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Artificial Intelligence Applications in Agricultural Mechanization

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Abstract -Agricultural automation has become a crucial and rapidly evolving field globally. With the world's population, expanding at an accelerated pace, the demand for food production is increasing significantly. This growing need is being unmet by traditional farming practices, which results in the overuse of dangerous chemicals that deteriorate soil quality and eventually make land unusable. This study looks at a number of automation technologies, including the Internet of Things, wireless communication, machine learning, artificial intelligence, and deep learning, that may help with significant agricultural issues. These cutting-edge methods can successfully address problems like agricultural diseases, poor storage management, excessive pesticide use, weed control, inefficient irrigation, and water resource management. The pressing need to mitigate the negative impacts of pesticide use, regulate irrigation, reduce pollution, and manage environmental effects on agriculture is emphasized. The automation of farming processes has demonstrated improvements in agricultural yield and soil fertility. In order to present a summary of recent developments in agricultural automation, this paper examines previous research. It also presents a suggested method for botanical farms that makes use of IoT technologies for automated irrigation and flower and leaf identification.

Keywords— Agricultural, IoT, Artificial Intelligence, Neural networks, Automation*.*

I. INTRODUCTION

The rapid advancement of technology and the growth of human cognitive abilities have led to the combination of artificial and biological intelligence. The discipline of artificial intelligence (AI), which enables machines to perform tasks that frequently need human intelligence, was born out of this continuous growth. Artificial intelligence (AI), a branch of computer science, aims to enhance productivity and success by perceiving its surroundings. AI may use experiences to make well-informed decisions and gradually enhance task performance. Machine learning (ML), convolutional neural networks (CNN), artificial neural networks (ANN), and deep learning are the subfields that expand on AI's capabilities. The Internet of Things (IoT) facilitates "thing-to-thing" communication with three primary goals: automation, cost savings, and improved connectivity. The application of IoT in agriculture has been thoroughly studied by Dr. D.K. Sreekantha and Kavya A.M., who have shown its potential advantages for human welfare. Numerous areas, including healthcare, education, finance, security, and agriculture, have already benefited greatly from AI. For AI to be implemented successfully, robots must be able to learn from statistical data and experiences in order to tackle complicated issues. A crucial area of artificial intelligence, machine learning allows systems to process massive datasets, identify patterns, and provide predictions. Artificial intelligence (AI) is a mathematical and computational approach to intelligent problem solving, and as AI developed, a number of problem-solving methodologies emerged, simplifying decision-making processes. These techniques include expert systems, neuro-fuzzy logic, artificial neural networks (ANN), and fuzzy logic. Applications like speech and facial recognition, weather forecasting, and medical diagnostics depend heavily on artificial intelligence. The development of big data and data science has also been accelerated by the advent of machine learning.

Artificial neural networks (ANN) are widely employed in research because of their structural and functional similarities to the human brain. The human brain is a complex network of neurons that exchange electrical signals via axons. These signals travel through synapses, allowing for information processing. Inspired by this biological process, ANN operates using a similar framework. Depending on the needs of the application, many training

methods are used, including Quick Prop, Delta-bar-delta, Rprop, Silva and Almeida's algorithm, and the Dynamic Adaptation algorithm. ANN models typically include nine neurons and work as task-based systems that follow predefined objectives rather than traditional programming logic. The input layer, the hidden (middle) layer, and the output layer are the three layers that comprise the ANN architecture (Fig. 1). The system parameters chosen to maximize learning in the feedforward backpropagation process are input layer-7, output layer-1, hidden layer-50, and number of iterations-1200. While the input layer employs a linear function, the hidden and output layers use activation functions that include the sigmoid function.
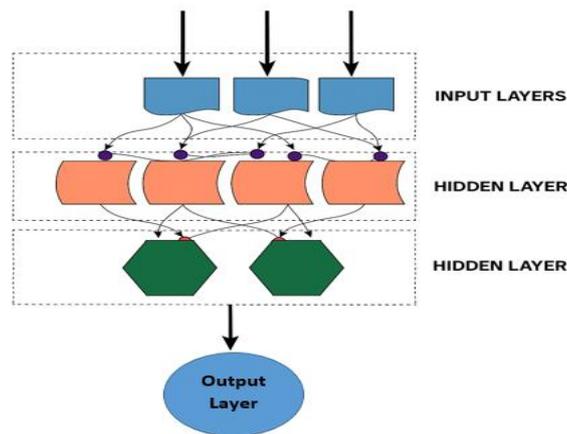

Figure 1. Artificial neural network layers.

