Research Article

Design and Implementation of Smart Hydroponics Farming Using IoT-Based AI Controller with Mobile Application System

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Hydroponics is the soil less agriculture farming, which consumes less water and other resources as compared to the traditional soil-based agriculture systems. However, monitoring of hydroponics farming is a challenging task due to the simultaneous supervising of numerous parameters, nutrition suggestion, and plant diagnosis system. But the recent technological developments are quite useful to solve these problems by adopting the artificial intelligence-based controlling algorithms in agriculture sector. Therefore, this article focuses on implementation of mobile application integrated artificial intelligence based smart hydroponics expert system, hereafter referred as AI-SHES with Internet of Things (IoT) environment. The proposed AI-SHES with IoT consists of three phases, where the first phase implements hardware environment equipped with real-time sensors such as NPK soil, sunlight, turbidity, pH, temperature, water level, and camera module which are controlled by Raspberry Pi processor. The second phase implements deep learning convolutional neural network (DLCNN) model for best nutrient level prediction and plant disease detection and classification. In third phase, farmers can monitor the sensor data and plant leaf disease status using an Android-based mobile application, which is connected over IoT environment. In this manner, the farmer can continuously track the status of his field using the mobile app. In addition, the proposed AI-SHES also develops the automated mode, which makes the complete environment in automatic control manner and takes the necessary actions in hydroponics field to increase the productivity. The obtained simulation results on disease detection and classification using proposed AI-SHES with IoT disclose superior performance in terms of accuracy, F-measure with 99.29%, and 99.23%, respectively.

1. Introduction

IoT in agriculture might be a game changer for humans and the whole planet [1]. We are now seeing how harsh weather, eroding soil, drying areas, and collapsing ecosystems make food production more difficult and costly. Meanwhile, we are not getting any fewer. According to a well-known forecast, there would be more than 9 billion people in 2050. Fortunately, owing to quickly emerging technology and IoT applications [2] for smart farming, there is still hope. According to

analysts, this industry will reach 23.14 billion US dollars by 2022, with 75 million IoT devices implemented for agricultural applications in the following several years. The Internet of Objects is all about making "dumb" things "smart" by linking them to one another and to the Internet. It permits the remote sensing and control of physical things, allowing for more direct integration of the real world with computer-based systems [3, 4]. IoT allows devices equipped with sensors to communicate and interact with one another via the Internet. Pumps, barns, and tractors, as well as weather stations and computers, may all be remotely monitored and operated in real time. Agriculture is the only source for food production in many countries including Ethiopia, India. It is a wealthy industry, but over the years, people and work force involved in this industry are reducing drastically. The traditional farming face lots of challenges for increasing the productivity [5]. Some of the challenges in rural areas are the global climate changes, pollutions, loosing soil integrity to grow the crops, rapid increment in urbanization, and agricultural land sacristy etc.. Therefore, farmers need to employ smart farming as shown in Figure 1, which can help in increasing the food yield production [6]. In addition, these new methods of farming along with traditional farming methods need some technological backing to counter global food crisis. To meet these challenges, it is necessary to adopt new technologies in farming like hydroponics, vertical forming, and polyhouse. Among those, the hydroponics is the best farming method, which directly involves with the technological requirements.

Some of the problems presented in the hydroponics are seedling (wilting, dead roots), system clogging, infestation (algae, pest), and nutrient deficiencies [7]. Because seedlings are susceptible to issues when they are in the beginning stages of their development, one of the most difficult tasks in the process of producing plants in hydroponics is cultivating healthy seedlings. Wilting occurs when a plant loses its stiffness, and its leaves begin to dry up. Wilting may be caused by a number of circumstances, including insufficient watering or extreme temperature [8]. There are a variety of factors that may contribute to dead roots, including the water's high temperature, a very high or extremely low EC, and over watering in thick substrates. Roots that have died might be an indication that a root rot pathogen is present in the system. It is generally agreed that clogging is the issue that arises most commonly in hydroponic systems, and this is particularly true for drip-style systems. The majority of the time, the tubes get clogged as a result of fragments of the growth media that become lodged inside of them. The circulation of the whole system is disrupted when there is clogging, which may cause significant harm to your crops. There is no way for producers to completely eliminate the risk of infection in hydroponic farms, no matter how well they manage their operations. During the early stages of an infestation, there are a few actions that you may do to combat the problem. In most cases, a grower will be able to identify a specific nutrient deficit by evaluating the symptoms, but this method is not fool proof and may occasionally lead to incorrect conclusions [9]. Checking the water temperature, pH of the nutrient solution, and electrical conductivity of the solution should come first before determining whether or not there is an issue.
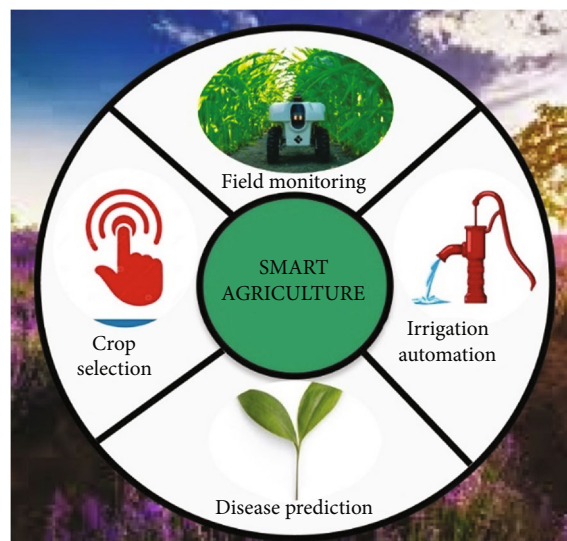

FIGURE 1: Sample illustration of smart farming.

Recently, AI-based autonomous robots with a variety of hardware controllers and industrial robots are playing the key role in hydroponics for minoring of plants [10]. However, they are failed to monitor the multiple sensors at the same time to solve the above-mentioned problems. Another major challenge presented in the traditional farming and hydroponics is the plant diseases, which affect the growth of plants and thereby reduce the productivity. Traditionally, either farmers are manually classifying the diseases or pathologist are identifying the disease through lab experiments. However, the performance of traditional systems is purely depending on their experience, and it also a time-consuming task [11, 12]. Further, the early detection and prevention of plant diseases can improve the hydroponics performance. Therefore, recently, image processing-based computer aided methods are widely developed for benefit of the farmers. Thus, image processing technologies for early detection and diagnosis is preferred [13], which is done by using color feature extraction, texture extraction, and shape feature extraction. To overcome these problems, the major contributions of these works are illustrated as follows:

(i) Design and implementation of AI-SHES by integrating Raspberry Pi controller, IoT environment with mobile application

(ii) Implementation of user-friendly environment for farmers using Agri-Hydroponic application, which provides hybrid monitoring and controlling of hydroponics farm field

(iii) Development of IoT based cloud environment for global monitoring of sensor data

(iv) In addition, an AI framework is implemented for alerting, and predictive analytics of sensor data, and plant diseases

Rest of the article is organized as follows: Section 2 deals with the literature survey with problems. Section 3 deals

with the detailed implementation of proposed AI-SHES. Section 4 deals with the detailed analysis of experimental results. Section 5 deals with the conclusion and future scope.

