Digital Agriculture: Harnessing IoT and Data Analytics for Smart Farming Solutions

D Ravichandran[1*], *S* Dhanabalan[1], *A* Santhanakrishnan[1], *S* Sarveshwaran[1] and *R* Yogesh[1]

[1]Department of Mechanical Engineering, Nandha Engineering College, Perundurai 638 052, Tamilnadu, India

Abstract. The integration of convolutional neural networks (CNN) and the Internet of Things (IoT) is an increasingly popular subject among scholars due to its potential to revolutionize the agricultural sector. The IoT will decrease resource wastage by enabling farmers to utilize sensor node data for decision-making instead of just depending on expertise. (e.g., fertilizers, water, pesticides, and fumigants). CNN enhances monitoring systems by predicting the amount of consumable resources needed to improve productivity and detect agricultural illnesses early. SAgric-IoT is a technological platform created for precision agriculture. It combines CNN and IoT to monitor physical and environmental factors, identify illnesses at an early stage, and manage greenhouse irrigation and fertilization. The findings indicate that SAgric-IoT is a dependable Internet of Things (IoT) platform characterized by minimal packet loss, significant energy conservation, and disease detection and classification processes exceeding 90% accurate.

1 Introduction

The unrestrained expansion of the global population is leading to a growing scarcity of water and food. The 9.15 billion individuals are anticipated to comprise the global population in 2050 [1]. As the global population continues to increase, there is a corresponding surge in the need for food. However, this growth has also led to a dearth of arable land and a decline in the number of individuals expressing interest in farming [2, 3]. One Virginia winery attempted to hire foreign laborers when American citizens lost interest in harvesting grapes [4]. Although it's essential for human survival, agriculture uses up the vast majority of the world's fresh water supply. The 33% of Europe's water is designated for agricultural use, impacting the amount and quality of surface water available for other uses. Approximately 76.12% of Mexico's water is utilized in agriculture [5, 6]. A loaf of bread, for instance, uses around 240 gallons of water, while 382 gallons is needed to make 1 pound of cheese. According to authors [7], 56 liters of water are required for just one cheese sandwich. This study introduces SAgric-IoT, a platform for precision farming that uses the IoT and CNN to monitor physical data and detect plant diseases. In order to maintain exact control over the production environment, the platform employs communication algorithms to monitor and analyze data. It categorizes and detects plant illnesses by utilizing convolutional neural networks. We aim to develop a cost-effective, dependable, and low-maintenance Internet of Things (IoT) platform to oversee and enhance agricultural productivity. Recently, the Internet of Things has experienced a significant boost. Farming, transportation, smart cities, classrooms, oceans, and healthcare are just a few of the fields that have benefited from the IoT designs and platforms proposed in the literature [8, 9]. The use of technology and Internet of Things applications to automatically monitor physical variables like soil temperature, moisture, and leaf wetness has been explored in multiple precision agriculture articles [10, 11]. The research drew up blueprints for the nodes, preliminary sketches for their potential Internet of Things (IoT) or wireless sensor network connection, and a communication network of nodes specifically designed to monitor crops. The use of cellular technologies and cloud services allows Internet of Things platforms to control water consumption [12]. The writers describe a partnership between process control and distant sensors [13]. Having said that, the writers failed to detail how various sources of data (sensors, actuators, coordinators) are collected and transmitted. Even at the academic level, most of these apps rely on proprietary technologies to produce and analyze massive volumes of data [14]. The fundamental issue with these works is that they are merely architectural ideas and do not include the development of prototype nodes for testing in real-world circumstances. The goal of the authors [15] was to analyze the inter-temporal variability of the environment and use wireless sensor networks for real-time monitoring in order to minimize production risk. Their research further confirmed that Internet of Things (IoT) technology assists in data collection by highlighting the significance of gauging and copy temporal aspects that influence activities enhancing agricultural productivity. Researchers examined the impact of energy balance on greenhouse output and

[*]Corresponding Author: ravigiriathani@gmail.com

strategies to enhance energy efficiency in grape production [16]. An analysis shows that greenhouses utilizing IoT technologies demonstrate up to a 31% reduction in consumption of energy related to none of individuals. Enhanced agricultural energy efficiency can be achieved through the implementation of cleaner crop production practices [17]. To be sure, technology is certainly not the only thing impacting contemporary farming [18]. A number of stakeholders, including technology, farmers, businesses, banks, and policy and decision-makers, must work together to ensure a seamless shift toward sustainable agriculture. In order to promote sustainable growth, this cooperation would eliminate inadequacies and settle disputes [19].

2 Platform Description for SAgric-Internet of Things

SAgric-Internet of things is a flexible platform that can be upgraded and used to manage and monitor Internet of Things (IoT) systems in order to boost agricultural productivity. SAgric-IoT is designed to meet the specific needs of farmers by utilizing inexpensive and energy-efficient components. SAgric-IoT intends to optimize water and resource usage, reduce human intervention, and enhance the efficiency of open and closed fields through monitoring, data processing, analysis, and interpretation. Here we will first go over the broad strokes of the SAgric-IoT scenario. After that, we will go into SAgric-IoT's logical architecture. We continue by outlining the specifics of our platform's hardware design. Here, we detail SAgric-IoT's dissemination protocol. Our description of the plant disease detection model using a convolutional neural network end.