AI and machine learning primarily revolve around hypotheses, theories, programming, and algorithms. Their practical implementation requires a robust hardware-software interface, which is where embedded systems play a crucial role. Embedded systems integrate hardware components, such as memory chips, with customized software to execute AI algorithms efficiently (Fig. 2).
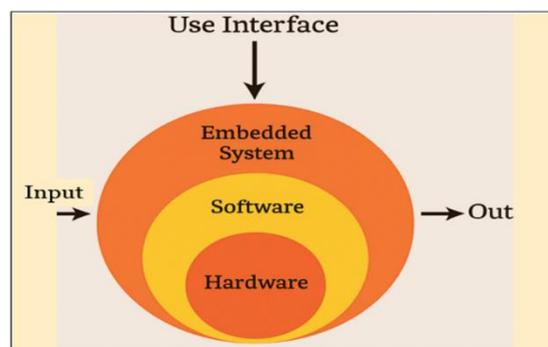

Figure 2. Embedded systems

The convergence of artificial intelligence and embedded systems in the agricultural industry is examined in this study. In 1985, McKin-ion and Lemmon first talked about the application of expert systems and artificial intelligence in agriculture [1]. Many nations, including South Korea, China, and North America, are investing heavily in cutting-edge agricultural technologies due to the vital role that agriculture plays in every nation. The world's population is growing exponentially, and this is reflected in the increase in food consumption. India, a major producer of spices and food crops, is mostly dependent on agriculture, which is a vital economic pillar. Agricultural automation has become essential as technology develops in many different sectors. Precision farming and agri-technology are essential for sustainable food supply because the strain on agriculture will only increase as the population grows. This field, often known as "digital agriculture," uses advanced computing systems to analyze a variety of agricultural factors, such as weed identification, crop prediction, yield calculation, and crop quality assessment (Liakos et al., 2018) [2]. This study offers a comprehensive review of the uses of ANN, ML, and IoT in agriculture, along with many models that help precision farming.

II. Literature survey

Over the past five decades, artificial intelligence (AI) has evolved significantly, becoming a powerful and widely applicable technology across numerous sectors, including agriculture. Despite being essential, agriculture is fraught with daily challenges that make it far from a seamless operation. Farmers often face persistent issues throughout the crop cycle from sowing to harvest including Crop disease outbreaks, Poor storage infrastructure, Inefficient pesticide application, Weed control challenges, Inadequate irrigation and drainage systems.

AI and machine learning (ML) have made substantial contributions toward addressing each of these challenges. Bannerjee et al. (2018) categorized these AI-driven advancements and provided an overview of various techniques used in the field [3]. Since the beginning of technological integration in agriculture in 1983, many systems have been put out to enhance agricultural operations, ranging from database management to decision-making. AI-based systems have shown to be the most dependable and useful of these, offering tailored solutions to specific, challenging circumstances, in contrast to broad approaches. This research review focuses on the major technical developments in agriculture from the early 1980s to 2018. It looks at more than fifty breakthroughs, beginning with the use of artificial neural networks and expert systems to address the main problems listed above. It concludes with a discussion of automation and the role of the Internet of Things (IoT) in contemporary agriculture after examining the contributions of fuzzy logic and machine learning systems.

III. Artificial neural networks in agriculture

A. The Role of AI and IoT in Agriculture

Over the past 50 years, artificial intelligence (AI) has developed gradually, becoming a vital tool in many industries, including agriculture. But farming has its own set of problems, from pest control and crop diseases to inadequate irrigation and poor storage management. Machine learning (ML) and artificial intelligence (AI) have been essential in addressing these challenges. Bannerjee et al. (2018) categorized AI advancements and provided an overview of various techniques [3]. Technology has been progressively incorporated into agriculture since the early 1980s, and AI-based solutions have proven to be the most effective at solving particular agricultural issues. An detailed review of literature from the 1980s to 2018 highlights important technological advancements in agriculture, such as artificial neural networks (ANN), expert systems, machine learning, and fuzzy logic. The evaluation also looks at automation in agricultural methods and the Internet of Things (IoT).

