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Implementation of Artificial Intelligence, Machine Learning, and Internet of Things (IoT) in revolutionizing Agriculture: A review on recent trends and challenges

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Abstract: Artificial Intelligence (AI) can revolutionize agriculture which impacts a country's economy, employing more than 30% of the world's population directly or indirectly. It can fulfill the needs of an ever-growing world's population through automation. Traditional farmland practices like weeding, pesticide spraying, irrigation, monitoring soil nutritional and moisture status, etc. can be performed quicker using robots, sensors, drones, and algorithms. It reduces water wastage and pesticide overuse, maintains soil fertility, helps in reducing labor and enhances crop yield and productivity despite world problems. However, its penetration into agriculture is still in its infancy due to its uneconomical nature, lack of expertise and big data requirement for accuracy among others. This paper delves deeper into the various applications and impacts of AI in agriculture, new tools being used, challenges and future scope related to this field. Combined with Artificial Neural Network (ANN) models and Machine Learning (ML), along with Expert systems (ES) and Internet of Things (IoT), AI can do wonders in agriculture in the subsequent years to come.

Introduction

By 2050, world population is predicted to reach almost 10 billion, and boosting agricultural by 50% is imperative to feed the growing population (The State of Food and Agriculture, 2017). Presently, nearly 38% of total land surface is utilized in farming. Agriculture is important in employment generation and rural development as it contributes significantly to economic prosperity of most nations. In countries, such as India, where agricultural sector consists of a major part of GDP (about 18%), the agricultural augmentation has caused significant per-capita rural income rise in India and employs more than half of country's workforce. Being a sensitive sector in economy on which other sectors are dependent on, it is imperative to automate agriculture. This will boost rural development and subsequently lead to rural transformation and structural transformation (Mogili and Deepak, 2018; Shah et al., 2019).

The term "Artificial Intelligence" was first coined in 1956 by John McCarthy (Ekmekci and Arda, 2020). Artificial Intelligence (AI) is a key area of computer science research due to its fast technological advancement and its applicability. AI has penetrated in different areas of therapeutics, agriculture, education, commerce, industry, and security. AI is extremely necessary is agriculture to achieve automation. Agriculture requires a lot of labor, perseverance, persistence on the part of the farmers. Low income, unpredictable weather changes or resource scarcity incur heavy financial losses on farmers, which has been a

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prime reason for farmer suicides (Pawar, 2020). The main reason for farmer suicides is lack of a secondary occupation due to time-consuming and energy-draining traditional agriculture. AI can solve these problems by reducing time consumption, hard work, better yield, and productivity, resulting in better lifestyle for farmers and hopefully decrease farmer suicide rates.

The application of AI is enhanced by technological advances in Machine Learning (ML), Machine Vision, Deep Learning (DL), Neural Networks (NN), and Internet of Things (IoT). Technology has become complementary with agriculture in today's world by the virtue of progress in development like robots, temperature and moisture sensors, drones, devices, machines, GPS development and information advancement. This has made agriculture continuously profitable, secure and environment friendly. Remote sensing, satellites, and Unmanned Aerial Vehicles (UAVs) can collect data all day over an entire field to screen soil condition, plant prosperity, temperature, etc. (Gupta, 2019; Faggella, 2020). AI makes the process of problem-solving simpler using many newly discovered logics and methods like Artificial Neural Networks (ANN)- most widely used for research purposes, Fuzzy Logic (FL), Neuro-Fuzzy Logic and Expert Systems (ES).

ANN is a processing algorithm involving computations and mathematics, which simulates neurons in the human brain to learn, think, take decisions, and solve problems (Shah et al., 2020; Shah et al., 2020). ANN is a task-based operating method based on inbuilt task and not a usual computationally programmed task. It can capture intricate details and provide the best-fit solution for a problem using ANN. Different algorithms which are used according to its application for training are Silva and Almeida's algorithm, Rprop, Quickprop, The Dynamic Adaption, Delta-bar-delta algorithm and so on. Nine neurons are used in the process. Embedded systems act as a hardware-software interface, having hardware-built memory-chip systems with programmed software in it for implementing algorithms and logic-based concepts (Ognjanovski, 2019). The ANN architecture has three layers such as Input layer, Hidden layer and Output layer (Figure 1).

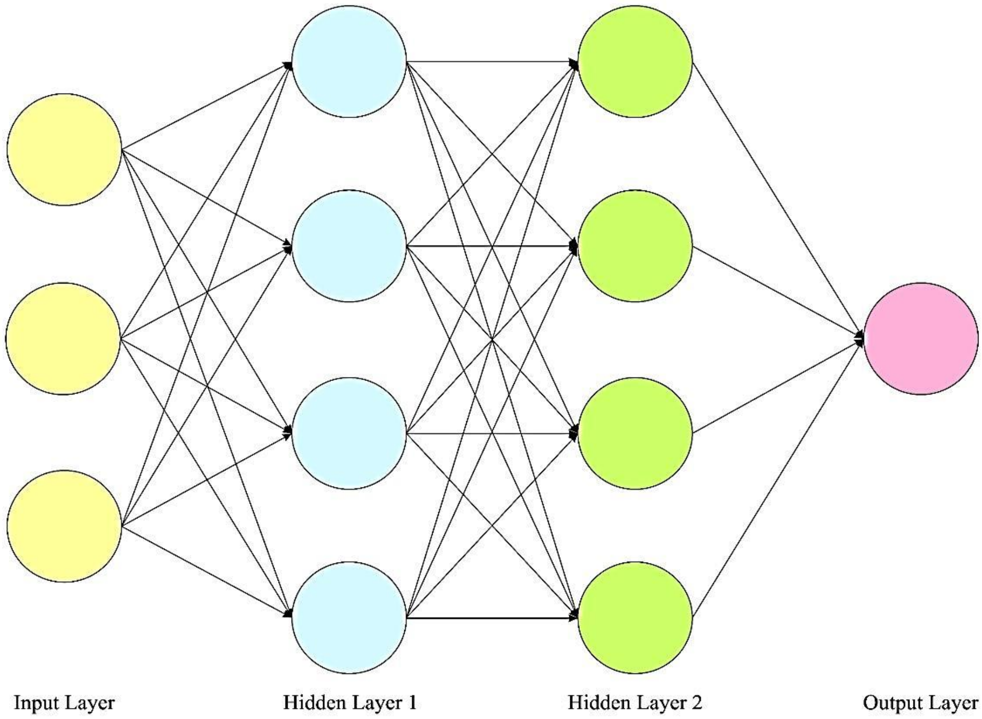

Figure 1. Diagrammatic representation of Artificial Neural Network

Agricultural IoT can be termed as a network in which biological components, environmental elements, and other virtual objects related to agricultural systems, are connected via internet to exchange data, and help in communication. It is useful in intelligent agricultural detection, tracking, and management. The system of agricultural IoT can also help in recognition, management, and controlling of several processes, elements, and systems related to agriculture dynamically. It also greatly enhances our understanding of agricultural plants, helps with controlling sophisticated agricultural systems, also enabling assistance in handling emergencies (Xu et al., 2022).

Table 1. Different AI techniques used for soil management

Techniques	Features
IBM's AgroPad ("AI on the edge")	It can test 5 indicators of soil using a colorimetric test. A 'microfluidic chip' performs chemical analysis. Instant test result is shown in mobile app using Machine Vision (IBM, 2018; Peskett, 2022).
Management-Oriented Modeling (MOM)	It uses a strategic search method called "hill climbing" / "best-first" and reduces only nitrate leaching as well as increases production though it is time-consuming (Li and Yost, 2000) (Figure 2).
FL: Soil Risk Characterization-Decision Support System (SRC-DSS)	It can do soil risk classification by knowledge acquirement, conceptual design, and system implementation (Lopez et al., 2008). DSS is also employed in reducing erosion, integrating Geographic Information Systems (GIS), Distributed modeling, and ES technologies. Although big data and more study are required to confirm its efficacy (Montas and madramootoo, 1992).
Different ANN models	Bare soil texture can be classified using ANNs operating on RS data (Zhai et al., 2006). Prediction of soil contents of sand, silt, and clay, for texture, by analyzing existing attributes of hydrographic parameters and coarse resolution soil maps obtained from a Digital Elevation Model (DEM) is also possible (Zhao et al., 2009). Soil moisture dynamics can be analyzed using Higher-Order Neural Network (HONN)-embedded Remote Sensing (RS) device (Elshorbagy and Parasuraman, 2008). Prediction of soil enzyme activity and classification of soil structure by attaching Digital Terrain Model (DTM) with ANN can be done (Tajik et al., 2012). Monthly mean soil temperature, texture and soil nutrient estimation after erosion can also be analyzed. But no solutions to improve soil texture/ performance are provided. It is also dependent on unpredictable weather predictions and limited to few soil enzymes. It considers only temperature for finding soil performance. For ANN model big data is required. It can estimate only NH_4 in soil (BiLgiLi, 2011; Levine et al., 1996; Kim and Gilley, 2008).
Fuzzy Inference System (FIS)	It determines optimum nitrogen levels for corn using field and crop features and recommends nitrogen fertilizer applications (Tremblay et al., 2010; Bhattacharya et al., 2021).
Support Vector Machine (SVM)	Soil's mean weight diameter is usually predicted using SVM (Bhattacharya et al., 2021).
Plantix	It is developed by Rob and Simone Strey. It identifies diseases, pests, nutrient deficiencies, and helps in countering crop damages and reduces unnecessary pesticide usage (Plantix).
Land suitability analysis	Farmers' Knowledge (FK) and scientific knowledge-based generation of fuzzy sets for land suitability classification using GIS is usually done. S-membership functions are used to evaluate texture, slope, and color of soil (Sicat et al., 2005). Land use land cover (LULC) change, weather, geography, soil, and infrastructure facilities are the criteria used along with Multi-Criteria Evaluation (MCE)-based pairwise comparison matrix for maize crop cultivation (Moisa et al., 2022).

