Survey for Smart Farming Technologies: Challenges and Issues

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Abstract

Internet of Things (IoT) has been a major influence in Agriculture since its application to the sector. This paper provides an extensive review of the use of smart technologies in agriculture and elaborates the state-of-the-art technologies for smart agriculture including, Internet of Things, cloud computing, machine learning, and artificial intelligence. The application of smart farming to crop and animal production and post-harvesting is discussed. The impact of climatic changes on agriculture is also considered. This paper contributes to knowledge by iterating the challenges of smart technology to agriculture while highlighting the issues identified from existing framework of smart agriculture. The authors identify many gaps in existing research affecting the application of IoT in smart farming, and suggest further research to improve the current food production globally, to provide better food management and sustainability measures across the globe.

Keywords: Artificial Intelligent, Internet of things, Cloud, Unmanned Area Vehicle, Smart Farming, sensors

1. Introduction

Smart technologies in agriculture will boost the production of farm crops and livestock since autonomous systems will be able to control actuators effectively, improve the utility, control resource usage, and ensure products conform to market requirements while maximizing profit and minimizing the cost of production [1]. Smart farming refers to the use of technologies such as IoT for collection of weather data, monitoring of crops' growth, early detection of crops diseases, prevention of crops wastage dues to effective harvesting of crops, monitoring of livestock's behavioral patterns, animal location within and outside the farms, increase of production for both crops and livestock. From figure 1 it can be inferred that agriculture has evolved from 12,000 B.C [104, 105, 106], using of application of diverse and improved farming strategies, technics for crop planting and harvesting, and the use of mechanized tools for agriculture. During the pre-historical age, farming was practiced using sticks, sickle, hand gathering of crops, and hunting of animals. According to [106], agriculture has changed. Farmers can now monitor their farms remotely from their smartphones and control devices. Farmers cultivate crops using seeds that have been genetically modified to prevent disease and infestation on the farm. These seeds also help improve the quality of the crops produced and boost the volume of the harvest. It can be deduced from [106], that the improved quality of crops, has reduced food scarcity across the globe. This paper discusses an overview of the various state of the art intelligent technologies on smart farming. Section 2 discusses smart farming technologies giving an overview of the application of intelligent technologies to smart farming, crop, animal production, and post-harvesting. Other intelligent technologies such as sensors, IoT, and unmanned aerial vehicles (UAV) are discussed in section 3. The impact of climate on smart farming is discussed in section 4.0. A critical review of the identified challenges and issues from existing research on smart farming is discussed in section 5.0. The use of cloud technologies and machine learning are discussed in section 7.

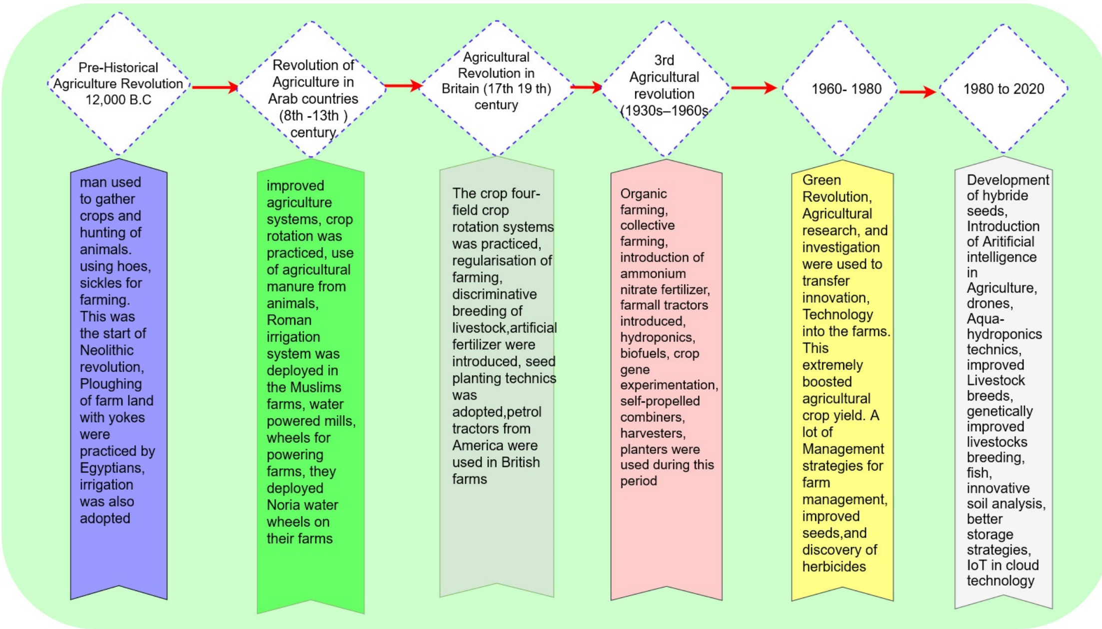

Figure 1: Showing the evolution of Agriculture practices from 12,000 B.C

2. Overview of State-of-the-Art Intelligent Technologies for Application in Smart Agriculture

2.1. Smart farming

Smart farming is the application of intelligent information and communication technology systems such as sensors, IoT, cloud-based processes, machine learning, artificial intelligence, networking to the farming system such as crop cultivation, livestock farming, aquatic, snail farming just to mention a few with the sole purpose of boosting the farm produce [4]. It can be inferred that smart farming involves the implementation of both technological software and hardware solutions to improve the farm's outcome. According to [5], farmers in the past years have tilled the soil using holes, animals to power the plow, used bush burning practices to clear farmlands for planting. Some have used animal waste for manure, but today fertilizers are used, which are rich in nitrogen, potassium, and many more minerals to make the soil suitable for effective farming practices. It can be inferred that new farming practices have changed over the years, from using holes and cutlasses to machine tilling the fields and machine harvesting the crops. In this respect, smart farming has introduced a more efficient technique where farmers use IoT to improve all farming practices and methodologies. Today farmers can monitor remotely their farmers many kilometers away from their farms and remotely activate actuators using IoTs installed on the farms. The authors in [1], have presented that IoT systems can be used to monitor every stage of crop and animal production. These IoT systems use AI to identify either low standard or faulty products in the food chain. This will help to boost customer safety desires through the system transparent life cycle information system. The limitation of this research is related to the security of the information system and the interoperability of the diverse networks from different players of the IoT ecosystem. According to [6], smart farming has improved water management system using IoT technologies. It can be deduced from their paper that better irrigation of water through smart farming devices is achievable. Smart farming has enhanced real-time climate forecast and soil management practices for agriculture. The authors discussed that smart farming has improved crop planting and growth, soil, temperature, moisture, pest infestation monitoring processes in the farms. The limitation of this research is that recommendations on the management of the data generated in smart farming have not been provided. According to [7], the authors discussed that by the year 2050, farmers will use IoT to boost food production by 70%. Their research has considered that sensors will be used in approximately 525 million farms globally by the year 2050. This paper reveals that a large number of sensors will be used, a large amount of data will be collected, analyzed, and transmitted across the various smart farms. According to [8], smart farming is a non-manual farming system, which makes use of information technology such as IoT within the farm. The authors in [9], have considered that smart farming has helped the irrigation system and fertilizer usage in farming. Therefore, smart farming techniques have reduced water wastage on the farms, enhance better crop yields offered better fertilizer application procedures. According to [10], smart farming has enhanced agriculture using robots for fruit harvesting and crop yield prediction. It can be deduced from their paper that smart farming technology through the digital image mapping system has enhanced insect, pests, disease, and fires monitoring. The limitation of their work is that the large data generated during the use of image mapping require high-end processing power computers to process and analyze them thereby limiting the effective use of smart farming technologies. More work is required in software development to address the demand for large data set analysis within the agricultural sector. The authors in [11] discuss the use of visualization in data analysis for smart farming applications. Their model has used a real-time statistical analysis approach to handle real-time responses to users' requests. It can be deduced from their work, that statistical analysis can be used to validate the elasticity and scalability of a farming data system.

2.2. Crops Production

The marked watershed algorithm has been used for the separation of specific leaf from background impeding of overlapping leaves [12]. It can be deduced from their research that the algorithm enhances the filtering of crop leaves. It can be inferred from their research that better segmentation of cucumber spot edges has been obtained by weighted neighborhood Grey values. The algorithm helped the researchers to obtain an intersection thereby minimizing the time of iteration, which invariably enhance the versatility and potency of the algorithm. A single-chip computer, which implements neural network analysis with very little computation power for identification and separation of plant diseases in the strawberry plant has achieved a success rate of 97%. The computational time for the analysis is approximately 1.2 seconds for the disease identification and grouping of diseases in the Cyprus region [13, 14]. The limitation of their research is that the single-chip computer has low computational power and for high vision resolution capturing and analysis of plant disease, a high-end computer faster than the human eye needs to be provided. The challenge of segmentation of the disease has not been overcome in their work, the plants can display many symptoms at the same time or show different symptoms at different stages which makes it very cumbersome to detect the exact type of infection of the crop. K-Means is the most reliable methodology [15] for the separation of plants with diseases. It can be inferred from their research that their approach involves using support vector machines and neural networks. Their approach is very fast, reliable, and precise. It has been observed in [12], [15], and [16], that smart farming has helped to monitor infections in crops at a much faster detection rate, also reducing the time of diagnosis of animal illness. However, there exist limitations in the algorithms, and the communication interaction among the sensors, computer devices, transmission protocol used for faster diagnosis and detection systems for both animals and crops.

