

Agriculture based on Internet of Things and Deep Learning

Marwa Abdulla*¹, Ali Marhoon²

¹ Computer Science, College of Education, University of Basrah, Basrah, Iraq

² Electrical Department, College of Engineering, University of Basrah, Basrah, Iraq

Correspondence

* Marwa Abdulla

Computer Science, College of Education, Basra, Iraq

Email: cepsm510006@aviccenna.uobasrah.edu.iq

Abstract

In smart cities, health care, industrial production, and many other fields, the Internet of Things (IoT) have had significant success. Protected agriculture has numerous IoT applications, a highly effective style of modern agriculture development that uses artificial ways to manipulate climatic parameters such as temperature to create ideal circumstances for the growth of animals and plants. Convolutional Neural Networks (CNNs) is a deep learning approach that has made significant progress in image processing. From 2016 to the present, various applications for the automatic diagnosis of agricultural diseases, identifying plant pests, predicting the number of crops, etc., have been developed. This paper involves a presentation of the Internet of Things system in agriculture and its deep learning applications. It summarizes the most essential sensors used and methods of communication between them, in addition to the most important deep learning algorithms devoted to intelligent agriculture.

KEYWORDS: Agriculture, CNN, Deep Learning, IoT.

I. INTRODUCTION

In most countries, agriculture is extremely important, so smart technologies are needed. In 2050, the global population is expected to reach nearly 9 billion people. With so many people, more nutrients must be produced.

An intelligent agricultural system aims to understand the ecosystem better and reduce the burden on farmers by continuously monitoring their farms remotely. The intelligent system for agricultural management can perform: monitoring, analysis, and wireless prediction sensors and the Internet of Things are used in the process of intelligent management of farms through firstly, environmental monitoring that helps the growth of the crop (temperature, humidity, water level, soil pH, etc.). [1] pests on plants were identified using the k-mean algorithm. [2] sensors of temperature, humidity, wind speed and direction, soil moisture were used to monitor the farm and analyze temperature and humidity data. [4] a design is presented for collecting environmental, soil and fertilization data, automatically correlating this data, calculating crop forecasts, and making recommendations. [5] building a system with sensors for humidity, PH, water level, sounds to manage the field and monitor the farm to prevent birds and animals from entering the field. [8] Temperature, humidity, and colour sensors were used, and their data were analyzed

