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Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides

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ABSTRACT

Agriculture plays a significant role in the economic sector. The automation in agriculture is the main concern and the emerging subject across the world. The population is increasing tremendously and with this increase the demand of food and employment is also increasing. The traditional methods which were used by the farmers, were not sufficient enough to fulfill these requirements. Thus, new automated methods were introduced. These new methods satisfied the food requirements and also provided employment opportunities to billions of people. Artificial Intelligence in agriculture has brought an agriculture revolution. This technology has protected the crop yield from various factors like the climate changes, population growth, employment issues and the food security problems. This main concern of this paper is to audit the various applications of Artificial intelligence in agriculture such as for irrigation, weeding, spraying with the help of sensors and other means embedded in robots and drones. These technologies saves the excess use of water, pesticides, herbicides, maintains the fertility of the soil, also helps in the efficient use of man power and elevate the productivity and improve the quality. This paper surveys the work of many researchers to get a brief overview about the current implementation of automation in agriculture, the weeding systems through the robots and drones. The various soil water sensing methods are discussed along with two automated weeding techniques. The implementation of drones is discussed, the various methods used by drones for spraying and crop-monitoring is also discussed in this paper.

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1. Introduction

The world's population is assumed to be nearly 10 billion by 2050, boosting agricultural order-in a situation of humble financial development by somewhere in the range of 50% contrasted with 2013 (FAO, 2017). At present, about 37.7% of total land surface is used for crop production. From employment generation to contribution to National Income, agriculture is important. It is contributing a significant portion in the economic prosperity of the developed nations and is playing an active part in the economy of the developing countries as well. The augmentation of agriculture has resulted in a significant increase in the per-capita income of the rural community. Thus, placing a greater emphasis on agricultural sector will be rational and apposite. For countries, like India, the agricultural sector accounts for 18% of GDP and provides employment to 50% of the country's workforce. Development in the agricultural sector will boost the rural development, further leading toward rural transformation and eventually resulting in the structural transformation (Mogili and Deepak, 2018; Shah et al., 2019).

With the advent of technology, there has been observed a dramatic transformation in many of the industries across the globe (Kakkad et al., 2019). Surprisingly, agriculture, though being the least digitized, has seen momentum for the development and commercialization of agricultural technologies. Artificial Intelligence (AI) has begun to play a major role in daily lives, extending our perceptions and ability to modify the environment around us (Kundalia et al., 2020; Gandhi et al., 2020; Ahir et al., 2020). Plessen (2019) gave a method for harvest planning based on the coupling of crop assignment with vehicle routing is presented. With this emerging technologies the workforce which were restricted to only a minimal industrial sectors are now contributing to numerous sectors. AI is based on the vast domains like Biology, Linguistics, Computer Science, Mathematics, Psychology and engineering. Jha et al. (2019) a brief overview of the current implementation of agricultural automation. The paper also addresses a proposed system for flower and leaf identification and watering using IOT to be implemented in the botanical farm (Patel et al., 2020; Albaji et al., 2010). The basic concept of AI to develop a technology which functions like a human brain (Parekh et al., 2020; Jani et al., 2019) This technology is perpetrated by studying how human brain thinks, how humans learn, make decisions, and work while solving a problem, and on this ground intelligent software and systems are developed. These softwares are fed with training data and further these intelligent devices provide us with desired output for every valid input, just like the human brain. Vast domains including Machine Learning and Deep learning are core part of AI (Patel et al., 2020a, 2020b; Pandya et al., 2019; Sukhadia et al., 2020). While AI is the science of making intelligent machines and programs, ML is the ability to learn something without being explicitly programmed and DL is the learning of deep neural networks (Kodali and Sahu, 2016; Kulkarni and Deshmukh, 2013). The main subjective of AI is to make problem solving facile which may include the use of ANN (Shah et al., 2020a, 2020b).

ANN is a processing algorithm or a hardware whose functioning is inspired by the design and functioning of a human brain (Shah et al., 2020a, 2020b). Neural networks have a remarkable ability of self-organization, and adaptive learning. It has replaced many traditional methods in numerous fields like Computer Science, Mathematics, Physics, Engineering image/signal processing, Economic/ Finance, Philosophy, Linguistics, Neurology. ANN undergoes the process of learning. Learning is the process of adapting the change in itself as and when there is a change in environment. There are two learning techniques, supervised learning and unsupervised learning. The work of Jha et al., 2019, encloses the connected relations between the various embedded systems and the AI technology coherent with the agricultural field, it gave a brief about the various applications of neural networks, ML in this sector for precision farming (Yang et al., 2007).

AI is an emerging technology in the field of agriculture. AI-based equipment and machines, has taken today's agriculture system to a different level. This technology has enhanced crop production and improved real-time monitoring, harvesting, processing and marketing (Yanh et al., 2007). The latest technologies of automated systems using agricultural robots and drones have made a tremendous contribution in the agro-based sector. Various hi-tech computer based systems are designed to determine various important parameters like weed detection, yield detection and crop quality and many other techniques (Liakos et al., 2018). This paper encompasses the technologies used for the automated irrigation, weeding and spraying to enhance the productivity and reduce the work load on the farmers. Various automated soil sensing techniques are discussed (Wall and King, 2004). Hemalatha and Sujatha (2015) brought together temperature and moisture sensors to close the loop holes of the vehicle predictions. The robots used in sensing were localized by GPS modules and the location of these robots was tracked using the google maps. The data from the robots was fetched through Zigbee wireless protocol. The readings were displayed on the 16×2 LCD display which was integrated to the LPC2148 microcontroller. The latest automated weeding techniques are discussed and the implementation of drones for the purpose of spraying in the fields is discussed followed by the types of sprayers utilized on UAVs. Further speaking about drones, yield mapping and monitoring is discussed beginning with the an outline of the yield mapping processs followed by the programming of the software and briefing about the calculation as well as calibration process. Finally the processing of these yield maps is illuminated.

2. Impact of AI on agriculture

The technologies which are AI-based help to improve efficiency in all the fields and also manage the challenges faced by various industries including the various fields in the agricultural sector like the crop yield, irrigation, soil content sensing, crop- monitoring, weeding, crop establishment (Kim et al., 2008). Agricultural robots are built in order to deliver high valued application of AI in the mentioned sector. With the global population soaring, the agricultural sector is facing a crisis, but AI has the potential to deliver much-needed solution. AI- based technological solutions has enabled the farmers to produce more output with less input and even improved the quality of output, also ensuring faster go-to- market for the yielded crops. By 2020, farmers will be using 75 million connected devices. By 2050, the average farm is expected to generate an average of 4.1 million data pointsevery day. The various ways in which AI has contributed in the agricultural sector are as follows:

2.1. Image recognition and perception

Lee et al. (2017) said that in recent years, an increasing interest has been seen in autonomous UAVs and their applications including recognition and surveillance, human body detection and geolocalization, search and rescue, forest fire detection (Bhaskaranand and Gibson, 2011; Doherty and Rudol, 2007; Tomic et al., 2012; Merino et al., 2006). Because of their versatility as well as amazing imaging technology which covers from delivery to photography, the ability to be piloted with a remote controller and the devices being dexterous in air which enables us to do a lot with these devices, drones or UAVs are becoming increasingly popular to reach great heights and distances and carrying out several applications.

2.2. Skills and workforce

Panpatte (2018) said that artificial intelligence makes it possible for farmers to assemble large amount of data from government as well as public websites, analyze all of it and provide farmers with solutions to many ambiguous issues as well as it provides us with a smarter way of irrigation which results in higher yield to the farmers. Due to artificial intelligence, farming will be found to be a mix of technological as well as biological skills in the near future which will not only serve as a better outcome in the matter of quality for all the farmers but also minimize their losses and workloads. UN states that, by 2050, 2/3rd of world's population will be living in urban areas which arises a need to lessen the burden on the farmers. AI in agriculture can be applied which would automate several processes, reduce risks and provide farmers with a comparatively easy and efficient farming.

2.3. Maximize the output

Ferguson et al. (1991) said in his wok that Variety selection and seed quality set the maximum performance level for all plants. The emerging technologies have helped the best selection of the crops and even have improved the selection of hybrid seed choices which are best suited for farmer's needs. It has implemented by understanding how the seeds react to various weather conditions, different soil types. By collecting this information, the chances of plant diseases are reduced. Now we are able to meet the market trends, yearly outcomes, consumer needs, thus farmers are efficiently able to maximize the return on crops.

2.4. Chatbots for farmers

Chatbots are nothing but the conversational virtual assistants who automate interactions with end users. Artificial intelligence powered chatbots, along with machine learning techniques has enabled us to understand natural language and interact with users in away more personalized way. They are mainly equipped for retail, travel, media, and agriculture has used this facility by assisting the farmers to receive answers to their unanswered questions, for giving advice to them and providing various recommendations also.

