, approximately 670 million people (8% of the global population) will face famine [3]. If such climate change persists, limitations on multiple cropping caused by drought and the gradual decline in cultivation frequency are expected to further deteriorate crop production [2].

In the case of South Korea, the rural population has declined by approximately 85%, from 14.42 million in 1970 to 2.16 million in 2022, while the proportion of those aged 60 and above has increased from 7.9% (1970) to 65% (2022), indicating a significant aging trend in rural communities. In addition, the cultivated land area of Korea ranks 22nd among the 38 member countries of the Organisation for Economic Co-operation and Development (OECD), placing it in the lower-middle tier. The total arable land area decreased by about 31.8%, from its 1975 level to 1,528,237 hectares in 2022 [2]. Consequently, agriculture has emerged as a key global issue in terms of food security, given the rising world population, shrinking farmland, climate change–induced food shortages, and instability in agricultural supply chains [4]. As an essential foundation for human survival, agriculture plays a crucial role in supplying food to sustain life, supporting economies, and driving growth worldwide [5].

In this context, smart agriculture not only holds new potential to drive innovation in modern farming and address the numerous challenges faced by today's farmers [6], but it has also become a national imperative for building a sustainable future [7]. Amid global challenges such as food crises, environmental change, labor shortages, and rapid technological advancement, smart agriculture has emerged as an inevitable alternative rather than a choice. It goes beyond the mere integration of ICT technologies into traditional farming; rather, it serves as a key instrument for establishing sustainable agricultural systems and ensuring food security for future generations [8]. Although the definition and concept of Smart Agriculture vary, it generally refers to the integration of advanced ICT technologies—such as artificial intelligence (AI), data analytics, sensors, and autonomous systems—into agriculture to enhance productivity and quality, remotely and automatically manage crop and livestock environments, and ultimately improve labor efficiency to realize sustainable future farming.

Smart agriculture creates innovation by converging ICT technologies, including data and AI, across all stages of the agricultural value chain—production, processing, distribution, and consumption—thus fostering a new paradigm of ICT-integrated agriculture [9]. Modern agriculture has continuously evolved from a system dependent on land, labor, and capital to one driven by advanced digital convergence technologies. Considering the economic, social, and technological factors that have directly or indirectly influenced the agricultural environment, this evolution can be categorized into five distinct stages [10-12]. The characteristics of each evolutionary stage in agriculture are shown in Table 1.

Table 1. This is a table. Tables should be placed in the main text near to the first time they are cited

Category	Characteristics	Representative technologies
Agriculture 1.0	• Manual, Traditional Agriculture • Labor-intensive with low productivity	Use of simple tools and animal draft power
Agriculture 2.0	• Mechanized Agriculture (Industrial-Revolution Era Influence) • Farm scale-up and productivity gains	Adoption of tractors, harvesters, and related agricultural machinery
Agriculture 3.0	• Precision Agriculture • Multi-variety, small-lot production; site-specific management	GPS-guided machinery, remote sensing, and geographic information systems (GIS)
Agriculture 4.0	• Smart Agriculture • Data-driven, predictive operations	Internet of Things (IoT), artificial intelligence (AI), big-data analytics, and robotics
Agriculture 5.0	• Fully Automated and Tailored Agriculture • Maximized productivity with ecological compatibility	The convergence of quantum computing, nanotechnology, and bioengineering

Agriculture 1.0 refers to pre-modern agriculture, characterized by strong labor-intensive practices and low productivity. Agriculture 2.0 marks the beginning of productivity improvements through the use of fertilizers, pesticides, and agricultural machinery in traditional farming. With the 1995 Uruguay Round negotiations leading to the opening of agricultural markets and the advancement of information technology, Agriculture 3.0 emerged, introducing automation into farming practices. Agriculture 4.0 represents the application of core technologies from the Fourth Industrial Revolution, leading to unmanned and intelligent farming where labor, experience, and knowledge are increasingly replaced by data. Agriculture 5.0 is a new paradigm aimed at addressing the limitations and challenges that Agriculture 4.0 could not fully resolve [10], [12].

Apples are one of the most widely cultivated fruits globally, including in South Korea. Rising temperatures caused by climate change have adversely affected apple production, and weather factors significantly influence apple growth and quality throughout all developmental stages, from budding to harvest [13]. Overall, variations in environmental factors such as temperature, humidity, and precipitation have a profound impact on the occurrence of plant and fruit diseases, thereby affecting the entire agricultural industry [14-16]. Therefore, this study proposes a method that utilizes IoT sensor data and AI-based smart agriculture technologies to predict diseases in open-field apple cultivation and to provide farmers with appropriate disease control and management information.

2. Related work

Smart agriculture aims to improve, enhance, and foster the agricultural environment by incorporating Information and Communication Technology (ICT) and digital technologies [17]. Unlike traditional, labor-intensive, and resource-intensive farming, these technologies are key to embracing data-driven agriculture [18]. Agriculture 4.0 is a concept aiming to build a future-oriented agricultural system that is hyper-precise and hyper-connected, particularly through AI, IoT, big data, cloud computing, robotics, and drones [19]. It facilitates shared, integrated tasks, competent decision-making, and autonomous operation. Figure 1 shows the key data interactions between technologies in Agriculture 4.0 [20, 21].

