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Artificial intelligence in agriculture, applications, benefits and challenges: A review

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Abstract
Agriculture is the foundation of long-term economic growth and is necessary for structural transformation, though, may vary by countries. However, from sowing to harvest, it encounters numerous challenges. Insufficient chemical application, Pest and disease infestation, incorrect drainage and irrigation, weed management, yield forecast etc. are the key concerns. As a result, agricultural modernization is critical to addressing these. A range of solutions have been presented to handle current agricultural concerns, ranging from database building to selection help frameworks. In terms of accuracy and robustness, artificial intelligence-based architectures have been shown to be the best performers. Use of artificial intelligence systems will enhance crop yields while reducing the water use, pesticides and fertilizers. Artificial intelligence technology can facilitate to diminish the impact on natural ecosystems while also boosting worker safety, which will assist in keeping food prices low and ensuring increased food production with the growing population.

Keywords: Agriculture, artificial intelligence, data analytics, automation, management

1. Introduction

During the nineteenth century's industrial revolution, Human labour was replaced by machines. The advent of Artificial Intelligence-powered machines began with the advancement of information technology and the use of computers in the twentieth century. In the contemporary day, artificial intelligence is gradually but steadily replacing human labor. Artificial intelligence refers to the replication of human intelligence in computers that are programmed to think and act like humans, including learning and problem-solving. Artificial intelligence includes machine learning as a subset as shown in Fig. 1. Machine learning is a technique for detecting, comprehending, and analyzing patterns in data. Artificial Intelligence is one of the most significant areas of research in today's advanced technological world of computer science. Because of its quick technological developments and wide applicability in situations that can't be solved well by standard computing structures or humans, this technology is gaining traction rapidly (Rich and Knight, 1991) [1]. Farming is a high-priority field, with about 30.7 percent of the world's population dedicated to 2781 million hectares of agricultural land (Dutta, *et al.*, 2020) [2]. As a result, from sowing to harvest, farmers face several problems. Yield protection, insufficient chemical use, pest and disease infestation, inadequate irrigation and drainage, weed management, and other issues plague agriculture. Agriculture is a dynamic sector in which it is difficult to draw conclusions that may be used to provide a comprehensive explanation. Artificial Intelligence approaches have enabled us to grasp the intricate details of each situation and give the best solution for that unique problem. Various artificial intelligence techniques are progressively unravelling progressive appropriate complicated challenges. The first application of artificial intelligence in agriculture occurred in 1983 (Baker *et al.*, 1983) [3]. Many techniques, ranging from databases to decision support systems, have been proposed to address the current challenges in agriculture (Thorpe *et al.*, 1992) [4]. Among these elucidations, Artificial Intelligence-based solutions outperform the competition in terms of robustness and accuracy. Climate change, rising production costs, dwindling irrigation water supplies, and a decline in the farm workforce have all wreaked havoc on agriculture production systems during the previous few decades (Jung *et al.*, 2021) [5]. Furthermore, disrupt of supply systems and food production is threatened due to the COVID-19 pandemic (Outlaw *et al.*, 2020) [6]. Such variables jeopardize the environment's.

long-term viability, as well as the current and future food supply chains (Andersen *et al.,* 2018) [7]. To keep ahead of the constant climate change, significant inventions are always required (Hatfield *et al.,* 2014) [8]. The obvious issue here is how to harvest sufficient quantity of food for the ever-increasing population. The research scientists are constantly applying cutting-edge knowledge and discovering new ways to incorporate it into the agricultural system (Jung *et al.,* 2021) [9].

2. Types of artificial intelligence

2.1 Weak or Narrow Artificial intelligence

This type of artificial intelligence is always ready to do a difficult task efficiently. Within the field of computer science, slender artificial intelligence is the most frequent and currently available artificial intelligence. Narrow artificial intelligence cannot work outside of its field because it has only been trained for single task. Narrow artificial intelligence would fail in unanticipated ways if it is allowed to go. Siri from Apple is a good example of artificial intelligence, although it only has a limited set of capabilities functions (Millar, 2000) [10].