3. Robots in agriculture

Robotics and Autonomous Systems (RAS) are introduced in large sectors of the economy with relatively low productivity such as Agri-Food. According to UK-RAS White papers (2018) the UK Agri-Food chain, from primary farming through to retail, generates over £108bn p.a., and with 3.7 m employees in a truly international industry yielding £20bn of exports in 2016. Robotics has played a substantial role in the agricultural production and management. The researchers have now started emphasizing on technologies to design autonomous agricultural tools as the conventional farming machineries lacked in efficiency (Dursun and Ozden, 2011). The main purpose of coming up with this technology is to replace human labor and produce effective benefits on small as well as large scale productions (Manivannan and Priyadharshini, 2016). In this sector, the room for robotic technologies has amplified productivity immensely (Pedersen et al., 2008). The robots are performing various agricultural operations autonomously such as weeding, irrigation, guarding the farms for delivering effective reports, ensuring that the adverse environmental conditions do not affect the production, increase precision, and manage individual plants in various unfamiliar ways.

The idea of coming up with such a technology came with the introduction of a machine called Eli Whitney's cotton gin. It was invented in 1794 by U.S. - born inventor Eli Whitney (1765–1825), a device which revolutionized cotton production by significantly accelerating the process of extracting seed from cotton fiber.It created 50 pounds of cotton in one day. Thus this gave birth to the autonomous agricultural robots. A basic automated model was introduced to determine the actual position of seeds (Griepentrog et al., 2005). Ultra high precision placement of seed was also established. Mechanisms that ensure that the seeds planted has zero ground velocity (Griepentrog et al., 2005). This is important as it ensures that the seed does not bounce from its actual position after the soil impact. The status or the development of plant was recorded by automated machines. Various biosensors were established to monitor the plant growth and also to detect plant diseases (Tothill, 2001).The process of manual weeding was replaced by the laser weeding technology, where a mobile focused infra-red light disrupts the cells of the weeds, this beam was controlled by computers (Griepentrog et al., 2006). For the effective use of water, automated irrigation systems were also established.

3.1. Irrigation

The agriculture sector consumes 85% of the available freshwater resources across the world. And this percentage is increasing rapidly with the population growth and with the increase in food demand. This leaves us with the need to come up with more efficient technologies in order to ensure proper use of water resources in irrigation. The manual irrigation which was based on soil water measurement was replaced by automatic irrigation scheduling techniques. The plant evapotranspiration which was dependent on various atmospheric parameters such as humidity, the wind speed, solar radiations and even the crop factors such as the stage of growth, plant density, the soil properties, and pest was taken into consideration while implementing autonomous irrigation machines.

Kumar (2014) discusses about the different irrigation methods with the primary motive of developing a system with reduced resource usage and increased efficiency. Devices like fertility meter and PH meter are set up on the field to determine the fertility of the soil by detecting the percentage of the primary ingredients of the soil like potassium, phosphorous, nitrogen. Automatic plant irrigators are planted on the field through wireless technology for drip irrigation. This method ensures the fertility of the soil and ensures the effective use of water resource.

The technology of smart irrigation is developed to increase the production without the involvement of large number of man power by detecting the level of water, temperature of the soil, nutrient content and weather forecasting. The actuation is performed according to the microcontroller by turning ON/OF the irrigator pump. The M2M that is, Machine to Machine technology is been developed to ease the communication and data sharing among each other and to the server or the cloud through the main network between all the nodes of the agricultural field (Shekhar et al., 2017). They (2017) developed an automated robotic model for the detection of the moisture content and temperature of the Arduino and Raspberry pi3. The data is sensed at regular intervals and is sent to the microcontroller of Arduino (which has an edge level hardware connected to it), it further converts the input analog to digital. The signal is sent to the Raspberry pi3 (embedded with KNN algorithm) and it sends the signal to Arduino to start the water source for irrigation. The water will be supplied by the resource according to the requirement and it will also update and store the sensor values. Jha et al. (2019) also developed an automated irrigation system with the technology of Arduino for reducing the man power and time consumption in the process of irrigation.

Savitha and UmaMaheshwari (2018) also developed the idea of efficient and automated irrigation system by developing remote sensors using the technology of Arduino which can increase the production up to 40%.

Another system for automated irrigation was given by Varatharajalu and Ramprabu (2018). In this approach different sensors were built for different purposes like the soil moisture sensor to detect the moisture content in the soil, the temperature sensor to detect the temperature, the pressure regulator sensor to maintain pressure and the molecular sensor for better crop growth. The installation of digital cameras. The output of all these devices is converted to digital signal and it is sent to the multiplexer through wireless network such as Zigbee and hotspot.

The first technique was the subsurface drip irrigation process, which minimized the amount of water loss due to evaporation and runoff as it is directly buried beneath the crop. Later researchers came with different sensors which were used to detect the need of water supply to the fields as soil moisture sensor and rain drop sensor, which were instructed through wireless broadband network and powered by solar panels. The rain drop sensor and soil moisture sensor informs the farmer about the moisture content in the soil through SMS in their cell phone using GSM module. Accordingly the farmer can give commands using SMS to ON and OFF the water supply. Thus we can consider that this system will detect part or area in the fields which required more water and could hold off the farmer from watering when it's raining.

Soil moisture sensors use one of the several technologies used to measure the soil moisture content. It is buried near the root zones of the crops (Dukes et al., 2009). The sensors help in accurately determining the moisture level and transmit this reading to the controller for irrigation. Soil moisture sensors also help in significantly conserving water (Quails et al., 2001). One technique of moisture sensors is the water on demand irrigation in which we set the threshold according to the soil's field capacity and these sensors permits your controller to water only when required. When the scheduled time arrives, the sensor reads the moisture content or level for that particular zone, and watering will be allowed in that zone only if the moisture content is below the threshold. The other was the suspended cycle irrigation which requires irrigation duration unlike the water on demand irrigation. It requires the start time and the duration for each zone (Yong et al., 2018).

3.1.1. Dielectric method

The moisture in the soil is calculated by the sensors which basically evaluate the moisture content in the soil based on the dielectric constant (soil mass permittivity) of the soil. The amount of irrigation needed can also be determined on the basis of the dielectric constant (Gebregiorgis and Savage, 2006). Kuyper and Balendonck (2001) proposes an automated system that uses dielectric soil moisture sensors for real time irrigation control. The measurement method based on the dielectric properties is considered to be the most potential one (Zhen et al., 2010). Hanson et al. (2000) gave the information regarding how soil types affect the accuracy to dielectric moisture sensors. The dielectric steady is only the capacity of soil to transfer power or electricity. The soil is comprised of various parts like minerals, air and water, subsequently the estimation of its dielectric consistent is determined by the general commitment of every one of these segments. Since the estimation of the dielectric value of water (Kaw = 81) is a lot bigger than the estimation of this consistent for the other soil parts, the estimated value of permittivity is primarily represented by the nearness of moisture in the soil. One method to calculate the relationship between the dielectric constant (Ka_b) and volumetric soil moisture (VWC) is the equation of Topp et al.:

$$VWC = -5.3 \times 10^{-2} + 2.29 \times 10^{-2} Ka_b - 5.5 \times 10^{-4} Ka_{b^2} + 4.3 \times 10^{-6} Ka_{b^3} \quad (1)$$

The other method used for determining the dielectric constant is the by the Time Domain Reflectometry (TDR). It is determined on the basis of the time taken by an electromagnetic wave to propagate along a transmission line that is surrounded by the soil. As we probably are aware, the propagation velocity (V) is an element of the dielectric constant (Kab), therefore it is legitimately corresponding to the square of the transmission time (t in a flash) down and back along the transmission line:

$$K_{ab} = (c/v)2 = ((ct)/(2L))2 \quad (2)$$

where c is the speed of electromagnetic waves in a vacuum (3·108 m/s or 186,282 mile/s) and L is the length of the TL in the soil (in m or ft).

3.1.2. Neutron moderation

This is another technique for deciding the moisture content in the soil. In this strategy fast neutrons are launched out from a decomposing radio dynamic source like 241Am/9Be (Long and French, 1967) and when these neutrons slam into particles having a similar mass as theirs(protons, H+), they drastically slow down, making a "cloud" of "thermalized" neutrons. As we already know that water is the primary wellspring of hydrogen in soil, the thickness of thermalized neutrons around the test is about corresponding to the division of water present in the soil. The arrangement of the test is as a long and limited chamber, comprising of a source and a finder. The estimations are taken in this test by bringing the test into an entrance tube, which is as of now presented in the soil. One can decide soil amount of moisture in the soil at various profundities by balancing the test in the cylinder at various profundities. The moisture substance is gotten with the assistance of this gadget dependent on a direct alignment between the check pace of thermalized neutrons read from the test, and the soil moisture substance got from adjacent field tests.