2.3. Livestock Production

A wireless neck collar connected to farm animals can enhance data transmission from the animal movement within the farm to the remote computer or device via the cloud [17]. It can be deduced from their research that the device is compatible with various farm environments. The limitation of their research is that the neck collar is battery operated within a lifetime. The accuracy of the labeling procedure is required for the development of an efficient algorithm, which will automatically identify the health and welfare of animals [16]. According to [18], using sea-lice counting and crowding control in smart fish farming can resolve aquaculture challenges. It can be deduced from their research that this methodology is very efficient in solving specific problems in smart fish farming. The limitation of this research is that it will hinder the exploration of other mathematical models using refined sensors for data capturing. Animal production has witnessed tremendous production due to smart farming technics. This has been reported in [17], [18] and [19], where smart farming has helped the farmers to monitor the movement of the animals within and outside the farm environment, determine the animal's attitude and behavioral pattern. Their work has informed us that smart farming applied to aquaculture has enabled the fish farmers to monitor and implement crowding within the fish farm. Some other limitations include battery-powered IoT devices within the farm, which may run out within a short period. It can be inferred that the psychological effect of the introduction of strange attachment to the animal's body has not been addressed by the researchers. This prompts the question of whether the animals accept all electronic devices attached to their body.

2.4. Post-Harvesting

Acquiring the color and shape features from the sweet peppers through the RGB-D sensor, have been used for the geometrical relationship between the sweet pepper and the peduncle for the harvesting of the crop [20]. It can be deduced from their research that this approach has enabled the researchers to calculate the crop volume. The limitation of their research is that the detection speed of the device is very slow, thus affecting the performance of the detection speed and rate process. This approach has been applied only to the sweet pepper peduncle. The best harvest age for a coconut plant can be determined using the Monte Carlo simulation [21]. It can be deduced from their research that, the determined harvest age of 16 days of a coconut per crop cycle has been achieved, which invariably influences the selling price of the coconut using regression analysis. The limitation of their research is that the simulation has been tested only on their farm. However, other factors such as demand, inventory, holding cost, and transportation cost have not been considered, which can influence the selling price of the coconut crop. Post-harvesting has been improved upon by introducing smart farming as reported in [20] and [21]. With all these reports, some limitations such as revising of the model used for sweet pepper harvesting to improve the speed of the machine which will boost crop production immensely have not been considered. It can be inferred from [21] that simulation has not considered other factors to help enhance the performance of his algorithm report which include the demand of the market, holding cost, transportation cost, government regulations concerning agriculture and government levies, taxes which reasonably affect the selling price of the determined harvest age of the coconut. It can be deduced from Table 1 below that smart farming devices used in animal production experience power issues [17, 18, 19] since the devices used for monitoring the animals are battery operated within hours. Many of the animals are believed to experience psychological issues [17, 18, 19] when electronic monitoring gadgets are attached to their body. From this same table, it is noted that transportation cost, inventory collection, market demand, has been a challenge for smart farming as cited in [20, 21]. Table 1 reveal issues in smart farming such as computational power, communication protocol [12, 15, 16].

Table 1: Comparison of the Crop Production, Animal Production and Post Harvesting in Smart Agriculture

Properties	**Crop Production**	**Animal Production**	**Post harvesting**
Computational Power of System	N	N/A	Y
Algorithm communication Language	N	N	N/A
Counting and crowd control	N	N	N/A
Operated by Batteries	N	Y	N
Psychological effect	N	Y	N/A
Detection speed	Y	N	Y
Demand of Market	Y	Y	N
Inventory	Y	Y	Y[21]
Holding cost	N	N	Y[21]
Transportation cost	N	N	Y [21]

Yes=Y, No=N, N/A= Not Applicable

3. Technologies

3.1. Sensors used in smart farms

It was discussed in [22] that sensors have been manufactured which are used to detect the water stress level within the leaf of plants, these sensors enable researchers to investigate the variation of the water stress level in leaves of plants, some of these sensors are embedded with the EM4325 UHF chip, this technic of detecting leaf water stress level is an added advantage in smart farming. The authors in [23], have discussed the use of LED lighting and dimming system incorporated with sensors thus reducing power consumption in farms and improving safety conditions for both men and animals. The authors in [24], research reveal that their platform for managing IoT sensor, help to determine and improve the performance of the IoT sensors at different layers from the networks up to the service layer. The Limitation of their research is that certain protocols such as MQTT or web sockets have not been discussed and the external storage engine API is limited. It can be inferred that [22, 23, 24] contributions can be used to improve smart farming when they are applied within a farm. Sensors are devices which help transmission of data from soil or liquid to various networks, [25] informed us that the IoT smart stick sensor which transmits soil moisture data within the network. As an example, the DS18B20 temperature sensor is a very reliable sensor used for capturing temperature data, it can be deduced that the soil moisture sensors have been used to capture data of the soil condition and transmitted by the sensor to the network. It can be inferred from [25] that sensors help researchers to automate the farming system and collect data within the farms.

3.2. Unmanned Aerial Vehicles (UAV) in Smart farming

According to [26], it has been possible to use deep learning technic for crop image classification, vegetation identification & segmentation, disease, weed, and crop nutrient detection with the aid of sensors with cameras mounted on the UAV. Therefore UAVs have been used to crop counting and yield prediction using deep learning. The authors in, [27] discuss how UAVs can be used to capture data in smart farms. The UAV can be equipped with cameras, sensors, GPS enabling the device to capture data in the smart farm from imaginable heights for diverse applications in smart farm management monitoring. The limitation of this research is that, the data collection and processing technic which still requires a lot of enhancement because imagery and voice data can be very complex to process compared to other formats. According to [28], using UAV in smart farms can help to achieve a special localization system, which enables the UAV to scan selected areas on the farm thereby collecting data from selected IoT nodes. Their work also educates us that this process helps to preserve node energy since the UAV handles the working load moreover. UAVs operate on low power frequency thus saving their energy usage. Also, their research indicates that the UAV enhances beaconing, localization of cluster head, and shunting of connected nodes. However, the limitation of their work is that they have not tested their model in a farm where using sensors, actuators, artificial intelligence, and UAV are deployed at the same time to check if maximum preservation of the UAV energy can be achieved. The authors in [29] have informed us that using UAV devices with special imaging modules such as multi-spectral, thermal, and visible video images is result-oriented for timely reliable information analysis for smart farms. Their research results using spectral, thermal and video imagery have been able to generate 3D models from their analysis. The authors in [30] have proposed a model, called CRownet, using Convolutional Neural Network (CNN) and Hough transform (HoughCNet), and SegNet. They can detect crops row by row despite many weeds on the farm. This is a remarkable achievement in smart farming since their result help in weed removal. Their research has considered a crop row detection performance of 93.5%, which has shown a high detection rate. The limitation of their research is that it has not been tested on a single CNN model to detect its performance. The authors in [31] discuss that UAV has been used for mapping of weed and management, vegetation growth monitoring and yield estimation, vegetation health monitoring and disease detection, irrigation management, and corps spraying. It can be deduced from the research of [26, 27, 28, 30, 31, 32], UAV has improved smart farming and enhanced crop yield. According to [33], crops can be spaced and from the UAV images, using segmentation methodology to ascertain the crop line. It can be deduced from their paper that the strategy of crop line segmentation is not very effective when the crops are very close to each other since they are seen as a single crop from the UAV image. The authors in [31] have used double cameras to capture crop images helping researchers to generate 3D dimensional models. This has enabled to detect the rice crops more efficiently from the images captured from the UAV. It can be inferred that the limitation of their research is that very few experiments have been carried out using this methodology. There is a need to conduct more varied experiments on different crop fields to give more authenticity to this approach. The authors in [34] discussed that edge nodes experience challenges during the transmission of data over long distances within a network. They suggested that using a drone on the farm can help in resolving it since the drones can establish connectivity between the nodes and the base stations using the LoRa protocol. The limitation of their research is that they have not tested their network design in a scenario using diverse edge nodes where the drones can fly in high altitudes. It can be inferred from Figure 2 showing a network architecture where a drone is used in a farm to capture data via Wi-Fi connectivity from the sensors installed on the farm animals and crops. The drone transmits these data via wireless connectivity to the base station so that the data eventually is transmitted to the cloud. According to [35], UAVs can be used to collect thermal and multispectral data from a farm to determine the relationship between the features of the images collected and the onion irrigation treatment. It can be deduced from their research that the UAV flight height can influence the accuracy of the onion irrigation system. Additionally, onion irrigation estimation can be affected, using neural networks, by different image spectral bands. Their result educates us that the Blue, Green, Red, and near-infrared (RGB_NIR) image band has produced the best accuracy from the analysis for the onion irrigation estimate. Many UAVs have been developed for agriculture over the years. The authors in [36] described some of the UAV namely, the Agdrone with the capacity to cover 600-800 acres within an hour at an altitude of 400 feet. Additionally, the DJI Matric 100 has a double battery facility and has an extra 40 minutes flight period compared to other drones. This UAV is incorporated with GPS, navigation systems. Furthermore, they informed us of other UAV systems such as Agras MG-1-DJI with the unique ability to carry 10KG of liquid over an area of 4000-6000 m2 within 10 minutes, manual spraying is 70 times slower than this UAV, DJI T600 can capture 4K video images, the EBEE SQ used mainly for plant monitoring from early growth to maturity, Lancaster 5 precision Hawk equipped with sensors for temperature and humidity data capturing and SOLO AGCO with high precision image capturing capabilities. It can be deduced from their paper that UAV has improved farming systems through high precision data capturing, faster spraying of farms, and effective monitoring of farms.