2.2 General Artificial intelligence

General artificial intelligence is a type of intelligence capable of completing any intellectual work as quickly as a person. The idea behind general Artificial Intelligence is to create a system that can become smarter and act like a person on its own. As generic artificial intelligence systems are still under investigation, developing such systems will take significantly more effort and time (Agrobot.es) [11].

2.3 Super Artificial intelligence

Super artificial intelligence could be defined as a level of machine intelligence that surpasses human intellect and can accomplish any task better than a person with psychological qualities. It's a result of artificial intelligence in general. Embracing its capability, embracing the power to assume, to offer reasons, to solve problems, to learn, to make judgments, plans, and to communicate on its own are some fundamental features of strong artificial intelligence. Super artificial intelligence is still just a concept in computer science. The real-world development or creation of such machines remains a challenging task. Large volumes of data sets are combined with rapid, recurring processing and clever algorithms to create artificial intelligence at its best. As a result, AI software may learn automatically from patterns in those massive data sets. Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are all words that are used interchangeably (Fig. 1), Machine learning, on the other hand, is a subset of AI that includes more advanced models techniques and that allow computers to learn from data, whereas deep learning is a subset of machine learning that employs multi-layered artificial neural networks to achieve high accuracy in tasks such as s language translation, speech recognition, and object detection.

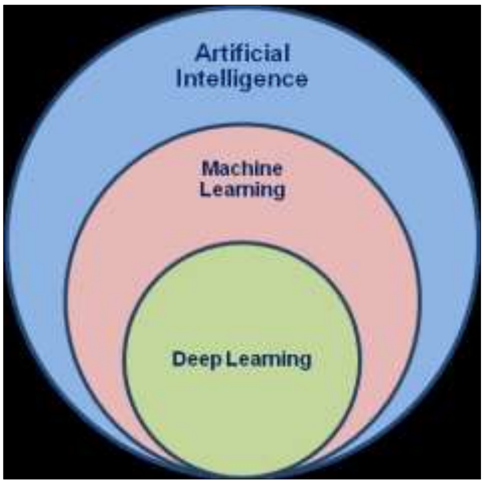

Fig 1: Artificial super intelligence

3. Need of artificial intelligence in agriculture

Artificial Intelligence (AI) can be used in a variety of fields, and it has the potential to change the way we think about farming. AI-powered solutions will not only allow farmers to do more with less, but it will also help farmers to obtain more yield, as per the growing exploitation of high tech machineries in general life, such as hospitals, education and even governance. Agriculture is the most important of all, with artificial intelligence focusing on ease of use and efficiency. Artificial Intelligence should be used to improve agricultural areas at minimal cost and with ease of processing. Various agricultural difficulties are controlled in a short period of time using Artificial Intelligence. Artificial intelligence uses tactics such as improving harvesting quality and introducing indoor farming to increase agricultural output rates. Artificial Intelligence has a wide range of uses that will benefit farmers, including Analyze farm data by enhancing crop quality and accuracy; target weeds may be detected with the use of Artificial Intelligence sensors, and it can also detect diseases in plants, pests, and so on. Artificial Intelligence addresses labour issues. As we all know, in this field less people are entering, thus farmers are experiencing a labour shortage and a lack of personnel. To this the solution to is agriculture bots who are supposed to work alongside farmers. This bot harvests crops in greater quantity and at a faster rate. In Blue River Technology, there are agricultural robots that are used to control weeds. Harvest CROO Robotics, which leads to agricultural harvesting, has developed a robot for farmers to pick and pack crops. AI also performs diagnostic analysis, such as satellites for weather prediction and crop sustainability, which would be extremely beneficial to farmers who had a prior understanding of weather changes. Driverless Tractors are one of the AI techniques, and because they run without the presence of a human inside the tractor, they will save farmers a lot of time and effort. One of the most intriguing technologies to mention is Farmer's Alexa, which will be able to speak with farmers in the same way as chatbots do to solve difficult problems. Aerial spraying is five times faster with drones than with regular technology, which benefits farmers. Agri-E Calculator is one of the smart apps launched in AI for farming. It assists farmers in selecting good and inexpensive crops and estimates their price. There are many more programmes in the market, but the problem is that they are expensive and difficult to use. In basic terms, the application of AI in agriculture allows farmers all over the world to operate more efficiently.

