ARTIFICIAL INTELLIGENCE IMPACT ON AGRICULTURE: A COMPREHENSIVE REVIEW

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ABSTRACT

This research paper explores the transformative effects of Artificial Intelligence (AI) on the agricultural sector. By analyzing the integration of AI technologies such as machine learning, computer vision, and robotics, we investigate the significant advancements in crop management, yield optimization, and sustainable farming practices. The paper also addresses the challenges and ethical considerations associated with the widespread adoption of AI in agriculture.

Keywords: Agriculture, Artificial Intelligence, Irrigation, Weeding, Crop Management;

1. OVERVIEW OF THE CURRENT STATE OF GLOBAL AGRICULTURE

The economy is significantly influenced by agriculture. Globally, the primary issue and burgeoning topic is agriculture automation. The population is growing at an exponential rate, which is simultaneously driving up demand for jobs and food. For the farmers to meet these needs, the conventional techniques they employed were insufficient. New automated techniques were consequently introduced. In addition to meeting the world's food needs, these new techniques gave billions of people jobs. A revolution in agriculture has been brought about by artificial intelligence. The agricultural production has been shielded by this technology from a number of threats, including population expansion, climate change, job concerns, and issues with food security. This paper's primary goal is to audit the different applications.

2. AI TECHNOLOGIES INFLUENCING AGRICULTURE

Artificial Intelligence is a new technology in agriculture. AI-powered machinery and equipment have raised the bar for today's agricultural sector. Crop productivity has increased along with real-time monitoring, harvesting, processing, and marketing thanks to this technology. Drones and agricultural robots, together with other advanced technologies, have revolutionized the Agro-based industry. Many advanced computer-based systems are made to identify numerous crucial factors, such as crop quality, production, and weed detection, among many other methods (Liakos et al., 2018). This paper discusses the technology that farmers can utilize to increase output and lessen their workload by using automated irrigation, weeding, and spraying. There is discussion of several automated soil sensing methods (Wall and King, 2004).

2.1. Image recognition and perception

According to Lee et al. (2017), autonomous UAVs have drawn more attention recently because to its potential uses in recognition and surveillance, human body detection, and geolocation. Bhaskaranand and Gibson, 2011; Doherty and Rudol, 2007; Tomic et al., 2012; Merino et al., 2006) discuss search and rescue operations as well as forest fire detection. Drones, or unmanned aerial vehicles, are becoming more and more popular as a means to reach great heights and distances and perform a variety of tasks due to their versatility and amazing imaging technology that covers everything from delivery to photography.

Additionally, the devices can be controlled with a remote controller and are nimble in the air, which allows us to do a lot with them.

2.2. Workforce and skill sets

According to Panpatte (2018), artificial intelligence enables farmers to compile vast amounts of data from public and government websites, evaluate it all, and offer answers to a number of unclear problems. It also gives us smarter irrigation techniques, which boost farmers' yields. In the near future, farming will be discovered to be a combination of biological and technological talents due to artificial intelligence. This will not only improve the quality of the product for all farmers, but also reduce their losses and burden. By 2050, it is predicted that there will be over nine billion people on the planet, necessitating a 70% increase in agricultural output to meet demand. The availability of undeveloped land may account for just 10% of this extra production; the remaining 90% should be met by stepping up current production. Using the newest technology to improve farming efficiency is still one of the most important things to do in this situation. Current agricultural production intensification tactics necessitate significant energy inputs, while the market demands food of superior quality.

2.3. Optimize the results

The maximum performance level for all plants is determined by variety selection and seed quality, according to Ferguson et al. (1991). The best crop selection has been made easier by developing technologies, which have also enhanced the selection of hybrid seed options that are most suitable for farmers' requirements. It has been put into practice by comprehending how varied soil types and weather conditions affect seeds. Plant diseases have less of a chance when this data is gathered. Farmers may effectively maximize the return on their crops since we can now meet market trends, annual results, and consumer wants.

2.4. Farmers' chatbots

Simply put, chatbots are conversational virtual assistants that perform user interactions automatically. Chatbots driven by artificial intelligence and machine learning techniques have made it possible for us to comprehend natural language and communicate with consumers in a more tailored manner. Their primary functions include retail, travel, media, and agricultural. agricultural has made use of this facility by helping farmers find the answers to their unanswered problems as well as by offering them guidance and a variety of recommendations.