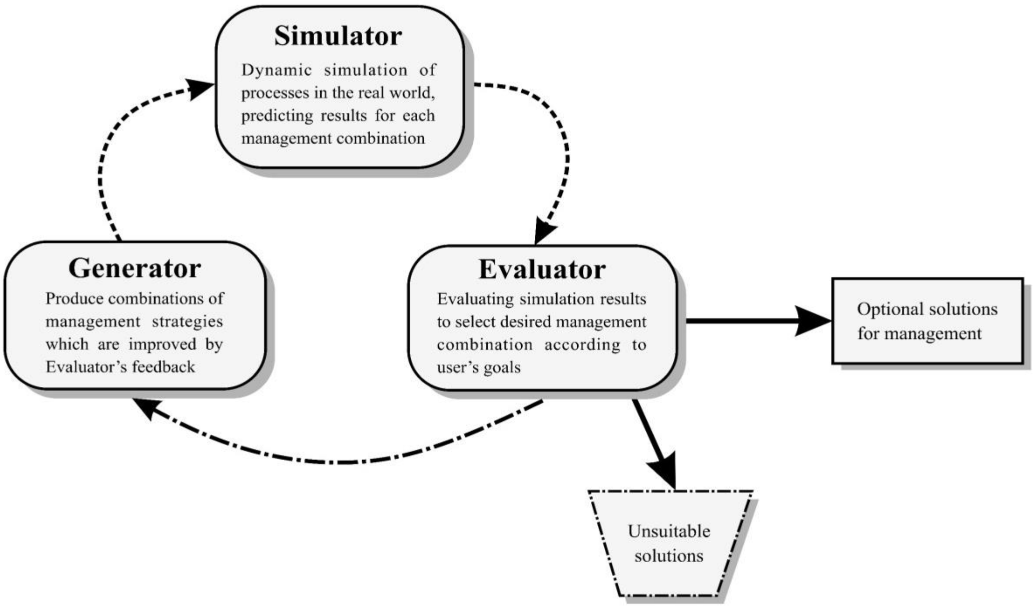

Figure 2. Management-oriented-modelling structure

Agribusinesses face several challenges from as early as seed sowing to as late as crop harvesting and they also include lack of proper soil quality, frequent weather fluctuations, lack of proper irrigation and drainage requirements, lack of proper storage management, diseases and pest infestations, weeds etc. Among all

Table 2. Different applications of AI in crop management

Techniques	Features
ES in crop management	PLANT/CD-ADVISE is an inference system which is used to predict corn black cutworm damage (Boulanger, 1983). POMME gives advises about apple scab disease, type and timing of spraying to avoid multiple pest infestations, winter injuries treatment and drought control (Roach et al., 1985). COTFLEX provide decision support in Texas cotton farms (Stone and Toman, 1989). COMAX finds the best strategy for irrigation, applying fertilizers, defoliants, and cotton boll openers in cotton to reduce production cost. It re-evaluates its recommendations daily based on sensor-fed report on weather conditions (Lemmon, 1986). CALEX is an integrated expert DSS which can formulate scheduling guidelines (Plant, 1989). PRITHVI is a fuzzy-based ES for soybean which improves yield by recommending sowing period, method, selection of crop, fertilizer, insect and pest according to variety (Prakash et al., 2013). CROPLOT is a rule-based ES which is used to determine crop suitability in different plots (Nevo and Amir, 1991). Web-based ES are usually used for detecting crops' nutrient deficiencies i.e., leaves, stems and roots disorders (Patil et al., 2009). FinARS is used to evaluate financial health of a farm business (Boggess et al., 1989).
FARMSYS-PROLOG	It is a whole-farm machinery management DSS built in PROLOG (PROgramming in LOGic) system. It uses location-specific data like climate, equipment, labor accessibility, and data on operators and tractors to evaluate the operational behavior of farm, crop output, gross earnings, and net gain. It can identify under-utilized dispensable farm tools without affecting timely field operations (Lal et al., 1992).
IoT-based robot	GPS-based remote-controlled robot uses sensors, camera, either Wi-Fi of ZigBee drone modules, actuators, and Raspberry Pi to execute jobs like smart irrigation weeding, spraying, sensing humidity, scaring away birds and animals, monitoring, etc. depending on data collected real-time, as well as warehouse management viz. temperature and moisture preservation, and thievery spotting (Gondchawar and Kawitkar, 2016).
Robotics in automated harvesting	Demeter is a computer-controlled speed-rowing machine, having video cameras and GPS. It can plan harvesting operations for an entire field (upto 40 hectares), cut crop rows, turn to cut following rows, relocate itself, and spot sudden impediments (Figure 3). It is expensive and consumes too much fuel (Pilarski et al., 2002). Robot which are used in harvesting cucumber are consist of two-computer vision (CV) systems for detection, the autonomous vehicle, manipulator, end-effector, 3D imagery of cucumber and environment, with a controlling system to generate collision less harvesting movements. Although it has 80% success rate and slow picking speed (van Henten et al., 2002).
VineView (Sky Squirrel Technologies)	It is a drone-based ethereal imaging system which helps in overall crop well-being by irrigation management, disease mapping, crop homogeneity optimization, and harvest planning (VineView).
Different ANN-based approaches	Using FL along with weed coverage and patchiness maps, precision herbicide-spraying system was developed. It reduced herbicide-based water pollution and also can differentiate between crop and weed by a pixel-by-pixel greenness method of comparison of RGB intensity values (Yang et al., 2003). It can detect crop nutrition disorder with >90% success rate (Song and Yong, 2005). Combination of ES and ANN can recommend fertilizer requirements for malting barley (Broner and Comstock, 1997).
Embedded Intelligence (EI)	"Intelligent Building Technologies" (IBT), i.e., smart farming, crop management, irrigation, and greenhouses along with technology roadmap (TRM) clarifies their challenges and opportunities (Yong et al., 2018).
Using CV	It can detect grape bunches based on color, with different illumination and occlusion levels, based on structure (FRST, HOG), texture (LBP) descriptors and a unique bunch separation strategy (Perez-Zavala et al., 2018). It is also possible to observe wheat heading stage using CV technology (Zhu et al., 2016).
RS techniques	RS, hyper spectral imagery, and 3D laser scanning can create crop metrics and enable crop-monitoring over huge areas of cultivable land. It can save time and effort (Patel and Patil, 2022).
FL-based air controllers	FL-based climate controllers are used for bulk storage facilities of potato for quality conservation (Gottschalk et al., 2003).