2.1 Architecture of Layered IoT

The SAgric-IoT system is designed to meet the requirements of remote monitoring, which helps to decrease the investment in human resources. SAgric-IoT establishes a five-tiered approach (Fig. 1) that allows for the open sharing of data in the precision agricultural domain and the transparent integration of all platform components. The sentences below outline the specified architecture, which includes all seven layers of the OSI model. The layers that make up the gathering layer stand for the physical infrastructure and data links. Between the data link and network levels is a communication layer. All the way from transport to session to presentation to application, the first four levels work closely together with processing and the end-user levels. As a transversal layer, the security layer establishes end-to-end security by interacting with different levels of the architecture.

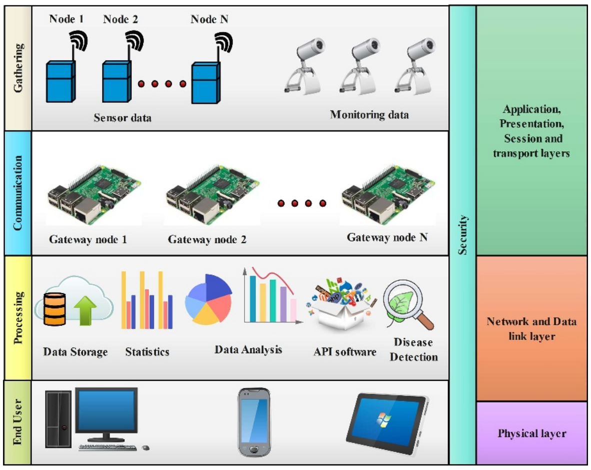

Fig. 1. 5-layered architecture of SAgric-IoT

2.1.1 Collection Layer

Various sources on farmland and sensor nodes in specific field areas provide data on physical environmental parameters, including air temperature, humidity, soil temperature, moisture, and pH, which are collected by the collection layer. With the help of the cameras set up all throughout the surveillance area, it also takes pictures. There has been a plethora of new radio technologies that allow direct-to-device communication in both local and wide area networks in the last decade, thanks to the many initiatives that have defined and implemented low-power direct-to-device (D2D) standards and solutions [20].

2.1.2 Communicating Layer

In order to gather data, the sensor nodes connect with each other and the gateway. The process for sending data is described here. The network architecture is static due to the stationary sensors. Furthermore, data transfer necessitates minimal latency, excellent reliability, and robust security to safeguard the acquired data. The gateway node can be connected to the network using Wi-Fi or ZigBee [21, 22]. Using criteria like RSSI and hop count, this layer determines the optimal path to transmit the data.

2.1.3 Process

Increased productivity and alarms are brought about by this layer's use of policy-based management to process massive amounts of data. Production maps are created by government agencies using processed data. The maps aid farmers choose the best water levels, fertilizers, and crops to use at each stage of production. Soil pH, soil temperature, ambient humidity, and temperature all have specific ranges of values that correspond to different crop types. On the platform, these values are documented. The ideal physical parameters for cucumbers are illustrated in Table 1. In order to identify abnormal situations, data is continuously analyzed for out-of-the-ordinary values of several physical parameters. Other systems (like irrigation systems) can be activated by the system depending on the data. The processing layer can support an enlarged database that stores the data transmitted from sensor nodes to the communication layer. Fig. 2 shows how the database interface is linked to real-time data visualization and evaluation processes. To store and process the CNN model for identifying and classifying agricultural diseases, the processing layer is implemented at the gateway node.

Table 1. Physical factors for cucumbers

Factor	Range
pH	~ 7
Temperature at Night	61 to 65 (˚F)
Humidity at Day	85 to 95(%)
Day temperature	70 (˚F)
Night humidity	65–75(%)

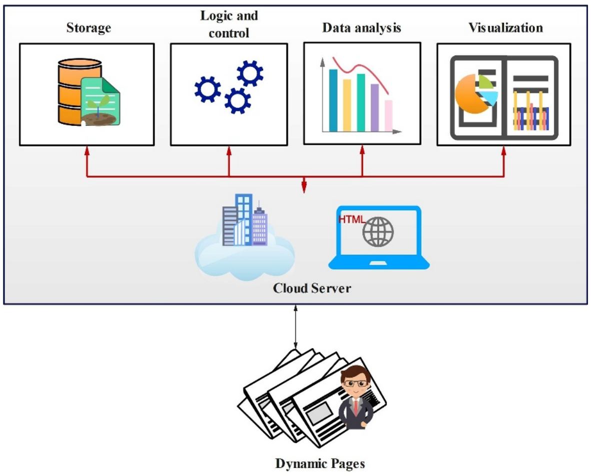

Fig. 2. An outline of the cloud server

2.1.4 User End

A software tools with web service accessible through an application are what its accountable for providing to the agriculturalist in order to accessing the data.

2.1.5 Security

The SAgric-IoT system relies on the secure transmission of sensor nodes. Nodes that adhere to the security protocols of the 802.15.4 standard offer device access control, symmetrical significant cryptoanalysis encryption, and integration verification to guarantee that established mounts have not been changed. Prior to transmission, the data is encrypted using 128-bit encoding, and decryption is performed at the retriever's end. We set up AES encryption in each Xbee node by configuring two parameters: E.E. = 1, which means enable AES encryption, and KY, which is a string of 32 hexadecimal characters that serves as the AES encryption key. Following that, the WPA2 security of the camera nodes. When it comes to processing and storage layer security, the provider is in charge. At last, the user logs in to the system over a secure HTTP protocol connection and a username and password.

2.2 Electronical Board

Creating energy-efficient hardware that could monitor, gather, and regulate physical parameters at a cheap cost was the primary goal of the SAgric-IoT design. There are four parts to the hardware board, as shown in Fig. 3: the wireless communication module, sensors and actuators, energy, and microprocessor.