3. AGRICULTURE WITH ROBOTS

In significant economic sectors like agri-food, which have relatively low productivity, robotics and autonomous systems (RAS) are being implemented. The UK agri-food chain, from primary farming to retail, generates about £108 billion annually, employs 3.7 million people, and is a genuinely global industry that produced £20 billion in exports in 2016, according to UK-RAS White Papers (2018). The production and management of agriculture have benefited greatly from robotic involvement. Due to the inefficiencies of the traditional farming equipment, researchers are now focusing on technologies to build autonomous agricultural implements (Dursun and Ozden, 2011). The principal objective behind developing this technology is to supplant manual labor and yield efficient outcomes for both small- and large-scale manufacturing (Manivannan and Priyadharshini, 2016). The use of robotic technologies in this industry has greatly increased productivity (Pedersen et al., 2008). The autonomous robots are carrying out a range of agricultural tasks, including irrigation, weeding, protecting farms to ensure efficient reporting, preventing production loss due to unfavorable environmental conditions, improving accuracy, and managing individual plants in novel ways.

The invention of a device known as Eli Whitney's cotton gin gave rise to the notion for developing such a technology. It was created in 1794 by American-born inventor Eli Whitney (1765–1825), and it dramatically accelerated the process of separating cotton fiber from seed, revolutionizing the manufacture of cotton. In a single day, it produced fifty pounds of cotton. As a result, autonomous agricultural robots were created. To ascertain the precise location of seeds, a simple automated model was presented (Griepentrog et al., 2005). Additionally, extremely precise seed positioning was achieved. systems that guarantee a seed's ground velocity of zero (Griepentrog et al., 2005). This is crucial because it guarantees that, upon the impact of the soil, the seed will not bounce from its original place. Automated devices documented the plant's progress or status. Numerous biosensors were set up to track plant development and identify plant illnesses (Tothill, 2001). The manual weeding method was superseded by laser weeding technology, which uses a mobile, focused infrared light beam controlled by computers to damage weed cells (Griepentrog et al., 2006). Additionally, automatic irrigation systems were developed to make efficient use of water.

3.1. Advancement in Irrigation

The agriculture sector consumes 85% of the freshwater resources that are available worldwide. As the population grows and the demand for food rises, this percentage is rising quickly. As a result, we must develop more effective systems to guarantee that water resources are used appropriately for irrigation. Automatic irrigation scheduling techniques took the place of manual irrigation, which was based on soil water measurement. When using autonomous irrigation machines, consideration was given to plant evapotranspiration, which was dependent on a number of atmospheric parameters including humidity, wind speed, and solar radiation, as well as crop factors like growth stage, plant density, soil characteristics, and pests.

The main goal of Kumar's (2014) discussion of irrigation techniques is to create a system that uses fewer resources and is more efficient. In order to assess the fertility of the soil, instruments such as PH meters and fertility meters are placed in the field to measure the proportion of the soil's main constituents, such as nitrogen, phosphorus, and potassium. Wireless technology is used to plant automatic plant irrigators on the field for drip irrigation. This technique guarantees both the soil's fertility and the efficient use of water resources.

By sensing the water level, soil temperature, nutrient content, and weather forecasts, smart irrigation technology is designed to boost productivity without requiring a lot of labor. To turn on the irrigation water supply, the signal is transferred to the Raspberry Pi3, which is equipped with a KNN algorithm. From there, it is sent to Arduino. The resource will update and store the sensor values in addition to providing water based on the requirements. To cut down on labor costs and time spent on irrigation, Jha et al. (2019) also created an automated irrigation system utilizing Arduino technology.

Varatharajalu and Ramprabu provided another automatic irrigation system (2018). This method used a variety of sensors, each with a specific function. For example, the soil moisture sensor measures the amount of moisture in the soil, the temperature sensor measures the temperature, the pressure regulator sensor keeps pressure levels constant, and the molecular sensor improves crop growth. the setting up of digital cameras. All of these devices' output is transformed to a digital signal before being transferred via a wireless network, like a hotspot or Zigbee network, to the multiplexer. The first method was subsurface drip irrigation, which immediately buried the water beneath the crop, minimizing

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water loss from evaporation and runoff. Subsequently, researchers developed various sensors, such as soil moisture sensors and rain drop sensors, that were controlled by wireless broadband networks and powered by solar panels to determine when the fields needed to be irrigated. Using a GSM module, the rain drops sensor and soil moisture sensor send an SMS to the farmer's cell phone informing them of the soil's moisture content. As a result, the farmer can turn on and off the water supply by sending directions via SMS. Therefore, we can assume that this system will identify a portion or region of the fields.