The installation of sensors plays an important role in the efficient implementation of irrigation robotics. One can use a single sensor to control the irrigation of multiple zones in the fields. And one can also set multiple sensors to irrigate individual zones. In the first case where one sensor is utilized for irrigating multiple zones, the sensor is places in the zone which is the driest of all or we can say the zone which requires maximum irrigation in order to ensure adequate irrigation in the whole field. The placement of the sensors should be in the root zone of the crops (ensuring that there are no air gaps around the sensor) from where the crops extract water. This will ensure the adequate supply of water to the crops. Later, we need to connect the SMS controller with the sensor. The controller will control the working after the sensor responds. After making this connection the soil water threshold needs to be selected. Then water is applied to the area where the sensor is buried and it is left as it is for a day. The water content now is the threshold for the sensor for scheduled irrigation as described earlier.

After fetching the data through the sensors the microcontrollers come into work. It is the major component of the entire automated irrigation process. The whole circuit is supplied with power up to 5 V with the help of transformer, a bridge rectifier circuit (which is a part of electronic power supplies which rectifies AC input to DC output) and voltage regulator. Then the microcontroller is programmed. The microcontroller receives the signals from the sensors. The OP-AMP acts as an interface between the sensors and the microcontroller for transferring the sensed soil conditions. The irrigator pumps thus operates on the information of the soil properties at run time (Fig. 1).The irrigation process can therefore be automated with the help of moisture sensors and microcontrollers (Rajpal et al., 2011). (See Table 1.)

3.2. Weeding

Zimdahl (2010) in his report on "A History of Weed Science in the United States" stated about Thomas K. Pavlychenko, a pioneer weed experimentalist, who did a study on the competition among plants. After his detailed research on the same, he came concluded that the competition among the plants for water begins when their roots in the soil overlap to absorb water and nutrients and weeds were the strongest competitors for water. The water requirement for the aerial parts of the plant is the number of pounds of water used to produce a pound of dry matter. The wild mustard plant (*Brassica kaber* var. *pinnatifida*) requires four times as much water as a well-developed oat plant, and the common ragweed plant (Ambrosia artemisiifol ia) requires three times as much water as a corn plant to reach maturity. One can calculate the water requirement per acre is determined by multiplying the production of the plant in pounds of dry matter per acre times the plant's water requirement. Light is also an essential component for the growth of the plants. Weeds which grow tall, generally blocks the way of light to the plants. Sometimes weeds like green foxtail and redroot pigweed are intolerant of shade but may times weeds like field bindweed, common milkweed spotted spuroe, and Arkansas rose are shade tolerant. According to a study by researchers of the Indian Council for Agricultural Research, the country India, loses agricultural produce worth over $11 billion — more than the Centre's budgetary allocation for agriculture for 2017–18 annually due to weeds. So to remove these weeds from the fields is of great importance otherwise it will not only occupy the land space but will also adversely affect the growth of other plants (Bak and Jakobsen, 2003).

Lie Tang et al. (2000) brought up a vision based weed detection technology in natural lighting. It was created utilizing hereditary calculation distinguishing a locale in Hue-Saturation-Intensity (HSI) shading space (GAHSI) for open air field weed detecting. It utilizes outrageous conditions like radiant and shady and these lightning conditions were mosaicked to discover the likelihood of utilizing GAHSI to find the locale or zones in the field in shading space when these two boundaries are displayed at the same time. They came about given by the GAHSI gave proof to the presence and severability of such a locale. The GAHSI execution was estimated by contrasting the GAHSI-portioned picture and a comparing hand sectioned reference picture. In this, the GAHSI achieved equivalent performance.

Before developing a weed control automated system we need to differentiate between the crop seedlings and the weeds (Bhagyalaxmi et al., 2016; Chang and Lin, 2018). A method was applied for recognition of carrot seedlings from those of ryegrass. Aitkenhead et al. (2003) implemented this method by the simple morphological characteristic measurement of leaf shape. This method has varying effectiveness mostly between 52 and 75% for discriminating between the plants and weeds, by determining the variation in size of the leaf. Another method for weeding was implemented using digital imaging. This idea involved a self-organizing neural network. But this method did not give appropriate results which were expected for commercial purposes, it was found that a NN based technology already existed which allows one to find the differences between species with an accuracy exceeding 75%.

In the contemporary world many automated systems are developed (See Table 2.) but earlier various physical methods were used which relied on the physical interaction with the weeds. Nørremark and Griepentrog (2004) proposed that weeding depends on the position and the number of weeds. Classical spring or duck foot tines were used to perform intra row weeding by breaking the soil and the interface of roots by tillage and thus promote the witling of the weeds. But this is not advisable method as tillage can destruct the interface

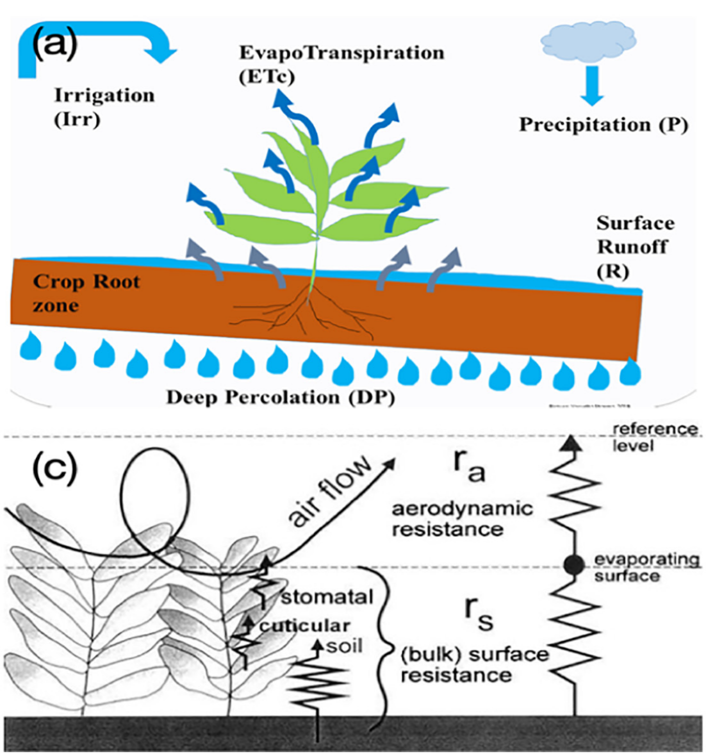

Fig. 1. (a) Soil Water Balance Components for Evapotranspiration Model Source: University of Minnesota (b) Flowchart for Evapotranspiration Reference (Jha et al., 2019) (c) FAO Penman-Monteith method.

Table 1
Summary of Irrigation Automation Using Various Artificial Intelligence Technologies.

No.	Algorithms	Method of evapotranspiration / desired calculation	Other Technologies	Advantages/Results	References
1.	PLSR and other regression Algorithms	Evapotranspiration model	Sensors for data collection, IOT Hardware Implementation	Increased efficiency and economic feasibility	Choudhary et al. (2019)
2.	Artificial Neural Network based control system	Evapotranspiration model	Sensors for measurement of soil,temperature,wind speed, etc.	Automation	Umair and Usman (2010)
3.	Fuzzy Logic	FAO Penman-Monteith method	–	Optimization	Kia et al. (2009)
4.	ANN (multilayer neural model), Levenberg Marquardt, Backpropagation	Penman–Monteith method	–	Evaporation decreased due to schedule and savings observed in water and electrical energy	Karasekreter et al. (2013)
5.	Fuzzy Logic	–	WSN, Zigbee	Experimental results verification. Can be applied to home gardens and grass	Al-Ali et al. (2015)
6.	ANN Feed Forward, Backpropogation	–	–	Optimization of water resources in a smart farm.	Dela Cruz et al. (2017)
7.	Fuzzy Logic Controller	Penman–Monteith method	Wireless sensors	Drip irrigation prevents wastage of water and evaporation	Anand et al. (2015)
8.	Machine Learning algorithm	–	Sensors, Zigbee, Arduino microcontroller	Prediction and tackles drought situations	Arvind et al. (2017)

between the crop and the soil. Thus, further no contact methods like the laser treatments (Heisel et al., 2001) and micro spraying, which do not affect the contact between the roots and the soil was developed. Nakai and Yamada (2014) explained the method of the use of agricultural robots for the suppression of weeds and developing methods of controlling the postures of robots in case of uneven fields in the rice cultivation. It used the method of Laser Range Fielder (LRF) for suppressing the weeds and controlling robot's posture. Åstrand and Baerveldt (2002) presented a robotic weed control system. The robot was embedded with different vision systems. One was the gray- level vision which was used in developing a row structure in order to guide the robot along the rows and the other vision was color-based which was most important and used to differentiate a single among the weeds. The row recognition system was developed with a novel algorithm with an accuracy of ± 2 cm. The first trial of this system was implemented in a greenhouse for weed control within a row of crops. The same technology was mentioned in the research done by Fennimore et al. (2016). The vision based technologies which were used to guide the robots along the row structure to remove weeds and to differentiate the single crop among the weed plants. The various weeding systems are:

3.2.1. Chemical based

In this technology, the system consisted of 8 nozzles at the back which were used for spraying herbicides. The whole system divided the images captured in 8×18 small rectangles or we can say blocks, each of these blocks covered an area of 8128 sq. mm. Later, each row which consisted of these blocks corresponding to number of nozzles was examined and processed one after the other. After examining the blocks, each box containing weeds are sprayed.

