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The Prospect of Artificial Intelligence (AI) in Precision Agriculture for Farming Systems Productivity in Sub-Tropical India: A Review

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Agriculture is becoming more integrated in the agro-food chain and the global market, while environmental, food safety and quality are also increasingly impacting on the sector. It is facing with new challenges to meet growing demands for food, to be internationally competitive and to produce agricultural products of high quality. To cope with these challenges, Agriculture requires a continuous and sustainable increase in productivity and efficiency on all levels of agricultural production, while resources like water, energy, fertilizers etc. need to be used carefully and efficiently in order to protect and maintain the soil quality and environment. Consequently, Agriculture needs help in handling the complexity, uncertainty and fuzziness inherent in this domain. It requires new solutions for all aspects of agricultural farming, including precision farming and optimized resource application. Artificial Intelligence (AI) technology helps various industries to improve production and productivity. In agriculture, AI also allows farmers to increase their

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productivity and reduce negative environmental impacts. AI is changing the way our food is processed, where emissions from the agricultural sector have decreased by 20%. Together with precision agriculture (PA) and other emerging technologies, artificial intelligence (AI) can play a key role in modernizing agricultural practices and achieving the goal of improving the productivity of alternative arable cropping systems. In offering progressive change with advanced approaches, AI's future in agriculture is well ahead. The aim of this paper is to review various agricultural intelligence applications and to reduce the use of colossal amounts of chemicals with the aid of these technologies, resulting in reduced spending, improved soil fertility and increased productivity. With AI tools and machine learning, farmers can improve yields, protect their crops and have a much more reliable source of food.

Keywords: Precision agriculture; smart farming; crop monitoring; water management; soil management.

1. INTRODUCTION

In current and future climate scenarios the resilience and productivity of agricultural systems will be increasingly jeopardized [1]. Furthermore, population growth trends, expected to reach 8.7 billion by 2030 and 9.7 billion by 2050 will further strain food production systems worldwide, which so far have not been able to keep pace [2]. Currently, about 37.7 percent of the total land area is used for the cultivation of crops. Agriculture is significant, from generating jobs to contributing to national income. It contributes a large portion to the nation's economic growth and also plays an important role in the country's economy. Increased agriculture has resulted in a substantial rise in the rural community's per capita income. Therefore, it would be fair and fitting to put greater focus on the agricultural sector. The agricultural sector accounts for 18 percent of GDP in India and provides 50 percent of the country's population with jobs. Progress in the agricultural sector would fuel rural development, contributing further to rural transformation and ultimately to systemic change [3,4].

Within this changing context, crops face a threefold obstacle: management-derived challenges as well as increased pressure from abiotic and biotic stressors. Thus, the application of all available advanced technologies towards managing crop variability and maintaining or improving yields and reducing negative impacts on environmental quality, namely advancements in precision agriculture [5] is central to approaching these issues. There has been a drastic shift in many industries across the globe with the advent of technology [6]. Surprisingly, agriculture has seen traction for the advancement and commercialization of agricul tural technology, despite being the least digitised. In everyday life, artificial intelligence (AI) has started to play a major role, expanding our perceptions and ability to alter the world around us [7,8,9]. The labour force, which was limited to a small manufacturing field, is now contributing to various industries with these new technologies. As new scientific fields have emerged, agri-technology and precision farming, now also known as digital agriculture, use data-driven approaches to drive agricultural production while minimising its effect on the environment. A number of different sensors provide the data produced in modern agricultural operations, enabling a better understanding of the operating environment and the process itself, leading to more detailed and faster decision-making.

In the agricultural sector, Artificial Intelligence (AI) is an emerging technology. AI-based equipment and machinery took the agricultural system today to a new level. This technology has increased crop production and enhanced tracking, harvesting, processing and marketing in real time (Yanh et al., 2007). In the agro-based market, the new developments for automated systems using agricultural robots and drones have made a considerable contribution. Different hi-tech computer-based systems are designed to recognise various important parameters such as weed detection, crop quality and yield detection and many other techniques [10]. This review paper covers the automated irrigation, weeding and spraying technologies used by farmers to increase production and decrease the workload. Hemalatha and Sujatha [11] placed temperature and moisture sensors together to close the loop holes of the vehicle predictions. The robots used in sensing were located by GPS modules and the position of these robots was tracked using Google maps. The information from the robots was obtained with the aid of the Zigbee wireless protocol. The new automated weeding techniques are discussed, followed by the types of sprayers used on UAVs, and the deployment of drones for the purpose of spraying in the fields. In addition, talking about drones, yield mapping and monitoring is built starting with an overview of the yield mapping processes, followed by software programming and briefing on the measurement and calibration process, and finally the processing of these yield maps is illuminated.

