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ARAŞTIRMA MAKALESİ **RESEARCH ARTICLE**

Early Identification and Notification of Diseased Crops Using AI Powered Internet of Things Device*

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Abstract

This work seeks to contribute to the realization, by 2030, of the United Nations' Sustainable Development Goal number two: "End hunger, achieve food security and improved nutrition and promote sustainable agriculture." To contribute to the attainment of this goal, farm crops must be in a healthy state and maintained in healthy conditions. So, a round-the-clock monitoring of plant conditions is vital. There have been some plant monitoring techniques, such as the conventional monitoring technique, in which human is involved with the physical inspection of crops on farmlands. Satellite monitoring of crops has been used in some other instances but are expensive and limited to large scale farmlands. To make crop monitoring technology available to all including peasant farmers in developing nations, the adoption of convolution matrix of artificial neural network and Internet of Things (IoT) gives birth to this new approach. The developed system demonstrated high accuracy of 0.51 from the classification report obtained while detecting crop diseases and defects, collecting real-time environmental data. The macro average value of 0.56 was obtained for precision of the developed model for the 21 samples considered. Classification recall weighted average value of 0.51 and weighted f1-score of 0.49 were obtained simultaneously. For the model's hardware, key components used by the system included an IoT-based sensor network, a camera system utilizing YOLOv8 for image processing, an automated response system, and a cloud-based platform for remote monitoring. Careful assembly of these components formed a formidable remote monitoring and reporting system that seeks to ease and improve methods of plant monitoring. For the analysis of the plant leaves, a neural network processes the image, and comparisons are made with the stored feature of healthy crop leaves. Confusion and classification results showed significant potential for enhancing crop management practices, improving resource utilization, and enabling data-driven agricultural decision-making. Validation of the AI-enhanced model was carried out using field data logged in cloud by means of IoT. All these operations are displayed on a liquid crystal display unit of the model. The successful implementation of this technology serves as a model for the broader adoption of smart farming techniques, with implications for improving agricultural productivity and sustainability. While further long-term testing is recommended, this work presents a significant contribution to the field of precision agriculture, offering promising solutions to critical food crisis challenges in the world.

Keywords: IoT, SDGs, FAO, UNICEF, Crop

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1. Introduction

As of 2021, verifiable data from FAO, IFAD, UNICEF, WFP, and WHO IN 2021 shows that one out of ten people is undernourished. One out of four is overweight. Factors such as floods, drought and wars contribute to food shortage problem that is currently ravaging most of the world (Sporchia et al., 2024). Statistically, the number of people going hungry as of year 2020 was 13% higher than in 2019 due to COVID-19 pandemic and insurgencies (Katoch, 2024). Aside these natural and man-made factors that contribute to food shortage, crop infestation is another factor that is silently contributing to food shortage across the world (Harsonowati, 2024). An infested crop shows sign of disease through its leaves (Mondal et al., 2022). If this sign is not noticed on time, the disease would spread rapidly and affect the yield of the farm. To combat this menace, the manual method of farming relies on direct human visitation and observation of crops on a particular farmland (Alarcon and Marty, 2024). For instance, in Nigeria, crop monitoring is predominantly carried out through manual inspection methods, as illustrated in *Figure 1* (Adetutu et al., 2024).

This approach, while time consuming, presents significant limitations in terms of efficiency and accuracy. Farmers often rely on visual cues and personal experience to assess crop health, growth stages, and potential issues (Tessema et al., 2023). This method is tedious and impairs productivity. To improve on the manual process, modern technologies have been put into good use (Fitri et al., 2024). CNN-LSTM framework was used to automatically detect anomalies in farmland using aerial images from UAVs (Oliveira et al., 2024). The impact of using Internet of Things technology has also been useful in obtaining useful information about crops on farmlands (Zhang et al., 2024). Fuzzy adaptive priority driven algorithm has also been used to drive autonomous farm machinery to carry out other farm activities to reduce human fatigue as much as possible (Chandrasekaran and Rajasekaran, 2024). This technology makes use of advanced control techniques which requires special expertise to handle in order to put such to a maximum utilization (Che et al., 2024). Satellite-based remote sensing and drone technology have been applied with good results about the conditions of crop for better analysis (Asante et al., 2024).