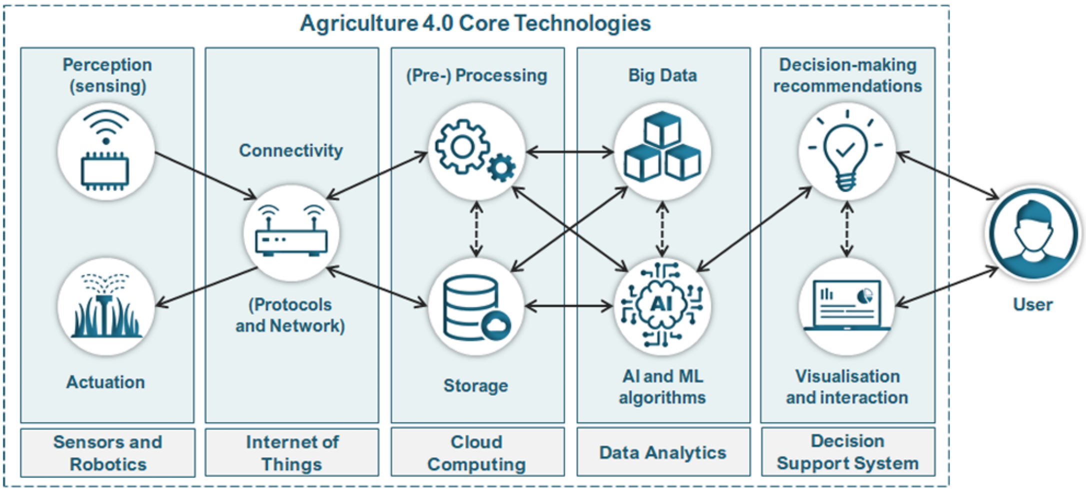

Figure 1. Core technologies of Agriculture 4.0

The Internet of Things (IoT) technology used in smart control collects data through sensors distributed throughout the environment. This data is transmitted to a central location (or cloud) via a wireless network, where it is used for system monitoring, analysis, and automatic control. Smart sensors are sophisticated devices that go beyond basic sensing to include data processing, storage, and communication capabilities. They can independently process collected data and communicate wirelessly, enabling real-time monitoring and integrated decision-making [22]. Smart agriculture contributes to economically reducing the complexity of agricultural activities. By utilizing IoT-based environmental sensors, critical factors such as moisture, temperature, soil composition, and nutrient distribution are precisely modeled, allowing for optimized crop growth and management [22, 23].

Large-scale data analysis and decision support systems are essential for collecting, processing, and analyzing vast amounts of agricultural data to help farmers make better, timelier decisions. These systems significantly expand agricultural productivity and potential. AI and machine learning are becoming key components of smart farms, enabling improved crop productivity, optimized resource use, pest management, and yield prediction [24]. By analyzing data collected from the field (weather, crop yield, growth patterns, pests, etc.) using AI and machine learning, management, prediction, and optimization can be achieved, while minimizing crop spoilage [25]. Digitalizing agriculture with data and AI improves efficiency, integrity, and equity, unlocking new innovations. In particular, AI helps improve farm profitability and addresses challenges in supply chains and technology.

Furthermore, pest and disease prediction models integrate historical and real-time data (e.g., weather, sensor readings, and occurrence history) to forecast pest outbreaks in susceptible crops such as pears and rice [26]. Crop forecasting models predict yields based on soil and cultivation history [27], which informs market supply and demand forecasts and distribution planning. Growth optimization systems use deep learning to recommend optimized fertilization, irrigation, and cultivation methods. Image analysis is used to rapidly diagnose diseases and monitor growth status using field photos, with AI diagnostic apps available via smartphones.

Agricultural robots are utilized in various fields, from monitoring growth environments to weeding, pest control, spraying, harvesting, and milking. They are evolving from semi-autonomous to fully autonomous systems [28]. These robots are categorized into open-field, facility, and livestock applications. Open-field robots incorporate precision technologies into agricultural machinery, such as tractors and combine harvesters. For facility applications, robotics is applied to most production processes, including sowing and harvesting. In livestock, robotic milking machines automate the entire process from milk production to herd management, saving time and labor [28, 29].

Autonomous driving systems, relying on GPS and precise positioning (RTK, etc.) for navigation, automatically perform tillage, sowing, and harvesting tasks [30]. Robotic harvesters support tasks such as sowing, pest control, and growth monitoring. They provide data necessary for supply and demand forecasts through video and sensor data collected by drones. Robotic harvesters automatically harvest fruits and vegetables, precisely detecting and picking crops like strawberries, tomatoes, and apples. Components of autonomous machinery include a GPS system for positioning, a CAN-based auto-steering system for path tracking, a Human-Machine Interface (HMI) for operation, and external sensors for obstacle detection. Drones (UAVs) act as remotely piloted aerial vehicles that move along pre-arranged paths. They operate as clustered systems for pest control, sowing, crop forecasting, and disease detection, enabling coordinated movement and operations [31-33].

Blockchain is a digital ledger that records transaction history using a chain of consecutively linked blocks. It maintains a ledger distributed across a Peer-to-Peer (P2P) network, where all nodes update and verify information, excluding the need for a central authority [34]. These technologies revolutionize transparency, reliability, and traceability across the entire agricultural production, distribution, and storage process [35]. Blockchain can be used for item history tracking, supply chain management, authenticity certification, transactions, and financing.

Specific productivity tracking records the entire process—including production site, harvest date, and distribution route—providing transparency for consumers and distributors [36]. Network management implements transactions based on trusted data distribution between stakeholders. Authenticity certification management integrates data such as GAP and HACCP in a tamper-proof manner, enhancing reliability. IBM Food Trust, a blockchain-based platform, transparently records and shares the food journey from production to the end consumer [37]. It records data from all supply chain stages to ensure traceability, prevent data tampering, and ensure the integrity of all records [14], [38].

3. SAG Architecture: IoT-Based Apple Disease Prediction and Management

The Smart Apple Guardian (SAG) Architecture is designed to predict apple diseases in open-field cultivation and provide corresponding pest control information to farmers, thereby supporting proactive disease management. The overall architecture of the SAG Platform is shown in Figure 2.