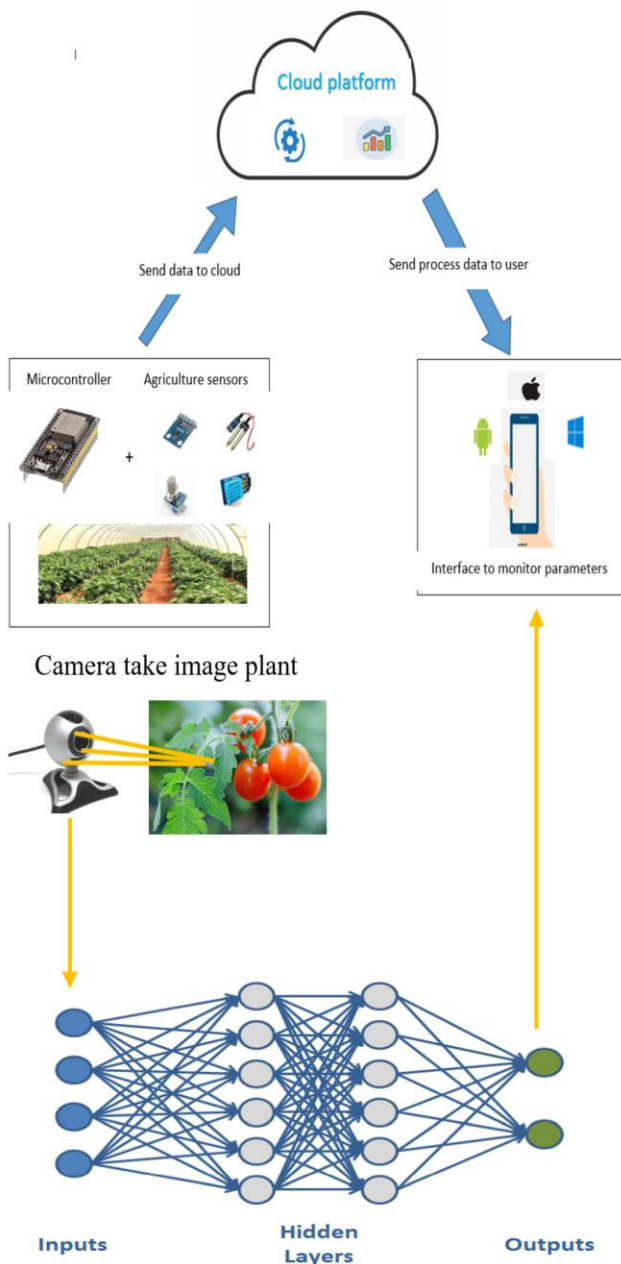
in ThinkSpeak to determine the presence of disease in the plant. [13] using a group of temperature sensors, soil moisture, and humidity to monitor the farm and design an automatic irrigation system. [14] designing a system based on sensors data to distinguish the disease approach. Secondly, monitor plant health using image processing and deep learning. [6] measurement of apple plant disease severity using CNN models. [12] classification of banana plant diseases using K-mean and RFC algorithms. [15] classification of diseases of 25 plant species using K-mean and CNN. Finally, it can be combined between environmental monitoring factors and a mechanism for detecting the plant's health status, [15] focuses on monitoring the environmental conditions of greenhouses using sensors and collecting pictures of plants to discover diseases. Thus the crop monitoring system using IoT and wireless sensors reduces the burden on farms. In addition to the introduction of deep learning in agriculture, it is essential in crop disease monitoring and classification, fruit counting, agricultural pest detection, crop classification, etc. The structure of smart agriculture is visualized in Fig.1. Aside from that, it is also characterized by low cost and ease of handling. This study summarizes the relevant research from 2014-2021 to learn about the most recent advances in intelligent agriculture research and the extent to which IoT and deep learning are used on farms. The content is arranged as follows:"



This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2022 The Authors. Published by Iraqi Journal for Electrical and Electronic Engineering by College of Engineering, University of Basrah.

monitoring in agriculture", "Agriculture Deep learning", "conclusion and future outlook".



Neural network to process image

Fig. 1: structure of intelligent agriculture.

II. MONITORING IN AGRICULTURE

Plant monitoring with wireless sensor networks and deep learning saves time and effort while providing accuracy

and speed, increasing crop output and quality. Sensors a low cost and easy to install, monitor the external environment and protect crops in the era of changing climatic conditions. The most essential sensors used in research in recent years to monitor the crop environment are temperature and humidity, colour, pH, light intensity, soil moisture level, movement sensors. [18].

Sensors are effective in greenhouses because they have artificial ventilation, lighting, and heating systems. The environmental conditions inside them can be controlled with the help of wireless sensor networks to manage equipment and provide an improved environment [9]. From this, it was concluded that greenhouses are more applicable to IoT technology. Moreover, in the environment of greenhouses, environmental conditions do not change quickly, so data does not need to be transferred frequently to the central server for treatment and analysis. The sensors are controlled and programmed by using a microcontroller. The data gathered by the sensors are uploaded to a cloud platform for analysis, understanding, and monitoring of plantings. Table I shows some research on plant monitoring, the Internet of Things (IoT) and the sorts of sensing devices used. Sensors require communication methods to transmit the collected data to the wired, wireless, or hybrid [9,10]. Table II shows the most essential communication techniques for connecting sensors and their features. The drip irrigation system uses soil moisture sensors to control water consumption in irrigation because its increase causes an increase in soil salinity and root rot [13].

III. AGRICULTURAL DEEP LEARNING

Deep learning is a cutting-edge technique for extracting precision features from photos and analyzing data with impressive outcomes and capabilities. The term "deep learning" refers to a type of machine learning. That adds depth to the model. Deep learning can improve accuracy for classification, segmentation, detection or reduce error [19], [31]. The architecture of deep learning algorithms consists of the following layers:

- convolution
- max pooling
- fully-connected layers
- activation function

Figure 3 shows the basic structure of a CNN and how it works. Deep learning can analyze any data type, including audio, video, natural language, voice, etc. Among the advantages of deep learning is the large number of its layers that help in learning features automatically from extensive data without manual intervention [16], [19], at the same time deep learning suffers from long training time, but at the same time, the test time is faster.