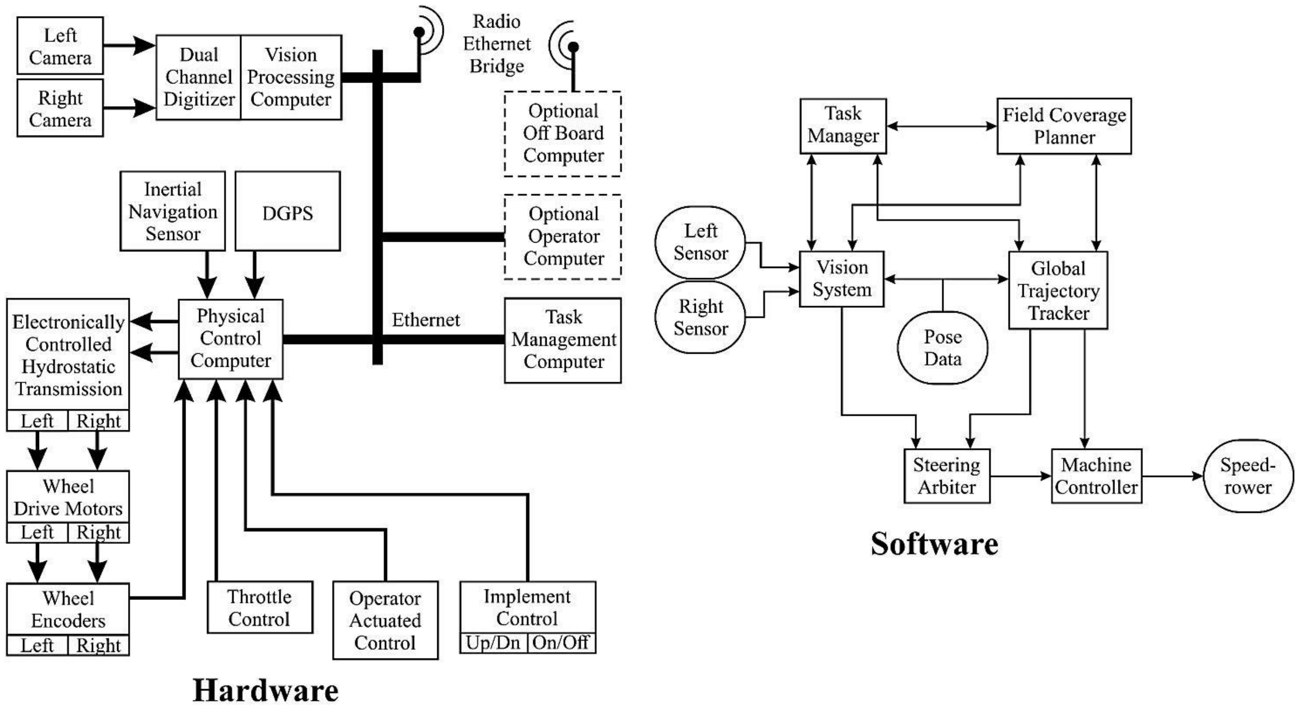

Figure 3. Block diagram of Demeter hardware and software system

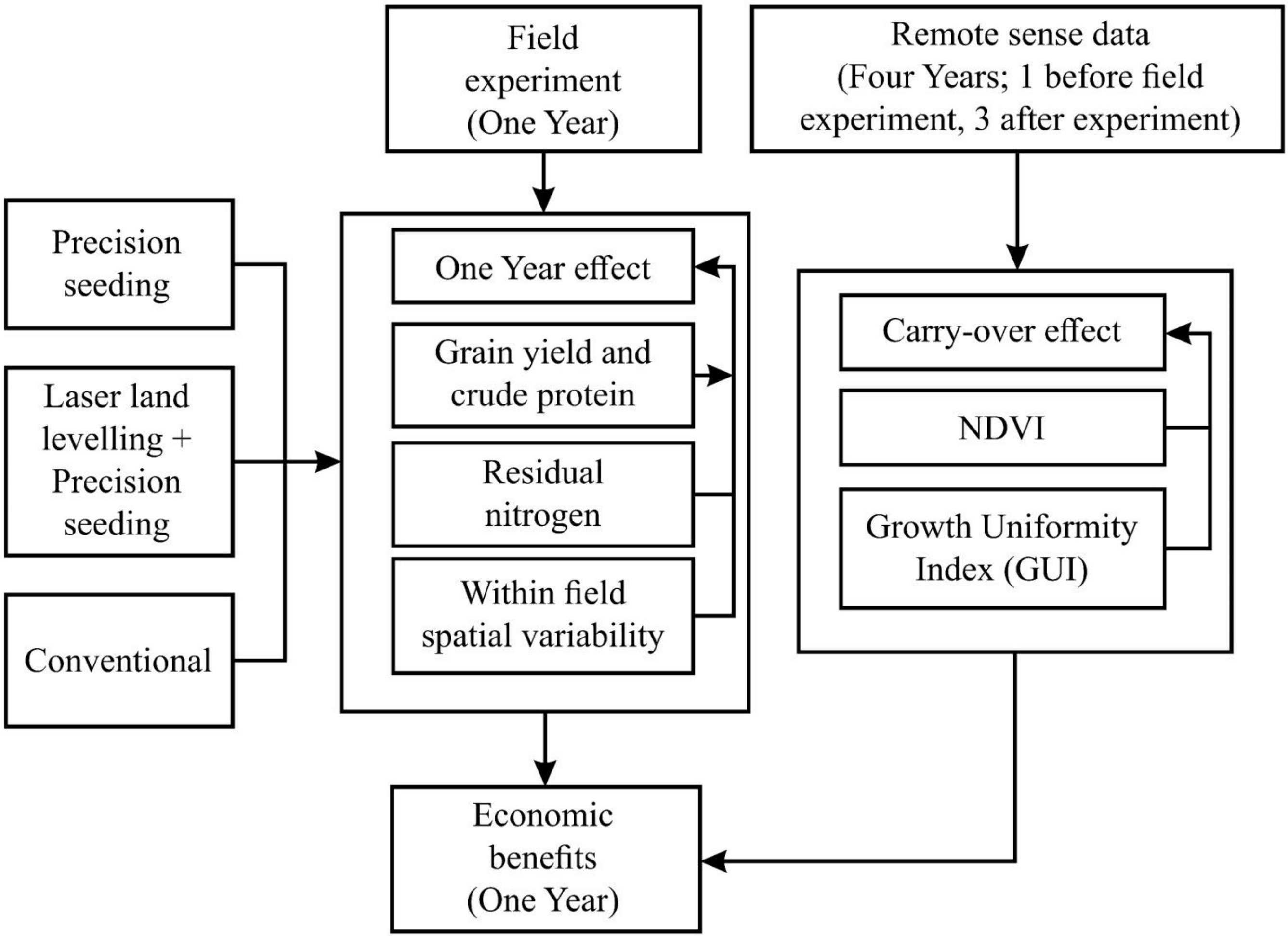

Figure 4. Flow diagram of Precision Study.

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possible solutions, AI-based systems are more feasible and reliable than others as it gives a situation-specific solution to a particular problem.

Methodology

As a review article, this study did not involve any original research or data collection. Instead, the methodology utilized in this study involved a comprehensive and systematic review of the relevant literature available on the implementation of Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) in agriculture. A search was conducted in various scientific databases such as Scopus, Web of Science, and Google Scholar using specific keywords such as "AI in agriculture," "ML in agriculture," "IoT in agriculture," and "precision agriculture." The search was conducted using Boolean operators such as "AND" and "OR" to identify relevant articles. The search was limited to articles published in the English language from the year 2010 to 2022. After identifying the relevant articles, a thorough screening process was conducted to ensure that only articles that met the inclusion criteria were selected. The inclusion criteria were articles that focused on the implementation of AI, ML, and IoT in agriculture, and articles that provided insights into the recent trends and challenges in the field. After selecting the articles, data were extracted and synthesized into a comprehensive review of the implementation of AI, ML, and IoT in agriculture. The findings were then analysed and presented in the form of a comprehensive review article.

Soil Management

Soil management is important in agriculture, and farmers need to be knowledgeable about types of soil along with soil conditions that will improve production as well as conserve resources. Soil porosity and aggregation should be improved by alternative tillage systems and compost application to improve soil quality and prevent soil degradation (Pagliai et al., 2004). Sensitivity to soil degradation and its ability to recover vary among soil types and are integral in sustainability of soil management practices for long-term soil productivity (Syers, 1997).

Crop Management

Crop management involves sowing, growth monitoring, harvesting, storage, and distribution. Precision Crop Management (PCM) is devised to maximize crop yield profitability and protect the environment through targeted crop and soil inputs as per their requirements. Its only issue is the dearth of well-timed data on soil and crop conditions (Moran et al., 1997). Farmers should integrate different flexible strategies to predict and deal with different weather patterns and choose among cropping alternatives (Debaeke and Aboudrare, 2004; Aubry et al., 1998). The concept of incorporating AI in crop management was first suggested by McKinion and Lemmon in 1985 by creating GOSSYM (cotton crop simulation model) using ES for optimizing cotton production (McKinion and Lemmon, 1985).

Precision Agriculture (PA)

Precision Agriculture reduces harm made to the environment and improves crop quality, yield, food safety, and agricultural economy. Current technologies of PA include the combined efforts of GIS, RS, Global Navigation Satellite Systems (GNSS) and sensors help in laser land leveling, varying fertilizer application rates, harvesting, planting, spraying, and water-saving (Figure 4.) (Chen et al., 2022; Cassman, 1999). Seeding is important in crop production, being directly related to crop development, yield and germination. Precision seeding is the source of PA advancement, and is necessary for encouraging other precision applications like fertilizer application, irrigation, and harvesting (Gebbers and Adamchuk, 2010). It can enhance germination rate, protect seeds, optimize population density, increase crop yields, and reduce labor involvements which all lead to better farm earnings & Land quality impacts seeding (Schieffer and Dillon, 2015; Kuehne et al., 2017). Laser land-leveling machines make precise leveling, thus, efficiently enhancing farmland conditions, and precision seeding. It can increase crop yields, improve fertilizer and irrigation efficiency, and thereby increase economic benefits (Feng et al., 2017). Three-layer framework is adopted in this Precision Agriculture (PA) system, which are data sensing layer, cloud service layer and user interaction layer as shown in Figure 5 from bottom to upper. Data Sensing Layer assembles temperature, moisture, light intensity and carbon dioxide, oxygen, ozone and nitrogen dioxide gas contents and using TCP Socket protocol, data sensing devices uploads real-time data to cloud (Figure 6) (Misra et al., 2022; Liu et al., 2017). Provisions for data storage in the form of video or viewing in real time are also available (Liu and Liu, 2018). Cloud Service Layer provides data maintenance and archiving, analyzing service and user-oriented application service. Data is stored in MySQL and archived to Hadloop HDFS analysis (Jabbar et al., 2016). User Interface Layer deals with web and android interface for user operation.

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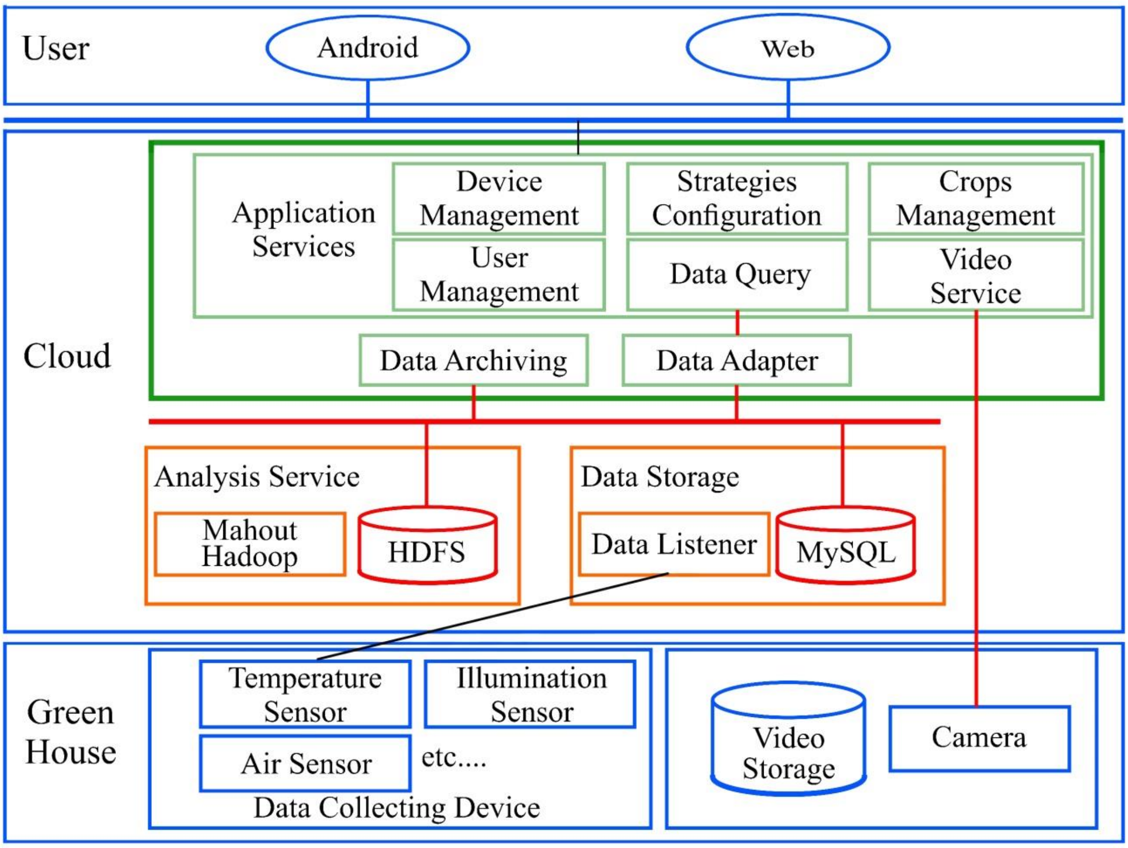