Soil moisture sensors employ one of the various methods available for determining the moisture content of the soil. It is interred close to the crop root zones (Dukes et al., 2009). The sensors assist in precisely measuring the moisture content and provide the reading to the irrigation controller. Significant water conservation is another benefit of using soil moisture sensors (Quails et al., 2001). One method of using moisture sensors is water-on-demand irrigation, where the controller is able to water only when necessary. The threshold is chosen according on the soil's field capacity. When the appointed time comes, the sensor determines the amount or moisture content for that specific zone, and watering will only be permitted in that zone if the moisture content is below the cutoff. The alternative type of irrigation was called suspended cycle irrigation, which, in contrast to water-on-demand irrigation, needed irrigation time. It needs each zone's duration and start time (Yong et al., 2018).

4. WEEDING

In his article on "A History of Weed Science in the United States," Zimdahl (2010) mentioned Thomas K. Pavlychenko, a pioneering weed experimentalist who conducted research on plant competition. He conducted extensive research on the subject and found that weeds were the greatest rivals for water, with plant competition starting when roots in the soil overlap to collect nutrients and water. The amount of water needed to generate one pound of dry matter is the amount needed for the plant's aerial portions.

In order to attain maturity, the common ragweed plant (Ambrosia artemisiifol ia) needs three times as much water as a maize plant, and the wild mustard plant (Brassica kaber var. pinnatifida) needs four times as much as an oat plant. By multiplying the plant's production in pounds of dry matter per acre by the water demand of the plant, one can compute the water requirement per acre. Another element that is necessary for plant growth is light. Tall weeds typically obstruct the plants' access to light. Certain weeds, including redroot pigweed and green foxtail, are shade intolerant, but other weeds, like Arkansas rose, field bindweed, and common milkweed spotted spuroe, may tolerate some shade. A study conducted by researchers from the Indian Council for Agricultural Research found that weeds cause India to lose agricultural produce valued at over $11 billion yearly, which is more than the Center's annual budgeted allotment for agriculture in 2017–18. We must distinguish between weeds and crop seedlings before creating an automated weed control system (Bhagyalaxmi et al., 2016; Chang and Lin, 2018). A technique was used to distinguish ryegrass seedlings from carrot seedlings. This method was applied by Aitkenhead et al. (2003) using a straightforward measurement of the morphological characteristics of leaf shape. This technique, which uses differences in leaf size to distinguish between plants and weeds, varies in efficacy between 52 and 75%. Digital imaging was used as another weeding technique. This concept made use of a neural network that organizes itself. However, this approach did not produce the intended results for commercial use. Instead, it was discovered that a NN-based system was already in place that could identify species distinctions with an accuracy of more than 75%.

Many automated techniques have been established in the modern world, however in the past, other physical methods that relied on physical interaction with the weeds were used.

Nørremark and Griepentrog (2004) suggested that the quantity and location of weeds determine how much weeding is necessary. To accomplish intra-row weeding, traditional spring or duck foot tines were utilized. This method broke the soil and the root contact by tillage, which encouraged the weeds to wile. However, because tillage can destroy the interface between the crop and the soil, this is not a recommended practice. Thus, no more contact techniques were created, such as micro spraying and laser treatments (Heisel et al., 2001), which have no effect on the root-soil contact.

In their 2014 paper, Nakai and Yamada described how agricultural robots are used to reduce weeds and develop strategies for manipulating the robots' postures on uneven rice-growing fields. It controlled the robot's posture and suppressed the weeds using the Laser Range Fielder (LRF) approach. A robotic weed management system was presented by Åstrand and Baerveldt (2002). The robot had many vision systems built in it. The first vision type was gray-level, which was utilized to create a row structure so the robot could be guided along the rows. The second type of vision was color-based, which was crucial since it allowed the robot to distinguish between individual weeds. A unique algorithm with a was used to construct the row recognition system.

4.1. Based on chemicals

Herbicides were sprayed using eight nozzles located at the back of the device in this technology. The entire system partitioned the photos taken into 8 × 18 tiny rectangles, or blocks if you will; each block measured 8128 square millimeters. Subsequently, each row—which was made up of these blocks—was inspected and processed sequentially based on the number of nozzles. Each box containing weeds is sprayed once the blocks have been examined.

It is also possible to divide the photographs into 16 × 40 blocks; in this example, each block is around 8768 square millimeters. Therefore, in this instance, 16 nozzles are required rather than 8. Based on the aforementioned conditions, the further processing, or spraying operation, was completed. The prerequisites are:

1. A block is classified as weedy if the percentage of weed pixels in it that make up the block is more than 10%.
2. Herbicides had been sprayed on every block that was inspected.
3. The weeds whose area is equal to or greater than 30% sprayed are then meant to be killed following these two requirements.
4. This method uses a selective herbicide that is sprayed.