TABLE I

Presents some of the sources that use the Internet of Things to monitor plants

<i>Reference</i>	<i>Sensors used</i>	<i>Target of research</i>	<i>Points of strengths and limitations</i>
[22] (López Riquelme et al., 2009)	Use four different knots: Gateway mote to ensure that the system's wireless network links the sensors to the ZigBee network The SHT71 sensor in the environmental mote measures the temperature and humidity in the environment. Mote of water A Stevens ES 250 sensor determines irrigation water quality. The Stevens Hydra probe II is used by the soil mote to assess soil temperature, moisture, and salinity. The Texas Instruments MSP 430F1611 microcontroller is used to control the sensors.	Control of cabbage plants	The wireless sensor network described here offers a real opportunity for monitoring soil and environment status in a crop, but they employ the ZigBee communication protocol; the monitoring distance is limited within the farm area and not remotely.
[23] (Park & Park, 2011)	Sensor unit for measuring air temperature and humidity, infrared sensor for measuring leaf temperature, MSP430 MCU control unit, data transmission unit with CC24240RF chip, power source, antenna, and 3.6 V battery	A monitoring system prevents dewdrops from condensing on the leaves in a greenhouse environment.	The system performance was verified by building a model like a greenhouse, but can additional monitoring parameters can be added
[2] (Soontranon et al., 2014)	Sensors for temperature and humidity, rainfall level, light intensity, soil moisture, and wind speed and direction	Establishing a farm monitoring system by taking sensor information every 5 minutes for analysis	The system is implemented in the field, but only temperature and soil moisture data were analyzed
[5] (Navulur et al., 2017)	Soil pH sensor, water level sensor, bee sound sensor to keep elephants away from the field.	construct a system that helps in managing the fields by scheduling the water pumping and monitoring the plant to protect against animals and insects using wireless sensors and the Internet of Things	The proposed model is good at monitoring farm environmental factors and preventing the entry of animals, but the research is under development
[8] (Yakkundimath et al., 2018)	Temperature and humidity sensors, colour sensors, connect to Arduino Uno and send data to the ThinkSpeak cloud via WiFi	Development of an automated system to determine the presence of disease in plants	A system that monitors environmental factors in addition to detecting diseases, but it is affected by sunlight in taking pictures and detecting diseases
[13] (Bayram et al., 2018)	The Arduino Uno R3 controls temperature and humidity sensors, soil moisture sensors, rain sensors, light intensity sensors, and the solar power system, and data is exchanged via ZigBee and GSM.	Design of a remote drip irrigation system using wireless sensors	The system uses these sensors to control the irrigation of a limited area using a ZigBee communication protocol. Good idea to reduce electric power consumption
[12]	Raspberrypi3 controls the temperature and humidity sensors	This research aims to monitor the field in addition to	this system enables early detection of diseases, and only monitoring is

(Devi et al., 2019)	and the soil moisture sensor, and the collected data is forwarded to the ThinkSpeak cloud platform.	determining the presence or absence of a plant disease	done here by temperature and humidity
[26] (Ersin et al., 2016)	Raspberry Pi, Webcam, Water Pump, Arduino UNO, Solar Panel, Soil Moisture Sensor	irrigation system with automatic watering	A system that provides monitoring before and after the irrigation of crops, but other sensors can be added to monitor the environment, not just for autonomous irrigation.
[14] (Nawaz et al., 2020)	Sensors for temperature and humidity, colour sensors and an Arduino UNO are used, and data is delivered to a cloud platform.	Creating a system that recognizes the disease's approach to the plant-based on data from sensors and comparing it to data as a threshold	Here he uses the parameters of temperature, humidity, and colour of the leaves and compares them with ideal values based on which the plant disease is classified. The result may be inaccurate. Image processing can be used to increase accuracy.
[15] (Khan et al., 2020)	Connect temperature and humidity sensors to the Arduino UNO and water flow and soil moisture sensors.	Establishing an automatic monitoring system for crops	Building a system that determines the proximity of disease in the plant. The obtained temperature and humidity values are not analyzed but only for monitoring
[17] (Fuke & Raut, n.d.)	Temperature and humidity sensors, colour sensors, and a camera for taking pictures are controlled by an Arduino UNO	A system that uses IoT to improve the quality of agriculture by monitoring temperature and humidity whose increase or decrease affects the plant and also uses image processing to detect plant disease	Sensor-based plant disease detection. but research presents only the variables of temperature, humidity, and colour to detect diseases, while other variables affect plant health