2. Literature Review

This section deals with the detailed analysis of existing methods with the drawbacks. In [14], the authors developed the Internet of Everything (IoE), which is considered a modern platform for advancement of IoT. This system considered the advanced soil sensors for monitoring the crop field. However, the proposed system conserves higher energy and decreases the efficiency, while calculating the heat index of the parameters to observe the surrounding for growth of crops. Further, efficient management of irrigation system (EFIS) [15] is developed for automatic water controlling to avoid the water sacristy problems in Ethiopia, Kenya, and South Africa countries. This work jointly monitors the soil conditions with water levels. However, this system reduces the current intake of the parameters and reduces the data transmission range of the system. Further, a machine learning model known as support vector machine (SVM) [16] is developed for plant disease classification along with the sensor data. In this model, a camera model equipped controller is designed with moisture, color, texture, humidity, and temperature of the leaf. However, this method suffers with the high computational complexity. In [17], authors focused on implementation of calculational intelligence technique for prediction and utilization of nitrogen in wheat crops. The calculation depends on the analysis of image of crops, which are captured the image in the real time field with different time samples and different lighting conditions. Further, artificial neural network with genetic algorithm (ANN-GA) is used to classify the plant diseases. However, this method suffers with the low classification accuracies. Further, MicConvNet [18] classifier is developed for red palm weevil larvae detection in initial stage for protection of date trees. This detection system consists of based on a modified mixed depth wise convolution network. Anyhow, this method did not implement the IoT environment due to complexity issues. Further, hybrid convolutional neural network (HCNN) [19] is trained with dual image database. The database consists of previously infected images, which is used for training the database for such diseases. Secondly, texture, color, and morphology features are extracted from image. However, this method consumed higher training time for feature training.

In [20], the authors integrated the deep learning with IoT for automatic disease identification from plants. The IoT is used for remote sensing of field parameters storage, with modified ResNET51 model which was used on the cloud for purpose of building smart disease detection. This method suffers with the low classification performance. In [21], the authors developed the mobile application, which displays the sensor values in efficient manner by administrating the field. Further, IoT is used to store the disease affected region with specific classes. Further, DeepLens [22] variations are introduced for continuous monitoring of data with ubiquitous access and reliability, which is accessed by cloud data integrating with recursive CNN classification. The RCNN is used to identify the condition of leaves of fruit trees and vegetable plan. However, this method is not useful for diagnosis of hand full of plants and trees diseases detection. In addition, AI and IoT enabled smart agriculture technologies' [23] system is developed with decision tree classification. The data from the hardware is processed by AI, which contains valuable data for prediction of the all the parameters of crop. However, this method suffering with power related issues in real time environment. In [24], the authors implemented the AI-based agriculture system with IoT environment, and this method gives the feedback to farmer for ideal maintaining of the crop production. The AI system utilizes fuzzy logic for predicting types of crop type, soil integration and weather conditions. In [25], the authors implemented the hydroponic automation system for plant growth analysis from seed stage to yield stage. Further, ESP32 microcontroller is used for controlling of different sensors and actuators. Further, LOTUS mobile application was updated with humidity, irrigation, and temperature monitoring. However, this method is a high computational complexity. In [26], the authors implemented the hybrid system with multiple monitoring parameters such as nutrient level, pH, and temperature of the water. Further, K-Nearest Neighbor– (KNN–) based machine learning approach is used to automate these parameters according to reference water levels generated by nutrient film technique. However, this method has low reliability and efficiency as compared to deep learning models.

3. Proposed Methodology

This section gives the detailed implementation analysis of AI-SHES, which is developed by integrating the Raspberry Pi, IoT environment with mobile application. Figure 2 shows the architecture of proposed AI-SHES. An AI-SHES is developed with the user-friendly environment for farmers using Raspberry Pi controller, IoT environment with Agri-Hydroponic application. The farmers monitor and control their hydroponics farm field using Agri-Hydroponic application with manual and automatic controlling modes of operation. The Raspberry Pi controller-based hardware system is placed in hydroponics farm field, which monitors the statics of plants using different sensors. Further, all these sensors' data is uploaded into cloud based IoT environment. An artificial intelligence system is placed across the cloud served with DLCNN, which continuously monitors the sensor data and plant disease status and sends the necessary alerts to the farmers using Agri-Hydroponic application. Finally, the farmer controls his hydroponics farm field during manual mode, so nutrients are supplied to plants as per farmer mentioned levels. In addition, the nutrients are applied to plants with standard reference levels during automated mode of operation.

3.1. Hardware Environment. The proposed AI-SHES implemented with the Raspberry Pi controller with the different types of sensors. Figure 3 shows the hardware environment of proposed AI-SHES. This environment uses different
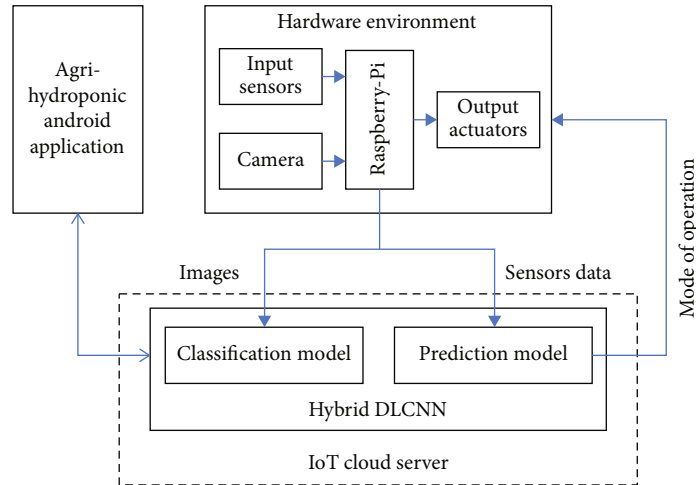
Figure 2: Proposed architecture of AI-SHES with IoT.

sensor for analysis of different parameters in the hydroponics farming methods. The proposed AI-SHES controls the parameters such as temperature, water level, water with nutrient considered fresh water, excessive sunlight, drain water, and cooler for temperature reduction.

