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Precision Farming Utilizing Internet of Things, Artificial Intelligence and Automation: An Overview

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Abstract

The food demand is rising enormously due to the increasing population worldwide. The farmers' conventional practices need to be revised to meet the dietary needs of the global masses. Moreover, the excess use of chemical fertilizers, pesticides, herbicides, and water degrades the environment and increases the production cost of cultivation. To satisfy the requirements of a rapidly rising global population, farming requires modern scientific and technological implementations like the Internet of Things (IoT), Artificial Intelligence (AI), and Automation. Technology-based precision farming has started to play an essential role in soil, insect, weed and irrigation management, eventually boosting agricultural output. AI-powered automation in precision farming can save water, pesticides, and herbicides, maintain soil fertility, and boost the productivity and quality of agricultural products by drastically lowering waste. Before AI-based automation can be extensively embraced by all types of farmers worldwide, several issues need to be resolved, such as the unequal distribution of mechanization, algorithms' capacity to reliably handle enormous volumes of data, and data security and privacy. In the study, we reviewed several scientific papers on the potential applications of IoT, AI, and some other emerging innovations for creating automated innovative farm machinery, irrigation systems and drones for the protection of plants, nutrient, pesticide and herbicide management and crop health monitoring.

1 Introduction

Since millennia, agriculture has played a crucial part in the world economy. Agriculture is estimated to generate around 4% of the world's global gross domestic product (GDP). Agriculture accounts for over one-fourth of the GDP in most third-world nations, with more than two-thirds of rural households relying on it for their livelihoods. Within 2050, the world's population will be almost 10 billion, necessitating an increased crop production by increasing yield per hectare (FAO, 2017). Green revolution significantly increased agricultural production (Campos et al., 2018; Evenson and Gollin, 2003; Tilman et al., 2002) and it was around 300 percent in the last sixty years; nevertheless, the widespread use of synthetic pesticides continuously polluting nature and also harming human health (Pingali, 2012; Evenson and Gollin, 2003). Still, most of the world's developing nations will continue to work toward higher food production by utilizing mineral fertilizers throughout the next 50 years (Swaminathan, 2007). In recent years, several challenges have jeopardized the economic and environmental viability of current and future food supply systems, including a lack of farmland, labour shortages, severe weather, a decline in soil fertility, and others. There has been a significant shift in most sectors in the world since the introduction of modern technologies, for example, computer vision (Pramanik et al., 2021a), machine learning (Sarkar et al., 2019b, 2020, 2019a), and deep learning (Sarkar et al., 2022). However, the agricultural sector still needs to catch up. As a result, using new technologies in agriculture will spur rural growth, paving the way for rural transformation and, ultimately, structural change (Mogili and Deepak, 2018). In our daily lives, AI is beginning to play a significant role. It can potentially expand our senses and influence our immediate surroundings (Gandhi et al., 2019; Kundalia et al., 2019). Automation of agriculture with artificial intelligence already improves production, harvesting, and processing (Dawn et al., 2023). Internet of Things (IoT) and AI have been considered crucial technologies for transforming contemporary agricultural methods in light of recent advancements in ICT (Information and Communication Technology). Artificial intelligence-assisted agriculture has gained widespread recognition as one of the possible answers to the world's food scarcity since it tackles problems that humans cannot adequately handle. The first attempt to apply AI to agriculture was made in 1985 with the creation of COMAX, an Expert System-based simulation model for cotton crops. Its objective was to maximize cotton yield while accounting for the effects of fertilization, weed control, irrigation, climate, and other aspects (Lemmon, 1986). Precision farming's main objective is to make the most of the resources that are already available while avoiding any adverse environmental consequences (Das, 2018). Real-time analysis made possible by agriculture's digitization aids in land monitoring, better spraying, and land and water management. Cutting-edge digital technology and agricultural automation may help minimize input costs and waste, apply sustainable practices, and increase productivity to meet the expanding food needs. In this study, we examine recent developments in agricultural automation driven by artificial intelligence for sustainable agriculture. We also discuss the present obstacles to the widespread adoption of these contemporary technologies in the near future, particularly for common farming communities.

2 Methodology

This current research used a systematic literature review approach to explore the adoption of Artificial Intelligence (AI), Machine Learning (ML) and the Internet of Things (IoT) in agriculture. The review was, therefore, not an empirical review that aimed at identifying new research or new data but rather a theoretical review that recruited works from already published databases. The articles were retrieved using Scopus, Web of Science and Google Scholar using various keywords, including "AI in Agriculture", "Machine Learning in Agriculture", and "IoT in agriculture and precision agriculture". Boolean operators were used to expand specific search strings, implying that only those articles were considered, which gave a richer understanding of these technologies in agriculture. The study focused on articles recently published in English. Primary and secondary screening were included, with title and abstract sources scrutinized, followed by full texts and quality as a final step after pre-screening. Information extraction aimed to find overviews, current tendencies and developments, potential uses and issues in the sphere, while synthesized knowledge described categories such as crop surveillance, yield estimation, and pest management. The findings of this review were then synthesized to offer a systematic account of the forms and uses of the approaches of AI, ML, and IoT in agriculture work, the issues encountered, and finally, the areas they highlighted for further research.

