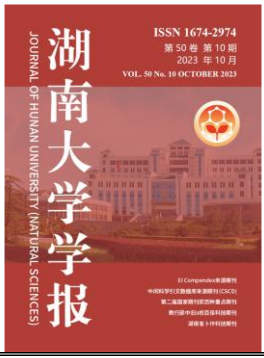

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A Review of the Internet of Things and Deep Learning in Agriculture: A Smart Agriculture Prespective

Azeem Ayaz Mirani[1]*, Shah Zaman[2], Rozina Chohan[3], Saima Siraj[4], Shamshad Lakho[5]

[1] PhD Scholar, Department of Information Technology, Quaid-e-Awam University, Nawabshah, Sindh, Pakistan

[2] Associate Professor, Department of Information Technology, Quaid-e-Awam University, Nawabshah, Sindh, Pakistan

[3] Associate Professor, Department of Computer Science, SALU Mirus, Pakistan

[4] Department of Information Technology, Quaid-e-Awam University, Nawabshah, Sindh, Pakistan

[5] Lecturer, Department of Computer Science, Quaid-e-Awam University, Nawabshah, Sindh, Pakistan

* Corresponding author: azeemayaz@sbbusba.edu.pk

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Abstract: The artificial intelligence revolution in smart agriculture raises many challenges and opportunities for researchers. The adoption of modern technologies in agriculture has led to very high results compared to the last few decades. IoT technologies in agriculture have brought many new trends in monitoring the status of crops that can lead to monitoring the real-time environment and parameters that directly impact crop yield. The weather, soil, and plant monitoring can determine the exact crucial conditions for crops. Deep learning methods help intelligent disease detection and classification from the learned image dataset. The sub-field of artificial intelligence (deep learning) can structure algorithms in layers to develop artificial neural network learning and make intelligent decisions. Deep transfer learning attempts to solve the problem of the learned model that performs a task and to modify the experimental model to solve another task. This study aims to review agriculture technologies related to the literature, applications, and challenges. IoT and deep learning from the agriculture perspective are the primary focus of this study.

Keywords: deep learning, smart agriculture, Internet of Things.

農業物聯網與深度學習回顧：智慧農業視角

摘要：智慧農業的人工智慧革命為研究人員帶來了許多挑戰和機會。與過去幾十年相比，現代農業技術的採用取得了非常好的成果。農業中的物聯網技術為監測作物狀態帶來了許多新趨勢，可以監測直接影響作物產量的即時環境和參數。天氣、土壤和植物監測可以確定作物的確切關鍵條件。深度學習方法有助於從學習的影像資料集中進行智慧疾病檢測和分類。人工智慧的子領域（深度學習）可以分層構造演算法來發展人工神經網路學習並做出智慧決策。深度遷移學習試圖解決執行一項任務的學習模型的問題，並修改實驗模型以解決另一項任務。本研究旨在回顧農業技術相關的文獻、應用和挑戰。從農業角度來看物聯網和深度學習是本研究的主要重點。

关键词：深度學習、智慧農業、物联网。

1. Introduction

Smart agriculture [1] involves the main areas of crop applications. It tackles many challenges in agricultural productivity, food security, yield improvement, crop sustainability, and primary environmental factors. Global agricultural production needs to increase as the world population is increasing. Agricultural quality and availability are critical challenges in the world. Meanwhile, improving crop cultivation and product yield should not negatively impact the environment. The agricultural domain is complex, multivariate, and unpredictable [2]. Deep learning [3] is an artificial intelligence subfield with a significant potential to handle various data [4]. It analyzes several image datasets. Agricultural science is a primary concern due to its economic benefits to stockholders. Crop disease [5] affects crop yield and causes damage to economic interests. Seasonal protection awareness of different types of diseases and their early-stage detection are crucial. Treating plant diseases via pesticides by farmers without justification and proper knowledge can cause more loss. Modern research has improved agricultural cultivation methods, monitoring of crop fields, and crop yield prediction [6, 7]. This area of study plays an essential role in human life in improving the reliability and efficiency of automated task-based approaches. In Pakistan, agriculture is the most focused area of research because of its significant impact on GDP and import/export business. Various crop products are cultivated in Pakistan, leading to unexpected crop yield production due to traditional crop cultivation, analysis, monitoring, and harvesting methods. Factors such as dull soil, plant nutrition, environmental pollution, and water pollution [8] are the main reasons for the low yield. IoT and deep learning technologies for monitoring, detecting, and identifying agricultural weather, soil, and diseases can lead to accurate yield estimation and timely decision-making [9, 10]. The timely precaution will lead to improved crop products sufficient for business growth. Plant disease [11] is a challenging aspect of agricultural crop development. Infection in plants has numerous stages, including leaves, roots, and stems, influenced by water absorbance, supplements, flowering, plant growth, cell division and extension, chemical change, and fruit development [3, 12]. Traditional methods of studying plant diseases are slow and lack accurate data, the collection of which often lacks credibility. Fig. 1 depicts several factors that can influence agricultural crop yield.