Further, sensor values are continuously updated in IoT-based cloud environment. Here, the grove sunlight sensor is used for analysis of sunlight, which generates the parameters of light in the sun rays such as IR rays, UV rays, and visible rays. These sensor parameters can used to determine the amount of photosynthesis taking place inside the leaf of the plant. The SHT-20 sensor is used for parameters such as temperature and humidity of atmosphere. In hydroponics farming, it is important to measure the minerals present in water continuously, because the nutrients are supplied to the plant's trough the water only. Therefore, the hardware environment of hydroponic system requires the greater number of water sensors. The DS18B20 waterproof probe sensor is used to measure the water temperature. Further, SEN0161 water sensor also used for extracting the P_H levels such as acidic and basic nature of the water. Then, WQ730 turbidity sensor is used to extract the turbidity of water. Further, NPK sensor is used to measure the amount of nitrogen, phosphorus, and potassium levels present in water, which acts as an alternative to soil moisture sensor. In addition, hydrostatic pressure level sensor also used for measuring the different water levels. Additionally, camera modules capture the images of plants with the specified time scale.

Finally, the Raspberry Pi receives all sensor values and images and sends these data to the DLCNN model of cloud server. Here, the Prediction-DLCNN model is effectively used to identify the nutrient deficiency of plants, which predicts the standard nutrient levels through comparison with trained reference levels. The plants also suffer with the different types of diseases due to nutrient's deficiency, so it is necessary to identify the plant diseases in early stage. Therefore, the Classification-DLCNN model is used to identify the different types of plant diseases form the camera captured images. Finally, the DLCNN model sends this information to the Agri-Hydroponic application, where the farmer

selects the mode of operation. Finally, the farmer controllers his hydroponics farm field during manual mode, so nutrients are supplied to plants as per farmer mentioned levels. In addition, the nutrients are applied to plants with standard reference levels during automated mode of operation. Further, the Raspberry Pi controllers control the output actuators (devices) based on the mode of operation generated by DLCNN environment. Therefore, the output devices such as motor and pump are controlled by this mode of operation directly from the mobile application. Here, two different pumps are used for pumping nutrient water and normal water, and they are supply water to plants till all the minerals and nutrients are observed. Further, heater output device is used to control water and air temperature inside the hydroponics structure. In addition, motors are used to regulate the sunlight intensity by controlling the outer environment of farm field.

3.2. AI-Based IoT Cloud Server.
The AI-SHES system contains two DLCNN models named as Prediction-DLCNN and Classification-DLCNN, which are placed at the cloud server. Here, the Prediction-DLCNN model is used to estimate the perfect nutrient levels based on reference values. Further, the Classification-DLCNN model is used to identify the different types of plant diseases. In addition, the operation of both models was performed in a parallel manner and updates the values to the farmer through mobile application. Figure 4 presents the architecture of Prediction-DLCNN. Here, input feature matrix is generated by concatenating the sensor data. Initially, the sensor data is monitored in the hydroponics filed during different environment conditions. Then, the Raspberry Pi controller controls this data and transfers to IoT cloud. Then, the Prediction-DLCNN models take these sensor data as test input. The DLCNN model is trained with the reference nutrient dataset, where the dataset contains the perfect nutrient levels according to the different sensor conditions. The dataset is formed in different environmental conditions, so the Prediction-DLCNN model perfectly estimates the new nutrient values for every combination of sensor data in all atmospheric conditions.
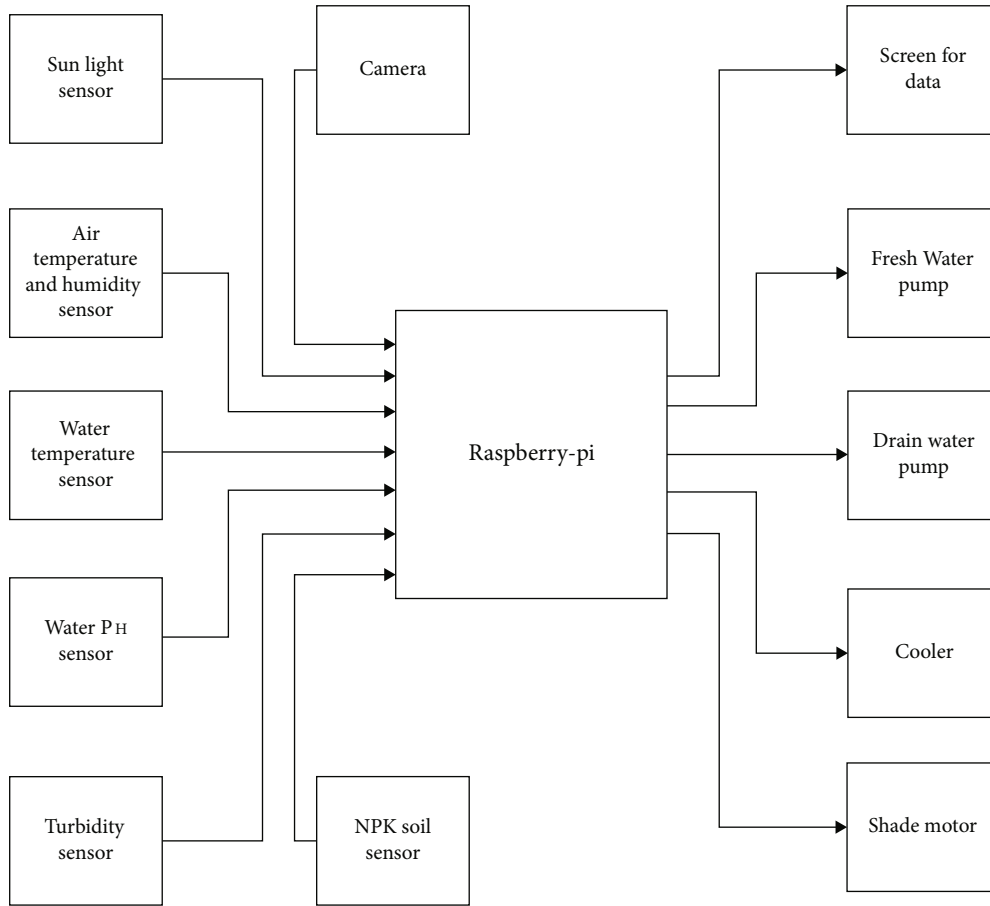
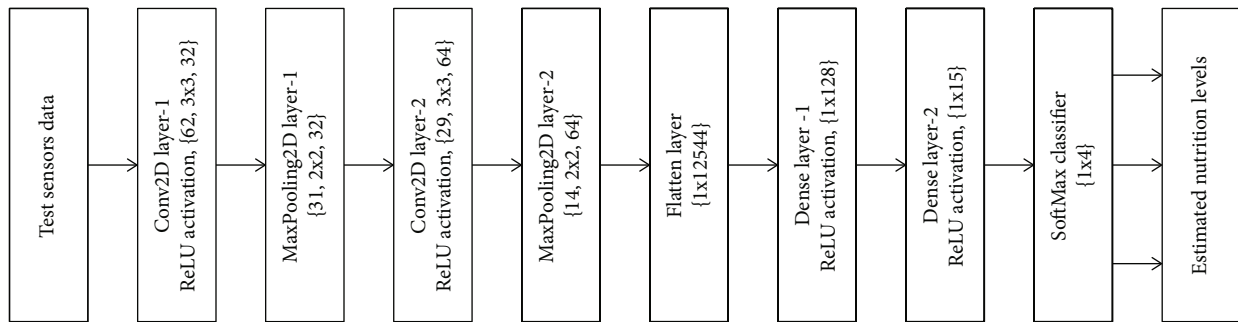FIGURE 3: Hardware environment of AI-SHES system.