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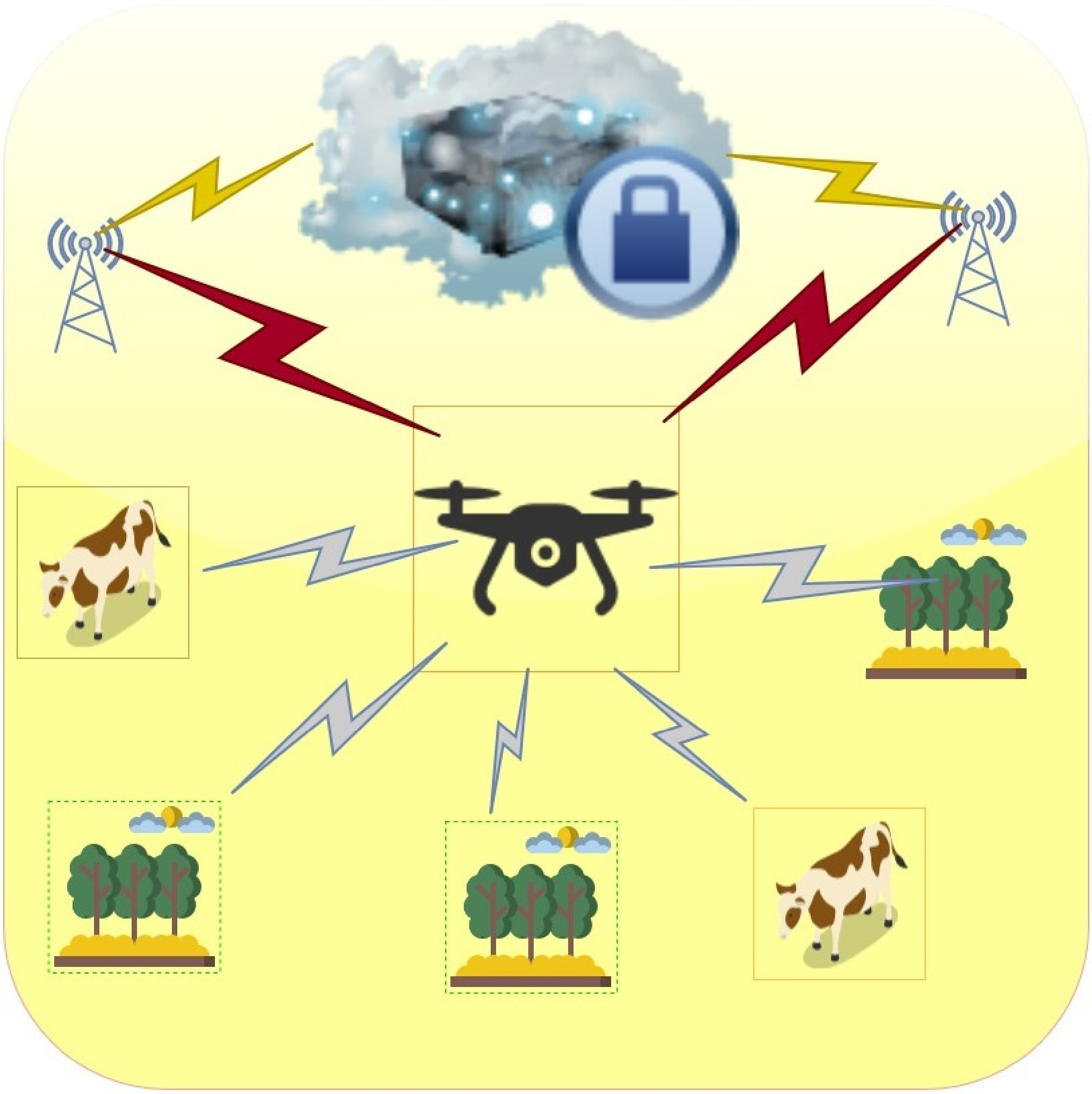

Figure 2: Network Architecture for a farm without Internet connectivity

LoRa protocol or Transmission control protocol to the base station so that the data eventually are transmitted to the cloud. According to [35], UAVs can be used to collect thermal and multi-spectral data from a farm in order to determine the relationship between the features of the images collected and the onion irrigation treatment. It can be deduced from their research that the UAV flight height can influence the accuracy of the onion irrigation system. Their research informs us that using neural networks, onion irrigation estimation can be affected by different image spectral bands. Their result educates us that the Blue, Green, Red and near infrared (RGB-NIR) image band has produced the best accuracy of 0.84 from the analysis for the onion irrigation estimate. Many UAV have been developed for agriculture over the years. The authors in [36] described some of the UAV namely, the Agdrone with capacity to cover 600-800 acres within an hour at an altitude of 400feet. Additionally, the DJI Matric 100 has a double battery facility and has extra 40 minutes flight period compared to other drones. This UAV is incorporated with GPS, sophisticated navigation system. They mentioned other UAV systems such as Agras MG-1-DJI with unique ability to carry 10KG of liquid over an area of 4000-6000 m2 within 10 minutes, manual spraying is 70 times slower than this UAV, DJI T600 can capture 4K video images, the EBEE SQ used mainly for plant monitoring from early growth to maturity, Lancaster 5 precision Hawk equipped with sensors for temperature and humidity data capturing and SOLO AGCO with high precision image capturing capabilities. It can be deduced from their paper that UAV has improved farming system through high precision data capturing, faster spraying of farms and effective monitoring of farms.

3.3. Internet of Things

IoT involves the connection of network hardware devices, software, and most importantly human beings that exchanging data for specified purposes, the researchers mentioned that the ability of computes within a network to take certain decisions without human involvement has been evolving over the years. It can be deduced from their paper that intelligent Technologies such as intelligent IoT within a farm can reduce crop loss and invariably reduce the loss of revenues by the farmers. [37]. According to [38], IoT has improved data analytics. Despite all these achievements with IoT, there is a great concern in the use of low power wide area communication technology for smart farming and they believe further work on the Narrowband IoT (NB-IoT) technology will enhance the use of IoT in agriculture. The NB-IoT is a non-wired transmission standard used in IoT, the protocol is very effective for data exchange where the little capacity of data is needed for connection, low bandwidth and prolonged battery for the edge devices are required As discussed in [39], IoT network devices use protocols for communication within a network, such as NB-IoT, Transmission control protocol/Internet Protocol. According to [40], Agri-IoT comprises the exchange and use of information among sensors, data streams, processes, web-based services, farm entities, open data, using semantic technologies to connect web data. It can be deduced from their research that the interoperability of Agri-IoT has helped the farmers to achieve better product quality, increase productivity, protect the environment, reduce the waste of resources, better responds to unpredictable events, and provide transparency to the customers. The limitation of the research is that the specific solution cannot protect crops for harvest during adverse weather conditions. The use of IoT in farming helps to reduce the risk of pesticides harming humans and animals that consume the crops [41]. They further iterated that IoT in smart farming can be used to scare away birds and wild animals that attack crops by producing different low-frequency ultra-sounds on the farm. The limitation of their research is that they have not provided an alternative option for the farmers to solve the problem of pests' attacks without using pesticides. The authors in [42], have stated that geospatial analysis and linked data cube for semantic analysis, can be used to integrate the equipment on the farm and control the quality of data transmitted from the farm. According to [43], big data will affect the range and magnitude of smart farming business at tremendous speed. It will make big data readily available providing real-time forecasting, tracking of farm devices, and providing autonomous operation on the farm. It can be inferred from [42] and [43] research, that IoT will help to integrate equipment on the farms. They further iterated that big data obtained from IoT will revolutionize the smart farming sector. However, data security has not been considered in this research. It has been discussed in [44], that using smart farming, diseases can be detected using image processing. It can be deduced from their work that farmers can take preventive measures against certain disease outbreaks while planting their crops to achieve a high yield. The limitation of this research is that the farmers cannot take preventive measures for the outbreak of the brand-new trend of diseases [45]. Their research informs us that the sensing and actuators as a service (SAaaS) can provide a cloud service, where data are exchanged from the infrastructure via the sensors, actuators, and the user through the cloud. The authors in [46], discussed that there is a need for further research in the Industrial Internet of Things (IIoT) to enhance the development of the sector by suggesting solutions to some of the existing challenges within IIoT. They highlighted some existing challenges in the IIoT including lightweight encryption for IIoT, failure detection, recovery, prediction for IIoT, data reliability & access control in IIoT, real attacks in IIoT. It can be deduced from [45, 47, 37, 40, 43] that the IoT-cloud can be used to provide smart solutions allowing the farmer to receive information from the farm via the Internet on devices real-time at various locations. The authors in [46] discuss IoT challenges associated with security, data validation and integrity, and trust. It can be deduced from [48] research that IoTs can be used to boost food production thus through the production of healthy and high-quality crops & animals and invariably reduce drastically the loss of crops and animals by processing the data received. Furthermore, algorithms have been used for disease recognition in crops and animals, and deep learning techniques for texture recognition, Their research has indicated some limitations in intelligent IoT such as the security of the data, privacy, and trust management in information within the system. According to [49], they informed us that using a multi-layered framework IoT data can be compressed by 90% with an error rate of 1%. Additionally, energy consumption is reduced by 45%. However, their work exhibits some limitations such as their framework can compress only numerical data. It was discussed in [50], that using map-reduce and Hadoop framework for IoT, big data, the cloud, and wireless sensor network. Therefore, the performance of the wireless sensor networks can be optimized to achieve optimal accuracy in error detection. Their work showed that all the computational and communication opacity can be kept away from the users. As discussed in [51], that video, image, and text compression respectively for IoT data, can lead to low bandwidth usage for data transmission. It can be inferred from [49, 50, 51] that using compression techniques, low bandwidth, low latency, and improved performance can be achieved in IoT data transmission. According to [52] paper, a fog- assistant smart -surveillance-based smart transportation system for IoT has been designed. , based on the fog-framework for intelligent public safety in vehicular environment (FISVER), their research results achieved enhanced computer processing unit (CPU) performance by 27.6%, network performance by 51.98% with an energy-saving efficiency of 62.14% when they compared it with existing experimental results. The limitation of their work is that their solution has not been tested in an over-saturated traffic network. It can be deduced from [53] research that using Vehicular Ad-Hoc Network (VANET) where they integrated a vehicular fog computing and vehicle-to-vehicle (V2V) communication technologies, they assumed vehicles as fog servers for their research, they were able to achieve low latency and optimal quality of service (QoS) for the IoT data traffic but despite their laudable achievement their research limitation is that it has not been tested for a vehicle supporting more than one vehicle at the same time or one vehicle following more than one host at the same time According to [54], the Internet of Vehicles (IoV) is a smart technology which enhances transportation where they incorporate Internet and vehicular cloud, their research considered the Wazid et al proposal of using Authenticated key management Protocol in a Fog computing system so that data exchange can be secure within a network comprising of vehicles, fog servers, and roadside units (RSUs) cloud computers. Their research indicated that the Wazid et al solution cannot achieve enhanced performance for the Internet of vehicles network, and they recommended that the solution needed great review since it cannot be used due to the poor performance of the Wazid et al solution. The vehicle impersonation, fog server impersonation, roadside units (RSUs) impersonation, cloud server attacks of their solution was very high, and they recommended it is not reliable for the internet of vehicles network. According to [55], IoV enables the infrastructures to update information at the same rate they receive the information, cybernation, and efficient tracking of installed devices. They further discussed that the integration of the intelligent transportation system (ITS), IoT devices, and the control of the ITS devices are referred as the cyber-physical system (CPS) despite the tremendous contribution with regards to the improved computational capability of the combination, these technologies attract high cost for deployment, management of the combination of ITS and IoT network still serve as limitations. It is observed from [52, 53,54, 55] vehicle Ad-hoc network, fog servers, and internet of vehicles smart technology improve transportation, the researchers assume the vehicles as fog servers for IoT and their results indicate the improved quality of service, low latency, CPU performance, network performance, energy-saving efficiency of 62.14% but the management of this technology is still a challenge that should be addressed. It can be deduced from the research of [38], [48], [56], [57], [58], and [59] that, IoT has contributed positively to agriculture to enhance the quantity and quality of food production. It has improved the processing of crops by fast-tracking harvesting, implemented control of disease and pest, and avoided the excessive and insufficient application of fungicide or pesticides. With all these achievements, research outcome has indicated that there are still challenges with the security of using IoT in Agriculture, especially with the issues of privacy and trust of the data management. These challenges have opened a window for further contribution in the academics to embark upon more research to improve on existing work, which has improved agricultural production using IoT. The concept of identifying these challenges to researchers to act is a contribution by this paper on the next step to be taken by future academic professionals.