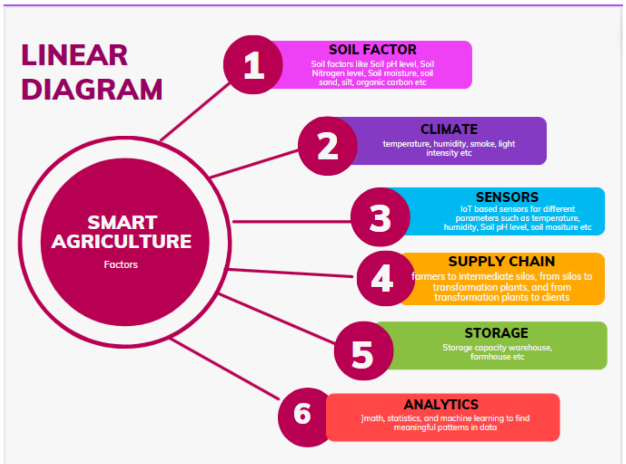

Fig. 1 Smart agriculture factors

The agricultural crop cultivation factors [13] include soil, climate, sensor technology, supply chain, storage, and data analytics. The soil factors include soil pH level, nitrogen level, moisture, water and irrigation quality, and quantity control [14], and soil silt and organic carbon are influential parts of soil fertility [15]. This gives rise to plant growth if it has a positive and normal range of parameters measurement; otherwise, it gives negative results at different crop growth stages. Climate factors affect crops substantially negatively if sudden climate changes occur. Climate effects such as temperature, humidity, smoke, and light intensity are major influential factors. The factor of IoT-based sensors involves intelligent data-gathering processes for different weather, soil, and crop management parameters [16]. Sensors are used for data gathering and provide substantial processes for better solutions. Supply chain management and blockchain technology [17] use computational methods to make intelligent decisions on different levels for agriculture product availability and sustainability. The sustainability of the product supply will economically lead to good practices for business growth. The food storage factor makes it necessary to consider a few sights where goods are stored, the environment, the capacity of the warehouse, and monitoring of the place where goods are stored [18]. The scientific community promotes analyzing agricultural activities using modern computer technology tools. Data analysis involves complex mathematical [19], statistical [20], and machine learning [21] tools. Machine learning models can process historical data for better prediction [6], which leads to timely action for better crop yield products. Image and video data are exploited and investigated by applying deep learning [22] and computer vision models [23] for evaluating, detecting, and identifying of disease, pests, and species activities.

2. Smart Agriculture Cycle

The agriculture cultivation process combines several processes and stages. These stages can be processed by applying different modern computational tools and techniques. The agriculture cycle [24] involving smart technologies such as IoT [25], machine learning [26], deep learning, and computer vision can provide quick and rapid response with positive growth. The smart precision agriculture cycle needs to apply since it can provide effective productivity. Fig. 2 shows the smart precision agricultural cycle.

