Indonesian Journal of Computer Science
ISSN 2549-7286 (*online*)
Jln. Khatib Sulaiman Dalam No. 1, Padang, Indonesia
Website: ijcs.stmikindonesia.ac.id | E-mail: ijcs@stmikindonesia.ac.id

Deep Learning Algorithms for IoT Based Crop Yield Optimization

Sozan Sulaiman Maghdid [1*)], Shavan Askar[2], Farah Sami Khoshaba[1], Soran Abdulrahman Hamad[1]
1sozan.maghdid@epu.edu.iq, 2 shavan.askar@epu.edu.iq
[1] Department of Information Technology, Khabat Technical Institute, Erbil Polytechnic University, Erbil, Iraq
[2] Department of Information Systems Engineering, Erbil Technical Engineering College, Erbil Polytechnic University, Erbil, Iraq

Article Information

Submitted : 21 Mar 2024
Reviewed: 25 Mar 2024
Accepted : 8 Apr 2024

Keywords

Precision Agriculture, Internet of Things (IoT), Deep Learning, Combining Data, Sensors IoT agricultures

Abstract

- Precision agriculture, with its objectives of optimizing crop yields, decreasing resource waste, and enhancing overall farm management, has emerged as a revolutionary technology in modern agricultural practices. The advent of deep learning techniques and the Internet of Things (IoT) has brought about a paradigm shift in monitoring, decision-making, and predictive analysis within the agriculture industry. This review paper investigates the relationship between deep learning, the (IoT), and agriculture, with an emphasis on how these three domains might work together to optimize crop yields through intelligent decision-making. The integration of deep learning techniques with (IoT) technology for precision agriculture is thoroughly analyzed in this study, covering recent developments, obstacles, and possible solutions. The paper investigates the role of deep learning algorithms in analyzing the vast amounts of data generated by IoT devices in agriculture. It scrutinizes various deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants applied for crop disease detection, yield prediction, weed identification, and other crucial tasks. Furthermore, this review critically examines the integration of IoT-generated data with deep learning models, highlighting the synergistic benefits in enhancing agricultural decision-making, resource allocation, and predictive analytics. This review underscores the pivotal role of IoT and deep learning techniques in revolutionizing precision agriculture. It emphasizes the need for interdisciplinary collaboration among agronomists, data scientists, and engineers to harness the full potential of these technologies for sustainable and efficient farming practices.

A. Introduction

Precision agriculture, sometimes referred to as precision farming or precision ag, is a cutting-edge farming management approach that makes use of technology to maximize crop yields, reduce waste, and boost resource efficiency. Precision agriculture is important because it can change conventional farming methods by using advanced analytics, remote sensing, and data-driven technologies [1].

Drones and other remote sensing technology give farmers comprehensive information about the state of their crops. This makes it possible to identify problems like diseases, pest infestations, and nutritional deficits early on. Precision agriculture relies on data collected from various sources, including sensors, GPS technology, and weather stations. This data is analyzed to make informed decisions about planting, irrigation, fertilization, and harvesting. It helps farmers optimize their practices based on real-time information [2].

Farmers can increase the productivity of their land by accurately adjusting inputs to the unique requirements of each area within a field [3] By supplying each plant with the materials it needs for healthy growth, this focused farming method increases agricultural yields. Precision agriculture lowers input costs for farmers by minimizing water, pesticide, and fertilizer applications that aren't essential. Enhancing economic efficiency is not the only benefit here; sustainability and environmental stewardship also benefit. Precision agriculture supports sustainable farming methods by reducing the use of agrochemicals and maximizing resource allocation. It lessens the harm that excessive runoff, soil erosion, and pesticide and fertilizer use cause to the ecosystem. Farmers who practice precision agriculture have the tools necessary to adjust to a changing climate [4] [10]. Precision agriculture is a revolutionary approach to farming that use technology and data to optimize resource utilization, improve decision-making, and eventually boost agricultural yields in an ecologically conscious and sustainable way. The Internet of Things (IOT) and deep learning have combined to drive a revolutionary transformation in precision agriculture in recent years. These developments have the potential to bring in a new era of precision agriculture by completely changing conventional farming methods [7].

The term "Internet of Things" describes a network of interconnected devices that are equipped with software, sensors, and other technologies to allow them to trade and gather data. IOT devices help in the development of extensive datasets by continuously collecting data. In agriculture to create an extensive network of data-generating nodes by being placed on machines, in livestock facilities, and across fields. IOT devices are used tractors, soil sensors, and weather stations, are all designed to record real-time data that is essential for making well-informed decisions. Many different types of data are collected by IOT devices, such as crop health, temperature, humidity, and soil moisture content. The use data in real-time, IOT makes precision agriculture possible by making it easier to apply resources like pesticides, fertilizers, and water precisely [6].

Agriculture uses deep learning algorithms to make sense of the enormous datasets produced by Internet of Things sensors. These algorithms are quite good at identifying complex links in data, which allows them to give farmers useful insights [5] [10].

Deep learning models are able to recognize image data patterns in sensor data and that point to crop diseases or nutritional deficits. This makes it easier to intervene early, stopping the spread of diseases and optimizing crop health. Deep learning systems can forecast agricultural yields by analyzing historical data, weather patterns, and soil conditions. Farmers can use this information to plan harvesting schedules and make well-informed decisions regarding market supply [9] [8].

The problem of this review paper in brief it is a conventional farming practices, which rely on human labor and crude techniques, do not match the increased demand of the world's population. The dual challenge of resource scarcity climate variability and soil degradation threaten the availability and reliability of essential resources for crop cultivation. Inefficiencies in resource utilization are exacerbated by the lack of real-time data and insights guiding decision-making. Uninformed decisions can result in overuse of agrochemicals, degradation of arable land, and economic losses for farmers. Many farmers, may lack access to or awareness of modern farming technologies, hindering their ability to make informed, data-driven decisions.

The remaining portions of the paper are arranged as follows. The second part provides information on various deep learning architectures and IOT utilized in crop production optimization, the third part addresses the agricultural datasets that are accessible for crop production optimization, and the forth part expands on the discussion of all deep learning models for IOT-based crop production optimization. This review will delve into the specific applications, challenges, and future prospects of this amalgamation, exploring how it shapes the trajectory of crop yield optimization in agriculture.