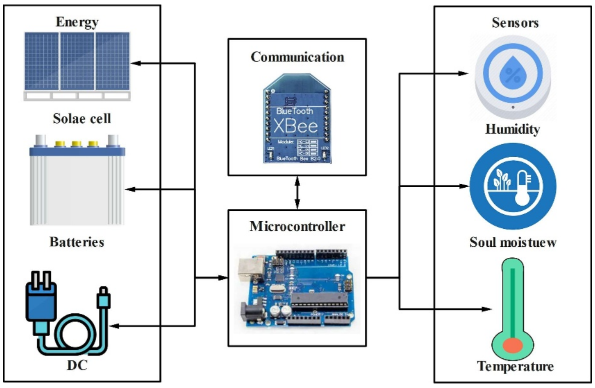

Fig. 3. Block diagram of sensor node

The microcontroller module communicates with the gateway node by collecting data from the connected sensors. The application specifies the microcontroller's power supply, which might be a battery, solar panels, or even backup batteries. The features and price of the Microchip PIC18LF46K22 microcontroller led us to choose it. It has a maximum throughput of 16 MIPS, or million instructions per second. The microcontroller has a maximum CPU current handling of 9.0 mA and requires an input voltage of 3.3 V. In addition to 3896 KB of RAM and 1024 KB of EEPROM, the microcontroller contains 64 KB of program memory. There is a total of 35 I/O pins and 28 analog input channels provided by the built-in 10-bit ADC. Precision agriculture makes use of sensors and actuators to track a variety of environmental variables. Table 2 shows the sensor that we use.

Table 2. sensors utilized in SAgric-Internet of things

Sensor devices	Model
Wind speed/direction	SEN-08942
Soil humidity sensor	SHT-10
Air temperature	AM2315
Sensor for Soil temperature	SHT-10
Case humidity	AM2302
Case temperature	AM2302
Air humidity	AM2315

The module has a line-of-sight range of 1200 meters outdoors and 60 meters indoors, allowing it to cover a large area. The output power for transmission is 3.1 mW. In ZigBee mesh networks, XBee modules allow end-point devices to connect wirelessly. The gateway nodes are equipped with four USB ports, which sports a micro-SD card slot, WiFi, a display interface (DSI), and Raspberry Pi 3 Model B, and Bluetooth 4.1 capabilities. The camera nodes are comprised of an OV2640 camera and a Wi-Fi and Bluetooth-enabled ESP32-CAM board. The microSD card interface on this module enables the storage of photographs captured with it.

2.3 New Protocol for Dissemination

Energy efficiency and dependability were two of the most important factors in the development of the distribution protocol. In the IoT, where applications require constant data from the network, energy consumption is the primary concern while developing dissemination methods. First, we established a static cluster-based network architecture for the dissemination protocol's design. Second, there are no energy constraints on the gateway node. Third, each sensor node must be able to communicate with the gateway node, which necessitates a multi-hop transmission. Finally, every node contains heterogeneous sensors. End nodes, routing nodes, and gateway nodes are the three types of nodes defined by our protocol. End nodes in the network can only receive data from sensors; they have no way of transmitting any data to the outside world. Various sensor nodes rely on routing nodes to gather data and retransmit it. Nodes maintain a routing table to aid in selecting the optimal path for data transfer. The state diagram of the protocol may be seen in Fig. 4.

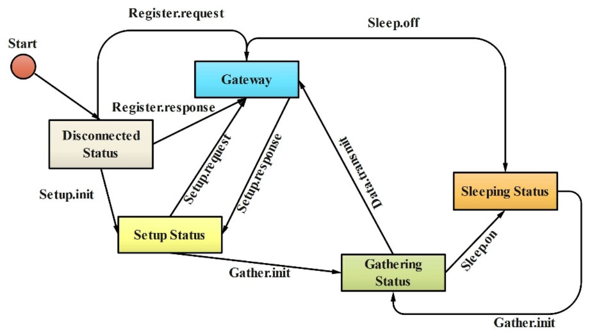

Fig. 4. The SAGric-IoT state flow

Data is defined and messages are regulated by our protocol. A sensor node must first have the protocol enabled. A control message known as Register. Request must be exchanged between the gateway node and each sensor node before the sensor node may join the IoT network. Upon joining the network, a newly added node immediately begins by establishing its identity. This node can be either a sensor or a routing node; the answer determines this based on the hop count of the message. In order to conserve energy, a sensor node assumes the role of an end node by powering down subsequent to the accumulation of data from numerous sensors and its subsequent transmission to a gateway node. The sensor nodes are routable and must wake up according to a schedule or a request for routing transmission if they are to retransmit data received from other sensors. In response to the response, the sensor node switches from disconnected to setup configuration. The setup request and setup response messages are then exchanged between the sensor and gateway nodes to determine the time of day for each sensor to gather data. When that happens, the gathering status is applied to the sensor node, and it is prepared to start gathering data. To communicate with the gateway node, sensor nodes in this mode collect data from sensors, organize it into frames, and then transmit them. A sensor node will instantly communicate any new data it receives with the gateway node. An IEEE 802.15.4-defined MAC data packet is consulted by SAgric-IoT during message construction (Fig. 5).

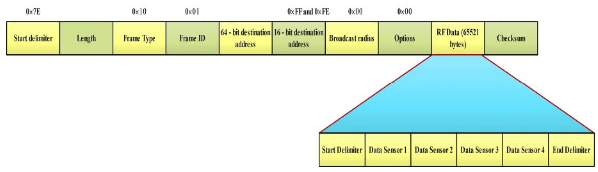

Fig. 5. Structure of data messages utilized by SAgric-IoT

Data fields containing sensor information, frame control fields, destination address fields, and a message integrity checksum field are all included in the message. The data is used to transmit the frame to the gateway node convey message. In order to conserve power for a predetermined duration after data transmission, the sensor node enters Sleeping mode (Sleep.on). The node is in a dormant state with all sensors and microcontroller deactivated. The sensor node either starts a new data collection session when its sleep period finishes or replies to a request for sensor data information from the gateway node. Nodes enter a sleep mode (Sleep.on) to save power once they have transmitted data to the gateway node.