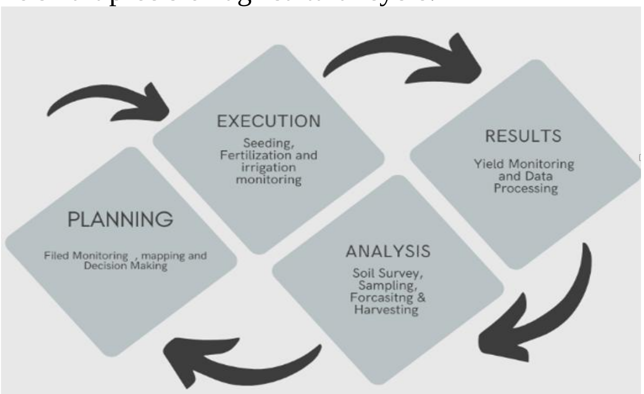

Fig. 2 Smart precision agriculture cycle

The above diagram shows the complete cycle of smart agriculture. This starts from planning to results, which is a critical and sensitive consideration. Planning involves field monitoring, mapping, and decision making for the future steps of crop [27]. The execution phase involves practical implementation step by step from seedling to final yield. The execution phase is next to the planning phase, and smart assessment [28] of seedlings, fertilizers, and irrigation monitoring must be performed efficiently. Execution requires certain pre-planned steps for the optimization of resource execution. The execution phase follows careful operations with few factors to be considered, such as precautions for human involvement, accurate period, and weather conditions. The importance of field and plant deficiencies that can be fully filled by adopting several fertilizer methods. These artificial fertilizers help improve the fertility of the soil, which helps plants grow well and rapidly.

The analysis phase requires a detailed survey of the soil that includes careful examination of soil parameters such as pH, moisture, nitrogen level, water infiltration rate, electrical conductance, nutrient reserves, soil organic carbon, and microbial biomass C [29]. Sampling of the soil and plant field can help to examine crucial parameters that are necrssary for soil and plants. Forecasting is also an important factor that requires careful analysis according to seasonal crop cultivation.

Harvesting needs complete and critical examination because the correct time for harvesting is important for good crop yield. Finally, the result measure implies crop historical data effects. Yield monitoring [30] is the process of collecting geo-referenced data. This can be achieved by adding farm-added devices, such as tractors and drones, and harvesting moisture levels, soil properties, and weather data. Yield monitoring provides a comprehensive recording of the final crop yield. The collected data from the initial to the final stage will be managed in a particular format. These data will be preprocessed to create a suitable format for implementing computational models. Computational models will help provide detailed analysis and interpretation of data.

3. Applications of Smart Agriculture

Smart agricultural farm management [31], soil monitoring [32], water irrigation control [33], autonomous machinery [34], warehouse monitoring [35], livestock monitoring [36], drones, and crop management [37] are important applications in smart agriculture. The sustainability of food for a longer time, crop protection, and crop yield are important and expected to meet world food production. The low-cost technology provides an easier way for the former to monitor their fields accurately. Smart agriculture has very important applications such as precision farming, which involves GPS-guided tracking and variable rate technology (VRT). VRT adjusts the input parameters or constraints such as fertilizers, water, and pesticides according to the specific needs of the agriculture field.

Precision farming involves soil and crop monitoring that implements IoT-based technology sensors and actuators. These sensors help monitor soil, weather, and plant status over time. Soil parameters such as pH, nitrogen level, moisture, and soil nutrition level. Weather involves parameters such as temperature, humidity, smoke and dust, light intensity, and carbon dioxide level in the environment. Drones and UAVs are also applications in smart agriculture. Drones equipped with cameras have multi-spectral and hyperspectral features that help capture high-resolution images from the field. It is important from the perspective of the image dataset, which can further help to assess, detect, and classify diseases.

IoT sensors are crucial in smart agriculture and can monitor various parameters such as temperature, humidity, smoke and dust, light intensity, and carbon dioxide level in the environment. Livestock monitoring entails a much broader range of real-time monitoring of the health and daily activities of the animals. This can also help monitor animal activities, optimize feeding schedules, and improve overall animal welfare. Livestock monitoring can also be helpful in measuring time-by-time updates for temperature, blood pressure, heart rate, and other important activities of the animal body. Automated irrigation is also a critical part of smart agriculture. A smart set of sensors can help to measure the need for water in the field. This helps determine how much and when water should pour into the field. Climate and weather forecasting helps access accurate data and allows stockholders to make timely decisions. Crop management software helps to manage, operate, and track the activities of farming operations. This can include water scheduling, crop cultivation planning, spraying schedules, fertilizers, and pest and disease management.