B. Literature Review

The Internet of Things has experienced significant growth in the past few years. Several publications in the literature suggested IoT designs and platforms that are appropriate for use in a variety of applications, including smart cities, agriculture, traffic control, education, marine environments, and health care. Sumathi et al. [36] used a dataset to train and test an improved soil quality prediction model using deep learning (ISQP-DL) and the DNNR technique. Findings reveale that the suggested model, when compared to current models, more accurately classifies soil and fits the data with improved generality and efficiency. With regard to soil quality prediction, the ISQP-DL model performs particularly well, with an accuracy rate of 96.7% [36]. Meng et al. [37] carry out end-to-end crop mapping using three convolutional neural network (CNN) models: 1D-CNN, 2D-CNN, and 3D-CNN. Mono-temporal and multi-temporal multispectral images (MSIs) of the same research area were carefully compared by Meng et al. [37]. According to the findings, classification accuracy with hyperspectral satellite images surpasses 94%, greatly outperforming mono-temporal MSIs and producing results that are on par with multi-temporal MSIs [37]. During the growing season for soybeans, Sagan et al. [38] used 25 Planet Scope (PS) and four WorldView-3 (WV-3) satellite photos. Through the integration of spectral, spatial, and temporal information from satellite data, Sagan et al. [38] developed 2D and 3D convolutional neural network (CNN) architectures. Hundreds of features that were carefully selected and found to be optimal for crop growth monitoring were then extracted and fed into the same deep learning model for comparison. The 2D and 3D CNN models found that a small subset of WV-3 photos performed better than multitemporal PS data because WV-3 contains certain bands like RedEdge and SWIR. Together, these models were able to explain around 90% of the variance in field-scale yield [38]. "Deep multisensory learning" is a unique approach presented by Zheng et al. [39] that does not require registration between several sensor modalities. According to the approach, the parameter distribution of sensor-specific and sensor-invariant operations accounts for the variations observed in deep models trained on data from different sensors. The technique used a sizable public dataset with high-resolution optical and SAR imagery to show the value of deep multisensory learning in an all-weather mapping situation with missing-modality data. approach performed better and more consistently than alternative learning techniques, demonstrating the importance of meta-sensory representation in multisensory remote sensing applications [39]. Adrian et al. [40] mapped ten crop kinds together with water, soil, and urban areas using a deep learning technique that makes use of denoised backscatter and texture information from multi-temporal Sentinel-1 SAR data and spectrum information from multi-temporal optical Sentinel-2 data. where an overall score of 0.941 was found after a comparison of several deep learning networks (3D U-Net, 2D U-Net, SegNet) and conventional machine learning techniques like Random Forest [40]. Garibaldi-Márquez et al [41] using multi-plant images to employed a classification method based on the CNN of Zea mays L. (Crop), narrow-leaf weeds (NLW), and broadleaf weeds (BLW). One method used for extracting regions of interest (ROI) is connected component analysis (CCA). The accuracy of the CNN-based approach is an astounding 97% [41]. Dogra et al. [51] suggested a CNN-VGG19 model with a transfer learning-based method for the precise identification and classification of rice leaf diseases. The accuracy is 93.0% in the deployment of the dataset of rice leaf disease and F1-score, with 89.9%, 94.7%, 92.4%, and 90.5%, respectively [51]. Tarek et al. [54] utilized standard pre-trained CNN architectures, such as AlexNet. Using ten datasets that represented various plant species, they developed an SVM classifier. The suggested model's average accuracy across all datasets is stated as 93.84, while AlexNet, GoogleNet, and SVM's respective averages are 85.49, 87.89, and 87.04, respectively [54]. Bharadwaj et al. [53] utilized a convolutional neural network (CNN) to classify plant species using image data. They made use of a dataset that had 10,000 images of plants. The CNN model performed with 93% accuracy [53]. Nagasubramanian et al. [45] introduced a novel approach using a 3D deep convolutional neural network (DCNN) designed to process hyperspectral data on a charcoal rot disease affecting soybean crops.3D DCNN has a 95.73% classification accuracy and an F1 score of 0.87 for infected classes [45]. Devarajan et al [52] suggested a two-stage, end-to-end smart agriculture system built on DRL. the ACO-enabled DQN (MACO-DQN) model in the first step to offload tasks like fire detection, pest detection, crop growth monitoring, irrigation scheduling, soil monitoring, climate monitoring, field monitoring, etc. In the second step, Devarajan et al. [52] suggested the RL-DQN (DRL-based DQN) model for task activity monitoring and prediction in agriculture. The proposed performance results were 98.5% precision, 99.1% recall, 98.1% F-measure, and 98.5% accuracy [52].

Punitha et al. [50] utilized an Automated Climate Prediction for Smart Agriculture developed a Pelican Optimization-based Hybrid Deep Belief Network (ACP-POHDBN). The approach was used in three steps. The first step was to convert the meteorological data into a standard format using the min-max normalization procedure. As a second step to forecast weather conditions, Punitha et al [50] used the Deep Belief Network (DBN) model to pre-process data. In the last step, Punitha et al. [50] applied the POA-based hyper parameter tuning technique to the DBN method's hyper parameters. The model performed had an accuracy of 95.03%, a sensitivity of 95.03%, a specificity of 95.03%, and an F-score of 95.03% [50]. Burhan et al. [48] applied five different deep learning models, namely Vgg16, Vgg19, ResNet50, ResNet50V2, and ResNet101V2.The rice field data set, which has been divided into four classes—Hispa, Healthy, Brown Spot, and Leaf Blast. The ResNet50 model demonstrated an accuracy of 75.0, while the ResNet101V2 model demonstrated an accuracy of 86.799 [48]. Abdalla et al. [47] suggested a method for classifying oilseed rape into nine nutrient status classes using a combination of long short-term memory (LSTM) and convolutional neural networks (CNNs). The Inceptionv3-LSTM obtained an accuracy of 95%, and the dataset 2017/2018 cross obtained an accuracy of 92%. [47]. Espejo-Garcia et al. [46] fine-tuned neural networks pre-trained on agricultural datasets instead of ImageNet. Some architectures, such as Xception and Inception-Resnet, presented an improvement of 0.51%, 1.89%, and 13.67% in the number of epochs reduced [46].