FIGURE 4: Architecture of Prediction-DLCNN model.

Figure 5 shows the architecture of Classification-DLCNN model, and Table 1 lists the description of layers employed in this architecture. The images captured in hydroponics filed are updated into IoT cloud through Raspberry Pi controller, and the same images are applied as input Classification-DLCNN model. The plants are suffering with different types of diseases due to nutrient deficiencies and disease attacks. Therefore, the proposed Classification-DLCNN model is capable of identifying the different types of diseases presented in plant images. Further, these disease classes and sensors' data monitored during test image captured time are applied as input to the Prediction-DLCNN

model. Now, the Prediction-DLCNN model estimates the new nutrient values based on input data. Finally, these information transfer to the farmer through Agri-Hydroponic application.

3.3. Agri-Hydroponic Application. The farmers monitor the sensor data and plant images continuously through the Agri-Hydroponic application. Further, the farmers can control the different types of motors, actuators, and output devices placed in the hydroponic farm field using Agri-Hydroponic application as shown in Figure 6. In order to provide the security to the famers data, the application is
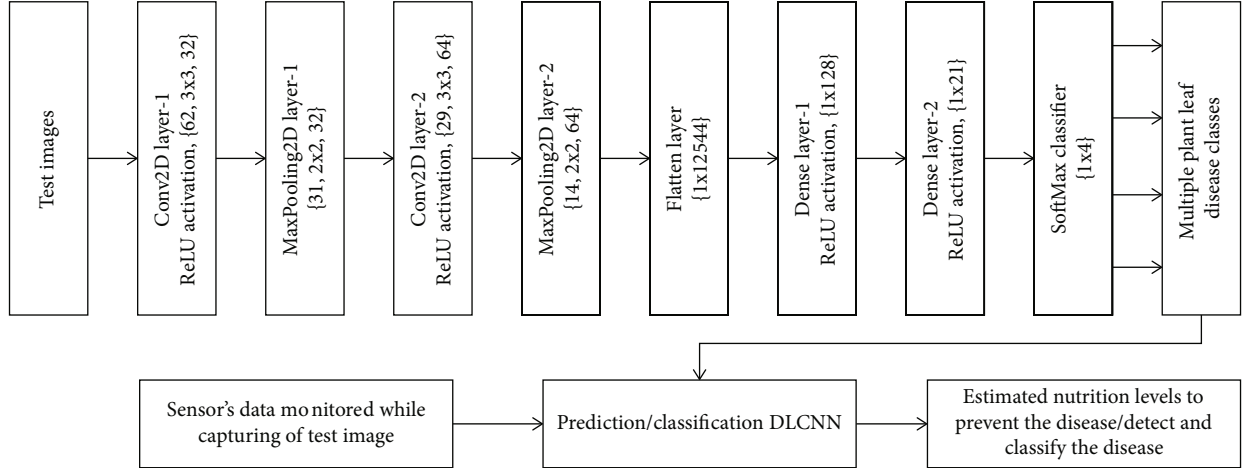
Figure 5: Proposed Classification-DLCNN model.

Table 1: Layer-wise analysis of Prediction-DLCNN and Classification-DLCNN models.

Layer name	No. of filters	Filter size	Feature size
Conv2D-1	32	3x3	62x62
MaxPooling2D-1	32	2x2	31x31
Conv2D-2	64	3x3	29x29
MaxPooling2D-2	64	2x2	14x14
Flatten	—	—	1x12544
Dense-1	—	—	1x128
Dense-2	—	—	1x15
SoftMax	—	—	1x4

developed with login page as shown in Figure 6(a). Therefore, intruders cannot control the field and cannot access the application. The RSA- and SHA-based hybrid security protocols are used in the application for maximum security. After successful login, the farmer can monitor and control the field using "plant disease prediction," "farm sensor data," and "farm controlling" buttons as shown in Figure 6(b). In the "farm sensor data" page, the different types of sensor data (water level, water turbidity, water pH UV light, visible light, IR light, air temperature, and water temperature, nitrogen, phosphorus, and potassium levels) are displayed as shown in Figure 6(c). The farmers can select the zone of hydroponics farm, which is divided into many sectors according to plantations. Therefore, the data is displayed based on average of all zones, whereas the farmer can also monitor individual zone-specific information. Further, the "farm controlling" operation is performed in two modes of operation such as automatic and manual modes as shown in Figure 6(d).

The farmers can control the devices presented in hydroponic filed during manual mode through Raspberry Pi controller as shown in Figure 6(e). Here, UV light, visible light, and IR light-based sunlight parameters are improper; then, the motors control the poly-cloth placed at the hydroponic

farm. So the poly-cloth will regulate the light intensity by multiple layers. Further, air conditioner is manually controlled from the application based on air and water temperature levels. In addition, moisture inside the farm field also controlled based on humidity of the atmosphere. Moreover, the nutrient water supplied to plants also controlled by the drain water and freshwater motors based on nitrogen, phosphorus, and potassium mineral levels. All these input sensor data are monitored, and output devices are controlled automatically by Raspberry Pi controller during the automatic mode selection by the farmer in the application as shown in Figure 6(f). The farmers can also monitor the diseases presented in the plants during "plant disease classification page." The Classification-DLCNN model classifies the type of plant diseases and transfers to the "plant disease classification page" as shown in Figure 6(g). Here, the farmer can manually capture the images by his own, and Classification-DLCNN model identifies the disease. Finally, the selected action (mode) of farmers is sent to the Raspberry Pi controller to control output devices though IoT cloud server.

4. Results and Discussion

This section gives the experimental and simulation results of proposed AI-SHES with IoT system. In addition, it also provides the performance of proposed Prediction-DLCNN and Classification-DLCNN models compared to the state-of-the art approaches using standard nutrition and plant leaf datasets.