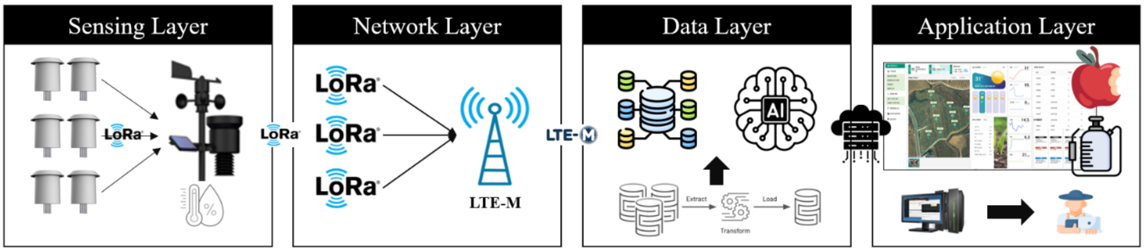

Figure 2. SAG(Smart Apple Guardian) architecture

The sensing layer consists of sensors that collect environmental data from open-field apple orchards, including soil conditions and meteorological parameters such as temperature, humidity, and wind speed. The network layer employs a LoRa network for inter-sensor communication, while data collected by the sensors are transmitted via LTE-M communication. The data layer extracts, transforms, and integrates diverse datasets—including sensor data, field information, disease data, pest control data, and training datasets—to build a unified data repository. Finally, the application layer presents various types of information, such as predicted apple disease occurrences and corresponding control recommendations, enabling end-users to make informed decisions based on the data collected and processed by the lower layers.

3.1 Collection of Open-Field Meteorological Data

Meteorological data in South Korea are measured and forecasted by the Korea Meteorological Administration (KMA) and the Rural Development Administration (RDA). While the KMA primarily collects meteorological data centered around residential areas, the RDA focuses on agricultural and mountainous regions to serve the needs of farmers. However, the data collected by these two institutions do not comprehensively cover all open-field conditions, resulting in limitations in both regional coverage and measurement accuracy. Therefore, in this study, meteorological sensors were installed in open-field apple orchards to directly measure and collect localized weather data.

The installed meteorological sensors collected seven types of atmospheric data—wind direction, wind speed, gusts/strong winds, precipitation, solar radiation, air temperature, and relative humidity. Additionally, soil sensors gathered eleven types of soil data, including surface temperature, ground humidity, ground temperature, soil moisture, electrical conductivity, pH, phosphorus, potassium, salinity, and total dissolved solids. The data generated from each sensor were transmitted via the LoRa network to a data collector, which then sent the aggregated data to a cloud server through the LTE-M network for storage and analysis. Figure 3 shows a conceptual diagram of sensor installation in open fields and the data storage process.

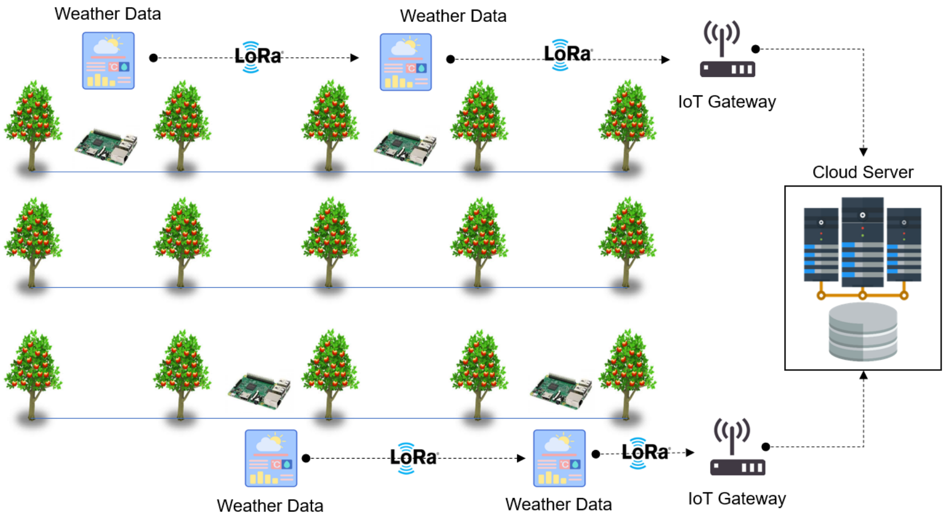

Figure 3. Conceptual diagram of sensor installation in open fields

3.2 Construction of Apple Disease Training Data

Apple diseases are caused by a variety of environmental and biological factors, among which temperature and humidity are the most significant [14, 15], [39, 40]. To predict the occurrence of apple diseases, it is essential to collect temperature and humidity data corresponding to the time of disease outbreaks and construct training datasets based on these conditions. Among the major apple diseases, anthracnose (Colletotrichum gloeosporioides) and Marssonina blotch (Diplocarpon mali) are primarily influenced by specific climatic conditions. Anthracnose generally occurs during July to August, proliferating under temperatures of 25–30°C and relative humidity above 70%, with an incubation period of 8–11 days [39].

Marssonina blotch, on the other hand, develops in humid environments at 20–25°C, with symptoms typically appearing from June and an incubation period of approximately 21 days [40]. These observations indicate that apple diseases emerge after distinct incubation periods determined largely by temperature and humidity conditions. To construct the training dataset for this study, disease occurrence data for apple anthracnose and Marssonina blotch were obtained through collaboration with the Disaster Response Division of the Rural Development Administration. Table 2 shows a sample of the dataset, which contains recorded outbreak data spanning from 2013 to 2024.