2. METHODOLOGY

The systematic literature review related to the topic concerned, were collected and studied for gathering the concepts and research findings in support of this study.

2.1 The Prospects of AI in Indian Agricultural Ecosystem

The major sub-areas of AI with immense potential for solving a complex problem include natural language processing (NLP), robotic technology, maschine training (ML), automatic reasoning, information representation, computer vision, speaking comprehension, automated interpretation, virtual reality, Augmented Facts, IoT (Internet of Things), cloud computing, statistical computing, deep learning, etc. AI-based technologies help to increase productivity in all fields and also manage the challenges faced by different levels, including the different fields in the agricultural sector, such as crop yield, irrigation, crop tracking, weeding, planting [12]. In order to provide a highly valued application of AI in the sector mentioned, agricultural robots are created. The agricultural sector is facing a crisis with the global population soaring, but AI has the ability to provide a much-needed solution. Technological solutions based on AI have allowed farmers to produce more production with less input and even improve output quality, also ensuring faster market entry for the crops produced. An average of 4.1 million data points are expected to be produced by the average farm every day by 2050. In agriculture, AI machines have great potential to provide farmers with information on soil quality, when to plant, where to spray herbicides, and where to anticipate insect infestations. Therefore, if AI systems were able to advise farmers on best practises, India could see a revolution in agriculture. However, with factors such as capacity expansion and cost reduction in mind, such a futuristic scenario has a daunting challenge of scaling it up to encompass the entire value chain.

Agriculture would definitely benefit greatly from AI applications, for sure. AI can be used to build intelligent systems that are embedded in computers that can run with greater precision and speed than humans and be sensitive like humans at the same time. AI can be the great enabler of precision farming along with the Internet of Things (IoT) and Sensor Technology. In the large scale implementation of Climate Smart Agriculture, AI can also play a critical role along with remote sensing technology. Some of the AI techniques, such as Mobile-based Recommender Systems and Expert Systems, can dramatically increase the rate of adoption of agricultural technologies such as high yielding or disease-resistant varieties, thus helping to increase the income of farmers. The paradigm shift from location-based advisory services to customised and context-specific advisory for the millions of farmers in our country can also be enabled by these AI techniques.

Precision farming area where we can take advantage of AI and help farmers optimise their space, to be more specific about crop types, weather patterns, and when and where we should go to raise crops. In agriculture, the best thing AI can do is to escape drudgery and tedium from many agricultural operations so that we can put our time and resources into much better ways of seeking a variety of innovative AI technologies to exceed human capabilities.

2.2 Vocational Skills

Panpatte [13] revealed that artificial intelligence enables farmers to collect large quantities of government and public website data, analyse all of it, and provide farmers with solutions to many ambiguous problems, as well as providing us with a smarter way of irrigating, resulting in higher farmers' yields. In the near future, farming will be a combination of technical as well as biological abilities due to artificial intelligence, which will not only act as a better outcome for all farmers in terms of efficiency, but also reduce their losses and workloads. Agricultural AI can be used to automate multiple procedures, reduce risks, and provide farmers with reasonably simple and productive farming.

Manivannan and Priyadharshini [14] also found that robotics has played a significant role in the development and management of agriculture.

The researchers have now begun to emphasise technologies for the design of autonomous agricultural instruments because productivity was lacking in traditional farming machinery. In this field, the room for robotic technology has significantly improved efficiency [15]. The robots autonomously carry out various agricultural operations, such as weeding, irrigation, farm guarding for efficient reporting, ensuring that adverse environmental conditions do not impact production, improving accuracy, and handling individual plants in various unfamiliar ways.

Griepentrog et al. [16] noted that Robotics and Autonomous Systems (RAS) replaced the laser weeding technology with the manual weeding procedure, where a mobile centred infra-red light disrupts the cells of the weeds, computer-controlled this beam. Automated irrigation systems were also developed for the efficient use of water. Automatic irrigation scheduling strategies were replaced by manual irrigation that was based on soil water measure.