3 Precision farming by drones

For precision farming to be sustainable, the availability and accuracy of field data is crucial. Due to sampling size limitations and inherent subjectivity, traditional methods of collecting crop data often need to catch up to capturing infield variations (Chang et al., 2017; Zhang et al., 2021). Accurate, flexible, fast and cost-effective measurements of plant development may be made using drones (Unmanned Aerial Vehicles) fitted with red, green, blue and multispectral sensors (Ampatzidis et al., 2017; Pajares, 2015; Singh et al., 2015). To evaluate the phenotypic attributes of citrus trees, Ampatzidis et al. (2017) successfully tested precision agricultural applications employing artificial intelligence and a cloud-based application (Agroview). Agroview processes, analyses, and visualizes data received by drones. He reported that this approach detected citrus trees with an accuracy of 2.3% in a commercial citrus

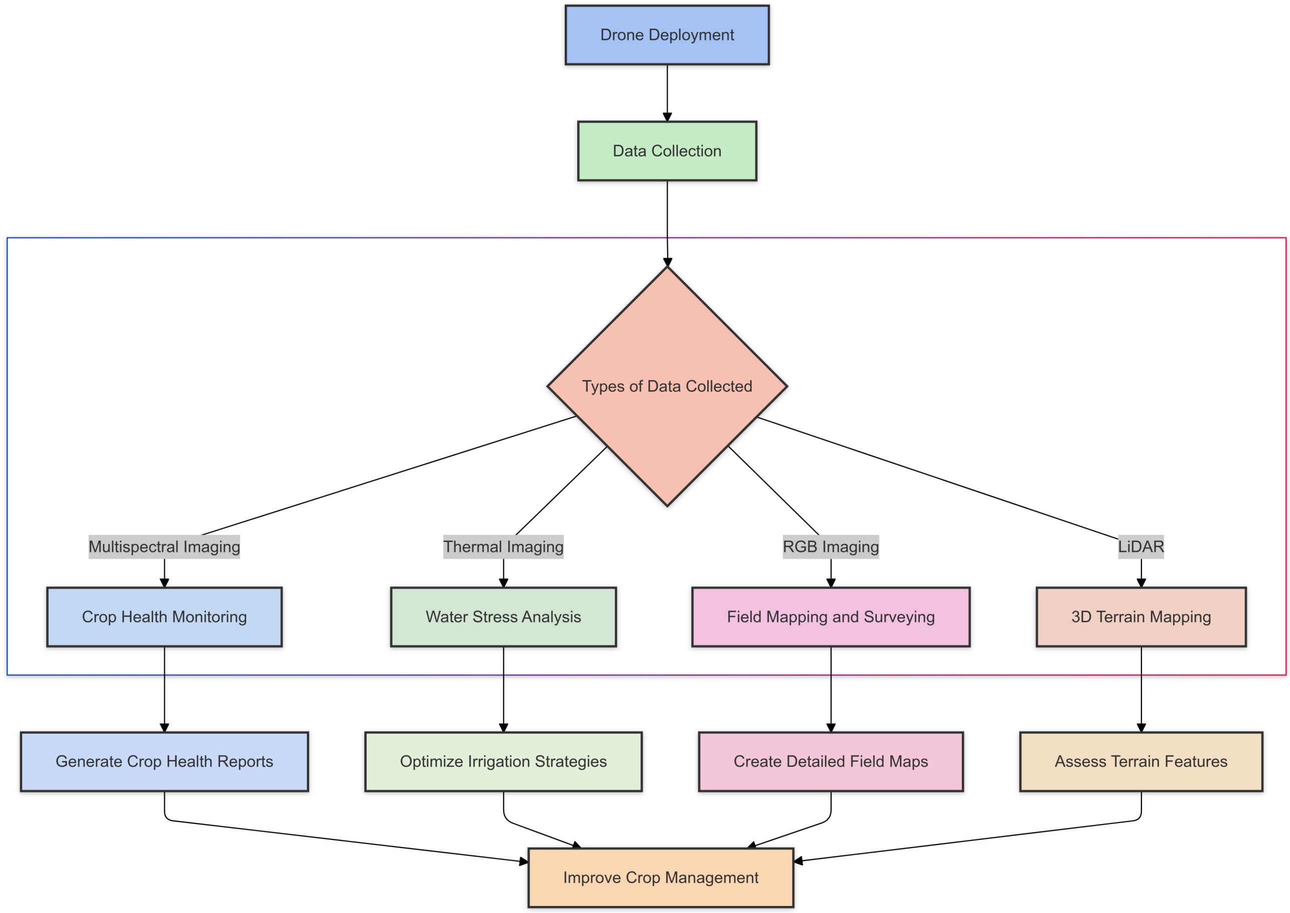

Figure 1: Drone-based data collection workflow.