4. Applications of artificial intelligence (AI) in agriculture

4.1 Crop management

Crop management begins with the sowing of seeds and continues with growth monitoring, harvesting, and crop storage and distribution. It can be characterized as practices that promote agricultural product growth and yield. Crop production will undoubtedly grow as a result of a thorough understanding of the many crop classes and their timing in relation to the thriving soil type. For a variety of reasons, agricultural harvesting is an appealing sector for automation. Harvesters, for example, have been built to operate at higher rates than the current standard of 4 miles per hour, but humans have difficulty controlling the machines correctly at these speeds for long periods of time. Furthermore, the technical barriers to automation are less daunting than in many other areas: harvesting equipment operate at a moderate speed, obstructions are rare, the environment is well-structured, and the work is extremely repetitious. Automation of agricultural harvesting equipment appears to be both economically and technically feasible in the near future. Demeter is a computer-assisted speed rowing machine featuring a global positioning system and two video cameras for navigation (Fig. 2). Demeter can plan and carry out harvesting procedures for an entire field by cutting crop rows, turning to cut succeeding rows, repositioning itself in the field, and detecting unforeseen barriers. The Demeter system automatically harvested 40 hectares (100 acres) of crop in a continuous run in August 1997 (excluding stops for refueling). The Demeter system harvested around 48.5 hectares (120 acres) of crop in 1998, cutting over a variety of fields (Pilarski *et al.*, 2002) [12]. Individual software and hardware components of the robot, such as the autonomous vehicle, the end-effector, the two computer vision systems for detection the manipulator and 3D imaging of the fruit and the environment, and a control scheme that generates collision-free motions for the manipulator during the period of harvesting, are all included in the use of AI in cucumber harvesting. The robot was capable to pick more than 80 percent of the cucumbers without any human intervention at an average speed of 45 seconds per cucumber. Vision

Fig 2: The Demeter automated harvester (Ollis and Stentz 1997) [13]

system spotted more than 95% of the cucumbers in the greenhouse. The technology was also capable to find out the cucumbers' maturity and weight. It was feasible to trace the cucumber in the 3D working environment using 3D vision technology. Furthermore, the thermal cutting technique effectively inhibited virus transmission from one plant to the next (Henten *et al.*, 2002) [14].

4.2 Soil management

Soil management is a crucial aspect of agricultural operations. Crop production will be improved and soil resources will be conserved with a thorough understanding of diverse soil types and conditions. It is the application of operations, techniques, and treatments to improve the performance of soils. Inadequate nitrogen (N) management has been blamed for rising nitrate levels in groundwater. Both N fertilization and irrigation application rates, timing, and procedures are significant management strategies that influence and control the fate and behavior of N in soil plant systems. Multiple applications of small amounts of fertilizer (e.g. split application) usually improve plant uptake and reduce potential nitrate leaching while raising expenses. Precision N management necessitates a model that evaluates so many options that conventional N models are pushed past their limits. Li and Yost (2000) [15] conducted research with the goal of building and testing a model that seeks for optimal nitrogen management to: (i) decrease nitrate leaching; (ii) maximize production; and (iii) maximize profits. Management-oriented modelling (MOM) minimizes nitrate leaching, according to the results of the experiment. It consists of a set of generated plausible management alternatives, a simulator that evaluates each alternative, and an evaluator that determines which alternative meets the user-weighted multiple criteria (Fig. 3). MOM employs "hill climbing" as a strategic search approach and "best-first" as a tactical search method to identify the shortest path between start nodes and goals.