3.4. Artificial Intelligence

AI can be used to monitor the movement and location of the animals on a farm [60]. It can be deduced from this research that the activities of the animals within the farm could be monitored when they walk, graze, rest, or run. The researchers can ascertain from the data obtained that different patterns can be obtained using unsupervised learning to determine whether either a poacher or an attacker is among the animals or within the farm. However, the limitation of the unsupervised learning technique is that it is not reliable since there is no prior knowledge of the input data. The machine is saddled with the responsibility to learn the data and use it to determine the hidden patterns. As cited in [61], Federated Learning (FL) methodology enables the network to be more comprehensive in processing raw data, unlike the centralized deep learning system. It can be inferred from their research that FL is a very husky system, which can handle user equipment and edge nodes, unbalanced and non-Independent Identical Distributed (non-IIDD) data successfully. The system can train the data using mini-batches to reduce the communication cost. Some of the limitations of their work include the issue of the AI management at the edge nodes and the multi-dimensional resources for the AI at the edge, which makes the splitting of AI tasks a challenging problem. It has been observed that FL in edge AI cannot iterate the edge nodes in real-time which indicates opportunities for further research. According to [62], ML which is a subset of AI that has been used in many sectors namely forecasting stock market patterns, diagnosing disease, estimating business patterns, creating circuits, speech monitored gadgets, human-computer interaction, self-driving vehicles, and natural language processing just to mention a few. It can be observed from table 2, that implementation of sensors, UAV, IoT, AI in smart farms comes with its concern, scenario, and issues. Sensors are cheap to deploy in a farm but UAVs, IoT, AI are very expensive to deploy on a mechanized farm. According to [61], FL data aggregation can be done at the global model, it is deduced as a limitation for sensors at the edge nodes as captured in table 2.

Table 2: Comparison of sensors, unmanned aerial vehicles (UAVs),internet of Things (IoT), Artificial Intelligence (AI) in Smart Agriculture

Properties	**[sensors]**	**[UAVs]**	**[IoT]**	**[AI]**
High Transmission speed	N	Y	N/A	Y
Provide connectivity where no internet is available	N	Y	N	Y
Cover long range of distance for data transmission	N	Y	N/A	Y
Mobility within the farm	N	Y	N/A	N/A
High Processing power	N	N	N/A	Y
Analyse data aggregate	N	N	N/A	Y
High security in transmission of data	N	Y	Y	Y
Capturing of Data by direct contact	Y	N	N	N
Run out of Power over time	Y	Y	N/A	N/A
Psychological effect on Livestock	Y	Y	N/A	N/A
Low Cost of deployment	Y	N	N	N

Yes=Y, No=N, N/A= Not Applicable

4. The impact of climate to smart farming

Comparing the soil heat storage, energy consumed during photosynthesis are factors that influence surface fluxes and advection of the soil [62]. It can be deduced from their work that irrespective of the advection condition from the data set, the heat storage enhances the energy balance closure. It is observed from this research that higher surface heat fluxes are relative to a thinner, well-watered canopy with regular advection. The limitation of this research is that the data have been used for a short period. A long period of captured data set would have given a far better result and robust evaluation and analysis. It is observed that early data set capture would have produced a better research result if they are captured at the beginning of the planting season. The model of [64] has indicated an increase in daily temperature, photoperiod, causes a decrease in the leaf senescence rate of the crops. It is observed from their research that a shortened photoperiod and decreased daily minimum temperature can start the leaf senescence process. This is used to determine the leaf coloration and brown-down dates indicating the climate change effect on vegetation and carbon cycle. The limitation of this research is that they have not discussed the rate of vegetation coloration change within a day or a specified period. The maximum efficiency of photosystem II (Fv/Fm) is the most reliable indicator as stated in [65] for detecting starting stage heat stress when only the photosynthetic parameters vary in wheat (Triticum aestivum L.) plant production. It can be deduced from this research that the photochemical reflectance index (PRI) is effective in detecting late-stage heat stress in the wheat plant when the chlorophyll parameters (i.e. physical and chemical variables) of the plant are influenced. The limitation of this research is that the experiment has not been applied to other species of plants to ascertain the stress conditions and vegetation indices. A smart surface sensing system (4S) could be used to monitor vegetation indices (VI), which is part of the photosynthetic active radiation (fPAR) and Leaf Area Index (LAI) [66]. 4S has enhanced knowledge in bio-sphere atmospheric relationships. It can be inferred from this research, that vegetation indices have been collected using a micro-computer, camera, multi-spectral spectrometer embedded in LED. It has been observed from this research that the proposed system is a low-cost cost solution for the remote monitoring of the sensing of the canopy structure and functions of the plant. The limitation of this work is that it cannot be used for monitoring of multiple remote sites simultaneously. According to [67], winter wheat species yield more harvest which invariably boosts agricultural business, market, and production. It can be inferred from this research that the proposed model performs better or give better results for data obtained from areas with high spatial resolutions or mountainous areas. The limitation of this research is that the system has not been applied to other crops in other counties to enable forecasting of the yield of the wheat plant. Vegetation indices (VI) and Gross Primarily Productivity (GPP) affinity are affected by many factors [68] such as frequency, duration of data capture. Higher vegetation and gross primary productivity are obtained when the data set captured monthly are used for evaluation, instead of using daily captured data set. It can be inferred from this research that the VI-GPP relationship is very weak since the VI variable is very uncertain and unstable at lesser frequency timescales in a dry land ecosystem. Additionally, the proposed model has been applied to Mesquite grass shrub alone and its application has not been implemented to other crops to ascertain its performance. The results obtained during the correlation of the observed sowing dates and simulated dates of sowing according to [69] for winter wheat crop show that the latitude of the location of the planting of the crop influence the weather conditions of the flowering of the crop. It can be inferred from their research that higher longitude locations provide weather conditions for effective flowering to maturity of the winter wheat crop production. The limitation of their research is that the model cannot predict the winter wheat crop yield inter-annual across Europe and cannot consider the effect of excess water conditions for winter wheat crops on the farm. The model has not been applied to simulate results considering diverse species of the winter wheat crop. Farming and climate can be said to operate a symbiotic relationship because they affect each other and influence the outcome of each other daily. It has been observed from [63], [64], [65], [66], [67], [68] and [69] that thinner crop leaves influence the heat lux storage of the plants. The reduction of the minimum daily temperature controls the leaf senescence, so climate affects the leaves' coloration rate of the crops. They also reported the prediction of heat stress on wheat production, forecasting, and production during different seasons. Nowadays, farmers are aware that latitudes affect the climate of the wheat crop during the flowering of the crop, which has reasonably improved the awareness in managing the crops. It is worth noting that some limitations and challenges exist in their research such as the collection of data for a short period which did not enable the researchers to simulate effectively it to other plants [64].