Figure 5. System Architecture used in Precision Agriculture

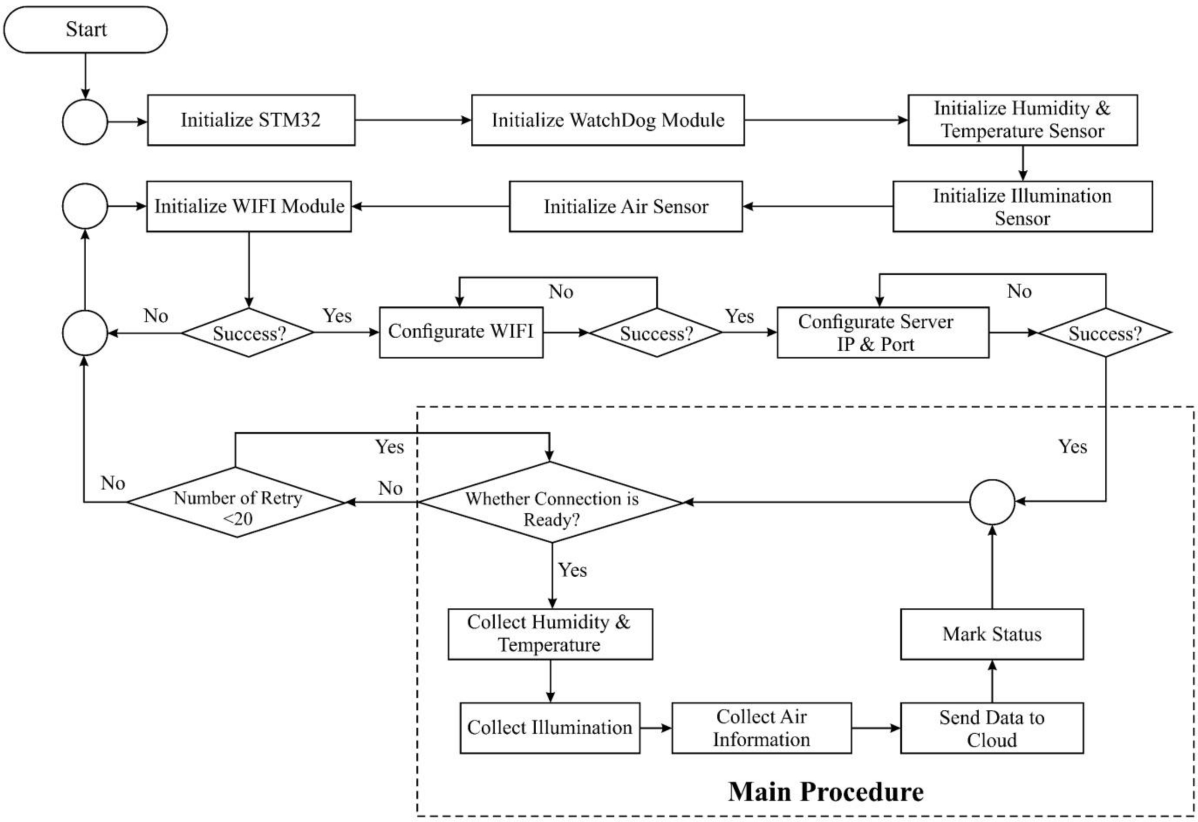

Figure 6. Workflow chart of data collecting devices

Crop Growth Environment Monitoring

Crop growth environment monitoring is designed such that IoT that is exclusive for agriculture is involved in sensing, transmitting and calculating various environmental information (Lv et al., 2022; Wu 2022). Sensors are mainly required to collect real-time information on temperature, CO_2 concentration in the atmosphere, humidity which can directly affect agriculture (Hamrita and Hoffacker, 2005; Lin et al., 2015). A 433 MHz radio frequency was used to transmit information and, MSP430F149 and LPC2478 were used respectively so that microcontrollers belonging to aggregation nodes and wireless sensor could collect information real time, aggregate it and helps in fusion of data pertaining to environment (Hwang et al., 2010; Yu et al., 2013). A WSN that used to work at 780 MHz frequency was formulated which was attuned with IEEE 802.15.4c environmental monitoring, standardized for millet farming (Haifeng et al., 2019). RFID technology was used in monitoring real-time temperature and soil moisture, which affect crop growth. A soil analysis system was developed that could provide reliable data source to gain further knowledge on plant growth and development. Collection of information on wheat growth and other environmental parameters helped in the development of an IoT system that would mainly be involved in diagnosis of seeding conditions in case of wheat (Qiu et al., 2014; Gonzalez et al., 2015). GIS or Geographic Information System was needed to understand the dynamics of agricultural environment monitoring from point to surface. ZigBee was able to aggregate information on sensing nodes belonging to the sensor network, which in turn, help in collecting real time data on temperature, CO_2 concentration and humidity (Kumar and Hancke, 2015).

Irrigation Management

Water, which is becoming scarce in today's world, is a compulsory element for the growth and development of crops, thus, making it an important factor for agricultural production (Wang et al., 2008; Talaviya et al., 2020). Traditional irrigation system requiring human intervention can be replaced by an automated one with the advent of AI, helping in reducing water wastage and labor (Wang et al., 2013). It also increases lodging resistance of crops, leading to a good yield. ANN was used for intelligent water-saving irrigation system which improved irrigation efficiency and drainage (Zhang et al., 2013). A well-managed irrigation scheduling system requires a sensor system that can be used to calculate the amount of water present in different soil layers and send predefined user orders to actuators to switch ON/OFF sprinklers (Mitra et al., 2019).

Weed Management

Weeds are an undesirable, persistent, damaging plant that muscle out the growth of other crop plants and consistently affects farmer's agricultural yield, profit and the country's economy (Eli-Chukwu, 2019; Neil Harker, 2001). Weeds impede the proper crop development by competing for light, moisture, and nutrients, interfering with harvesting equipment, causing health problems in humans and animals and adversely affecting natural ecosystem and aquatic resources (Ministry of Agriculture, Land and Fisheries, 2020). Traditional weed management approaches are too inefficient compared to automated weed identification and classification (Subeesh et al., 2022). Weedicide usage can negatively impact public health by environment pollution. AI-based weed detection systems can precisely spray on the target location, lowering costs and crop damage (Partel et al., 2019).

Disease and Pest Management

Genetic, soil type, weather, wind, temperature, etc. influence the causation of diseases, making large-scale farming a challenge due to their unpredictable nature. Farmers must implement an integrated disease management model using AI, which encompasses all three chemical, physical as well as biological measures to effectively control diseases and minimize losses in less time-consuming and cost-effective manner (Eli-Chukwu, 2019). AI-based image recognition systems can accurately recognize specific plant diseases, gradually paving the way for field-based crop-disease identification using farmers' smartphones (Liu, 2020).

Process of disease detection include many steps like plant imaging which ensures that leaf images has been partitioned to the background and both diseased and non-diseased part of leaf portion, advanced processing in which the diseased part is reaped, transfer to laboratory, disease or pest identification and nutrient deficiency sensing etc. (Sharma, 2021). Pests are obnoxious nuisances of farmers, harming the agricultural yields and economy globally. Pest control companies use drones to virtually visit crops and provide full time monitoring to find diseases, pests, irregular crop degradation, or dead soil. Farmer can gather the data from any crop area and take suitable measures. Integrated Pest Management (IPM) is a green method for pest management, versus overuse of pesticides in the long run (Peshin et al., 2014).

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Table 3. Different AI techniques used for Irrigation management

Techniques	Features
ANN-based irrigation	Using MATLAB, intelligent irrigation scheduling system is developed. Modelling is done on the input parameters such as soil moisture, humidity, temperature, and radiations. Ecological conditions, Evapotranspiration (ET) and crop type are used to determine the amount of water needed for irrigation followed by simulation of associated results (Umair and Usman, 2010). Neuro-Drip estimates spatio-temporal subsurface wetting pattern illustrations and a statistical description of spatial and temporal distribution of water from a single drip emitter (Hinnell et al., 2010). It can create different irrigation systems to determine water requirement in paddy fields based on ET data using factors like temperature, wind, solar radiation, and relative humidity. This helps in water conservation aided by intelligent irrigation system (IIS) application technology. ET estimation was done using maximum, minimum, and average air temperature for one model and solar radiation, air temperature data and precipitation for the second model. Soil moisture estimation is given by both the models utilizing the least labor and time consumption along with least meteorological data (Arif et al., 2012). Using Dehradun’s monthly climate data and ANN model (using MATLAB) like Penman-Monteith (PM) and Levenberg-Marquardt back-propagation (BP) algorithm methods in estimation of ET. Of the training algorithms used, most precision with the best number of neurons came while training with 75% data feed was done (Nema et al., 2017).
Arduino	It is an automated irrigation system which measures soil conditions using soil moisture & water level sensors (Figure 7). Based on water availability, the pump is turned ON/OFF automatically after irrigation (Okoye et al., 2018). Remote sensors can be developed using Arduino technology for efficient and automated irrigation system which increases production by 40% (Savitha, 2018).
ANFIS-PEGASIS: Irrigation controlled system-data gathering in Wireless Sensor Network (WSN) using Internet of things (IoT)	Fuzzy inference system (FIS) has its usage in selection of an optimum cluster head based on residual energy and distance. Power-Efficient Gathering in Sensor Information System (PEGASIS) collects irrigation data, and a chain is formed amongst sensor nodes (SNs). After node to CH communication, data is transferred to the base station (BS). Finally, based on sensor-delivered-information, Adaptive Neuro-FIS (ANFIS) is used in decision making process of automated irrigation (Figure 8). Sensors like soil moisture, temperature, light intensity, and humidity are used to sense various soil properties and switch ON/OFF irrigation accordingly (Kumar and Jayaraman, 2020).
Raspberry Pi3	It is an autonomous system where sensors for soil moisture detection and Nod MCUs spread orderly throughout irrigation area and WLAN connects the nodes with Raspberry Pi3. It predicts weather at regular intervals using Random Forest regressor and has the ability to subsequently adapt to the climate conditions of the region (Karthikamani and Rajaguru, 2021). Small-scale smart irrigation system based on IoT was developed where sensors sense temperature and humidity changes and gives signal to the Raspberry Pi. It can control water motor automatically and monitor the plant growth using webcam. It is comfortable, less energy-consuming, efficient and less time-consuming (Kumar et al., 2022).
Automated Irrigation system using Machine-to-Machine (M2M) technology	In M2M, machines undergo autonomous interaction with amongst themselves. A cloud-based online server is used to store data directly. Automated robot detects moisture content and temperature at defined intervals followed by sending analog signals to Arduino microcontroller (with an edge level hardware connection). It is converted to digital signals and sent to KNN algorithm embedded Raspberry Pi3. Signal is sent back to Arduino to begin irrigation as per requirement. Sensor values are updated and stored (Shekhar et al., 2017).
Thermal imaging technique	Cloud-based thermal imaging system (non-contact and non-intrusive technique to analyze surface temperature of agricultural field and give recommendations) helps in irrigation scheduling, determining field area which needs irrigation the most and maintaining uniformity to prevent crop growth hampering. Its other applications are plant physiology studying, pre- and post-harvest operations, yield forecasting, detecting termite attack, etc. (Roopaei et al., 2017; Ishimwe et al., 2014).
ES-based Irrigation techniques	**BDM-EXPERT-** Combined with CASIMBOL (Computer Aided Simulation of Irrigation Management Below Outlet) for dealing with water shortage and crop planning (Elango et al., 1992). **IRRIGATOR**- Schedule supplemental irrigation of crops in Ontario (Clarke et al., 1992). **CALEX/Cotton-** Intelligent front-end ES containing methods used in scheduling irrigation, like, water budget methods, leaf water potential and growing-degree days, based on stage of crop development, crop water status and soil-water availability, with farmer preference. Irrigation amount and time are determined at the back-end (Plant et al., 1992). Prototype rule-based ES for the hydraulic design and micro-irrigation systems’ evaluation DESIGNER computer model was developed (Bralts et al., 1993). Combined with ES, a water-saving, economical, stable, portable and easy to promote irrigation system based on a CAN bus was designed which can solve water management problems (Zhang et al., 2015; Gao et al., 2011).