4.2. High-voltage discharge via pulse

The need to lower the prices of chemicals used in farming and the environment is driving up demand for non-chemical weeding techniques. Non-chemical weed control is becoming more popular as a result of the growing interest in organic farming (Bond and Grundy, 2001). There have been studies on mechanical, electrical, and biological weed control techniques (Parish, 1990). One such non-chemical weed management technique, called pulse high voltage discharge, was primarily used to eradicate tiny weeds. These tiny weeds, which measure roughly 5 cm tall and have a stem diameter of 2 mm, may be eliminated with a single spark that has 153 mJ of energy and 15 kV of voltage. On the other hand, a 20 Hz charge can eradicate the huge weeds, which range in height from 80 to 120 cm and have a stem diameter of 10 to 15 mm. These spark charges have a negative impact on the weeds' stems and roots, which disrupts the movement of the waiter to the different areas of the

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weeds. So, a few days after the spark, the weeds wilt. Instead of the nozzles used in the prior chemical-based weeding approach, spark discharging devices are installed on the system in this method. In this case, the system is set up to only apply spark to weed-detected areas. Similar to the chemical procedure that was previously explained, this method likewise has certain predetermined criteria. The following criteria apply:

1. The center of the region is determined by calculating the average of all the pixel coordinates in the photos.
2. This center is where the spark discharge used for weeding is applied.
3. The plant in question is deemed destroyed if it is exposed to the spark discharge.

5. USING DRONES FOR FARMING

In a mechanical context, unmanned aircraft that may be remotely controlled are known as automatons, also known as unmanned aeronautical vehicles (UAVs) or unmanned ethereal frameworks (UAS) (Mogli and Deepak, 2018). They collaborate with the GPS and other installed sensors. In agriculture, drones are being used for disaster management, weed identification, crop health monitoring, irrigation equipment monitoring, herd and animal monitoring, and more (Veroustraete, 2015; Ahirwar et al., 2019; Natu and Kulkarni, 2016).

Agriculture is being greatly impacted by remote sensing, which uses unmanned aerial vehicles (UAVs) to capture, process, and analyze images. (2015) Abdullahi et al. According to Pederi and Cheporniuk (2015), the rural industry seems to have embraced ramble innovation with gusto, using these powered tools to transform the way that agriculture is currently conducted. According to a current PwC investigation, the total addressable estimation of automation-fueled arrangements in every pertinent area is crucial and exceeds USD 127 billion. They can be compared to a typical easy-to-use camera for clear images; however, while a standard camera can provide some information about plant development, inclusion, and other topics, a multispectral sensor increases the procedure's usefulness and allows farmers to see objects that are invisible to the naked eye.

Wireless Sensor Networks (WSN) are integrated into the UAS development process. The WSN's data recovery allows the UAS to improve its use, such as limiting its spraying of artificial substances to precisely designated areas. The ecological conditions are always changing; thus, the control circle must most likely react as quickly as is reasonably possible. Along that approach, the reconciliation with WSN can be helpful (Costa et al., 2012). UAVs are primarily used in precision agriculture for tasks like pesticide spraying (Faiçal et al., 2017; Faiçal et al., 2014a, Faiçal et al., 2014b, Faiçal et al., 2012), crop monitoring (Bendig et al., 2012), soil and field analysis (Primicerio et al., 2012), crop height estimations (Anthony et al., 2014), and crop height estimations (Bendig et al., 2012), Faiçal et al., 2014b, Faiçal et al., 2014c; Huang et al., 2009), height estimations (Anthony et al., 2014).

6. CROP MANAGEMENT

Farmers now have a plethora of innovative options to boost yields and minimize crop damage thanks to the development of sophisticated sensors and imaging capabilities. In recent years, unmanned aircraft that are utilized for practical purposes have had some strange flights. Advanced cameras on UAVs serve as the client's eyes on the ground, and new sensors are constantly being developed and tested. Optimal protocols for data collection, surveying, and analysis are also being tested. In actuality, aerial surveys have long been used in the agricultural industry. Large croplands and forests have been inspected by satellites for the past ten years, but the deployment of UAVs has brought precision and flexibility to a new

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level. Unmanned Aerial Vehicle (UAV) flights can be conducted without reliance on satellite positions or favorable weather. Since UAV photos are acquired 400–500 feet above the ground, they yield higher quality and more accuracy.