C. IoT in Agriculture

The Internet of Things (IoT) is the result of the rapid development of 5G infrastructures and IoT sensors into robust technologies. Although IoT is still in its infancy, the applications and trends it encompasses are reshaping the future with enormous business potential [11]. In general, the IoT system provides data flows and is further utilized to execute automatic image analysis, data prediction, data integration, data interpretation, etc. [12]. The Internet of Things (IoT) has enabled better and more effective farming operations, which has revolutionized several industries, including agriculture [13]. These technologies enable farmers to make data-driven decisions for optimal agricultural operations through the use of networked devices, sensors, and systems that gather, transmit, and analyze data. IOT platforms and devices are part of an expanding ecosystem that seeks to revolutionize agriculture by facilitating data-driven decision-making and enhancing productivity and sustainability in agricultural methods. Better resource management, lower expenses, and increased production in agriculture can result from the integration of these technologies [14]. The integration of IoT for better user outcomes in agriculture has been shown in figure 1

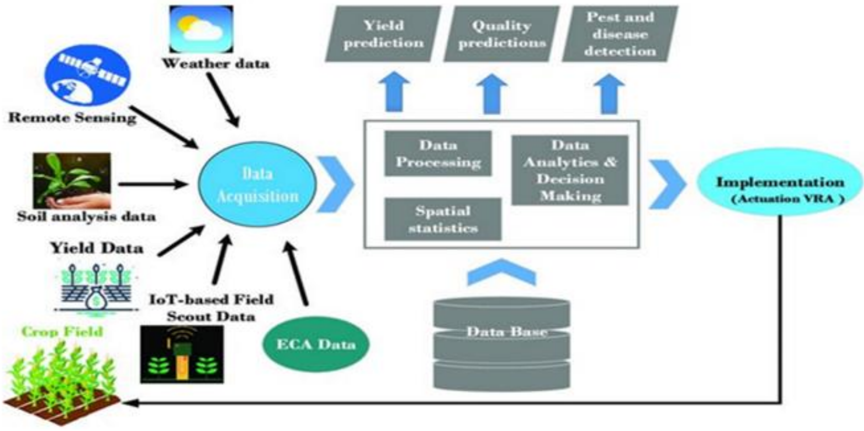

Figure 1. Use integration of IoT in Precision agriculture in [11]

3.1 Sensor Networks Types

The sensors are an essential component of the data collection system, which works with an intelligent controller to transfer the data the sensors collect to the data storage location. To detect physical quantities and translate them into an electrical signal that the controller can comprehend [15]. The following is a list of the most frequently utilized precision agriculture sensors:

• Temperature

As the most widely used sensor in the Internet of Things, temperature sensors monitor changes in both soil and ambient air temperatures. Crops depend on the air's temperature, and excessive heat can ruin crops [16].

• Humidity

The air's humidity is measured with this sensor. Too much moisture stunts the growth of plant leaves. Humidity measurement is therefore one of the crucial factors. The crop requires less watering when the air moisture content is greater than 50%. The agriculture system can incorporate these water-saving measures. Various humidity sensors exist, distinguished by their construction and operational mechanism [17].

• PH sensor

The pH of the soil and nutrient shortages (fertilizers found in the ground) are measured using a pH sensor. This sensor detects the acidity and alkalinity of the soil, which can lead to leaf discoloration, crop or plant stunting, and poor plant health. When soil acidity and alkalinity are too high, the land becomes unusable for farming. A pH of less than 5.5 inhibits the growth of plants. The pH range of 5.5 to 7.5 is optimal. Fertilizers alter the pH of the soil, which alters the quantities of nutrients in the soil. However, hydroponics also makes extensive use of pH sensors to continuously monitor the quality of the acidic or alkaline water [19].

• Light dependent resistor (LDR) sensor

This sensor is used in greenhouses to enable sunshades to be lowered during periods of intense sunlight and opened early in the day, based on the amount of light available. In these cases, an LDR sensor is employed since the sapling stage of plant growth requires a specific amount of sunlight [20].

• Wind speed sensor

Wind speed sensor utilized for pesticide application, crop harvesting timing, and weather forecasting. The wind's direction and speed are detected by the wind speed sensor. The accuracy of the sensor is highly dependent on its location [21].

• Red, Green and Blue (RGB) camera

This sensor is used to take photographs. They process data using algorithms based on the image and compare it to a final crop harvesting image in order to estimate crop harvesting time, monitor plant health, and provide security [22].

• Nitrogen, phosphorus and potassium (NPK) sensor

The NPK sensor for soil aids in determining the concentrations of potassium (K), phosphorus (P), and nitrogen (N) in the soil. In addition to predicting soil fertility, these three are necessary for the best possible plant growth. It helps by informing the farmer when to apply fertilizers to the land in order to keep the soil's nutrients intact [23].

• Rainfall sensor

Rain and rainfall totals are measured by this sensor hourly. With this sensor, farmers may be prepared by knowing when heavy rain is expected, as it might damage crops if the field becomes completely submerged in water. The advanced water and flood control system on the farm works with it. Water needed for irrigation can be saved by using this sensor, which is connected to the controller, to detect whether an irrigation schedule is in place [24].

• Hyperspectral camera

A hyperspectral camera captures numerous images in the visible (400 nm to 700 nm) and infrared (IR) bands of the electromagnetic spectrum. It makes it possible for specialized farmers to accurately track irrigation, crop productivity, and fields. A filter is used to process each image data set that a hyperspectral camera captures in order to concentrate light on a specific color or wavelength [25]. Based on the sensors used, following a careful examination, Table 1 presents an extensive summary of the literature about precision agriculture sensors and their deployment.

Table 1. Sensors used in IoT Precision agriculture.