2.4 CNN Model

The following paragraphs detail the suggested model structure for identifying and categorizing plant leaf diseases. Color images of plant leaves are inputted into the suggested model. A picture and a set of labels describing the plant's leaf health status (healthy or sick) are displayed in the result.

2.4.1 Dataset

A public dataset called Plant Village, which contains 20,600 photos divided into 10 categories, was utilized [23]. The dataset's categorized information is displayed in Table 3. The project's model was tested using a total of 16,012 photos, all belonging to the cucumber categories [24]. A total of 12,810 photos, or 80% of the dataset, were used for training purposes, while 3,202 images were used for validation. Overfitting, in which the model "memorizes" the dataset, is a potential issue with the models that might arise during training [25]. So, to expand the dataset, we used a technique called data augmentation [26]. The dataset was supplemented with new photos that were made utilizing transformation methods such as brightness correction, rotation, and Gaussian noise.

Table 3. Sorts of the plant village dataset

Sort	No of Images
Carrot___Early_blight	1000
Carrot___healthy	152
Carrot___Late_blight	1000
Cucumber_Bacterial_spot	2127
Cucumber__Target_Spot	1404
Cucumber_Early_blight	1000
Cucumber_Leaf_Mold	952
Cucumber_Septoria_leaf_spot	1771
Cucumber_Late_blight	1909
Cucumber__Cucumber_mosaic_virus	373
Cucumber_Spider_mites_Two_spotted_spider_mite	1685
Cucumber__Cucumber_YellowLeaf__Curl_Virus	3209
Cucumber_healthy	1591
Pepper__chilli___Bacterial_spot	998
Pepper__chilli___healthy	1579

2.4.2 Creation of Model

A model was developed for the purpose of detecting plant illnesses using an architecture based on convolutional neural networks. The training and validation inputs for the model need 200×200 color pictures that have been normalized to values between 0 and 1. The five convolutional layers that make up the neural network use 256, 128, 64, 32, and 16 filters in that order. A 3×3 kernel size was used by the 2D convolution window. To activate each convolutional layer, we used the Rectified Linear Unit (ReLU). All of the convolutional layers were trained with MaxPooling. The data was transformed into a column vector using a global average pooling layer. Connected to a dense layer that uses SoftMax as its activation function, this layer has ten output nodes that stand in for the model's categories.

2.4.3 Training of Model

The Adam optimization algorithm and model training elements are shown in Table 4. As a loss function, the model made use of categorical_cross_entropy, a popular choice among multi-class classification algorithms. There were two hundred epochs.

Table 4. Factors for the training model

Factors	Range
Number of epochs	200
Activation function	ReLU
Validation steps	3202
Steps per epoch	16,012
Optimization algorithm	Adam
Batch size	32
Loss function	Definite cross-entropy

3 Results and Discussions

3.1 Assessment of Prototype

The advantages of SAgric-IoT were demonstrated by analyzing two cases. We use controlled laboratory testing in the initial scenario to verify that the node as well as the data gathered from all sensors are operating as intended. The sensor nodes were linked in a star topology with a distance of 10 meters from the main base station. These nodes collected data on environmental factors like as temperature and humidity at one-minute intervals over a period of three days. At maximum sense frequency, we aimed to find out how much power the node needs and how reliable its data transmissions are. In the second scenario, the data-transmission performance of the dissemination technique was tested by deploying sensor nodes throughout the ground. Over the course of three days, data on environmental parameters was measure every five minutes. The group of sensor nodes, seen in Fig. 6, covered an area of 200 × 200 m and were spaced about 50 m apart. We enabled the multi-hop transmitting model by defining levels.

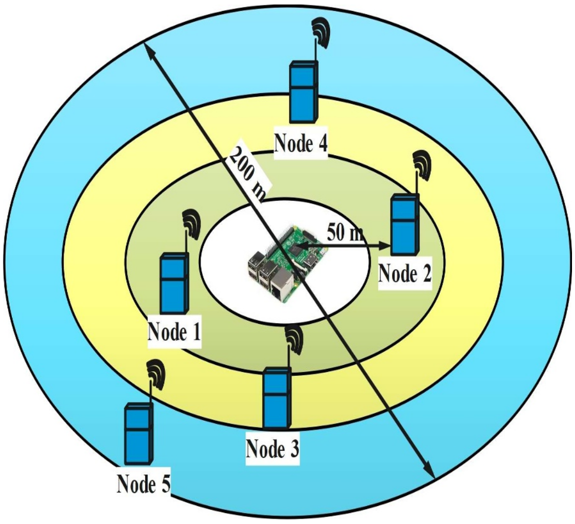

Fig. 6. Node dispersal in case 2

By examining the energy consumption and dependability of the nodes, we were able to assess SAgric-IoT's performance. Finally, we compared the SAgric-IoT protocol's performance to that of a typical transmission model that does not incorporate a sleep function within the node. Weather, soil temperature, air humidity, and soil temperature were the four physical variables that were monitored by two sensors per node. The cloud server utilized for operating Apache then MySQL was powered by Ubuntu 14.04. The Raspberry Pi 3 Model B, which functions as the gateway node, is distinguished by its four USB interfaces, DSI display interface and micro-SD card slot. Connecting to wireless networks is a breeze with this device because it comes preloaded with Bluetooth 4.1 and Bluetooth Low Energy (BLE). The command to gather data on a separate variable was communicated to each sensor node every five minutes. We gathered around 5,000 sensor readings during the test and stored them in a database located on a cloud server.