B. The Use of Artificial Neural Networks (ANN) in Agriculture

Artificial neural networks are commonly employed in agriculture because of their capacity to predict outcomes based on pattern recognition. Neural networks are taught rather than explicitly built, in contrast to conventional programming. While Maier and Dandy (2000) used neural networks to predict water supplies, Gliever and Slaughter (2001) successfully used artificial neural networks to differentiate between weeds and crops [4]. In a similar vein, Song and He (2005) assessed crop nutrient levels using ANN and expert systems. Neural networks often help overcome the limitations of traditional expert systems (ES). To predict the occurrence of frost in Sicilian farmlands, for instance, Robinson and Mort (1997) developed an artificial neural network (ANN) model [5]. A neural network predictor was fed historical meteorological data (temperature, precipitation, humidity, etc.) that had been transformed into binary form. Through back-propagation, the model efficiently predicted frost occurrence, proving the reliability of ANN in agricultural forecasting. Two expert systems were specifically developed to optimize cotton production. The first, COMAX, was created in 1986 by Lemmon and integrated with the Gossym model for continuous monitoring of irrigation, nitrogen levels, and cotton growth. The second, COTFLEX, was designed by Stone and Toman (1989) using a rule-based expert system on a UNIX-powered Pyramid 90× computer [6]. This system helped Texan farmers make informed agricultural decisions by utilizing field and farm databases.

C. AI-Based Crop Management Systems

AI-driven crop management has extended beyond cotton farming. Batchelor et al. (1989) introduced SMARTSOY, a soybean crop growth model using a knowledge-based approach [7]. This system combined two methodologies positivistic and normative to assess insect damage rates and recommend pesticide use. The accuracy of yield loss calculations and pest treatment recommendations was improved by combining the two methods. For Rajasthan

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soybean farming in India, Prakash et al. (2013) created PRITHVI, an expert system based on fuzzy logic [8]. This technology gathered data from magazines and agricultural experts to provide personalized farming guidance. PRITHVI was able to boost soybean output by utilizing MATLAB as its interface. The agricultural sector adopted a similar strategy. In order to prevent apple scab disease, Roach et al. (1987) developed POMME, an expert system that calculates the optimal time for pesticide treatment [9]. The method used a disease cycle model rather than theoretical infection levels, and the results were encouraging and verified by experts.

D. AI-Powered Crop Prediction and Smart Farming

An ANN-based crop prediction model for cellphones was evaluated in 2016 by academics Ravichandran and Koteshwari [10]. The three-layer model employed a number of training algorithms, including Silva and Almeida's algorithm, Delta-bar-delta, and Rprop. Researchers attempted to determine the optimal number of hidden layers to increase accuracy. The finished system, which was created using an Android APK platform, suggested appropriate fertilizers in addition to crops. Water management has also benefited greatly from artificial intelligence. Nema et al. (2017) evaluated the effect of ANN on evapotranspiration (ET) estimation in a study carried out in Dehradun, India [11]. Climate data from the Forest Research Institute was analyzed using ANN models trained with six different algorithms. The study concluded that an ANN-based approach could optimize irrigation strategies by predicting ET more accurately than conventional methods. AI has also been employed in precision agriculture to distinguish weeds from crops using image-processing techniques, achieving over 75% accuracy [12]. Additionally, IoT-based smart agriculture systems have been developed to transmit real-time field data to cloud servers, where automated decisions can be made based on sensor inputs [13].

E. AI in Soil and Irrigation Management

Additionally, AI has shown promising results when estimating soil moisture. Arif et al. (2012) developed two artificial neural network (ANN) models to assess soil moisture in paddy fields using limited meteorological data [14]. These models were evaluated using actual soil moisture data, and the findings demonstrated that they improved irrigation planning while saving time and labor. Drip irrigation has also benefited from artificial intelligence. A neuro-drip irrigation system using ANNs to forecast subsurface water distribution patterns was reported by Hinnell et al. (2010) [15]. Farmers were able to maximize water utilization and improve irrigation efficiency as a result. Similarly, Singh and Prajneshu (2008) investigated maize productivity using a multi-layered feed forward ANN (MLFANN) with gradient descent algorithms (GDA) and conjugate gradient descent algorithms (CGDA) for prediction.
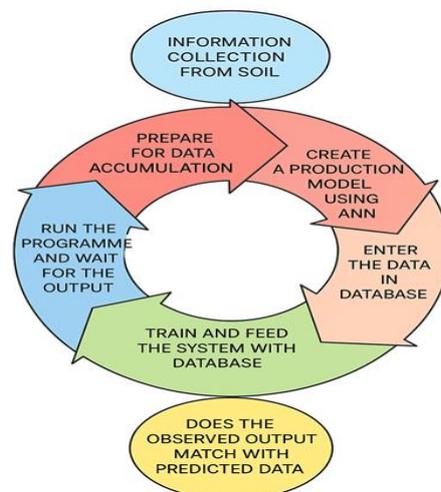