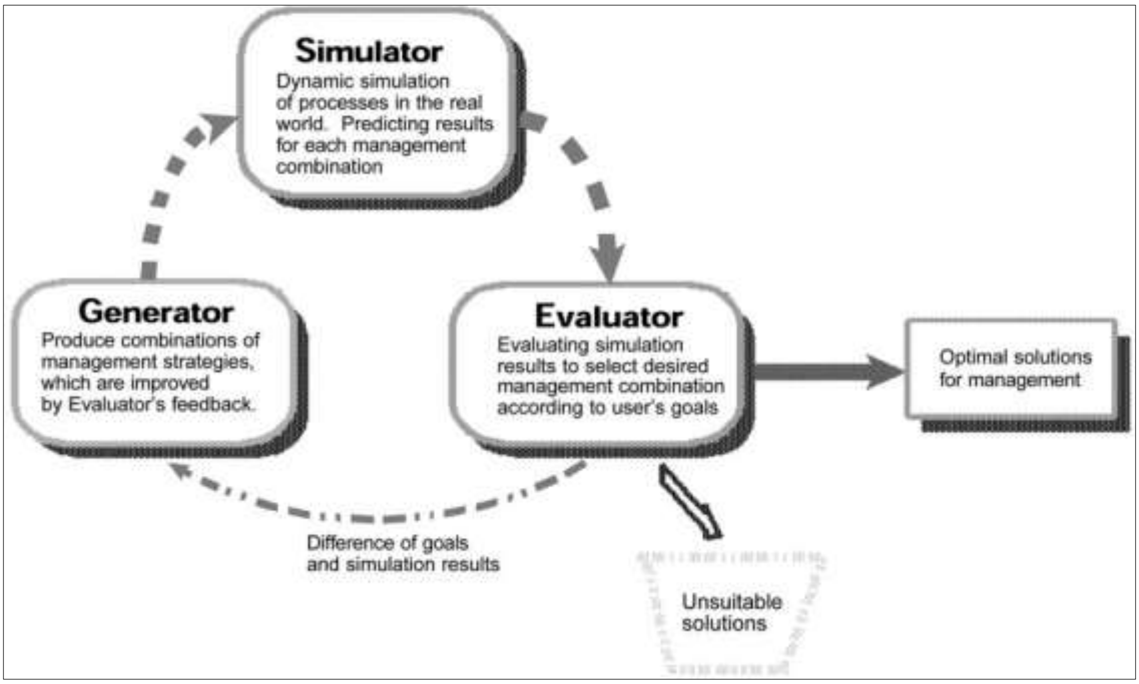

Fig3: Management-oriented-modeling structure (Li and Yost, 2000) [15]

Based on features gathered from current coarse resolution soil maps paired with hydrographic parameters produced from a digital elevation model (DEM), an artificial neural network (ANN) model predicts soil texture (sand, clay, and silt concentrations). Zhao *et al.* (2009) [16] conducted an experiment with the goal of developing an artificial neural network (ANN) model to predict soil texture (sand, clay, and silt contents) using soil attributes derived from existing coarse resolution soil maps and hydrographic parameters derived from a digital elevation model (DEM). A back-propagation ANN model was built in this work based on the schematic diagram in Fig. 4, the clay and sand contents. The Levenberg–Marquardt optimization technique outperformed the commonly used training method based on the robust back-propagation algorithm, according to the findings. The trained ANN model was put to the test on an experimental farm in southeastern New Brunswick, roughly 180 kilometers from the Black Brook Watershed, where it was calibrated for the first time. If the relative range of input parameters was similar to the region where the model was calibrated, the ANN model may be used in the areas where it was calibrated (for interpolations) or in other areas with sufficient training.

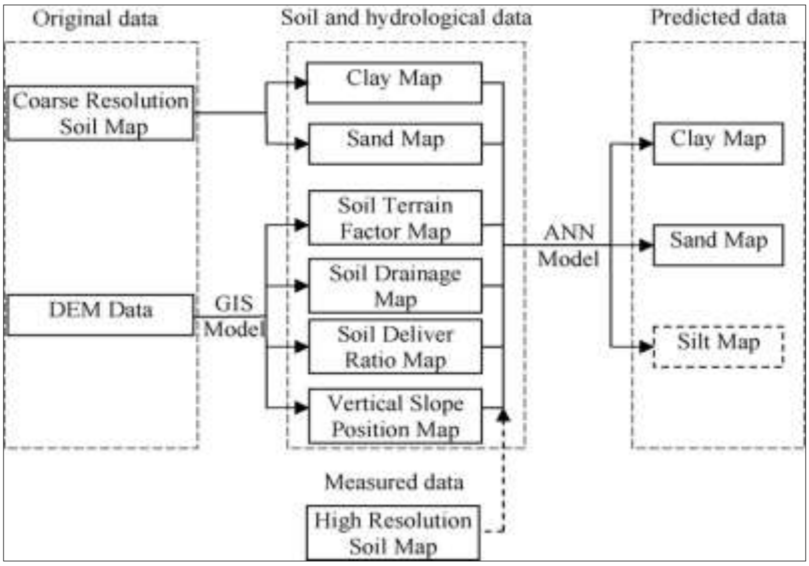

Fig 4: Structure and flow of the artificial neural network model for predicting high-resolution soil texture maps (Zhao *et al.*, in 2009) [16].

