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Review Article

A comprehensive survey on IoT and AI based applications in different pre-harvest, during-harvest and post-harvest activities of smart agriculture

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ABSTRACT

Today farmers around the world are gradually embracing Smart farming assisted by different cutting-edge technologies. The Internet of Things (IoT) is playing a major role in the development of smart agriculture applications. Artificial intelligence, edge computing, cloud computing, big data, etc are other forefront technologies used in smart agriculture. Stages of Agriculture activities for a certain crop can be broadly classified into three categories, viz, pre-harvest, during harvest and post-harvest phases. In each phase, many activities have to be performed. Pre-harvesting stage involves seed selection, land preparation, crop selection, etc., during harvesting includes irrigation, disease analysis, pathogens detection, etc. and Post harvesting involves storage, cooling, reaping, etc. In the current work, we have carried out a thorough literature review of these activities involving smart farming one by one. We have attempted to find the flaws in terms of IoT devices, security, dataset, and methodologies used in these existing works. Based on the research gaps a 5G-based smart farming framework has been proposed. We have also presented a brief comparative analysis between our survey and the existing surveys. Our survey has been found to be more comprehensive compared to the existing ones in many regards.

1. Introduction

One of the most important pillars of human society is agriculture. According to the food and agriculture organization (FAO), to cater the needs of growing population, food (FAO, 2009) production need to be increased by 70–65 % in 2050. Farmers must put in more effort while using the traditional agricultural approach, which also uses resources inefficiently. Several issues, including population expansion, climatic circumstances, a shortage of resources, etc., occur from this ancient farming approach. The term smart agriculture refers to digital farming practices that are used to maximize effectiveness instead (Javaid et al., 2022) of capability. This system performs structured and optimal input and output analytics through smart technologies, objective-focused analysis, planning, and monitoring. As a result of collecting and pooling analytical data using advanced sensor, a methodology group is built that is optimized for achieving this objective-oriented analysis. For monitoring and managing agricultural operations, this cutting-edge technology combines Internet of Things (IoT) networks, devices, AI, and big data analytics. Through the use of diverse electronic, biochemical, and electrical sensors and actuators, various farming field data can be collected, and through this data, different sub-operations of farming applications can be developed. Using IoT to monitor crops (Sreekantha and Kavya A.M., 2017), detect diseases and pests, predict crop yields, robotics-based harvesting of crops, and much more. The creation of a wireless sensor network (WSN) can be accomplished using various types of wireless connections, each with a range, bandwidth, and topology that varies. A novel kind of wireless network can be built using topologies like bus, star, and mesh and a variety of communication technologies including Bluetooth, ZigBee, LTE-M, thread, Sigfox, etc. to communicate data from one node to another about the farming field. The edge gateway layer where all sensor node data are stored and processed for further analysis is connected to this sensor network. The data can be communicated to a different distributed network over the internet to a cloud server for additional analysis and monitoring at the user end by using application protocols like "Hypertext transfer protocol" (HTTP), "Message queuing telemetry transport protocol" (MQTT), etc. The gateway can be utilized as single-board microcontrollers and computers similar the Raspberry Pi (Charania and Li, 2020). Digital transformation is the main advancement in agricultural development which (Baryshnikova et al., 2022) transforms 1.0 into 5.0 in the twenty-first century. The key to advancing digital transformation in smart agriculture from version 5.0 to version 6.0 is the development of

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wireless communication technology. A number of wireless communication technologies, including "Long Range Radio (LoRa)", Radio frequency module (RFM69)", "Narrow Band IoT (NB-IoT)", and "SigFox" etc (Hidayat et al., 2020) have been utilised in agriculture. It is possible to create a secure smart farm system, also known as a 5G beyond Smart agriculture system (Tomaszewski et al., 2022) by fusing several technologies including IoT, Edge computing, cloud computing, artificial intelligence (AI), and Blockchain (Andreadis et al., 2022; Kasera et al., 2022). The ability to manage and achieves a variety of computing workloads and necessities for storage can be encouraged by developing a hybrid or dispersed sensor network employing cloud computing and edge computing. In this regard, edge computing will be able to regulate jobs that demand speed or limitations on connectivity. In addition, cloud computing will be able to accommodate operations that demand higher processing capabilities, for instance, machine learning (MCLRN), as well as managing enormous volumes of data by utilizing load-balancing techniques. From this type of technologies farmers will be able to access farming field status remotely and the system will be entirely automated through interoperability between machines (Li et al., 2021). Considering the research strategy that was used to write this review article is discussed in Fig. 1 below.

The dotted arrow in Fig. 1 denotes the simplified structure of how the review article is organized. Based on pre-, during-, and post-harvesting operations, the various IoT-enabled smart agriculture literature has been identified and categorized. After classifying and reading the literature, each pre-harvesting, during-harvesting, and post-harvesting operations' existing subsystems have been thoroughly discussed and its weaknesses analyzed. This analysis has been accomplished based on the IoT-enabled technologies, data set gathering, and approaches that have been used in the past and it also includes an overall thorough assessment of the pre-, during-, and post-harvesting subsystem's research gaps. Based on this research gap a modified 5G IoT-based smart agriculture framework has been proposed to reduce the shortcomings of the existing work.

The Pre-harvest to post-harvest activities have been categorized in this article to explain the existing work for the smart farming system. The classification of pre- to post-harvest activities is presented in the Fig. 2.

The paper is presented as per the following structure: The problem with traditional agriculture is introduced in section (**1**), along with how smart agriculture uses cutting-edge technology through 5G connection to tackle the problem, and the classification of various farming processes from pre-harvesting through post-harvesting. The section (**2**) discusses the IoT-based existing works on various pre-harvesting farming processes. The section (**3**) provides information on the IoT-based existing works in the harvesting process. The section (**4**) provides information on several existing works for the post-harvesting process. The modern metaheuristic technique for creating intelligent farm systems is covered in section (**5**). The section (**6**) analyses the current and future communication technologies used for smart agriculture up to this point. The section (**7**) provides information on the existing dataset that can be used in solving smart agriculture problems. Section (**8**) discuss the problem exist in the existing IoT based system on various pre to post harvesting subsystem, section (**9**) contributes the recommendation based on existing problem for developing pre to post harvesting subsystem, section (**10**) a comparison of the proposed 5G based smart agriculture framework with existing smart agriculture framework is discussed and in last section (**11**) overall summary of the proposed survey has been discussed.

2. Pre-harvesting system (PHRS)

Throughout the pre-harvest process, there are a number of land preparation (LPR) sub-activities that considerably increase agricultural yield. Researchers, scientists, and engineers have made a number of advancements in the past to create a smart PHRS using smart agriculture technology (Gaikwad et al., 2021), that can choose the crop in advance depending on climate conditions, region, area, etc. and prepare the land for production. The sub-areas of PHRS that are used when preparing the land for farming are depicted in Fig. 3.

2.1. Crop yield prediction (CYP)

IoT-based method for yield prediction in which sensor node data is shared with data centers (Gayatri et al., 2015) and made available to the sons of the soil. To anticipate agricultural yield, supervised MCLRN is carried out utilizing (Kumar et al., 2020) the "Random Forest" (RADF) and "Decision tree" (DT) algorithm. In this situation the RADF's accuracy is superior compared to the DT's. A two-tier MCLRN model called the "adaptive k-Nearest Centroid Neighbour Classifier (aKNCN)" and the "Extreme Learning Machine algorithm (ELM)" were proposed to predict crop yield. By applying ELM to (Gupta and Nahar, 2023) increase performance accuracy, the suggested system optimize the weights using a modified version of the Butterfly Optimisation Algorithm (mBOA). The creation of an algorithm for predicting crop yield (Bhojani and Bhatt, 2020) three new activation functions called "DharaSig," "DharaSigm," and "SHBSig" are employed to enhance the neural network's performance on agricultural datasets. K Closest neighbor procedure is employed to identify the crop that is most acceptable (Gajula et al., 2021). For the purpose of forecasting the yield of the sorghum crop,

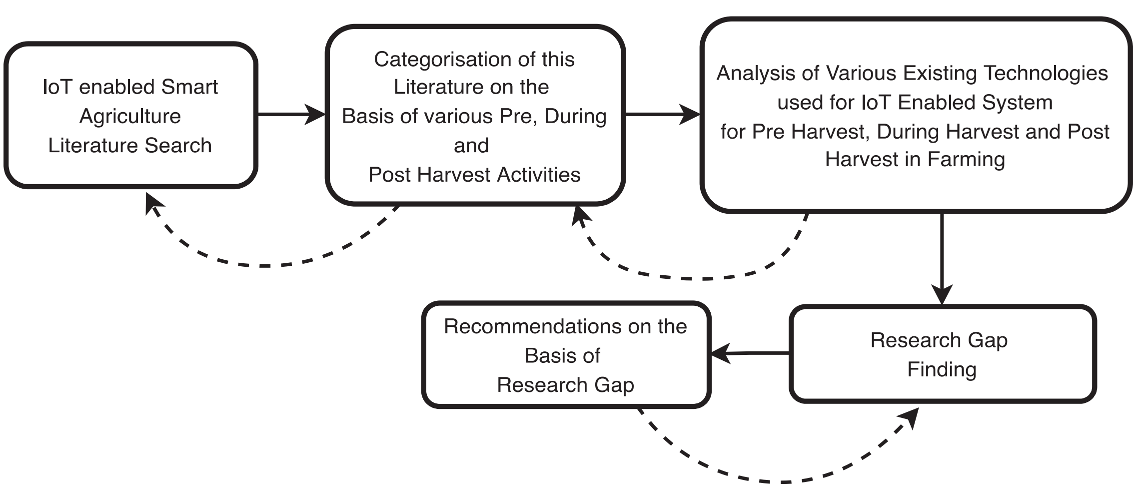

Fig. 1. The flow of research methodology.

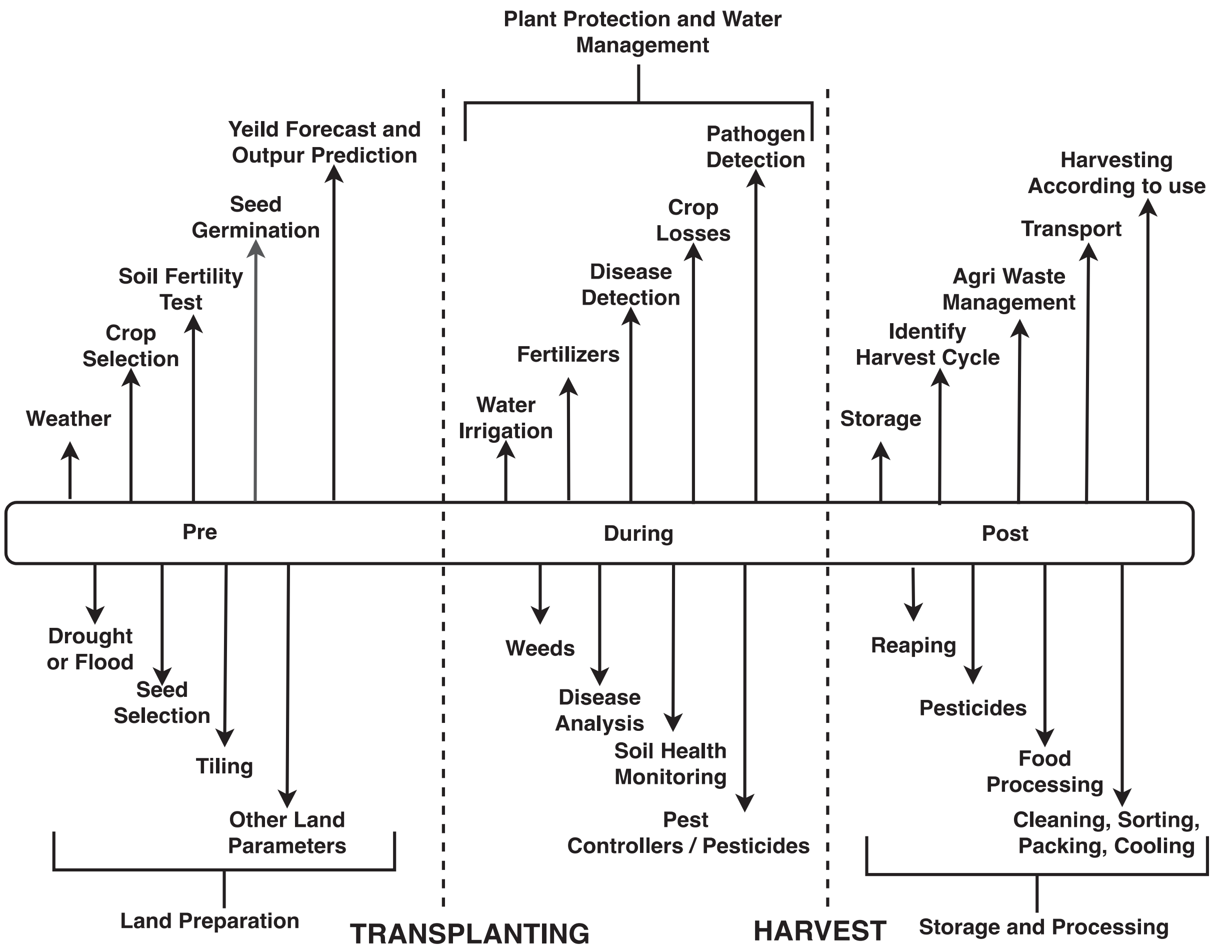

Fig. 2. Pre to post harvesting process (S R et al., 2020).

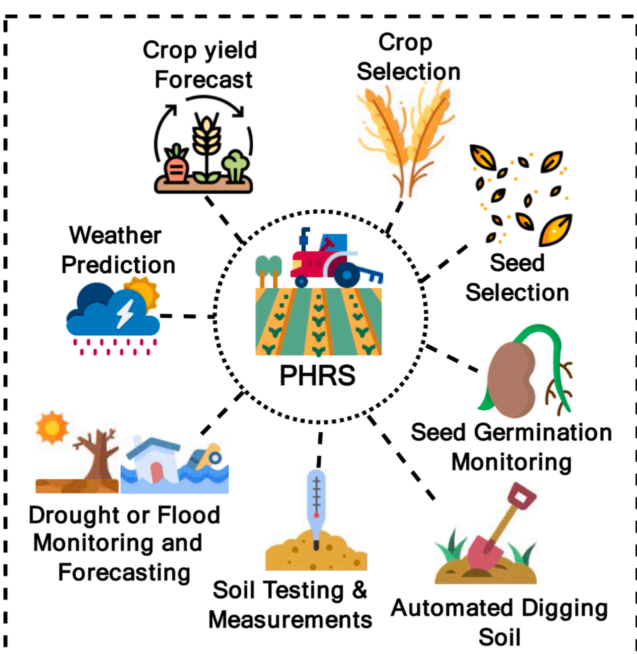

Fig. 3. PHRS subsystem classification.