On can also divide the images into 16×40 blocks, in this case each blocks covers an area of approximately 8768 sq. mm. Thus, in this case we need 16 nozzles instead of 8. The further processing, that is, the task of spraying was done on the basis of the conditions mentioned. The conditions are:

1. 1 If the block examined consisting of weed pixels exceeding 10% of the total area of the block, then it is categorized into a weed block.
2. 2 All the blocks examined are sprayed with herbicides.
3. 3 Then after these two conditions, the weeds whose area equal to or more than 30% is sprayed are supposed to be destroyed.
4. 4 The herbicide which is sprayed in this method is a selective herbicide, which destroys only the weeds and not the other plants.

The first two conditions mentioned above defines the where the herbicides are to be sprayed, that is, defines the areas which requires spraying. The first condition mentioned reduces the areas which contains very small amount of weeds and which does not require spraying. This is an important part of weeding. To destroy weeds, all the parts of the weeds does not require

Table 2
Summary of applications of AI in weeding operations.

No.	Application	Crop	Algorithms for Weed Detection	Weed Removal Methods	Accuracy	Reference
1.	Precision Weed Management	Pepper plants, artificial plants	Machine Vision, Artificial Intelligence	A smart sprayer	–	Partel et al. (2019)
2.	Autonomous Weeding Robot.	Sugar beet	Machine vision algorithm	High power lasers for intra-row weeding proposed.	–	Bakker et al. (2006)
4.	Weeds Detection in Agricultural Fields	–	Data augmentation for image preprocessing; Convolutional neural networks for weed detection	Herbicide Spray	70.5%	Ngo et al. (2019)
5.	Robot for weed control	Sugar Beets	Machine Vision	Rotatory hoe/ Mechanical removal	92% (detection)	Åstrand and Baerveldt (2002)
6.	Weeding Robot	Rice	–	Motion of robot prevents weed growth	–	Nakamura et al. (2016)
7.	Weed Prevention Robot	Rice	–	Motion of robot	–	Maruyama and Naruse (2014)
8.	Weed Detection	Sugarcane	Color Based and Texture Based algorithms; Greenness Identification; Fuzzy Real Time Classifier	Robotic arms for mechanical removal	92.9%	Sujaritha et al. (2017)
9.	Weed Control System	Lettuce	Machine Vision	Electrical Discharge	84% (detection)	Blasco et al. (2002)
10.	Robotic Weed Control	Cotton	Machine Vision algorithm based on Mathematical morphology	Chemical spraying	88.8% sprayed	Lamm et al. (2002)

spraying, but only spraying enough areas is important as when spraying is done on one part of weeds it is absorbed by different parts of the weeds ultimately destroying the weeds. But one needs to take care that enough areas in a weed are sprayed because if the sprayed areas are too small then, in that case the weeds may not destroy. Thus we define a minimum spraying area in the condition 3.The defined condition 4 is there to calculate the reduction in the amount of herbicides used as compared with the spraying in the overall area. The evaluation of this weeding method requires the calculation of the destroyed weed rate, the correct spray rate, the false spray rate and the herbicide reduction rate. The following data is to be calculated as follows:

$$\text{Destroyed weed rate} = (N_K/N_W) \times 100$$

$$\text{Correct spray rate} = (N_{CSR}/N_{SNWB}) \times 100$$

$$\text{False spray rate} = (N_{FSB}/N_{SB}) \times 100$$

$$\text{Herbicide reduction rate} = (1-N_{SB}/N_B) \times 100$$

Here N_K is the number of weeds killed, N_W is the total number of weeds in the block, N_{CSB} is the number of sprayed weed blocks, N_{FSB} is the number of sprayed non-weed blocks, $_{NSB}$ is the total number of sprayed blocks and N_B is the total number of blocks examined.

3.2.2. Pulse high voltage discharge method

There is an increase in the desire to implement non-chemical weeding methods as the pressure to reduce chemical costs on the environment and farming increases. The interest in organic farming has also led to the rise in interest of non-chemical weed management (Bond and Grundy, 2001). Non-chemical weed control methods were studied (Parish, 1990) and include mechanical, electrical, and biological methods. The pulse high voltage discharge method is one such non- chemical weed control method that was implemented mainly to destroy small weeds. These small weeds (of an approximate size of about 5 cm tall and stem diameter of about 2 mm) can be destroyed with just one spark with energy of 153 mJ and a 15 kV. Whereas the large weeds (which vary in size from about 80 cm to 120 cm tall and a stem diameter of about 10–15 mm) can be destroyed with a charge of 20 Hz. Because of these spark charges, the stem and the roots of the weeds gets adversely affected, thus leading to a disruption in the transportation of waiter to the various parts of the weeds. Thus, the weeds wilt within a few days after the spark. In this weeding method, spark discharging devices are set up on the system in place of the nozzles in the previous chemical based method. Here the system is designed to apply spark only on the areas where weeds are detected. Once the sites having weeds are detected, the selection of weed points is done by the system for spark discharge, these weed points represent the weed areas. Like the above discussed chemical method, in this method also some conditions are defined. The conditions are as follows:

1. The average of all the coordinates of the pixels in the images is calculated and it is defined as the center of that region.
2. The spark discharge applied for weeding is applied at this center.
3. If a weed receives the spark discharge, then that particular weed is considered as destroyed.

The first two conditions are established in order to select the spar discharging points in the fields and the third condition is for setting the potential of weed destruction. In this method some more factors are evaluated along with the three factors calculated in the previous method, the correct spark rate and the false spark rate.

$$\text{Correct spark rate} = (N_{CSK}/N_{SK}) \times 100$$

$$\text{False spark rate} = (N_{FSK}/N_{SK}) \times 100$$

Here N_{CSK} is the number of sparked weed pixels, N_{FSK} is the number of sparked non-weed pixels and N_{SK} is the total number of sparked points.

4. Drones in agriculture

Unmanned aeronautical vehicles (UAVs) or unmanned ethereal frameworks (UAS), otherwise called automatons, in a mechanical setting are unmanned aircrafts that can be remotely controlled (Mogli and Deepak, 2018). They work in confluence with the GPS and others sensors mounted on them. Drones are being implemented in agriculture for crop health monitoring, irrigation equipment monitoring, weed identification, herd and wildlife monitoring, and disaster management (Veroustraete, 2015; Ahirwar et al., 2019; Natu and Kulkarni, 2016). Remote Sensing with the use of UAVs for image capturing, processing, and analysis is making a huge impact on agriculture. (Abdullahi et al., 2015). The rural business appears to have grasped ramble innovation with great enthusiasm, utilizing these propelled instruments to change current agricultural methods (Pederi and Cheporniuk, 2015). The complete addressable estimation of automation fueled arrangements in every single relevant industry is critical – more than USD 127 billion, as indicated by an ongoing PwC analysis. They can be contrasted with a normal simple to use camera for unmistakable pictures, yet while a standard camera can give some data about plant development, inclusion and different things, a multispectral sensor extends the utility of the procedure and enables farmers to see things that can't be found in the noticeable range, for example, moisture content in the soil, plant health monitoring. These could help defeat the different restrictions that obstruct agrarian production. The development of the UAS is incorporated with Wireless Sensor Networks (WSN). The data recovered by the WSN enables the UAS to advance their utilization for instance to restrict its spraying of synthetic compounds to carefully assigned regions. Since there are abrupt and continuous changes in ecological conditions the control circle must almost certainly respond as fast as could reasonably be expected. The reconciliation with WSN can help toward that path (Costa et al., 2012). In precision agriculture, UAVs are mainly applicable for agriculture operations such as soil and field analysis (Primicerio et al., 2012), crop monitoring (Bendig et al., 2012), crop height estimations (Anthony et al., 2014), pesticide Spraying (Faiçal et al., 2017; Faiçal et al., 2014a, b, c; Huang et al., 2009). (See Table 4.) However, their hardware implementations (Maurya, 2015) are purely adherent on critical aspects like weight, range of flight, payload, configuration and their costs. A research involving technologies, methods, systems and limitations of UAVs are examined (Huang et al., 2013). About more than 250 models are analyzed as well as summarized in order to choose an appropriate UAV in agriculture (S.R. Kurkute et al., 2018) (See Table 3.). The agricultural drone market is expected to grow over 38% in coming years. It is believed that the need for efficient agriculture is only going to become more important due to increasing population levels and changing climate patterns (Puri et al., 2017).

4.1. Crop spraying

The UAV_S, otherwise called drones, are chiefly established on the innovations of sensors and microcontrollers which are grown especially with an expectation to make up for the nonattendance of the pilot and accordingly empower the trip of unmanned vehicles and their independent conduct (Spoorthi et al., 2017). These drones have been utilized as substance sprayers by farmers since numerous years now and they are considered as effective and of great importance in the situations of cloudy climate and has also solved the problem of inaccessibility to a field of tall crops, for example, maize (Sugiura et al., 2005; Simelli and Tsagaris, 2015). Additionally, they are likewise accepted to have a

Table 4
Summary of various applications of drones in agriculture.