4.3 Predictive analytics

Forecasts are becoming more crucial for crop yields as a result of climate change, as farmers can no longer rely solely on conventional knowledge. Farmers may be able to choose the best days for planting or harvesting if forecasts are more precise. Reinforcement learning is used in AI approaches to learn from prior predictions and results. Data is fed into an algorithm that employs deep learning techniques to learn and generate predictions based on historical data to aid with weather forecasting. Forecasting the weather Artificial intelligence in agriculture, combined with satellite data, can be used to forecast meteorological conditions, examine crop sustainability, and assess farms for pests and illnesses. In farming, artificial intelligence (AI) can give billions of data points, such as temperature, precipitation, wind speed, and solar radiation. Efficiency in the supply chain Farmers would be able to evaluate market demand for their products, as well as client preferences and seasonality, using AI. Farmers will be able to earn a better return on their produce as a result of this. AI-powered supply chains, on the other hand, can help companies boost their profits by lowering the costs of managing distributed operations and a slew of middlemen. Smaller farmers will be able to manage their path to market more efficiently and reap benefits as a result of this smart routing. They'd also be able to bring their perishable items to market faster without the need for middlemen, resulting in less wastage and losses.

4.4 Insect Pest and Disease Management

Disease control is required for an optimal yield in agricultural harvest. Plant and animal illnesses are a key stumbling block to increasing productivity. Genetics, soil type, rain, dry weather, wind, temperature, and other elements all have a role in the incubation of these illnesses that target plants and animals. Managing the consequences of these factors, as well as the unpredictability of some illnesses' causal influences, is a major issue, especially in large-scale farming. A farmer should use an integrated disease control and management approach that incorporates physical, chemical, and biological measures to successfully control illnesses and minimise losses. The explanation block (EB) provides a clear picture of the reasoning followed by the expert system's kernel. Balleda *et al.* (2014) [17] investigated Agpest Expert. Agpest is a very effective rule-based expert system for pest and disease prevention in rice and wheat crops. The system's Explanation Block (EB) provides an explanation for a specific decision made by the system. The explanation block provides a clear perspective of the reasoning that is followed by the expert system's kernel. After multiple experiments and a real-time simulation environment, it was discovered that the AgPest's advice or choice is consistent, accurate, and complete. The Expert System for Diagnosing Oyster Mushroom Diseases was created utilising a rule-based approach to assist in the faster and more convenient recognition and diagnosis of oyster mushroom disease treatment via an online system (Munirah et *al.*, 2013) [18]. This system uses an online expert system to help users diagnose diseases caused by mould, bacteria, viruses, insects, and other problems that mushroom farm owners encounter. Furthermore, the technology provides users with recommendations or remedies for specific mushroom diseases in a faster time frame. The user will respond to questions based on the status and symptoms of the mushroom. It will then assist in the detection of linked disorders as well as therapy recommendations. A rule based and forward chaining inference engine has been employed for the creation of the system. This technology assists and allows users to diagnose mushroom illnesses using an internet approach and provides beneficial recommendations.