Vertical farming and hydroponics involve the integration of multiple technologies such as IoT, deep learning, artificial intelligence applications, robotics, and big data analytics. Supply chain optimization is a hot area of smart agriculture that shares, controls, manages, and moves agricultural products from time to time and region to region. This helps to ensure that the quality and quantity of the product monitoring must meet standard health parameters. Market analysis and decision support help to adopt modern methods of market activities and consumption of agricultural products.

This helps to control product quality, quantity, and prices. Smart agriculture also involves autonomous machinery that performs automated driving, drone spraying, harvesting, and monitoring of crop fields. Automated machines use GPS and sensor technologies for navigation and capturing real-time scenarios. The historical data are analyzed and processed to predict future patterns and trends. This includes crop yield, pest outbreaks, and market prices. Implementation of these smart technologies helps improve agricultural productivity, reduce environmental impact, and improve sustainability of overall farming activities. It is a very crucial field having a broader domain and addressing the challenges of global agricultural products. This will help improve and fulfill the agriculture products supply chain and minimize resource consumption.

4. Smart Agriculture Applications with IoT and Deep Learning

Smart agriculture [35, 36] provides automated methods for including IoT and WSN architectures. Data warehouse management and auto-monitoring of the warehouse are now a crucial part of the data-obtaining process. The important parameters for a crop within the premises can easily be imparted. Deep learning, machine learning, and IoT-based smart systems are collectively involved in fulfilling the Smart agriculture activities and paradigm.

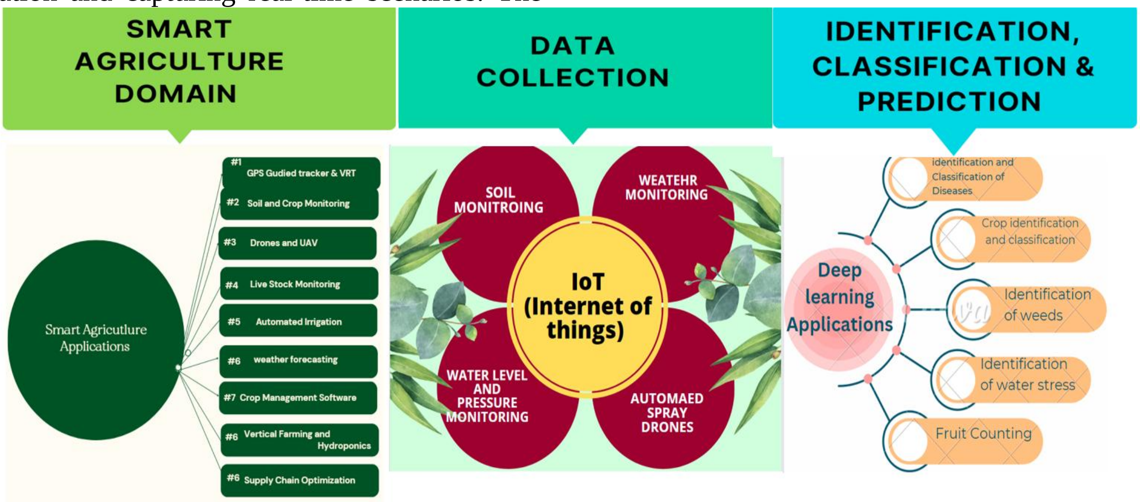

Fig. 3 Smart agriculture paradigm

Fig. 3 depicts the applications and relationships of smart agriculture with IoT and deep learning. Smart agriculture domain selection is a fundamental step. After the selection of the domain, data gathering using an IoT smart sensor is deployed for the preparation of the dataset of the relevant selected agricultural domain. Data collection requires several parameters that are used in IoT in sensor technology for data gathering from different sources.

Data gathering is for dataset construction, which is needed for further deep-learning models for analysis, optimization, and prediction. The next step is to classify, identify, and predict different application parameters according to the dataset. Smart agriculture applications include GPS-guided tracker and VRT soil monitoring, drones and UAVs, livestock monitoring, automated irrigation, weather forecasting, crop management software, vertical farming and hydroponics, and supply chain optimization. The IoT network implementation is for data collection from agricultural field applications given in the diagram. Selecting the domain and collecting data from the agriculture field, deep learning applications are also included for disease classification, identification, crop identification, identification of weeds, identification of water stress, and fruit counting.