As advancement in technology increases, cloud computing is of great essence to access crop data obtained from farmland. Cloud computing has served as a tool for proper monitoring of food chain activities which has enhanced farming operations (Quy et al., 2022). Cloud computing also serves as a medium which accommodates data from satellite, IoT platforms, and other electronic-based farm monitoring devices (Xin and Zazueta, 2016). Of a great advantage of cloud computing is its real-time data access capability which would make informed decisions quick and reliable. This would allow farmers to save time and increase their productivity especially with accessibility to internet (Hakimi et al., 2024). Farm managers are the happiest with this facility as more farms could be monitored instantaneously thereby saving productive time and resources (Baitu et al., 2023).

Refinement in cloud technology capacity is greatly enhanced by the confluence of several tools to bring information cheaply and timely to the farm stakeholders (Li et al., 2024). Confirmation of the success of cloud-based platform in terms of its integration with other tools has been established for the overall good of crop management (Jaramillo-Hernández et al., 2024). Also, cloud computing has facilitated knowledge-sharing amongst experts in crop and general farm operations (Aithal and Aithal, 2024). Moreso, extension workers, researchers, and field farmers have been able to have a common platform for critical deliberations and policy formulation to enhance profitability in farming activities (Kommey and Fombad, 2024).

Simplicity in terms of engaging cloud computing platform has made it accessible and usable amongst various levels of farmers via mobile devices and other internet enabled devices (Patil et al., 2023). This democratization of access to agricultural technology has the potential to significantly improve productivity and sustainability across the farming sector (Akinyuyi, 2024).

As an improvement over cloud computing, especially to connect multiple devices, this AI powered Internet of Things (IoT) device would scan and analyze the health status of crops by comparing its leaves status with a standard parameter of similar crop which has been programmed into the device using AI. The developed device scanned and transmitted such to an internet enabled device for further analysis and action. A camera is installed on the device that captures periodic images of crops and processes them using the YOLOv8 algorithm for defect, disease, and pest infestation detection. All the components are integrated using Raspberry Pi 4 as the main controller.

Figure 1. Manual inspection of crop

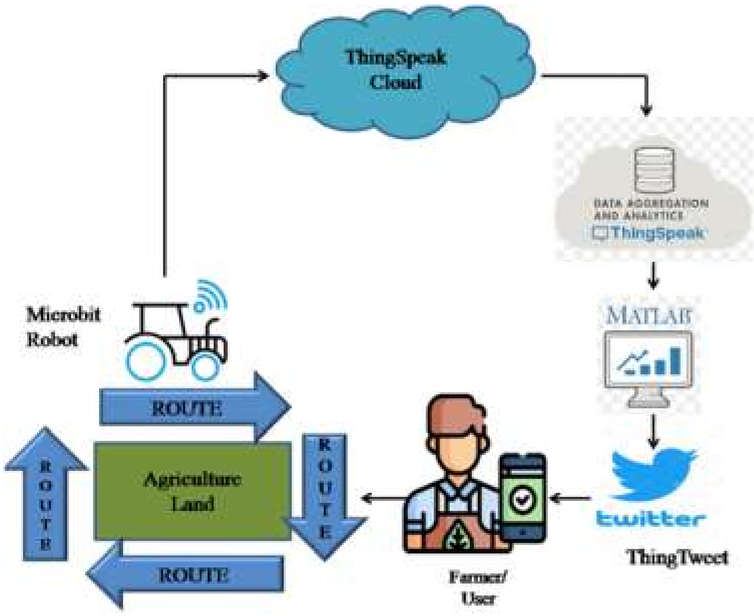

Figure 2. Cloud-based agricultural data management system

2. Materials and Methods

2.1. Image capturing process

Four key crops, such as tomato, cassava, cashew, and maize, are used to develop an effective AI model for crop monitoring and disease detection using a comprehensive dataset of collected images. This data collection process involved two primary methods:

i. Direct field photography: Researchers visited the farm and captured high-resolution images of crops in various stages of growth and health conditions. This method ensured that the dataset accurately represented the specific varieties and environmental conditions present at Obasanjo Farms.