Author	Type of Sensors	Highlights
Placidi et al.	Sentek commercial	Precision farming utilizing a low-cost Lora WAN-enabled soil moisture sensor
Jani and Chaubey	SMAIoT network	Precision agricultural IOT is effective in gathering and evaluating real-time data from a variety of pricey sensors, automating processes.
Almuhay et al.	LoRaWAN network	Long-Range Wide-Area For applications such as smart agriculture, networks are effective. The sensors' gadgets securely save each other's data.
Ahmed, Shakeel	Biosensors	Agriculture can utilize biosensors to identify particular biological processes and enzymes in soil samples.
Rajak et al.	Acoustic	Fruit harvesting, seed variety classification, pest monitoring, and detection
Aggarwal et al.	Airflow	Assessing the structure, moisture content, and air permeability of soil in a stationary or mobile environment
Rabak et al.	Electrochemical	assess the pH and nutritional content of soil

Pathirana et al.	Electromagnetic	logging soil's organic composition, electrical conductivity, electromagnetic reactions, and leftover nitrates
Wei et al	Field programmable gate array (FAAA) based	Monitoring the irrigation, humidity, and transpiration of plants in real time
LeVoir et al	Light detection and ranging (LIDAR)	surveying the land, identifying the type of soil, creating 3D models of farms, tracking soil erosion and loss, and forecasting yield
Alghazzawi et al	Mass flow	monitoring yield using a combine harvester's grain flow as a basis
Machleb et al	Mechanical	Mechanical resistance or compaction of the soil
Matus et al.	Optical	Organic matter in the soil, soil moisture, color, mineral content, composition, and so forth. Fruit maturation is monitored by optical sensors based on fluorescence. Combining microwave scattering and optical sensors to describe orchard canopies
Zhang et al.	Optoelectronic	Sort different kinds of plants to find weeds in crops grown in large rows.
Dhanaraju et al.	Soft water level-based (SWLB)	utilized in catchments to describe the characteristics of hydrological processes (water level, water flow, and time-step acquisitions).
Pyingkodi et al.	Telematics	Evaluating farm and machine operating activities, travel routes, and locations
Khan et al.	Ultrasonic ranging	Monitoring the crop canopy, weed detection, object detection, spray distance measurement, uniform spray coverage, and tank monitoring.
Ullo and Sinha	Remote sensing	Crop evaluation, modeling yield, yield date forecasting, mapping land cover and degradation, forecasting, and pest and plant identification.

D. Optimizing Crop Yield With Deep Learning Algorithms

Deep learning-based precision agriculture has the potential to revolutionize farming practices, boost productivity, reduce resource waste, and build more sustainable and fruitful agricultural systems [25]. But in order for technology to be extensively implemented on farms of all sizes, problems with accessibility, scalability, data quality, and model interpretability need to be fixed [26]. Deep learning steps in Optimizing Crop Yield shows in figure 2.

Figure 2. Deep learning steps in Optimizing Crop Yield in [49]

4.1 Deep learning models

Deep learning methods have transformed many facets of agriculture by providing creative answers to problems that farmers and the agricultural sector face [27]. Large datasets, strong computing capabilities, and neural network topologies are all used in these methods to maximize agricultural practices, enhance decision-making, and extract insightful information. We provide an overview of deep learning techniques and their applications in agriculture [28].

4.1.1 Convolutional Neural Networks (CNNs)

Deep learning is utilized in agriculture a number of applications, including early crop disease identification, plant disease differentiation, weed detection to reduce the need for herbicides, and crop health assessment from drone or satellite photos [29]. Neural networks, particularly Convolutional Neural Networks (CNNs), have been essential in processing intricate data and identifying patterns in a variety of agricultural domains [30]. For applications like crop classification, yield calculation, and plant disease detection, CNNs are especially useful since they excel at processing visual data. Convolutional neural networks (CNNs) excel at analyzing images, making them invaluable for tasks like plant disease identification, weed detection, and crop monitoring using aerial imagery [31]. CNNs are able to identify pests and diseases by analyzing photographs of crops. CNNs able to recognize minor indicators of diseases or infestations by learning features and patterns from photos, which helps farmers take prompt action. CNNs are used to distinguish weeds from crops in photos, enabling focused weed management techniques that don't damage the primary crop [32]. This increases crop productivity while lowering the need for herbicides. These networks help with plant breeding and biodiversity monitoring by using photos to distinguish different plant species or types. CNNs analyze data gathered from drones or satellite imaging to track crop health, forecast yield, evaluate soil quality, and offer management insights for the entire farm. As a result, resource allocation is optimized, and areas for improvement are identified [33].

Neural networks forecast crop yields by evaluating past data and present environmental conditions, enabling farmers to allocate resources and make well-informed decisions regarding planting, harvesting, and other agricultural practices [34]. Convolutional layers are used by CNNs to extract features in a hierarchical fashion. For example, in the field of disease detection, these layers pinpoint particular disease-related patterns, including leaf lesions or discoloration [35]. Agriculture frequently uses transfer learning using pre-trained CNN models (like VGG, ResNet, or Inception) trained on large datasets (like ImageNet). Using smaller agricultural datasets, researchers refine these models and use the learned features for targeted applications [36]. Using data augmentation methods like rotation, flipping, or scaling in conjunction with CNNs, limited labeled data can be addressed by artificially increasing the size of the training dataset, which enhances the generalization capabilities of the model [37]. CNNs may distinguish particular regions of interest within images, such as pinpointing disease-affected areas or locating individual plants in a field, by performing object localization and segmentation [38]. CNNs with OCR capabilities are useful in farm management because they can read and interpret text from images, which is useful for tasks like labeling machinery or agricultural items [39]. The NNs Algorithms for IoT Based Crop Yield Optimization shown in figure 3.