TABLE II

Shows the most essential communication techniques used in agriculture monitoring

<i>communication technology</i>	<i>feature</i>
ZigBee	The ad hoc on-demand distance vector routing protocol is used for traffic routing. It is used to communicate with devices inside greenhouses since it can communicate within 10-20 meters and has a low working cycle and low energy usage.
GPRS	GSM devices that use a packet-based service that delivers regular warnings to a farmer's phone and captures greenhouse data in a greenhouse setting are being developed.
WiFi	The sensors are connected to the central server via a communication range of 20-100 meters, with a speed of 2-54 Mbps, allowing data to be transferred with acceptable delay.
LoRa	It has an extended range of kilometres and uses little power. It is mainly utilized as a communication gateway between central servers.
Bluetooth	It was designed for a wireless personal area network and used less electricity. Depending on the version, it can offer 1-3 Mbps speeds.

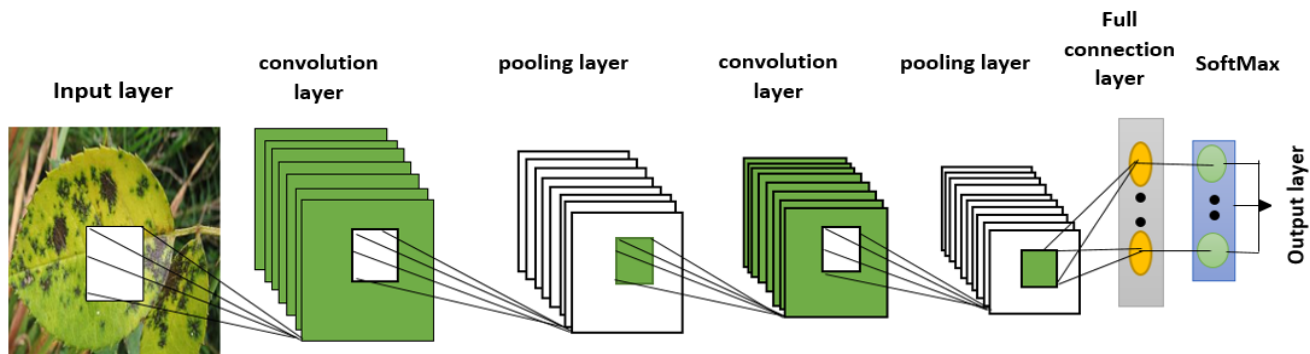


Fig. 3: Basic structure of CNN.

There are many CNN models. Researchers can use transfer learning for these models to train their data instead of starting from scratch, such as:

- Alex Net
- CafeNet
- VGG
- GoogleNet
- Inception –ResNet

Table III highlights some agriculture-related deep learning research and the dataset and categories used. The following are the most widely used platforms and tools for deep learning research:

- Theano
- Tensorflow
- Keras

Figure 4 shows the most used algorithms in the reading research. Algorithms in deep learning need the data entered

into them to be different to extract the important characteristics and properties. Before entering the model, it's critical to pre-process the data. [11,19].

- Resize photos.
- Segment images to increase their size or to facilitate the learning process.
- Remove photo background.
- Pixel extraction using unique masks.
- Convert images to grayscale or HSV.

But sometimes, the data set is small in this case, and we need to increase it to be suitable for inclusion in deep learning models to get the best result from training and prevent overfitting. The researcher receives training on artificial images due to augmentation and testing on real images [19].

Common ways to increase data are: cropping, scaling, decreasing, rotating, flipping, etc.