ii. Historical image repository: The farm's existing database of crop images, which included various varieties and documented cases of diseases and defects, was also utilized. This historical data provided a broader range of examples, particularly for less common diseases or pest infestations.

Table 1 presents a breakdown of the collected image samples for each crop, categorized into healthy and diseased/infested specimens:

Table 1. Research data collection sample

Crop type	Number healthy crop samples	Diseased/Infected crop samples
Tomato	128	79
Cassava	150	86
Cashew	240	157
Maize	250	72

This diverse dataset, totaling 1162 images, provides a robust foundation for training the AI model. Including healthy and diseased/infested samples is crucial for training the model to distinguish between healthy crop conditions and samples of unhealthy crops.

Figure 3 is a display of quality of leaves used as the training samples.

Figure 3. Sample leaves for AI training

2.2. Workflow for training the samples

At this point, Artificial Neural Network (ANN) is used as the AI tool for the training of samples. The workflow involves:

i. Collection of data: crop images were taken and pre-processed by using Python.

ii. Image Annotation and Labelling: Each image in the dataset is carefully annotated and labelled to identify healthy crops, diseased areas, or pest infestations. This is the basis for learning by the developing system.

iii. Data Segmentation: The data is segmented into training, testing, and validation data in the ratio: 70:15:15

iv. Adopted YOLOv8 Model Training: The YOLOv8 (You Only Look Once version 8) algorithm was adopted for the training due to its excellent results accuracy and real-time capacity.

v. Testing: Having satisfactorily trained the network, the test data were used to test the model's overall performance.

vi. Model Deployment: Once satisfactory performance is achieved; the model is deployed on the Raspberry Pi 4 for real-time crop monitoring on the farm.

The workflow of the training algorithm is presented in *Figure 4*.

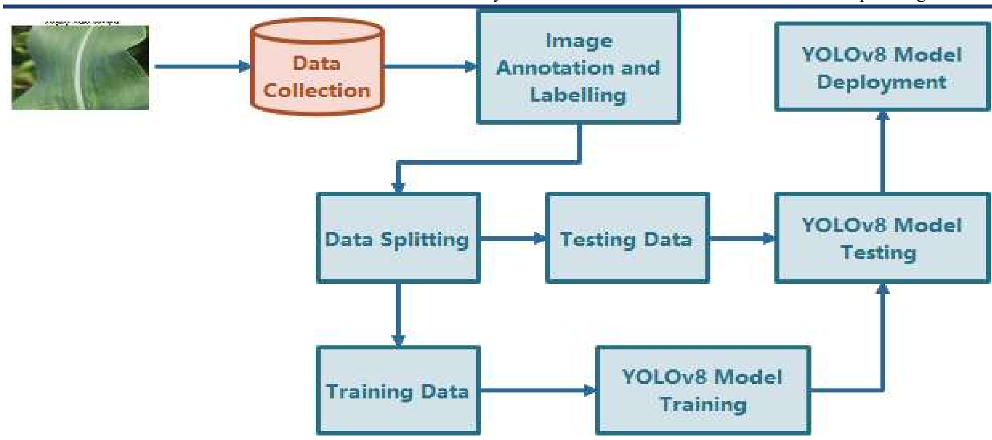

Figure 4. Training workflow of the AI model

The system circuit diagram is shown in *Figure 5*.

i. The Raspberry Pi 4 communicates with the LCD via I2C (SDA and SCL pins).

ii. GPIO pins connect the DHT11 and soil moisture sensors to monitor environmental parameters.

iii. The PICAMERA module interfaces directly with the Raspberry Pi's camera interface.

iv. L298 motor driver modules (L1 and L2) regulate pumps for precise pesticide, insecticide, and irrigation control, managed through Raspberry Pi GPIO.

v. The ESP-01 WiFi module links to the Raspberry Pi via UART, enabling internet connectivity for remote operations and data transmission.