No.	Application	Technologies/algorithms used	Results	Reference
1.	Pesticide Spraying	Wireless Sensor Networks, Gyroscope and Accelerometer sensors	N/A	Garre and Harish (2018)
2.	Crop Monitoring, Mapping, and Spraying	DJI Phantom 3 Advanced UAV and other softwares	UAVs could be used in order to detect abnormalities and identify potential problems.	Psirofonia et al. (2017)
3.	Crop Monitoring	Multispectral sensor	Linear regressions between NDVI and plant nitrogen, aerial biomass, etc. were significant. This has the potential to provide insight to good management practices and techniques.	Vega et al. (2015)
4.	Pesticide Spraying	Spray motor	Worked satisfactorily when tested on groundnuts and paddy crops	Yallappa et al. (2017)
5.	Remote Sensing	Multispectral camera	The UAV remote sensing system was tested on a turf grass field and was capable of monitoring the temporal changes in the field.	Xiang and Tian (2011)
6.	Remote Sensing	Spectral Spatial classification, Bayesian information criterion (BIC)	Manual Tomato detection is difficult so using this technology, the areas could be classified into tomato and non tomato regions. Detection was carried out successfully on two representative images.	Senthilnath et al. (2016)
7.	Crop Monitoring	Hyperspectral Frame Camera	Camera flight campaign successfully delivered the hyperspectral data. This enables the monitoring of the leaf nitrogen concentration in rice.	Zheng et al. (2016)
8.	Crop Monitoring	Camera and Softwares	Accurate way to monitor various aspects of the farm like creating digital map of field, detecting problems with crop health, etc.	Reinecke and Prinsloo (2017a, 2017b)
9.	Precision Agriculture Monitoring	–	Provides an approach for the segregation of sparse and dense areas within a sugarcane field. It makes use of satellite data. Accuracy was 87% for testing.	Murugan et al. (2017)
10.	Spraying Fertilizers and Pesticides	Accelerometer and Gyroscope Sensors, Arduino	It has the ability to reduce time and human effort.	Pharne et al. (2018)

solid favorable position contrasted with satellite airborne sensors of high picture resolution (Jannoura et al., 2015; Simelli and Tsagaris, 2015). Giles et al., 1987 retrofitted an air-carrier plantation sprayer with a microcomputer based sprayer control framework. A foliage volume estimation framework, in view of ultrasonic range transducers was interfaced to a PC which controlled the 3-nozzle manifolds on each side of the sprayer by the utilization of control calculations dependent on the amount of spray deposited. Kale et al. (2015) utilized drones for spraying synthetic substances on the yield where the drones are joined to actualize a control circle for horticulture applications. These drones were implemented with sensors conveyed on the crops in the field known as remote sensor networks (WSN) which controlled the way toward applying the synthetic compounds. The data recovered by these remote sensors limited drones to spray the synthetic substances only into the assigned regions. Huang and Reddy (2015) built up a low volume sprayer for an unmanned helicopter. The helicopter utilized in this investigation has a principle rotor distance across of 3 m and a most extreme payload of 22.7 kg. For like 45 min one gallon of gas was involved. This technique and the systematic outcomes from this methodology gives a precursor that could be utilized in creating UAV flying application frameworks for higher yields which has a higher target rate and bigger VMD droplet size.

Xue et al. (2016) built up an unmanned airborne vehicle based programmed flying praying framework. The framework utilized a profoundly coordinated and ultra-low power MSP430 single-chip miniaturized scale PC with a free practical module. This permitted course was programmed to coordinate the UAV for spraying at the required or the desired areas on the fields. The spray consistency for these UAV tests was better than the Standard Requirement for ultra-low volume spraying variety coefficient. Zhu et al. (2010) developed a PWM Precision Spraying Controller for Unmanned Aerial Vehicles. This paper shows another Pulse Width Modulation (PWM) controller for Unmanned Aerial Vehicle (UAV) accuracy sprayer for farming utilizing a TL494 fixed-recurrence beat width modulator together with an information obtaining board and created programming. A UAV can be remotely controlled or automated by pre-modified flight plans. Therefore to this examination, PWM controller develops as a high exactness system for the spraying applications. Zhang et al. (2015) assessed powerful swath width and bead circulation of aeronautical showering frameworks on M-18B and Thrush 510G planes. In this examination they assessed the powerful swath width and consistency of the droplet dispersion of two agrarian planes, M-18B and Thrush 510G, which flew at 5 m and 4 m tallness, individually. The consequence of this examination expresses that the flight stature prompts the distinction in swath width for both the farming planes.

Table 3
Classification of Drones for Agricultural Application.

UAV	ROTARY WINGS	FIXED WINGS
Flight duration	Fly upto 20 min	Fly up to an hour
Wind pressure	Can be flown from in winds gusting from 20 to 50 mph	Fly in and out of the wind for satisfactory images
Flexibility in changing direction	Allow new direction during flight for re-direction	Allow new direction upload during flight for re-direction
Price range	$500 to $100,000	$500 to $100,000
Deployable option	Highly deployable	Highly deployable

The sprayer is the one which crumbles the sprayed liquid which is possibly a suspension, an emulsion or an answer into tiny drops and launch it with negligible power for circulating it appropriately (Nørremark et al., 2008). It is additionally in charge of the guideline of the measure of pesticide in order to maintain a strategic distance from extreme application. Intemperate use of pesticides may demonstrate inefficient or harmful to the dirt too the yield. Likewise, the residue definitions of pesticides are disseminated with the assistance of dusters. Based on vitality required to atomize and to toss out the shower liquid, sprayers are arranged into four categories namely: The hydraulic energy sprayer, the gaseous energy sprayer, the centrifugal energy sprayer and the kinetic energy sprayer (Fig. 2).

4.1.1. Hydraulic energy sprayer

In Hydraulic Energy Sprayer, the material to be sprayed is pressurized up to 40–1000 psi in any of the two potential ways. Either straightforwardly by utilizing a positive uprooting siphon or by utilizing a vacuum apparatus which will make the gaseous tension over the shower material noticeable all around tight holder. This pressurized material is shot out through the splash spout. Here, the siphon supplies the vitality which conveys the material to the plant foliage. Water driven Sprayers produce a splash with most beads in the 200–400 μm width

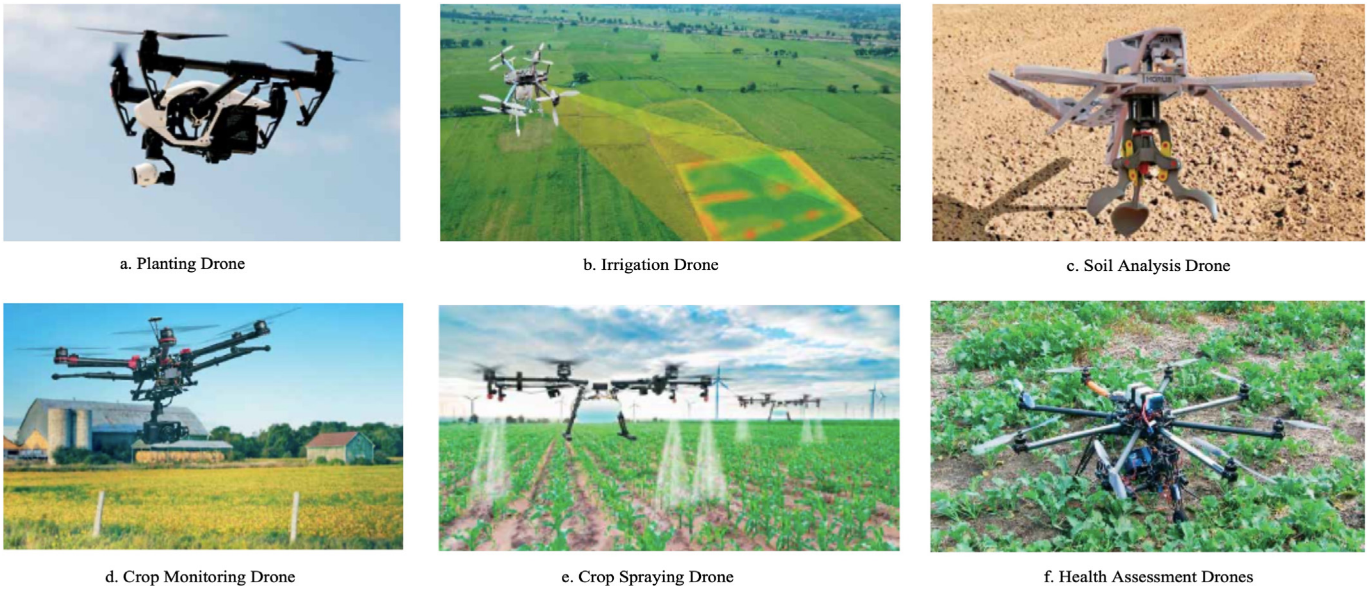

Fig. 2. Types of agricultural drones.
Source: modern agriculture drones (Unpaprom et al., 2018).

extend. As the beads framed are very little the structure a fog or haze which results in uniform inclusion and better contact with the bug or illness. In spite of the fact that, if the beads are little, they will in general vanish immediately when the mugginess is low and probably won't arrive at the objective. A water driven sprayer contains the accompanying parts: tank, siphon with instigator, weight measure, controlling valve, help valve, control valves, funneling and spouts, control source and bolster outline.