Table 2. Data of Apple Disease Occurrence Survey

Date	Apple variety name	Latitude	Longitude	No. of leaves infected with Marssonina blotch/640	Marssonina blotch prevalence	Number of fruits infected with Anthracnose/ 750	Anthracnose prevalence
20230517	Fuji	127.504045848	37.8519728567	0	0	0	0
20230601	Fuji	127.504045848	37.8519728567	0	0	0	0
20230615	Fuji	127.504045848	37.8519728567	0	0	0	0
20230701	Fuji	127.504045848	37.8519728567	10	1.6	0	0
20230716	Fuji	127.504045848	37.8519728567	13	2	0	0
20230801	Fuji	127.504045848	37.8519728567	25	3.9	0	0
20230816	Fuji	127.504045848	37.8519728567	51	8	0	0
20230903	Fuji	127.504045848	37.8519728567	53	8.3	0	0
20230916	Fuji	127.504045848	37.8519728567	67	10.5	20	2.7
20231003	Fuji	127.504045848	37.8519728567	70	10.9	20	2.7

In this study, to predict apple diseases, learning data were constructed by introducing an additional incubation period of 15 days, along with the previously identified incubation periods of 11 days for anthracnose and 21 days for Marssonina blotch. Table 3 shows the metadata of the learning dataset used for predicting apple diseases based on the three incubation periods (11, 15, and 21 days). The primary attributes of the metadata include the survey date, latitude, longitude, disease incidence rate of apple diseases, and meteorological data such as average temperature, maximum temperature, minimum temperature, humidity, wind speed, precipitation, and solar radiation.

Table 3. Metadata of the Learning Dataset

Item		Description
Date		The date when apple disease occurrence was recorded.
Latitude		The latitude coordinate of the area where the apple disease occurred.
Longitude		The longitude coordinate of the area where the apple disease occurred.
Prevalence		The prevalence rate of the observed apple disease.
N-day Weather data*	Average temperature	The mean temperature observed over a 24-hour period.
	Highest temperature	The highest temperature recorded during the observation period.
	Lowest temperature	The lowest temperature recorded during the observation period.
	Humidity	The amount of water vapor present in the air, expressed as a percentage of the maximum amount the air can hold at that temperature.
	Wind speed	The rate at which air moves horizontally past a given point, measured per unit time.
	Precipitation	The amount of rainfall measured during the observation period.
	Solar radiation	The amount of solar energy reaching the Earth's surface.
Disease		A binary indicator denoting whether the apple disease occurred (1) or not (0).

* N-Day weather data: These are the weather variables recorded repeatedly over the incubation period (N days). For example, if the incubation period is 8 days, the corresponding weather data entries are repeated eight times, representing daily observations throughout the incubation period

The learning dataset was constructed using the metadata presented in Table 3. To predict apple diseases, weather data preceding the incubation period (11, 15, or 21 days) from the time of disease occurrence were analyzed. Specifically, from the historical weather records, the process begins by identifying the first date when rainfall exceeds '0', and then aggregates the corresponding weather data over the entire incubation period. Table 4 shows the pseudo code for constructing the learning dataset using a 15-day incubation period for apple disease prediction.

Table 4. Pseudo Code for Building the Apple Disease Learning Dataset

```
Module 1. Diseased Apple Training Data
    • Step 1. Extract the survey date and latitude–longitude coordinates of locations where apple diseases occurred.
    • Step 2. For each data point extracted in Step 1, identify the first date prior to the survey date when rainfall > 0.
    • Step 3. Using the date extracted in Step 2 as the center, collect agricultural weather data for 7 days before and after, and combine it with the data extracted in Step 1.

Module 2. Healthy Apple Training Data
    • Step 1. Extract agricultural weather data for the incubation period (15 days) prior to the date of healthy apples.
    • Step 2. Combine the selected survey date, survey location, and occurrence-related information with the newly extracted agricultural weather data from Step 1.
```

3.3 Integration of Apple Disease Control Data

In the proposed system, when an apple disease is predicted, various datasets—such as field information, sensor data, disease information, and pest-control records—are collected and integrated to provide comprehensive decision support for preventive measures. Field Information includes details such as the orchard name, location (latitude, longitude), and type of fruit, which are stored and managed in the database. Sensor Installation Information records details on the installation locations, number, and types of sensors (weather and soil) deployed in each orchard. Apple Disease History Information stores and manages the training datasets for apple disease prediction, along with the daily prediction rates. When a disease is detected, the system sends notifications and alerts to farmers through SNS (Social Networking Services), provides environmental management information, and records pest-control activities and history for subsequent analysis. The overall integrated data architecture for apple disease prediction and control is shown in Figure 4.

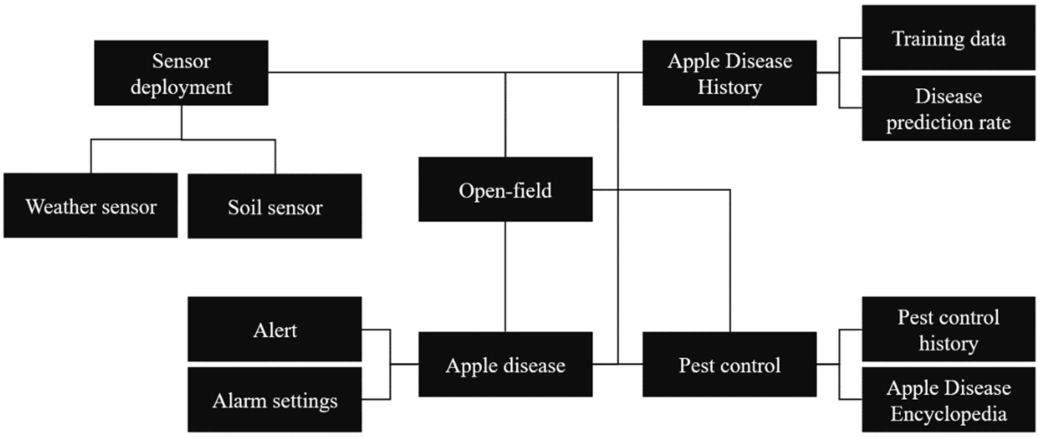

Figure 4. Integrated data architecture for apple disease prediction and control

4. Apple Diseases Prediction

This study employed various artificial intelligence (AI) models—CNN, RNN, and LSTM—to predict apple diseases. A performance comparison was conducted between incubation periods of 11 days, 21 days, and the proposed 15-day period. The purpose of introducing the 15-day incubation period was to reduce inefficiency in constructing training datasets for multiple disease types. By applying this standardized incubation period across diseases, model performance was evaluated and compared.