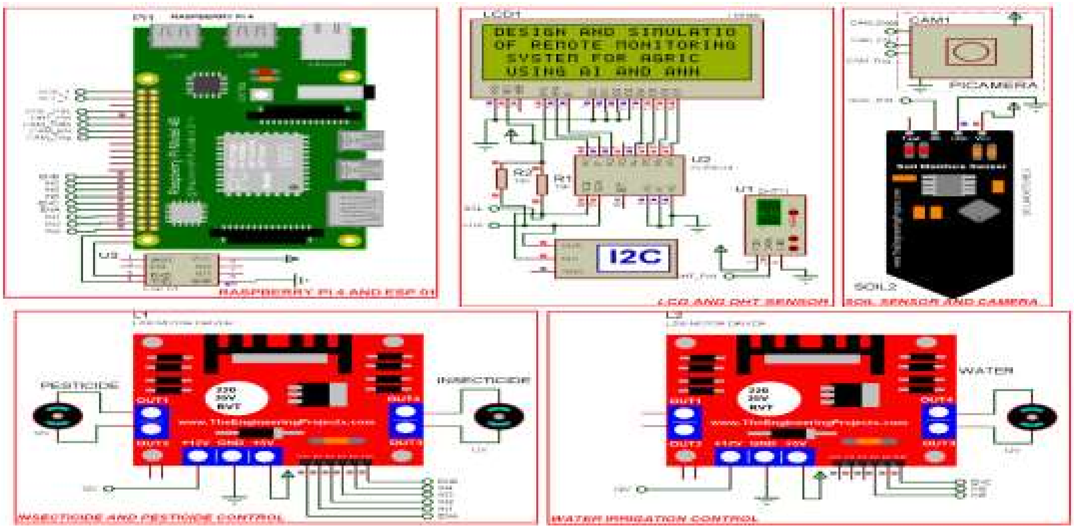

Figure 5: System circuit diagram

These hardware components collectively form a robust infrastructure supporting advanced monitoring and management capabilities enhance agricultural efficiency and sustainability. This hardware setup enables comprehensive monitoring of crop conditions, automated responses to detected crop anomalies, and seamless integration with the AI model and cloud-based management system.

3. Results and Discussion

3.1. Built model results

The deployment of built model to the farm to analyze crop images that were taken to be used to provide their status information is presented in *Figure 6*. These crop conditions are categorized and displayed accordingly.