2.3 Yield Prediction

For yield mapping, yield estimation, matching crop supply with demand, and crop management to improve productivity, yield prediction, one of the most important topics in precision agriculture, is of high importance. For a more precise prediction, the established method used satellite imagery and obtained crop growth characteristics fused with soil data. A method for detecting tomatoes based on EM and remotely sensed red green blue (RGB) images captured by an unmanned aerial vehicle (UAV) was proposed by Senthilnath et al. [17]. Su et al. [18] developed a technique based on SVM and basic geographic information obtained from weather stations in China for the rice production process prediction. Finally, another study proposed a generalised approach for forecasting agricultural yields [19]. The method is based on the application of ensemble neural networks (ENN) on agronomic data generated for a long period (1997-2014). The study addresses regional forecasts based on helping farmers to avoid market supply and demand imbalances induced or accelerated by crop quality.

2.4 Weed Detection

Another critical issue in agriculture is weed identification and control. Many farmers refer to weeds as the most significant threat to the production of crops. For sustainable agriculture, accurate identification of weeds is of high importance, as weeds are difficult to identify and discriminate against crops. Again, in conjunction with sensors, ML algorithms can lead to precise detection and discrimination of low-cost weeds without environmental concerns and side effects. ML for weed detection can allow instruments and robots to be established to kill weeds, minimising the need for herbicides.

Pantazi et al. [20] also found that a new approach for the identification of Silybum marianum, a weed that is difficult to eradicate and causes significant losses in crop yield, is based on counter propagation (CP)-ANN and multispectral images taken by unmanned aircraft systems (UAS). In the second research, Pantazi et al. [21] developed a new technique for crop and weed species identification based on ML techniques and hyperspectral imaging. More specifically, the authors built an active learning method to recognise maize (Zea mays) as a crop plant species and as weed species, Ranunculus repens, Cirsium arvense, Sinapis arvensis, Stellaria media, Tarraxacum officinale, Poa annua, Polygonum persicaria, Urtica dioica, Oxalis europaea, and Medicago lupulina. Precise identification and discrimination of these species for economic and environmental reasons was the main objective.

Hagras et al. [22] have shown that autonomous mobile robots are also instruments used for various tasks in precision agriculture, as shown in (Fig. 1). Most autonomous robots have sensors for input information which is then processed by the control unit. The robot control system may be based on fuzzy logic. Robots can be used for inspection and treatment of plants by inbuilt gripper systems and eye-hand systems [23].

Waheed et al. [24] investigated the potential of hyperspectral remote sensing data to provide better crop management information. Hyperspectral Image processing can be used for all kinds of new and efficient agriculture purposes [25] such as leaf nitrogen accumulation, nitrogen deficiency, and invasive weed species.

2.5 Maximize the Output

Ferguson et al. [26] concluded that the optimum production standard for all plants is set by variety selection and seed quality. Emerging technologies have led to the best variety of crops and have also increased the option of hybrid seed choices that are best suited to the needs of farmers. By understanding how the seeds respond to different weather conditions, different soil types, it has been implemented. The chances of plant diseases are lowered by gathering this knowledge. We are now able to meet industry dynamics, annual results and customer needs, so farmers are able to optimise the return on crops effectively.

Aqeel-ur-Rehman et al. [27] reviewed WSN technology and their applications in different aspects of agriculture, the need of wireless sensors in agriculture and reported existing system frameworks in the agriculture domain. Keshtgari and Deljoo [28] used Wireless Sensor Networks (WSNs) for precision agriculture in 2011. WSN are usually used for collecting, storing and sharing sensed data. The outcome was a drastic reduction in cost and improved quality agricultural production and precision irrigation on combining applications of precision agriculture and WSN. Hakkim et al. [29], concluded that an increase economic returns as well as reduce the energy input and environmental impacts of agriculture through precision farming. Tools and equipment used were Global Positioning System (GPS), sensor technologies, geographic information system (GIS), grid soil sampling and variable- rate fertilizer (VRT) application, crop management, soil and plant sensors, rate controllers, precision irrigation and in pressurized systems, software, yield monitor and precision farming on arable land, precision farming within the fruits, vegetables and viticulture sectors.