Figure 3. ANN-based crop predictor using smartphones

IV. WIRELESS SYSTEMS NETWORKS AND AUTOMATION IN AGRICULTURE

All sectors must evolve with time, and agriculture is no exception. Automation-driven developments have forced the sector to adapt. With the use of technologies like automated irrigation, smart greenhouses, intelligent crop

management, and smart farming, Yong et al. (2018) introduced the new field of study known as embedded intelligence (EI), which is crucial to agriculture [16]. Integrating such technologies is critical for national growth, especially given the importance of agriculture in many other areas. In their study, Yong et al. also presented a Technology Roadmap (TRM) to help resolve uncertainties in the adoption of smart agricultural systems such as those listed above. Patil and Thorat (2016) created a method to anticipate grape diseases ahead of time due to the socioeconomic significance of agriculture in India [17]. In the past, signs of grapevine disease were not found until significant harm had been done, often affecting entire vineyards. Numerous sensors, including ones for temperature, humidity, and leaf wetness, were part of their system and were placed throughout the vineyard. A ZigBee server was used to send real-time data from these sensors to a database. Any wireless sensor network (WSN) implementation must adhere to a set of rules. The ZigBee Alliance has created four layers of global standards: network, application, media access control (MAC), and physical. Within the WSN, each of the three ZigBee devices the Coordinator (ZC), the Router (ZR), and the End Device (ZED) has a specific role. A comprehensive ZigBee-based strategy in agriculture was investigated by Kalaivani et al. (2011) [18]. The Hidden Markov Model (HMM) algorithm on the system's server was utilized to analyze sensor data by recognizing anomalies and learning typical environmental trends. Farmers receive SMS warnings whenever there are changes in temperature, humidity, or leaf wetness all of which could be signs of grape disease. Accurate early diagnosis of grapevine diseases is made possible by the system's early integration of machine learning. It might also suggest appropriate insecticides, which would eliminate the requirement for manual disease detection [17]. A comparable machine learning-based technique was also used to track paddy crop growth. This method proved to be dependable and cost-effective in its efforts to increase agricultural productivity and yield (Fig.4) [19].
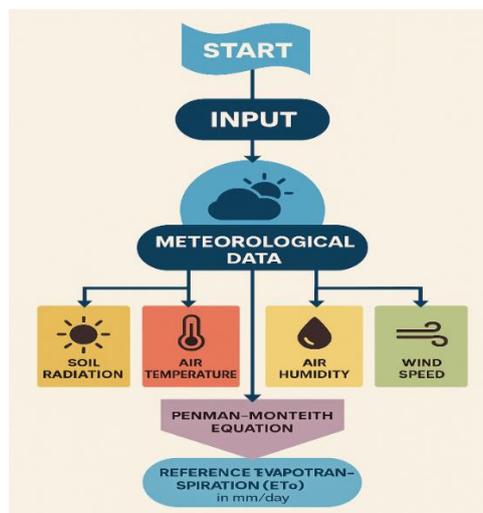

**Figure 4**. Flowchart explaining evapotranspiration process.

The sensors used to monitor agricultural fields, as seen in Figure 5, are described in detail in Figure 6. Among them are the MQ4 and MQ7 sensors, which detect natural gas and carbon monoxide, respectively. While a soil moisture sensor continuously detects and records the moisture content of the soil, the DHT11 sensor keeps an eye on both temperature and humidity. The ESP8266 Wi-Fi module makes it easier for consumer devices and the hardware system to communicate. Installing an intelligent irrigation system (IIS) has various benefits, including lowering soil stress from temperature and moisture, making optimal use of water, and removing the need for human intervention in flood irrigation scenarios, according to a study done in Ankara, Turkey. The three primary parts of this system the Base Unit (BU), Valve Unit (VU), and Sensor Unit (SU) are powered by solar panels. The BU provides the SU with a communication address following installation. The sensors in the SU collect data on soil moisture and transmit it to the relevant BU. The BU instructs the VU to replace the valve and begin watering if the data indicates that irrigation is required.