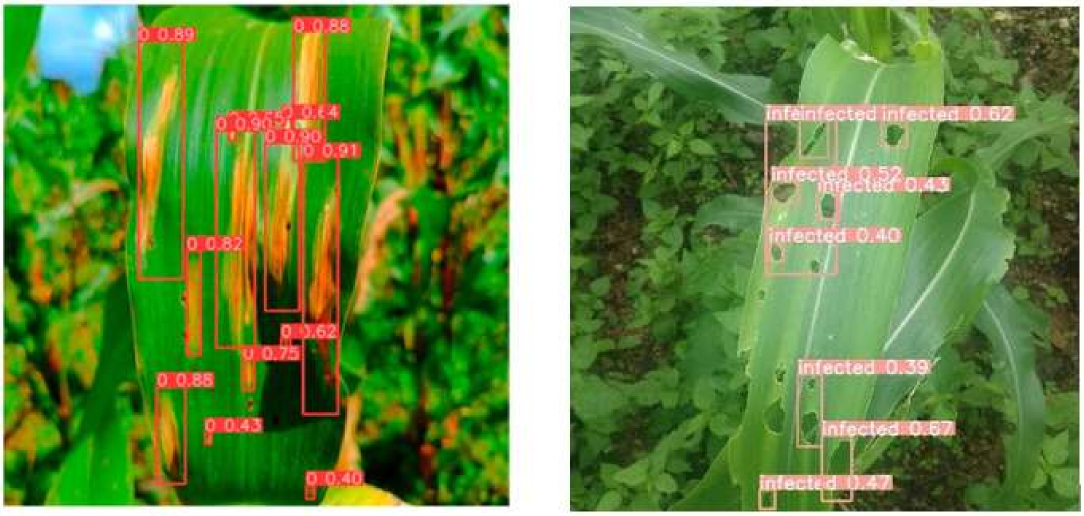

Figure 6. Detected diseased crop and classification

In order to evaluate the performance of the built model, confusion matrix and classification report were used. The global performance of the built model was evaluated using confusion matrix. The accuracy of the built model in terms of the condition of the crop and its exact prediction accuracy and errors, if any, were determined by the confusion matrix as presented in *Figure 7*. These results were then used to improve the overall performance of the built model for subsequent operations.

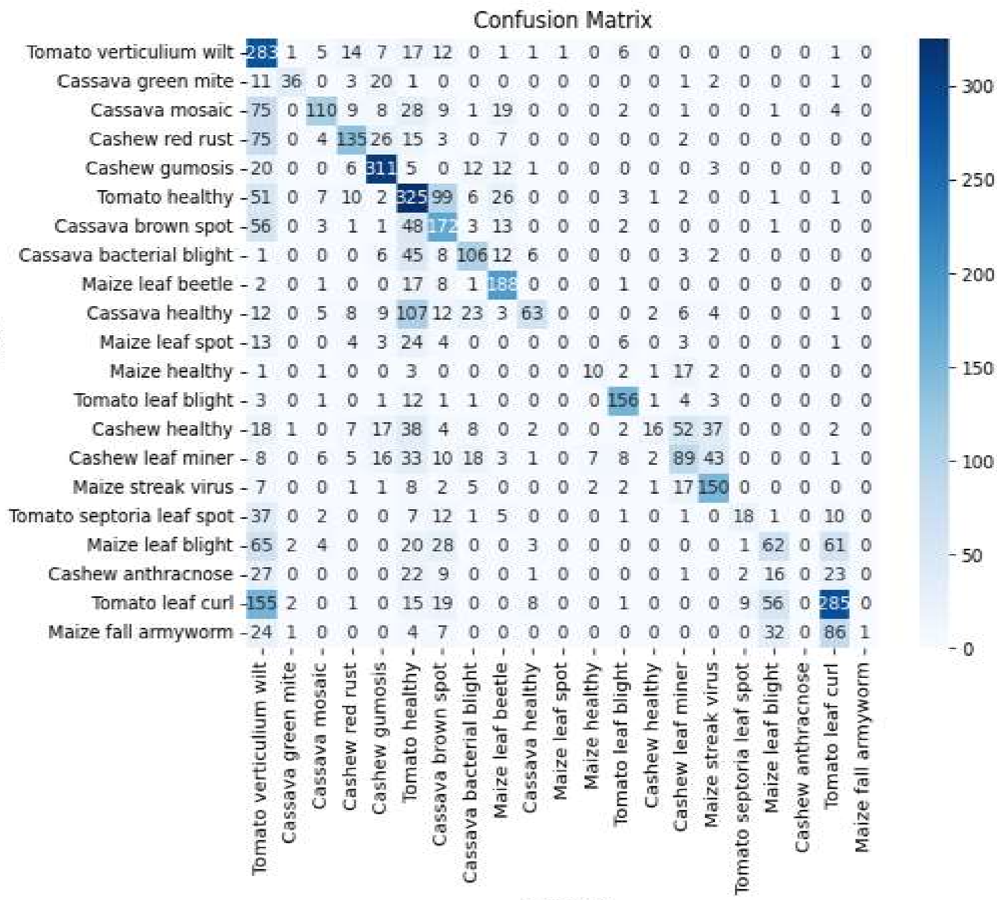

Figure 7. Confusion matrix results for the build model

Classification Report:

	precision	recall	f1-score	support
1	0.30	0.81	0.44	349
2	0.84	0.48	0.61	75
3	0.74	0.41	0.53	267
4	0.66	0.51	0.57	267
5	0.73	0.84	0.78	370
6	0.41	0.61	0.49	534
7	0.41	0.57	0.48	300
8	0.57	0.56	0.57	189
9	0.65	0.86	0.74	218
10	0.73	0.25	0.37	255
11	0.00	0.00	0.00	58
12	0.53	0.27	0.36	37
13	0.81	0.85	0.83	183
14	0.67	0.08	0.14	204
15	0.45	0.36	0.40	250
16	0.61	0.77	0.68	196
17	0.60	0.19	0.29	95
18	0.36	0.25	0.30	246
19	0.00	0.00	0.00	101
20	0.60	0.52	0.55	551
21	1.00	0.01	0.01	155
accuracy			0.51	4900
macro avg	0.56	0.44	0.43	4900
weighted avg	0.56	0.51	0.49	4900

Figure 8. Classification report of the performance of the built model

The classification report of *Figure 8* shows the performance of the built model. Precision, recall, f1-score, and backend support provided are all on display. Needed information about diseased crops are adequately captured, ready for thorough analysis that would inform decisive actions by the farm stakeholders.