5. Applications of Deep Learning in Smart Agriculture

The deep learning model architecture refers to the design and structure of a neural network model used for deep learning tasks. The architecture determines how the network is organized, including the number and types of layers, connections between neurons, and the flow of information through the network. Factors such as dull soil, plant nutrition, environmental pollution, and water pollution [8] are major reasons for the low yield. IoT and deep learning technologies for monitoring, detecting, and identifying agricultural weather, soil, and diseases can lead to accurate yield estimation and timely decision-making [9, 10]. The timely precaution will definitely lead to improved crop products that can be sufficient for business growth. Plant disease [11] is a challenging aspect of agricultural crop development. The deep learning model covers a broader range of applications. Table 1 shows some important applications in smart agriculture.

Table 1 Application of agriculture in deep learning

Applications	**Problem Description**	**Dataset**	**DL Model**	**Framework**	**Data preprocessing**	**Results**
Identification and classification of crop diseases [38]	Leaf disease identification and classification	Plant leave data set	Ant colony optimization (ACO) with convolutional neural network	Deep learning	Color, texture, and plant leaf arrangement are subtracted using the CNN Classifier	Accuracy of CGAN - 98%, CNN - 100%, SGD - 85%, and ACO-CNN - 100%. CGAN accuracy, precision, recall, and F1Score are 98%, 97%, 97%, and 97%. CNN accuracy, precision, recall, and F1 score are 100%, 98%, 99%, and 100, respectively. SGD accuracy, precision, recall, and F1 score are 85%, 86%, 85%, and 86%.
Crop identification and classification [39]	Crop classification	Winter, summer, permanent, and fallow crop datasets	Supervised classification approach	Deep learning	14 crop classes arranged and modified	F1 score 75% and accuracy 70%
Identification of weeds [40]	Crop identification	Cotton data set consisting of 5187 color images 15 weed classes	27 DL models evaluated ResNet 101 and DTL outputs best results	Transfer learning		ResNet 101 F1 score 99.1% DTL F1 score 95%
Identification of water stress [41]	Water identification	Maiz, soybean, and okra	AlexNet, GoogleNet, and Inception V3	Deep learning	Undesired illumination effect and eliminating noise using a Wiener filter. Histogram equalization adjusted the contrast	GoogleNet Accuracy 98.3%, 97.5%, and 94.1%
Fruit counting [42]	Deep learning-based fruit detection and counting	Reviews	Semantic segmentation technique	Deep learning	Data augmentation and annotation	NA
Smart irrigation [42]		Temperature and humidity data	LSTM	Deep learning	Improving data values, combining and sorting, resampling, handling missing values, and downsampling	Reported high accuracy RMSE 2.35%

6. IoT and Deep Learning Challenges in Agriculture

Smart agriculture provides a broader range of solutions for the modern world to meet global food requirements. Modern technology has revolutionized the agriculture field for the sustainability of agriculture. In this context, smart agriculture provides efficient solutions for good crop yield. It has many challenges that need consideration to adapt to real-world scenarios. Tables 2 and 3 depict smart agriculture challenges using IoT and deep learning.

Table 2 Smart agriculture and IoT challenges

No.	**Smart agriculture and IoT challenges**	**Description**
1	Lack of infrastructure [43]	IoT infrastructure implementation is a major issue in rural areas where limited resources are available. Connectivity for accessing stable networks is a challenge for researchers.

Continuation of Table 2

2	High Cost [44]	IoT costs have three categories: software, hardware, and service. The expensive sensors, equipment, and infrastructure are hardware. Software, programs, and protocols comments are in the software category that needs to be maintained and configured time by time also need high financing. The services from different vendors include high costs to implement and maintain software and hardware.
3	Lack of security [45]	Sensitive data collection and storage requires high security. Different physical devices are connected and operate via software. The heterogeneity of the system needs to maintain a security standard. Security is also a critical factor and a challenge to apply security standards.
4	Connectivity issue [46]	Heterogeneity creates many conflicts between standards and protocols. This is a challenging issue for IoT infrastructure. Different types of devices in one network are challenging.
6	Maintenance and reliability [47]	IoT devices are mostly deployed in remote areas where human approaches are difficult to reach. Therefore, it is challenging to maintain and make reliable network activities.