4.5 Weed Management

Weed regularly lowers predicted profit and yield for farmers (Harker, 2001) [19]. If weed infestations are not controlled, a survey confirms a 50% drop in output for dry beans and corn crops (Harker, 2001) [19]. Weed competition has resulted in a 48 percent reduction in wheat yield (Fahad *et al.*, 2015) [20]. A research on the influence of weed on soybean yields found that yields were reduced by from 8% to 55%. (Datta *et al.*, 2017) [21]. Over the last few decades, rigorous herbicide control has been used to decrease the impact on crops. Crop losses are still higher even with this management approach. As a result, a more professional weed management strategy is required to compensate for this loss. A system can divide an image, compute and convert to binary the vegetation indexes, recognise crop rows, tune parameters, and develop a classification model using unmanned aerial vehicle (UAV) imagery. Because crops are typically structured in rows, using a crop row recognition method aids in accurately separating weed and crop pixels, which is a common problem due to the spectral similarity of both (Ortiz *et al.*, 2016) [22] Online weed detection employing digital image analysis acquired by a UAV (drone), computer-based decision making, and GPS-controlled patch spraying can be used to control weeds in sugar beet, maize, winter wheat, and winter barley (Gerhards and Christensen, 2003) [23]. Digital image analysis methods were utilised by Chapron *et al.* (1999) [24] to identify plant species based on typical shape, colour, and texture attributes for each individual object in the image. These systems might identify weeds and crops in real time and apply selective pesticides to specific crops on a site-by-site basis.

4.5.1 Real-time weed identification using multispectral image analysis

Three digital bi-spectral cameras were put in front of the sprayer for autonomous weed detection (Gerhards *et al.*, 2002) [25] Each bi-spectral camera captured two images in two different light spectra at the same time (Fig. 5). Using a cold-light mirror, light reflected by the weeds was split into near-infrared and visible light. In front of the CCD cameras, filters were installed. One image was captured in the near-infrared spectrum (770-1150 nm), while the other was captured in the red spectrum (550–570 nm). In realtime, the pictures from both cameras were normalised and removed (NIR-VIS). The Danish Institute of Agricultural Sciences has developed a Decision Algorithm for Patch Spraying (DAPS) broad-leaved weeds in cereals (Christensen *et al.*, 1999) [26]. The most economical herbicide dose is calculated using competitiveness of weed species, weed density, crop and pesticide pricing, and dose–response parameters. A treatment map was created using kriging and GIS. When compared to whole-field spraying with PC-Plant Protection prescription, a preliminary trial with sitespecific weed control using DAPS reduced herbicide input by 41%. (Heisel *et al.*, 1997) [27].

4.5.2 Site-specific weed control

Based on geo-referenced maps of weed seedling distribution, certain experiments have been undertaken to apply post-emergence herbicides in maize, winter barley, winter wheat and sugarbeet (Gerhards *et al.*, 1997 [28], Tian *et al.*, 1999 [29], Timmermann *et al.*, 2003 [30]). Weed distribution maps for grass weeds, Galium aparine L., and other broad-leaved species were drawn in winter barley and winter wheat and an economic weed threshold model (Gerhards & Kuhbauch, 1993) [31] was used to identify areas where herbicide use was warranted in all three maps. All three binary maps were overlayed in one weed treatment map using a GIS. Herbicide use was lowered by 60% for herbicides against broad-leaved weeds and 90% for herbicides against grass weeds in a four-year research using map-based strategy (Timmermann *et al.*, 2003) [30]. Weed threshold values in sugarbeet and maize were lower than in winter grains (Williams *et al.*, 2000) [32]. As a result, the sprayer was only shut off in areas where there were no or very few weeds. By adapting the herbicide dose to the geographical heterogeneity of weed species composition and weed density, the herbicide rate in sugarbeet and maize was lowered compared to standard broadcast applications (Williams *et al.*, 2000) [32]. In a four-year trial, average savings for grass weed pesticides were 78 percent in maize and 36 percent in sugarbeet. Herbicides against broad-leaved weeds were saved 11 percent in maize and 41% in sugarbeet.

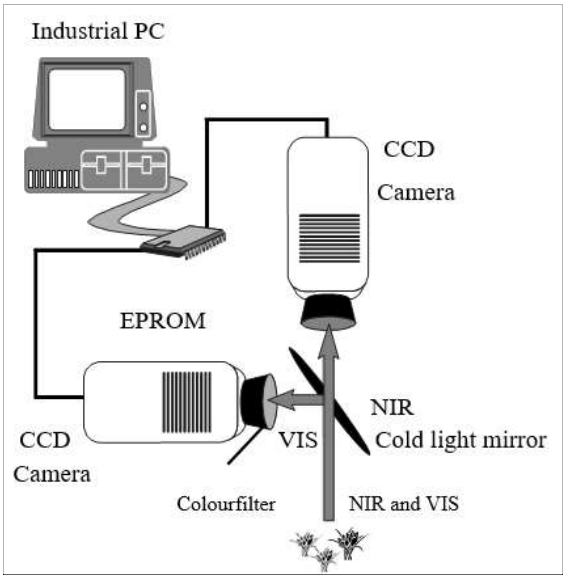

Fig 5: Diagram of the bi-spectral camera system (Gerhards *et al.*, 2002) [25]