plantation with 1,75,977 plants. In recent times, tree recognition and counting (Salamí et al., 2019), height and canopy estimate (Mu et al., 2018), and growth and yield prediction (Jiménez-Brenes et al., 2017; Sarron et al., 2018) have all been developed using drone-based approaches. At its core, a drone is a collection of actuators and motors that can perform the necessary tasks, as well as various sensors that can gather information about the surrounding environment. The remote control and radio frequency communication are used to communicate with this. Drones equipped with thermal and multispectral sensors can survey large-scale terrain in a single flight (Hoummaidi et al., 2021).

Drones can also spray pesticides, which is an important consideration. The spraying system connects the sprayer and pesticide tank via a hose that runs along the bottom of the drone. Using the controller, the sprayer's nozzle can be turned on and off. This approach saves labour and time and takes care of health hazards from chemical pesticides. The agricultural sector is embracing drone technology to revolutionize precision farming in the modern age. Most countries' security concerns make establishing clear regulations for drone use a major challenge. As a result, scientists have also considered utilizing drone data to evaluate plant phenotypic traits at the field level (Gracia-Romero et al., 2019; Yeom et al., 2019). The usage of drone has also been utilized to assess water stress (Santesteban et al., 2016), monitor crop disease (Shakoor et al., 2017), map weeds (Gašparović et al., 2020), as well as estimate biomass and yield (Niu et al., 2019; Olson et al., 2019; Duan et al., 2019). Yallappa et al. (2017) reported satisfactory test results while spraying pesticide on groundnuts and paddy crops by using a drone fitted with a spray motor. A sugarcane field was successfully divided into sparse and dense sections using a drone by Murugan et al. (2017) for precision agricultural monitoring. A significant benefit of drones is that they may be used to spray pesticides on crops like maize, which are otherwise difficult to reach in cloudy weather. Ashapure et al. (2019) and Moeckel et al. (2018) have shown that high chronological resolution data may be used to evaluate crop factors like canopy height, canopy cover and vegetation indices, whereas Jung et al. (2018) picked out genotypes, and Zhou et al. (2017) even predicted crop yields.

The workflows instrumental to precision farming using drones and advanced technology are best understood by reference to Figs. 1 and 2 above. The Drone-Based Data Collection Workflow is described in Fig. 1 as showing how UAVs are used in data collection workflows then preprocessing the data so that it is ready for analysis. In addition to this, Fig. 2 shows the Workflow of image and Data upload from UAVs to the Agroview website – this depicts how the collected data from UAVs is efficiently transferred for further processing and application in the view of making intelligent decisions in matters relating to agriculture. The Precision Viticulture System is presented in further detail in Fig. 3, wherein IoT devices, AI, and automation are employed for crop management monitoring, evaluation, and prediction.

4 Nitrogen fertilizer management by canopy reflectance sensors for precision farming

Most of the smallholders in developing nations prioritize nitrogen (N) fertilizer application many times more than the local guidelines to maximize yields, especially in irrigated cereal-based cropping systems, which cannot account for the dynamic geographical heterogeneity in soils' N-supplying capability. Overdose of N fertilizer increases production costs and pollutes the environment. To apply the optimum amount of N fertilizer, a Sensor-based Nitrogen Rate Calculator (SBNRC) took a significant role in precision agriculture. This technique records the NDVI (Normalized Difference Vegetative Index) (refer to Eq. (1)) using the GreenSeekerTM sensor. In this equation, RINR indicates reflectance in the near infra-red band and RRED denotes reflectance in the red range of the red band. The principles of proximal sensing deploy canopy reflectance sensors and must be either in direct touch with or within two meters of the target and can direct the need-based target-specific nitrogen fertilization in various field crops (Mulla, 2012). Hunt et al. (2010) found that green NDVI and leaf area had a good correlation by analyzing UAV multispectral images for crop monitoring. It calculates cereal crops' fertilizer N requirements using projected yields and attainable leaf greenness, which have a significant advantage over generally recommended dose or need-based N management technologies like the SPAD meter and the leaf color chart. Plant health and vigor are measured in NDVI measurements using the GreenSeekerTM portable sensor, which is simple to use and can be hand-held or fitted in a drone. Red (650 ± 10 nm wavelength) and near-infrared (770 ± 15 nm wavelength) light from the sensor is briefly pulsed, and then the amount of light reflected from the plant is measured. Most of the red light is absorbed, and healthy green plants reflect most infrared radiation. Reflectance readings from different wavelengths are used to calculate.

$$NDVI = \frac{R_{INR} - R_{RED}}{R_{INR} + R_{RED}} \tag{1}$$

NDVI ranges from -1 to 1, with 1 signifying the most excellent crop density and 0 signifying the lack of vegetation. These studies measure crop health and identify insect infestations. An algorithm is needed to transform canopy reflectance sensor measurements into the quantity of fertilizer N needed to alleviate crop N stress (Samborski et al., 2009). The creation of reference strips with enough N fertilizer (Sripada et al., 2008) allowed for the development of N response functions, which are a crucial part of the algorithm that converts sensor signals to the quantity of N fertilizer the crop needs to provide the anticipated yield (Scharf et al., 2011).

