European Journal of Applied Sciences – Vol. 12, No. 06
Publication Date: December 25, 2024
DOI:10.14738/aivp.1206.17824.
Surekha, M. N., & Vasuki, V. (2024). Robotics and Artificial Intelligence in Today's Agriculture. European Journal of Applied Sciences, Vol - 12(06). 116-134.

Robotics and Artificial Intelligence in Today's Agriculture

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ABSTRACT

The increasing population poses an ever-increasing demand for food production amidst major constraints like decreasing agricultural labour, increased growth rate of industrialization, urbanization, reduced land and water availability for agriculture, and drudgery in farm works. With rapid development of technology in the field of robotics and AI, has created new horizons for its application in agriculture and allied sectors. These latest technologies help farmers in facing the challenges in food production to ensure food security, environmental sustainability and labour efficiency in the age-old industry. In this review article, a comprehensive view of the current state and future trends of robotics and AI in various agricultural domains, like crop monitoring, weed control, harvesting, sorting and transportation are discussed.

Keywords: Agriculture, Artificial Intelligence, Machine learning, Robotics.

INTRODUCTION

With the exponential growth of global population and subsequent increase in food and employment demand, agriculture, one of the vital industries, is undergoing significant transformation. By 2050, it is approximated that the world population will be 10 billion, thereby increasing the demand for food grains [1]. Traditional farming methods employed by farmers are insufficient to meet these demands. At present, the production of crops deals with unforeseen events such as climate change, water stress, labour shortage, reduction in soil fertility, etc. making the results uncertain. Similarly, events which are difficult to predict, like diseases, financial crisis and frequent price fluctuations in agricultural products and inputs, increases the uncertainty and concerns about farming activity.

Necessity for automation is becoming more crucial due to alarming increase in industrialization posing decreased agricultural labour availability. AI could play a vital role in aiding farmers with various components, technologies and applications [2]. These AI algorithms create connections between inputs and outputs, allowing them to make predictions and find solutions to a range of simple and complex problems [3]. AI-based solutions and agricultural robotics can enhance various aspects of farming, such as crop varieties, irrigation, soil detection, crop scouting, weeding, and crop establishment [4]. Predictive analytics and enhanced farm and crop management systems ensure the availability and quality of crops. Crop health monitoring and acreage can be achieved using satellite imagery and weather data [5].

BRIEF HISTORY OF ROBOTICS AND AI

Scientists and government officials acknowledge the significance of AI, despite its relatively brief existence. The concept of combining AI techniques into crop management systems was introduced [6]. They highlighted potential benefits of utilizing AI in agriculture for more effective and efficient crop management and has developed a cotton crop simulation model, GOSSY which utilized an Expert System, allowing farmers to optimize cotton production by considering factors like irrigation, weed control, climate, fertilization, and more.

An expert system called POMME that was designed to assist with the management of apple plantations [7]. In the field of cotton crop management, an expert system called COTFLEX was introduced [8]. The rule-based expert system COMAX for the management of cotton crops was developed [9]. A system using a multi-layered feed-forward ANN (artificial neural network) to safeguard frost-damaged citrus crops in Sicily, Italy [10].

A binary encoding method was developed to train and test their network, using both input and output parameters. They experimented with different input configurations to find the most accurate model, ultimately achieving a 94% accuracy rate with six inputs and two output classes. Additionally, they proposed an image-based AI technique for wheat crop analysis, utilizing a pixel labelling algorithm and Laplace transformation to enhance image information [11].

The creation of the AURORA robot in 1996 aimed to address the difficulties faced by humans in navigating and performing tasks in agricultural environments, particularly greenhouses. These environments often involve exposure to harmful chemicals such as pesticides and fungicides, which can lead to skin allergies, chronic illnesses and sometimes death. The researchers designed the AURORA robot to operate autonomously or be remotely controlled, enabling it to perform labour-intensive tasks that might require human involvement [12]. An example of an agricultural robot, like a tractor, receives instructions on its travel path from the Global Positioning System (GPS) as an input. Additionally, use of machine vision allows the robot to operate alongside the crop line [13]. During 2003, for mapping weed populations, a design was developed to test a robotic platform and the main focus of this design was on mobility of four-wheel system and user-friendliness. The functionality of the system was primarily carried out using standard communication protocols and embedded controllers [14].