4.1 Experimental Setup

The prediction models were developed using Python 3.11.7 and TensorFlow 2.16.0. To forecast apple anthracnose and Marssonina blotch, three models—CNN, RNN, and LSTM—were trained and evaluated. The hyperparameters for each artificial intelligence model include learning rate, optimizer, batch size, number of epochs, dropout, activation function, and loss function. The learning rate determines the speed at which the model learns; in this study, it was set to 0.0001 for the CNN and RNN models, and 0.001 for the LSTM model. The optimizer is the algorithm used to update the model's weights, and the Adam algorithm was employed. The batch size is the number of data samples used in one weight update; it was set to 72 for the CNN and RNN models and 16 for the LSTM model.

The number of epochs refers to the number of times the entire training dataset is passed through the model, and comparisons were made for 100, 150, and 200 epochs. Dropout is a technique to prevent overfitting by deactivating a certain proportion of neurons, and it was set to 0.5 for the CNN, RNN, and LSTM models. The activation function determines the output of neurons, and the Sigmoid function was used for all models. The loss function measures the difference between predicted and actual values, and the Binary Cross-Entropy (BCE) loss function, suitable for binary classification problems, was selected for all models. The hyperparameters used for each model are shown in Table 5.

Table 5. Hyperparameters for Each Artificial Intelligence Model

Hyperparameter	CNN	RNN	LSTM
Learning rate	0.0001	0.0001	0.001
Optimizer	Adam	Adam	Adam
Batch	72	72	16
Epoch	100, 150, 200	100, 150, 200	100, 150, 200
Dropout	0.5	0.5	0.5
Activation function	Sigmoid	Sigmoid	Sigmoid
Loss function	BCE	BCE	BCE

4.2 Performance Evaluation

The experiments compared the performance for the incubation period of 11 days for anthracnose, 21 days for Marssonina blotch, and the 15-day incubation period proposed in this study. The performance evaluation metrics used in the experiments were Accuracy, Specificity, and Sensitivity. Accuracy represents the proportion of the total data correctly predicted, including both the presence and absence of disease. Specificity refers to the proportion of healthy apples correctly identified as normal, and Sensitivity refers to the proportion of apples actually affected by the disease that were correctly identified as diseased. Figure 5 shows the overall procedure for predicting apple diseases and evaluating performance.

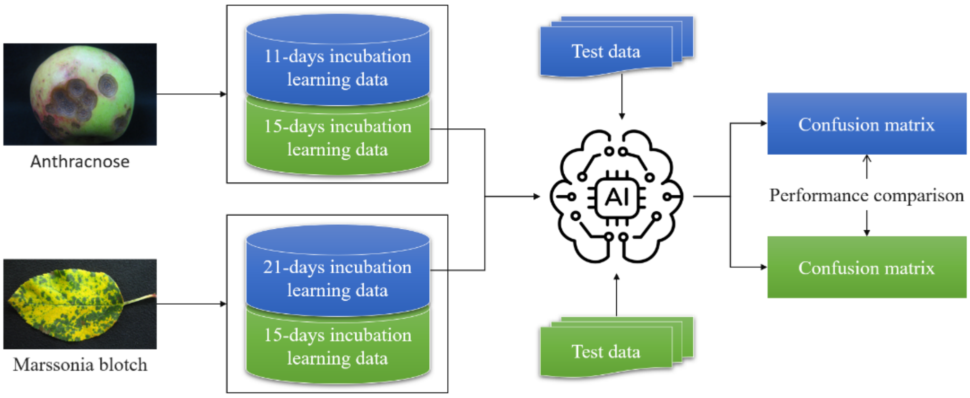

Figure 5. Procedures for predicting apple disease and evaluating its performance

Table 6 shows the performance evaluation for anthracnose with incubation periods of 11 days and 15 days. For the CNN model, at epoch 150, the 15-day incubation period achieved an accuracy of 0.9318, specificity of

0.9455, and sensitivity of 0.9182, showing the best performance. Similarly, the RNN model at epoch 150 achieved an accuracy of 0.9727, specificity of 0.9455, and sensitivity of 1.0000. The LSTM model at epoch 150 showed an accuracy of 0.9341, specificity of 0.9364, and sensitivity of 0.9318. Overall, the performance evaluation indicates that the 15-day incubation period outperforms the 11-day incubation period for anthracnose prediction.