5 Precision irrigation by using sensor-based AI

Farming uses more than 70% of the world's freshwater, which will only increase with an increasing global population and need for food. Irrigation is crucial for agricultural development, especially in dry and semiarid regions, because without it, there is a high likelihood of crop failure or a significant decrease in yield (Haghverdi et al., 2016). Because of this, we must design more efficient irrigation systems to guarantee that water supplies are effectively used. Several methods are employed in modern irrigation systems to optimize water use efficiency. AI-powered sensor-based automatic irrigation systems (Figure

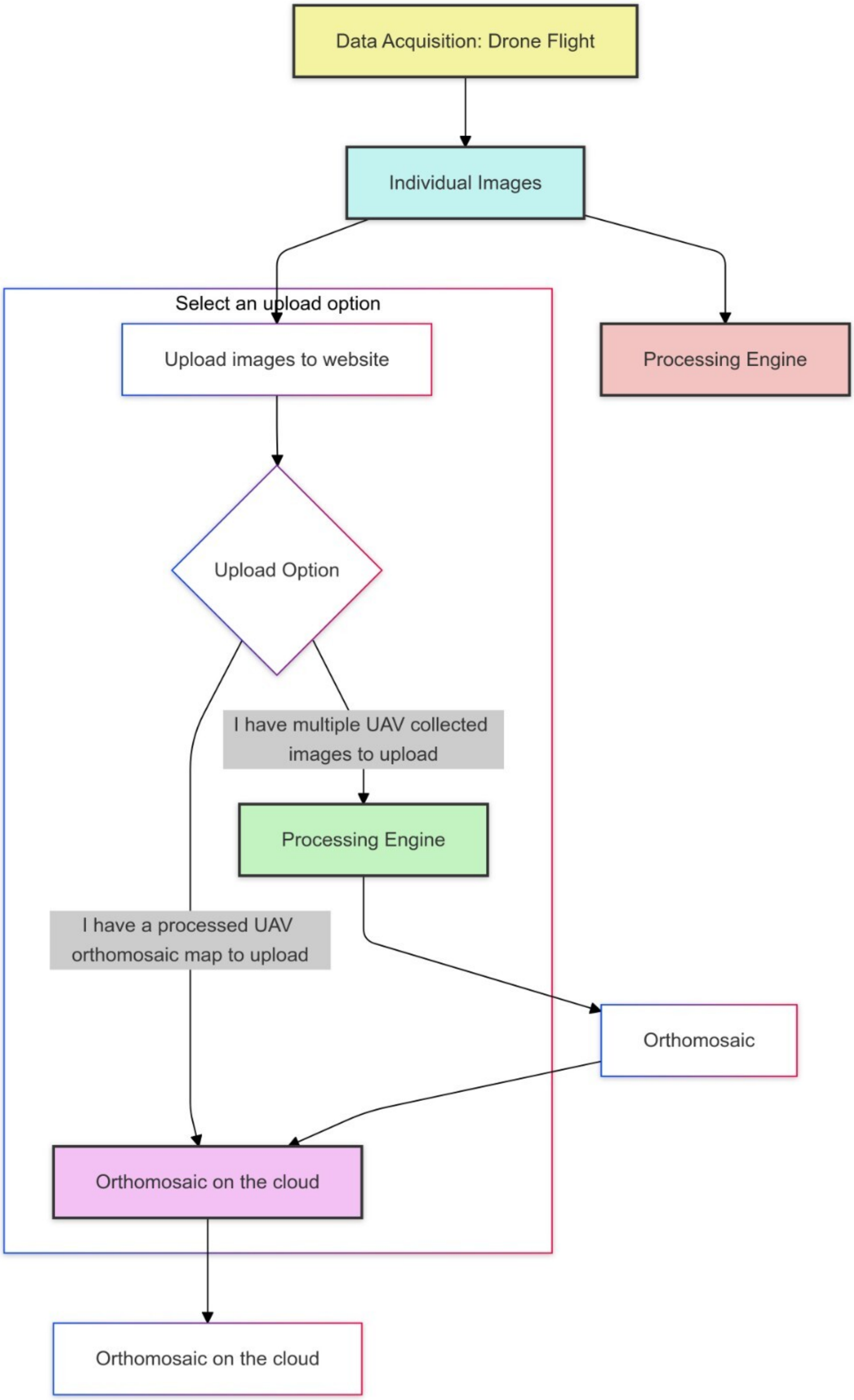

Figure 2: Workflow flow for uploading images and data from UAVs to the Agroview website.