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Takagi-Sugeno-Kang Fuzzy Inference System (TSK-FIS)	Soft-computing hybrid techniques find its application in estimating stem water potential using 5 fuzzy rules considering input variables: soil water content found at 0.3m depth, mean daily air temperature and day of the year (Valdes-Vela et al., 2015).
Wireless Irrigation System via Phone Call & SMS	Outputs from digital cameras and sensors built for soil moisture, temperature, pressure, and molecules undergo conversion to digital signal. Then, it is forwarded to multiplexer via wireless network. Sensors for soil moisture and rain drops inform the farmer regarding content of moisture in soil by SMS using GSM module. Farmers can give switch ON/OFF water commands using SMS (Varatharajalu and Ramprabhu, 2018).
Dielectric constant method	Dielectric soil moisture sensors can be used to measure dielectric constant for real-time irrigation control (Gebregiorgis and Savage, 2006; Kuyper and Balendonck, 2001).
IoT-based techniques	IoT based agriculture farmland and Losant platform for monitoring soil moisture sends real-time SMS/email alerts to farmer if anything anomalous is observed on the field (**Figure 9**) (Kodali and Sahu, 2016). GPRS DTU-based intelligent agricultural irrigation system was designed to implement control systems as per crop growth requirement (Wang et al., 2013).
Automatic drip irrigation system	It optimizes fertilizer and water use using FL and wireless sensors that collect real-time temperature and soil humidity data (Anand et al., 2015). Drip irrigation of dwarf cherry trees is controlled using WSN for cheap wireless-controlled irrigation and real-time soil water monitoring. Solar-powered wireless acquisition stations are used for data acquisition and also for controlling irrigation. It prevents moisture stress of trees and salinification, facilitates efficient use of freshwater, and removes labor for irrigation (Dursum and Ozden, 2011).
Aquaponic irrigation	It regulates nutrient concentrations in aquaponic irrigation for achieving optimal plant growth using Bolstered error estimation and ML algorithms (Dhal et al., 2022).

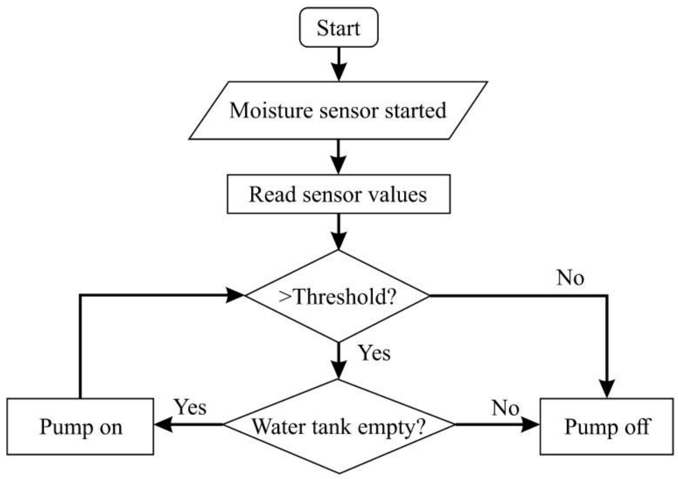

Figure 7. Arduino based irrigation system mechanism flow diagram

Weather Sensing

Weather is hugely responsible for disease development (Hardwick, 2002). The weather-disease correlation can be explained by the disease triangle concept (Figure 11) (Scholthof, 2007; Bos and Parlevliet, 1995). Farmers can deal with adverse weather and climate changes in a reliable and manner if the warning for natural calamity is provided timely (Shah et al., 2019). Also, correct disease forecast can quantitatively determine pesticide usage and timing (Kang et al., 2010).

Weather forecasting system **(**Figure 12**)** comprises of an Automated Weather Station (AWS) consisting of wireless communication infrastructure, internet system, and a high-resolution camera. Relative humidity, LWD, temperature, wind speed, solar radiation, and precipitation rate greatly impacts plant disease occurrence (Gleason et al., 2008; Magarey et al., 2007). Pathogens

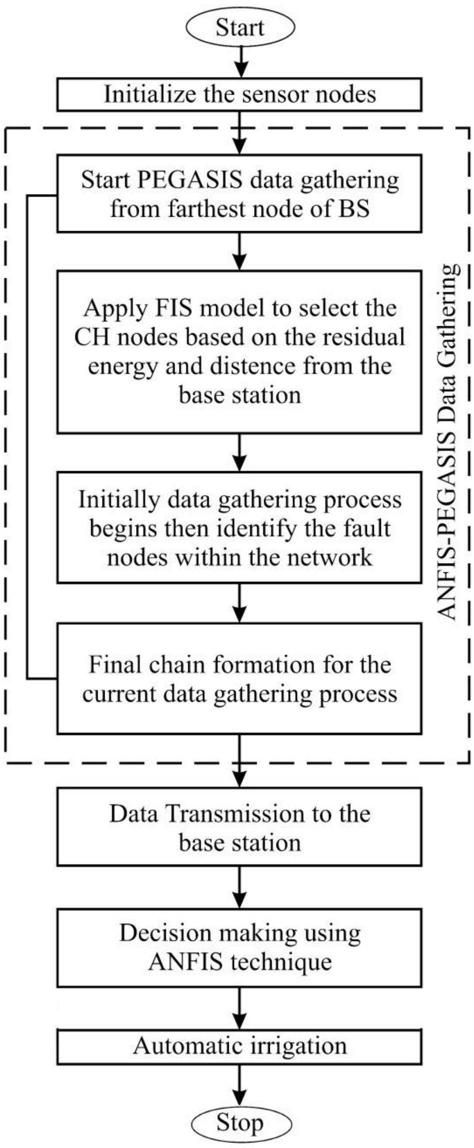

Figure 8. ANFIS-PEGASIS data gathering scheme

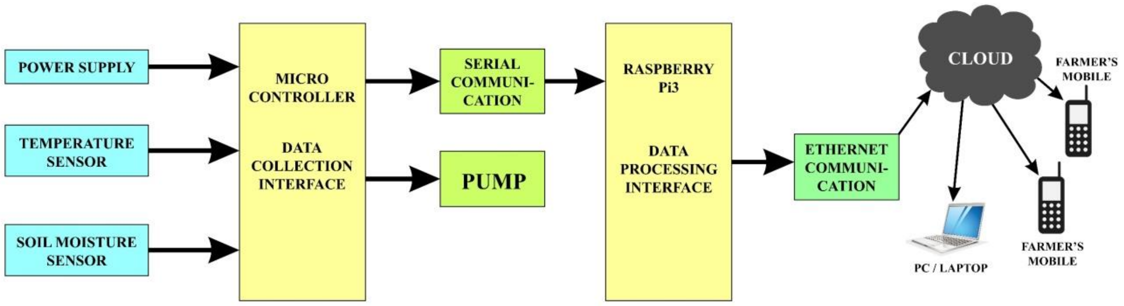

Figure 9. IoT based automated irrigation system

mostly develop and grow on the leaf surface (Jain et al., 2019). LWD, the measure of amount of moisture associated with the vegetation, is an important parameter to predict possible disease growth (Morales et al., 2018; Cassardo et al., 2003). LWD is measured mainly by two approaches. First approach is done by using sensors. In this case measurement and accuracy depends upon the number of sensors and their location (Sentelhas et al., 2004). Jacobs et al. (2009) provides a useful insight on leaf wetness analysis present in canopy of potato plant. A notable disadvantage is the cost involved. Second approach is done by using mathematical models. It measures variables like heat reflux rate, soil moisture, wind speed, etc. (Agarwal and Mehta, 2007; Kim et al., 2002). It is difficult to accurately estimate all variables (Gleason et al., 2008). Relative humidity and temperature are most important in estimating LWD (Orlandini et al., 2008).

Table 4. Various percentage of yield losses recorded in different crops due to weed infestations (Neil Harker, 2001; Khan and Haq, 2003; Fahad et al., 2015; Rao et al., 2014; Datta et al., 2017; Mruthul et al., 2015).

Crops	% Yield loss due to weeds
Dried beans	50%
Corn	50%
Wheat	48-60%
Soybeans	8-55%
Sesame	50-75%

Plant Life Information Monitoring

Information on plant life can be recorded mainly via visual aid like growth of fruit and crops, diseases and pests, characteristics and other information of leaf like the amount of chlorophyll present, nitrogen content of crops, and the rate of photosynthesis (Porto et al., 2014). Scientists summarized the concept of keeping a track of nutrients of plants, sensing of various pests and disease associated with it, and plant information with technologies like spectroscopic and NMR imaging, required for the acquisition of the respective information (Figure 13) (He et al., 2013). Diseases caused by condensation were controlled by automatic adjustment of greenhouse environment (Park and Park, 2011). Safe monitoring of greenhouse where plant grows was established and information on plant height and leaf crown projection area was collected (Teng and Li, 2003).

Crop readiness identification

Farmers can segregate fruits based on their ripening using high-definition pictures taken by drones or helicopters under white/UV light. A field map is created that helps in identifying areas that require fertilizer, water or pesticides (Panpatte, 2018). Growth stages of wheat can be monitored using AI without requiring manual labor by capturing images at different growth stages and light conditions, which helped in creating a "two-step coarse-to-fine wheat detection mechanism". It outperformed identifying wheat growth stages by human observation. Another CV was developed in order to estimate maturity in tomatoes by an algorithm to analyze color from five different parts of tomato (Liu and Wang, 2020).

Yield prediction and management

Yield mapping allows farmers to view spatial variety of the field and past outcomes, required for future activities and management. It involves gathering geographical information on harvest yield like soil moisture content and in-field fluctuations, which arranges for several compost maps which contains the list of supplements added to the soil and which are removed during harvest collection. Grain yield mapping framework consists of a grain volume gathering sensor, moisture sensor, GPS antenna and receiver and travel speed sensor (Talaviya et al., 2020). Grain flow sensors, composed of volume and mass flow methods, are used in crop yield monitoring (Figure 14) (Chung et al., 2016). Yield is harvested volume per unit area, or yield sensor stream rate determined every 1–2s while collection. Several systems have been developed that are instrumental in removing problems associated with inaccurate sensor and information on land. Yield sensors should be recalibrated when factors change (Searcy et al., 1989; Birrell et al., 1996).