5. Challenges and Issues of Smart Farming

The authors in [70], have considered the use of high vision resolution capturing and analysis of plant diseases. [16] have expressed their concerns in the communication protocol used for interaction within the smart farms, these protocols were effective for only short distance coverage areas. It has been observed in [17], [18], [19] that some of the intelligent devices have been operated using batteries, this has reduced the operational hours of the edge nodes devices since they stop transmitting data once they run out of power. Computational overhead is a challenge experienced in networks within smart farms as cited [70]. The network cannot dynamically update its data without the high overhead. Intelligent IoT systems handle large data, which have privacy concerns. There is a need for effective trust, privacy, and security of these data. It has been stated in, [1, 2, 3, 48, 56, 59] that there are challenges associated with data security, privacy, and trust management. Quality of Service (QoS) and network latency are other network issues within smart farms as cited in [2] which require further research. It can be inferred from [72] that a lot of concerns have arisen in smart farming from the harming of animals and humans due to the use of pesticides on the farm. The effect of climatic conditions on farming globally has been discussed in many forums. The authors in [40] have discussed the lack of proper detection of weather conditions which has drastically affected farming across the globe. With the introduction of IoT in smart farming, big data transmission is experienced within the network and the authors in [73] have identified the improper protection of these data during transmission which raises a security concern. The authors in [61] have discussed the communication cost issue with regards to the transmission of data in smart farming and believe there exists a high overhead communication cost in data transmission in smart farming, more research work can help to address this issue. Different architectures have been used for smart farming networks globally. The authors in [74] have proposed a Cross-Layer Multi-Cloud Application Monitoring and Bench-marking as-a-Service which enables efficient monitoring, detecting Quality of service in a multi distributed cloud environment. It can be deduced from [46] that data encryption in IIoT is another serious challenge that has affected smart farming and improvement in data encryption enabling farmers to implement IoT in smart farming for better agricultural productivity and enhance IoT in smart farming research. IoT application in smart farming is no doubt changing the trend of work in smart farming but there exists a limitation in the faster disease detection in crops and there is a need for further research in this area according to [12], [15]. Smart farming provides the technology for farmers to monitor their farms remotely but [19] discussed that monitoring of animals on the farm requires more research attention since effective monitoring of animals location, health, and change in their behavior pattern within the farm will provide real-time information about the animals in the farm. Different plants require different soils for effective production within a farm, The authors in [66] have informed us of the limitation in knowing soil condition in smart farming, further research is needed in determining the soil condition when it's used for crop cultivation to ensure a productive harvest. Some research work has been conducted to use machine learning for early detection of disease in crops. The authors in [77, 78] have discussed that despite these efforts there is a limitation in this area and more models need to be developed to predict disease early enough before the farm harvest is reduced drastically due to disease infestation. In a mixed cropping scenario, there is a challenge to identify the fruits [78]. There is a need to develop models or algorithms to help farmers to detect crops fruit early enough to prevent over-ripening of fruits and wastage. Smart farming has opened an opportunity for researchers to investigate the leaf water stress level in plants as cited in [79] which will help understand the certain effect of climate on crops and plant water loss through their leaves. It can be deduced from Tables 3, 4, 5,6 present many challenges that exist with the application of IoT to smart farming. These challenges range from monitoring crops leaf water stress level to the monitoring of locations, health, behavior pattern of animals, however, all these challenges have created opportunities for research for academics.

Table 3: Comparison of IoT issues in smart farming

Properties	[37]	[39]	[40]	[72	[56]	[59]	[3]	[1]	[71]	[48]	[2]
Security	N/A	N/A	N/A	N/A	N	N	N	N	N	N	N/A
Control actuators	N/A	Y	N	N	N	Y	Y	Y	N	N/A	N/A
Network Lifetime	N/A	N/A	N/A	N/A	N	N	N	N	N	N/A	Y
Network Latency	N	N	N	N	N	N/A	N/A	N/A	N/A	N/A	Y
Transmission reliability	N	N	N	N	N	N	N	N	N	N	Y
Quality of experience QoE)	N	N	N	N	N	N	N	N	N	N	Y
Reduce risk of Pesticides harming Animals or Human	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Y	N/A	N/A
Semantic interoperability	N	N	N	N	Y	N	N	N	N	N	N
Detection of weather conditions	N/A	N/A	Y	N	N	N	N	N	N	N	N

Yes=Y, No=N, N/A= Not Applicable

6. Cloud-Based IoT Smart Farming

ICT technologies can improve the level of interaction as stated by [80] between the small-scale farmers and the farming expert tremendously. It can be inferred from their research that the GeoFarmer solution can help the farmers share their experience with both the favorable experiences and challenges they encountered in the farm [80]. It has been observed that the GeoFarmer solution also provided Interactive Voice Response (IVR) features enabling the farmers to have voice conversations with the facilitators via their smartphones. This has helped them to give a better explanation of the outcome of the professional advice they received from the farming experts especially in areas where internet connectivity is very limited. It is noticed that the solution provided an expert to the farmer, farmer-to-farmer interaction which helped information sharing, data collection, and evaluation process. The limitation of their research is that the solution cannot monitor the farmers' attitudes and practices toward the GeoFarmer solution which provides room for further studies in the research. The involvement of users with little or no ICT skills has created a challenge for these categories of users.

Table 4: Comparison of IoT issues in smart farming(Part 2

Properties	**[44]**	**[42]**	**[43]**	**[46]**	**[45]**	**[74]**	**[73]**	**[71]**	**[60]**	**[61]**
Security	N	N	N	N	N	N	Y	N/A	N/A	N/A
Preventive measures using IoT	Y	Y	Y	Y	Y	Y	N	N	Y	N
Semantic interoperability	N	Y	Y	N	N	N	N	N	N	N
Architecture	N	N	N	N	N	Y	N	N	N	N
Reduce communication Cost	N	N	N	N	N	N	N	N	N	Y
Quality of Service (QoS)	N	N	N	N	N	Y	N	N	Y	Y
Sensing and actuators as a service (SAaaS)	N	N	N	N	Y	N	N	N	N	N
handle multi-keyword search.	N	N	N	N	N	N	N	Y	N	N
increase in computation overhead.	N/A	N/A	N/A	N	N	N	N	Y	N	N
Lightweight encryption for IIoT	N N		N	Y	N	N	N	N	N	N
Failure detection	N	N	N	Y	N	N	N	N	N	N
prediction for IIoT	N	N	N	Y	N	N	N	N	N	N
data reliability	N	N	N	Y	N	N	N	N	N	N
access control in IIoT	N	N	N	Y	N	N	N	N	N	N
real attacks in IIoT	N	N	N	Y	N	N	N	N	N	N
Management of IIoT designs and software	N	N	N	Y	N	N	N	N	N	N
validation of safe trust in IIoT	N	N	N	Y	N	N	N	N	N	N

Yes=Y, No=N, N/A= Not Applicable

According to [81], IoTs can be used to regulate the opening of valves for actuators installed for the irrigation system to avoid water stress to the crops. It can be deduced from their research that farmers are informed remotely of the soil water condition via text message saving time of travel within the farm, making the farming system an automated one and gives precise measurable water condition of the soil on the farm. This will help prevent disease within the soil due to excessive watering of the soil. The limitation of this work is that the application developed cannot measure the daily water needs of the plant. It has been stated in [82] that using an IoT with various sensors for data transmission via the cloud to a server for collection of the temperature and humidity data, which are analyzed by the researchers. This helps them control the mildew disease spread within a farm. It can be deduced from this research that this approach can assist to regulate the application of fungicides within the farm. The limitation of this research is that the decision support system used by the researchers cannot collect the images of the leaves, analyze the transformation of the leaves such as change of color that indicates the signs of disease infection on the plant. Moving of animals' feeder around in the field according to [83] causes high contamination of the water table underneath the field through the excreta of the animals, more so their hooves cause soil compaction and high spread of E.coli disease within the farm. It can

Table 5: Comparison of IoT issues in smart farming (part 3)

Properties	**[12]**	**[70]**	**[15]**	**[65]**	**[16]**	**[17]**	**[18]**	**[19]**	**[20]**	**[21]**	**[63]**	**[64]**	**[59]**
noise filtering capacity	Y	N	N	N	N	N	N	N	N	N	N	N	N
Architecture	N	Y	N	N	N	N	N	N	N	N	N	N	N
Increased Computational time	N	Y	N	N	N	N	N	N	N	N	N	N	N
faster detection rate for crop disease	Y	N	Y	N	Y	N	N	N	N	N	N	N	N
reduced the time of diagnosis of animal illness.	Y	N	Y	N	Y	N	N	N	N	N	N	N	N
Enhanced Data Transmission	N	N	N	N	N	Y	N	N	N	N	N	N	N
monitor the movement of the animals within and outside the farm	N	N	N	N	N	Y	Y	Y	N	N	N	N	N
determine the animals attitude and behavioral pattern	N	N	N	N	N	Y	Y	Y	N	N	N	N	N
monitor health changes among the animals	N/A	N/A	N/A	N/A	N/A	Y	Y	Y	N/A	N/A	N/A	N/A	N/A
Color, Shape from 3D sensor	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Y	N/A	N/A	N/A	N/A

Yes=Y, No=N, N/A= Not Applicable

be deduced from their work that it is better to use the static feeder to provide feeds to animals on the farm, resulting in a higher reduction of the spread of disease and infection. Strategic decision-making methods [84] for its management yields a better production than adopting short-term decision technics, which has been exemplified by the fruit farmers. Their research is very informative because it reveals that there are alternative techniques, which the crop farmers can consider for the management of their farms such as Cohort. Table 8 provides an overview of the advantages and limitations of cloud-based IoT for smart farming. According to [85], IoT storage demand can be decreased using two-layer compression, first compressing the data in the fog layer yielding data reduction by 50% upon and then in the cloud compressing the data up to 90%. A limitation of this work is that it compresses only numerical data. As cited in [86], it has been observed that data curation of IoT big sensing data is applied in the cloud methodology to improve the retrieval of lost data. The adopted MapReduce and graph-based compression technique have resulted in the apportionable squeezing of the dataset. It can be inferred from this research that the error detection in IoT big sensing data is impressive, however, this solution offers better ratability of the data in the cloud. Their work also has experienced some limitations such as in situations where there exists an identity curve function between two-time series, their regression model was not able to achieve impressive predictions The paper in [87] uses intelligent IoT devices where several parameters can be sensed at the edge node. It can be deduced from this research that intelligent IoT devices using 5G