(Jayaram and Marad, 2012) a fuzzy inference approach is implemented. A fuzzy model's input tools are physio-morphological features. Due to estimates and ambiguity, the model's performance depends on quantum data. A method for managing massive data and predicting crop productivity three different types of (Fan et al., 2015) approaches have been employed that is MapReduce weather data for computing large datasets; nearest neighbor weather data for comparing distances across like years; and, finally, an "Autoregressive moving average" (ARMA) model for forecasting. To determine crop yield, a "Support vector machine" (SVM) and DT approach are used. While choosing (Reshma et al., 2020) features for a specific location, factors like soil type, temperature, humidity, groundwater level, local population, farmers' availability, variety of plantations, and variety of farmed land were taken into account. Analysis has been conducted based on these traits to determine the optimal crop. A mixed MCLRN approach was put forth to estimate agricultural yield. The most precise (Anbananthen et al., 2021) MCLRN prediction from two models is combined using the stacking generalization model. Cross-validation is used to evaluate a hybrid MCLRN model's performance to that of other MCLRN models for evaluation. For the purpose of predicting agricultural yield (Sajja et al., 2021) an MCLRN simulation is designed, where crop segments are built up experimentally for the training of models using SVM, random forest, and ID3. In which case SVM outperforms other methods.

The key advantage of the current CYP is that most systems classify soil nutrients and geographic data for crop yield prediction using data mining techniques like KNN, ID3 and fuzzy inference systems, which produce superior prediction outcomes. The geographic information was gathered using a GPS approach that is IoT-enabled. The RGB-D camera is utilized as a mobile platform to enhance the CYP. Crop quality, data-driven decision-making, cost reduction, and resource optimization are all improved by using IoT-enabled data mining approaches.

The shortcomings of the existing techniques are as follows: prediction based on time series analysis, area-wise analysis, soil quality analysis, country-wise analysis, and geospatial analysis remain to be explored. There is no hybrid MCLRN algorithm for handling huge datasets. Full IoT based system still need to be worked upon.

2.2. Crop selection (CSL)

Enhancing Agricultural Sustainability through Crowdsensing (Ginige and Sivagnanasundaram, 2019) a mobile-based agricultural information-sharing system is developed for monitoring real-time farming activities (CSL LPR, "seed selection", "seed sowing", "irrigation, "crop growth", "fertilizing", and "harvesting") with the help of a crop calendar marker. IoT-based system for crop selection and monitoring precision farming (Bhojwani et al., 2020) various sensors are employed to measure environmental variables and interface with the microprocessor. An IoT gateway using ESP8266 sends the data acquired to a cloud server. On the basis of data collected earlier from the cloud server, the existing working model uses K-Nearest Neighbours (KNN) to estimate prospective predictions to be able to make precise decisions about what crops to grow in a particular environment. Maximize the crop yield (Kumar et al., 2015) for selecting which crops to cultivate over a season the MCLRN method predict yield rates based on environmental variables including weather, soil type, water density, and crop type. Smart agriculture-based crop selection analysis utilising (Tseng et al., 2019) big data a platform is created to track environmental elements on a farm and use those environmental factors to evaluate farmers' agricultural practices. The findings suggest that farmers can determine a crop's suitability for their land with greater insight. This is so they can take a look at things like soil moisture levels and temperature. The suggested environmental factor analysis methodology aids farmers in learning which crops they can produce. In order to optimize food production (Udutalapally et al., 2021) an innovative agricultural solution is proposed that uses AI and IoT for selecting crops, disease monitoring, and automated irrigation systems. The fuzzy MULTI-MOORA technology on (Balezentiene et al., 2013) language and numerical reasoning is provided as a fuzzy-based system for crop selection in Lithuanian climatic conditions. "Johnson's reduct" classifier method is used (Deepa and Ganesan, 2019) to produce classification rules for three crops, including rice, "groundnut", and "sugarcane", in a decision-based system for crop selection. According to present environmental (Bakthavatchalam et al., 2022) circumstances a system has been established for precision agriculture that uses IoT and classifier-based MCLRN algorithms to recommend the crop for irrigation and acquire the highest yield. AI for characterization and forecasting the (Amkor and El Barbri, 2023) results of potato samples cultivated with "Nitrogen", "Phosphorus", "Potassium" (NPK) fertilizers has been suggested in which KNNs are used for classification and nonlinear autoregressive models for prediction.

Machine learning and artificial intelligence advancements for the existing CSL system improve the decision-making for planting crops according to climate conditions and location. By using IoT-enabled solar power-based crop recommendation systems, energy consumption is reduced. Genetic optimization is the most common method for optimizing CSL performance. Crop guidance is improved when weather conditions are forecasted through the development of a crop calendar-based system.

Some of the shortcomings may be as follows: the current CSL solution lacks self-sustainability, testing for additional crops, security of sensor node data, system optimization, and subsystem integration.

2.3. Seed selection (SSL)

A tillage drip architecture is used for recommending seeds for (Indira et al., 2018) planting. Additionally, it discusses how effective seed selection based on soil can produce precise results. Seed selection is possible in the first phase, automatic watering is covered in the second phase, and plant disease diagnosis is covered in the third phase. A computer vision to identify (Koklu and Ozkan, 2020) different dry bean seed kinds the user interface was created using MATLAB, and 13,611 grains of seven different types of dry beans were photographed. The model has undergone 20-fold cross-validation and has been constructed using a variety of MCLRN classification methods, including MLP, SVM, KNN, and DT. When compared to other classification model results, SVM performance performed better. Deep-learning methods for seed classification were proposed in which fourteen (Hamid et al., 2022) different types of seeds were gathered and pre-trained using "MobileNetV2″ to create a model. The trained model claimed accuracy of 98 % on the training set and 95 % on the test set after rigorous experiments, extensive pre-processing, and fine-tuning.

The advantage of the current SSL system is that it chooses the appropriate seeds for individual fields using a computer vision-based method based on MCLRN and AI. Water, insecticides, and fertilisers may all be used more efficiently by farmers. This has good effects on the environment in addition to lowering costs.

The existing work lacks a fully automated system and limited use of data. Need more research for various types of seed classification based on climate condition, geographical region wise, and land wise.

2.4. Seed germination (SGM)

Proposed and created a smart germination assistance (SGA) system for SGM. "Temperature", "humidity", "light intensity", "moisture", and soil "pH" are all factors that (Islam et al., 2019) affect SGM. Using particular sensors, the system continuously measures the values of various factors in the surrounding environment. Each sensor reading from a different seed is kept and connected to an ideal value. Using a low-power embedded system (Shadrin et al., 2019) an AI method is proposed that can recognise SGM dynamics without necessitating heavy data transfer between nearby nodes. 97 % accuracy is attained with a "convolutional neural networks" (CNNs) model for seed recognition. A system based on the IoT was proposed to monitor, manage, and (Theparod and Harnsoongnoen, 2022) collect data regarding the effects of narrow-band light emitting diodes (LEDs) on sunflower nodes. With the help of "narrow-band LEDs" and dynamic germination, it was found through research that the germination of sunflower seeds was more successful in the red-light zones. IoT-based study is carried out for indoor tomato SGM (Seyar and Ahamed, 2023) systems at thresholds. Where transplanted seedlings were grown outdoors with a comparison of two irrigation systems using soil water balance methods with a long-range LoRa communication system, and the subsurface drip irrigation system produced the highest seedling levels of growth based on agronomical parameters at a 12 % threshold.

A feature of the current SGM system is the usage of a LoRa-based data communication system for various modules during the SGM process, such as irrigation and seed growing status. For the dynamic seed germination process, the usage of IoT-based "narrow-band LEDs" produces better results.

The system in place uses only one type of seed for testing, and it is not entirely IoT-based. As a result, there is a lack of a fully validated testbed system that uses an ideal sensor, is self-sustaining, and can be utilised for other crops. The current system still has flaws as it does not deal with plant biomass growth, flowering, fruits, and other types of crops utilising IoT-based technique and image processing algorithm.

2.5. Drought or flood monitoring (DFM)

A “WPART” IoT-enabled smart farming system is established that uses MCLRN (Rezk et al., 2021) to anticipate crop productivity and drought for informed decision-making. The following data factors are used to pick features: year, month, rainfall, temperature, air pressure, season, crop, “area”, “production”, and productivity. An IoT-based tackle has been put up for agricultural drought (Ping, 2014) data transmission and accumulating. The outcome shows that the system’s data capture and transmission performance is flawless, and it has good application value for gathering and analysing agricultural drought data. An MCLRN/IoT-based flood tracking system is portrayed (Rani et al., 2020) to gauge the water level in a flood-prone site. The intensity of floods is gauged using raindrop and water sensors. An IoT-based dam water monitoring alerting system is developed (Ganesh et al., 2022) for calculating how much rain fell, one may determine how much water will be released from the dam. The signal is analysed and judgements are made using the Arduino UNO.

IoT data collection in real-time and MCLRN analysis and drought result prediction are two benefits of the current DFM. For obtaining and analysing data on agricultural drought, the gearbox performance is faultless, and it has strong application value.

Absence of a long-term analysis based on previously established value and absence of coverage based on humidity and rainfall across a vast area were observed. There is lack of long-distance data connection methods in remote fields. The absence of dark shadow detection in the current technology makes it difficult to detect noisy pixels values in unmanned aerial vehicles (UAVs) for flooded regions, which can lead to erroneous data.

2.6. Soil testing and measurement (STM)

The optical transducer is used as a detecting sensor. This sensor (Goswami et al., 2020) comprises of three LEDs as a light source and an as “Light detector” (LDR) for assessing the results of soil tests performed on four distinct types of soils. Each nutrient’s threshold values divide its level into three voltage levels: Low, Mid, and High. A technique for monitoring soil health utilising four dynamic parameters was developed. In which the (Ramson et al., 2021) effectiveness of a network made up of nine soil health monitoring units was tested over the course of several weeks in an agricultural field site. Soil sensing, wireless range, power consumption, life expectancy, and implementation cost were all evaluated. An IoT-powered soil health tracking (Sengupta et al., 2021) approach that can manage agricultural parameters has been created. The variations in stimuli, including those related to light, heat, sound, motion, magnetic fields, etc., are converted into electrical signals by a sensor node and then processed and graphically displayed by the Thingspeak cloud server. Using cellphones or personal computers, a methodology is proposed for sensing (Saikia and Khatoon, 2022) the percentage of wetness of the soil and temperature remotely and continuously. Raspberry Pi-based soil nutrient monitoring system for tomato plantations is proposed using various soil sensors (Manickam, 2020) such as PH and Soil NPK sensors for monitoring the soil continuously.

The present STM’s strongest point is its use of an IoT-enabled method to assess soil health. Thanks to the existing technology that farmers can precisely administer fertilisers, insecticides, and water based on the soil’s nutrients, PH, and type, crop disease is reduced, and crop yields are increased.

There are still lack of sensor assessment based on a specified period, in-depth data analysis, additional parameters for optimising soil testing in various existing activities etc. There is a demand for an affordable, universal solution that can be used to all kinds of farms.

2.7. Weather prediction & monitoring (WPM)

An agro weather station (AWS) that is intended for farmers and researchers is (Faid et al., 2021) develop using four layers: perception, transmission, presentation, and administration. For various end users, it offers frequently data and AI-based insights. IoT-based intelligent energy-efficient approaches have been originated for monitoring and managing greenhouse interior temperatures. Many (Subahi and Bouazza, 2020) simulations utilizing a greenhouse temperature transfer function are run to show the usefulness of the recommended strategy. For temperature and irrigation control a computerized procedure is acquired. Using an Android app that connects (Kori et al., 2021) to the controller, many agricultural parameters, including as temperature, humidity, soil wetness, and rainfall, are tracked and visualised. A strategy to schedule weather forecasts was put out in order to foresee (Li et al., 2019) adoption of weather prediction information as well as future energy harvesting values based on historical harvesting values. A low-cost solar-powered (Devapal, 2020) soil and weather analysis system has been offered that looks at different soil properties and weather patterns to set up a high-tech smart farm for farmers. IoT, data mining, and android mobile applications are all used in the system’s development. Integrating a provincial weather station with dual modules to serve as a LoRa-based soil sensor node (Singh et al., 2022) for scrutinizing the state of the soil and the weather. During experiment, a LoRa portable communication device and an IoT cloud are used to transmit meteorological data. Constructed, and tested a flexible (El-magrous et al., 2019) meteorological-soil sensor station for acquiring site-specific maps of soil elements, atmospheric information, and yield information for the 2018 soybeans season of cultivation.

Farmers were able to make well-informed decisions on soil selection, irrigation, planting, and harvesting thanks to the use of sophisticated tools for weather forecasting and data from already-existing systems.

The existing weather monitoring and forecasting systems have a number of drawbacks, including the absence of AI fault detection approaches, a lack of integration with the existing IoT-based agriculture system, and a lack of optimize long-range communication technologies. There is a need for an intelligent weather system that can identify the soil’s nutritional needs and suggest a suitable crop.

2.8. Soil digging (SDG)

To enhance tillage processes more significant by fusing IoT, “cloud computing”, and “Decision support system” (DESS) technologies (Fawzi et al., 2021) the ”Tillage Operations Quality Optimization (TOQO)“ model is constructed using two levels: ”Tillage Depth 1 (TD1)“ and ”Tillage Depth 2 (TD2)“. TD1 = 10–15 cm and TD2 = 25–30 cm. The TOQO standard’s tested results improve long-term evolution for the agribusiness by maximizing farmer expenditures, accelerating field productivity, and optimizing tillage routines.

Real-time monitoring of soil-digging machinery, which enables farmers to optimise the depth and spacing of rows or holes, is a strength of the current system. This accuracy supports resource utilisation that is efficient and minimises reductions in waste.

Due to the significant differences in soil properties, such as moisture content and hardness, the current system needs to be improved in terms of performance, affordability, and sensor calibration. Analysis to reduce the environmental impact of soil tilling is still lacking in the system. More accurate measurements may be possible by the use of the cutting-edge MCLRN algorithm.

The average growth rate of research publications published between 2012 and 2023 for PHRS applications that are based on IoT, AI, MCLRN, and other techniques is shown in Fig. 4.