Table 6. Experimental Results for Anthracnose

Model		**11days**			**15days**		
		Acc.	**Spe.**	**Sen.**	**Acc.**	**Spe.**	**Sen.**
CNN	100	0.8182	0.9864	0.6500	0.9273	0.9636	0.8909
	150	0.9091	0.9136	0.9045	0.9318	0.9455	0.9182
	200	0.9341	0.9227	0.9455	0.9205	0.9636	0.8773
RNN	100	0.8636	0.9273	0.8000	0.9500	0.9636	0.9364
	150	0.8818	0.8955	0.8682	0.9727	0.9455	1.0000
	200	0.9068	0.9045	0.9091	0.9659	0.9591	0.9727
LSTM	100	0.8795	0.8955	0.8636	0.9250	0.9909	0.8591
	150	0.8909	0.9273	0.8545	0.9341	0.9364	0.9318
	200	0.9250	0.9318	0.9182	0.9341	0.9818	0.8864

* Acc.: Accuracy, Spe.: Specificity, Sen.: Sensitivity

Table 7 shows the performance evaluation for Marssonina blotch with incubation periods of 21 days and 15 days. For the CNN model, at epoch 200, the 15-day incubation period achieved an accuracy of 0.9018, specificity of 0.9273, and sensitivity of 0.8764, showing the best performance. Similarly, the RNN model at epoch 200 achieved an accuracy of 0.9018, specificity of 0.8364, and sensitivity of 0.9673. Unlike the other models, the LSTM model at epoch 150 achieved the best performance, with an accuracy of 0.9200, specificity of 0.8982, and sensitivity of 0.9418. Although the LSTM model's performance at epoch 150 and epoch 200 is similar, considering the evaluation metrics of accuracy, specificity, and sensitivity, the results at epoch 150 are superior. Therefore, similar to anthracnose, the performance evaluation for Marssonina blotch demonstrates that the 15-day incubation period outperforms the conventional incubation periods.

Table 7. Results for Marssonina Blotch

Model		**21days**			**15days**		
		Acc.	**Spe.**	**Sen.**	**Acc.**	**Spe.**	**Sen.**
CNN	100	0.8182	0.9864	0.6500	0.9273	0.9636	0.8909
	150	0.9091	0.9136	0.9045	0.9318	0.9455	0.9182
	200	0.9341	0.9227	0.9455	0.9205	0.9636	0.8773
RNN	100	0.8636	0.9273	0.8000	0.9500	0.9636	0.9364
	150	0.8818	0.8955	0.8682	0.9727	0.9455	1.0000
	200	0.9068	0.9045	0.9091	0.9659	0.9591	0.9727
LSTM	100	0.8795	0.8955	0.8636	0.9250	0.9909	0.8591
	150	0.8909	0.9273	0.8545	0.9341	0.9364	0.9318
	200	0.9250	0.9318	0.9182	0.9341	0.9818	0.8864

* Acc.: Accuracy, Spe.: Specificity, Sen.: Sensitivity

Examining the performance evaluation of models predicting apple diseases, it is evident that the performance for the 15-day incubation period proposed in this study is superior. For anthracnose, the RNN model showed excellent and stable performance, while for Marssonina blotch, the LSTM model was generally superior. These results indicate that the proposed models can predict apple anthracnose and Marssonina blotch with high reliability. Furthermore, they suggest that the choice of AI model should depend on the type of apple disease being predicted.

5. Conclusions

Data-driven smart agriculture has become an essential solution to overcome the challenges posed by climate change and the aging rural population. This study proposes the "Smart Apple Guardian (SAG)" architecture, which integrates Internet of Things (IoT) sensor data and artificial intelligence (AI) technologies to predict major apple diseases, namely anthracnose and Marssonina blotch, and provide corresponding management information. The construction of training data and the accuracy of AI models are critical for predicting apple diseases. Instead of using the conventional disease-specific incubation periods (11 days for anthracnose and 21 days for Marssonina blotch), this study proposes a new 15-day incubation period to construct the training dataset. Performance evaluation results show that applying the proposed 15-day incubation period achieved higher predictive accuracy across all models (CNN, RNN, and LSTM) compared to the conventional incubation periods. This suggests the potential for a standardized incubation period not limited to specific diseases and provides a foundation for efficiently constructing training datasets for multiple diseases.

Analysis of AI model performance indicates that the RNN model was most effective and stable for anthracnose prediction, while the LSTM model performed best for Marssonina blotch. This demonstrates that the optimal AI model may vary depending on the type and characteristics of the apple disease, highlighting the need for disease-specific predictive models. By integrating real-time environmental data collected via IoT sensors with AI analysis, the platform enables scientific and precise disease management. However, despite proposing various methods to enhance AI model performance, limitations remain. Future research will address these limitations by conducting performance evaluations considering different periods of agricultural weather data. In addition, beyond the training data construction method proposed in this study, more diverse approaches will be explored, and advanced AI models such as CNN and RNN will be applied to further improve performance. The ultimate goal is to develop more accurate and efficient disease prediction models for smart agriculture.

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Conflicts of Interest: The authors declare no conflict of interest.

References

[1] N. N. Thilakarathne, M. S. A. Bakar, P. E. Abas, and H. Yassin, "Internet of things enabled smart agriculture: Current status, latest advancements, challenges and countermeasures," Heliyon, vol. 11, no. 3, e42136, Feb. 2025, doi: https://doi.org/10.1016/j.heliyon.2025.e42136.

[2] U. J. Jang, Strategies to Promote Korea's Smart Farm Industry: A Focus on International Policies and Corporate Success Stories. (2024). Accessed: Nov. 24, 2025. [Online] Available: https://www.kita.net/researchTrade/report/tradeFocus/tradeFocusDetail.do?no=2569

[3] A. H. Wudil, M. Usman, J. Rosak-Szyrocka, L. Pilař, and M. Boye, "Reversing Years for Global Food Security: A Review of the Food Security Situation in Sub-Saharan Africa (SSA)," International Journal of Environmental Research and Public Health, vol. 19, no. 22, 14836, Nov. 2022, doi: https://doi.org/10.3390/ijerph192214836.

[4] A. Saleem, S. Anwar, T. Nawaz, S. Fahad, S. Saud, T. Ur Rahman, and T. Nawaz, "Securing a sustainable future: the climate change threat to agriculture, food security, and sustainable development goals," Journal of Umm Al-Qura University for Applied Sciences, vol. 11, pp. 595-611, Jul. 2025, doi: https://doi.org/10.1007/s43994-024-00177-3.