4.1. Dataset Description

4.1.1. NUOnet (Nutrient Use and Outcome Network). This dataset is collected by Agricultural Collaborative Research Outcomes System (AgCROS), which is a publicly available dataset. The most effective methods of nutrient management are very necessary for ensuring successful economic returns, preserving greater yields, minimizing negative effects on the environment, maximizing nutritional quality, and delivering
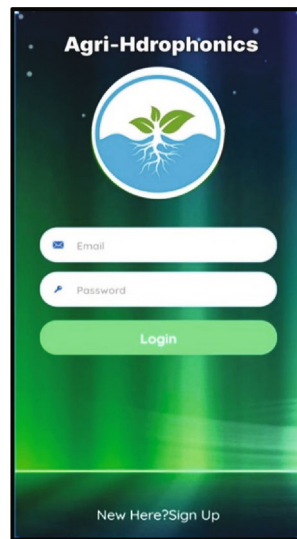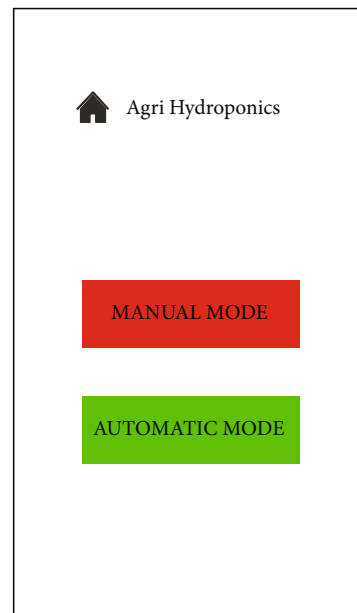
(a)
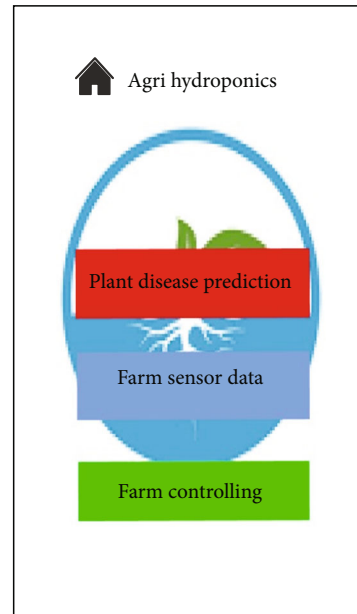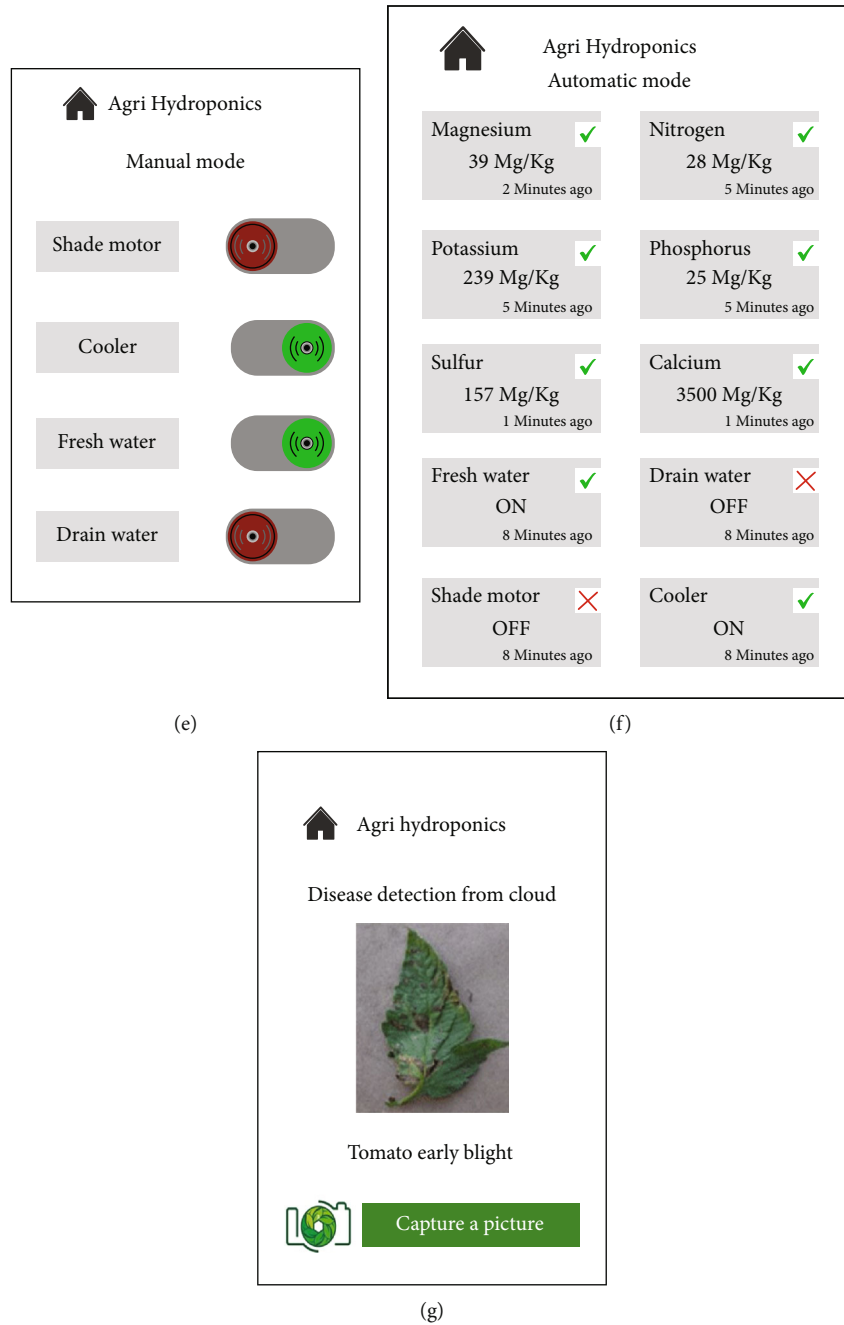
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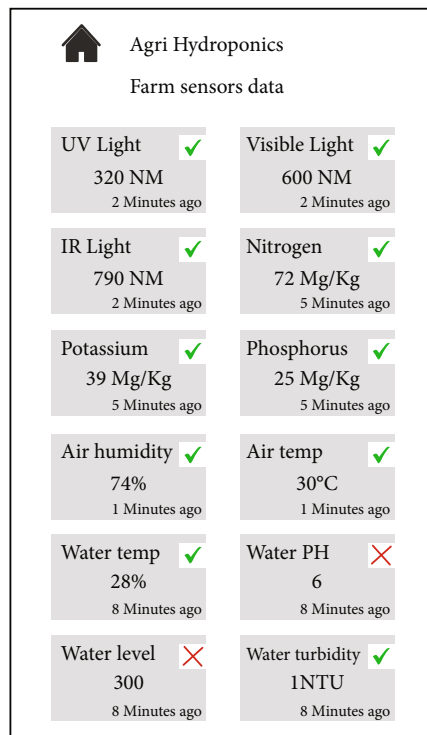
(c)

(d)

FIGURE 6: Continued.