Table 6: Comparison of IoT issues in smart farming,(Part 4)

Properties	[67]	[66]	[68]	[69]	[80]	[81]	[104]	[82]	[91]	[77]	[76]	[78]	[93]	[79]
Interactive voice response with farmers	N	N	N	N	Y	N	N	N	N	N	N	N	N	N
Determination of soil condition	N	N	N	N	N	Y	N	N	N	N	N	N	N	N
Soil conductivity	N	N	N	N	N	N	Y	N	N	N	N	N	N	N
Protection of crop disease using IoT	N	N	N	N	N	N	N	Y	N	N	N	N	N	N
color segmentation to determine grapes for harvest	N	N	N	N	N	N	N	N	Y	N	N	N	N	N
early disease detection using image capture technic	N	N	N	N	N	N	N	N	N	Y	Y	N	N	N
support vector machine for recognition of fruit	N	N	N	N	N	N	N	N	N	N	N	Y	N	N
three dimensional point cloud(TDPC)	N	N	N	N	N	N	N	N	N	N	N	N	Y	N
monitor the leaf water stress	N	N	N	N	N	N	N	N	N	N	N	N	N	Y

Yes=Y, No=N, N/A= Not Applicable

topology have been used to monitor air contamination, their suggested device was able to detect the quantity of nitrogen IV oxide (NO2), carbon monoxide (CO), sulphur IV oxide (SO2) within the tested location. It can also be inferred from their research that intelligent IoT has been applied to electricity metering using Wi-Fi and NB-IoT protocols to reduce the bandwidth required for data transmission. Table 8-11 gives us an overview of the benefits and limitations of IoT cloud-based Smart farming. It can be deduced that AI has improved and enhanced smart farming in many ways. From Table 12-17, a broad view of the comparison of the various observed advantages and shortcomings of the Internet of things cloud-based smart farming is illustrated. It has been stated in [88] that using a Fog-assistant framework for smart transport system network with smart surveillance functionalities use case are very reliable for crime investigation. It is inferred from their research that this intelligent IoT cloud-based device when tested in a laboratory resulted in an execution enhancement of the network by 51.98%, saving of energy by 62.14%, computer performance of 27.76% when they compared it with the conventional installation of the system. It can be deduced from [89] that Cloud Internet of Things open room for further research in cloud computing and IoT due to its limitations such as scalability, reliability, privacy, security, heterogeneity of the hardware used, energy and power optimization, service level agreement implementation, billing and pricing. The incorporation of intelligent IoT devices into a network improves the data transmission between the edge nodes and the cloud through data compression and pruning [85, 86, 87, 88] As cited in [90], humans have been using technology to combat the food shortage experienced globally using IoT, robotics, and AI to detect crops and animal diseases early to reduce crops and Livestock wastage during harvest. It can be deduced from their paper that technology has been used to reduce physical labor on the farm and boost crop and animal production geometrically. Monitoring of crops with the aid of technology has taken lesser time producing optimal results which are more informative compared to physical inspection of the farm.

7. Application of Machine Learning to Agriculture

Authors in [82, 94, 77, 76, 83, 84] have reported that farms' performance over the years has not met their expectations due to disease infections, poor farm management strategies, adoption of old farming practices, and lack of technical skills for early disease detection for crops. However, the introduction of information technology using IoT aiming to collect data for generating analytics. As an effect, many of the challenges can be reduced drastically to boost agricultural food production. Using a support vector machine (SVM) for 3D descriptor with color fusion and genetic algorithm [78] have resulted in high performance and accuracy in the recognition of apple fruit, branches, and their leaves. It is observed that this research work will boost the fruit harvesting, but the solution has not been widely used among farmers. IoT has contributed immensely to the agricultural sector in Colombia [92], using an open-source platform called Things board. It has helped the government to collect farmers' data across the country and enhance their monitoring as a service activity. It can be deduced that the Internet of Things will enhance cloud-based farming for farm extension services. H. Laser scanning of the surface shape of rice seed based on the three-dimensional point cloud (TDPC) methodology, the shape dimensions of the rice seed can be calculated [93]. It can be deduced from this research that the TDPC methodology result had an average error value of less than 1.5% when compared with the physically measured value. It has been observed that the concave package algorithm enabled the researchers to obtain the contour of the projected point cloud, this helped to obtain the volume of the rice seed unit by summing up all the volume of all the vectoral contour triangle area which was obtained by the sum of the sectional area of the point cloud for the rice seed. It can be inferred that there is high accuracy in their research when the measured surface area obtained from the triangular algorithm is compared to the theoretical surface area of the rice seed. The research has indicated that minimal error of 0.58mm3, the average error of 1.37%, standard deviation of 0.10 when the theoretical volume is compared to the measured volume. Technology usage in Agriculture has enabled researchers to determine the volume of a grain seed despite the tiny size [93], data collection in developing countries are now achievable due to IoT [78], SVM has been used to capture fruits shape and leaves color for analysis purposes [76]. we are approaching a stage where IoT application using a cloud-based farming system will reveal information which has been mysteries over the years relating to crop diseases, fruit, leaves, color detection for decision making on how best to cultivate and increase food production worldwide. The leaf patch clamp pressure probe method produced high accuracy in the result as cited in [79] when used to monitor the leaf water stress and schedule irrigation in an orchard. This was a case study where it was carried out on olive trees and the results obtained were very impressive. It can be deduced from their work that automatic identification of leaf pressure, stem water potential, and leaf stomata conductance can be investigated which broadens the area of research in the study of the structure of the tree leaves. The limitation of this work is that this work has been carried out in olive trees alone. The evaluation of data in Agriculture has been done in different ways over the years. Four regression methodologies have been used to compare the spatial down-scaling of soil organic carbon stocks maps yielded different results. They have confirmed that the random forest and cubist have indicated better mass-preserving constraint when compared with Edgroi case studies [94]. They have found out that in complex case studies the random forest and cubist yield better results. Additionally, the simpler regression test, the linear model, and the generic addition model have shown better performance. It can be deduced from their research paper that different regression models provide the opportunity to get the best result for the investigation. Farm sourcing is another approach which has been used as a crowd sourcing initiative for tasks, local observation, dissemination of data acquired from sensors, their review emphasizes the fact that collection of data, the information in agriculture has faced serious challenges because the land used by farmers are private lands and access is restricted most times due to privacy issues [95] but their work has not addressed the behavioral issues associated with people in private farms. An IoT prototype system was developed which was tested in the vineyard for the spraying operation of the farm and it was able to effectively monitor and acquire data from the operation. When the experimental values and theoretical values were compared namely the spray pressure, flow rate, application rate to ascertain the efficiency. The result of their research was very informative [96], but the limitation of their work was found when the system was applied to a tractor with a sprayer attached, moving uphill which generated an inaccurate application rate, more so regular cleaning of the calibrator for spraying pesticide was required to obtain accurate experimental results. Ofoot researchers have developed a system which is a combination of the cropping model called CropSyst and a user interface to compare the carbon footprint implications of changing farm management or inputs [97]. It can be deduced from the paper that their work has been reliable because the results are consistent with the existing literature report [97]. However, Ofoot tool is an online tool; for locations without Internet access, the tool cannot be used. A dissection for color information in greenhouse vegetables to detect foliar disease spots in a real field situation using a comprehensive color feature map is reported in [98]. The paper discussed accurate data input in the convolutional neural network (CNN) and the proposed algorithm yields a better result than K-mean clustering and OTSUs algorithm used for disease detection. The limitation of this research is that this algorithm has not been tested on other crops and under different conditions which are not a greenhouse. As cited in [98], using smart farming hydroponics devices, the farmers can produce crops that are better than crops produced from manual control farms with a gain difference between 20% to 60% for all parameters such as weight of the crop, size, and coloration. Their research work has indicated that farmers could receive good ecological, economic benefits from their farms when they adopt smart intelligent farming systems. The limitation of their work is that the data used for their research have been collected over a very short period. The introduction of IoT devices in Pig farms to monitor the weight and gait of pigs using gadgets such as smart mat device to know their next gestation period, lameness during pregnancy of the pigs informed us that effective monitoring and observation of pregnant pigs can be conducted to avoid miscarriage during pregnancy and production of healthy piglets [99]. but the limitation of their research is that this approach has not been applied to other animals to determine the effectiveness and efficiency of the methodology. According to [97], IoT in smart farming can be used to collect information such as soil moisture, temperature, these were used to make disease prediction in cotton crops. It can be deduced from their research that smart farming can be used to determine the infection on crops and invariably determine the post-harvest production for the cotton crop and this will help predict the production along the value chain to produce cotton. The limitation of their work is that their algorithm has not been used to evaluate other crops. [100] discussed that the random forest ML algorithm has been used to establish a relationship between the volumetric soil moisture, Synthetic Aperture Radar (SAR), Normalized Difference Vegetation Index (NDVI), and data from a high-resolution surface model. It can be deduced from their research that the vegetation indices, radar remote sensing, and topographical attributes can be used for soil moisture recovery for hilly scenery [100]. The limitation of this research is that the model cannot be used in locations where there is low cloud coverage. Table 7 provides an overview of the comparison of existing survey papers on smart farming, it informs us of the challenges relating to IoT based Agriculture Monitoring System and their impact on optimal utilization of Resources [101], Clustering Techniques in WSNs [2], Securing the Internet of Things and Wireless Sensor Networks via Machine Learning [102]. Figure 3 shows a cloud-based IoT network for agriculture designed to implement machine learning models to capture and analyses data within a farm, this proposed network advantage is that it can use Tensor processing unit (TPU) processors for faster computational processing of data received, models running TensorFlow, Keras ML libraries and TensorFlow lite ML library for mobile devices for remote accessibility of the data within the farm. Application of technology in Agriculture has enabled researchers to measure the soil moisture content and the data was displayed on a developed website and can be accessed via mobile devices. This has aided people working remotely to view the results in real-time on their mobile phones [103]. The limitation of their work is that their research has not been applied to other environmental parameters such as temperature and relative humidity. To monitor the environmental conditions in a farming system, the authors in [101] can use a low-cost solution and due to its programmability to suit different environmental situations.