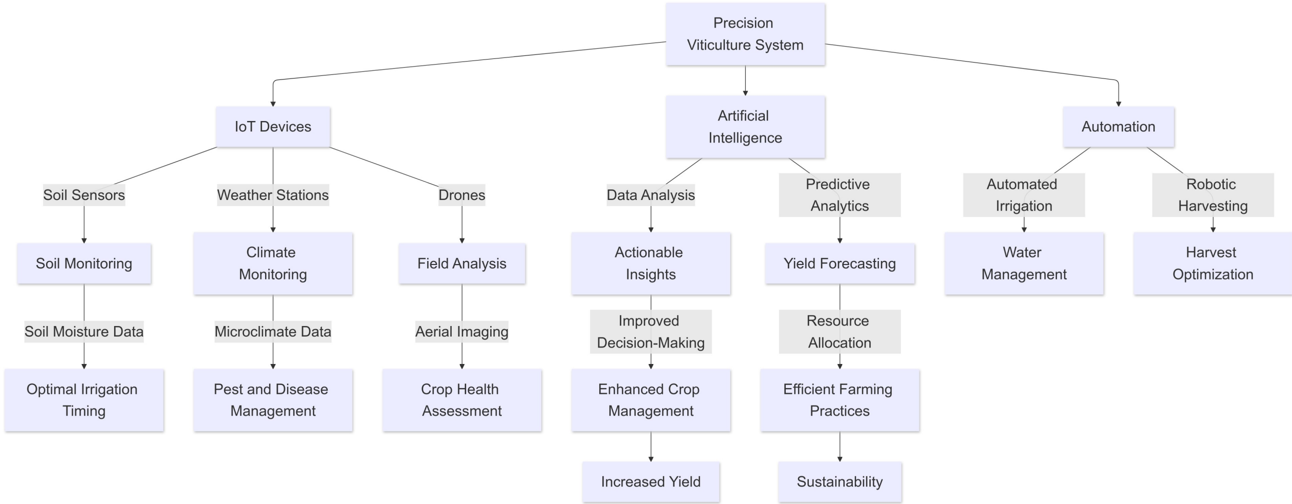

Figure 3: Precision Viticulture System Using IoT Devices.

4) can measure the soil's moisture content in real time when installed near the crops' root systems. Jain et al. (2023) also present an IoT-based soil analysis system that employs optical sensors and multivariate regression to enhance the accuracy and efficiency of soil property assessment. The sensors transmit this signal to the microcontroller for need-based irrigation, which significantly cuts down water use (Qualls et al., 2001). Based on the soil's field capacity, moisture sensors can set a threshold, allowing the controller to water only when necessary. According to Avatade and P (2015), the primary goal of constructing an irrigation system is to minimize resource use and boost efficiency. Temperature and moisture sensors may be employed at a time, which will optimize the frequency of watering and will reduce human error, saving time and labour. This technology, known as Machine-to-Machine (M2M), is a new technology designed to make it simpler for farmers to connect and exchange data with each other and with a server or cloud (Pramanik et al., 2021b). The site, an autonomous robotic model has been made using Arduino and Raspberry Pi3 to measure the temperature and moisture content. The data is detected periodically and delivered to the Arduino microcontroller. Digital signals are generated from the analog input, and the Raspberry Pi 3 receives a signal that activates the water supply for irrigation. Depending on the need, the resource will provide water and sensor data will be updated and stored. In 2013, Galande and Agrawal designed a fully automated low-cost drip irrigation intelligence system using the ARM7TDMI-S microcontroller and the 89C51 microprocessor. The PIC 18f4520 microcontroller was utilized by Madli et al. (2016) for his intelligent, automated precision irrigation system, which is responsible for keeping an eye on soil moisture, air temperature and humidity in the field. In order to gather sensor data and send it to a server mobile phone for processing, the microcontroller uses the PIC16f877A and the HC-05 Bluetooth module as part of its implementation. Arvind et al. (2017) also worked on a Machine Learning Algorithm-based automatic irrigation system based on Arduino. This system was designed to combat drought scenarios.