(e)

(f)

(g)

FIGURE 6: Agri-Hydroponic application options. (a) Login page. (b) User-access menu. (c) Sensor data. (d) Modes of operation. (e) Manual mode controlling. (f) Automatic mode controlling. (g) Plant disease classification page.

ecosystem services. Nutrient losses from agricultural systems may be reduced by using best management practices, which are techniques that increase the efficiency with which nutrients are used. This collection includes crop composition data derived from investigations that were carried out over the course of a number of years in sites all over the globe. The information that it carries offers some understanding of the inherent variation that exists in the nutritional profile of hydroponic crops.

4.1.2. PlantVillage Dataset. PlantVillage is a well-known and extensively used database that can be accessed without cost

and is used for the training and testing of CNN models. Additionally, the database is frequently utilized. The Plant-Village collection has 20798 color leaf photos with a constant background. Additionally, the collection contains 19 crop-disease pairs. To accomplish the prediction and classification objective of this study, the given dataset is partitioned into train, test, and validation subsets using an 80-10-10 splitting ratio. As a result, there are a total of 16638 images in the training set (i.e., 80% of available dataset), 2130 images for training (i.e., 10% of total dataset), and another 10% for validation. Normalization was considered by dividing the pixel values by 255. This was done to make
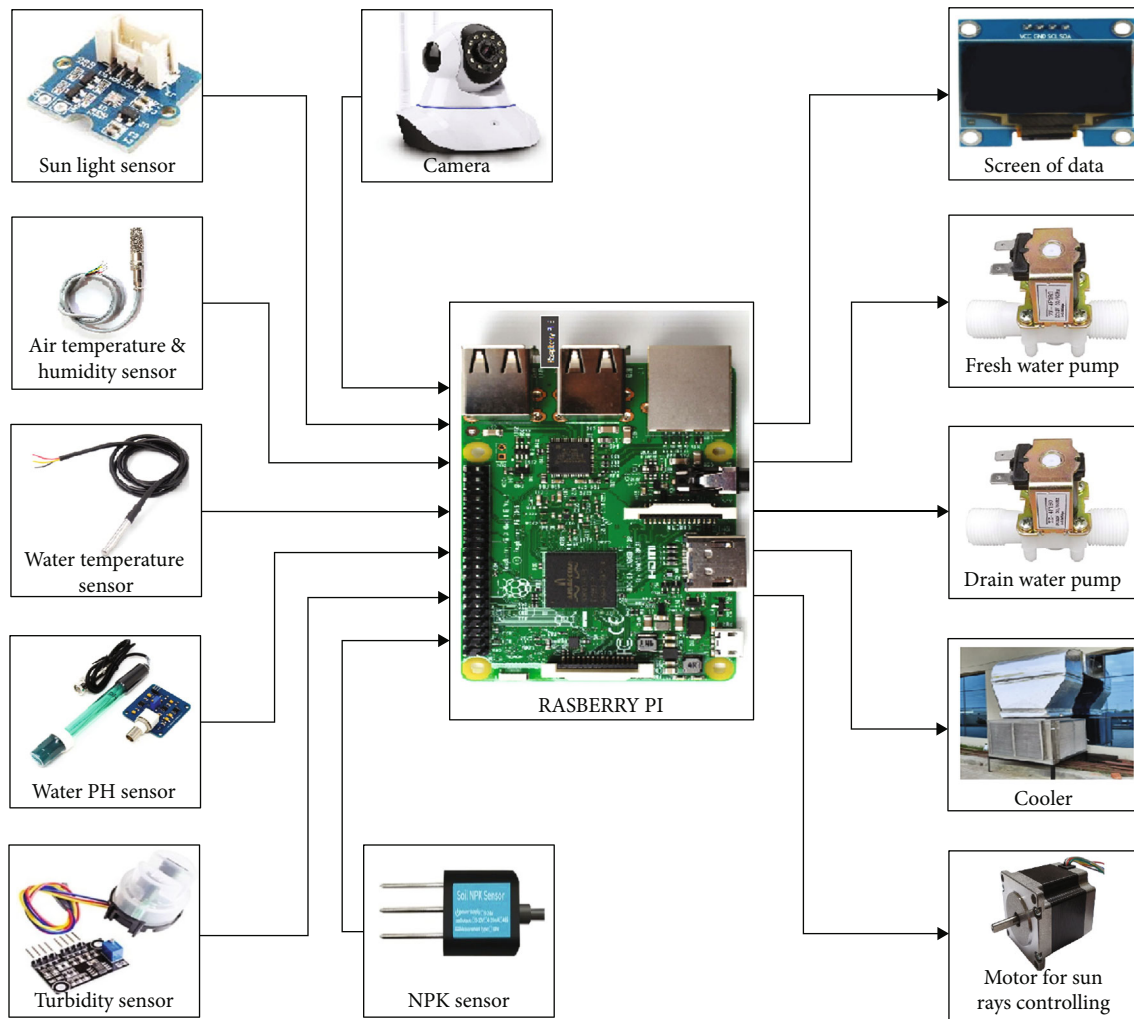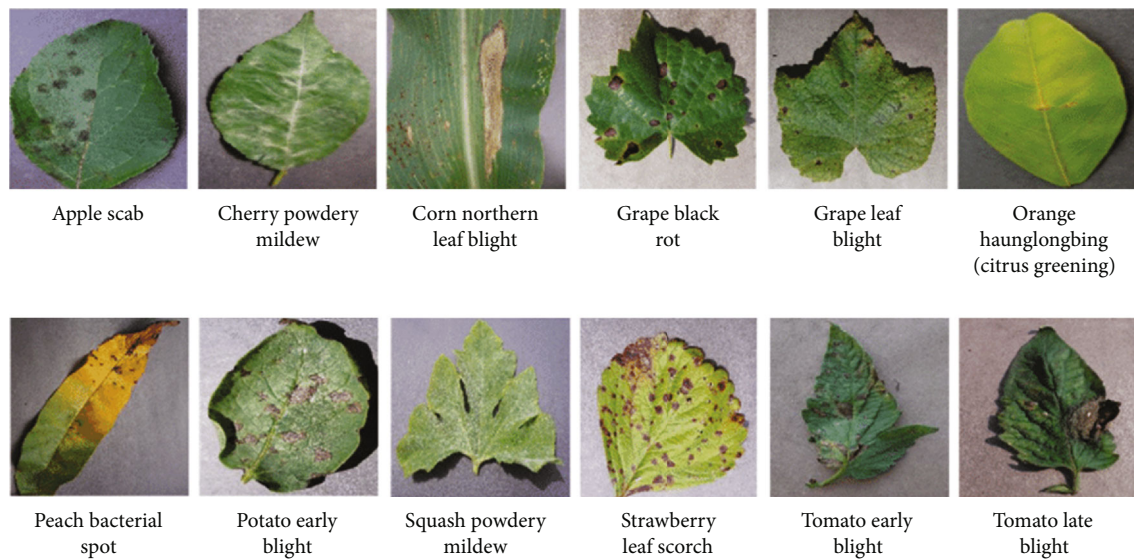
FIGURE 7: Hardware setup.