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Although the concept of site-specific automated irrigation emerged in the early 2000s, it has since proven highly effective in lowering operational costs, enhancing feasibility, and simplifying system complexity. Additionally, the system can be expanded to deliver fertilizers and pesticides using similar automation, though this would require the calibration of specialized sensors to ensure accurate data transmission [20]. Technologies based on ET, ICT, and IIS have all been assessed in a number of studies. Sprinkler and drip irrigation systems combined with ICT and IIS technologies were used to study wheat and tomato crops in Riyadh. IIS outperformed both ET and ICT systems in terms of water conservation, boosting water-use efficiency by 18% to 27%, according to a graph that plotted weekly water depth against crop growth time (Al-Ghobari and Mohammad, 2011). In a different development, Kodali and Sahu (2016) showed how to monitor agriculture using the Losant platform, an effective and user-friendly IoT-based cloud service [21]. It provides users with immediate access to field data and notifies users via email or SMS if anomalies are discovered. Gutiérrez et al. (2014) [22] suggested an automated irrigation system that communicates via a GPRS module. This system uses 90% less water than conventional irrigation methods because it is controlled by a microprocessor-based gateway that controls water flow. In a similar vein, Kim et al. (2008) used a distributed wireless network to remotely monitor and manage irrigation activities [23].
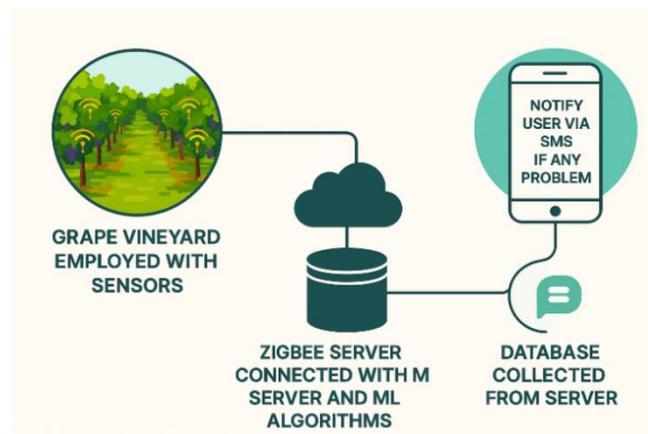
Figure 5. Machine learning methods to identify grape disease

Adoption of cutting-edge technology, including the Internet of Things (IoT), is crucial for increasing productivity, efficiency, and global competitiveness while lowering dependency on human labor, time, and expense. A network of linked devices that share data without requiring human interaction is known as the Internet of Things (IoT). IoT aids in agriculture's shift to smart farming by collaborating with automation tools to boost productivity. The importance of the Internet of Things in converting conventional farming into smart agriculture was highlighted by Malavade and Akulwar (2016) [24]. Wireless connection has transformed modern information transfer, and applying this technology to agriculture can significantly improve automation standards. The Internet of Things gateway can be separated into several functional nodes, including wireless networks, actuators, sensors, and interfaces, which allow components to communicate with one another [25]. In order to maximize communication in automated systems, they also investigated bandwidth needs and frequency estimation. The literature discusses the use of Wireless Sensor Networks (WSNs) in agriculture and its potential uses. Several IEEE standards, such as IEEE 802.15.1 for PAN/Bluetooth and IEEE 802.15.4 for ZigBee, are essential when creating sensor networks for agricultural applications. Researchers have also examined how IPv6, the Internet Protocol used for wireless communication, and the hardware configurations required to construct a working WSN operate. WSNs enable precision agriculture, which enables more targeted and data-driven crop management. Sensors collect a variety of environmental and crop-related data, which is stored by the system. Next, using sensor data from the past, the system decides what to do in the future [26]. In a pecan orchard, Ganjegunte et al. (2012) evaluated the performance of three soil moisture sensors: the Tensiometer Model R, Watermark 200SS, and ECH2O-5TE. They concluded that site-specific calibration is required for these sensors to produce accurate data.