Table 3 Smart agriculture and deep learning challenges

No.	Smart agriculture and deep learning challenges	Description
1	Data quality and quantity [48]	Smart agriculture data for deep learning requires high quality and quantity. It is necessary to maintain the quality of the data set. A clearer quality will provide an effective output.
2	Model interpretability [49]	Understanding the deep learning model operations is a very complex part of this study, whereas the model provides cause of operation having effective decision making. The process of understanding model interpretability is challenging in research.
3	Resource intensiveness [50]	The smart agriculture domain has many applications, and bulk amounts of data in text, values, and images for datasets. The deep learning model needs high computation resources for developing and analyzing these data. A high graphic machine such as a GPU with high RAM is needed to perform computational operations.
4	Adaptability of local conditions [51]	The adaptability of local conditions is also a challenging aspect of agriculture using deep learning. Deep learning adopts many new trends and techniques for pattern recognition, which involves a crucial part of agricultural data. The deep learning model is adaptable to work with different levels of data but has few complex processes that need to be followed.
5	Real-time processing and inference [52]	Real-time processing using deep learning is the main part of experimentation, which is difficult to manage in remote areas where internet access is almost not possible. Real-time processing requires time, complex hardware, software, and ML/DL libraries, and the sustainability of the models for data is difficult to implement in a real-time environment.
6	Generalization across crops and regions [53]	Deep learning with machine learning models can help across a specific area of crop. Generalization of crop region characteristics/parameter identification and classification is challenging in deep learning. Deep learning models need specific areas like classification, identification, and prediction, but generalization is a big challenge in the agriculture domain.
7	Ethical consideration [26]	Legal and ethical considerations are challenging when work is done across regional and international vendor involvement. Smart agriculture equipment and deep learning libraries are a challenge for research to implement in real scenarios.

The smart agriculture domain requires a high initial cost to implement technological tools. However, careful selection and management of equipment usage and processes are required. The second challenge is limited access to technology because many underdeveloped countries do have not proper technology access for farmers and stockholders. This requires an active part of internet access and tools connectivity, termed as IoT. Data security and privacy are a big challenge in smart agriculture. Data collection in huge amounts plays an important role in future prediction. Data are collected for analysis and sharing long the long-term phase. Deep concern exists about sensitive data privacy and security. Heterogeneity and integrity are challenging when different levels of protocols, methods, and platforms are used in the model. The integration and compatibility of all resources are a significant challenge. Digital literacy is an important aspect of using smart agriculture tools. The adoption of digital technology requires a certain level of training and detailed knowledge. Unreliable connectivity is also a big challenge in rural areas where the internet is not connected. Vendor policy and regulatory authority are also challenged in less developed countries. The regulatory issues and barriers can create hurdles in certain smart agriculture technologies. Heavy export and import duties on goods are also a challenge. The power supply for smart agriculture equipment in rural areas is also a challenge for farmers. The limited energy source and electricity can result in loss of the crucial activity of the crop. Environmental factors have a greater impact, and careful consideration is needed to implement smart agriculture technology. The deployment of new technology led to energy consumption and environmental disturbance. Ethical considerations are needed to be involved very seriously in smart agriculture development. Issues such as displacement of labor, control over decision making, and potential inequalities toward technology are primary ethical considerations.

7. Conclusion

Generally, this study entails smart agriculture, IoT, and deep learning modern trends, applications, and challenges. Smart agriculture, in addition to IoT and deep learning, can cover a broad range of research. It is critical to add modern technologies for the expansion of crop production. This study will help new research to understand trends in smart agriculture from seedling to cultivation adaptation. The reader will understand deep learning and IoT applications and challenges in agriculture with the latest trends. Finally, this study provides multidiscipline field application and challenges, an essential study area.

As a recommendation, this study can be extended by focusing on crop data from different domains of agriculture, IoT, and deep learning experimentation. Deep learning model exploration will help to solve and discover complex data patterns for future prediction.

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