7. CHALLENGES AND FUTURE SCOPE

Significant challenges facing agriculture include the lack of an irrigation infrastructure, temperature fluctuations, groundwater density, food scarcity and waste, and many more. The acceptance of different cognitive answers greatly influences the destiny of cultivating. The industry is still severely underserved, despite the fact that extensive research is still ongoing and some applications are currently on the market (Shobila and Mood, 2014). Farming is still in its infancy when it comes to managing the real-world problems that farmers confront and applying autonomous decision-making and predictive solutions to tackle them. Applications must be more reliable in order to fully explore AI's vast potential in agriculture (Slaughter et al., 2008).

Then and only then will it be able to adapt to frequent changes in the external environment, support decision-making in real time, and utilize the proper framework or platform for effectively gathering contextual data. The expensive price of the many cognitive farming technologies on the market is another significant factor. For the technology to be widely used, the solutions must become more reasonably priced. The solutions would be more economical on an open-source platform, which would hasten acceptance and increase penetration among farmers. Farmers will benefit from the technique by receiving higher yields and better seasonal crops on a regular basis. Farmers in many nations, including India, rely on the monsoon for their crop production. Their primary reliance is on the forecasts provided by several departments.

AI-powered sensors are a great tool for extracting vital agricultural data. The information will help to improve output. There is a vast application for these sensors in agriculture. Scientists studying agriculture can determine factors such as soil quality, weather patterns, and groundwater levels, among other things. These data can be used to enhance the farming process. To obtain data, robotic harvesting equipment can also be equipped with AI-enabled sensors. It is estimated that 30% more production could be achieved with the help of AI-based advisory. The largest problem facing farmers is crop destruction from pest attacks and other natural calamities. Most often, farmers lose their crops because they do not have the necessary knowledge. In the era of the internet, the

Most often, farmers lose their crops because they do not have the necessary knowledge. Farmers could employ technology in this cyber age to safeguard their crops from many types of threats. In this regard, AI-enabled image identification will be helpful. Drones have been used by numerous businesses to monitor production and spot pest assaults of any kind. Numerous instances of success with such initiatives serve as motivation for the development of a system to watch over and safeguard crops. A tomato seedling's bright blossom is magnified by a robotic lens. An artificial intelligence program uses photos of the plant to determine exactly how long it will take for the flower to turn into a ripe tomato that is suitable for harvesting, packaging, and other uses.

NatureFresh Farms, a 20-year-old enterprise that grows veggies on 185 acres between Ontario and Ohio, is where the technology is being developed and researched. According to Keith Bradley, IT Manager at NatureFresh Farms, knowing precisely how many tomatoes will be available for sale in the future facilitates the sales team's work and positively impacts the company's financial results. This is only one instance of how AI is revolutionizing agriculture; this is a new trend that will contribute to a revolution in agriculture. Artificial intelligence can help humanity tackle one of its greatest 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. AI can do everything from detect pests to predict which crops will yield the best returns. The

Appropriate AI application in agriculture will facilitate cultivation and set the stage for market success. According to statistics from prestigious institutes, there is a significant global food waste problem that may be solved with the use of the correct algorithms. Doing so will not only save time and money but also promote sustainable growth. With the support of technologies like artificial intelligence, the possibilities for digital transformation in agriculture are brighter. However, everything is dependent on the massive amount of data, which is challenging to collect due to the production process, which occurs only once or twice a year. Nevertheless, farmers adapt to the changing landscape by using AI to bring about a digital transformation in agriculture.

8. CONCLUSION

The agricultural sector has to deal with a number of obstacles, including ineffective irrigation systems, weeds, difficulties monitoring plants because of crop height, and harsh weather. However, technology can help to improve performance, which means that these issues can be resolved. Several AI-driven solutions, such as the use of remote sensors to determine soil moisture content and GPS-assisted automated irrigation, can be used to improve it. Farmers faced the challenge of using precision weeding techniques to mitigate the significant crop loss that occurs during the weeding process. These self-governing robots not only increase productivity but also lessen the requirement for needless herbicides and insecticides.

In addition, farmers may use drones to efficiently apply pesticides and herbicides on their farms, and plant monitoring is no longer a hardship. To begin with, man-made intelligence can help us understand resource and employment constraints in agribusiness-related difficulties. Conventional methods involved a significant amount of labor-intensive manual testing to get agricultural attributes such as plant height, soil texture, and content. Rapid and non-destructive high throughput phenotyping would be possible with the aid of the many technologies under investigation, offering the benefits of flexible and favorable activity, on-demand information access, and spatial objectives.

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