The growth rate of publication has been assessed based on the quantity of articles published in a given year for a specific PHRS application, such as CYP, CSL, SSL, SGM, DFM, STM, WPM, and SDG, and the average growth rate analysis has been assessed based on the

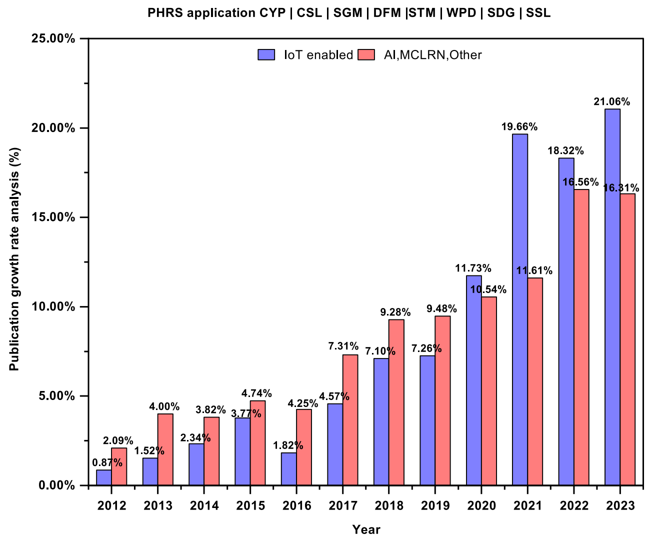

Fig. 4. Publication growth rate analysis of PHRS application based on IoT and AI, MCLRN and other methodology from 2012 to 2023.

overall quantity of publications for PHRS application year-wise. As observed in Fig. 4 graph, a growing number of publications based on IoT, AI, MCLRN, and other approaches for PHRS application are made each year, with a high percentage of IoT-based PHRS applications. Thus, it can be concluded that the number of PHRS-based smart agriculture applications is growing steadily as a result of the convergence of IoT, edge, cloud, and AI technologies.

3. During harvesting system (DHRS)

After preparing the land for the cultivation of crops, there are numerous sub-operations engaged during harvesting. The subsystem of the DHRS is shown in Fig. 5. Using cutting-edge technologies to automate crop monitoring and irrigation (IoT, MCLRN, Data Mining, etc.). It

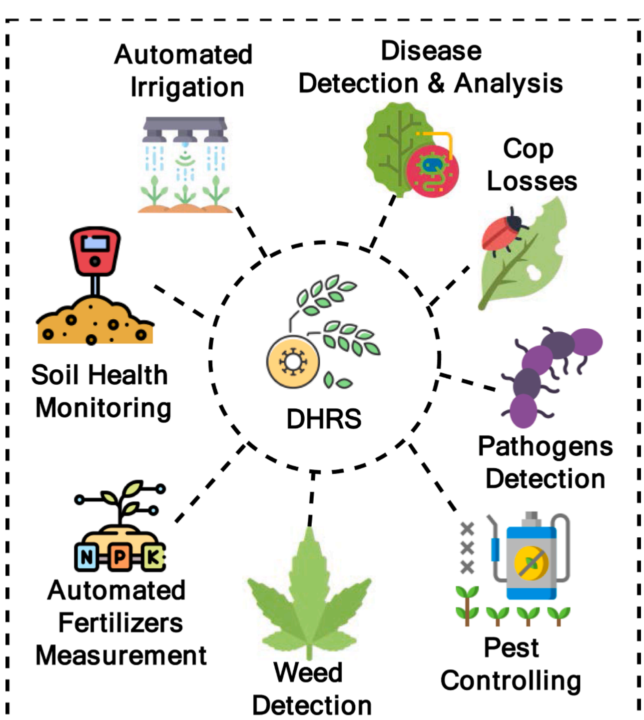

Fig. 5. DHRS subsystem classification.

not only emphasises the value of improved production but also strongly emphasises data analytics and environmental sustainability. This is done to assess the needs and anticipate the compatibility of crops and fertilisers in light of the soil and environment.

A wireless sensor network is essential for the implementation of smart agriculture (Haseeb et al., 2020). There are numerously IoT-enabled prior related work that has been done (Ahmed et al., 2018; Anagha et al., 2023; Sah Tyagi et al., 2021) in the domain of during the harvesting process.

3.1. *Smart irrigation (SIR)*

Low-cost intelligent smart irrigation system using IoT is proposed in three modules. Combined (Nawandar and Satpute, 2019) sensor module, irrigation module, and sensor communication module. The combined sensor module is used to access crop, plantation, and soil-related information. After accessing sensor monitoring data it uses a neural network model to make an intelligent decision. These decisions are sent to an irrigation module and sensor communication module. The aforementioned data determines whether the water machine has to be turned on or off in a certain location. The system keeps track of incoming data, and the sensor communication module logs it via the MQTT broker. The "AtMega 328" microcontroller and (Saraf and Gawali, 2017) Zigbee communications are used to monitor and control sensor data in the existing work. Each field's central node stores sensor data in the cloud database. The report on automatic irrigation is delivered to a user via an Android application. An intelligent irrigation (Alomar and Alazzam, 2018) system is achieved using IoT and fuzzy logic. As environmental variables, air climate and humidity sensors, soil wetness sensors, and light intensity sensors are used. By utilizing all the sensor information, a Mamdani fuzzy controller controls the flow of water. IoT, a DPLRN, and fuzzy computation are combined to form an ecosystem for creating a self-sustaining irrigation system. Soil wetness, atmospheric (P. Patel et al., 2022) variables, and the state of crops are all input variables in this operational simulation. Leveraging the Raspberry Pi, a device called an IoT gateway allows for uploading data to the cloud. To estimate if a crop is healthy or slumping, an assortment of DPLRN algorithms are used. In order to determine the appropriate time to irrigate the crops, all measured input variables are analyzed with a fuzzy logic controller. RFID and sensors to establish an efficient farm tracking framework exploiting (Saha et al., 2022) "Long range wide area network" (LoRaWAN) protocol with six distinct harvesting issues, prohibiting fungal attacks on crops, screening cattle, appropriate watering, accurate soil wellness inspection, accurate inspection of crops, and enhancing productivity. It maintains appropriate irrigation while conserving water by using incredibly effective temperature and humidity sensors. Four distinct categories of sensors are used in the soil and crop wellness tracking system to gauge the "NDVI" readings of the crops, the "pH" rating of the soil, the percentage of nutrients that are contained in the soil, the soil's compaction, and the amount of water in the soil. Cowlar is used by the cattle monitoring system to continuously check on the health of the cows. Smart farm decision-making powered by IoT and the cloud system that has been designed in order to communicate sensor (Lova Raju and Vijayaraghavan, 2022) data using "NRF24L01" modules. A suitable irrigation is schedule in which the author, without (Sayanthan et al., 2018) the assistance of labour, employed an Arduino soil moisture analyzer to measure water requirements at various phases of eggplant growth. Using an "Arduino Uno R3" board and an "Arduino DUE", the (Jamroen et al., 2020) intelligent irrigation system is scheduled. For data connectivity, the "NRF24L01" module is intended. The current method guards against crop water stress situations using a fuzzy inference system. The MCLRN-enabled autonomous watering mechanism has been constructed. The raspberry pi and (Vij et al., 2020) Arduino mega are two different types of microcontrollers employs in this method. The Arduino Mega is equipped with a number of sensors. Arduino Mega sends sensor data to Raspberry Pi through the wifi module. Weather data will be retrieved using an open-source Application programing interface (API), and a raspberry pi will operate to alert a system using weather data and sensor node data. A soil type's propensity for irrigation is predicted using MCLRN. A way to regulating irrigation (Mohammed et al., 2023) systems using DPLRN that takes into account the moisture and soil structure. In their methodology, soil pictures and moisture sensors are used to gather data, which is then processed using real-time videos to determine the crop's need for irrigation and moisture levels. A "VGG-19" model analyses the type of image and crop seeded to predict irrigation needs. "TensorFlow" lite is used to run experiments on cheap computational hardware and test the proposed model on a private dataset. A remote irrigation water pump monitoring, management, and (Kirar, 2022) security is developed. The sensors used in this work to detect supply voltage and motor current to estimate operating conditions and offer protection. The user receives the measured parameters via the SIM900 GSM component regarding the intent of remote oversight and management. The Android application was created with a better user interface, timer-based functionality, notifications for feedback and pump status, among other features. An ATmega 328P microprocessor that is included into the Arduino Uno board protects the pump. To track agricultural factors like temperature and relative humidity (Hamouda and Elhabil, 2017) a greenhouse smart management mechanism is suggested. The watering and cooling of greenhouses are managed and controlled automatically by the system. An intelligent system is created to track and control several subsystems, including irrigation, (Cecchetti and Ruscelli, 2022) lighting, heating, and solar. To enable sensor data to be connected to the farm Ethernet network, RS485 bus Ethernet convertor is employed. Automation of the heating system, irrigation system, circulation pump, and solenoid valve are accomplished using a relay board coupled to a Raspberry Pi 4 microcontroller, which is controlled using the HTTP. PHP scripts handle the system's overall business logic. A connected device WSN is created using the "SIXFAB" module (Kiani and Seyyedabbasi, 2018) to irrigate crops in agricultural fields, and the Arduino component of the module transmits data to a Raspberry Pi-based IoT gateway.

One of the strengths of the existing SIR system is its use of WSNs and machine learning techniques for monitoring and scheduling irrigation of crops for large and small farming fields by collecting wet and dry soil data according to the climate and soil condition, which ensures crops are irrigated at the right time and irrigation systems optimize crop growth.

There should be irrigation and crop-specific field monitoring, which are weaknesses of the current approaches. The current system relies on a single kind of irrigation for a variety of crops. There are lackings of self-sustaining system and sensor calibration system. Based on the soil nutrients, moisture, temperature, and humidity, more data analysis needs to be done. Heuristic techniques for improving irrigation and minimising water use are still lacking. To prevent water waste for different crops, the water irrigation system can be scheduled or rain harvesting strategies need to be used. Transparency of sensor data is lacking. The current process is unable to communicate with another system. The system's performance can be enhanced by using simple cryptographic techniques to safeguard data flowing from all the sensors. Communication over long distances for data is still unpredictable.

3.2. Soil health monitoring and fertilizer management (SHMFM)

A methodical approach that accumulates instantaneous data from the farm site, such as light strength, wetness of the soil, surface temperature, humidity, etc was proposed to provide local access (Bachuwar et al., 2018) to soil temperature, humidity, soil wetness, and light intensity, an ESP826612E transmits sensor data over a Wi-Fi network using the "IEEE 802.11" protocol. A method to produce data sources made up of temperature, humidity, and N, P, and K nutrient content (Rahman et al., 2019) that are produced from soil data sensor readings. In order to create a soil fertility data warehouse, sensor data is uploaded using IoT technologies. By combining Light Dependent Resistor (LDR) and Light Emitting Diodes (LED) in a novel NPK sensor (G et al., 2020) an IoT-based system took into account. To determine whether N, P, and K deficiencies exist in the soil chosen for testing, the Mamdani inference procedure is used. At regular intervals, the farmer is alerted to the quantity of fertilizer to be applied. A technique that (Postolache et al., 2022) can aid in the evaluation of changes in soil nutrients for more effective administration of drainage and fertiliser control. The appliance may gather information on the amount of NPK in the soil, further information on soil temperature, conductivity, pH, and moisture. A solar fertigation control mechanism for watering using a hybrid model and forecasting control (Ahmad et al., 2022) is built on a weather-based system accompanied by a crop a repository controlled by real-time sensors that keep track of the water condition of the plants as well as the soil moisture and water quality. The continuous gauging system for evaluating the water in the soil and nutrients for citrus (Zhang et al., 2017) moisture and nutrient status in citrus orchards, so that fruit farmers can understand their orchard's condition in time and adjust fertilization and irrigation strategies according to the data. To make it simpler for farmers to plant citrus seeds, (Pratama et al., 2021) an IoT-enabled gadget that indicates the soil's nutrients for citrus seedlings using a "NPK" indicators and feeds the outcomes to the Thingspeak cloud. A soil wetness monitoring system was developed using LoRaWAN detectors with (Hossain et al., 2022) blended transmission modules, no in-field root stations or routers, and an unmanned aircraft system (UAS)-based mobile router to retrieve the gauges of soil wetness taken from buried indicators for a variety of crops. A continuous measurement system is proposed for soil nutrition content using an automated fertilizer unit for (Visvesvaran et al., 2021) greenhouse systems. The fertilizer system automatically provides the plants with the nutrients required once the measurement value reduces under the trigger value. The NodeMSU is utilized throughout the system for data communication.

The performance of the LoRaWAN network beats that of the current system for long-distance data transmission, and the "Mamdani inference" optimization method based on IoT fuzzy logic yields the best results for measuring soil health.

From the discussion above, it can be seen that the current system has some drawbacks, such as a lack of standardisation due to the fact that different soil sensors use different data formats and protocols to collect data. Due to the dependence of soil temperature on climate, sensor calibration is still lacking. To better manage soil surface and fertilisation, the current system has to be optimized.

3.3. Disease detection and analysis (DDAN)

For autonomously identifying and categorising plant diseases from leaf photos, a DPLRN algorithm is suggested. Using the collected images, (Sladojevic et al., 2016) CNNs are trained and validated along with fine-tuning. A convolutional neural network model with squeeze net architecture is utilised (Hidayatuloh et al., 2018) to distinguish between healthy and diseased tomato plant leaves. There are four steps to creating a DPLRN based (Andrianto et al., 2020) smartphone application for spotting rice plant diseases. These are creating a system architecture for plant disease detection, creating a cloud server application and a smartphone application, testing the smartphone application, and assessing the system's performance. The MLP simulation of plant diseases, which acquires information as 10 characteristics and 4139 data points, was put forward as a real-time (Kumar et al., 2021) detection method. The four common forms of disorders are accurately detected by the neural network. An app for cellphones that makes use of deep convolutional neural networks to (Pallagani et al., 2019) anticipate crop diseases. A total of 38 different diseases have been predicted by the app. Farmers everywhere can make use of it even without an internet connection. Controlling a pandemic illness with an IoT-based gauge is a crucial agricultural (Khattab et al., 2019) application. The system architecture can forecast a variety of plant diseases, and the model has been put to the test on tomato and potato crops in lab settings. An electronic method designed to communicate with mobile phones (Nagasubramanian et al., 2021) to manipulate disease classification, environmental objects, and farmer suggestions. MCLRN algorithms, SVMs, and CNNs are used to develop the farming suggestion. A leaf detection analysis is put forward using (Thorat et al., 2017) an assortment of sensors, such as temperature and soil moisture meters, etc. After processing, the leaf image is collected and uploaded to the server. The status of the leaf disease is also communicated to the farmer via the mobile app. Using "MDFC-ResNet" and DPLRN-based IoT (Hu et al., 2020) devices, a crop diagnosis of illnesses IoT system for several crop types is being developed. A publicly accessible collection of 54,306 pictures of ailing and healthy plant leaves has been assembled (Mohanty et al., 2016) in which a deep CNNs was utilised to identify 14 crop types and 26 illnesses from this controlled sample. An IoT-based system that uses MCLRN to deliver conveniently (Truong et al., 2017) available real-time local environmental data in rural crop fields. With the method, it is possible to both identify fungal illnesses and forecast their potential spread among crop fields. A "Tiny Machine Learning" (TinyMl)-based technique for plant disease identification is designed. Once the model has been trained using (Adeola et al., 2022) MCLRN methods, it is transformed into a lightweight model with a kilobyte (KB) size that can be placed into devices with external memory. Tensorflow lite is used to perform the model conversion with the already installed library.