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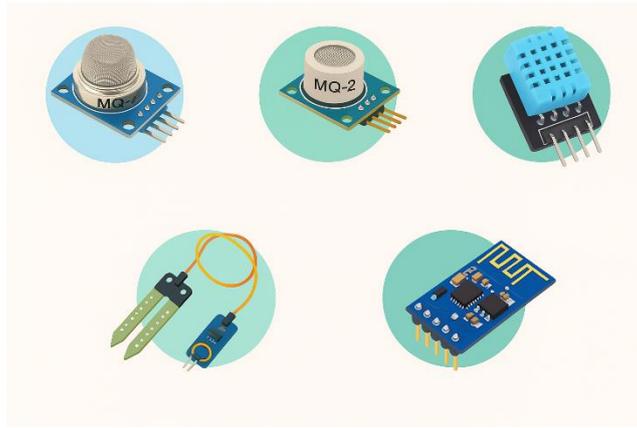
Figure 6. Various kinds of sensors are employed in detection

Gondchawar and Kawitkar (2016) proposed several key innovations in smart agriculture [27]. These include a GPS-based, remotely controlled robot capable of performing tasks such as weeding, pesticide spraying, moisture sensing, scaring away birds and animals, and surveillance. The second feature involves smart irrigation with real-time databased control. The third focuses on smart warehouse management, which involves detecting theft and controlling humidity and temperature. A computer or smart device with an Internet connection can be used to remotely monitor and control all of these actions. Together with sensors, cameras, Wi-Fi or ZigBee modules, and actuators, the system consists of a Raspberry Pi and microcontroller. Thermal imaging is a crucial non-contact, non-intrusive technique for measuring the surface temperature of agricultural fields and providing useful data for irrigation management. A cloud-based thermal imaging system that assesses equipment performance and pinpoints regions in the field that need more water was discussed by Roopaei et al. (2017) [28]. Crop growth may be negatively impacted by uneven water distribution; thermal imaging reduces this danger. Pre-harvest activities, nursery monitoring, irrigation scheduling, yield forecasting, greenhouse gas detection, termite infestation, and machinery diagnostics are just a few of the agricultural uses of thermal imaging that highlighted [29]. Katariya et al. (2015) also looked at robotics in agriculture and developed a robot designed to follow a white-line track in the field [30]. This robot can perform tasks including plowing, water supply, seed sowing, and pesticide spraying while recognizing other surfaces as brown or black to avoid. In 2016, researchers used a framework comprising monitoring modules and a knowledge base (KM) to develop an e-Agriculture application. In order to deliver real-time field data across Wi-Fi or 3G networks, the system, which was developed with the aid of cloud computing and the Internet of Things, heavily emphasizes reliable architecture. The TI CC3200 RFID Launch Pad and additional electronics were used to construct a prototype. To help both seasoned and inexperienced farmers, the Knowledge Base contains intricate structured and unstructured data. Finding pertinent information quickly is still difficult, though. In order to help with better agricultural decision-making, the system strives to provide comprehensive, well-organized, and contextually relevant advice services [31].

As automation becomes increasingly important across industries, early design of mechanical and electronic systems is essential to minimize human intervention. One major challenge in agriculture is weed management, and computer vision technologies are being developed to address this. Convolutional Neural Networks (CNNs) are useful for automating weed control because they can distinguish between crops and weeds. Additionally, CNN algorithms make it possible to identify plants and offer information for planting that is optimum. Fruit recognition and counting are two common item detection tasks that use regional CNNs, or R-CNNs. Bargoti and Underwood (2017) employed R-CNN models to detect fruits in orchards using three-channel color (BGR) images of varying sizes [32]. They experimented with the VGG16 network, consisting of 13 convolutional layers, and the ZF network, with five layers. The training dataset was increased and variability was included by data augmentation, which ultimately increased model accuracy. Their results demonstrated that Faster R-CNN significantly beat the ZF network in terms of apple and mango detection. In agriculture, cloud-based decision support systems are becoming more and more common. The Decision Support and Automation System (DSAS) allows farmers to monitor and control a variety of farming processes in real time via a centralized internet interface. Its support for device

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interconnectivity allows users to control equipment such as fertilizer dispensers, irrigation systems, and pesticide sprayers using sensor inputs such as soil moisture and nitrogen levels [33]. Kumar (2014) introduced a wireless sensor-based drip irrigation system that uses pH and fertility meters to detect the composition of the soil [34]. Ingale and Kasat (2012) created a water-saving smart irrigation system that only activates water when moisture and humidity drop below a set threshold using the IC 89c52 microcontroller [35]. A semi-automatic irrigation system in okra fields was assessed by Soorya et al. (2013) using a PIC16F877A microcontroller and four moisture sensors [36]. The system only activates irrigation valves when a drop in voltage across sensor pairs indicates insufficient moisture, and it continues until optimal levels are restored.