FIGURE 8: Classified plant diseases using DLCNN.

TABLE 2: Prediction-DLCNN response.

	Devices	Sample 1	Sample 2	Sample 3
	Sunlight	HIGH	LOW	LOW
	Air temperature (°C)	38	30	28
Sensor data	Water temperature (°C)	32	28	30`
	pH	6	8	7
	Turbidity (%)	80	30	40
	NPK	72	65	80
	Nitrogen (mg/kg)	25	26	31
	Phosphorus (mg/kg)	39	40	42
Predicted nutrients	Potassium (mg/kg)	41	50	36
	Magnesium (mg/kg)	157	142	138
	Sulphur (mg/kg)	3500	3150	3420
	Calcium (mg/kg)	ON	OFF	OFF
	Fresh water pump	OFF	ON	ON
	Drain water pump	ON	OFF	OFF
Output actuator action during automatic mode	Cooler	ON	ON	OFF
	Motor	HIGH	LOW	LOW

TABLE 3: Performance estimation of Prediction-DLCNN model.

Method	Accuracy (in %)	Precision (in %)	Recall (in %)	F-measure
EFIS [15]	90.898	92.514	90.355	91.673
SVM [16]	92.960	94.117	91.518	93.234
MicConvNet [18]	93.264	95.515	92.885	94.596
RCNN [23]	94.599	96.889	93.614	95.845
Prediction-DLCNN	99.82	98.64	99.937	99.283

TABLE 4: Performance estimation of Classification-DLCNN.

Method	Accuracy (in %)	Precision (in %)	Recall (in %)	F-measure
KNN [13]	89.28	88.384	88.24	83.484
ANN-GA [17]	90.898	92.514	90.355	91.673
HCNN [19]	92.960	94.117	91.518	93.234
ResNET51 [20]	93.264	95.515	92.885	94.596
Prediction-DLCNN	99.297	99.382	98.58	99.237

the images more acceptable for the beginning values of the models, which was accomplished by dividing the pixel values by 255. The images were resized to a size of $224 \times 224 \times 3$ pixels, and their dimensions were changed to reflect this. Rice brown spot, rice healthy, rice leaf blast, rice leaf blight, pepper bell healthy, and pepper bell bacterial spot are all included in this dataset. Tomatoes may be susceptible to a variety of pests and diseases, including the tomato healthy disease, the tomato mosaic disease, the tomato yellow leaf curl disease, and the tomato target spot disease.

4.2. Hardware Setup. Figure 7 shows the hardware setup of proposed AI-SHES with IoT, which is working model and integrated with Raspberry Pi controller with sensors, cloud server, and Agri-Hydroponic application. Here, the sensors placed in different zones of field are controlled by Raspberry Pi; then, these data are transferred to the laptop equipped cloud server. Magnesium and calcium are measured according to crop requirement, and we place magnesium and calcium probes in water/soil to measure these. For example, spinach has high volume of magnesium, hence we will provide magnesium raw materials in water. This will be similar with even calcium as well. For sulfur, we have sulfur gas sensor, and we can measure by boiling small amount of water and measure the contents of sulfur in water. Further, the farmers monitor and control the field using Agri-Hydroponic application through

electronic devices like mobile phones and tablets. It also shows the output devices like water motors controlling the supply of water in hydroponics field.

4.3. Results of AI-Based IoT Cloud Server. Figure 8 shows the classified plant diseases using DLCNN model. The proposed model accurately classified the apple scab, cherry powdery mildew, corn northern leaf blight, grape black rot, grape leaf blight, orange disease, peach bacterial spot, potato early blight, squash powdery mildew, strawberry leaf scorch, tomato early blight, and tomato late blight diseases.

Table 2 presents the Prediction-DLCNN response for three samples of sensor data. Here, sample-1 data is considered during rainy season, sample-2 data is considered during winter season, and sample-3 data is considered during summer season. The Prediction-DLCNN analyzed these sensor data and resulted in the perfect predicted nutrients. Further, Table 2 also presents the output action of actuators during automatic mode of operation.

Table 3 shows that the proposed Prediction-DLCNN model accurately estimated the nutrient values as compared to state-of-art approaches like EFIS [15], SVM [16], Mic-ConvNet [18], and RCNN [23]. These conventional methods considered the reference data during perfect atmospheric conditions, so they failed to result in the best prediction for all environmental situations. In addition, these conventional methods considered a smaller number of input sensors as compared to proposed system, which is also impacted the nutrition prediction performance.

Table 4 shows the disease detection and classification performance of proposed Classification-DLCNN. Here, the proposed method resulted in superior performance as compared to conventional methods like KNN [13], ANN-GA [17], HCNN [19], and ResNET51 [20] for all performance metrics.

5. Conclusion

This article presented the design and implementations of AI-SHES with IoT, which is developed by integrating the Raspberry Pi, IoT environment with mobile application. The farmer observes and manages his hydroponics farm field using the Agri-Hydroponic program, which has manual and automated control modes. A Raspberry Pi controller-based hardware design is installed in a hydroponics farm field to monitor plant statics using various sensors. Furthermore, the data from these sensors is transferred to a cloud-based IoT system. An AI system is deployed in the cloud serviced by DLCNN, which continually analyzes sensor data, plants disease condition, and gives alerts to farmers via the Agri-Hydroponic application. Finally, the farmer operates his hydroponics farm field in manual mode, ensuring that nutrients are provided to plants at the amounts specified by the farmer. Furthermore, nutrients are applied to plants at specified reference levels during automated mode of operation. This system can be extended with hybrid deep learning architectures and optimization methods.

Data Availability

The data used to support the findings of this study are included within the article.