The existing method's strength is its effectiveness in locating the illness at the plant's root system using information on the soil and environment of a given region. The performance of the "Tiny Machine Learning" (TinyMl)-based technique to identify the kind of sickness was superior to that of existing DPLRN systems.

For gathering a vast number of statistics on various plants and climatic circumstances, the aforementioned existing method still has several shortcomings. Lack of ability to detect and control various diseases. To identify plant diseases, several existing systems used CNN-based DPLRN algorithms, but the algorithm performance still has to be optimized in terms of accuracy, usefulness and real time plant disease analysis.

3.4. Pathogens detection (PDT)

Biosensors possessed the ability to develop into the forefront of diagnostic techniques for various fields of biological studies, which comprises immediate assessment of human blood (Sonu and Chaudhary, 2022) ingredients for both animal and plant infection recognition, environmental surveillance, and airborne pathogen identification. As a result variety of techniques for detection of (R. Patel et al., 2022) plant pathogens and mechanisms of biosensing systems have been examined, whose two main categories of conventional analytical methods for the detection of plant diseases are the "Digital droplet polymerase chain reaction" and the "Quantum dots-based biosensor".

The exploration of techniques for agricultural disease detection is the overall strength of the present work. The analysis illustrates the benefits of miniaturized sensors in terms of convenience in production; affordability, speed of reaction, and responsiveness, establishing those instruments useful for observations in the field.

In terms of high levels of automation, the work currently being done for pathogen detection still has a research gap. It is lacking sensor standardisation. It is necessary to improve the methods for detecting various pathogen types, sensor calibration, dataset gathering, and technology integration. A cheap sensor needs to be deployed in the creation of an affordable, eco-friendly system. Due to the need for further optimisation of IoT-enabled systems, there is still a gap in field testing.

3.5. Pest controlling (PCN)

IoT and CNN-based insect recognition techniques are combined in a system. The technology is (Ramalingam et al., 2020) utilized by pest management businesses to keep an eye on pests in a variety of settings, including food storage areas, hospitals, gardens, etc. Using the IoT for crop monitoring and pest control (Tian et al., 2021) an infrastructure for simultaneous and collaborative simulation strategy has been provided. Based on the results, the applied simulation with IoT assistance system is the most efficient and accurate solution. An artificial IoT and DPLRN (Chen et al., 2020) technology can be used to analyze crop growth and predict pest occurrences in an environment. A neural network algorithm called "You Only Look Once (YOLO)" is used to identify pests in images. A system for the detection and control of pests embedded in an embedded environment is proposed in which (Vijayalakshmi et al., 2019) if the acceptable limit gets surpassed in terms of both temperature and humidity, then the "raspberry pi" captures the image of the plant and compares it to the database, and if pests are found, the farmers are notified to fertilize. A "Multi-Agent System (MAS)" by deploying a (Debauche et al., 2020) Docker environment orchestrated by "Kubernetes" in the Edge AI-IoT architecture is constructed. The system utilizes an AI algorithm to identify plant diseases and pests and uses an irrigation pivot to treat the crop. The positive aspects of MCLRN algorithms like KNN and the (Materne and Inoue, 2018) linear regression framework are used to construct a prediction model in a plantation to forecast disease and insect outbreaks.

The upside of already-existing systems is that building a decentralized and accordance simulation structure with the IoT for pest control and crop monitoring in combination to increase crop yields, lessens the load on one GPU, and contributes to the operation evenly and concurrently with all accessible GPUs and perceives data.

Based on the usefulness of data, the current pest management method still has a gap. For a robotic technique based on DPLRN to detect different kinds of insects and rodents, the current solution still has to be improved. Due to various data formats and IoT protocols, there are still issues when integrating the current system with another system. The amount of manual field monitoring by farmers can be decreased, for example, by merging deep irrigation systems with current pest management techniques. By including preprocessing to normalise the image before the prediction to minimise the effects of photo exposure (varying light intensity in outdoor situations), plant disease and pest detection can be enhanced. IoT-based security and privacy of sent data still require improvement.

3.6. Weed detection (WDT)

Robotic weed control that uses MCLRN and IoT to detect weeds in onion fields and (Arakeri et al., 2017) spray them with the required herbicide. Installing a weed detecting system in a chilli (Islam et al., 2021) field using RADF, KNN, and SVM, among other MCLRN and image processing algorithms. Systems were built using MATLAB. In order to identify weeds in soybean crops (Razfar et al., 2022) a DPLRN based vision-based weed identification system is prepared. Three unique CNNs models and MobileNetV2 are employed in the five-layer DPLRN architecture. In order to increase agricultural productivity (Dasgupta et al., 2020) a concept is suggested by utilizing wireless sensor networks and AI models for crop forecast and weed identification. In this approach, MCLRN is used to create a model after data are collected from sensors via WSN. CNN is used in conjunction with this to detect marijuana in drone-taken photo. An algorithm is designed based on CNNs to identify and (Jabir and Falih, 2022) locate weeds in wheat harvests in the region of Beni Mellal-Khenifra, Morocco, using an intelligent system. The YOLO model is used to construct a real-time detection and identification model on the Raspberry Pi. A network is established for detecting weeds (Kulkarni and Angadi, 2019) using a CNN. The CNN is constructed as a pooling layer, and the activation function is a "ReLU". A remote-controlled robot based on a Raspberry (Dankhara et al., 2019) Pi is used to detect weed using an image processing technique. A model has been formed for precision (Karthikeyan et al., 2021) agriculture based on K-means clustering to classify weed plants. A "CNN" technique associated with IoT is used for image processing.

When compared to another neural network technique, the performance of a WSN employing a Raspberry-based system with the DPLRN approach is superior. More accurate results were obtained.

The above-discussed existing work has flaws based on real-time mobile application monitoring of weed detection; more parameters can be added to make the DPLRN model performance optimised so that real-time weed can be detected accurately; and analysis of weed mapping method still has a gap where more research can be carried out. Improvements still need to be made to real-time UAV-based technique optimisation. The existing system does not incorporate the integration of various environmental sensors, actuators, or feedback controllers for monitoring. More research is still needed to develop a custom deep learning algorithm that can identify different weed types based on plants.

3.7. Crop losses (CLO)

To gain an adequate understanding of crop health, an apparatus has been (Shafi et al., 2020) put together that combines multi-modal data from the IoT nodes and drone photos. The fused data was subjected to MCLRN and DPLRN algorithms for crop health classification and creating health maps. Data from the sensor nodes is transmitted via a LoRa module. The system is intended to design, develop, and test a next generation of automated (Pérez-Ruiz et al., 2015) and robotic systems for efficient pest management in agriculture and forestry operations using a real-time kinematics (RTK) and "Global positioning system" (GPS) controlled autonomous tractor for straight-line tracking. A drone-based system is designed in which a "Raspberry Pi" module is integrated (Saha et al., 2018) with an array of 64 separate temperature sensors over 12C, an RGB-D camera for taking real-time photos, and a GPS navigation module. The cloud server receives and stores all sensor data. A system that makes use of multiple sensors to assess the temperature, humidity, pH level and scent of the leaves is compared and examined (Giri Babu and Anjan Babu, 2020) to check if the gathered leaf values fall within the range specified in the actual dataset for tracking crop health. Using IoT and remote sensing (Shukla et al., 2021) a method is proposed for agricultural health monitoring. To identify healthy crops, IOT-connected UAVs and MCLRN are used. Prescription maps are important because they make use of resources like pesticides, water, and fertilizers. Farmers are able to decide what resources are necessary to ensure that crops are healthy at every stage of growth. An IoT platform is constructed that uses image processing and a classifier algorithm to detect plant illnesses. If an (Ayalew et al., 2022) automatic medicine system identifies ailments, a sprinkler sprays medication. Additionally, disease transmission is tracked based on changes in weather using soil humidity and temperature sensors. An automated decision-making (Grimblatt et al., 2021) tools and metrics that track plant development and health, which have an immediate and measurable effect on farmers' ability to produce crops. Experiments are carried out using two separate sensors, soil moisture and temperature, to ascertain the significance of each parameter as the foundation for plant growth. An agricultural production system simulation is designed (Matsumoto et al., 2017) to carry out intricate business-based assessments of the abundance of inventories and crop destruction brought on by an absence of knowledge about the quantity of food acquired, the number of unit crops, and the enlargement of cultivated fields. IoT-Edge module (Park and Kim, 2021) collects strawberry hydroponic environment data and strawberry photos, allowing for monitoring and determining strawberry harvest time. Utilizing a Wide-area inexpensively network (LPWAN) based on the "NB-IoT" (Chang et al., 2018) a smart lighting system is developed for greenhouses of expensive crops. Using the temperature, humidity, and methane gas sensors MQ4, LDR, and DHT11 (Mahfuz et al., 2020) an embedded system is established based on microcontrollers. Its purpose is to keep track of the atmosphere all over the greenhouse. In the event that any sensor value is outside of its acceptable range, the Arduino will send the user a notification SMS using a SIM 900 GSM modem. Through the Android app, a new threshold value is also configured.

The performance of the smart monitoring of healthy crops is outperformed by the IoT that utilises drone and hybrid MCLRN to detect healthy crops in the growing environment. The data is transmitted quickly and cheaply between the edge and the cloud using an LPWAN based on the "NB-IoT".

It has been determined through research of the already-existing system previously described that there is still a gap in monitoring and controlling the crop from numerous losses. The current system is missing data processing steps and robotic sensors with intelligence that can detect different soil parameters, such as soil PH, soil water levels, and other characteristics. The ability for mobile-based applications to provide the end user with real-time access to farming field information from any location still needs refinement. For example, alerts for watering plants, temperature control notifications, and disease detection alarms based on the disease types and how this disease might be controlled. The examination of extensive data based on various crop types is still lacking. Because of climatic circumstances, dissimilar data formats, and dissimilar communication protocols, the system is not self-sustaining; it is dependent on a certain region and environmental condition. It is also unable to integrate with another subsystem.

Fig. 6 exhibits the average annual growth rate of papers on research produced throughout 2012 and 2023 for DHRS implementations based on IoT, AI, MCLRN, and other procedures.

According to Fig. 6, the DHRS application research publication growth rate analysis has been conducted similarly to that of the PHRS application research publication growth rate analysis. The DHRS publishing analysis graph shows an increase in the number of research published articles year over year. Comparing IoT-based DHRS applications to AI, MCLRN, and other techniques, the publishing growth rate was higher between 2019 and 2022. This is because more research is being done on SIR, DDAN, and CLO-based applications. In comparison to the period from 2012 to 2018, the average annual growth rate of publications for SIR-based applications between 2019 and 2022 has been calculated to be 69.23 %. In contrast, between 2019 and 2022, the average growth rates for CLO and DDAN, respectively, were 53.26 % and 63.98 %. It is therefore possible to predict that there will be an increase in the number of research publications using IoT and AI-based approaches for developing DHRS applications.

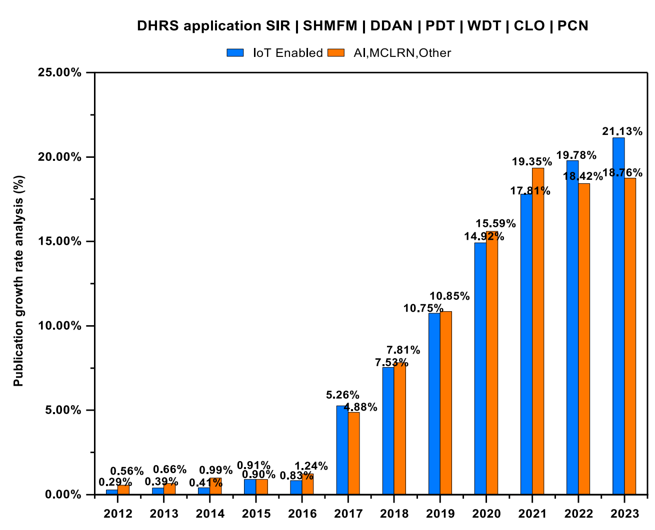

Fig. 6. Publication growth rate analysis of DHRS application based on IoT and AI, MCLRN and other methodology from 2012 to 2023.

4. Post harvesting system (POHRS)

When preparing the ground for agricultural cultivation, farmers that practice traditional farming face a number of challenges. These challenges were brought on by the rising demand for agricultural production, and it is not simple to match this rising demand for food processing, storage, and supply. The Fig. 7 shows the post-harvesting subsystem in which various existing research work has been done based on storage, harvesting cycle, supply chain, food processing, etc. (Abouelsaad et al., 2022).

The post-harvest physiology and management of fruits and vegetables are covered in this area, along with topics like harvesting, handling, packaging, storage, hygienic practises, transportation, crop waste, etc. In the context of severe weather, it also covered postharvest handling.

4.1. Reaping, sorting, cooling, and storage (RSCS)

An agricultural robot design is incorporated that would use "Autodesk Fusion 360″ (Sazid et al., 2022) and "Webots Simulator" for reaping, seed sowing, excavating, unmanned ploughing, watering, fertilising, and harvesting. "Proteus 8.9" simulates the complete system. For data analysis, "MATLAB" is being used. An IoT-based microcontroller farm robot automates the system as a whole. An IoT-based low-cost solution is structured in which warehouse's (Banerjee et al., 2020) hazardous gas, CO2, is detected using a gas sensor. Tilts or lateral motions of the rack are picked up by shock sensors. To safeguard grains from fire, a warning is issued if a fire flame is discovered. The Node-Red dashboard allows a user to view the findings of live sensor data anywhere, at any time. IoT has been used to monitor and manage food grain waste in warehouses. A "DHT11" indicator (Devi et al., 2021) for temperature and humidity, a CO2 sensor for air quality, a PIR sensor for moving object detection, and other sensors are integrated using "Arduino" to act as a rat and insect repellant. A fan is activated to cool the room if the temperature and humidity are above and below, respectively, the threshold levels. All sensor node data is accessible on the mobile application. Immediate terms surveillance equipment powered by IoT that (Siddiqua et al., 2022) can track temperature, humidity, brightness, and gas concentration in freezing storage and notify the user of potentially dangerous values when the levels surpass the thresholds. The "Arduino UNO" microcontroller regulates sensor data and provides it to the ESP32. The MIT App Inventor is used on either a computer or an Android phone to monitor the status of the storage room. Using a combination of blockchain technology (Sangeetha et al., 2021) a system for gauging crop quality and monitoring storage that links farmers with distributors directly. Data is gathered in real-time both in the warehouse and on the field. All sensor nodes are linked together using Arduino, and information is transmitted to the Raspberry Pi-based IoT gateway using Lora communication. Farmers and distributors can visualise and analyse data via a web application, which is stored in Azure SQL databases. The invention of a stated IoT-enabled warehouse management system in which (Anoop et al., 2021) the NodeMSU microcontroller is set up to receive temperature and humidity data in this study. A DT method is used to examine the temperature swings that took place in Kerala during the past five years. To assess and display the warehouse's climate state, this climate data is transmitted to the cloud server Thingspeak. A system based on IoT is established for controlling and monitoring food (Hema et al., 2020) instantaneous grain storage and procurement. To monitor the overall status under the granary, the system makes use of gauges for climate control, moisture, gas, real-time clocks, and burning flame gauges. Sensor data is visualized using the thingSpeak cloud platform. An MQTT-based application control warehouse system is developed for fruits and vegetables storage. Using MQTT and COAP protocol (Deshmukh and Bhalerao, 2017) sensor information can be displayed on a web page and accessed via mobile apps. Compared two techniques, "Evaporative Cooling Chambers" (ECCs) (Verploegen et al., 2018) and "clay pot coolers," and proposed employing non-electric cooling and storage devices as a potential solution to the post-harvest warehouse issues in rural Mali. An IoT-enabled approach is structured that employs sensors to track the condition of agricultural fields and warehouses in real-time. The (Nayak et al., 2022) necessary region is surrounded by a number of sensors that can identify any impending dangers and notify the appropriate people.