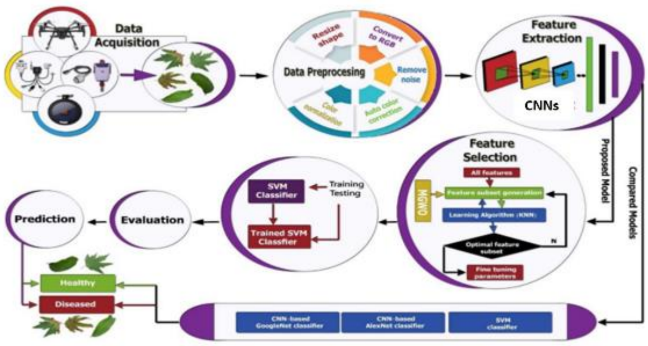

Figure 3. The NNs for IoT Based Crop Yield Optimization diagram in [54]

4.1.2 Recurrent Neural Networks (RNNs)

Deep learning models like Recurrent Neural Networks (RNNs) used to analyze historical data such as weather patterns, soil conditions, and crop growth stages to predict future yields [40]. Forecasting crop yields based on weather forecasts and environmental factors aids farmers in planning and decision-making [41]. One type of neural network that excels at representing sequential data is called a recurrent neural network (RNN)[42]. RNNs are used in agriculture for a variety of time-series data-related tasks, including crop production prediction, weather forecasting, modeling pest and disease outbreaks, and historical farming data analysis [43]. RNNs are capable of predicting future weather conditions by analyzing historical weather data. Planning farming operations such as planting, irrigation, and harvesting depends on accurate weather forecasts [44]. RNNs are capable of forecasting future crop yields by examining historical farming data, such as weather patterns, soil characteristics, and prior crop yields. With the use of this data, farmers are better able to choose crops, allocate resources, and develop marketing plans [45]. RNNs are capable of analyzing patterns in data, including temperature, humidity, and plant health indicators, that are associated with pest and disease outbreaks [46]. By taking preventative action, farmers can lessen crop loss and the need for excessive pesticide use by forecasting epidemics. RNNs are capable of modeling soil moisture content by using environmental parameters and historical data. This data helps to maintain soil health, optimize irrigation timing, and ensure effective water usage. RNNs are capable of analyzing time-series data on plant growth parameters that are gathered using imaging or sensor methods, such as biomass, leaf area, and height [47]. This helps detect stress conditions and track the stages of crop development. RNNs use progressive memory retention to handle sequential data [48]. They are appropriate for assessing time-dependent agricultural data because of their memory capacity, which allows them to take historical data into account when generating forecasts. A specific type of RNN called an LSTM can detect long-range relationships in sequential data because it has gates to regulate information flow [49]. Since long-term trends are important in agriculture, long-short term memory (LSTM) models are effective in learning patterns over extended time periods [50]. Figure 4 shows the suggested RNN-based IoT smart farm network architecture.

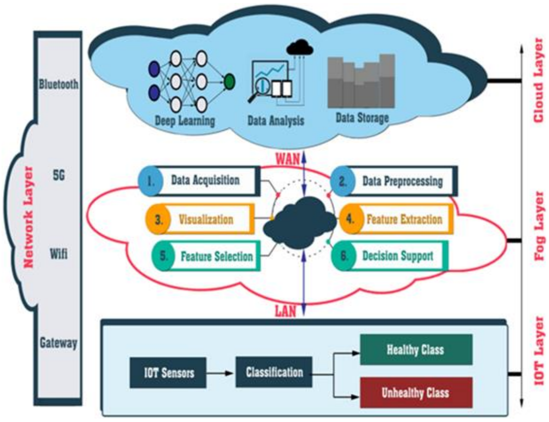

Figure 4. The suggested RNN-based IoT smart farm network architecture in [53]

RNN-based models offer predictive analytics to help stakeholders in agriculture, including farmers, make well-informed decisions [51-56]. These models improve decision-making processes, be it planting schedules, resource management, or risk mitigation [57-58]. RNNs provide a comprehensive view for improved agricultural management by integrating data from multiple sources, including historical records, satellite imagery, IoT sensor data, and environmental data [58-62]. Deep learning methods have drawn a lot of interest and demonstrated tremendous promise in a number of fields, including agriculture. In the framework of agricultural crop yield optimization using IOT-based intelligent decision-making [63-67].

E. Performance Comparison and Accuracy of Models

Table 2 shows the comparative performance of the deep learning techniques for integration with IoT discussed in this review paper. We have included only deep learning models and presented the best accuracy found in the review paper in Table 2.

Table 2. Performance Comparison and Accuracy of Model.

Author	Model	Accuracy
Sumathi et al.	DNNR	96.7%
Rani et al.	LSTM RNN	96.437%
Punitha et al.	ACP-POHDBN	95.03%
Dogra et al.	Transformer model	91.41
Devarajan et al.	CNN-VGG19	93.0%
Bharadwaj et al.	CNN	90%
Garibaldi-Márquez et al.	CNN	97%
Bhujel et al.	ResNet20	99.69%
Kaur et al.	Hybrid CNN	98.7%
Meng et al.	CNN	More than 94%

Sagan et al.	2D and 3D ResNet	Nearly 90%
Zheng et al.	Deep SAR-Net	92.94%
Adrian et al.	3D U-Net	Overall 0.941
Espejo-Garcia et al.	Xception, Inception-Resnet, VGNets, MobileNet, DenseNet	F1 Score, 99.29%
Abdalla et al.	CNN-LSTM	95%
Burhan et al.	VGG & ResNet	75.0% , 86.799%
Kaya et al.	AlexNet,VGG-16 with LSTM	99.11%
Nagasubramanian et al.	DCNN	95.73%

F. Conclusion

Precision agriculture's application of deep learning and Internet of Things (IoT) technologies has shown enormous promise for transforming conventional farming methods. Through the utilizations’ of advanced algorithms and network connectivity, this collaborative effort has yielded notable improvements in agricultural operations' sustainability, productivity, and efficiency. Precision agriculture has benefited greatly from the confluence of IoT and deep learning technologies, which have improved farming methods' profitability, sustainability, and productivity. The agricultural industry will become more resilient, efficient, and sustainable as a result of embracing new technologies and conducting additional research and development. This will help to meet the increasing need for food production while reducing the negative effects on the environment. With deep learning and IoT in precision agriculture, we expect that this work will draw the interest of agricultural communities and encourage more pertinent research.

G. References

[1] T. Balamurugan, S. Uma, M. Suman, R. Sarojini, S. Ramalingam and S. Karthick, "Artificial Intelligence Based Smart Farming and Data Collection Using Deep Learning," 2023 International Conference on Sustainable Communication Networks and Application (ICSCNA), Theni, India, 2023, pp. 1042-1048, doi: 10.1109/ICSCNA58489.2023.10370624.