Disclosure

It was performed as a part of the Employment of Salale University, Ethiopia.

Conflicts of Interest

Authors declared that there is no conflict of interest in publication.

References

[1] W. Tao, L. Zhao, G. Wang, and R. Liang, "Review of the internet of things communication technologies in smart agriculture and challenges," *Computers and Electronics in Agriculture*, vol. 189, article 106352, 2021.

[2] S. Qazi, B. A. Khawaja, and Q. U. Farooq, "IoT-equipped and AI-enabled next generation smart agriculture: a critical review, current challenges and future trends," *IEEE Access*, vol. 10, pp. 21219–21235, 2022.

[3] D. Das, J. Sahoo, M. B. Raza, M. Barman, and R. Das, "Ongoing soil potassium depletion under intensive cropping in India and probable mitigation strategies. A review," *Agronomy for Sustainable Development*, vol. 42, no. 1, pp. 1–26, 2022.

[4] M. O. H. D. B. K. Putra and N. Nopriadi, "IOT based SMART agriculture using fuzzy logic," *Computer and Science Industrial Engineering (COMASIE)*, vol. 6, no. 2, pp. 52–61, 2022.

[5] K. Lova Raju and V. Vijayaraghavan, "A self-powered, real-time, NRF24L01 IoT-based cloud-enabled service for smart agriculture decision-making system," *Wireless Personal Communications*, pp. 1–30, 2022.

[6] E. S. Mohameda, A. A. Belal, S. K. Abd-Elmabod, M. A. El-Shirbeny, A. Gad, and M. B. Zahrana, "Smart farming for improving agricultural management," *The Egyptian Journal of Remote Sensing and Space Science*, vol. 24, no. 3, pp. 971–981, 2021.

[7] E. Nigussie, T. Olwal, G. Musumba, T. Tegegne, A. Lemma, and F. Mekuria, "IoT-based irrigation management for smallholder farmers in rural sub-Saharan Africa," *Procedia Computer Science.*.

[8] A. Sharma, M. Georgi, M. Tregubenko, A. Tselykh, and A. Tselykh, "Enabling smart agriculture by implementing artificial intelligence and embedded sensing," *Computers & Industrial Engineering*, vol. 165, article 107936, 2022.

[9] M. E. Karar, A. H. Abdel-Aty, F. Algarni, M. F. Hassan, M. A. Abdou, and O. Reyad, "Smart IoT-based system for detecting RPW larvae in date palms using mixed depthwise convolutional networks," *Alexandria Engineering Journal*, vol. 61, no. 7, pp. 5309–5319, 2022.

[10] H. Pang, Z. Zheng, T. Zhen, and A. Sharma, "Smart Farming," *International Journal of Agricultural and Environmental Information Systems (IJAEIS)*, vol. 12, no. 1, pp. 55–67, 2021.

[11] A. Khan, U. Nawaz, A. Ulhaq, and R. W. Robinson, "Real-time plant health assessment via implementing cloud-based scalable transfer learning on AWS DeepLens," *PLoS One*, vol. 15, no. 12, p. e0243243.

[12] F. Sabrina, S. Sohail, F. Farid, S. Jahan, F. Ahamed, and S. Gordon, "An interpretable artificial intelligence based smart agriculture system," *Computers, Materials & Continua*, vol. 72, no. 2, pp. 3777–3797, 2022.

[13] D. Adidrana, A. R. Iskandar, A. Nurhayati et al., "Simultaneous hydroponic nutrient control automation system based on Internet of Things," *JOIV: International Journal on Informatics Visualization*, vol. 6, no. 1, pp. 124–129, 2022.

[14] V. Bhatnagar and R. C. Poonia, ""sustainable development in agriculture: past and present scenario of Indian agriculture." research anthology on strategies for achieving agricultural sustainability," *IGI Global*, pp. 1342–1364, 2022.

[15] N. G. Rezk, E. E.-D. Hemdan, A.-F. Attia, A. El-Sayed, and M. A. El-Rashidy, "An efficient IoT based smart farming system using machine learning algorithms," *Multimedia Tools and Applications*, vol. 80, no. 1, pp. 773–797, 2021.

[16] P. Wang, B. A. Hafshejani, and D. Wang, "An improved multilayer perceptron approach for detecting sugarcane yield production in IoT based smart agriculture," *Microprocessors and Microsystems*, vol. 82, article 103822, 2021.

[17] Z. Khan, M. Zahid Khan, S. Ali et al., "Internet of things-based smart farming monitoring system for bolting reduction in onion farms," *Scientific Programming*, vol. 2021, 15 pages, 2021.

[18] E. T. Bouali, M. R. Abid, E. M. Boufounas, T. A. Hamed, and D. Benhaddou, "Renewable energy integration into cloud & IoT-based smart agriculture," *IEEE Access*, vol. 10, pp. 1175–1191, 2022.

[19] J. Arshad, M. Aziz, A. A. Al-Huqail et al., "Implementation of a LoRaWAN based smart agriculture decision support system for optimum crop yield," *Sustainability*, vol. 14, no. 2, p. 827, 2022.

[20] M. Cicioğlu and A. Çalhan, "Smart agriculture with internet of things in cornfields," *Computers and Electrical Engineering*, vol. 90, article 106982, 2021.

[21] D. Manikandan, S. Prabhu, P. Chakraborty, T. Manthra, and M. Kumaravel, "IoT-Based Smart Irrigation and Monitoring System in Smart Agriculture," in *Futuristic Communication and Network Technologies*, pp. 45–56, Springer, Singapore, 2022.

[22] H. N. Saha, R. Roy, M. Chakraborty, and C. Sarkar, "Development of IoT-based smart security and monitoring devices for agriculture," *Agricultural informatics: automation using the IoT and machine learning*, pp. 147–169, 2021.

[23] P. S. Chatterjee, N. K. Ray, and S. P. Mohanty, "LiveCare: an IoT-based healthcare framework for livestock in smart agriculture," *IEEE Transactions on Consumer Electronics*, vol. 67, no. 4, pp. 257–265, 2021.

[24] S. Biswas, L. K. Sharma, R. Ranjan, S. Saha, A. Chakraborty, and J. S. Banerjee, "Smart farming and water saving-based intelligent irrigation system implementation using the internet of things," in *Recent Trends in Computational Intelligence Enabled Research*, pp. 339–354, Academic Press, 2021.

[25] I. L. Maldonado, J. M. M. Reyes, H. F. Breceda, H. R. Fuentes, J. A. V. Contreras, and U. L. Maldonado, "Automation and Robotics Used in Hydroponic System," in *Urban Horticulture - Necessity of the Future*, Open, London, United Kingdom, 2019.