4.1.2. Gaseous energy sprayer

In Gaseous Energy Sprayer a blower produces a high speed air stream. This air stream is coordinated through the pipe toward the finish of which spray liquid will be available which will be permitted to be streamed by the activity of gravity through a diffuser plate. A fluid or residue is sustained into air stream to be conveyed to the objective.

4.1.3. Centrifugal energy sprayer

The Centrifugal Energy Sprayer consists of a fast turning devise, for example, level, a concave or a convex plate, a wire mesh cage or a bucket, a puncture strainer or chamber or a brush. At the focal point of this gadget, the shower liquid is nourished under low weight which is additionally atomized by diffusive power as it leaves the outskirts of the atomizer. The droplets are conveyed by the air stream created by the blower of the sprayer or by the common breeze, if the sprayer isn't furnished with a fan.

4.1.4. Kinetic energy sprayer

In Kinetic Energy Sprayer the spray liquid streams by gravity to a vibrating or swaying spout which delivers a coarse fan like spray design. This is explicitly utilized for the spraying of herbicides.

The spray effectiveness of any of the above utilized showers can be determined by utilizing the equation given underneath:

$$\text{Spray proficiency } (\%) = \text{Minimum spray volume required} \times 100\%$$

The plant foliage which is tainted by a pest or weed or any other reason has to be sprayed. The region which is required to be sprayed differs with separation between the lines of plants, separation between the plants in a similar line just as the development of the harvest. In addition, it is important to complete sprayer alignment practice before embraced real spraying work to guarantee uniform use of pesticides on the yields. We can process the spraying volume by utilizing the formula:

$$\begin{aligned}&\text{Application Rate in Liter per Acre or Hecter}\\&\quad = (\text{Constant fig.495 or 600 British Matric}\\&\qquad * \text{Nozzle Discharge Rate in Liter every Minute})\\&\qquad /(\text{Effective Swath Width in Feet or Meters}\\&\qquad *\text{Spraying speed in Mile or Kilometer every hour})\end{aligned}$$

Pesticides are for the most part connected on the objective of the sprayed droplets which comprises of both, fine and coarse drops. They are characterized in term of their distance across and thickness on the objective. In fact, now and again the objective leaf area which is required to be secured might be a lot more prominent than the ground region. The Leaf Area Index (LAI) is the proportion of Leaf Area to Ground Area. LAI tents to shift with various yields and only from time to time surpasses around 6–7. Henceforth this is the reason behind per section of land requirement of water in a sprayer changing from harvest to yield contingent on the complete leaf territory to be secured. However numerous advances are being made in the sprayers which are to be utilized alongside the UAVs which give high inclusion also is effective spraying.

4.2. Crop monitoring

The advanced sensors and imaging capabilities have provided the farmers with many new ways to increase yields and reduce crop damage (See Table 5.). Unmanned airplanes which are used for practical purposes in recent years have taken a bizarre flight. New sensors mounted on UAV, with high-tech cameras being the eyes of the client on the ground and optimal procedures for survey, data acquisition and analysis are continuously developed and tested. As a matter of fact, the use of aerial surveys is not new to the agricultural world. Satellites have been used for a decade to inspect large croplands and forestry but a new level of precision and flexibility has been obtained with the use of UAVs. To carry out UAV flights, one does not need to depend on the position of the satellite or having the correct weather conditions and as UAV pictures are taken 400–500 ft. from the ground level, they result in better quality and provide precision.

Table 5
Summary of the literature of the weeding, soil moisture detection, spraying and crop yield monitoring.

Sr no.	Function	Method	Description	Challenges and future scope	References
1.	Weeding	Bradley Method	The Bradleys used their approach to successfully remove weeds in Ashton Park, part of Sydney Harbor National Park, NSW, from a 16-hectare (40-acre) reserve.	The word 'bush regeneration 'currently includes practices other than weed removal, such as replanting and adding species to an environment where soil, water, or fire regimes have transferred the correct type of plant to the region.	Buchanan (1989).
2.	Weeding	Computer vision assisted system	The mechanically weeding actuator consists of an integrated servo motor coupled with the computer vision aided system to detect plant sites and direct the weeding actuator to perform mechanical weeding operations without harming crops.	The accuracy of the system is found to be 93.6% using haar cascade classifier using OpenCV open source framework. Hence, it can be continued using in future.	Nanda and Reddy (2018)
3	Soil moisture detection	Moisture Analyzers and METTLER TOLEDO	Precise temperature control with halogen heating technology and outstanding weighing technology	Robust construction, built-in performance tests and a comprehensive service offering	(Hanson et al., 2007)
4	Spraying	Telerobotic navigation and target selection	Targeted selection focuses on the development of a user interface suitable for targeted spraying, while simultaneously telerobotic navigation acknowledges the robot along the rows, so the farmer will be at a safe place away from hazardous materials during the spraying process.	Operator has to guide the robot in any given environment; it may be harsh, mild, etc. Aims to develop further for making it applicable in AgriRobot Project.	George Adamides et al. User Interface Design Principles for Robotics in Agriculture: The Case of Telerobotic Navigation and Target Selection for Spraying
5	Spraying	Filter-paper ratio assured methods for spraying droplets	In this method, the spraying droplet is measured through filter paper ratio-assumed titration,and works out the corresponding function relationship between the diameter of coloured spots and diameter of liquid drops with regression analysis	Provides simpler way for gathering data, sampling, measuring spraying droplet and research on new type of plant protection machine.	Chen Zhenyu et al. (1996) Shang et al. (2004)
6	Crop Yield Monitoring Systems	Grain flow sensors for crop yield monitoring	It includes mass flow and volume flow methods which are located below the pivoted auger under the grain tank and in the middle of the elevator respectively. Mass flow methods use weighing type, impact-type, and radiometric-type units while Volume flow methods include paddle wheel type and optical type units.	Design and fabrication of any particular crop might be affected by the sensing approach which is employed. Signal processing as well correction approaches should be implemented for accurate monitoring	Sun-Ok-Chung et al. (2016) Kormann et al. (1998)

ER Hunt et al. (2005) evaluated Digital Photography from Model Aircraft for Remote Sensing of Crop Biomass and Nitrogen Status. In their examination, they advanced an aerobatic model airplane for capturing images utilizing a buyer arranged computerized camera and the hued canvases were utilized to adjust the images. They watched huge contrasts in computerized number (DN) for a similar reflectance and that was a result of contrasts in the introduction settings chosen by the advanced camera. Further they utilized Normalized Green–Red Difference Index (NGRDI) and directly related it to the standardized contrast of the green and red reflectances, individually. The aftereffects of this investigation mirrored that for soybeans, horse feed and corn, dry biomass from zero to 120 $g \cdot m^{-2}$ was straightly corresponded to NGRDI, however for biomass more noteworthy than 150 $g \cdot m^{-2}$ in corn and soybean, NGRDI did not increment further. Sun et al. (2010) demonstrated the achievability of utilizing a continuous kinematic (RTK) worldwide situating framework (GPS) to consequently delineate area of transplanted column crops. They utilized a positive-situation vegetable harvest transplanter retrofitted with a RTK GPS recipient, plant, tendency, and odometry sensors, and an on-board ongoing information lumberjack for transplant mapping in the field during planting. Field test outcomes demonstrated that the mean blunder between the plant map areas anticipated by the planting information and the over viewed areas in the wake of planting was 2 cm, with 95% of the anticipated plant areas being inside 5.1 cm of their real areas. Sonaa et al. (2016) showed UAV multi spectral overview to guide soil and harvest for exactness cultivating applications. Multi spectral and multi temporal orthomosaics were delivered over a test field, which was a 100 m × 200 m plot inside a maize field, to delineate and soil files, just as yield statures, with reasonable ground goals.

A low cost multispectral imaging system was designed and developed for application to crop monitoring (De Oca et al., 2018). It consists of a microcontroller along with two cameras embedded into the drone. One camera is sensitive to Infrared radiation while the other is a common RGB camera. This system provides images and information which are used by a software to compute the NDVI and subsequently the health status of a crop.