A device comprising five sensors, i.e. ultrasonic distance sensors, thermal infrared radiometers, NDVI sensors, portable spectrometers, and RGB web cameras for high-throughput phenotyping in plant breeding was shown by Bai et al. [30]. These multiple sensors were used to measure crop canopy characteristics from the field plot, GPS was used to geo-refer the sensor measurements and two environmental sensors (a solar radiation sensor and air temperature/relative humidity sensor) were integrated to collect simultaneous environmental data. In the field tests, the results obtained from the soybean and wheat fields using the performance of the sensor system were satisfactory and robust.

Fig. 1. Autonomous mobile robots that are used in precision farming. Fig. (a) Robotic Phenotypin [31]; (b) Agricultural robot [32]; (c) Strawberry harvesting Robot [33]; (d) Autonomous Robot (e) Robotic Apple Harvester [34]; (f) Autonomous Agriculture Robot "Vinebot" [35]; (g) Agriculture Robot Use in Field [36]; (h) Weed Removing Robot [37]; (i) Autonomous Agriculture Robot "BoniRob" [38]; (j) Agricultual Vehicle Robot [39]; (k) Agriculture Robot [40]; (l) Agriculture spraying robot [41]

Kuska et al. [42] also found that hyperspectral imaging and non-imaging sensors are alternative useful instruments that can be used to collect data on both the quantitative and qualitative dimensions of plant resistance. Four different kinds of hyperspectral sensor technologies are available: push broom scanner, whisk broom scanner, filter-based sensor and non-imaging sensor and each one of these technologies have their advantages based on application. They may be applied for the phenotyping of disease resistance in crops [43]. Another platform is tower- based phenotyping [44]. An architecture that consists of a combination of two platforms: an autonomous ground vehicle (Vinobot) and a mobile observation tower (Vinoculer) [45]. This system is advantageous in the sense that the ground vehicle could collect data from individual plants, while the observation tower could provide an overview of an entire field, identifying specific plants for further inspection by the Vinobot the different platforms are depicted in Fig. 2.

Under three conditions, Liu et al. [46] examined crop phenotyping. The first was in managed conditions, for example, green houses or specially built platforms, using high-throughput phenotyping techniques. RGB, 3D laser scanning, multi and hyper spectral imaging, fluorescent sensing, and thermal IR cameras are some of the sensing techniques for high throughput phenotyping. Li DAR (Light Detection and Ranging) is an alternative technology for remote sensing capable of accurately acquiring three-dimensional (3D) data. It has its potential in application to crop Phenotyping and has been successfully used for 3D high-throughput crop phenotyping [47].

The second was under a semi-controlled environment such as lodge, drought and disease resistance by phenotypic reinforcement test. The third approach was multi-environmental traits (MET) in unregulated environments; crop plants are treated according to farmers' cultural practises. Research on methods and tools for test design and analysis, phenotypic acquisition and management to help the establishment of a reliable MET crop cultivar system, to enhance testing performance and reliability, as well as to reduce the risk of selection and introduction of cultivars, has therefore been concluded to be urgent.

Paez-Garcia et al. [48] aimed to improve root traits and phenotyping strategies. The idea of a combination of phenotypic root screening approaches was proposed which ultimately focused on higher yields in rain-fed systems by establishing a relation between young root systems for rapid root screening in the laboratory or greenhouse. The proposed strategies here can help to incorporate “root breeding” which would result in sustainable agricultural systems worldwide.

2.6 Irrigation

Almost 85% of the available freshwater resources worldwide are used by the agricultural industry. And with population growth and the rise in food demand, this percentage is increasingly growing. This leaves us with the need to come up with more effective technologies to ensure that irrigation water supplies are properly used. Automatic irrigation scheduling methods have been substituted for manual irrigation based on soil water measurement. During the implementation of autonomous irrigation machines, plant evapotranspiration, which depended on different atmospheric parameters such as humidity, wind speed, solar radiation and even crop factors such as the stage of growth, plant density, soil properties and pests, was taken into consideration.

Kumar [49] stated that the various irrigation techniques were primarily intended to establish a system with reduced use of resources and improved production. In order to assess the fertility of the soil by detecting the percentage of the primary soil ingredients, instruments such as the fertility metre and the PH metre are set up on the field. By means of wireless technology for drip irrigation, automatic plant irrigators are planted on the ground. This technique preserves the fertility of the soil and ensures that water supplies are used efficiently.