6 Weed detection by AI and automation in weed management

Common issues with traditional manual, mechanized, and chemical weeding include high crop loss throughout the weeding process. Autonomous precision weeding by robots or AI-guided UAVs (Figure 5) improves efficiency and reduces herbicide wastage. It has been noticed that by analyzing UAVs, AI-captured images of rice fields in an entirely conventional network method can recognize 88% of weeds accurately, and its weed mapping accuracy is almost 94% (Huang et al., 2018). It was observed that a computer vision-aided weed control system was 93.6% accurate utilizing the haar cascade classifier and the OpenCV open-source framework. The computer-aided system uses computer vision to direct

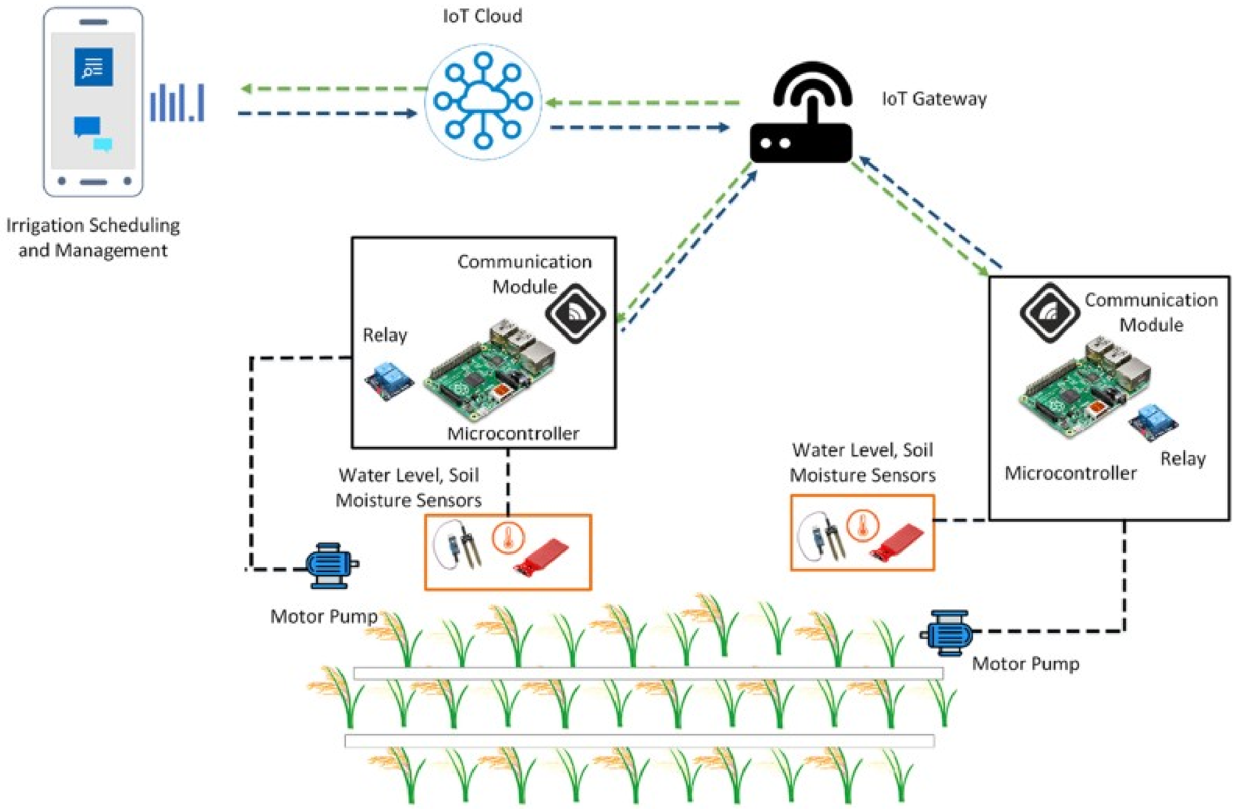

Figure 4: Automated irrigation systems using IoT (Source: Subeesh & Mehta, 2021).

the wedding actuator to carry out weeding operations (mechanical) without damaging the plants in the field (Chang and Lin, 2018; Verma et al., 2022). In their research, Zhang et al. (2021) showed that a convolutional neural network can recognize complex weed flora during grass establishment when the weeds are mature with accuracy and recall over 90%.

7 Weather-based plant disease forecasting system

A weather-based plant disease forecasting system (Fig. 6) uses UAV technology and data analysis for precautionary stewardship in agriculture (Gao et al., 2020). The beginning of the system is to have a UAV to capture images of the field. After that, the images go through a preprocessing stage where their quality is improved, and they are prepared for analysis. Segmentation and feature extraction enable the identification of crucial plant and environmental data narratives. Further classification techniques are used to predict if the images show the risk of disease or healthy crops. Subsequent processes include weed localization and mapping, or crop health assessment, which produces maps on the distribution of weeds or reports on crop health. The gathered facts consequently contribute to the decision-making about the specific eradication of weeds or diseases. They become crucial for farmers because they help make timely decisions to minimize threats and maintain good crop conditions. This system optimizes agricultural advancement through weather information, image processing and AI for disease identification and intervention.