[2] F. Maita and L. Maiolo, "Low power Wireless Sensor Network for precision agriculture: a battery-less operation scenario," 2021 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor), Trento-Bolzano, Italy, 2021, pp. 75-79, doi: 10.1109/MetroAgriFor52389.2021.9628772.

[3] R. Raju and T. M. Thasleema, "An IoT Solutions for Ungulates Attacks in Farmland," 2023 2nd International Conference for Innovation in Technology (INOCON), Bangalore, India, 2023, pp. 1-6, doi: 10.1109/INOCON57975.2023.10100983.

[4] Udutalapally, V., Mohanty, S. P., Pallagani, V., & Khandelwal, V. (2020). sCrop: A novel device for sustainable automatic disease prediction, crop selection, and irrigation in Internet-of-Agro-Things for smart agriculture. IEEE Sensors Journal, 21(16), 17525-17538.

[5] S. Redhu, A. P. Singh, R. M. Hegde and B. Beferull-Lozano, "A Cluster based Sensor-Selection Scheme for Energy-Efficient Agriculture Sensor Networks,"

2021 IEEE 18th Annual Consumer Communications & Networking Conference (CCNC), Las Vegas, NV, USA, 2021, pp. 1-4, doi: 10.1109/CCNC49032.2021.9369595
[6] Pyingkodi, M., Thenmozhi, K., Nanthini, K., Karthikeyan, M., Palarimath, S., Erajavignesh, V., & Kumar, G. B. A. (2022, January). Sensor based smart agriculture with IoT technologies: a review. In 2022 international conference on computer communication and informatics (ICCCI) (pp. 1-7). IEEE.
[7] P. T. K. Bai, D. Lissy and S. L. Nesamani, "Role of IoT in Precision Agriculture and Detecting and Classifying Rice Leaf Diseases using CNN Method of Deep Learning," 2023 International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE), Chennai, India, 2023, pp. 1-5, doi: 10.1109/RMKMATE59243.2023.10369919.
[8] M. I. Arefin Hossain, A. Kiser, I. J. Mitu and S. M. Binta Haque, "Intelligent IoT-based Combined Crop-type and Disease Prediction System with Different Machine Learning & Deep Learning Techniques," 2023 10th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), Palembang, Indonesia, 2023, pp. 412-417, doi: 10.1109/EECSI59885.2023.10295872.
[9] O. Jouini, K. Sethom and R. Bouallegue, "The Impact of the Application of Deep Learning Techniques with IoT in Smart Agriculture," 2023 International Wireless Communications and Mobile Computing (IWCMC), Marrakesh, Morocco, 2023, pp. 977-982, doi: 10.1109/IWCMC58020.2023.10182720.
[10] S. Aguiar and E. Barros, "A Soil pH Sensor and a Based on Time-Series Prediction IoT System for Agriculture," 2023 XIII Brazilian Symposium on Computing Systems Engineering (SBESC), Porto Alegre, Brazil, 2023, pp. 1-6, doi: 10.1109/SBESC60926.2023.10324263.
[11] Bhat, Showkat Ahmad, and Nen-Fu Huang. "Big data and ai revolution in precision agriculture: Survey and challenges." IEEE Access 9 (2021): 110209-110222.
[12] M. F. Shahid, S. S. Hussain, A. Zehrah, H. S. Khan and M. A. Ahmed, "Predicting Temperature and Humidity for Cotton Field Using Deep Learning Models in Smart Agriculture System," 2023 IEEE 8th International Conference on Engineering Technologies and Applied Sciences (ICETAS), Bahrain, Bahrain, 2023, pp. 1-6, doi: 10.1109/ICETAS59148.2023.10346477.
[13] Hemavathi and S. Akhila, "Deep Learning Based Approach for Plant Leaf Disease Detection for Smart Farming," 2023 International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems (ICAECIS), Bangalore, India, 2023, pp. 496-500, doi: 10.1109/ICAECIS58353.2023.10170703.
[14] P. Dhoke, N. Purohit and P. P. Lokulwar, "Smart Farming Using Machine Learning and Deep Learning: A Review," 2023 International Conference on IoT, Communication and Automation Technology (ICICAT), Gorakhpur, India, 2023, pp. 1-7, doi: 10.1109/ICICAT57735.2023.10263691.
[15] Sinha, Bam Bahadur, and R. Dhanalakshmi. "Recent advancements and challenges of Internet of Things in smart agriculture: A survey." Future Generation Computer Systems 126 (2022): 169-184.

[16] Placidi, P.; Morbidelli, R.; Fortunati, D.; Papini, N.; Gobbi, F.; Scorzoni, A. Monitoring soil and ambient parameters in the iot precision agriculture scenario: An original modeling approach dedicated to low-cost soil water content sensors. Sensors 2021,21, 5110.

[17] Jani, K.A.; Chaubey, N.K. A Novel Model for Optimizing Resource Utilization in Smart Agriculture System Using IoT (SMAIoT). IEEE Internet Things J. 2021, 9, 11275–11282.

[18] Almuhaya, M.A.M.; Jabbar, W.A.; Sulaiman, N.; Abdulmalek, S. A Survey on LoRaWAN Technology: Recent Trends, Opportunities, Simulation Tools and Future Directions. Electronics 2022, 11, 164.

[19] Alzuhair, Ahmed, and Abdullah Alghaihab. "The Design and Optimization of an Acoustic and Ambient Sensing AIoT Platform for Agricultural Applications." Sensors 23, no. 14 (2023): 6262.

[20] Rajak, Prem, Abhratanu Ganguly, Satadal Adhikary, and Suchandra Bhattacharya. "Internet of Things and smart sensors in agriculture: Scopes and challenges." Journal of Agriculture and Food Research 14 (2023): 100776.

[21] Steeneken, Peter G., Elias Kaiser, Gerard J. Verbiest, and Marie-Claire ten Veldhuis. "Sensors in agriculture: towards an Internet of Plants." Nature Reviews Methods Primers 3, no. 1 (2023): 60.