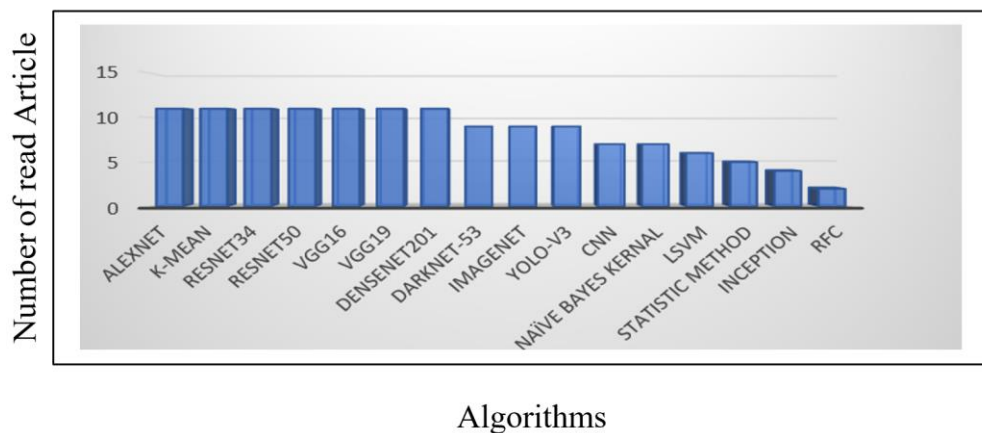


Fig. 4: most used algorithms in the reading research.

TABLE III

Shows some previous studies on the use of image processing algorithms and deep learning in agriculture.

<i>research</i>	<i>Purpose of research</i>	<i>Dataset</i>	<i>Algorithm result</i>	<i>Algorithm used</i>	<i>Points of strengths and limitations</i>
[1] (Faithpraise & Chatwin, 2013)	Automatically identify plant pests	collected from a variety of web sources, including ALABAMA NURSERY AND LANDSCAPE Paul S. Hamilton and Maria Iannotti	Identify pests and their locations in the photo	k-mean algorithm + correspondence filter	The algorithm's ability to detect plant pests from a 360-degree angle due to the use of a corresponding filter, but the number of pests in the image cannot be detected
[20] (Sladojevic et al., 2016)	Discover leaf diseases	The researcher created a data set	15 class	CafeNet CNN	3,000 images were collected from the Internet for 13 plant diseases, and 30,000 images were generated.
[24] (Patil & Thorat, 2016)	A monitoring method that detects the early stages of the grape disease	Data on temperature and humidity and soil moisture and leaf wetness.	Detecting the beginning of the grape disease in its early stages and predicting its occurrence	Statistical method, hidden Markov model	Because environmental factors are the primary cause of plant diseases, data analysis in this work is helpful for the early detection of disease, but sensor data could lead to erroneous readings
[25] (Padol & Yadav, 2016)	Classification of grape leaf diseases	137 photographs of grape leaves, one section obtained with a digital camera and the other from the Internet	Powdery leaf and downy leaf disease were detected with a total accuracy of 88.89% percent.	Leaves segmentation and classification using k-mean clustering and LSVM	Because the data set is tiny, the accuracy of the prediction is low. Despite the lack of training data, the accuracy is good
[6] (Wang et al., 2017)	Based on the picture, the severity of the disease is estimated	photos of healthy apple leaves and images of Botryosphaeria obtusa-caused apple leaf black rot	The leaves in the healthy stage are spotless. Small circular patches with widths less than 5 mm can be found on early-stage leaves. The leaves in the middle stage have more than three dots, at least one of which is a frog's eye. End-stage leaves are so diseased that they will fall off the tree.	ResNet50, VGG16, VGG19, Inception-v3, and VGG16. The VGG16 model, which has been fine-tuned, performs best, with an accuracy of 90.4 percent on the test set.	confusion matrix for VGG16 is suitable, but there is a problem in classifying the middle case because it is once classified as early-stage and once as end stage