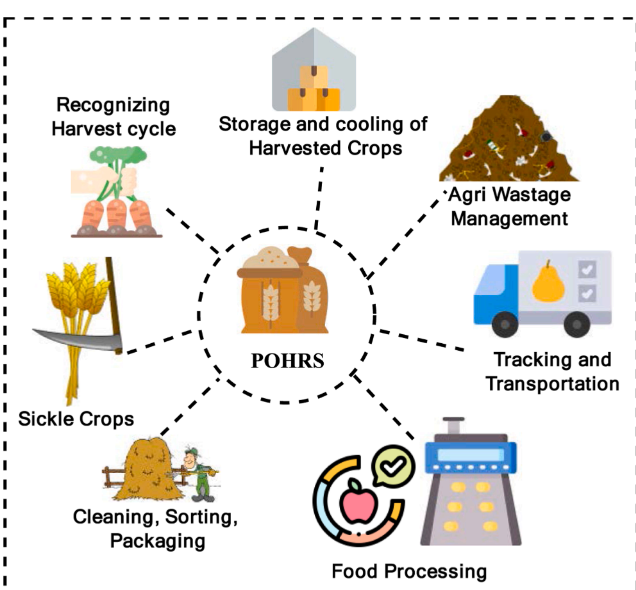

Fig. 7. POHRS subsystem classification.

The infrastructure for safeguarding the harvested crops in the warehouse and monitoring the same in real time through an IoT sensor network performs better than the performance of the entire existing system for developing refrigeration sections through WSN-based clay pots. The system is affordable and accessible to all farmers.

The aforementioned summary of current research has a number of drawbacks based on harvesting, storing, and cooling. There is a dearth of smart alert notifications in the storage system. The current storage system still lacks real-time monitoring of insects and rodents. There is a need for such a sophisticated intelligent-based algorithm that can regulate the warehouse's temperature automatically in accordance with diverse environmental factors and locales. For different fruits and vegetables, storage systems should be based on weight and long-term storage capability, which is still lacking in the current work. On the security and usability of the system at the user end, there is a research gap. To boost the performance of the current system, other sensors can be added, including RFID, sound sensors, and various gas sensors.

4.2. Crop waste management (CWM)

A solution to identify (Chihana et al., 2018) warehouse breaches and track grains using IoT prototypes is suggested. The usage of cloud storage, WSN, and RFID technologies increases accountability and efficiency while reducing theft and administrative mistakes. Using an IR sensor, microcontroller, and Wi-Fi module a smart garbage management (Jayalakshmi et al., 2017) system built on IOT. After garbage levels reach maximum, dustbins are cleaned as soon as possible. A framework is formed for smart (Bong Cassendra P. C. et al., 2018) agriculture based on a smart waste management perspective. The author discusses the various sensor and communication protocols that can be used to track the waste of crops in agriculture.

The current system's main strength is its ability to collect data instantaneously on the amount and type of agricultural waste. These data are examined using cloud computing to determine where crop waste is accumulating and to evaluate the risk of fire, illness, and pest infestation. Satellite images and ground-based sensors can be used to monitor crop waste degradation. Farmers at present have access to information on greenhouse gas emissions and decomposition rates.

According to a study of previous research, smart agro-waste control research is still in its early stages. Low-energy power sensors and sophisticated techniques for managing post-harvest waste are not used. Research is still needed for all forms of crop loss management.

4.3. Transportation and tracking (TTN)

A three-layer perishable generate fog computing model is proposed (Musa and Vidyasankar, 2017) in which the RFID-embedded sensors that generate sensor readings for the monitoring and control layer are among the data producers. A system for the effective distribution and transportation of fresh fruit is developed by utilizing the MQ3 sensor. The (Elavarasi et al., 2019) system's result was that it lessened fruit contamination. When damaged fruit is discovered, an SMS is delivered to the user's mobile device, and through a remote, the system removes the spoiled fruit using a pick-and-place robot. In this article the author go into great (Onwude et al., 2020) detail about how cutting food losses during postharvest cold chain activities might enhance food security. IoT and blockchain were suggested (Pervez and Haq, 2019) as a means of digitally disrupting supply chains and logistics. The supply-chain architecture built on a block chain is designed using a direct acyclic graph data structure. The IoT-based technologies used in the management of the agricultural supply chain in a developing nation like India are discussed. Real-time data sharing (Luthra et al., 2018) uses embedded components including actuators, sensors, and network connectivity. Digital technologies enable the (Dadi et al., 2021) creation of effective agri-food supply networks. "Big data" and IoT are a combination of several technologies that the system uses to evaluate enormous amounts of information quickly. RFID can sense the food environment. The Blockchain-based supply chain management plan (Bhutta and Ahmad, 2021) that places an emphasis on employing IoT devices and Blockchain technology to securely identify, trace, and track agricultural food during transportation. The methods used to anticipate backorders include SVM, KNN, RADF, and AdaBoost. The IoT-based dairy supply chain model is suggested and put into practise. In which (Jachimczyk et al., 2021) the related solution and the domain-oriented knowledge model are well matched for the integration and synergy-enabling processes. RFID is used to capture and share data for production, warehousing, sales, supply, and other processes. Advocated in China by integrating blockchain and RFID in the (Feng Tian, 2016) supply chain. Information is transferred securely and made public via the traceability system by using blockchain.

Real-time monitoring of the climate, humidity, and geolocation guarantees that harvested crops get to their destination in the best feasible conditions, reducing spoiling and improving crop quality. Blockchain technology leveraging RFID-based sensor nodes optimises supply chains for all crops in real-time. It reduces waste and guarantees that crops get there at their intended location in the best feasible condition.

It has been determined from the discussion of the TTN's current system that the secure supply chain technique has to be updated for all agricultural products. Sensor-based technologies, device security and failure, software security, and power management all require improvement. The current infrastructure does not allow for the dynamic scheduling of transportation based on the agricultural products' shelf lives. There are significant research gaps in the areas of cloud platform load balancing, computational cost, and security protocol. Logistical processes based on smart contracts can be added to the system to increase its efficiency and power. There is still a need for an autonomous system that unifies numerous subsystems using IoT with technologies like blockchain and AI.

4.4. Food processing (FDP)

"Big data" analytics, MCLRN, and the IoT are used to build a (Konur et al., 2023) cyber-physical / IoT based food manufacturing system. The intelligent production control system offers intelligent decision assistance. A tools is structured for tracking and (Jagtap et al., 2021) lowering energy and water consumption (FEW), as well as a decision-support system with pertinent hardware and software components, utilizing an IoT four-layer architecture. FEW data are gathered and used in the food manufacturing sector to examine and improve procedures.

The food processing system is more effective when IoT, big data analytics, MCLRN, and cyber-physical systems are incorporated than when they are automated. Additionally, this analysis teaches data professionals new information about how to forecast the baking process for achieving product consistency. Productivity may be raised, and performance and profitability can be raised by analyzing these data.

The current research has been examined for individual agricultural goods. For all agricultural goods, testing can be done based on the ingredients and food processing. It is necessary to integrate seamless IoT devices to improve food processing. The current system lacks a strong security system to safeguard system data.

Based on IoT, AI, MCLRN, and other processes, Fig. 8 presents the average annual growth rate estimation of research publication for POHRS application from 2012 to 2023.

For the TTN and RSCS system implementations, a large number of research articles have been published between 2018 and 2022. The average growth rate for the IoT and blockchain-based TTN system has been measured as 63.23 % between 2018 and 2021, and the average growth rate has been measured for the IoT and AI-based system for storage and cooling at 58.41 % between 2018 and 2021. However, there has been less growth in research publications on the topics of IoT and AI for the other POHRS applications, such as FDP, CWM, sorting, and cooling, between 2012 and 2022. Therefore, there is a need for greater study in that area. Using IoT, AI, MCLRN, and other methodology categories, the average growth rate of research papers for PHRS, DHRS, and POHRS was 41.12 %, 43.23 %, and 36.10 %, respectively, till January 2023.

5. Metaheuristic based algorithm in smart agriculture application

From growing to reaping, an agricultural application (Kiani et al.,

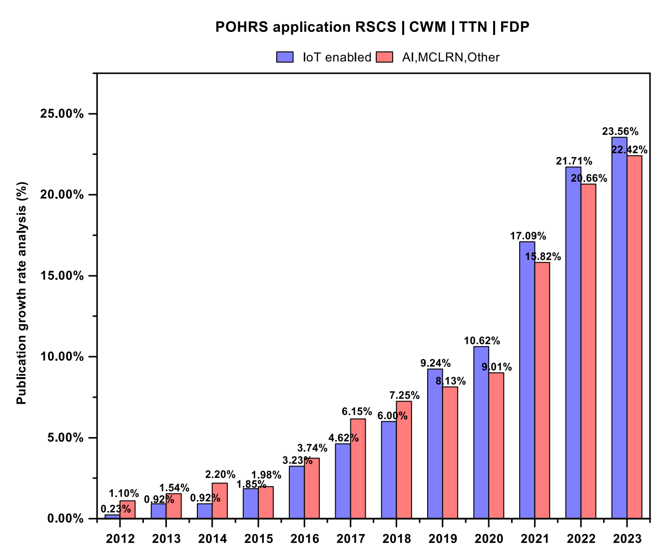

Fig. 8. Publication growth rate analysis of POHRS application based on IoT and AI, MCLRN and other methodology from 2012 to 2023.

2022a) uses a *meta*-heuristic approach. In the first unit, the “Sand Cat Swarm Optimization” (SCSO) based algorithm has been created to delegate the cultivation work to the appropriate autonomous machines, reducing the labor factor. In the second unit, IoT devices keep track of cultivated crops. For crop harvesting in the third unit, an improved “ANT colony optimization” (ACO) algorithm has been created. A 3D strategy approach has been (Kiani et al., 2022b) employed using a couple of Progressive enhancement Grey Wolf Optimisation (I-GWO) and Improved Grey Wolf Optimisation (Ex-GWO) for self-sustaining farm operations to search for a collision-free feasible route in a sufficient period with minimal expenditure in various atmospheric conditions and for multiple barriers. The goal is to tackle the NP-hard problem of successful crop harvesting by identifying the finest and most suitable paths for UAVs. The results indicate an endeavor to avoid any local optima pitfalls and determine the most effective response in an adequate span of duration. The fuzzy logic-based “Non-dominated sorting (Fathollahi-Fard et al., 2023) genetic algorithm” (NSGEA) model has been developed as a metaheuristic optimization strategy where the model incorporates the advantage of multiple factors of apprehension such as harvesters’ effectiveness, waves of crops that become ripe, parameter weather, as well as adjustments in the value of commodities. The framework takes into consideration a wide range of desired results, including profitability optimization, preventing waste, and carbon dioxide emissions reduction, and it is utilized to calculate the optimum amount of day’s labor for farmers and laborers on every block of land.

The usefulness of the currently available SCSO, ACO, I-GWO, Ex-GWO, and NSGEA metaheuristic algorithms put into effect in IoT-based agriculture exceeded other approaches, and the model suggested may be used for different applications in a variety of agricultural areas.

There are still some issues with the optimised performance technique that is currently being used to solve NP-hard issues in the field of smart agriculture. Lack of standardisation for big croplands utilising IoT and IoT of transportation employing a portable robot system to monitor the farming field based on SIR, SCL, CSL, CYP, SGM, SSL, STM, SHMFM, DDAN, PDT, WDT, PCN, CLO, TTN, FDP, and RSCS. While supply chain optimizer for several harvested crops is currently lacking, the used NSGEA algorithms in multiobjective problems can be extended by “Benders decomposition” or “Lagrangian relaxation”.

6. Technologies based on the IoT for smart agriculture

The development of IoT-enabled smart agriculture systems has relied on a variety of technologies in the past. It is possible to use this technology wirelessly or wiredly. It is conceivable to build an infrastructure for intelligent agriculture at a low cost by combining sensors, controllers, and communication technologies. Through the synthesis of IoT, artificial intelligence, edge computing, and cloud computing, IoT-enabled technologies have made advancements in developing smart agriculture systems as well. This section analyses various technologies for developing smart agriculture systems in the different major areas of farming operations on the basis of discussion in sections 2, 3, 4, and 5. The estimation average rate of several technologies utilised to create smart PHRS, DHRS, and POHRS system is depicted in Fig. 9 of the graph. According to the existing survey (Kalyani and Collier, 2021) and proposed survey report, this is the estimated percentage of technologies used in smart agriculture methods.

According to an average percentage analysis of various technologies conducted between 2012 and 2022, the use of IoT and other technologies for the development of smart agriculture would increase by 2028 (Research and Markets, 2023).

Table 1 presents cutting-edge technologies, sensor or devices that can be applied to build smart agriculture using IoT architecture (Chamara et al., 2022) based on PHRS, DHRS, and POHRS. From Table 1 it can be seen that the use of IoT has advanced the field of smart agriculture from 2012 to 2023. The advancement has been done by deploying various IoT devices / sensors (Pyingkodi et al., 2022), wireless communication protocols (Khanh et al., 2022), and UAVs using microelectromechanical system (MEMS) technologies to automate the farming field operations (Boursianis et al., 2022). It is possible to communicate from machine to machine using a variety of communication standards (Orfanos et al., 2023).