Shekhar et al. [50] also found that by detecting the amount of water, soil temperature, nutrient content and weather forecasting, smart irrigation technology is built to increase productivity without the intervention of large numbers of human power. By turning the irrigator pump ON/OF, the actuation is carried out according to the microcontroller. The M2M, Machine to Machine technology, is designed to enable communication and sharing of data with each other and to the server or cloud via the main network between all agricultural nodes.

Automated Irrigation System: Water wastage is one of the main disadvantages of traditional

Fig. 2. Different sensor platforms for crop phenotyping: (a) robotic field platform [51] (b) Robotic platform [45], (c) Ground based platform [52] (d) Robotic platform with artificial vision [53], (e) Ground based platform [54] (f) Robotic platform [55] (g) Robotic based platform [56] (h) UAV platform [57] (i) Robotic platform [58] (j) Robotic platform [59] (k) Robotic platform [60] (l) Robotic platform [61]

irrigation systems. A sensor-based smart irrigation system for efficient water use has been developed by many businesses with the aid of advanced technology. In this system, soil moisture and temperature sensors interact directly with embedded components on the field and take care of required water distribution among crops without farmer's interaction. This system helps maintain the desired soil and the optimum water range for plant growth in the root zone. Jha et al. [62] have also developed an automated irrigation system with Arduino technology to decrease human power and time consumption in the irrigation process. The concept of an effective and automated irrigation system was also created by Savitha and Uma Maheshwari [63] by developing remote sensors using Arduino's technology that can increase output by up to 40 percent. One of the many technologies used to measure the quality of soil moisture is used by soil moisture sensors. It is buried near the crop root areas [64]. The sensors assist in assessing the moisture level accurately and relay this reading to the irrigation controller. Sensors for soil moisture also help to substantially conserve water [65].

2.7 6 Main Areas Where Agriculture Can Benefit From AI

2.7.1 Io T-driven Development

Every day, huge data volumes are produced via IoT in both structured and unstructured formats (internet of things). These concern historical pattern details, soil reports, new research, rainfall, plague, drone, camera images, etc. All this knowledge can be sensed by Cognitive IOT solutions and provide clear insights to maximise yield.

2.7.2 Measuring the soil

Proximity Sensing and Remote Sensing are two technologies that characterise intelligent data fusion. Soil testing is one useful example of this high-resolution data. Although remote sensing needs sensors to be installed into airborne or satellite systems, soil-contact or very close-range sensors are needed for proximity sensing. This assists in soil characterization in a specific location depending on the soil below the surface.

2.7.3 Generation of image-based insight

Drone-based images can assist in in-depth field research, tracking crops, field scanning, and so on. To ensure quick action by farmers, they can be paired with computer vision technology and IOT. These feeds will produce weather warnings for farmers in real time.

2.7.4 Crop disease detection

Using Computer Vision Technology under white/UV-A light, images of different crops are captured. Before sending it to the market, farmers may then organise the product into different stacks. Image pre-processing ensures that the leaf images are segmented for further diagnosis into regions. Such a system can more distinctly classify pests.

2.7.5 Optimal blend of agricultural products

Cognitive computing allows recommendations to farmers on the simplest choice of crops and seeds based on multiple parameters such as soil condition, weather outlook, type of seeds, infestation around a certain area. The advice is further customised based on the farm's demand, local circumstances, and past achievements. External variables may also be taken into account by artificial intelligence, such as industry dynamics, costs or customer needs.

2.7.6 Plant health monitoring

In order to build crop metrics across thousands of acres, remote sensing techniques alongside hyper spectral imaging and 3D laser scanning are necessary. It could usher in a groundbreaking shift in terms of how farmers track croplands in terms of time and resources. This technology will monitor crops during their entire life-cycle and produce reports, if any, to detect anomalies.

An AI-sowing app was created by ICRISAT. The app is powered by Intelligence Suite and Power Business Intelligence from Microsoft Cortana. The Cortana Intelligence Suite includes technology which, by translating it into readily actionable forms, helps to increase the value of data. Using this technology, the app will more accurately forecast and inform local farmers on when they should plant their seeds by using weather models and data on local crop yield and rainfall.