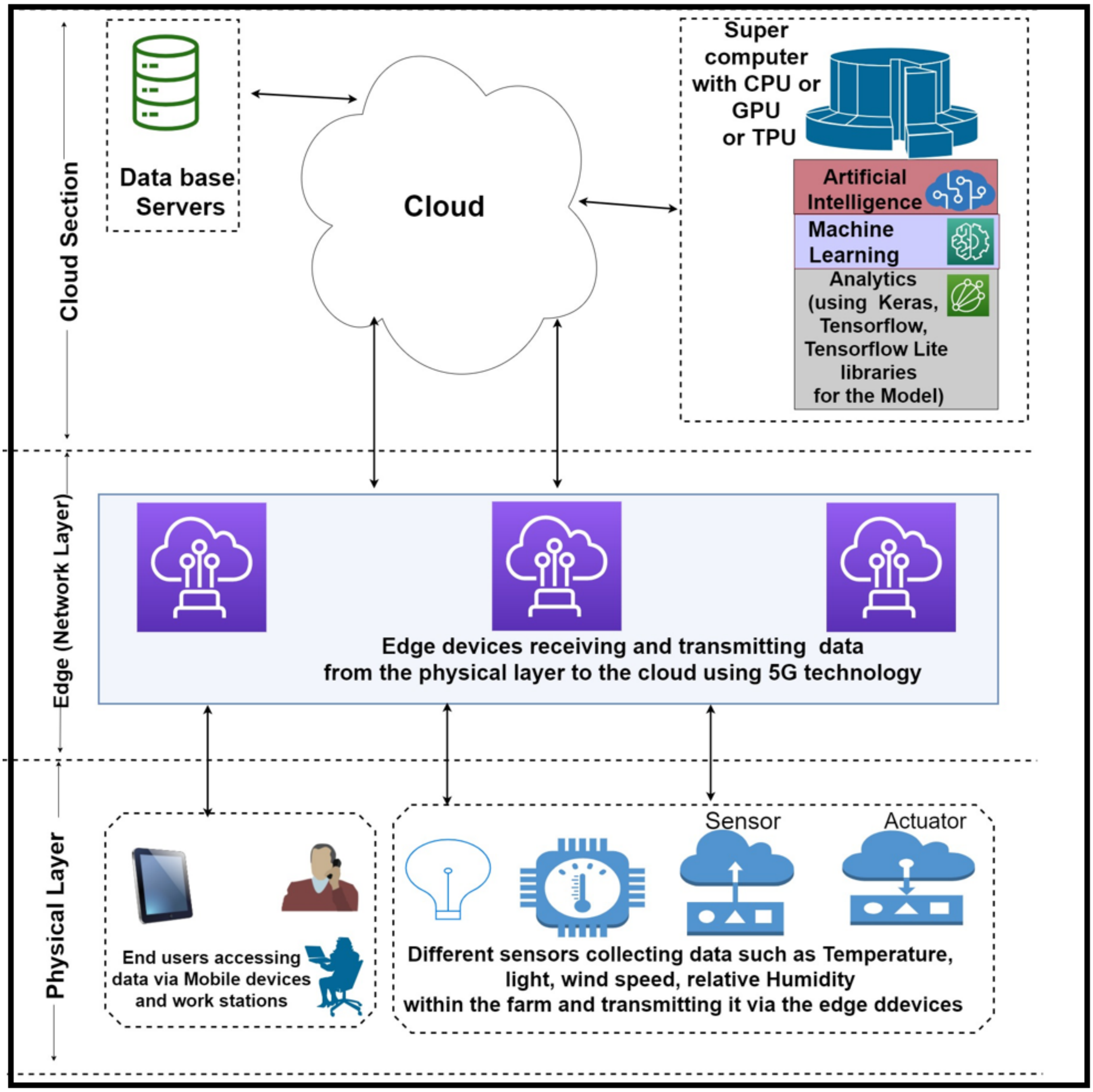

Figure 3: Internet of Things cloud based smart farming

Table 7: Comparison of existing survey papers

Properties	[101]	[39]	[2]	[105]	[106]	[102]	[107]
IoT based Digital Agriculture Monitoring System and their impact on optimal utilization of Resources	Y	N	N	N	N	N	N
Prominence of Internet of Things with cloud	N	Y	N	N	N	N	N
Clustering Techniques in WSNs and Consideration of the Challenges of Applying Such to 5G IoT Scenarios	N	N	Y	N	N	N	N
Connectivity and Cloud Automation Technologies for The Internet of Things	N	N	N	Y	N	N	N
Analytics for the Internet of Things	N	N	N	N	Y	N	N
Securing the Internet of Things and Wireless Sensor Networks via Machine Learning	N	N	N	N	N	Y	N
Machine Learning Techniques Applied to Software Defined Networking	N	N	N	N	N	N	Y

Yes=Y, No=N, N/A= Not Applicable

Table 8: Advantages and short comings of Internet of things cloud based Smart farming

	References	Advantages	Short comings
Smart farming for crop production	[12]	Better segmentation of cucumber spot edges was obtained by weighted neighborhood gray values using the algorithm developed.	The experiment was carried out only on cucumber crop and the algorithm need to be tested on other crops.
	[13]	Identification and separation of plant disease in strawberry plant, a success rate of 97% and computational time for the analysis was 1.2seconds for the disease identification and grouping of Cypriot diseases	Low computational power computer for resolution capturing and analysis of plant disease
	[15]	The K-means methodology using a support vector Matrix and neural network to separate plants with diseases	The research did not explore the unsupervised Learning models for training its dataset for better analysis
Smart Farming for Animal production	[16]	labeling procedure used to develop an efficient algorithm that automatically identifies the health and welfare of animals.	It is a Labor intensive procedure, time consuming too, the procedure can only be performed by trained professionals
	[17]	A wireless neck collar connected to the farm animals for data transmission from the animal to the cloud and remote computer.	The neck collar is battery operated which run out after some time.

Table 9: Advantages and short comings of Internet of things cloud based Smart farming (continuation)

	References	Advantages	Short comings
Smart Farming for Animal production	[18]	sea-lice counting & crowding control in fish farming to enhance fish farming	it uses sensors for data capturing
	[19]	Using IoT to monitor livestock behavior, movement (lying down, walking, grazing, standing)	Security in the transmission of the data via the cloud, sudden death of the animal during the experiment could affect the results.
Smart farming in Post harvesting	[20]	RGB-D sensor used for harvesting of sweet pepper by cutting the peduncle, this approach enabled the researchers to calculate the crop volume.	the detection speed of the device is very slow, and this affects the performance of the detection speed and process
	[21]	Monte Carlo simulation used to determine the best harvest age of a coconut. The determined age influenced the selling price of the crop.	other factors such as demand, inventory, holding cost and transportation cost were not considered which also influence the selling price of the coconut crop
Effect of climate on smart farming	[63]	soil heat storage, energy consumed during photosynthesis are factors that influence surface fluxes and advection of the soil. It is observed from their research that higher surface heat fluxes are relative to a thinner, well-watered canopy with regular advection.	dataset used was for a short period, a long duration captured dataset would have given a far better result and robust evaluation & analysis of the research. Data were not captured at the beginning of the planting season for better results.
	[64]	A model developed for predicting autumn phenology, to determine how leaf senescence is controlled by photo-period and temperature coupling.	The rate of vegetation coloration change within a day or within a specified period is unknown.

Table 10: Advantages and short comings of Internet of things cloud based Smart farming (continuation)

	References	Advantages	Short comings
Effect of climate on smart farming	[65]	photo-chemical reflectance index (PRI) is effective in detecting late-stage heat stress in wheat plant when the chlorophyll parameters (physical & chemical variables) of the plant are influenced.	The experiment was not applied to other species of wheat or other crops for reliable results
	[66]	smart surface sensing system (4S) used to monitor vegetation indices (VI) which is part of the photosynthetic active radiation (fPAR) and Leaf area index (LAI).	it cannot be used for monitoring of multiple remote sites simultaneously.
	[67]	Evaluation of the near-surface air temperature data sets from the ERA-Interim (ERAI), Japanese 55-Year Re-analysis, Modern-Era Retrospective Analysis for Research and Applications Version 2	Inability to integrate the data from minimum and maximum temperatures to be used as indicators of possible stress situation in the forecast model.
	[68]	Understanding the relationship between vegetation greenness and productivity across dry land ecosystems through the integration of PhenoCam, satellite, and eddy covariance data.	model was only applied to Mesquite grass shrub alone and its has not been applied to other crops to ascertain its performance.
	[69]	Improving WOFOST model to simulate winter wheat phenology.	model cannot predict the winter wheat crop yield inter-annual across Europe and cannot consider the effect of excess water condition for winter wheat crop in the farm

Table 11: Advantages and short comings of Internet of things cloud based Smart farming (continuation)

	References	Advantages	Short comings
Artificial Intelligence	[60]	AI in edge computing used to monitor the movement (running, walking, grazing, resting) and location of the animals in a farm. Different pattern using unsupervised Learning to determine when a poacher or attacker is among the animal or within the farm.	the unsupervised learning technic is less reliable since there is no prior knowledge of the input data. The model is saddled with the responsibility to learn the data and use it to determine the hidden patterns.
	[61]	FL is used to handle user equipment and edge nodes for unbalanced and non-Independent Identical Distributed (non- IDD) data. The system has ability to train the data using mini-batches to reduce the communication cost	FL in edge AI not giving results in real-time, FL not applied In-edge AI to a heterogeneous network to test its performance