The graph in Fig. 10 represent how much data is consumed in GBPS by PHRS, DHRS, and POHRS subsystems. This data bandwidth estimate is evaluated and (Annual Internet, 2023; Virtual Cisco, 2017) measured using prior research. This information is obtained through a variety of IoT sensors and actuators, including cameras, DHT temperature and humidity sensors, air pressure sensors, rain sensors, distance sensors, water flow metres, and others. These sensors and actuators are utilised

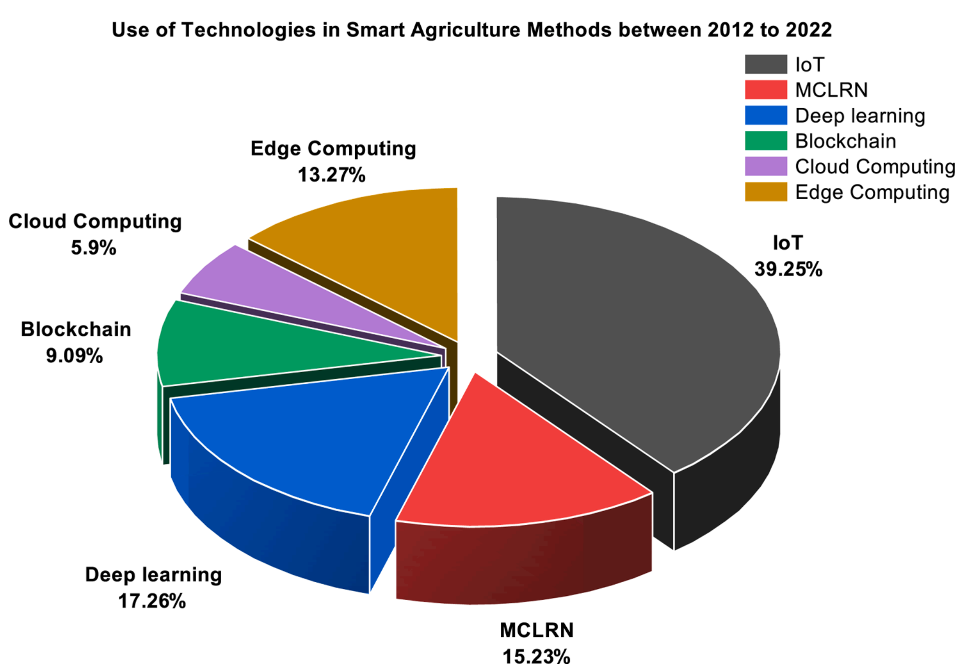

Fig. 9. Growth rate of various technologies used in PHRS, DHRS, POHRS subsystem between 2012 and 2022.

Table 1
Analysis of Technologies used in the smart agriculture between 2012 and –2022.

References and year	Application layer			Processing layer		Network layer	Perception layer
	PHRS	DHRS	POHRS	Technologies	Software / programming's / tools	Connectivity / Protocols	Sensors / Devices
(Jayaram and Marad, 2012)	✓	x	x	Fuzzy Inference Systems, MCLRN	MATLAB	LAN	Intel GPU
(Balezentiene et al., 2013)	✓	x	x	Multimoora Fuzzy, MCLRN	MATLAB	LAN, Ethernet Shield,	Intel GPU
(Ping, 2014)	✓	✓	x	Machine Learning, IoT	Network testing tool	Ethernet, HTTP, TCP, WSN	Arduino Uno, Infrared detector 512X10, Motor, DHT11/22, Water Level Sensor
(Fan et al., 2015; Pérez-Ruiz et al., 2015)	✓	✓	x	Machine learning, IoT, Big data	Python, C++	HTTP, TCP, GPRS WIFI Internet, 3G	AtMega 32, AVR Microcontroller, GSM module, Motor, DHT11/22, Water Level Sensor, GPS, Soil sensor, Light sensor
(Feng Tian, 2016; Sladojevic et al., 2016)	✓	✓	✓	MCLRN, IoT, Deep Learning CNN, Blockchain	TensorFlow, Ethereum	WIFI router, HTTP, TCP	DHT11, Camera, RFID, GPS
(Deshmukh and Bhalerao, 2017; Musa and Vidyasankar, 2017; Thorat et al., 2017)	✓	✓	✓	MCLRN, IoT, Deep Learning CNN, Image processing, Fog computing	Android OS, OrCAD, MikroC PRO, Visual Basics 6.0, Matlab, Apache server, MySQL, Wireshark	WIFI router, USB Wifi dongle, HTTP, TCP, SMTP, MQTT, CoAP, IEEE 802.15.1, Bluetooth Communication, LoRaWAN	Arduino uno, ARM7 LPC2138, Raspberry Pi, DHT11, Camera, RFID, GPS, HC-05 Bluetooth, Solenoid Valve
(Ahmed et al., 2018; Indira et al., 2018; Luthra et al., 2018)	✓	✓	✓	MCLRN, IoT, Cloud Computing, Data Mining, Fog computing, CNN	ContikiMAC, Cooja simulator, Python, C++	MQTT, MAC protocol (IEEE 802.11), IEEE 802.15.4, WIFI Internet, LoRaWAN, 6LoWPAN, SIXFAB module	Arduino uno, Raspberry Pi,, Radio antenna transmitter, Pressure sensor, RFID
(Elavarasi et al., 2019; Islam et al., 2019; Khattab et al., 2019)	✓	✓	✓	Big Data, IoT, MCLRN	ThingSpeak, Python, R	GSM communication, WIFI, ZigBee, WSN, TCP	Arduino uno, Raspberry Pi, Arduino Mega, SIM900 GSM Module, Light sensor, PH sensor, Water pump, Camera, soil sensor, Solar panel (6v, 9 W), MQ3 sensor
(Bhojwani et al., 2020; Chen et al., 2020; Hema et al., 2020; Jamroen et al., 2020)	✓	✓	✓	Supervised and unsupervised MCLRN, Fuzzy logic, YOLOv3 CNN	TensorFlow, ThingSpeak, Python, MATLAB	TCP, MQTT, IEEE 802.15.4, IEEE 802.15.1, Wireless Star Topology, LPWAN, SMTP	Arduino Uno, Raspberry Pi, ESP8266, NRF24Lo1 Module, SX1276 Lora, NPK sensor, BMP180, MQ135, Soil Moisture, Camera, GY-30
(Bhutta and Ahmad, 2021; Ramson et al., 2021)	✓	✓	✓	MCLRN, CNN, IoT, Particle Swarm Optimization, MLP, Blockchain, Edge computing	ThingsSpeak, iOS and Android based OS, MATLAB, WAFW00F	LoRa, WSN, LoRaWAN, NB-IoT	Arduino Uno, Raspberry Pi, GPS, SHMU unit, DHT11/22, RFID, Co2 sensor
(Andreadis et al., 2022; Kasera et al., 2022; Kiani et al., 2022b)	✓	✓	✓	MCLRN, Metaheuristic optimization (Genetic algorithm, ACO, Benders decomposition) Deep learning, Blockchain, GIS, Edge computing	SSL, Ettercap, IP scanner, ThingsSpeak, Blynk, Adafruit, AWS, Ethereum, TensorFlow, Python, MATLAB	MQTT, HTTP, TCP, COAP, IEEE 802.15.1, IEEE 802.15.4, GSM network, WSN, 6LOWPAN, 4G, 5G	Arduino Uno, Raspberry Pi, LORA SX1276x, NRF24L01, GSM module, ZigBee, Moisture sensor, Pi camera, Pi camera, DHT11, RFID

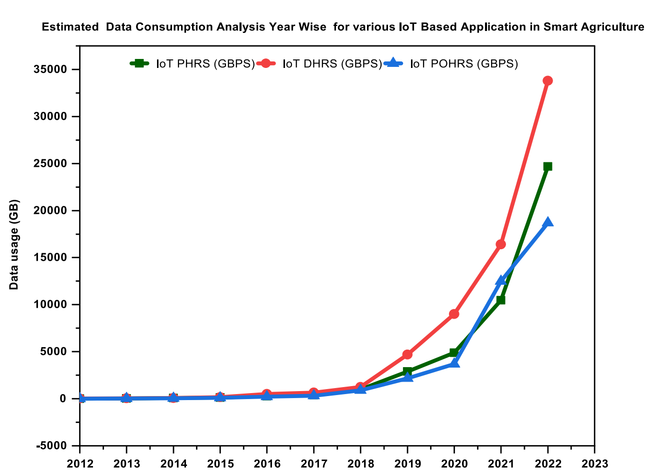

Fig. 10. Data consumption analysis (GB) used by IoT devices year wise for various IoT based subsystems in smart agriculture.

to create smart PHRS, DHRS, and POHRS subsystems. Information for real-time crop management is updated often, like every minute or hour. In the upcoming years, it is anticipated that the average data bandwidth for IoT-based PHRS, DHRS, and POHRS subsystems would keep expanding. The rapid development of sensors and actuators, as well as the rising demand for real-time crop management data, are to blame for this. As technology has developed, the maximum data bandwidth for IoT-based smart agriculture systems has increased year over year. The available data bandwidth for various IoT based PHRS, DHRS and POHRS applications from 2012 to 2022 is shown in the graph Fig. 10.

IoT technologies were still in their infancy between 2012 and 2014, and data storage capacity for applications in the IoT remained quite constrained. Data rates ranging from a few kilobyte per second (Kbps) to a few megabyte per second (Mbps) were accessible via wireless technologies including 2G and 3G cellular networks, which were widely used. The data bandwidth for IoT applications has increased dramatically between 2015 and 2018 thanks to 4G LTE cellular networks technologies. Higher data speeds were offered by 4G networks, which typically oscillated between tens of Mbps to hundreds of Mbps. This made it possible to collect and analyse more data thoroughly while also enabling the transfer of data more quickly. Improvements to 4G networks and the rollout of 5G networks, which promise even more data bandwidth and lower latency, started in 2019 to 2021. Data rates of up to several gigabits per second (Gbps) are available with 5G technology. Even while 5G was not yet widely available, its promise for fast data transfer was becoming more and more clear. The global rollout of 5G networks, which are currently in development, will continue in 2022 and 2023. This will result in enhanced data bandwidth for IoT-based smart agriculture applications. Although the actual data rates that can be achieved in real-world settings depend on network coverage and infrastructure, the data bandwidth needed for IoT-based smart PHRS, DHRS, and POHRS subsystems might vary depending on the implementation and the amount of data being communicated. The overall bandwidth needs will be influenced by elements including the volume of data gathering, the number of sensors placed, and the complexity of the data being conveyed. Communication involves a number of factors, such as the data rate, the frequency bands, the range, the application, and the cost. A systematic analysis of these factors has been conducted in Table 2 to determine which communication standards are to be used in PHRS, DHRS, and POHRS subsystem. As from Table 1 and Table 2, some IoT-based communication technologies can also be considered in the 5G/ 5G beyond smart agriculture system.

7. Dataset collection

Various datasets is collected based on PHRS, DHRS, and POHRS. This dataset can be used to solve a problem in CYP, SSL, SIR, DDAN, PCN, WDT, and CWM operations. Existing public dataset has been reviewed for several farming operations (Lu and Young, 2020) including SSL, DDAN, WDT, CWM, etc., and classified this dataset based on the specific problem that can be solved using the IoT based computer vision algorithm for PHRS, DHRS, and POHRS subsystems. Including some existing external datasets created by various authors can be found in Table 3. This collection includes many plant-leaf diseases that affect fruits, vegetables, and seeds. For instance, tomatoes, brinjal, potatoes, guava, wheat, cotton, apples, oranges, and so forth.

Table 3
Analysis of dataset that can be used for developing smart agriculture based subsystem.

References	Details
(Rauf and Lali, 2021)	This dataset of healthy and unhealthy guava fruits and leaves can be used to solve plant disease-related issues using computer vision techniques. The illness categories in this image dataset are Dot, Canker, Mummification, and Rust. Pakistan is the source of the images.
(**Yogesh** Suryawanshi et al., 2022)	An image collection consists of four vegetables: “Bell Pepper”, “Tomato”, “Chili Pepper”, and “New Mexico Chile”. The five distinct substructure classes in each vegetable collection are Ripe, Old, Dried, and Wounded.
(**Natnael** Tilahun, 2022)	This image collection was gathered from a potato farm in Holeta, Ethiopia to help in the detection of potato leaf disease. The aforementioned collection comprises two distinct varieties of photos. Both “Healthy” and “Late Blight” have 363 and 63 images, respectively. The potato disease issue can be resolved with this dataset.

8. Comprehensive shortcomings of PHRS, DHRS, and POHRS

As discussed above in sections 2, 3, 4 and 5, some shortcomings have been addressed from the existing work on IoT-enabled smart agriculture systems. Individually, these gaps are identified according to the various farming activities. The gaps that are noticeable for PHRS, DHRS, and POHRS are discussed in the Table 4 from which it can be analysed that smart agriculture is a broad research area and the developed existing IoT-enabled system still has shortcomings in terms of standard protocols, inconsistencies in collected data, and inconsistencies of IoT devices (such as there are multiple temperature sensors but their data formats are different and also it is difficult to interface that sensor with multiple subsystem microcontroller because of the varying platform), difficult to integrate existing system to multiple regions because of the

Table 2
Comparative analysis of various communication technologies used in smart agriculture.

Communication Technologies	Frequency Bands	Data Rate	Range (m)	Application (PHRS/ DHRS / POHRS)	Cost	Pros	Cons
ZigBee (short range)	868 MHz – 2.4 GHz	250 kbps	75–100	CSL, STM, SIR, SHMFM, DDAN, WDT, CLO, RSCS, TTN, WPM	Low	Trustworthy and self-repairing.	Limited coverage range and low transmission rate
Wi-Fi	2.4 – 5 GHz	600 Mbps	70 – 250	CSL, DFM, SIR, STM, TTN, SSL, SGM, WPM, CYP, CWM, SHMFM, SDG, DDAN, PDT, PCN, WDT, CLO, RSCS, CWM, FDP	Medium	Accessible and versatile	Electromagnetic (radio) interference can cause installation and security issues.
BLE	2400 MHz	1 Mbps	100	CSL, SIR, STM, TTN, SSL, SGM, WPM, CYP, CWM, SMT	Low	As far as interoperability is concerned, Bluetooth does not face any problems	Several security concerns, hackable
LoRa	I69 MHz, 433 MHz (Asia), 868 MHz (Europe) and 915 MHz (North America)	0.3 – 50 kbps	20,000	CSL, DFM, SIR, STM, TTN, WPM, SHMFM, DDAN, PCN, WDT, CLO, RSCS	Low	By adjusting output data rates/RF output, battery life can be maximized.	The data rate is low, and packets are occasionally not recognized.
SIGFOX	862 – 968 MHz	100—600 bps	15,000	CYP, CSL, SGM, STM, SDG, SIR, SHMFM, PDT, WDT, RSCS, CWM, TTN	Low	A narrowband wireless system can accommodate several channels in the same space compared to a wideband wireless system.	Strong interferences are occurred to surrounding wideband systems by the narrow band spectrum that Sigfox end devices emit, hence the presence of more Sigfox devices will amplify these interferences.
LTE-M	Cellular	1–14 Mbps for 3GPP	11,000	CYP, CSL, STM, SIR, SHMFM, DFM, WPM, DDAN, PDT, CLO, RSCS, CWM, TTN	Low	Utilizing TCP/IP to connect to any server. High data rate	Unsuitable for high-speed data transport.
NB-IoT	450 – 3500 MHz	250 kbps	5000—–15000	TTN, SMT, SIR, WPM, SHMFM, SGM, CSL	Low	There is an encryption feature as well as SIM-based authentication	Neither VoLTE nor Voice Over LTE is supported

Table 4
In depth shortcomings analysis of the existing smart agriculture system based on PHRS, DHRS and POHRS.