[5] R. D. Tchonkouang, H. Onyeaka, and H. Nkoutchou, "Assessing the vulnerability of food supply chains to climate change-induced disruptions," Science of the Total Environment, vol. 920, 171047, Apr. 2024, doi: https://doi.org/10.1016/j.scitotenv.2024.171047.

[6] V. Kumar, K. V. Sharma, N. Kedam, A, Patel, T. R. Kate, and U. Rathnayake, "A comprehensive review on smart and sustainable agriculture using IoT technologies," Smart Agricultural Technology, vol. 8, 100487, Aug. 2024, doi: https://doi.org/10.1016/j.atech.2024.100487.

[7] M. Gemtou, G. Isakhanyan, and S. Fountas, "Advancing climate-smart agriculture: Integrating technology, behavioural insights and policy for a sustainable future," Smart Agricultural Technology, vol. 11, 100861, Aug. 2025, doi: https://doi.org/10.1016/j.atech.2025.100861.

[8] T. Qureshi, M. Saeed, K. Ahsan, A. A. Malik, E. S. Muhammad, and N. Touheed, "Smart agriculture for sustainable food security using internet of things (IoT)," Wireless Communications and Mobile Computing, vol. 2022, 9608394, May. 2022, doi: https://doi.org/10.1155/2022/9608394.

[9] Smart Agriculture and the Changing Business Ecosystem. (2020). Accessed: Dec. 15, 2025. [Online] Available: https://kpmg.com/kr/ko/home/insights/2020/03/issue-monitor-125.html

[10] A, Holzinger, I. Fister, H. P. Kaul, and S. Asseng, "Human-centered AI in smart farming: Toward agriculture 5.0," IEEE Access, vol. 12, pp. 62199-62214, Apr. 2024, doi: https://doi.org/10.1109/ACCESS.2024.3395532.

[11] S. Mandal, V. Yadav, F. A. Panme, K. M. Devi, and S. K. SM, "Adaption of smart applications in agriculture to enhance production. Smart agricultural technology," vol. 7, 100431, Mar. 2024, doi: https://doi.org/10.1016/j.atech.2024.100431.

[12] K. D. Bissadu, S. Sonko, and G. Hossain, "Society 5.0 enabled agriculture: Drivers, enabling technologies, architectures, opportunities, and challenges," Information Processing in Agriculture, vol. 12, no. 1, pp. 112-124, Mar. 2025, doi: https://doi.org/10.1016/j.inpa.2024.04.003.

[13] M. R. Kim, and S. G. Kim, "Examining Impact of Weather Factors on Apple Yield," Korean Journal of Agricultural and Forest Meteorology, vol. 16, no. 4, pp. 274-284, Dec. 2014, doi: https://doi.org/10.5532/KJAFM.2014.16.4.274.

[14] B. A. Latorre, M. E. Rioja, C. Lillo, and M. Munoz, "The effect of temperature and wetness duration on infection and a warning system for European canker (Nectria galligena) of apple in Chile," Crop Protection, vol. 21, no. 4, pp. 285-291, May. 2002, doi: https://doi.org/10.1016/S0261-2194(01)00099-0.

[15] F. Liu, B. H. Li, S. Lian, X. L. Dong, C. X. Wang, Z. F. Zhang, and W. X. Liang, "Effects of temperature and moisture on the infection and development of apple fruit rot caused by Phytophthora cactorum," Plant Disease, vol. 102, no. 9, pp. 1811-1819, Jul. 2018, doi: https://doi.org/10.1094/PDIS-07-17-1028-RE.

[16] A. U. Rehman, Y. Alamoudi, H. M. Khalid, A. Morchid, S. M. Muyeen, and A. Y. Abdelaziz, "Smart agriculture technology: An integrated framework of renewable energy resources, IoT-based energy management, and precision robotics," Cleaner Energy Systems, vol. 9, 100132, Dec. 2024, doi: https://doi.org/10.1016/j.cles.2024.100132.

[17] V. Choudhary, P. Guha, G. Pau, and S. Mishra, "An overview of smart agriculture using internet of things (IoT) and web services," Environmental and Sustainability Indicators, vol. 26, 100607, Jun. 2025, doi: https://doi.org/10.1016/j.indic.2025.100607.

[18] J. U. M. Akbar, S. F. Kamarulzaman, A. J. M. Muzahid, M. A. Rahman, and M. Uddin, "A comprehensive review on deep learning assisted computer vision techniques for smart greenhouse agriculture," IEEE Access, vol. 12, pp. 4485-4522, Jan. 2024, doi: https://doi.org/10.1109/ACCESS.2024.3349418.

[19] F. Maffezzoli, M. Ardolino, A. Bacchetti, M. Perona, and F. Renga, "Agriculture 4.0: A systematic literature review on the paradigm, technologies and benefits," Futures, vol. 142, 102998, Sep. 2022, doi: https://doi.org/10.1016/j.futures.2022.102998.

[20] S. O. Araújo, R. S. Peres, J. Barata, F. Lidon, and J. C. Ramalho, "Characterising the Agriculture 4.0 Landscape—Emerging Trends, Challenges and Opportunities," Agronomy, vol. 11, no. 4, 667, Apr. 2021, doi: https://doi.org/10.3390/agronomy11040667.

[21] M. A. Dayioğlu, and U. TÜRKER, "Digital transformation for sustainable future-agriculture 4.0: A review," Journal of Agricultural Sciences/Tarim Bilimleri Dergisi, vol. 27, no. 4, Dec. 2021, doi: https://doi.org/10.15832/ankutbd.986431.

[22] P. Rajak, A. Ganguly, S. Adhikary, and S. Bhattacharya, "Internet of Things and smart sensors in agriculture: Scopes and challenges," Journal of Agriculture and Food Research, vol. 14, 100776, Dec. 2023, doi: https://doi.org/10.1016/j.jafr.2023.100776.