5. Benefits of adopting artificial intelligence in agriculture

In agriculture, artificial intelligence aids farmers in comprehending and analysing data such as solar radiation, wind speed, temperature and precipitation. Farmers are able to compare the data analytics findings to previous values.

- Artificial intelligence (AI) is allowing for more efficient delivery, collection, and sale of fundamental yields.
- AI execution focuses on identifying insufficient yields and enhancing the potential for sound harvesting.
- The advancement of Artificial Intelligence innovation has bolstered agro-based businesses' ability to operate more efficiently.
- AI is being used in applications such as mechanised machine alterations for climate deciding, virus detection, and vermin detection (Kawamura *et al.*, 2019) [33].
- Artificial intelligence can boost crop yields across the board. Currently, a number of tech companies are investing in agriculture counts.
- Artificial intelligence (AI) systems may be able to address issues that ranchers encounter, including as climate change, irritations, and weeds that reduce production.

6. Challenges in adopting artificial intelligence in agriculture

Because they can provide site-specific, integrated, and interpreted guidance, expert systems are useful tools for agricultural management. Expert systems for agriculture, on the other hand, are a relatively new discovery, and their usage in commercial agriculture is still uncommon (Rajotte *et al.*, 1992) [34]. Although AI has improved the agricultural sector significantly, it still has a lower-than-average influence on agricultural activities when compared to its potential and impacts in other industries. There is still work to be done to improve agricultural activities using AI because it has numerous limitations.

A. Response Time and Accuracy

An intelligent or expert system's ability to execute tasks accurately in a short amount of time is a key feature. The majority of the systems are lacking in either response time or accuracy, or both. A user's task strategy selection is influenced by a system delay. The cost function combining two factors: I the effort necessary to synchronise input system availability, and (ii) the accuracy level afforded, is speculated to be the basis for strategy selection. People who want to save time and effort can use one of three strategies: automatic performance, pacing, or monitoring (Teal and Rudnicky, 1992) [35].

B. Big data required

The volume of input data is also used to determine an intelligent agent's strength. A real-time AI system must keep track of a massive amount of data. Much of the incoming data must be filtered away by the system. It must, nevertheless, stay sensitive to significant or unexpected developments (Washington and Roth, 1989) [36]. A field expert must have a thorough understanding of the system's task, and only the most relevant data should be used to improve the system's speed and accuracy. The creation of an agricultural expert system necessitates the collaboration of experts from various sectors of agriculture, as well as the involvement of the producers who will utilise it (Rajotte *et al.*, 1992) [34].

C. Method of implementation

Any expert system's beauty is in its execution approach. Because it makes use of enormous data, the mechanism for digging for information and training should be well-defined in terms of speed and accuracy.

D. High data cost

Because most AI systems are internet-based, their application is limited, especially in rural or isolated areas. The government can assist farms by developing a web service that allows devices with cheaper tariffs to work with AI systems for farmers. Farmers will benefit greatly from a form of "how to use" orientation (training and re-training).

7. Conclusion

Artificial intelligence technologies will assist ranchers in examining land, soil, harvest health, and other factors, saving time and allowing ranchers to generate the optimum output in each season. AI-based projections make it possible to recommend the best insecticides, crops, and locations at the right moment, before a large-scale infection occurs. With so much open space in agriculture for the disruption of programmed responsive frameworks, there are tremendous opportunities for agribusiness to use emerging innovation of catboats to assist ranchers with all of their inquiries and to offer significant guidance and suggestions to their specific homestead related issues. AI agents can be used to analyse the history of a field and provide a variety of useful predictions.

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