Table 12: Comparison of Advantages of existing papers

Properties	**[12]**	**[70]**	**[15]**	**[16]**	**[17]**	**[19]**	**18]**	**[20]**	**[21]**	**[63]**
Better segmentation of crop spot edges	Y	N	N	N	N	N	N	N	N	N
identification and separation of plant disease in fast computational time	N	Y	N	N	N	N	N	N	N	N
The K-means methodology using support vector Matrix and neural network to separate plants with diseases in WSNs	N	N	Y	N	N	N	N	N	N	N
algorithm which automatically identify health and welfare of animals.	N	N	N	Y	N	N	N	N	N	N
A wireless neck collar connected to the farm animals for data transmission	N	N	N	N	Y	N	N	N	N	N
Using IoT to monitor livestock behavior, movement (lying down, walking, grazing, standing)	N	N	N	N	N	Y	N	N	N	N
sea-lice counting & crowding control in fish farming to enhance fish farming.	N	N	N	N	N	N	Y	N	N	N
RGB-D sensor used for harvesting of sweet pepper by cutting the peduncle	N	N	N	N	N	N	N	Y	N	N
Monte Carlo simulation used to determine the best harvest age of a coconut.	N	N	N	N	N	N	N	N	Y	N
soil heat storage, energy consumed during photosynthesis that influence surface fluxes and advection of soil.	N	N	N	N	N	N	N	N	N	Y

Yes=Y, No=N, N/A= Not Applicable

Table 13: Comparison of Advantages of existing papers(continuation)

Properties	**[12]**	**[70]**	**[15]**	**[16]**	**[17]**	**[19]**	**[18]**	**[20]**	**[21]**	**[63]**
A model developed for predicting autumn phenology, to determine how leaf senescence is controlled by photoperiod and temperature coupling.	N	N	N	N	N	N	N	N	N	N
photo-chemical reflectance index (PRI) is effective in detecting late-stage heat stress in wheat plant when the chlorophyll parameters of the plant are influenced.	N	N	N	N	N	N	N	N	N	N
smart surface sensing system (4S) used to monitor vegetation indices (VI) which is part of the photosynthetic active radiation (fPAR) and Leaf area index (LAI).	N	N	N	N	N	N	N	N	N	N
Evaluation of the near-surface air temperature data sets from the ERA-Interim (ERAI)	N	N	N	N	N	N	N	N	N	N

Yes=Y, No=N, N/A= Not Applicable

Table 14: Comparison of Advantages of existing papers(continuation)

Properties	**[12]**	**[70]**	**[15]**	**[16]**	**[17]**	**[19]**	**[18]**	**[20]**	**[21]**	**[63]**
Understanding the relationship between vegetation greenness and productivity across dry land ecosystems through the integration of PhenoCam, satellite, and eddy covariance data.	N	N	N	N	N	N	N	N	N	N
Improving WOFOST model to simulate winter wheat phenology	N	N	N	N	N	N	N	N	N	N
AI in edge computing used to monitor the movement and location of the animals in a farm	N	N	N	N	N	N	N	N	N	N
FL is used to handle user equipment and edge nodes for unbalanced and non-Independent Identical Distributed (non- IDD) data successfully	N	N	N	N	N	N	N	N	N	N

Yes=Y, No=N, N/A= Not Applicable

Table 15: Comparison of Advantages of existing papers (Part 2)

Properties	**[65]**	**[66]**	**[93]**	**[66]**	**[67]**	**[68]**	**[69]**	**[60]**	**[61]**
Better segmentation of crop spot edges	N	N	N	N	N	N	N	N	N
identification and separation of plant disease in fast computational time	N	N	N	N	N	N	N	N	N
The K-means methodology using support vector Matrix and neural network to separate plants with diseases in WSNs and Consideration	N	N	N	N	N	N	N	N	N
algorithm which automatically identify health and welfare of animals.	N	N	N	N	N	N	N	N	N
A wireless neck collar connected to the farm animals for data transmission	N	N	N	N	N	N	N	N	N
Using IoT to monitor livestock behavior, movement (lying down, walking, grazing, standing)	N	N	N	N	N	N	N	N	N
sea-lice counting & crowding control in fish farming to enhance fish farming.	N	N	N	N	N	N	N	N	N
RGB-D sensor used for harvesting of sweet pepper by cutting the peduncle	N	N	N	N	N	N	N	N	N
Monte Carlo simulation used to determine the best harvest age of a coconut.	N	N	N	N	N	N	N	N	N
soil heat storage, energy consumed during photosynthesis that influence surface fluxes and advection of soil.	N	N	N	N	N	N	N	N	N

Yes=Y, No=N, N/A= Not Applicable

Table 16: Comparison of Advantages of existing papers(Part 2 continuation)

Properties	**[65]**	**[64]**	**[93]**	**[66]**	**[67]**	**[68]**	**[69]**	**[60]**	**[61]**
A model developed for predicting autumn phenology, to determine how leaf senescence is controlled by photo period and temperature coupling.	N	Y	N	N	N	N	N	N	N
photo-chemical reflectance index (PRI) is effective in detecting late-stage heat stress in wheat plant when the chlorophyll parameters of the plant are influenced.	Y	N	N	N	N	N	N	N	N
smart surface sensing system (4S) used to monitor vegetation indices (VI) which is part of the photosynthetic active radiation (fPAR) and Leaf area index (LAI).	N	N	N	Y	N	N	N	N	N
Evaluation of the near-surface air temperature data sets from the ERA-Interim (ERAI)	N	N	N	N	Y	N	N	N	N

Yes=Y, No=N, N/A= Not Applicable

Table 17: Comparison of Advantages of existing papers(Part 2 continuation)

Properties	**[65]**	**[64]**	**[93]**	**[66]**	**[67]**	**[68]**	**[69]**	**[60]**	**[61]**
Understanding the relationship between vegetation greenness and productivity across dryland ecosystems through the integration of PhenoCam, satellite, and eddy covariance data.	N	N	N	N	N	Y	N	N	N
Improving WOFOST model to simulate winter wheat phenology	N	N	N	N	N	N	Y	N	N
AI in edge computing used to monitor the movement and location of the animals in a farm	N	N	N	N	N	N	N	Y	N
FL is used to handle user equipment and edge nodes for unbalanced and non-Independent Identical Distributed (non- IDD) data successfully	N	N	N	N	N	N	N	N	Y

Yes=Y, No=N, N/A= Not Applicable

8. Discussion

The use of IoT has improved crop and livestock production through monitoring, tracking, and tracing, agriculture machinery, greenhouse, and livestock production. IoT has reduced water wastage in irrigation and improved water quality, more so enhanced weather and soil monitoring, it has helped to manage the disease and pest control, improved data analytics, and boost the automation of farming. The use of unmanned aerial vehicles for monitoring of crops, monitoring of livestock activities on the farm is another contribution of IoT to smart farming. Thermal image features have been used to estimate irrigation accuracy and the collection of data using sensors has also enhanced smart farming. All these numerous achievements in the use of IoT in smart farming have enhanced farming practice but these have not come with its share of limitations such as security and privacy concerns, data governance, lack of change in culture by the stakeholders to accept the IoT system innovation. This paper reveals sectors in smart farming that researchers can consider for further research to add more academic knowledge to the global vast contributions by numerous academic professionals globally. These opportunities for further research ranges from Wireless sensor network, Unmanned area vehicles, cloud-based smart farming, application of IoT to crop, livestock production, post-harvesting, monitoring of crops, monitoring of livestock activities, the effect of climate on agriculture, use of Artificial intelligence in farming, latency issues in data transmission in smart farms, improvement of smart farming network architecture, incorporation of a cloud platform to smart farming network, ML for smart farms while training data at the edge nodes, training of edge nodes in federated learning network within a smart farm.

9. Conclusion

A review of intelligent IoT in smart farming has been done extensively. Many issues relating to wireless sensors application in smart farming, application of IoT in crop and livestock production, post-harvesting, use of UAV, ML have been identified. This write-up contributes to knowledge through the identification of the gaps and challenges in existing research in smart farming. Such challenges include the computational power of IoT devices used in smart farm, AI for early disease detection, detection of leaf water stress in crops, detection of soil condition, livestock illness, and behavior pattern within the farm. The world population is increasing daily, massive wastage of crops and livestock through poor storage and disease infestation is still evident. An effective Intelligent IoT system for smart farming can start the beginning of the journey towards the reduction of food wastage, boost food production, and provide more information within the farming system for non-academics and researchers.

10. Further work

A lot of research has been done on intelligent IoT for smart farms, but these laudable contributions have opened opportunities for further research namely the implementation of the Fog-technology framework for farming, application of the combination of unsupervised learning algorithms and federated learning to smart farming. It will be an interesting research to be able to use intelligent IoT to understand the physiological activities within a plant during a sudden change in climatic condition within its environment. Further work should be investigated using intelligent IoT in smart farms to decode the livestock voices during pain or in reaction to a sudden change within its environment.

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Appendix A. Authors

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Appendix A.1.

Tasos Dagiuklas is a leading researcher in the fields of Internet and multimedia technologies for smart cities, and smart agriculture. He is the Head of Cognitive Systems Research Centre. He has a degree from the University of Patras, Greece, MSc at the University of Manchester, PhD at the University of Essex, UK in 1989, 1991,1995 respectively, all in electrical engineering.

Appendix A.2.

Muddesar Iqbal is Senior Lecturer in Mobile Computing in the Division of Computer Science and Informatics, School of Engineering. He is an established researcher and completed his Ph.D. in wireless networks from Kingston University in 2010. His research interests include 5G, Beyond 5G (B5G) and 6G enabling Technologies, Smart IoT systems, Blockchain, AI-enabled Social and Collaborative Computing, AI and Chatbots.