III. CONCLUSION AND OUTLOOK

Sensors and deep learning algorithms have given farmers various options for increasing yields and reducing yield loss in new crops. Monitoring the farm with wireless sensor networks, on the other hand, saves time, effort, money and improves data collecting and irrigation control accuracy. This information can be incorporated into deep learning algorithms to predict future plant growth, classify or monitor plant health, and so on. As a result, this method outperformed expensive traditional methods of data collection and plant monitoring, so this presentation focused on wireless sensor networks and deep learning in the agricultural field and the most pressing problems that researchers faced to address and reduce them in future research. Noticed when reading previous research on the internet of things and deep learning in the agricultural field that it is not enough, and few of them have been applied in the real environment of the farm. As for the future of this field, it is possible to set up an integrated system that monitors the cases of multiple farms simultaneously and makes appropriate decisions to solve the problem remotely. It is also possible to create a database of plants with a greater diversity of traits to improve the model's accuracy when training and testing it in deep learning.

CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

REFERENCES

- [1] B. Faithpraise and C. Chatwin, "Automatic Plant Pest Detection And Recognition Using K-Means Clustering Algorithm And Correspondence Filters," vol. 4, no. 2, pp. 189–199, 2013.
- [2] N. Soontranon, P. Tangpattanukul, P. Srestasathien, and P. Rakwatin, "An Agricultural Monitoring System: Field Server Data Collection and Analysis on Paddy Field," 14th International Symposium on Communications and Information Technologies (ISCIT), 2014.
- [3] P. P. Jayaraman and D. Palmer, "Do-it-Yourself Digital Agriculture Applications with Semantically Enhanced IoT Platform," no. April 2015, pp. 7–9, 2020.
- [4] P. P. Jayaraman, A. Yavari, D. Georgakopoulos, A. Morshed, A. Zaslavsky, "Internet of Things Platform for Smart Farming: Experiences and Lessons Learnt. Sensors", Vol. 16, 2016. <https://doi.org/10.3390/s16111884>.
- [5] S. Navulur, A. S. C. S. Sastry, and M. N. G. Prasad, "Agricultural Management through Wireless Sensors and Internet of Things," International Journal of Electrical and Computer Engineering (IJECE), Vol. 7, No. 6, 2017. doi: 10.11591/ijece.v7i6.pp3492-3499.
- [6] G. Wang, Y. Sun, and J. Wang, "Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning," Computational Intelligence and Neuroscience, vol. 2017, 2017.
- [7] M. Bacco *et al.*, "Smart Farming: Opportunities, Challenges and Technology Enablers," IoT Vertical and Topical Summit on Agriculture - Tuscany (IOT Tuscany), 2018.
- [8] R. Yakkundimath, G. Saunshi, and V. Kamatar, "Plant Disease Detection using IoT," vol. 8, no. 9, 2018.
- [9] A. Kochhar and N. Kumar, "Wireless sensor networks for greenhouses: An end-to-end review Number of papers in IEEE digital library Number of papers in Springer," vol. 163, 2019, doi: 10.1016/j.compag.2019.104
- [10] X. Shi, X. An, Q. Zhao, H. Liu, and L. Xia, "State-of-the-Art Internet of Things in Protected Agriculture," Sensors 2019, Vol. 19, No. 8, 2019.
- [11] J. Boulent, S. Foucher, and J. Théau, "Convolutional Neural Networks for the Automatic Identification of Plant Diseases," vol. 10, no. July, 2019, doi: 10.3389/fpls.2019.00941.
- [12] R. D. Devi, S. A. Nandhini, R. Hemalatha, and S. Radha, "IoT enabled efficient detection and classification of plant diseases for agricultural applications," *Int. Conf. Wirel. Commun. Signal Process. Networking, WiSPNET 2019*, pp. 447–451, 2019, doi: 10.1109/WiSPNET45539.2019.9032727.