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Table 5. Different AI techniques used for management of weeds

Techniques	Features
ANN-based approaches	Evolutionary ANN for weed identification using Genetic Algorithm (GA) minimizes the classification training time and error rate. It reduces trial-and-error process of network inputs estimation (Tobal, 2014). ANN and image analysis are used to discriminate crop and weeds. It reduces chemical usage by spot-spraying. Its' accuracy is more than 75% without prior data (Aitkenhead et al., 2003). Deep Convolutional Neural Network (DCNN)-based weed detection from bell paper field by obtaining RGB images using GoogLeNet, Alexnet, Xception and InceptionV3 (best results), models were evaluated. It is precise, accurate and has good recall features (Subeesh et al., 2022). Color Co-Occurrence Method (CCM) for texture analysis is used to evaluate 3 NN classifiers namely, BP (best results as it has lesser computational requirements of the three), Radial Basis Function (RBF), Counter Propagation (CP), and, in real-time weed control systems and its accuracy is almost 97% (Burks et al., 2005). Real-time data processing and precision herbicide application is done in corn fields by detecting weeds using Learning Vector Quantization (LVQ-ANN) and RGB image analysis (Yang et al., 2002). Hybrid ANN-Invasive Weed Optimization (IWO) (a metaheuristic algorithm, resembling weeds' ecological behavior) is used to solve potato classification problem, where Multi-Layer Perceptron network (MLP) manages constraints of the problem. It is cost-effective and has good optimization but low adaptation rate with new data (Molallem and Razmjooy, 2012).
ES in weed management.	SELOMA has high adaptation rate and prediction level. It requires big data and expertise (Stigliani and Lesina, 1993). Weed Adviser ES (Pasqual) is a rule based microcomputer ES which is used to identify and eliminate weed in oats, barley, triticale, and wheat, and recommends treatments and control measures (Pasqual, 1994).
Unmanned Aerial Vehicle (UAV), GA	It divides image, computes and converts vegetation indices to binary numbers, detects crop rows using algorithms, optimizes parameters and develops a classification model (PereOrtiz et al., 2016; Lopez-Granados, 2011; Ahngar et al., 2022). It is quick and efficient monitoring requiring human expertise. It is expensive, little or no controls on weeds due to spectral similarity of weed and crop rows.
Digital Image Analysis (DIA), Global Positioning System (GPS)	It has more than 60% success rate and is a time-consuming process. Weed control in winter wheat, maize, winter barley, and sugar-beet can be done by applying online detection of weed using a UAV (drone), GPS-controlled patch spraying and computer-based decision making (Gerhards and Christensen, 2003). It identifies plant species by shape, color, and texture attributes, pertaining to every object in the image, individually (Gerhards et al., 2021).
Robotics, Sensor ML	It removes resistant weeds in no time. It is expensive and might reduce soil productivity by using heavy machinery constantly. Non-chemical weed controller using 15000V electrical discharge is applied to kill weeds in lettuce (Blasco et al., 2002). Raspberry Pi-based fuzzy real-time image classification system is employed by robotic model along with suitable input-output subsystems like cameras, light sources, and motors with power systems to identify sugarcane crop among 9 different weeds at 92.9% accuracy and 0.02s processing time (Sujaritha et al., 2017). Autonomous weeding robot using high power lasers for intra-row weeding is suggested (Bakker et al., 2006). Another autonomous robot puts into practice two systems for vision. First one is gray level vision system which recognizes and directs the robot with the crop rows and another one is a color-based vision system which recognizes a crop among weeds (Astrand and Baerveldt, 2002).
Support Vector Machine (SVM) for weed and nitrogen stress detection in corn	It detects crop stress by classifying hyperspectral images according to weed management processes and nitrogen application rates and helps in timely site-specific remedies (Karimi et al., 2006).

GIS programming is used to show the determination of crop yield per crop land area. The initial paperwork contains records as the grain moves through a consolidate. This unspecific information is required in order to get information on grain stream improvement in method incorporating programming and yield mapping

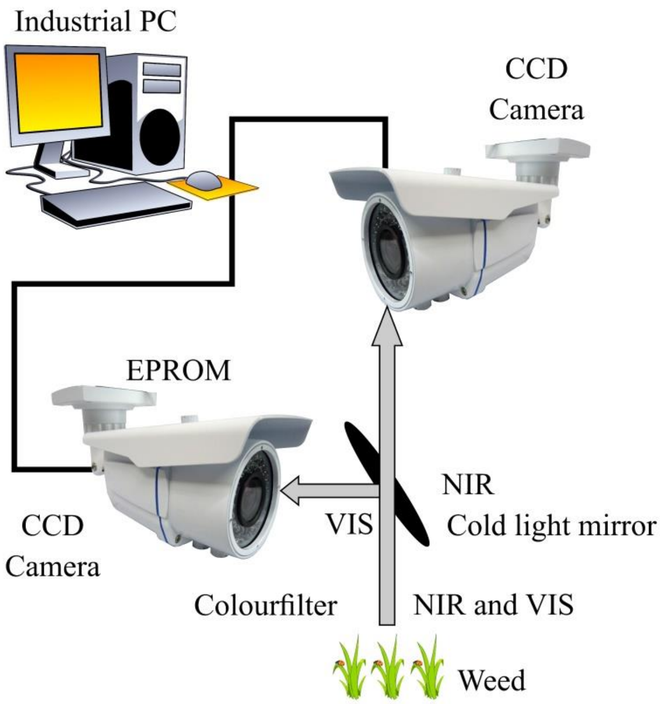

Figure 10. Bi-spectral camera system for weed detection

frameworks (Cillis et al., 2018; Verma et al., 2022). Advanced technologies like satellite imaging, cloud ML are instrumental in gaining information on maximum possible yield on an average so that they are profitable. ANN model along with a BP knowledge algorithm was used to gather more information on the constituents of the topsoil and how it would affect the harvest (Liu et al., 2005). Statistical inferences developed from data on climate and moisture content from data on local rainfall and soil moisture can be estimated by using AI models to provide forecasts of best sowing periods (Sharma, 2021). Microsoft and International Crop Research Institute for the Semi-Arid Tropics (ICRISAT) were involved in developing an AI-controlled app associated with planting. A Nature Fresh Farms technology evaluates plant health data, and forecasts harvest for maximum yield by calculating time taken for crop growth (Grand View Research, 2019).

Agricultural product quality safety and traceability

Monitoring of product, storage and distribution are applications of IoT. WSNs observe workshops and transport associated with storage and distribution in order to trace the source and target of the agricultural products (Pinto et al., 2006). In order to gain information on agricultural products and safety parameters, TIC manageable traceability tools are applied in food industry (Jiang and Sun, 2007). Based on GS1 coding framework, sea cucumbers, dairy products, and pork were coded which led to accurate tracing of products in each transfer and allowed consumers to interact with a query platform which manages the tracking (Cao et al., 2009). In prior studies, safety supervision systems and vegetable quality were designed, based on RFID technology that could retrieve information on the life cycle of the crops, thus, improving quality and safety (Guo et al., 2018; yang and Zhao, 2013).

Blockchain technology (BT) is a promising technology with respect to today's economy with a huge growing potential in upcoming years (Hidayat and Mahardiko, 2021). BT is a digital database, capable of storing chunks of information ranging from records, transactions and events comprising of rules for information updates (Sikorski et al., 2017). As more information are added, this network grows continuously as blocks developing a system and using a hash, blocks form a chain, after getting linked with each other. An ordered list of blocks, containing transactions, invocations, and smart-contract creation can be thus called a Blockchain Network (Figure 15) (Chen et al., 2018).

BT offers traceability with trusted information, involving collection and sharing by transferring original and precise data in processing, sourcing, warehousing, distribution followed by sales (Kamble et al., 2019; Hastig and Sodhi, 2020). By tallying with timestamps, any sort of information is possible to be linked back to a particular block. The characteristics of BT like the provision of a secure shared and a decentralized database enhances efficiency, trust and reputation through transparency and traceability for transaction of goods, data, and financial resources (Sharples and Domingue 2016; Kshetri, 2017; Fartitchou et al., 2020; Kamble et al., 2019). It allows data inspection and real-time audit, bringing clarity and lucidity (as blockchain network makes an exactly similar copy at every node) and visibility to all network stakeholders, eliminating a trusted intermediary (Abeyratne and Monfared, 2016). It opens a new dimension in reorganizing network reputation and helping to reduce frauds (Cai and Zhu, 2015). It allows supply chain organizations to be transparent about the benefit obtained by acquisition and usage of additional data, which could unlock more company investments to support further improvements. Farmers would benefit more by sharing their farm data, even as continuous real-time data feeds, e.g., for animal welfare reasons (Wathes et al., 2008).

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Table 6. Various AI applications used in pest and disease management