8 Fruit harvesting by AI-enabled automated robot

Another intriguing use of AI in agriculture is automatically detecting fruits and harvesting using a robotic arm (Fig. 7). Several scientists have made many approaches (Bulanon et al., 2004; Rakun et al., 2011) to develop automated fruit harvesting robots using spectral, color, or thermal cameras. These techniques

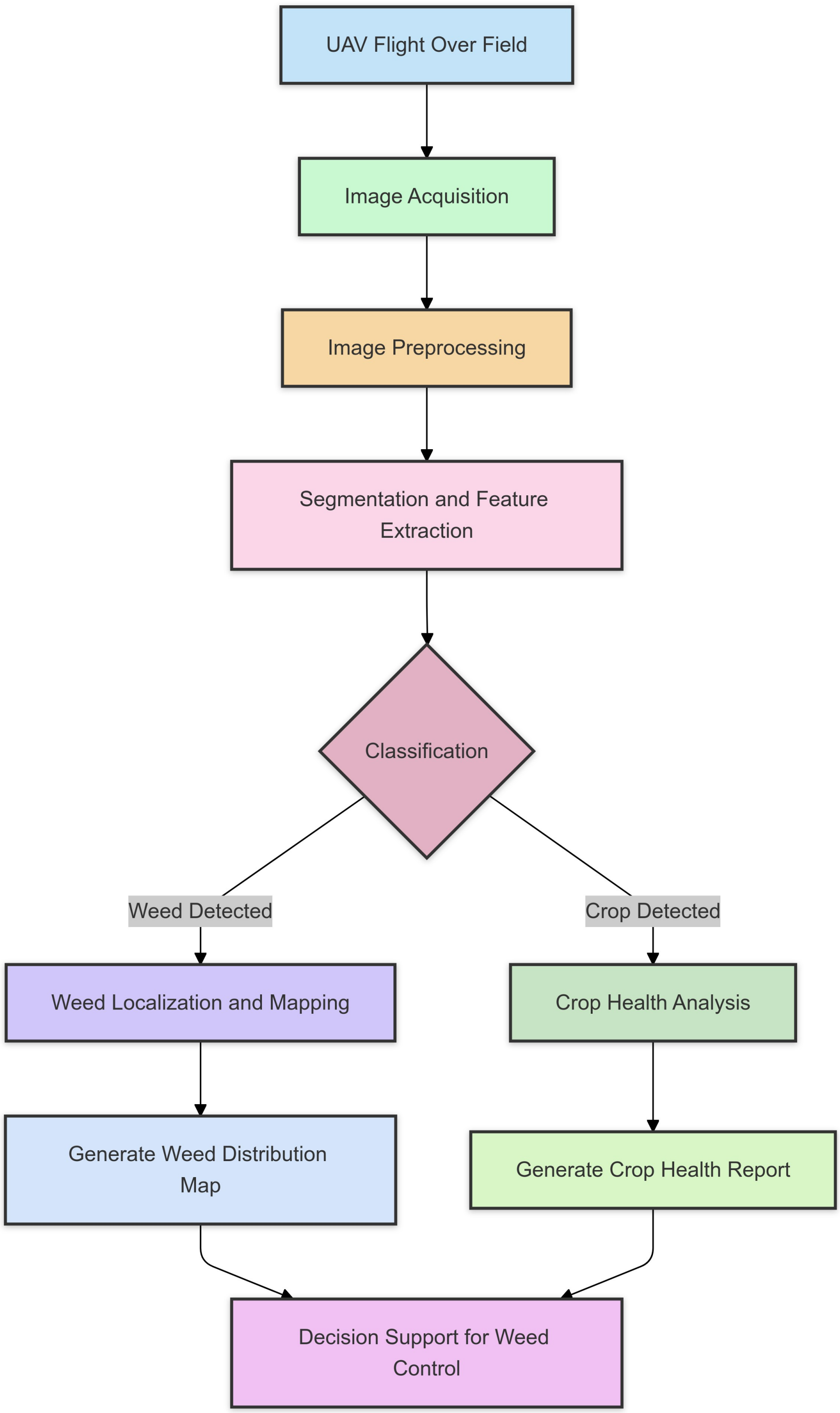

Figure 5: UAV-Based Image Processing Workflow for Weed Detection and Crop Health Assessment.