Reinecke and Prinsloo (2017a, 2017b) studied the benefits of drones in agriculture, and their limitations, illustrating from examples how drones operate on farms. They discussed different features of deones and specifically how they assist farmers in maximizing their harvest by detecting problems early, and managing the crops by using specific cameras to detect pests and water shortages. (S. Nema et al., 2018) performed a detailed study on Spatial Crop Mapping and Accuracy Assessment Using Remote Sensing and GIS in Tawa Command. They did special crop mapping using satellite Landsat * data for Hoshangabad district of Madhya Pradesh and also carried out a Satellite data classification accuracy which resulted in overall accuracy as 87.60%.

4.2.1. Yield mapping and monitoring

One of the key segments of the unprecedenting progressions in exactness cultivating frameworks, yield mapping, enables the farmer to see spatial variety over the field perceiving zone for future activities and outcome of the past sessions, management. It alludes for the most part to the way toward gathering geo-referenced information on harvest yield and qualities, for example, showing in-field fluctuation, and the soil moisture content of the yield giving a benchmarking apparatus, when the yield is being harvested. In combination with soil examining data, yield maps empowers the arrangement of variable compost maps which considers soil supplement levels just as the supplement which was expelled in the collected harvest. Last result of yield mapping is typically a tonal or shaded guide showing scopes of yield inside a field. Fundamental segments of grain yield mapping framework incorporate grain fow sensor (determines grain volume gathered), grain moisture content sensor (remunerates for grain moisture variability), GPS antenna (receives satellite sign), Yield screen show with a GPS receiver (geo-reference and records information), header position sensor(distinguishes estimations logged during turns), travel speed sensor (determines the separation the join goes during a specific logging interim) (Fig. 3).

4.2.2. Programming of the software

For yield mapping, there are basically 5 errands which are to be managed; information procurement, information preparing, LCD displaying < contact screen info and information sparing. The details of each one of them can be alluded from the Fig. 4:

These 5 undertakings inside and out, structures in performing various tasks sometimes bring about clashes. Predominantly these contentions are identified with the time arrangement. To conquer these contentions and to mull over every one of the undertakings we utilize four interfere with wellsprings of P80C592 in the framework, which are the clock intrude on source, the outer intrude on source, the ADC end-of-transformation intrude on source and the UART sequential I/O port intrude on source.

4.2.3. Yield calculation and calibration

Yield is characterized as harvest weight (lbs for cotton) or volume (bu for grains) reaped per unit region, which is in a roundabout way estimated by the yield sensor stream rate/(speed x swath width). Yield stream rate is commonly determined each 1–2 s during collecting. The begin and end times for each line pass are balanced relying upon the measure of time the harvest takes to travel through sifting, isolating, and cleaning to the area of the yield sensor. The deferrals for beginning of-pass and end-of-pass will rely upon the yield and speed of the consolidate. Scientific interjection systems have been utilized to expel commotion because of blunders and regular spikes in the crude sensor and area information (Searcy et al., 1989; Birrell et al., 1996).

Yield is by implication estimated as a mass power or volume estimation by the yield sensors. Presently the yield count needs to join an

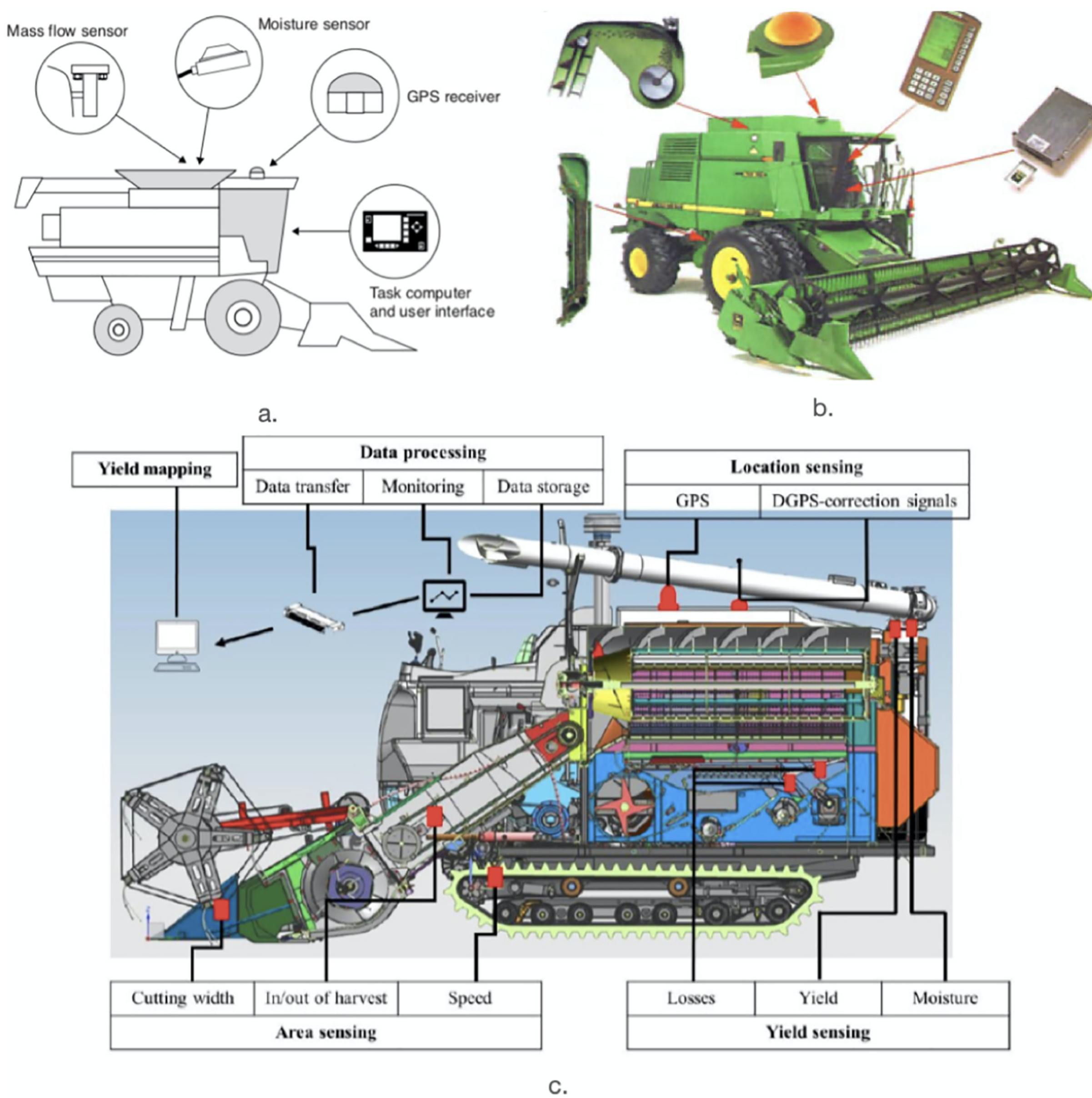

Fig. 3. Yield mapping devices - (a) diagram (b) (Plant et al., 2000) (c) yield mapping harvester equipped to do both tasks (Kormann et al., 1998).