Techniques	Features
ANN-based approaches	Application of CV, GA, and ANN helps to quickly identify tomatoes with physiological diseases automatically (upto 100% accuracy) (Fang et al., 2005). CV-based automatic disease diagnosis can be done in rice. Diseased leaf areas, textural descriptors with GLCM and color moments are extracted to produce a 21-D feature vector. GA-based relevant feature selection generates a 14-D feature vector. ANN and SVM are used for classification giving classification accuracy of 87.5% and 92.5% respectively (Ghyar and Birajdar, 2017). It is possible to spectrally predict tomato late blight infections by a BP-ANN using gradient-descent learning algorithm and trained using field experiments and remotely sensed image datasets. It has high accuracy and prediction rates (both >90%) (Zhang et al., 2013). BP-ANN, stepwise logistic models and multivariate discriminant were used regularly recorded environmental variables to predict wheat leaf wetness. Dew period prediction was done via classification tree discrimination using a physical model and relative humidity indicator. Logistic models and ANN gave better results than previous models for dew duration prediction. It is advantageous for disease forecasting since these models can predict leaf wetness caused by both dew and rain (Francl and Panigrahi, 1997). ES were also developed for fruit tree disease and insect pest diagnosis based on ANN and GIS (ArcInfo) (Liu et al., 2006). Image dispensation prototype combined with ANN is applied to detect *Phalaenopsis* seedling diseases using color and texture features. It shows high accuracy (89.6%) and detection capability (97.2%, without classifying disease type) (Huang, 2007). DCNN-based detection of Multi-Crops Leaf Disease (MCLD) is done by image extraction using Visual Geometry Group (VGG) model to classify sick and healthy leaves. Its accuracy is increased by 98.40% in grapes and 95.71% in tomatoes (Paymode and Malode, 2022). K-means-based segmentation and ANN-based classification are also applied in some cases. It is rapid, precise (93%), affordable, and has accurate image-processing-based solutions (Al Bashish et al., 2011; Al Hiary et al., 2011).
Rule-based ES for Pest management	**AgPest Expert** helps in controlling of pest and prevention of disease in wheat and rice. Its Explanation Block (EB) generates clear explanation for the decisions taken followed by ES's kernel. It gives highly consistent and complete advice (Balleda et al., 2014). Online ES along with rule-based forward chaining inference engine is used for fast, cost-effective and convenient diagnosing of Oyster mushroom diseases. It gives therapy recommendations via an online system, based on user response to questions on mushroom status. Constant monitoring is required to check whether the pest has developed immunity for the preventive measure (Munirah et al., 2014). **PEST** (Pest Expert SysTem) provides insect identification and control recommendations by knowledge engineering techniques (Pasqual and Mansfield, 1988). **TEAPEST** provide object-oriented approach using a phase-by-phase identification and consultation process for pest management in tea (Ghosh and Samanta, 2003). Later this was re-designed by employing a multi-layered BP-ANN and then reformulated using RBF model to achieve higher classification rates (Samanta and Ghosh 2012; Banerjee et al., 2017). **SMARTSOY** is a prototype for soybean insect pest management (Batchelor et al., 1989; Batchelor et al., 1992). **CORAC** helps in hop plant protection using simplified simulation models (Monzy et al., 1993). **Dr. Wheat** provides Web-based diagnosis of wheat diseases. DSS is used for forecasting *Aphis fabae* outbreaks (Knight and Cammell, 1994). **DIARES-IPM** is a diagnostic advisory rule-based ES (Mahaman et al., 2003). Integrated stress and pest management by diagnosis and treatment is used to reduce jute fiber losses by diseases, biotic and hydric stresses (Chakraborty et al., 2013; Ghosh, 2015). **AMRAPALIKA** is an ES which helps identification of disorders, diseases and pests in Indian mango (Prasad et al., 2006). **VEGES** is a multilingual ES for diagnosing diseases, nutritional disorders and pests in 6 greenhouse vegetables (Yialouris et al., 1997). The agricultural management knowledge is mostly imperfect and imprecise, so rule-based ES may lead to anomaly.

Using FL-based approaches	**SOYPEST** (Soybean Pest Expert System) is used in management of soybean pest (Saini et al., 2002). **FuzzyXpest** is an online pest information system with high predictive precision (Siraj and Arbaiy, 2006). **IPEST** is an indicator of pesticides' environmental impact (van der Werf and Zimmer, 1998; Roussel et al., 2000). FL-based plant disease forecasting system are developed using minimum weather data which are responsible for growth of disease-causing microorganisms like-temperature, humidity, and Leaf Wetness Duration (LWD) (Tilva et al., 2013). Using FL, a flexible DSS was developed combining GRASS-GIS, Mapserver, and Perl and PHP computer languages, to gather data concerning *Bactrocera oleae* distribution in Olive culture according to soil cover, temperature, and topography (Jesus et al., 2008). Web-Based Intelligent Disease Diagnosis System (WIDDS) is highly accurate and helps in quick oil seed disease diagnosis. It has high resolution with highly effective web-based text-to-talking interface using Text-to-Speech (TTS) converter (Kolhe et al., 2011). Grading leaf diseases can be done by machine vision (healthy part is segregated from diseased part by k-means clustering). Total leaf and diseased area calculation, and final accurate disease grading can be done by FIS (Sannakki et al., 2011).
ZigBee and WSN in grape disease early detection	It is a monitoring system for predicting grape disease by using Hidden Markov Model, which provides SMS alerts. Temperature, leaf wetness, and relative humidity sensors send data to ZigBee database. Wireless System Network (WSN) is mainly used. ZigBee has 4 layers such as physical, medium access control, network, and application layers. ZigBee End Device (ZED), ZigBee Router (ZR) and ZigBee Co-coordinator (ZC) have dissimilar functions in the Wireless System Network (Patil and Thorat, 2016).
MaxEnt Predictive model	It is an Ecological Niche modeling (ENM) based approach for early-warning pest and disease outbreaks and selecting sustainable cropland management practices (Bestelmeyer et al., 2020; Peters et al., 2020; Wakie et al., 2019; Neven et al., 2018).
Few-shot learning for plant biotic stress classification of coffee leaves using Prototypical Networks and Triplet Networks	It shows high accuracy and result was significantly better and more promising than previously reported for plant biotic stress recognition (Tassis and Krohling, 2022).

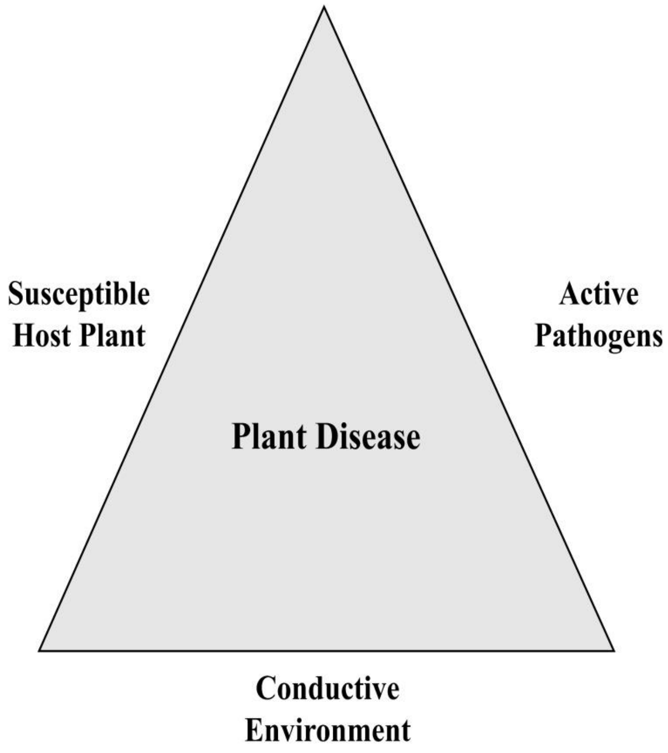

Figure 11. Plant disease triangle and affecting factors

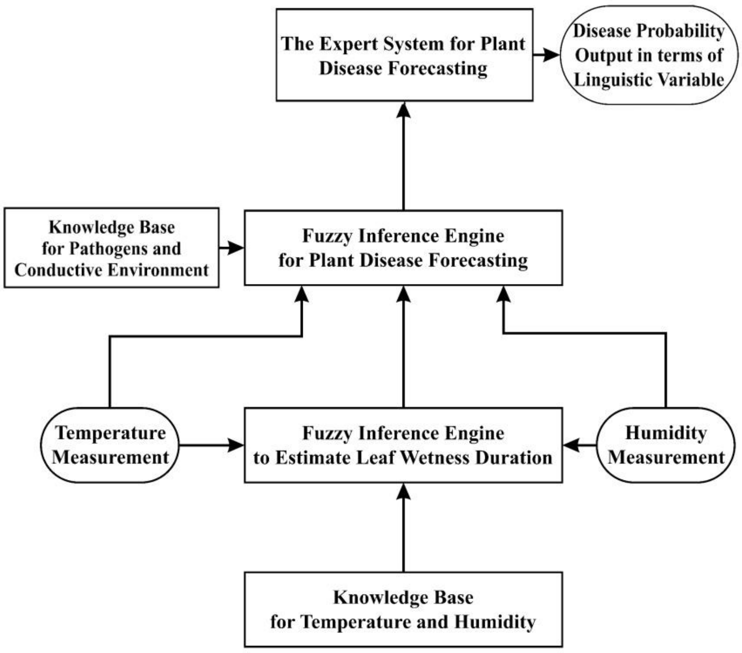

Figure 12. Diagrammatic representation of weather-based plant diseases forecasting system

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Challenges in implementation of AI in agricultural sector

Skill Requirement

A different level of skill set is required for AI usage in agriculture along with education and training at each level to operate these technologies properly (Teal and Rudnicky, 1992; Mundt and Connors, 1999). The utility of any ES lies on its success of execution. Usage of huge data requires the algorithm of searching, training and updating needs to be formulated for maximum speed and high accuracy (Misra et al., 2022). The gap between farmers, who usually do not study AI, and AI engineers, who do not possess agriculture-related ideas must be bridged for better AI penetration (Qazi et al., 2022).

Response Time and Accuracy

Crop behavior must be analyzed in lowest time interval with accurate information. Since a crop has a fixed season and responses will be very difficult to carry out if much time is wasted on analysis. Thus, accuracy and response time are important components of agriculture in this regard (Liu et al., 2021). The crop data can only be obtained once, annually or biannually when crop grows. Thus, it requires a lot of time to construct a robust ML model (Jha et al., 2019). The systems can be either lower in accuracy or response time, or even both. A delayed response by the system can affect a farmer's selection of work strategy. Selection of strategy is done by combining two factors such as difficulty to synchronize input system availability and accuracy level afforded. By an interplay amongst automatic performance, pacing, and monitoring we can achieve our objective of minimizing effort and maximizing accuracy (Teal and Rudnicky, 1992).

Durability

A technology deployed must be durable and long-lasting. Changing of AI Components, viz. sensors in short intervals are not feasible amongst poor farmers. In rural areas, these are internet-based systems have several restrictions upon their usage. The ideal scenario can be government coming forward with a cheap internet service-based device to work complementarily with the farmers' AI systems (Sarkar et al., 2022).

Cost

Majority of the farmers are not wealthy enough to afford and use these technologies due to the high initial installation cost (Awasthi, 2020). Companies can start renting their machinery for farmers' benefit (Eli-Chukwu, 2019). Maintenance of the sophisticated hardware is also a big issue as it gets added up with crop investment costs (Sharma, 2021). If maintenance cost is higher, then crop price will be higher than others, leading to crop wastage as small farmers cannot afford such costs (Eli-Chukwu, 2019).