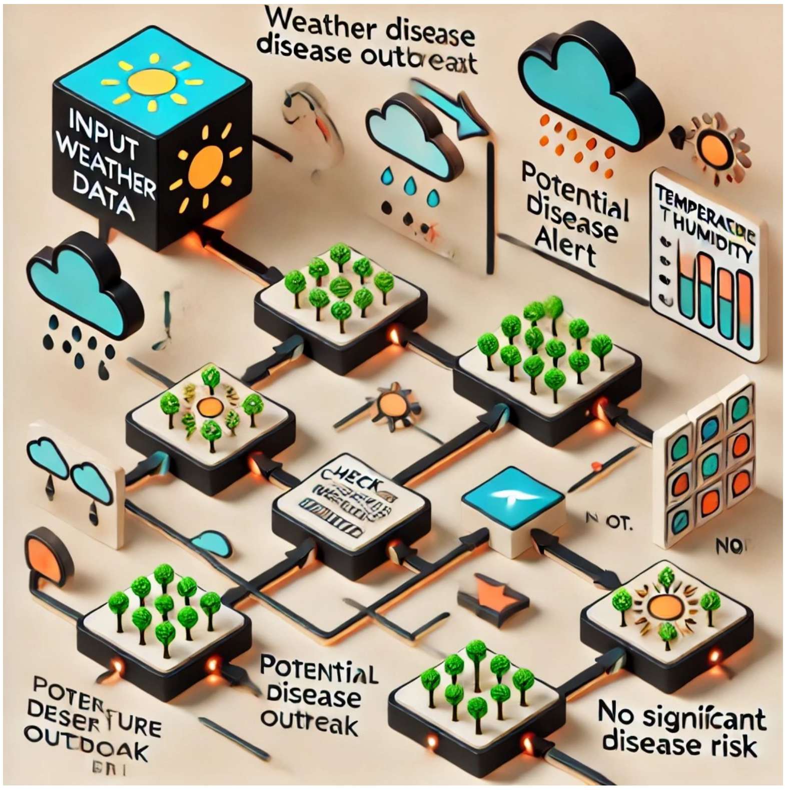

Figure 6: Weather-based plant disease forecasting system.

are challenging to employ under varying lighting circumstances because insufficient color information may be collected. Fruit detection should utilize several characteristics, such as texture, color, reflection, and shape, to improve accuracy and get around problems like clustering and fluctuating lighting. To classify peach, Kurtulmus et al. (2013) developed an artificial neural network that worked with high precision. Onishi et al. (2019) found more than 90% harvesting accuracy, and the robots' harvesting time per fruit is 16s. The fruit's three-dimensional location is detected using a stereo camera and a quick and accurate Single Shot MultiBox Detector technique. Once the joint angles at the target position have been calculated using inverse kinematics, the robot arm instantly moves there and twists its hand axis to pick the fruit.

9 AI-based tractor autopilot for intelligent farming

In the face of a persistent labor crisis in agriculture, tractor autopilot has the potential to save farmers time and money while automating formerly manual tasks in a precise manner. Three primary subsystems make up the tractor autopilot system. A vision or perception system transforms footage from cameras mounted on the machine into beneficial characteristics like the location and orientation of the plants before harvest, for example. Deep learning with supervision is used to create the perception system. Afterward, the vehicle has a human action-coding system that tells it when to raise or drop its cutting arm, among other things. This was created utilizing supervised deep learning. Finally, a feedback control system also transforms high-level vehicle motions into hydraulic motor instructions that are supplied to and activate the machine using motors. Traditional control technologies were used to build this. AgGPS Autopilot system (Trimble, California, USA) is a new introduction of autopilot system. The AgGPS Autopilot system is linked with satellites for row-crop operations and automatically guides tractors within inches. The driver may turn off the system by turning the wheel. Redundant computers independently examine various system sensors, values, end-of-row alarms, and operator alerts. The system's core is a high-performance Trimble GPS navigator. There is an AgGPS 214 Real-Time Kinematic receiver, an AgGPS 70 Remote Display and a Logger attached to the controller. Row crops, including cotton and

Figure 7: Harvesting target apple (Source: Onishi et al., 2019).

vegetables, are the primary focus of the AgGPS Autopilot system's initial iteration.

10 Challenges and future scopes

The adoption of various cognitive solutions will significantly impact the future of agriculture. However, the absence of easy solutions for smoothly integrating and embedding AI-based automation in agriculture is a fundamental hurdle for mainstream adoption by common farming communities because they need more time or digital know-how to delve into the world of complicated technology-based solutions independently. Researchers consistently improve their discoveries and concepts to make them precise, approachable, and marketable. Accessible autonomous decision-making and predictive solutions are still in their infancy for typical agricultural communities, so the solutions on the market need to be more accurate. Applications need to be more reliable if we will fully explore AI's immense potential in agriculture (Slaughter et al., 2007). Then, it can handle quick environmental changes, assist real-time decision-making, and acquire contextual data efficiently.

11 Conclusion

According to recent findings, AI-enabled agricultural digitalization has progressed from the idea to the implementation stage. Recent advances in IoT and drone-based automation have greatly and effectively increased agricultural systems' resource usage efficiency and significantly curtailed many of their difficulties. The high cost of various cognitive solutions like AI-based autopilot tractors for smart and precision farming currently on the market is one of the primary difficulties. For the technology to be accessible to the common farming communities, the solutions must be accurate, affordable and user-friendly. The solutions would be more accessible to farmers if they were built on an open-source platform, lowering the entry barrier. In order to anticipate future issues in agricultural automation techniques, data collected by numerous sensors must be handled and analyzed using AI and machine learning technologies.

Conflict of Interest

The authors declare that there is no conflict of interest in this work.

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