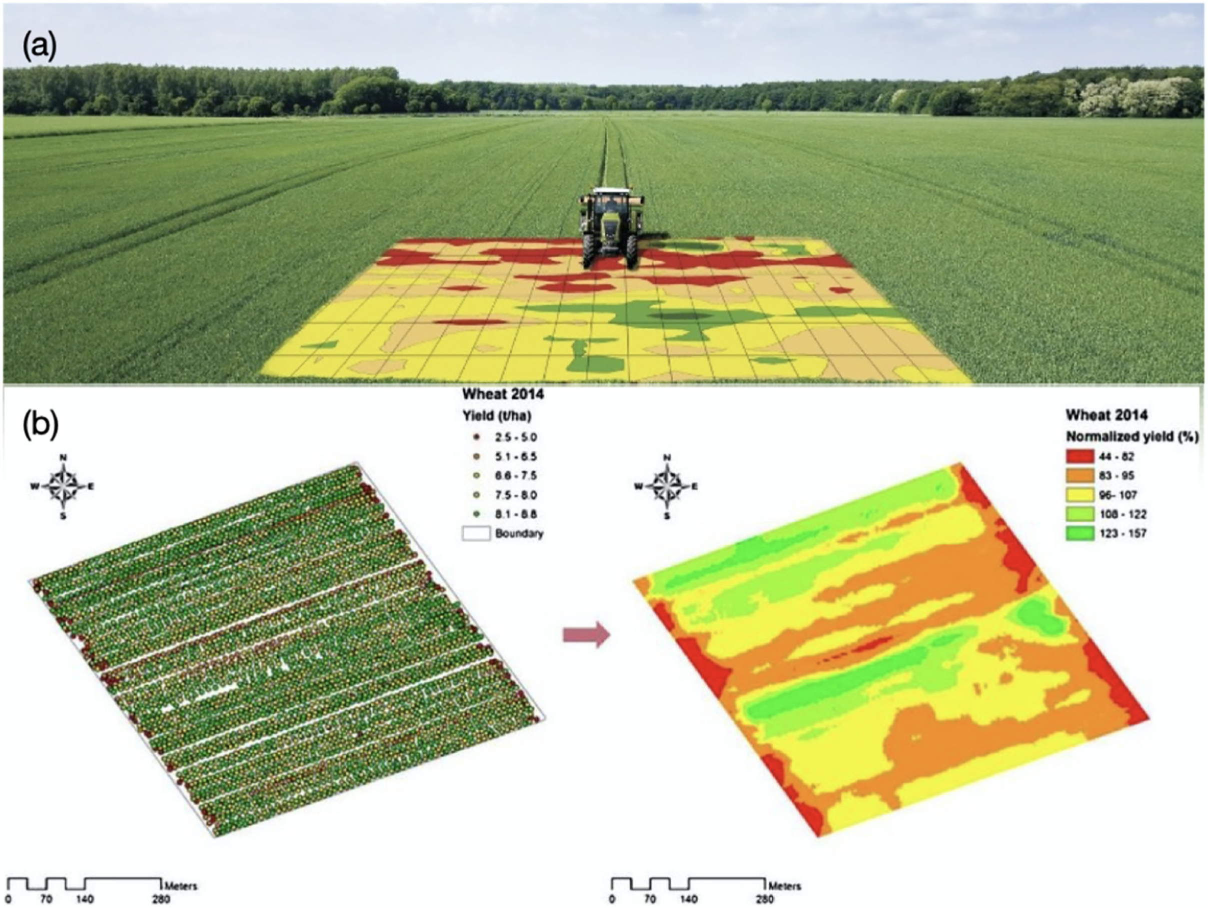

Fig. 4. Yield Mapping (a) Sensing for yield (Source: Utah State University) and (b) example of raw yield map versus interpolated yield map using GIS (Source: Cillis et al., 2018).

adjustment factor because of the way that the yield figuring that changes over to weight relies upon the harvest. To acquire an exact yield information a legitimate sensor alignment is imperative. Contrasting the scale loads of four with five burdens with the determined yield decides an alignment bend. Yield sensors ought to be recalibrated as factors change, for example, dampness substance or half breed. However, utilizing the Yield Sense screen evacuates the requirement for recalibration after the underlying alignment toward the start of the period (Precision Planting).

4.2.4. Processing yield maps

With the utilization of a Geographic Information System (GIS) programming, the yield determined at each field area can be shown. The raw log document, contains focuses which are recorded during turns and as the grain move through a consolidate is a deferred process (unless ongoing amendment is connected), the sensor estimations neglect to compare to the careful gather areas. To dispense with these conspicuous mistakes, the crude information is moved to make up for the joining delay. Increasingly finished, the focuses which compare to the header up position are evacuated. Settings for grain stream postponement are join and some of the time even harvest explicit, yet run of the mill esteems for grain yields extend from around 10 to 12 s.

Typically a couple of focuses toward the start and toward the finish of a pass ought to be expelled too. These focuses are alluded to as begin and end-pass delays. Begin pass postponements happen when the grain stream has not balanced out in light of the fact that the lift is bit by bit topping off yet the consolidate begins gathering the yield. Thus, end-pass deferrals happen when the join moves out of the yield and grain stream progressively decreases to zero when the lift is totally exhausted. Moving of raw information to address for grain stream postponement and exclusion of focuses that speak to header status up and begin and end-pass deferrals is the essential information separating method incorporated with programming provided with yield mapping frameworks.

5. Challenges and future scope

Agriculture has been tackling significant difficulties like absence of irrigation system, change in temperature, density of groundwater, food scarcity and wastage and substantially more. The fate of cultivating depends to a great extent on reception of various cognitive solutions. While large scale research is still in progress and some applications are already available in the market, the industry is still highly underserved (Shobila and Mood, 2014). When it comes to handling realistic challenges faced by farmers and using autonomous decision making and predictive solutions to solve them, farming is still at a nascent stage. In order to explore the enormous scope of AI in agriculture, applications need to be more robust (Slaughter et al., 2008). Only then will it be able to handle frequent changes in external conditions, facilitate real-time decision making and make use of appropriate framework/platform for collecting contextual data in an efficient manner. Another important aspect is the exorbitant cost of different cognitive solutions available in the market for farming. The solutions need to become more affordable to ensure that the technology reaches the masses. An open source platform would make the solutions more affordable, resulting in rapid adoption and higher penetration among the farmers. The technology will be useful in helping farmers in high yielding and having a better seasonal crop at regular interval. Many countries, including India, the farmers are dependent on monsoon for their cultivation. They mainly depend on the predictions from various departments over the weather conditions, especially for rain-fed cultivation. The AI technology will be useful to predict the weather and other conditions related to agriculture like land quality, groundwater, crop cycle, and pest attack, etc. The accurate projection or prediction with the help of the AI technology will reduce most of the concerns of the farmers. AI-driven sensors are very useful to extract important data related to agriculture. The data will be useful in enhancing production. In agriculture, there is a huge scope for these sensors. Agriculture scientist can derive data like quality of the soil, weather and groundwater level, etc.; these will be useful to improve the cultivation process. AI empowered sensors can also be installed in the robotic harvesting equipment in order to get the data. It is speculated that AI-based advisories would be useful to increase production by 30%. The biggest challenge to farming is the crop damage due to any kind of disasters including the pest attack. Most of the time due to lack of the proper information farmers lose their crops. In this cyber age, the technology would be useful for the farmers to protect their cultivation from any kind of attacks. AI-enabled image recognition will be useful in this direction. Many companies have implemented drones to monitor the production and to identify any kind of pest attacks. Such activities have been successful many times, which gives the inspiration to have a system to monitor and protect crops. A robotic lens zooms in on the yellow flower of a tomato seedling. Images of the plant flow into an artificial intelligence algorithm that predicts precisely how long it will take for the blossom to become a ripe tomato ready for picking, packing, and the produce section of a grocery store. The technology is being developed and researched at NatureFresh Farms, a 20-year-old company growing vegetables on 185 acres between Ontario and Ohio. Knowing exactly how many tomatoes will be available to sell in the future makes the job of the sales team easier and directly benefits the bottom line, said Keith Bradley, IT Manager for NatureFresh Farms. It's only one example of AI transforming agriculture, an emerging trend that will help spur an agricultural revolution. From detecting pests to predicting what crops will deliver the best returns, artificial intelligence can help humanity confront one of its biggest challenges: feeding an additional 2 billion people by 2050, even as climate change disrupts growing seasons, turns arable land into deserts, and floods once-fertile deltas with seawater. The United Nations estimates we will need to increase food production 50% by the middle of the century. Agricultural production tripled between 1960 and 2015 as the world's population grew from 3 billion people to 7 billion. While technology played a role in the form of pesticides, fertilizers, and machines, much of the gains can be attributed to simply plowing more land—cutting forests and diverting fresh water to fields, orchards, and rice paddies. We will have to be more resourceful this time around. AI is likely to transform agriculture and the market in the next few years. The technology has been useful for the farmers to understand various types of hybrid cultivations which would yield them more income within the limited time frame. The proper implementation of AI in agriculture will help the cultivation process and to create an ambiance for the market. As per the data with leading institutions, there is a huge wastage of the food across the world and using the right algorithms, this problem can also be addressed which will not only save the time and money but it will lead to sustainable development. There are better prospects for digital transformation in agriculture backed by leveraging technologies like AI. But, it all depends on the huge data which is quite difficult to gather because of the production process which happens once or twice in a year. However, the farmers cope up with changing scenario to bring digital transformation in the agriculture by implementing AI. It's only one example of AI transforming agriculture, an emerging trend that will help spur an agricultural revolution. We will have to be more resourceful this time around.

6. Conclusion

The agricultural industry faces various challenges such as lack of effective irrigation systems, weeds, issues with plant monitoring due to crop height and extreme weather conditions. But the performance can be increased with the aid of technology and thus these problems can be solved. It can be improved with different AI driven techniques like remote sensors for soil moisture content detection and automated irrigation with the help of GPS. The problem faced by farmers was that precision weeding techniques overcome the large amount of crops being lost during the weeding process. Not only do these autonomous robots improve efficiency, they also reduce the need for unnecessary pesticides and herbicides. Besides this, farmers can spray pesticides and herbicides effectively in their farms with the aid of drones, and plant monitoring is also no longer a burden. For starters, shortages of resources and jobs can be understood with the aid of man-made brain power in agribusiness issues. In conventional strategies huge amount of labor was required for getting crop characteristics like plant height, soil texture and content, in this manner manual testing occurred which was tedious. With the assistance of various systems examined, quick and non-damaging high throughput phenotyping would occur with the upside of adaptable and advantageous activity, on-request access to information and spatial goals.

Authors contribution

All the authors make substantial contribution in this manuscript. TT, DS NP HY and MS participated in drafting the manuscript. TT, DS, NP and HY wrote the main manuscript, all the authors discussed the results and implication on the manuscript at all stages.

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Declaration of competing interest

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

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