- [13] M. Bayram, A. Sciences, T. Faculty, and E. Engineering, "Wireless sensor network based remote drip irrigation system," vol. 6, no. 4, pp. 554–563, 2018, doi: 10.21923/jesd.443576.
- [14] M. A. Nawaz *et al.*, "Plant disease detection using internet of thing (IoT)," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 1, pp. 505–509, 2020, doi: 10.14569/ijacsa.2020.0110162.
- [15] F. A. Khan, A. A. Ibrahim, and A. M. Zeki, "Environmental monitoring and disease detection of plants in smart greenhouse using internet of things," *J. Phys. Commun.*, vol. 4, no. 5, 2020, doi: 10.1088/2399-6528/ab90c1.
- [16] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: a review," *Plant Methods*, Vol. 17, No. 22, 2021, pp. 1–18, 2021.
- [17] M. R. P. Fuke and N. V. Raut, "IOT Based Solution for Leaf Disease Prediction," *International Journal of Innovative Research In Computing*, pp. 76–81, 2020.
- [18] C. Vision, "Computer Vision, IoT and Data Fusion for Crop Disease Detection Using Machine Learning: A Survey and Ongoing Research," *Remote Sensing*, Vol. 13, No. 13, 2021.
- [19] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Comput. Electron. Agric.*, vol. 147, pp. 70–90, 2018. doi: 10.1016/j.compag.2018.02.016.
- [20] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," *Comput. Intell. Neurosci.*, vol. 2016, 2016. doi: 10.1155/2016/3289801.
- [21] M. Rahneemoonfar and C. Sheppard, "Deep count: Fruit counting based on deep simulated learning," *Sensors (Switzerland)*, vol. 17, no. 4, pp. 1–12, 2017. doi: 10.3390/s17040905.
- [22] J. A. López Riquelme, F. Soto, J. Suardíaz, P. Sánchez, A. Iborra, and J. A. Vera, "Wireless Sensor Networks for precision horticulture in Southern Spain," *Comput. Electron. Agric.*, vol. 68, no. 1, pp. 25–35, 2009, doi: 10.1016/j.compag.2009.04.006.
- [23] D. H. Park and J. W. Park, "Wireless sensor network-based greenhouse environment monitoring and automatic control system for dew condensation prevention," *Sensors*, vol. 11, no. 4, pp. 3640–3651, 2011, doi: 10.3390/s110403640.
- [24] S. S. Patil and S. A. Thorat, "Early detection of grapes diseases using machine learning and IoT," *Proc. - 2016 2nd Int. Conf. Cogn. Comput. Inf. Process. CCIP 2016*, 2016, doi: 10.1109/CCIP.2016.7802887.
- [25] P. B. Padol and A. A. Yadav, "SVM classifier based grape leaf disease detection," *Conf. Adv. Signal Process. CASP 2016*, pp. 175–179, 2016, doi: 10.1109/CASP.2016.7746160.
- [26] Ç. Ersin, R. Gürbüz, and A. K. Yakut, "Application of an automatic plant irrigation system based arduino microcontroller using solar energy," *Solid State Phenom.*, vol. 251, pp. 237–241, 2016, doi: 10.4028/www.scientific.net/SSP.251.237.
- [27] H. Wani, "An Appropriate Model Predicting Pest / Diseases of Crops Using Machine Learning Algorithms," 4th International Conference on Advanced Computing and Communication Systems (ICACCS), pp. 4–7, 2017.
- [28] S. Yadav, N. Sengar, A. Singh, A. Singh, and M. K. Dutta,

- "Identification of disease using deep learning and evaluation of bacteriosis in peach leaf," *Ecol. Inform.*, vol. 61, p. 101247, 2021, doi: 10.1016/j.ecoinf.2021.101247.
- [29] V. Tiwari, R. C. Joshi, and M. K. Dutta, "Dense convolutional neural networks based multiclass plant disease detection and classification using leaf images," *Ecol. Inform.*, vol. 63, no. March, p. 101289, 2021, doi: 10.1016/j.ecoinf.2021.101289.
- [30] V. Udutalapally, S. P. Mohanty, V. Pallagani, and V. Khandelwal, "sCrop: A Internet-of-Agro-Things (IoAT) Enabled Solar Powered Smart Device for Automatic Plant Disease Prediction," ArXiv, abs/2005.06342, pp. 1–23, 2020.
- [31] G. Bbass and A. Marhoon, "Iraqi License Plate Detection and SegmentAation based on Deep Learning," *Iraqi J. Electr. Electron. Eng.*, vol. 17, no. 2, pp. 102–107, 2021, doi: 10.37917/ijeee.17.2.12.