V. Fuzzy logic systems' application in agriculture

A fuzzy knowledge (FK)-based approach for evaluating land suitability was presented by Sicat et al. (2005), combining knowledge from farmers and science [37]. Fuzzy sets were created using S-membership functions to assess variables including soil color, texture, and slope. This study was carried out in a number of villages in the Andhra Pradesh, India, and district of Nizamabad. Interestingly, standard lower and upper limits (0 and 1) are not required for FK-based fuzzy factor maps because membership functions in knowledge-driven models can be specified in any way as long as they match the modeled factor.

Similarly, Si et al. (2007) implemented fuzzy control theory in a land leveling controller, resulting in improved precision [38]. The system interprets field height deviations using two fuzzy variable sets E (error) and EC (error change) which include qualitative terms such as "High" and "Very High." Nine fuzzy sets were defined for E and two for EC. This control logic guided the positioning of the leveling bucket based on signals received from field sensors. An alternative method for grading pomegranate leaf diseases was created by Sannakki et al. (2011) [39]. Image acquisition, pre-processing (filtering, scaling), color image segmentation using k-means clustering to differentiate between healthy and diseased regions, area computation, and disease grading using a fuzzy inference system (FIS) comprise its five phases. Similarly, Tremblay et al. (2010) determined the optimal nitrogen fertilizer rates based on crop and field conditions using FIS [40]. Fuzzy logic (FL) was used by Kavdir and Guyer (2003) to assess apple quality [41], and FIS was used by Valdés-Vela et al. (2015) to predict stem water potential [42].

Additionally, fuzzy logic was used for environmental management. A fuzzy logic-based air controller was designed by Gottschalk et al. (2003) to keep potatoes at the proper storage temperature [43]. Using "IF...THEN" logic, Escobar and Galindo (2004) created simulation software (SCD) that supported rule-based fuzzy control systems [44]. Because of its graphical user interface, the software could be used with a variety of fuzzy logic simulations. Tilva et al. (2013) similarly developed an FIS to forecast plant diseases based on weather data, aiming to prevent disease outbreaks by analyzing temperature and humidity conditions that favor disease propagation [45]. Water scarcity is a critical issue, especially in countries like India and China, which together account for 2.7 billion people living under water stress. Agriculture consumes around 70% of total water usage, making it a key area for optimization. Conventional irrigation methods contribute to water wastage, and urban infrastructure faces uncontrollable leakage. As water demand is projected to rise by 50%, smart irrigation systems have emerged as a promising solution. According to Gupta et al. (2016), smart irrigation can reduce water consumption by up to 20% [46]. Conflicts over the distribution of water from the Nile River in nations like Egypt emphasize how crucial it is to maximize irrigation. Sensor-based irrigation systems that control water use, track pollution, and handle other problems have been developed as a result of extensive study. Automated water distribution without human intervention is made possible by the integration of temperature and moisture sensors into embedded systems. Regardless of the irrigation technique, water quality is still an important consideration. Aquaculture and agriculture are both using IoT and AI more and more. Encinas et al. (2017) developed a system using advanced automation to monitor water quality [47]. Despite not addressing water pollution, Wall and King (2004) introduced a smart sprinkler valve controller that used temperature and moisture sensors [48]. Miranda et al. (2003) [49] presented a distributed irrigation system based on soil water readings. Machine-to-machine (M2M) communication, which allows for autonomous device interactions and real-time cloud storage, is still in its early stages of development. Shekhar et al. (2017), who made it possible for machines to communicate with themselves, enhanced this technique. A sensor-based, multi-layered, self-organizing intense irrigation system was presented by Yang et al. (2007). Additionally, Savitha and Uma Maheshwari (2018) concentrated on IoT-based irrigation automation [50], while

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Pawar et al. (2018) showcased a small-scale smart irrigation system prototype [51]. Despite these advancements, a fully autonomous system with complete elimination of human intervention has yet to be realized. The present work aims to address existing gaps using AI and embedded systems to create a comprehensive, intelligent irrigation solution.