[23] H. Shahab, M. Naeem, M. Iqbal, M. Aqeel, and S. S. Ullah, "IoT-driven smart agricultural technology for real-time soil and crop optimization," Smart Agricultural Technology, vol. 10, 100847, Mar. 2025, doi: https://doi.org/10.1016/j.atech.2025.100847.

[24] S. Ajith, S. Vijayakumar, and N. Elakkiya, "Yield prediction, pest and disease diagnosis, soil fertility mapping, precision irrigation scheduling, and food quality assessment using machine learning and deep learning algorithms," Discover Food, vol. 5, no. 1, 1-23, Mar. 2025, doi: https://doi.org/10.1007/s44187-025-00338-1.

[25] N. N. Misra, Y. Dixit, A. Al-Mallahi, M. S. Bhullar, R. Upadhyay, and A. Martynenko, "IoT, big data, and artificial intelligence in agriculture and food industry," IEEE Internet of things Journal, vol. 9, no. 9, pp. 6305-6324, May. 2020, doi: https://doi.org/10.1109/JIOT.2020.2998584.

[26] T. Domingues, T. Brandão, and J. C. Ferreira, "Machine learning for detection and prediction of crop diseases and pests: A comprehensive survey," Agriculture, vol. 12, no. 9, 1350, Sep. 2022, doi: https://doi.org/10.3390/agriculture12091350.

[27] S. B. Dhal, and D. Kar. "Transforming agricultural productivity with AI-driven forecasting: Innovations in food security and supply chain optimization," Forecasting, vol. 6, no. 4, pp. 925-951, Oct. 2024, doi: https://doi.org/10.3390/forecast6040046.

[28] Y. Jin, J. Liu, Z. Xu, S. Yuan, P. Li, and J. Wang, "Development status and trend of agricultural robot technology," International Journal of Agricultural and Biological Engineering, vol. 14, no. 4, pp. 1-19, Jul. 2021, doi: https://doi.org/10.25165/j.ijabe.20211404.6821.

[29] J. Rodenburg, “Robotic milking: Technology, farm design, and effects on work flow,” Journal of Dairy Science, vol. 100, no. 9, pp. 7729-7738, Sep. 2017, doi: https://doi.org/10.3168/jds.2016-11715.

[30] M. S. Hossain, M. Rahman, A. Rahman, M. M. Kabir, M. F. Mridha, J. Huang, and J. Shin, “Automatic navigation and self-driving technology in agricultural machinery: A state-of-the-art systematic review,” IEEE Access, vol. 13, pp. 94370-94401, May. 2025, doi: https://doi.org/10.1109/ACCESS.2025.3573324.

[31] M. Hussein, R. Nouacer, F. Corradi, Y. Ouhammou, E. Villar, C. Tieri, and R. Castiñeira, “Key technologies for safe and autonomous drones,” Microprocessors and Microsystems, vol. 87, 104348, Nov. 2021, doi: https://doi.org/10.1016/j.micpro.2021.104348.

[32] A. Rejeb, A. Abdollahi, K. Rejeb, and H. Treiblmaier, “Drones in agriculture: A review and bibliometric analysis,” Computers and electronics in agriculture, vol. 198, 107017, Jul. 2022, doi: https://doi.org/10.1016/j.compag.2022.107017.

[33] D. Yaga, P. Mell, N. Roby, and K. Scarfone, “Blockchain technology overview,” arXiv preprint arXiv, Jun. 2019, doi: https://doi.org/10.48550/arXiv.1906.11078.

[34] G. S. Sajja, K. P. Rane, K. Phasinam, T. Kassanuk, E. Okoronkwo, and P. Prabhu, “Towards applicability of blockchain in agriculture sector,” Materials Today: Proceedings, vol. 80, pp. 3705-3708, 2023, doi: https://doi.org/10.1016/j.matpr.2021.07.366.

[35] A. Kamilaris, A. Fonts, and F. X. Prenafeta-Boldú, “The rise of blockchain technology in agriculture and food supply chains,” Trends in food science & technology, vol. 91, pp. 640-652, Sep. 2019, doi: https://doi.org/10.1016/j.tifs.2019.07.034.

[36] V. Singh, and S. K. Sharma, “Application of blockchain technology in shaping the future of food industry based on transparency and consumer trust,” Journal of Food Science and Technology, vol. 60, no. 4, pp. 1237-1254, Apr. 2023, doi: https://doi.org/10.1007/s13197-022-05360-0.

[37] H. Nguyen, and L. Do, “The adoption of blockchain in food retail supply chain: Case: IBM food trust blockchain and the food retail supply chain in Malta,” Lahti Univ., Lahti, Finland, 2018. [Online] Available: https://urn.fi/URN:NBN:fi:amk-2018121321426

[38] U. Tiwari, “Application of blockchain in agri-food supply chain,” Britain International of Exact Sciences (BIoEx) Journal, vol. 2, no. 2, pp. 574-589, May. 2020, doi: https://doi.org/10.33258/bioex.v2i2.233.

[39] R. R. Moreira, N. A. Peres, and L. L. May De Mio, “Colletotrichum acutatum and C. gloeosporioides species complexes associated with apple in Brazil,” Plant Disease, vol. 103, no. 2, pp. 268-275, Nov. 2018, doi: https://doi.org/10.1094/PDIS-07-18-1187-RE.

[40] H. S. Kim, J. H. Jo, W. S. Kang, Y. S. Do, D. H. Lee, M. I. Ahn, H. P. Park, and E. W. Park, “MBCAST: A forecast model for Marssonina blotch of apple in Korea,” The plant pathology journal, vol. 35, no. 6, pp. 585-597, Dec. 2019, doi: https://doi.org/10.5423/PPJ.OA.09.2019.0236.