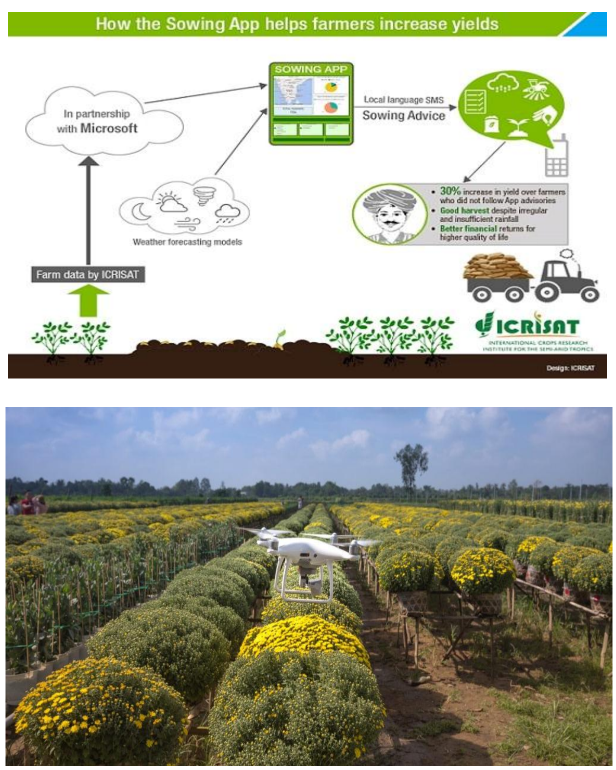

Chart 1. Flow chart showing how the app helps farmer to increase yield

2.8 Improving Crop Productivity

Climate change has resulted in outdated conventional agricultural know-how, especially in predicting weather patterns that decide seasonal farming practises. For farmers, the use of predictive analysis with the assistance of AI could be extremely helpful. It could help to identify suitable crops for growing on productive terrain in a favourable climate and sowing technique to increase productivity and lower costs.

2.9 Soil Quality Monitoring

Soil health, consisting of a sufficient level of moisture and nutrients, is the secret to achieving the best yield, along with favourable weather conditions. To take corrective measures to restore soil health, distributed soil monitoring performed through image recognition and deep learning models can be used. Historical monsoon data, local farm snapshots, crop-output information, soil health history, and more serve as inputs for the development of AI models. These models provide essential farmland information, assist farmers in planning activities related to soil regeneration, crop development, watering of farms, etc.

2.10 Water Management

Efficient agricultural water management can have a major effect on the looming issue of water scarcity. Using thermal imaging cameras that continuously track whether crops are getting enough water, the use of water in agriculture can be optimised. When used in agriculture, AI, combined with appropriate image classification models, can result in improved yield performance, reduced manual involvement, and decreased instances of crop disease.

2.11 Weather Data Forecasted

In an advanced way, AI helps farmers stay up-to-date with weather forecasting info. The projected data allows farmers to increase yields and income without risking the crop. By understanding and learning with AI, the analysis of the produced data allows the farmer to take precautions. By enforcing such procedure, a smart decision can be made on time.

2.12 Crop and Soil Quality Monitoring

The use of AI is an important way of performing or tracking the detection of potential soil defects and nutrient deficiencies. AI detects potential faults with the image recognition method by images collected by the camera. Analysis of flora patterns in agriculture is developed with the aid of AI deep learning framework. In understanding soil defects, plant pests, and diseases, these AI-enabled applications are helpful.

2.13 Diminish the Use of Pesticides

By integrating computer vision, robotics, and machine learning, farmers may use AI to control weeds. With the aid of the AI, information is collected to keep a check on the weed that only allows farmers to spray chemicals where the weeds are. This directly decreased the use of an entire field for chemical spraying. As a consequence, AI decreases the use of herbicides in the field compared to the amount of chemicals usually sprayed.

2.14 AI Bots for Agriculture

AI-enabled agricultural bots help farmers find ways to protect their crops from weeds more effectively. This also helps to solve the difficulty of labour. In the agricultural sector, AI bots can harvest plants more frequently and at a faster pace than workers. It assists in monitoring and spraying the weed with computer vision. Farmers can also find effective ways of defending their crops against weeds by using artificial intelligence.