3.2 Case Results

For case 1, Fig. 7 (a) and (b) displays the energy consumption in a controlled environment with various nodes. Findings reveal the system's battery life through the continuous recording of measuring data. We found that the battery life of a SAgric-IoT node dropped by about 11% from its maximum level. On the other hand, a node's battery life dropped 66% from its maximum level when using regular transmission without sleep mode. Consistent monitoring and data transmission over only a few days drastically reduced the battery life, leading to lower data quality and more frequent battery replacements. As a result, it is recommended to avoid these scenarios. When compared to a conventional transmission that does not use sleep mode, SAgric-IoT significantly lowers energy usage, cutting it by about 44% on average. For both kinds of transmission, Fig. 7 (b) displays the proportion of packets received per node. With a 99% success rate, both transmission models produce the same rate of received packets when a directly connected situation is considered.

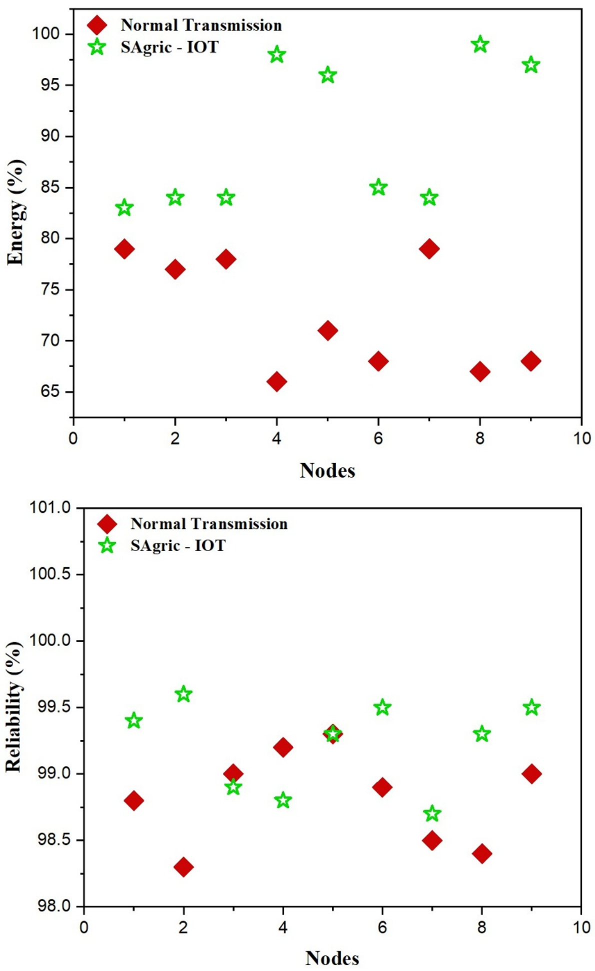

Fig. 7. Case 1 outcomes: (a) energy usage and (b) packets received per node

Fig 8a illustrates the energy consumption of several elements in the field environment. The data obtained for the second situation is shown in Figure 8. Each node's energy consumption was significantly different from the others. In terms of energy consumption, the nodes ranked as follows: 1–2 accounted for 13%, 3–5 for 9%, 6–7 for 5.6%, and 8–9 for 3%. The volume of transmissions per node is a key factor in the difference. Nodes near the gateway node engage in escalating data exchange, involving their own data as well as data from other nodes. In comparison to nodes that did not utilize our slumber mode for transmission, SAgric-IoT nodes demonstrated an approximate 26% improvement in battery life.

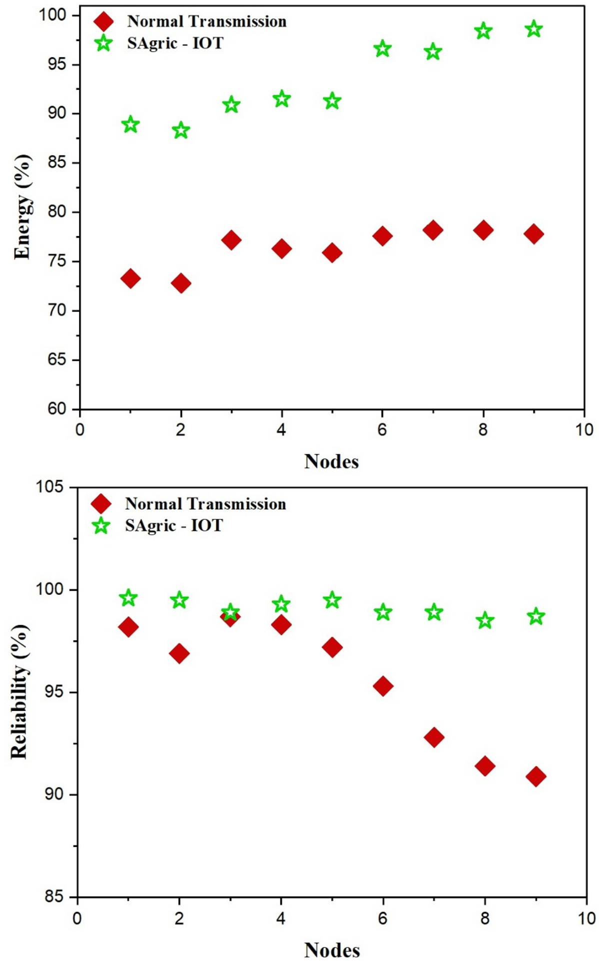

Fig. 8. Case 2 outcomes: (a) energy usage; (b) packets received per node

When considering a multi-hop scenario, the two transmission mechanisms show considerable differences according to the data. As seen in Fig. 8, the further model had a whole loss of 8% while SAgric-IoT only experienced a maximum packet loss of 2%. SAgric-IoT's efficiency appears to be derived from its capacity to optimize the energy usage of the sleep state. The sensor nodes get the most out of their energy resources and last longer on a single charge if the microcontroller and sensors' power consumption is controlled.