[22] Aggarwal, Kapil, G. Sreenivasula Reddy, Ramesh Makala, T. Srihari, Neetu Sharma, and Charanjeet Singh. "Studies on energy efficient techniques for agricultural monitoring by wireless sensor networks." Computers and Electrical Engineering 113 (2024): 109052.

[23] Rabak, Anika, Kiranmai Uppuluri, Fabiane Fantinelli Franco, Naveen Kumar, Vihar P. Georgiev, Caroline Gauchotte-Lindsay, Cindy Smith, Richard A. Hogg, and Libu Manjakkal. "Sensor system for precision agriculture smart watering can." Results in Engineering 19 (2023): 101297.

[24] Pathirana, Sashini, Sébastien Lambot, Manokarajah Krishnapillai, Mumtaz Cheema, Christina Smeaton, and Lakshman Galagedara. "Ground-Penetrating Radar and Electromagnetic Induction: Challenges and Opportunities in Agriculture." Remote Sensing 15, no. 11 (2023): 2932.

[25] Ahmed, Shakeel. "Energy Aware Software Defined Network Model for Communication of Sensors Deployed in Precision Agriculture." Sensors 23, no. 11 (2023): 5177.

[26] Wei, Zhiqing, Zeyang Meng, Meichen Lai, Huici Wu, Jiarong Han, and Zhiyong Feng. "Anti-collision technologies for unmanned aerial vehicles: Recent advances and future trends." IEEE Internet of Things Journal 9, no. 10 (2021): 7619-7638.

[27] LeVoir, Samuel J., Peter A. Farley, Tao Sun, and Chong Xu. "High-accuracy adaptive low-cost location sensing subsystems for autonomous rover in precision agriculture." IEEE Open Journal of Industry Applications 1 (2020): 74-94.

[28] Alghazzawi, Daniyal, Omaima Bamasaq, Surbhi Bhatia, Ankit Kumar, Pankaj Dadheech, and Aiiad Albeshri. "Congestion control in cognitive IoT-based WSN network for smart agriculture." IEEE Access 9 (2021): 151401-151420.

[29] Machleb, Jannis, Gerassimos G. Peteinatos, Benjamin L. Kollenda, Dionisio Andújar, and Roland Gerhards. "Sensor-based mechanical weed control:

Present state and prospects." Computers and electronics in agriculture 176 (2020): 105638.
[30] Matus, Vicente, Victor Guerra, Cristo Jurado-Verdu, Stanislav Zvanovec, Jose Rabadan, and Rafael Perez-Jimenez. "Design and implementation of an optical camera communication system for wireless sensor networking in farming fields." In 2021 IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), pp. 1-6. IEEE, 2021.
[31] Zhang, Shaohui, Songrui Wei, Zeng Liu, Tianzhong Li, Chaozhou Li, Xiang Long Huang, Cong Wang et al. "The rise of AI optoelectronic sensors: from nanomaterial synthesis, device design to practical application." Materials Today Physics (2022): 100812.
[32] Dhanaraju, Muthumanickam, Poongodi Chenniappan, Kumaraperumal Ramalingam, Sellaperumal Pazhanivelan, and Ragunath Kaliaperumal. "Smart farming: Internet of Things (IoT)-based sustainable agriculture." Agriculture 12, no. 10 (2022): 1745.
[33] Pyingkodi, M., K. Thenmozhi, K. Nanthini, M. Karthikeyan, Suresh Palarimath, V. Erajavignesh, and G. Bala Ajith Kumar. "Sensor based smart agriculture with IoT technologies: a review." In 2022 international conference on computer communication and informatics (ICCCI), pp. 1-7. IEEE, 2022.
[34] Khan, Arsalan, Sumair Aziz, Mudassar Bashir, and Muhammad Umar Khan. "IoT and wireless sensor network based autonomous farming robot." In 2020 international conference on emerging trends in smart technologies (ICETST), pp. 1-5. IEEE, 2020.
[35] Ullo, Silvia Liberata, and Ganesh Ram Sinha. "Advances in IoT and smart sensors for remote sensing and agriculture applications." Remote Sensing 13, no. 13 (2021): 2585.
[36] Sumathi, P., V. V. Karthikeyan, M. S. Kavitha, and S. Karthik. "Improved Soil Quality Prediction Model Using Deep Learning for Smart Agriculture Systems." Computer Systems Science & Engineering 45, no. 2 (2023).
[37] Meng, S.Y.; Wang, X.Y.; Hu, X.; Luo, C.; Zhong, Y.F. Deep learning-based crop mapping in the cloudy season using one-shot hyperspectral satellite imagery. Comput. Electron. Agric. 2021, 186, 106188.
[38] Sagan, V., Maimaitijiang, M., Bhadra, S., Maimaitiyiming, M., Brown, D. R., Sidike, P., & Fritschi, F. B. (2021). Field-scale crop yield prediction using multi-temporal WorldView-3 and PlanetScope satellite data and deep learning. ISPRS journal of photogrammetry and remote sensing, 174, 265-281.
[39] Zheng, Zhuo, Ailong Ma, Liangpei Zhang, and Yanfei Zhong. "Deep multisensor learning for missing-modality all-weather mapping." ISPRS Journal of Photogrammetry and Remote Sensing 174 (2021): 254-264.
[40] Adrian, Jarrett, Vasit Sagan, and Maitiniyazi Maimaitijiang. "Sentinel SAR-optical fusion for crop type mapping using deep learning and Google Earth Engine." ISPRS Journal of Photogrammetry and Remote Sensing 175 (2021): 215-235.
[41] Garibaldi-Márquez, Francisco, Gerardo Flores, Diego A. Mercado-Ravell, Alfonso Ramírez-Pedraza, and Luis M. Valentín-Coronado. "Weed Classification from Natural Corn Field-Multi-Plant Images Based on Shallow and Deep Learning." Sensors 22, no. 8 (2022): 3021.