A vision-based technology for weed detection in natural lighting was developed by Tang et al. [66]. Using hereditary calculation to distinguish a locale for the detection of open air field weeds in Hue-Saturation-Intensity (HSI) shading space (GAHSI) was developed. It uses outrageous conditions such as radiant and shady, and these lightning conditions were mosaiced to discover the possibility of using GAHSI when these two boundaries are shown at the same time to find the position or areas in the field in shading space. They came about as the GAHSI gave evidence of the existence and severability of such a site. By comparing the GAHSI-portioned image and a comparable hand-sectioned reference image, the GAHSI execution was calculated. In this, comparable output was obtained by the GAHSI. It was suggested by Nørremark and Griepentrog [67] that weeding depends on the location and the number of weeds. By breaking the soil and the interface of roots by tillage, classical spring or duck foot tines were used to conduct intra row weeding and thus encourage the witling of the weeds. Nakai and Yamada [68] revealed that, in the case of uneven fields in rice cultivation, the use of agricultural robots for the suppression of weeds and the creation of methods of regulating the postures of robots.

2.15 Spraying of Crops

Spoorthi et al. [69] also discovered that the UAVS, otherwise referred to as drones, is mainly focused on the inventions of sensors and microcontrollers, which are built especially with the aim of compensating for the pilot's non-attendance and thus enabling unmanned vehicles to move and their independent actions. These drones have been used by farmers as material sprayers for many years now and are regarded as reliable and of great importance in cloudy climate situations and have also solved the issue of inaccessibility to a tall crop area [70]. Giles et al. [71] retrofitted an air-carrier plantation sprayer with a sprayer control system based on microcomputers. In view of the ultrasonic range transducers, a foliage volume estimation system was interfaced with a PC that controlled the 3-nozzle manifolds on each side of the sprayer by using control calculations based on the amount of spray deposited.

A low-volume sprayer for an unmanned helicopter was constructed by Huang and Reddy [72]. The helicopter used in this investigation has a maximum rotor length of 3 m and a maximum weight of 22.7 kg. For about 45 minutes, there was one gallon of gas involved. This methodology and the systematic findings of this methodology provide a precursor that could be used to build UAV flying application frameworks for higher yields with a higher target rate and greater droplet size for VMD. On planes M-18B and Thrush 510G, Zhang et al. [73] assessed good swath width and bead circulation of aeronautical showering frameworks. The powerful swath width and consistency of the droplet dispersion of two agricultural planes, M-18B and Thrush 510G, which flew separately at 5 m and 4 m tall, were evaluated in this test. The outcome of this analysis indicates that for both the farming planes, the flight stature induces the swath width distinction. The sprayer is the one that crumbles the sprayed liquid, which may be a suspension, an emulsion or a response into tiny drops, and starts it properly with negligible power to circulate it [74] [Fig. 3].

2.16 Crop Monitoring

Farms use technologies to grow crops increasingly, from task-tracking systems that control watering and seeding to drones that capture aerial images. There is an estimation that the world will need to produce 50% more food by 2050 due to increase in the population. Based on the report, the most common agricultural AI applications fall into three major categories.

2.17 Agricultural Robots

Companies design and programmed autonomous robots to perform critical agricultural tasks at a higher volume and faster speed than humans, such as weed control, planting seeds, harvesting, environmental monitoring and soil analysis.

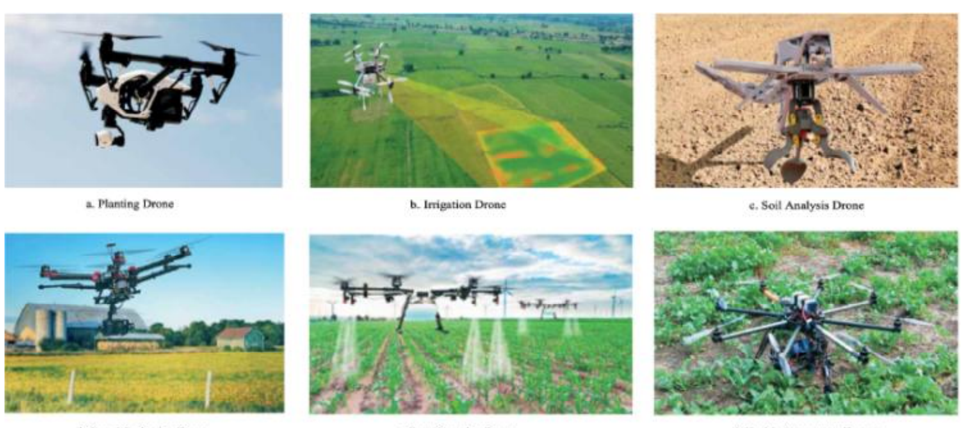

Fig. 3. Types of agricultural drones
Source: modern agriculture drones [75]