3.3 Model Evaluation

Python modules like TensorFlow and Keras, together with NumPy, Matplotlib, and Tensor Board, were utilized to construct the model. The parameters used for evaluation were recall, accuracy, precision, and f1 score [27, 28]. Each can be calculated using the following formulae.

$$\text{Accuracy} = \frac{TP+}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+F} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

$$F1\ \text{Score} = 2 \times \frac{(\text{precision}\times\text{recall})}{(\text{precision}+\text{recall})} \tag{4}$$

There are four possible outcomes: FN for false negatives, TN for negative projections, FP for false positives, and TP for optimistic predictions.

3.4 Obtained Results

Fig. 9 indicates the outcomes of the model's training and validation processes for classifying and identifying leaf diseases. The training phase achieved an accuracy of 97.4%, while the validation phase reached 92.2%, which are considered respectable and consistent with Fig.10 reported in other studies.

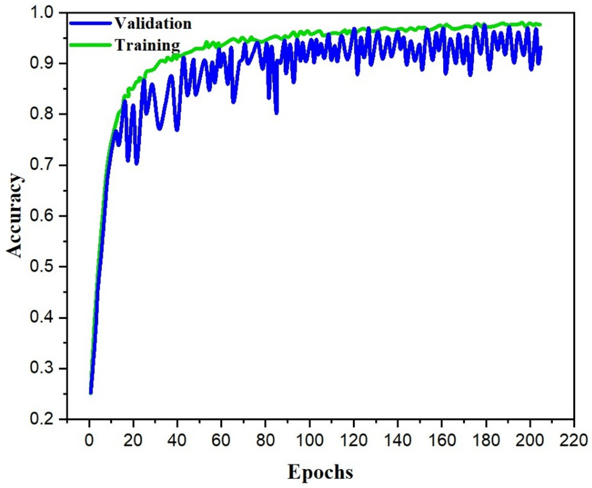

Fig. 9. The accuracy values of the model through the trained and validated phases

To examine the outcomes of our supervised algorithm's performance, a confusion matrix was built. At a 98% accuracy rate, the projected model correctly predicted more than half of the classes, according to the results. Out of all the classes that underwent training, only the cucumber mosaic virus class achieved a 94% accuracy rate. The outcomes of the proposed model's disease classification process for each class are presented in Table 5. The recall metric shows consistently high values for all categories in the dataset, suggesting that the proposed model accurately identifies diseases with over 90% accuracy.

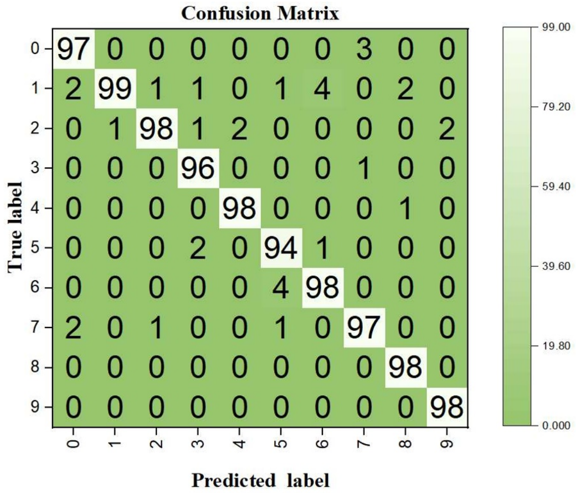

Fig. 10. Confusion matrix of the enhanced model

Table 5. Performance of each class in the novel model

Sort	Support	Recall	Precision	f1-Score
cucumber mosaic virus (5)	100	0.98	0.94	0.91
cucumber healthy (9)	100	0.98	0.98	0.98
cucumber late blight (1)	100	0.98	0.99	0.98
cucumber Septoria leaves spot (4)	100	0.97	0.98	0.99
cucumber spider mites (8)	100	0.99	0.98	0.97
cucumber leaf mold (7)	100	0.97	0.96	0.99
cucumber yellow leaves curl virus (2)	100	0.99	0.99	0.98
cucumber bacterial point (0)	100	0.97	0.96	0.97
cucumber earlier disease (3)	100	0.97	0.96	0.97
cucumber target spot (6)	100	0.98	0.98	0.98

In conclusion, a comparison was conducted with a study that examines various disease detection methodologies for cucumber plants [29-32]. A comparison was made between Xception, DenseNet ShuffleNet, ResNet50, and MobileNet, and the 5-techniques implemented in this study. In contrast to the dataset utilized in that study (Plant Village), our model was trained using 13,112 images. 20% of the dataset was allocated for validation and 80% was designated for training. There was a comparison of the training procedure's precision. The findings are illustrated in Fig. 11. Based on the obtained results, two conclusions can be drawn. The initial observation is that the proposed model exhibits a marginal 1.2% underperformance compared to the VGG16 model structure. The second finding shows that the suggested model is stable, since our model maintained its performance even when trained with less images.