VI. PROPOSED IDEA

Automation has numerous practical uses and is now essential in the agricultural sector. For irrigation in particular, automation is essential to ensuring efficient use of water resources. Soil moisture sensors are essential because they continuously monitor moisture levels and initiate irrigation systems as soon as values fall below a predefined threshold that the farmer has set. Embedded systems and the Internet of Things (IoT) can be used to create small, self-sufficient water level control systems that don't require human interaction.

Machine learning (ML), artificial intelligence (AI), deep learning (DL), neural networks, and fuzzy logic are just a few of the cutting-edge technologies that can be used to reduce manual labor. Although each of these approaches has its own benefits and drawbacks, their efficacy depends on how they are used. Although there is currently little study on deep learning applications in agriculture, this method offers promise, particularly when it comes to photo analysis and plant or flower recognition based on historical data. The significance of deep learning in contemporary agriculture was highlighted by Kamilaris and Prenafeta-Boldú (2018), who also highlighted its potential in a number of subfields. [52]. Deep learning builds upon machine learning by adding complexity through additional model layers, allowing more accurate classification from raw data. It is particularly helpful for activities like production prediction, fruit estimation, and plant identification. A significant amount of text or image data is needed to train a deep learning model. Data collection, pre-processing, variability enhancement, and augmentation are crucial steps in the process to get the model ready for practical use. Convolutional Neural Networks (CNNs) were effectively used by Ferentinos (2018) to identify plant illnesses, with an astounding accuracy of 99.53% [53]. Since agronomists frequently struggle with illness detection, these automated tools offer a trustworthy substitute.

The VGG16 model, chosen for its simplicity and effectiveness, was used to train the system. It has 16 weight layers with dimensionality lowered by max pooling, made up of tiny 3x3 convolutional filters grouped to deepen the network. A softmax layer completes the classification after two fully linked layers with 4096 nodes each. VGG, ResNet, Inception, and Exception are among the architectures supported by the Python deep learning package Keras. After being trained on numerous datasets containing images of plants and flowers, the model is able to accurately identify species from novel inputs. Because each species flourishes under particular environmental and irrigation circumstances, this classification aids botanists and farmers in better managing plant care. As a result, deep learning in agriculture improves precision and automates procedures, resulting in improved agricultural yields and more environmentally friendly methods.

VII. FUTURE SCOPE

Younger farmers are generally more inclined to invest in agricultural automation and adopt new technologies compared to older generations. However, the introduction of advanced technologies in agriculture must be gradual to ensure smooth adoption. The sector is steadily shifting toward precision farming, where management practices are tailored to individual plants. Techniques such as deep learning are being used to identify plant or flower species, enabling farmers to create optimal environmental conditions that support healthy and sustainable growth.

As a result, it is anticipated that more specialized plants and customized crops will be produced, which will lead to more varied products and creative farming practices. Rapid developments in artificial intelligence (AI) have made it possible to use models like recurrent neural networks (RNNs), convolutional neural networks (CNNs), and other computational frameworks for tasks like weed identification and plant disease detection in agriculture. Although it has always required a great deal of human intervention, greenhouse farming offers the possibility of controlled settings. IoT and wireless technologies are vital in this situation. By integrating advanced sensors and modern communication protocols, real-time weather monitoring and environmental control systems can be implemented, allowing for fully automated greenhouse operations without direct human involvement.

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With applications spanning from planting and seeding to fertilization, irrigation, weeding, spraying, harvesting, and even livestock management, robotics is another rapidly expanding field in agriculture. Because they can operate continuously, these agricultural robots greatly reduce the requirement for manual labor, frequently taking the place of 25 to 30 people in some situations. Furthermore, real-time field condition monitoring is made possible by the combination of drone technology with infrared imaging. Thermal camera-equipped drones may identify low-water locations, allowing for targeted irrigation that saves water and avoids both overwatering and under watering. This guarantees that crops get enough water for the duration of their growing cycle. All things considered, using these technology makes agriculture more productive and sustainable. AI, robotics, IoT, and remote sensing can all work together to greatly increase productivity while cutting down on manual labor and resource waste.

VIII. CONCLUSION

In order to supply the growing demand for food worldwide and minimize human interference, agricultural monitoring is essential. Crop selection, fertilizer application, and intelligent irrigation are all greatly enhanced by technologies like artificial intelligence, deep learning, and the Internet of Things. These developments improve production, maximize water use, and solve problems like flooding and water scarcity. To ensure sustainable agricultural development and replace ineffective old farming methods, automation and contemporary technologies must be integrated.

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