Problems Focused	Description
PHRS	
Inconsistency with Standards	Security protocols, device compatibility, and firmware still need to be standardized for IoT-based CSL, YPR, STM, SSL, SGM, DFM, WPM, and SDG systems. Compared to other methods and outcomes, the existing systems are difficult to compare. Standardized procedures and frameworks are necessary for assessing and comparing different methods.
Limited Data analysis	IoT is dependent on the volume of data. Most of the time that information is not easily accessible because of non-availability of open source data. More trustworthy sensor data and adequate data-gathering techniques are required because still depended on external source data. Data should be location-wise, all types of data, and should be validated with real-time and existing data. There is need for advanced data analytics techniques to make sense of these vast generated data.
Inadequate scalability	For IoT-based CSL, YPR, STM, DFM, and WPM applications, there are many active research projects; nevertheless, there is still work to be done to scale this system for commercial applications. SGM, SSL and SD-based IoT-based systems require more research. This system are not fully automated.
Inadequate knowledge	Performing experiments on the crop relies on understanding of the crop physiology as well as a range of environmental factors, which is yet not fully understood. More study is needed on the physiological processes of various crops, as well as the effects of environmental conditions on crop growth and development.
Inability to integrate with current agricultural systems	To make the fully IoT-based pre-harvesting method more effective, the system can be incorporated with the existing agricultural systems such as smart crop recommendation system based on weather, location, seed selection and soil nutrients analysis, smart soil digging, etc. There is a lack of research in this area of integration. The study has to be performed to discover the potential benefits and drawbacks of the integration.
Limited Accuracy	Currently, most IoT devices lead to erroneous and inconsistent data, as they have limitations in terms of accuracy, reliability, and precision. In addition, sensor calibration is also important despite being complex and time-consuming and can result in inconsistent results if not done. Also, these devices have to place optimally to ensure correct data collection, which can be further used for analysis. The study has to be performed to make a system accurate and reliable.
Cost Effective	IoT-based systems can be expensive to install and maintain and thus can be a barrier while adopting the technique, especially for small-scale farmers. Although the cost of devices has decreased in recent years, the overall integration can still lead to a higher cost. Research has to be focused to investigate cost-effective solutions.
Use of MCLRN approaches	The present work has used MCLRN techniques in IoT-based systems, however due to the overfitting issue, the trained MCLRN model still cannot make an accurate forecast.
DHRS	
Multi-technology incorporating	IoT makes it possible for the system to apply a variety of technologies during the harvesting process. These technologies can be combined to create a system, but research is needed to determine the best way to do so. According to the study of the current work, several systems have not been fully incorporated. Such as SIR with SHMFM, PCN, PDT, WDT, CLO etc.
System for Enhancing Irrigation	Research must be conducted to point out the efficient way to irrigate the plants as compared to the traditional methods of irrigation. Such as irrigation system should be managed automatically on behalf of different of types crops.
Acquiring and adopting users	Existing IoT-based DHRS systems are still mishandled and challenging to adopt in various environments. Research must be performed to make a system that can be easily handled and adopted by end users in different environments.
Soil health	The DHRS process includes IoT enabled system for crop monitoring and SHMFM. Research must be performed to examine how SIR affects soil systems, microbial residents, and nutrient process for various crops.
Environment's impact	Still, research is to be investigated based on environmental factors such as calibration of temperature, humidity, and rainfall during SHMFM and DDAN.
Privacy and Security	As far as the security of IoT-based DHR systems is concerned, very little research has been conducted.
Detecting the diseases accurately	Although IoT-based systems can provide real-time plant health data, there are still limitations to how precise the data is. Various factors affect accuracy and research must be done to monitor those factors, which can impact accuracy.
Efficient Energy	Continuous data collection is difficult in remote regions. A cost-effective, self-sustaining, and optimised technique should be implemented in the current IoT-based systems for PDT, DDAN, SHMFM, and WDT so that field monitoring data can be gathered continually.
Analysing pest behaviour	The system to detect pests accurately still needs improvement. As various pests respond differently in different environments.
Optimization of Object Detection algorithms	Need more research in the areas of IoT-enabled systems for WDT, PDT, CLO, and PCN to provide optimized solutions for accurate results. So system performance can be increased.
POHRS	
Security and Privacy	While most harvesting data must be stored properly and securely. Various IoT-based systems can be implemented to monitor and store the data. In this era of cyber threats, the system must be made in such a way to make the data properly stored, thus making it secure.
Innovative solutions with a low cost	Developing IoT enables cost-effective solutions in post-harvest activities is challenging based on security and privacy. As in POHRS, there are still some shortcomings in the existing system, which needed to be addressed. Such as in RSCS, SWM, and TTN there is still lacking data security, data storage, and low-cost automated system of fruits and vegetables monitoring. Research must be done to deeply understand such a situation and make a cost-efficient system so that it can be used by small-scale farmers also.
Miniature studies	In POHRS most of the ongoing work is focused on TTN, RSCS, and CWM but missing this existing system on a large scale for post-harvest phases. In the current automated RSCS system, the sorting technique management can be improved by including scheduling and weightage systems for post-harvest storage of crops during the TTN process, because Indian farmers have fewer low-cost smart facilities. Research can be done to investigate the effectiveness of the IoT system on a large scale as well.
Incorporating multiple methods	IoT system integrates different components which are somehow correlated to each other. Research should be carried out to determine how those components must be integrated as a

(*continued on next page*)

Table 4 (*continued*)

PHRS	
Problems Focused	Description
	distributed system that develops a self-sustainable and cost-efficient system.
Availability and Reliability	The IoT-based system should be readily available for the end users. Research should be done regarding the improvements in the availability of the data during TTN as well as while RSCS, utilizing real-time monitoring.

environmental factor, cost, lack of technologies enhancement of the system and endorsement with real-time information with external source information. As from sections, **2**, **3**, **4** and **5** it can be extrapolated that more examination needs to be performed to accomplish IoT-based solutions for the SSL, SGM, SDG, PDT, affected crop sorting, CWM, and FDP. Research can be conducted on different crop types location-wise. IoT data security is a significant uncertainty, so there is a need for scalable WSN or robust mechanisms to protect data.

9. Proposed architecture for smart agriculture

From PHRS to POHRS, a number of existing smart methodologies have been established for all different types of farming tasks, and they are all covered above along with their benefits as well as their drawbacks. By using the proposed architecture the limitations of the present structures can be reduced in light of the discussion above. A compact sensor network is made possible. Thanks to the integration of IoT, MCLRN, metaheuristic optimisation algorithm, AI, edge computing, cloud computing, SDN, cryptography for data security, UAVs, etc. Using 5G (gNB architecture) and 5G beyond networks (Abdulghaffar et al., 2021), the recommended IoT-facilitated smart farming architecture is designed on the basis of IoT layered architecture in the Fig. 11. The sensor layer consists of different types of sensors, and data transmitters ("sx1276", "nrf24l01", etc.), cameras, high-frequency navigation (GPS), etc. It acts to collect and transmit facts it to the central server utilizing a 5G network connectivity via an edge gateway for data processing and analytics. The central server gives the farmers useful information using miscellaneous algorithms and standard procedures. These details may be on the choice of crop, seed germination, irrigation, soil analysis, and status, livestock status, crop diseases detection, crop sorting and storage, tracking, etc. The collected data are about the PHRS subsystem, DHRS subsystem, and POHRS subsystem. These subsystems are interconnected to each other to make the overall agriculture system automated. So that farmers can optimize their farming procedures and enhance crop yields. Under this system, the automated actuators can be used to enable farmers to remotely control some of the devices such as irrigation motors, pest control, soil digging, etc. Layer by layer, smart agriculture can be developed as follows:

9.1. Perception layer

In this layer, multiple sensor networks can be created by deploying various sensor nodes for the PHRS subsystem, DHRS subsystem, and POHRS subsystem. This subsystem is communicated to each other as

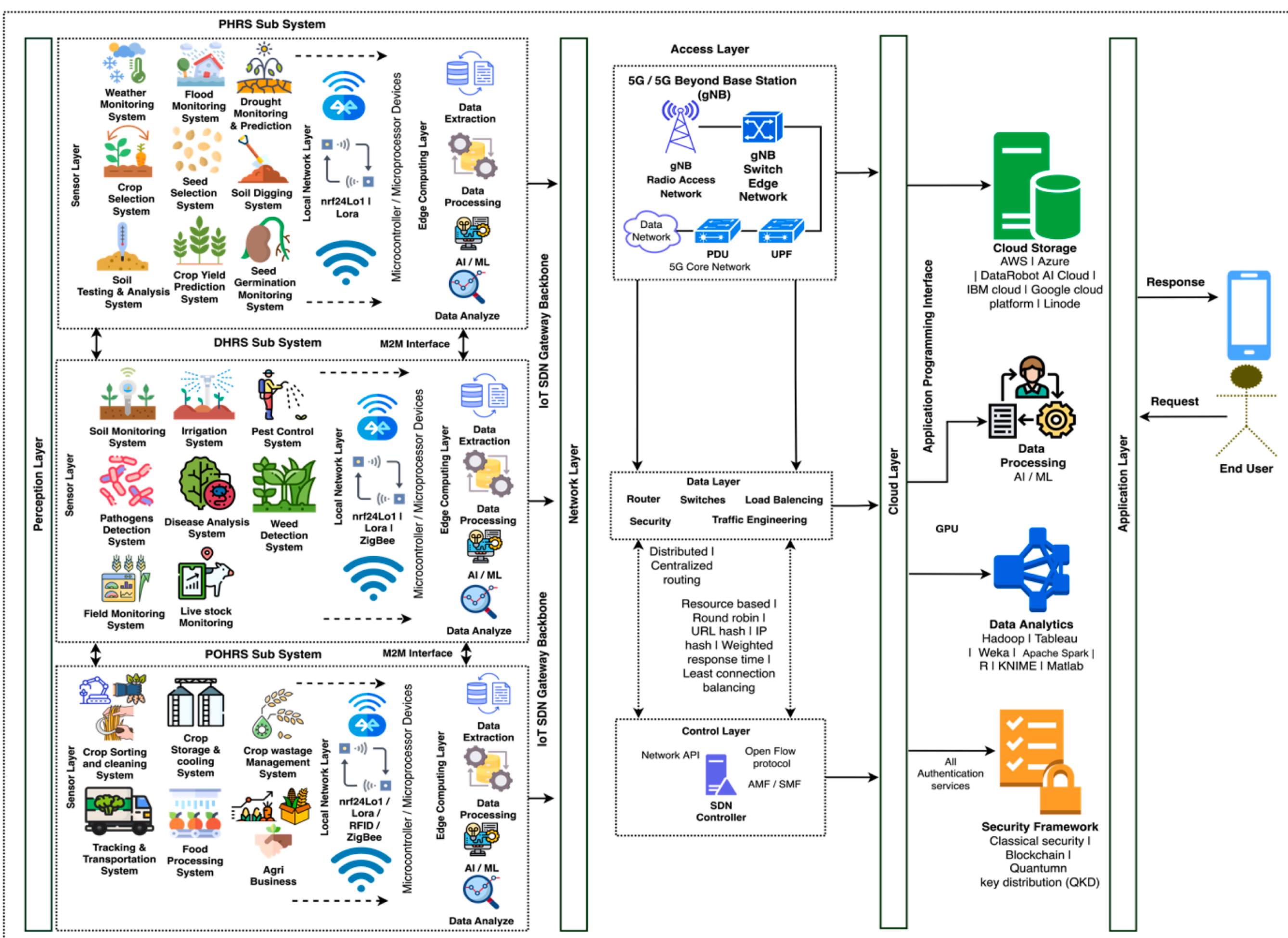

Fig. 11. Proposed 5G based Smart Agriculture Framework.

machine-to-machine communication (Sakthivel and Vidhya, 2021) and connected to an each 5GIoT base edge gateway. The PHRS subsystem retrieves the data of various environmental factors, including water in the soil, fertiliser, temperature, and humidity, sunlight, flood and drought-related, etc, and transmits this data to the local IoT edge gateway for further computation and analysis. The DHRS subsystem consists of the sensor data of irrigation, NPK, pest controlling, weed detection, disease prediction, livestock, insects sound, crop field, etc. This data is also transmitted to a local IoT edge gateway and the same as POHRS sensor network data will be collected and transmitted to its IoT local edge gateway for further computing and analysis. This all sub-systems are the backbone of the IoT sensor network.

9.2. Network layer

The entire IoT AGRI subsystem is designed based on the 5G network, but it can enable 5G beyond the network as needed. Essentially, a 5G core network is a high-level network that is made up of a radio access network and one or more edge networks. The 5G base stations are connected to open flow switches which are known as gNB switches (edge network). For traffic offloading and "quality of service (QoS)" implementation, SDN controllers can interface with base stations using the open flow protocol. The "protocol data unit (PDU) session" or "user plane function (UPF)" is used in the core network to connect the data network (DN). The SDN controller controls all gNB, UPF, and data plane switches. This layer is responsible for all transmissions and communications between sensors, IoT gateways, and cloud servers.

9.3. Cloud layer

The network layer's via SDN controller would transport the sensor data acquired from the perception layer to the cloud layer platform, where analytics would be carried out utilising tools like AI, MCLRN, Weka, and Hadoop, among others. Cloud platforms include "AWS", "Azure", "IBM Cloud", etc. To handle and analyse the data gathered from the sensors, this cloud service offers storage and computational capabilities. The designed API gateway is used to manage communication between the edge gateway and the cloud server while utilising all authentication services.

9.4. Application layer

The insights produced by the cloud server will be available to the end user through mobile applications, web applications, etc., including farmers, stack holders, suppliers, ranchers, purchasers, etc. So that farmers may make informed judgements, this programme gives them real-time information regarding the PHRS, DHRS, and POHRS.

9.5. Data storage and processing layer

Depending on the particular applications and the volume of data collected, the data storage needs for IoT-based PHRS, DHRS, and POHRS subsystems can change. Numerous services, including data source, data processing, decision support, transmission system, authorization, storage space, and reliability, are offered in the data storage and processing layer. The digital footprint of the data collection and storing for the IoT-based PHRS, DHRS, and POHRS subsystems in smart agriculture is shown in Fig. 12.