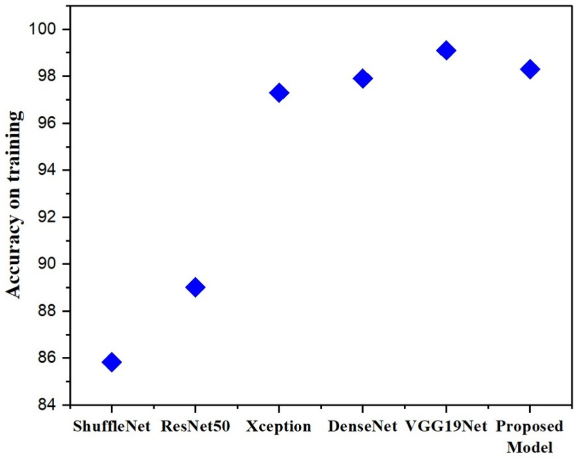

Fig. 11. Evaluation of the projected and the prevailing models

4 Conclusions

This study assessed the energy consumption and packet delivery ratio of SAgric-IoT, an Internet of Things (IoT) platform, in a controlled laboratory environment and on a test bed in a small-scale network. The evaluation encompassed the algorithms, communication protocol, and embedded system of the IoT platform. SAgric-IoT accelerates the dissemination of information and minimizes the labor-intensive nature of current agricultural data collection methods. The results demonstrated that SAgric-IoT is preferable in terms of transmission reliability and energy efficiency. Conversely, the CNN model exhibits high levels of accuracy in disease identification for crops, as evidenced by its average values surpassing 95%. The reliability of this value is deemed satisfactory in identifying early disease issues that may have an impact on the yield. SAgric-IoT, a wireless platform utilizing low-power algorithms to collect data, is seen a feasible alternative for improving precision agriculture. Subsequent research endeavors will center on enhancing the security of the platform in order to prevent data integrity issues that may result in output reductions of either quality or quantity. Transferring images created in the field to models trained using images taken in the laboratory will be a big challenge that needs to be overcome in the next phase. Deep learning models that were trained on pictures of individual leaves may need further training to accurately identify plant illnesses in full-body plant photos, because these images lack context and because plants look different in different lighting and other environmental factors. Plant diseases can be more accurately identified by combining images of the entire plant with those of individual leaves, according to a number of studies that used deep learning techniques. A deep learning model's capability to detect plant diseases from whole plant photos may be hindered if it was only trained on single leaf images. Combining leaf and whole plant photos with deep learning techniques has the potential to significantly improve the accuracy of plant disease identification. Further development will involve training the model using comprehensive plant images, followed by its application in a real-time plant monitoring scenario. Implementing this approach would enable the assessment of crop health through the examination of leaf samples and the direct observation of plants through camera system images, thereby achieving a complete integration with the SAgric-IoT platform.

References

1. M. J. Villasenor-Aguilar, J. A. Padilla-Medina, J. Prado-Olivarez, S. Martinez-Diaz, I.-I. Mendez-Gurrola, A. I. Barranco-Gutierrez, Fuzzy Classification of Color Carrots (Dacus Carota) using Raspberry Pi towards Farming 4.0, in 13th IEEE Annual Computing and Communication Workshop and Conference, (2023).
2. L. Xu, S. Liu, D. Li, Key technology of south sea pearl industry management information service platform based on the internet of things. in IFIP Advances in Information and Communication Technology. (2012).
3. P. Visconti, N. I. Giannoccaro, R. de Fazio, S. Strazzella, D. Cafagna, IoT-oriented software platform applied to sensors-based farming facility with smartphone farmer app. Bulletin of Electrical Engineering and Informatics. **9,** 3 (2020).
4. M. A. Uddin, U. Kumar Dey, M. Akter, Proposing A Cloud and Edge Computing Based Decision Supportive Consolidated Farming System by Sensing Various Effective Parameters using IoT, in IEEE International IOT, Electronics and Mechatronics Conference, IEMTRONICS, (2022).
5. H. Youness, G. Ahmed, B. E. Haddadi, Machine Learning-based Smart Irrigation Monitoring System for Agriculture Applications using Free and Low-Cost IoT Platform, in International Conference on Microelectronics, ICM, (2022).
6. P. Visconti, R. de Fazio, P. Primiceri, D. Cafagna, S. Strazzella, N. I. Giannoccaro, A solar-powered fertigation system based on low-cost wireless sensor network remotely controlled by farmer for irrigation cycles and crops growth optimization. International Journal of Electronics and Telecommunications. **66,** 1 (2020).
7. K. Adithya and R. Girimurugan, Benefits of IoT in automated systems, Integration of Mechanical and Manufacturing Engineering with IoT: A Digital Transformation, (Scrivener Wiley, USA, 2023).
8. S. Jegadeesan, M. Navaneetha, P. Poovizhi, S. Pavithra, P. Santhiya, Blockchain based Lightweight and Secure Aggregation Scheme for Smart Farming, in Second International Conference on Sustainable Computing and Data Communication Systems, ICSCDS Proceedings, (2023).
9. Pandya, O. Odunsi, C. Liu, A. Cuzzocrea, J. Wang, Adaptive and Efficient Streaming Time Series Forecasting with Lambda Architecture and Spark, in 2020 IEEE International Conference on Big Data Proceedings, (2020).