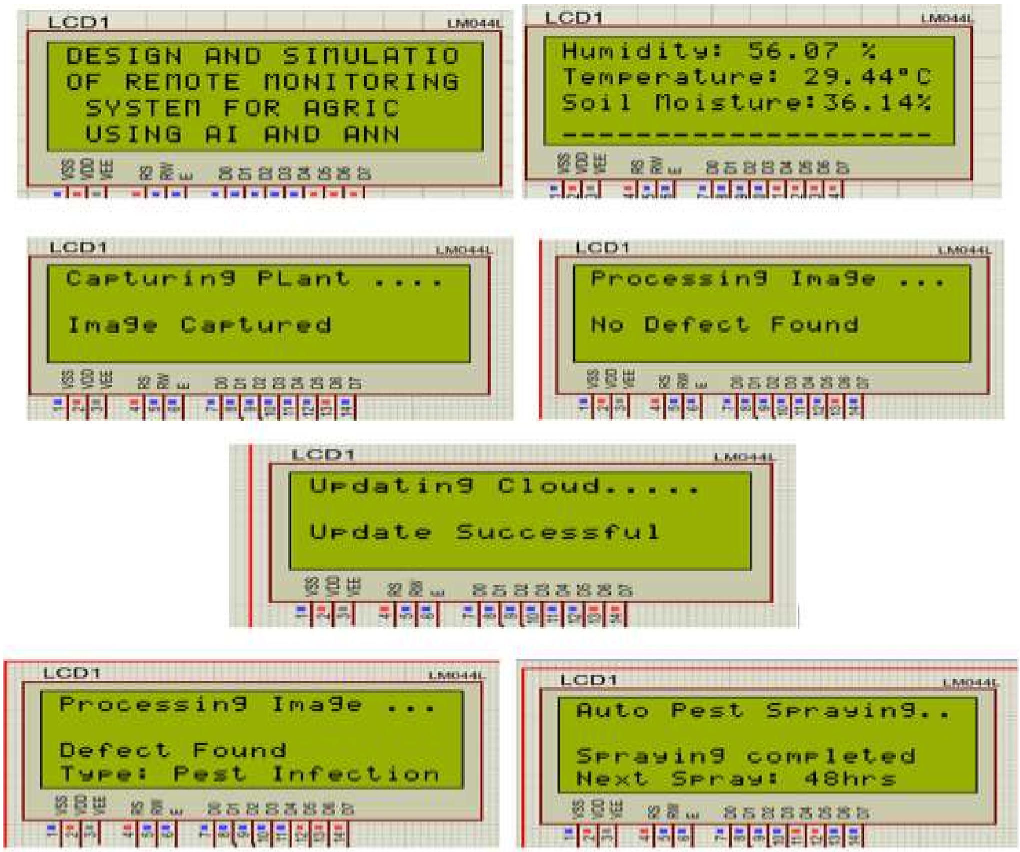

Figure 9. Device function, climatic and soil

3.1.1. Hardware system implementation results

Following the development and testing of the AI model, the hardware system was implemented and tested. The results of this phase are presented chronologically, showcasing the system's various functionalities. First, upon booting, the main function of the AI powered device was displayed followed by the farm climatic and soil information in real time as shown in *Figure 9*. Then the crucial crop images were captured and processed real-time. The functionality of this device is taken further to store the collected data into cloud for remote monitoring as well. This would provide remote access and monitoring of farm conditions. In the presence of diseased condition, the system could activate a spraying machine automatically in order to contain the situation before it escalates.

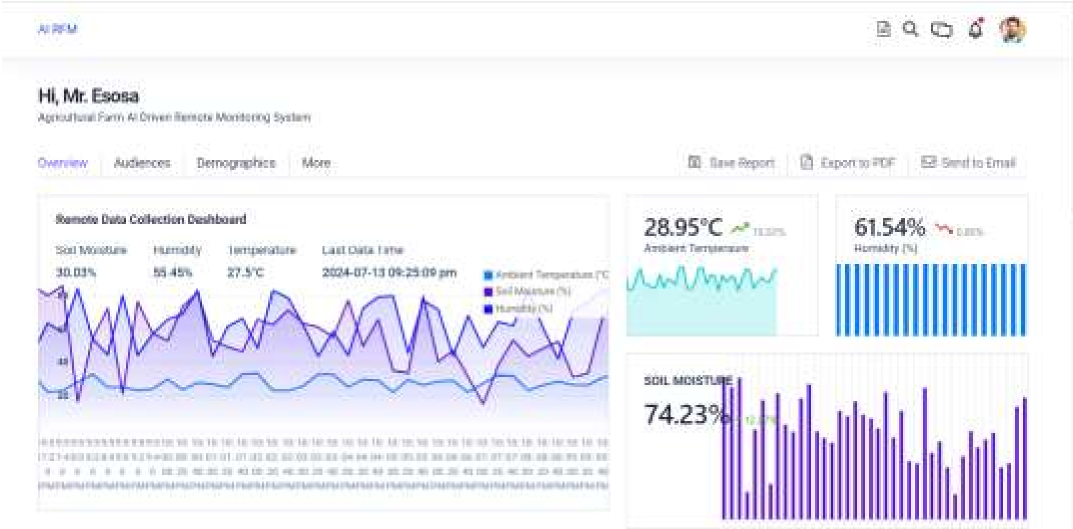

Figure 10: Remote user dashboard

The IoT is finally complete with the development of the monitoring interface having the user dashboard and data table as displayed in *Figure 10*.

To validate the AI-enhanced model results, the sample of field information obtained remotely from cloud server and used for validation, is displayed in the raw state and presented in *Figure 11*.

3.2. Discussion

The results presented demonstrate the successful development and implementation of an AI-powered IoT-based remote monitoring device for enhancing crop management on farmland. The model's ability to accurately identify and classify various crop conditions, represents a significant advancement in remote monitoring of crop conditions in real time. This capability has the potential to revolutionize the early detection of crop diseases and defects, allowing for timely interventions that could significantly reduce crop losses and optimize resource utilization. The confusion matrix and classification results provide quantitative evidence of the model's robustness across different crop conditions. Based on the results obtained, it is clear that the developed system would conveniently obtain and analyze crop data across farm locations. This is the bedrock of the progress sought over manual farm operations.