Data gathering: Obtaining information from numerous agricultural fields (F) using a variety of sensors, including those that measure things like temperature, humidity, soil moisture, soil ph, soil NPK, air pressure, RFID, rodents, insects, and other animals, as well as things like plant color recognition, rainfall, disease detection, and recognization through cameras, storage and cooling control of harvested vegetables or fruits, transportation and tracking, water flow measurement, level, and pump control. This sensor and actuator data is sent to the server for analysis and decision-making for the farm fields, or real-time monitoring. Depending on the sensor type and frequency, a single sensor node may generate data on average in the range of KB to a megabyte (MB) each day. The expected data storage, for instance, can range from GB to terabytes (TB) per year if there is a vast farming area with numerous sensors. In addition, image and video data are gathered from drones to monitor crop health, pest detection, weed detection, and crop yield. This data contains high-definition images of farms in 5 to 100 MB sizes. It is possible to estimate total storage capacity by estimating the frequency of capturing such imaginary data. The sensor data for CYP, CSL, SGM, STM,

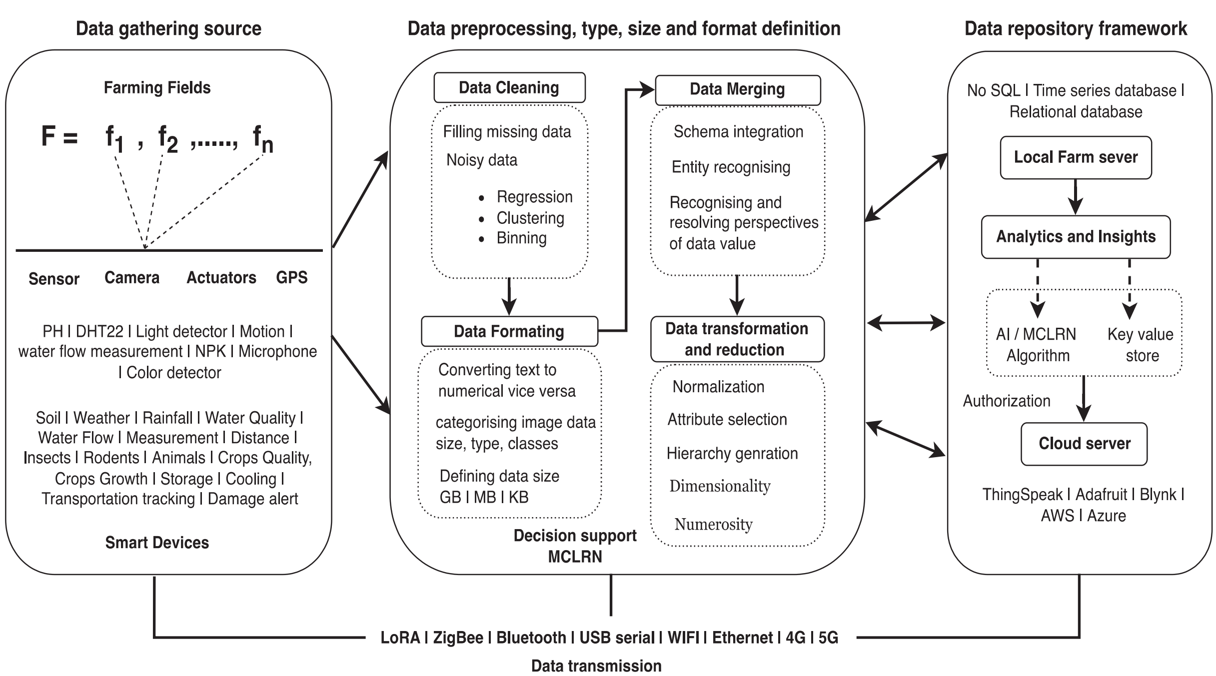

Fig. 12. Data processing and storage footprint.

SDG, SIR, RSCS, CWM, DDAN, PDT, CLO, WDT, SHMFM TTN, and FDP systems as well as scheduling irrigation, measuring insect control effectiveness, managing livestock, keeping track of crop yields, and managing agribusiness depend on the overall dimension of the farm, the variety of crops grown there, and the amount of detail that can be gathered. For each crop every year, this data size can be in the KB to MB range. However, WPM generates climate-related data that can be recorded for historical research and transmitted in KB each hour or day.

Data pre-processing: In the pre-processing, the gathered data are prepared for further analysis. Which is used to fill in the missing data, remove the redundant data, format the data into its size, type, and classes, and normalize the data to make data more reliable and knowledgeable.

Data repository: The local storage server, which may be a NoSql, time-series, or relational database, stores all pre-process data. It is quite difficult to make the data more trustworthy and long-lasting because the database storage can come from a variety of sources of different types and sizes. The data is cleaned using a variety of pre-processing techniques throughout the pre-process. There are different, specialised cleaning techniques for text and picture data, such as stemming and lemmatization, as well as image geometric conversions, image filtering, segmentation, Fourier transform, and image restoration, among others. Data from both the past and the present is kept in the storage repository. In the edge computing layer, data transmission management is carried out between this data processing layer. The interval between acquisition and utilisation might vary extensively, ranging from a couple of seconds, minutes, or hours to a few weeks, or possibly a full year in extreme circumstances. Therefore, several transmission techniques can be used for quick and secure long-distance transmission via wired or wireless means. High-speed data connection, such as a 5G communication network, is also necessary. Various data flow control techniques, including stop and wait, feedback control, sliding windows, two-directional communications, etc., will be used to manage the data communication traffic between these two communications. Throughout all of these steps, data analyses are carried out utilising different MCLRN and AI algorithms to send actions and notifications to the user's cloud server. A suggested approach for smart farming system data footprint is developed based on smart PHRS, DHRS, and POHRS existing work deficiencies using a 5G data communication network. For the storage of this PHRS, DHRS, and POHRS application, the maximum average data volume analysis is shown as a graph in Fig. 13. The regular data volume analysis is estimated in Fig. 13 as a graph based on the communication

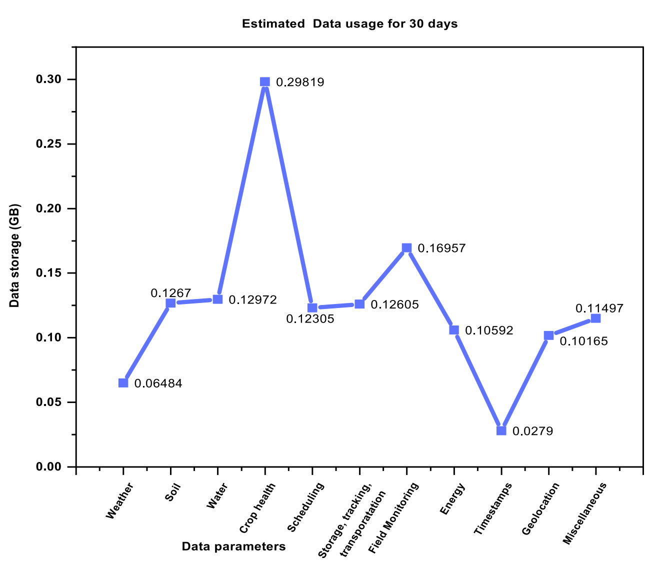

Fig. 13. Estimated digital footprint for one month of proposed PHRS,DHRS and POHRS Systems.

technologies range, periodicity of the sensor devices, camera resolution, data bandwidth, etc. Using different types of agricultural activity properties, this average data volume utilisation analysis over the past 30 days has been calculated. The analysis of the 30-day total average data volume was calculated at 1.38856 GB. Depending on the particular PHRS, DHRS, and POHRS application, the data transfer frequency changes.

For instance, a system used to track soil temperature and nutrient content might release information once each hour or day. Meanwhile, a different system will deliver data every minute for crop growth assessment. As more smart sensors are deployed and technology is developed, the amount of data conveyed for different crops in soil and crop growth monitoring will expand in the future. Aspects that can increase the volume of data include the number of sensors used, the type of data (image, text, or numerical), frequency, distance, time, cost of data transmission, size of the farmed area, crop type, climate, irrigation method, soil type, disease type, etc.

10. Comparative analysis of existing smart agriculture system with proposed 5G based architecture

For the recommendation of a 5G-based smart agriculture framework, some of the existing available research surveys have already (Liu et al., 2023) been carried out, in which the major technologies and technological barriers preventing the advancement and development of smart agriculture applications leveraging 5G technologies are described. The resultant effect of 5G on the IoT for smart agriculture is outlined. An exploration of precision agricultural (Majumdar et al., 2023) applications has been explored using green IoT-based solutions, utilizing UAVs, LPWANs, and 5G networks as well as an assortment of technical issues. Utilizing 5G networks and beyond, the long-lasting expansion of digital farming through the incorporation of green IoT technology enables the IoT greener. The proposed architecture above has been recommended by incorporating each multiple-edge gateway grid with the central controller for all small and large farming area data based on the existing 5G-based smart agriculture architecture. The advantages of using this agriculture system over existing IoT-based agriculture systems include the immediately apparent advancement across multiple agriculture applications, centralised archives of data, estimation process power, etc. Existing smart agriculture exhibits challenging obstacles and demands to handle high volume data storing processes, computation power, and managing various agriculture applications of small and large farming areas. Therefore, in this instance, data computation, interpreting, and other capabilities can be offered close to the network's edge, where initially the data are originated. Edge computing power has benefits such as decreased latency, bandwidth savings, reduced downtime, increased trustworthiness, improved privacy and security, etc. The proposed IoT-based architecture allows for the best provisioning of resources using SDN, network segmentation, route optimisation, load balancing, and other practises. A evaluation of current smart farm systems with the proposed IoT architecture is shown in Table 5 below based on the various parameter. Some of the characteristics are identical in the proposed 5G-based smart agriculture architecture and the existing smart agriculture architecture. The comparison has been verified based on this characteristic.

As a result of the discussion in Table 5 above, it can be concluded that creating the proposed 5G based smart agriculture system using edge computing could effortlessly extend to meet the increasing necessities of modern farming. The entire structure can be customized by how the agricultural operation grows and network changes or whether its operations require more sensors and devices. The below Table 6 discusses the proposed literature survey information with existing surveys information.

According to Table 6, the proposed review fills the gap in existing reviews for IoT-based smart agriculture by classifying pre- and post-harvest activities into PHRS, DHRS, and POHRS subsystems. Based on

Table 5
Advantages of the proposed 5G based smart agriculture system with existing smart agriculture system.

Comparative parameter	(Udutalapally et al., 2021)	(Liu et al., 2023)	Proposed 5G based IoT agriculture architecture system
Bandwidth	Low Bandwidth	Fast bandwidth with single edge network	Fast bandwidth with single and multiple edge network with LPWAN communication
Latency	High latency rate and risk of data loss during cloud transmission.	Delay time will be increased for large farming area.	Delay time is reduced as of using multiple edge gateway.
Interruption	Interruption rate are high	Interruption rate can be high if switching to 5G beyond network or multiple edge network.	Interruption are reduced because authenticated edge connection for small and large farming field WSN and can be customized based on the network.
Data storage	Limited storage capacity and complicated database management because of limited globalization.	High storage capacity at the cloud end, as the architecture is for small farming area.	Capable of managing databases at the edge network and storage capacity will be maximum as using distributed system.
Energy efficient	Requires a lot of energy for calculation and processing while transmitting various types of data at long distances.	More energy required as system is not fully distributed.	Less energy consumption as system is distributed. Minimises the necessity for transmission of data over long distances.
Real time decision	Real-time decision-making can be accomplished although has a larger latency, which restricts its effectiveness for circumstances where timeliness is essential.	Real time decision possible but lack in independency at each edge network.	Increase productivity and yield by enabling real-time decision-making with exposure to the constantly changing conditions on the farm.
PHRS Subsystems	Integration of PHRS sub systems is possible with other farming sub system but need much enhancement, as limited range of network connections and no such algorithm for intelligent decision making at the edge level.	Since PHRS module data differ from farm to farm, there are chances of data overload at the edge network level because there are no such discussions on NP-hard problem optimization strategies.	Using of metaheuristic-based algorithms it is possible to increase the efficiency of PHRS, sub-systems in 5G-based or beyond networks.
DHRS Subsystems	Integration of DHRS sub-systems is limited as it provides a huge volume of image and video-type data.	Integration of the DHRS subsystem is achievable as discussed about the UAVs-based system for various image vision problems.	Integration of DHRS with PHRS subsystem is achievable using NB-IoT M2M communication.
POHRS Subsystems	Integration of POHRS subsystem is limited.	POHRS subsystem integration for supply chain management.	Management of POHRS subsystems for TTN, FDP, cooling, harvesting, and farmers' inventory. The system becomes more efficient and capable with the help of 5G, SDN, and distributed edge computing structures and is able to oversee massive amounts of network traffic and data authentication.
Security and privacy	Device security, data authentication, network slicing, and encryption still need to be improved.	There is no analogous method discussed for recognising security ambiguity while deploying IoT devices for securing inconsistent energy-efficient communication devices for considerable distance and durability.	

Table 6
Comparative analysis of proposed survey from existing survey.

References	Classification of farming operations from pre- to post-harvest	IoT based hybrid methodology for PHRS DHR, POHRS subsystem	Recommendation based on existing system shortcomings	Use 5G / 5G beyond
(Tao et al., 2021)	Existing survey discussed the plant management, Agri supply management, and challenges in IoT technology that can be used year-wise.	x	Recommendation about devices, data and platform not fully expressed in terms of security, self-sustainable, and cost	x
(Da Silveira et al., 2021)	A systematic review based on the research question and use of agriculture 4.0 development	x	x	Systematic review on the basis of research question with 5G technology
(Xu et al., 2022)	x	Discussed about IoT technology in agriculture for plant monitoring	Details about the problem with its Prospection.	x
(Van Hilten and Wolfert, 2022)	x	Focused on drone technology	Recommendation on the basis of aggregation, management cycle, and decision making level.	5G
Proposed Survey	✓	✓	✓	✓

this categorization, various existing work has been discussed in detail with an analysis of the IoT communication technologies and meta-heuristic approach used in the IoT based smart agriculture system. As a result of the discussion of the problem in existing work, the 5G and 5G beyond smart agriculture system architecture are being prepared. With this recommended framework, the shortcomings of the existing work can be reduced, and the system can be optimized.

11. Conclusion

IoT-based smart agriculture is the advancement of the digital transformation of various traditional farming subactivities. In this a comprehensive review by categorizing the farming subactivities based on the Pre, During, and Post harvests of the smart agriculture-based existing application has been discussed in detail. We have also observed the research gaps for each and every activity separately. Based on these research gaps it has been analyzed that developing an intelligent farming system is still a challenging process. We have tried to address these challenges and enhance the performance of the existing systems by proposing a 5G-based hybrid framework for smart agriculture. The outcome of the proposed survey is validated by comparison with the existing survey papers. It is found that various existing surveys have not been represented considering the smart agriculture applications according to the Pre, During, and Post harvesting phases. Therefore, our survey methodology and outcome seem to outperform the other surveys conducted so far for smart agriculture. In future work the technology wise survey for the different aspects of smart agriculture may be conducted. For example, we can have a comprehensive survey on the use of Machine learning algorithms for each activity of smart agriculture. Also crop wise comprehensive survey can be conducted involving all the pre, during and post-harvest activities.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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