2.18 Crop and Soil Monitoring

To detect potential defects and nutrient shortages in the soil, businesses invest in computer vision and deep learning algorithms to process data collected by drones or by software-based technology.

2.19 Predictive Analytics

Machine learning models are designed to control and forecast different environmental effects on crop yields, such as weather and climate change.

The advanced sensors and imaging capabilities have created many new ways for farmers to improve yields and decrease crop damage. The feasibility of using a continuous kinematic (RTK) global situating system (GPS) to subsequently delineate the region of transplanted column crops was demonstrated by Sun et al. [76]. For field transplant mapping while planting, a transplant transplant for positive situation vegetable harvest, with RTK GPS receiver, plant, trend and odometry sensors and an on-board data lumberjack was used. Field test results showed that the mean error between the plant map areas anticipated by the planting data and the missed areas in the wake of planting was 2 cm, with 95% of the plant areas anticipated being within 5.1 cm of their real areas. In order to direct soil and harvest for precision cultivation applications, Sonaa et al. [77] showed a multi-spectral UAV overview. Agriculture has been addressing major problems such as lack of irrigation system, climate rise, groundwater density, food shortage and waste and much more. To a huge extent, the fate of cultivation depends on the acceptance of different cognitive solutions. Although research on a large scale is still ongoing and some applications are already available on the market, the industry is still highly underserved [78]. Farming is still at a nascent stage when it comes to handling practical problems faced by farmers and using automated decision making and predictive solutions to address them. Applications need to be more robust in order to explore the vast scope of AI in agriculture.

3. CONCLUSIONS

Farm management systems are transforming into real artificial intelligence systems by applying machine learning to sensor data, offering richer recommendations and observations for subsequent decisions and behaviour with the ultimate reach of improvement in output. In future, the use of Machine Learning (ML) models is expected to be much broader for this purpose, which will allow for integrated and applicable tools. Currently, both approaches concern individual approaches and strategies and are not sufficiently linked to the decision making process as seen in other fields of application.

This incorporation of automated data recording, data processing, implementation of ML, and decision-making or support would provide realistic fees that are compatible with so-called knowledge-based agriculture to increase production levels and the quality of bio-products. With the assistance of GPS, various AI-driven techniques such as remote sensors for soil moisture content detection and automatic irrigation can be enhanced. The issue faced by farmers was that during the weeding process, precision weeding techniques resolve the large number of crops that are lost. These autonomous robots not only increase performance, they also reduce the need for pesticides and herbicides that are unnecessary. In addition, with the help of drones, farmers can spray pesticides and herbicides effectively on their farms, and plant monitoring is also no longer a burden.

Agricultural industries face problems such as crop yields, soil and plant health, and artificial intelligence-driven technology can be used to combat weeds. Efficiency can also be significantly enhanced with the help of available equipment. Artificial intelligence in agriculture can also, to a large degree, solve problems such as resource scarcity as well as labour. Traditional techniques require work to acquire crop features such as plant height, leaf colour, leaf area index, chlorophyll content, biomass, and time-consuming yield. Using various techniques, rapid and non-destructive high-performance phenotyping will take place with the benefit of versatile and convenient service, data access on demand and spatial resolution.

The use of AI technology can help to forecast weather and other agricultural conditions, such as soil quality, groundwater, crop cycle, and identification of plant diseases, which are critical issues. However, agriculture cannot be totally dependent on AI as they cannot work outside of what they were programmed for. Also, farmers especially in rural areas lack the technical knowhow and awareness about the existence of such technologies. As more awareness is created and technologies become accessible to the average farmer, there is a future where agriculture can be semi-autonomous with artificial intelligence leading the way.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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