[42] Bhujel, A.; Kim, N.E.; Arulmozhi, E.; Basak, J.K.; Kim, H.T. A lightweight Attention-based convolutional neural networks for tomato leaf disease classification. Agriculture 2022, 12, 228.
[43] Kaur, P.; Harnal, S.; Tiwari, R.; Upadhyay, S.; Bhatia, S.; Mashat, A.; Alabdali, A.M. Recognition of Leaf Disease Using Hybrid Convolutional Neural Network by Applying Feature Reduction. Sensors 2022, 22, 575.
[44] Kaya, A.; Keceli, A.S.; Catal, C.; Yalic, H.Y.; Temucin, H.; Tekinerdogan, B. Analysis of transfer learning for deep neural network based plant classification models. Comput. Electron. Agric. 2019, 158, 20–29.
[45] Nagasubramanian, K.; Jones, S.; Singh, A.K.; Sarkar, S.; Singh, A.; Ganapathysubramanian, B. Plant disease identification using explainable 3D deep learning on hyperspectral images. Plant Methods 2019, 15, 98.
[46] Espejo-Garcia, B.; Mylonas, N.; Athanasakos, L.; Fountas, S. Improving weeds identification with a repository of agricultural pre-trained deep neural networks. Comput. Electron. Agric. 2020, 175, 105593.
[47] Abdalla, A.; Cen, H.Y.; Wan, L.; Mehmood, K.; He, Y. Nutrient status diagnosis of infield oilseed rape via deep learning-enabled dynamic model. IEEE Trans. Ind. Inform. 2020, 17, 4379–4389.
[48] Burhan, S.A.; Minhas, S.; Tariq, A.; Hassan, M.N. Comparative study of deep learning algorithms for disease and pest detection in rice crops. In Proceedings of the 2020 12th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Bucharest, Romania, 25–27 June 2020.
[49] Rani, S., Mishra, A. K., Kataria, A., Mallik, S., & Qin, H. (2023). Machine learning-based optimal crop selection system in smart agriculture. Scientific Reports, 13(1), 15997.
[50] Punitha, A., and V. Geetha. "Automated climate prediction using pelican optimization based hybrid deep belief network for Smart Agriculture." Measurement: Sensors 27 (2023): 100714.
[51] Dogra, R., Rani, S., Singh, A., Albahar, M. A., Barrera, A. E., & Alkhayyat, A. (2023). Deep learning model for detection of brown spot rice leaf disease with smart agriculture. Computers and Electrical Engineering, 109, 108659.
[52] Devarajan, G. G., Nagarajan, S. M., Ramana, T. V., Vignesh, T., Ghosh, U., & Alnumay, W. (2023). DDNSAS: Deep reinforcement learning based deep Q-learning network for smart agriculture system. Sustainable Computing: Informatics and Systems, 39, 100890.
[53] Bharadwaj, A. J., C. Thakuria, J. M. Rabha, G. K. Das, and K. Das. "Smart Agriculture via Object Detection." Indian Journal of Science and Technology 16 (2023): 1-5.
[54] Tarek, Z., Elhoseny, M., Alghamdi, M.I. et al. Leveraging three-tier deep learning model for environmental cleaner plants production. Sci Rep 13, 19499 (2023). https://doi.org/10.1038/s41598-023-43465-4
[55] Tua Halomoan Harahap, Sofiene Mansouri, Omar Salim Abdullah, Herlina Uinarni, Shavan Askar, Thaer L. Jabbar, Ahmed Hussien Alawadi, Aalaa Yaseen Hassan, An artificial intelligence approach to predict infants' health status at birth, International Journal of Medical Informatics, Volume 183, 2024, 105338, ISSN 1386-5056,

[56] Diana Hayder Hussein; Shavan Askar, “Federated Learning Enabled SDN for Routing Emergency Safety Messages (ESMs) in IoV Under 5G Environment”, IEEE Access, Volume 11, 2023.

[57] Media Ali Ibrahim; Shavan Askar, “An Intelligent Scheduling Strategy in Fog Computing System Based on Multi-Objective Deep Reinforcement Learning Algorithm”, IEEE Access, Volume 11, 2023.

[58] Saman M. Omer, Kayhan Z. Ghafoor & Shavan K. Askar , “Lightweight improved yolov5 model for cucumber leaf disease and pest detection based on deep learning” Journal of Signal, Image and Video Processing, 2023

[59] Shavan Askar, “Deep Forest Based Internet of Medical Things System for Diagnosis of Heart Disease”, ARO Journal, 2023.

[60] Nafees Zaman; Ahmad Abu Saiid; Md Arafatur Rahman; Shavan Askar; Jasni Mohamad Zain , “A Data-Intelligent Scheme Toward Smart Rescue and Micro-Services”, IEEE Access Volume 11, 2023.

[61] Dezheen H. Abdulazeez; Shavan K. Askar, “Offloading Mechanisms Based on Reinforcement Learning and Deep Learning Algorithms in the Fog Computing Environment” IEEE Accesss Volume 11, 2023.

[62] Saman M. Omer, Kayhan Z. Ghafoor, Shavan K. Askar, “Plant Disease Diagnosing Based on Deep Learning Techniques” ARO journal, 2022.

[63] Saman M. Omer, Kayhan Z. Ghafoor, Shavan K. Askar, “An Intelligent System for Cucumber Leaf Disease Diagnosis Based on the Tuned Convolutional Neural Network Algorithm” Journal of Mobile Information systems, Volume 2022.

[64] Shavan Askar & Chnar Mustaf Mohammed & Shahab Wahhab Kareem, 2021. "Deep Learning in IoT systems: A Review," International Journal of Science and Business, IJSAB International, vol. 5(6), pages 131-147.

[65] Shavan Askar & Kurdistan Ali & Tarik A. Rashid, 2021. "Fog Computing Based IoT System: A Review," International Journal of Science and Business, IJSAB International, vol. 5(6), pages 183-196.

[66] Shavan Askar & Zhala Jameel Hamad & Shahab Wahhab Kareem, 2021. "Deep Learning and Fog Computing: A Review," International Journal of Science and Business, IJSAB International, vol. 5(6), pages 197-208.

[67] D. H. Abdulazeez and S. K. Askar, "A Novel Offloading Mechanism Leveraging Fuzzy Logic and Deep Reinforcement Learning to Improve IoT Application Performance in a Three-Layer Architecture Within the Fog-Cloud Environment," in IEEE Access, vol. 12, pp. 39936-39952, 2024