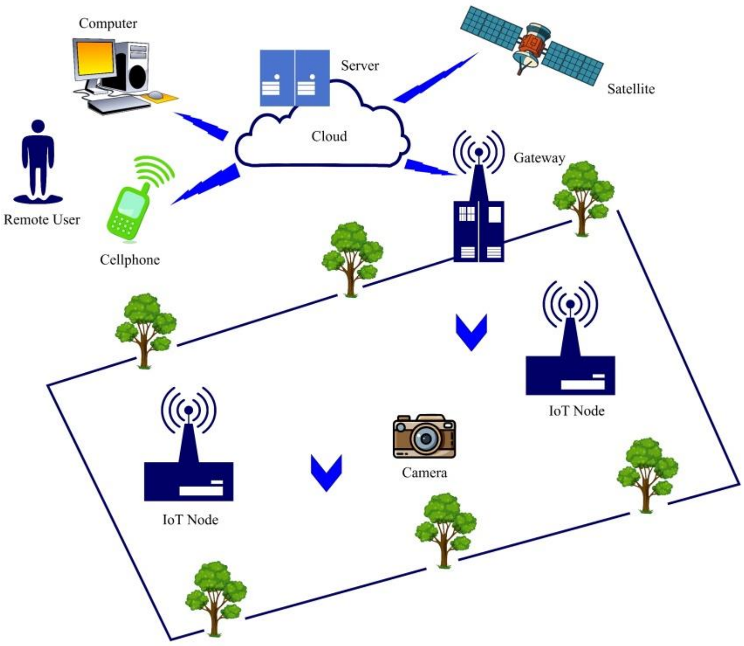

Figure 13. Typical plant life information monitoring system

Regular Updates

Regular updates of machine and software are required. With improvement in technology, farmers must modify their system with latest updates to enable access to fresh information with higher accuracy. Older versions of software do not work with certain systems (Sharma, 2021). Lack of flexibility in the subsystems have made interfacing of the subsystems into an integrated environment a potent challenge, even though progress has been made in implementation of AI techniques for independent tasks (Mowforth and Brakto, 1987).

Big Data Required

Input data volume also determines strength of an intelligent system (Sharma, 2021). Immense volume of data needs to be monitored (Fan et al., 2014). While filtering out the incoming data, it should continue to be responsive towards unexpected or important events (Marx, 2013). A field expert must possess high expertise of the system's task and the system's speed and accuracy should be improved using most relevant data. A multidisciplinary effort is required to develop ES coordinating with the producers who would utilize it (Rajotte et al., 1992).

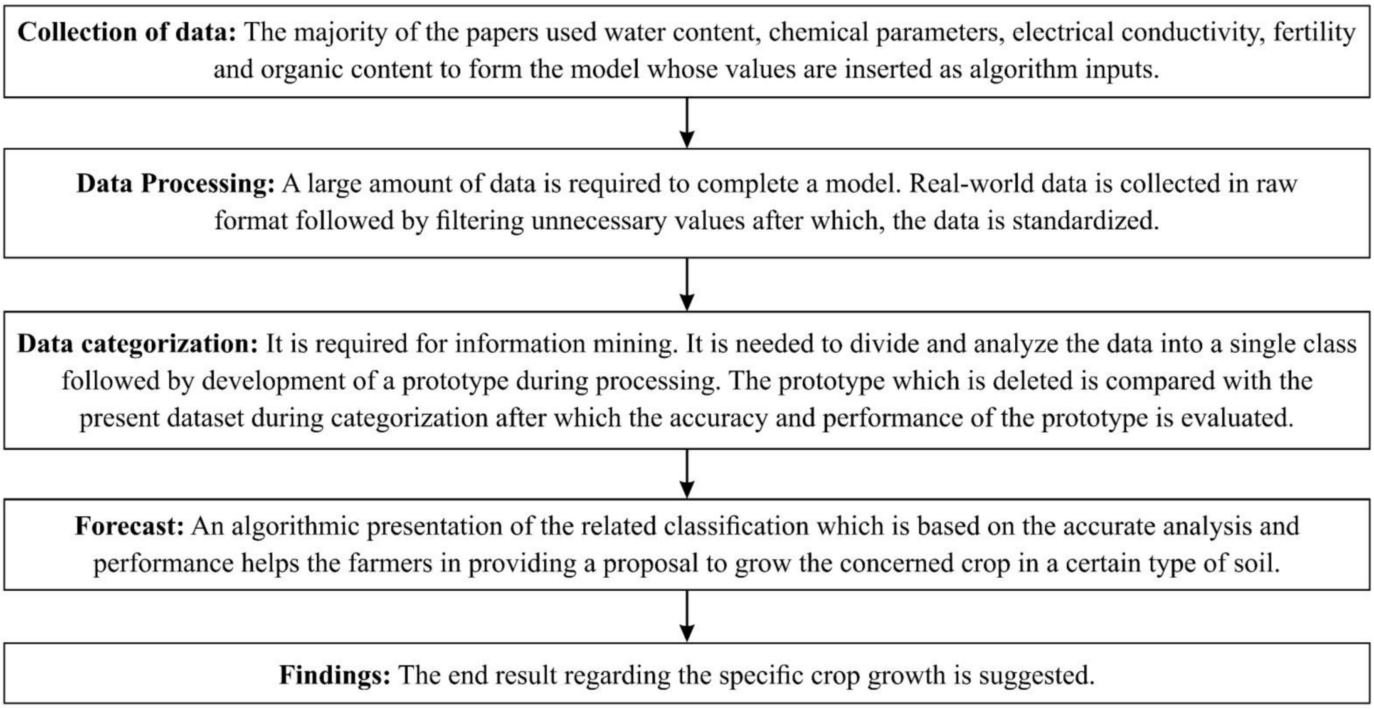

Figure 14. Crop yield prediction system

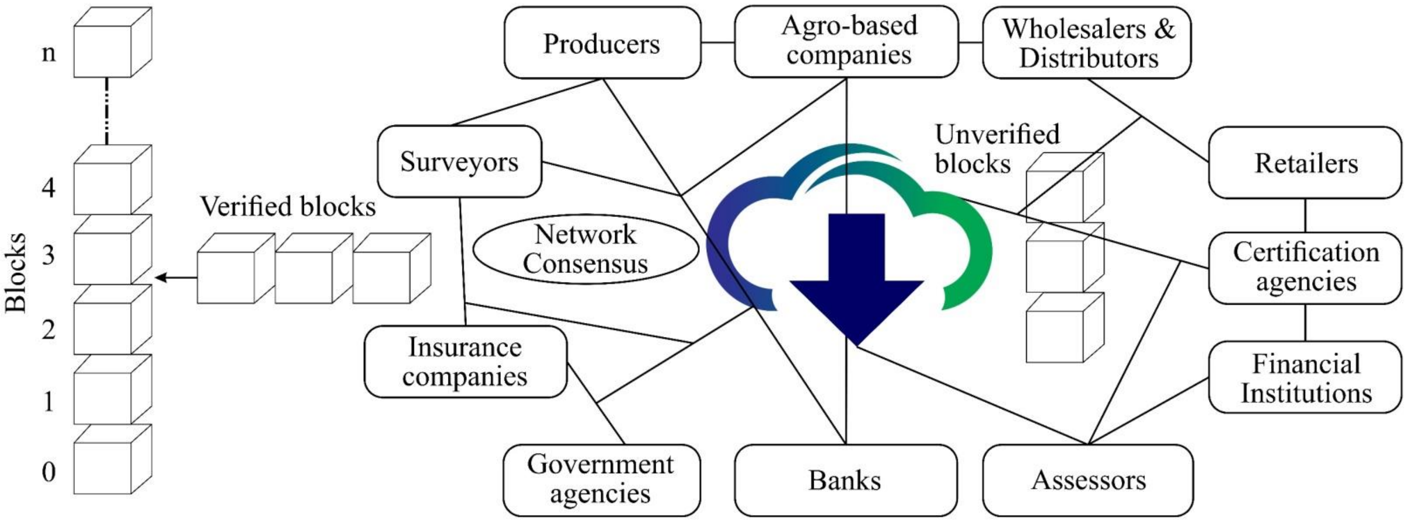

Figure 15. Use of block chain technology (a representative diagram) in agriculture supply chain

Future perspective and discussion:

Integration of Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) in agriculture holds great potential for revolutionizing the industry. The reviewed literature highlights the recent trends and challenges in implementing these technologies in agriculture. The adoption of these technologies can lead to increased productivity, reduced costs, and improved resource management. However, there are also several challenges that need to be addressed, such as data privacy and security concerns, technical barriers, and lack of awareness and training among farmers. Looking to the future, it is anticipated that there will be more significant investments in research and development in AI, ML, and IoT technologies in agriculture. As a result, the implementation of these technologies will become more widespread and accessible to farmers globally. This would not only increase efficiency and productivity but would also help address some of the challenges facing the agriculture industry, such as climate change and food insecurity. Additionally, the integration of AI, ML, and IoT in agriculture would lead to the development of more sophisticated predictive models and algorithms that can identify trends and patterns in data that were previously not possible. This would lead to better decision-making and more precise agricultural practices. Furthermore, with the increasing use of robotics and automation in agriculture, the potential for the development of autonomous systems that can perform tasks such as harvesting, planting, and fertilizing would be

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significantly improved. Overall, it is clear that the integration of AI, ML, and IoT technologies in agriculture holds immense potential for revolutionizing the industry. However, it is vital to recognize and address the challenges associated with these technologies' implementation to ensure their success and widespread adoption.

Conclusion

Predictive ability of AI and its accuracy will reduce farmers' concern about unpredictable weather patterns. Sensors can be installed to extract important agricultural data to enhance crop yield and productivity (by up to 30%) (Talaviya et al., 2020). Autonomous robots improve weeding efficiency and reduce pesticide usage. Crop monitoring and pesticide spraying can be done effectively using drones, without needing excess manpower. IoT is important in real-time data monitoring, mainly in IIS. The biggest challenge to farmers is crop damage by diseases and pest attack, which can be alleviated greatly by AI-enabled image recognition, drones for crop-monitoring and pest attack identification. Crop readiness identification and yield prediction help in prior analyzing and predicting harvest quality amount to be available for selling.

Despite large-scale research, the agriculture industry is plagued by problems. Agricultural production has tripled between 1960 and 2015, but mainly by ploughing more land. Almost 11% of total land area is used for agriculture. From managing pests to predicting crop suitability, AI can help in revolutionizing agricultural to win the challenge of feeding 9.8 billion people by 2050, in the face of climate change consequences (United Nations, 2017). According to the Food and Agriculture Organization (FAO) of the United Nations, overall food production should increase by around 70% between 2005-2050, and in developing countries, it should almost double (FAO, 2009). As per reports, farmers' yield and consequently, incomes are projected to rise by AI's usage and, huge global food and water wastage can be curtailed using appropriate algorithms, thus saving time and money. With respect to AI in farming, it is still at an early stage and to make use of its full potential, applications need to be more robust to collect and use contextual data efficiently, provide real-time decision making and, handle changes in external conditions (Slaughter et al., 2008). AI, ML and IoT can do wonders in agriculture through automation and replace traditional farming with precise cultivation for better crop yield to meet our growing needs.

Conflict of Interest

All authors declare that there exist no commercial or financial relationships that could, in any way, lead to a potential conflict of interest.

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