To confirm the ability of systems to be integrated with cloud computing, all networked devices worked effectively to deliver the needed results at optimal level. From the initial booting of the system to its precise reading of data in real-time, it shows that if challenges are experienced with any of the units, replacement of the defect module is all that is required and not the overall discard of the entire system. İt should be reiterated that data are updated instantaneously as new data are transmitted to the cloud server. This makes the data obtained remotely to be reliable to work with.

The instantaneous autonomous response capability of this system makes the automation of farm operations seamless. The entire system is modular and with proper integration provides easy operation, maintenance, and remote service operation as and when necessary. Overall, the results obtained from this device are promising. However, it is essential to acknowledge potential limitation in the need to subject it to a long-term field trials across different seasons and crop types. This would be beneficial to fully validate the system's reliability and effectiveness across different seasons and crops. In other words, as many crops as possible should be used to train the device to make it universal.

Remote Data Log

Search:

S/N	DATE	SOIL MOISTURE (%)	AMBIENT TEMPERATURE (°C)	HUMIDITY
1	Sat Jul 13 2024 21:29:20 GMT+0100 (West Africa Standard Time)	47.19	30.35	78.13
2	Sat Jul 13 2024 21:29:40 GMT+0100 (West Africa Standard Time)	69.09	29.46	78.79
3	Sat Jul 13 2024 21:30:00 GMT+0100 (West Africa Standard Time)	55.72	29.09	75.82
4	Sat Jul 13 2024 21:30:20 GMT+0100 (West Africa Standard Time)	85.45	29.18	52.5
5	Sat Jul 13 2024 21:30:40 GMT+0100 (West Africa Standard Time)	32.33	29.1	52.71
6	Sat Jul 13 2024 21:31:00 GMT+0100 (West Africa Standard Time)	84.49	29.02	73.4
7	Sat Jul 13 2024 21:31:20 GMT+0100 (West Africa Standard Time)	27.66	28.27	60.93
8	Sat Jul 13 2024 21:31:40 GMT+0100 (West Africa Standard Time)	27.35	22.18	72.82
9	Sat Jul 13 2024 21:32:00 GMT+0100 (West Africa Standard Time)	47.66	28.68	69.18
10	Sat Jul 13 2024 21:32:20 GMT+0100 (West Africa Standard Time)	27.28	28.93	79.45

Figure 11. Field data as logged on cloud server for AI-enhanced model validation

4. Conclusions

The built system has been able to obtain crop data from farmland, process the data, and transmit the results to the cloud for the usage of the stakeholders. Decisions and immediate actions taken to protect crops from avoidable catastrophe due to infestation. Furthermore, the system is simple to assemble being modular in nature with inherent advantages in terms of maintenance, upgrade, and software update as and when necessary. Stakeholders have access to real-time data via mobile devices and other internet-enabled devices from where prompt and concise information and decisions are taken. This saves crops from widespread infestation and boost food production in the short and long term. However, long-term field testing of the built system is necessary to fully validate its effectiveness across diverse agricultural crops and weather conditions. At the moment, results obtained, thus far, indicate that this AI-driven, IoT-based device presents a significant step forward in the field of precision agriculture. The successful implementation of this technology at a pilot farm is a promising model for the broader adoption of smart farming techniques, potentially contributing to enhanced food security and sustainable agricultural practices. This step is in the right direction towards the realization, by 2030, of the United Nations' Sustainable Development Goal number two: "End hunger, achieve food security and improved nutrition and promote sustainable agriculture."

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Ethical Statement

There is no need to obtain permission from the ethics committee for this study.

Conflicts of Interest

We declare that there is no conflict of interest between us as the article authors.

Authorship Contribution Statement

Concept: Adewuyi, P.; Data Collection or Processing: Ojo, K.; Statistical Analyses: Adewuyi, P.; Literature Search: Adewuyi, P., Ojo, K.; Writing, Review and Editing: Adewuyi, P.

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