10. L.-C. Liu, D. J. A. Rustia, T.-T. Lin, Remote surveillance video activity recognition using spatiotemporal convolutional neural networks for greenhouse workload analysis, in American Society of Agricultural and Biological Engineers Annual International Meeting, ASABE, (2021).
11. M. A. Tawfeek, N. Yanes, L. Jamel, G. Aldehim, M. A. Mahmood, Adaptive Deep Learning Model to Enhance Smart Greenhouse Agriculture. Computers, Materials and Continua. **77,** 2 (2023).
12. R. Girimurugan, P. Selvaraju, P. Jeevanandam, M. Vadivukarassi, S. Subhashini, N. Selvam, S.K. Ahammad, S. Mayakannan, S.K. Vaithilingam, Application of Deep Learning to the Prediction of Solar Irradiance through Missing Data. International Journal of Photoenergy. (2023).
13. Y. Juan, Z. Ke, Z. Chen, D. Zhong, W. Chen, L. Yin, Rapid density estimation of tiny pests from sticky traps using Qpest RCNN in conjunction with UWB-UAV-based IoT framework. Neural Comput Appl. (2023).
14. P.-Y. Kow, M.-H. Lee, W. Sun, M.-H. Yao, F.-J. Chang, Integrate deep learning and physically-based models for multi-step-ahead microclimate forecasting. Expert Syst Appl. **210,** (2022).
15. S. Mayakannan, M. Saravanan, R. Arunbharathi, V. P. Srinivasan, S. V Prabhu, and R. K. Maurya, Navigating Ethical and Legal Challenges in Smart Agriculture: Insights from Farmers, (CRC Press, Boca Raton, 2023).
16. B. Karthikeyan, G. Praveen Kumar, R. Saravanan, Alberto Coronas, Ramadas Narayanan, R. Girimurugan, Solar powered cascade system for sustainable deep-freezing and power generation-exergoeconomic evaluation and multi-objective optimization for tropical regions. Thermal Science and Engineering Progress. **50,** (2024).
17. N. Fatima, S. A. Siddiqui, A. Ahmad, IoT-based Smart Greenhouse with Disease Prediction using Deep Learning. International Journal of Advanced Computer Science and Applications. **12,** (2021).
18. Gejea, S. Mayakannan, R. M. Palacios, A. A. Hamad, B. Sundaram, W. Alghamdi, A Novel Approach to Grover's Quantum Algorithm Simulation: Cloud-Based Parallel Computing Enhancements, in Proceedings of the 4th International Conference on Smart Electronics and Communication, ICOSEC, (2023).
19. Morales-García, Juan, Andrés Bueno-Crespo, Raquel Martínez-España, Francisco J. García, Sergio Ros, Julio Fernández-Pedauyé, José M. Cecilia. SEPARATE: A tightly coupled, seamless IoT infrastructure for deploying AI algorithms in smart agriculture environments. Internet of Things. **22**, (2023).
20. W. Alghamdi, S. Mayakannan, G. A. Sivasankar, J. Singh, B. Ravi Naik, C. Venkata Krishna Reddy, Turbulence Modeling Through Deep Learning: An In-Depth Study of Wasserstein GANs, in Proceedings of the Fourth International Conference on Smart Electronics and Communication, ICOSEC, (2023).
21. M. Zhu, J. Shang, Remote Monitoring and Management System of Intelligent Agriculture under the Internet of Things and Deep Learning. Wirel Commun Mob Comput. (2022).
22. P. Karthikeyan, M. Manikandakumar, D. K. Sri Subarnaa, P. Priyadharshini, Weed identification in agriculture field through IOT. in Advances in Intelligent Systems and Computing. (2021).
23. T. Frikha, J. Ktari, B. Zalila, O. Ghorbel, N. B. Amor, Integrating blockchain and deep learning for intelligent greenhouse control and traceability. Alexandria Engineering Journal. **79,** (2023).
24. H. Li, Y. Guo, H. Zhao, Y. Wang, D. Chow, towards automated greenhouse: A state of the art review on greenhouse monitoring methods and technologies based on internet of things. Comput Electron Agric. **191,** (2021).
25. V. Deepika, A. Kalaiselvi, G. Dhivyaarthi, Monitoring of Hydroponics Plant and Prediction of Leaf Disease using IOT, in 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation, ICAECA, (2021).
26. E. Elango, A. Hanees, B. Shanmuganathan, M. I. Kareem Basha, Precision Agriculture: A Novel Approach on AI-Driven Farming. in Signals and Communication Technology. (2024).
27. R. Kavitha, T. Shanthi, P. Maithili, J. Roopika, K. Naveen Kumar, K. Saravanakumar, Deep Learning and Internet of Things based Detection of Diseases and Prediction of Pesticides in Fruits, in Seventh International Conference on Trends in Electronics and Informatics Proceedings, ICOEI, (2023).
28. K. Khuwaja, A. Aliza, N. Mukhtiar, R. Tarcă, D. Noje, M. Juman, B. Ali, Sustainable Agriculture: An IoT-Based Solution for Early Disease Detection in Greenhouses, In 17th International Conference on Engineering of Modern Electric Systems (EMES), (2023).
29. R. Cantini, F. Marozzo, A. Orsino, Deep Learning Meets Smart Agriculture: Using LSTM Networks to Handle Anomalous and Missing Sensor Data in the Compute Continuum. in Internet of Things. (2024).
30. Subeesh, C. R. Mehta, Automation and digitization of agriculture using artificial intelligence and internet of things. Artificial Intelligence in Agriculture. **5,** (2021).
31. R.K.G. Radhakrishnan, U. Marimuthu, P.K. Balachandran, A.M.M. Shukry, T. Senjyu, an intensified marine predator algorithm (MPA) for designing a solar-powered BLDC motor used in EV systems. Sustainability. **14,** (2022).
32. P. Indira, I.S. Arafat, R. Karthikeyan, S. Selvarajan, P.K. Balachandran, Fabrication and

investigation of agricultural monitoring system with IoT & AI. SN Applied Sciences. **5,** (2023).