STATUS OF ADAPTATION

The projections between 2011 and 2013, suggest that America experienced an average yearly increase in robot shipments of approximately 9%, while Asia-Australia is expected to see a 12% increase, and Europe an 8% increase in reports released by European Robotics Research Network, 2010. Based on this data, it is projected that the adoption rate of robots for commercially available technologies will reach 15% and 75% by 2030 and 2045, respectively.
At present, application of autonomous devices and robots in agriculture is still in its early stages. Though they are now being used effectively in greenhouses and dairy farms, their use in other farming activities is limited. However, robots are in infant stage for commercial use or are still in the prototype phase. Their impact on global agriculture is currently minimal and

may take more time and investment for these latest technologies to surpass the existing technology [15].

AI requires time before the gathered data can effectively optimize decisions related to planting, irrigation, input application and harvesting. The lack of sufficient high-quality training data poses a challenge. For instance, to accurately detect pests or plant diseases in user-generated photos, a computer vision-based AI application needs to be trained on a diverse and extensive dataset of pest images. These images often differ in terms of lighting, angles and background colours. Leveraging existing farming knowledge may serve as a base for developing practical and scalable AI applications in agriculture [16]. Farming involves many steps and stages, most of which are done by hand. AI can assist with hardest and most repetitive tasks by adding to the current technology. When fused with other technology, it can collect and analyse huge amounts of data on a digital platform, decide the best way to proceed and even start that action [17].

SCOPE OF AI AND ROBOTICS IN AGRICULTURE

AI is prevalent in most of the industries along with agriculture. Although it can be difficult to imagine agriculture undergoing a digital transformation, AI is playing a vital role in modernizing this age-old industry [18]. It has many uses in agriculture, like precision farming, where AI enables farmers to monitor water usage, manage crop rotation, improve harvesting techniques, select suitable crops and control pests. These tasks are accomplished by leveraging data gathered through machine learning algorithms [19]. This is mainly important as consumer behaviour evolves with increased disposable income. The global adoption of AI in agriculture presents one of the main promising opportunities to develop strategies that help farmers manage or reduce risks [20].

Robotics and autonomous systems (RAS) are primed to revolutionize global industries, particularly those with comparatively lower productivity levels, like the agro-food sector encompassing food production from farm to retail. In the United Kingdom, the agro-food chain accounts for an annual revenue of over £108 billion and employs approximately 3.7 million individuals in an internationally oriented industry that yielded £20 billion in exports in 2016 [21].

The surveillance systems based on AI and Machine Learning (ML) in agriculture offer practical insights for crop monitoring, pest identification and diagnosing soil issues. This technology enables farmers to determine the optimal time for planting seeds to maximize yield [22]. Weed infestations pose a threat to agricultural activities, leading to decreased output, crop invasion, pasture suffocation and occasional harm to livestock. By using AI sensors, farmers can identify areas affected by weeds and determine the most suitable herbicide for the specific location [23]. AI systems can also predict weather patterns, evaluate crop health and detect diseases, pests or inadequate plant nutrition. Using AI-powered drones, farmers can observe and monitor the well-being of their crops. Experts examine the images captured by these drones and create comprehensive reports on the farm's health, aiding in pest control. To streamline labour-intensive and physically demanding tasks, some farmers are employing agricultural robots. These robots assist in reducing manual labour costs and lessening the workload on human workers [15].

ML can be utilized in precision agriculture management to determine the optimal timing, location and type of agrichemicals to be applied in cropping areas, whether they are in open-air fields or greenhouse settings. The accurate detection and classification of crop quality features is crucial for farmers to enhance the price of their products and minimize waste. By analysing data, machines can identify and uncover new characteristics that greatly influence the overall quality of crops. In addition, water management plays a crucial role in agriculture, impacting factors like agronomics, climatology and hydrology. ML-based applications can estimate evapotranspiration on a daily, weekly or monthly basis, enabling more efficient utilization of irrigation systems [24].

Large corporations should invest in AI technology for agriculture as it can offer benefits such as anticipating pricing, calculating tomato output and yield and identifying pest and disease infestations. It enables businesses to provide advice to farmers on demand levels, crop varieties, pesticide usage, and future pricing patterns, ultimately improving profitability [25]. AI's ability to handle the increasing complexity of modern agriculture is crucial in mitigating resource and labour shortages. Across various industries, AI technology has proven to enhance productivity and efficiency [26].

APPLICATIONS OF AI IN AGRICULTURE

AI technology is making significant contributions across various sectors, including finance, transportation, healthcare and agriculture, by helping individuals and businesses overcome traditional challenges [18]. The effectiveness of AI in addressing agricultural problems relies heavily on the quality of available data. AI is considered a promising technology that might bring about groundbreaking solutions for agriculture [27]. However, obtaining necessary information at the level of individual farmers poses a significant challenge [28]. By integrating image classification techniques with distant and local sensing data, the use of farm machinery can be transformed, especially in tasks such as weed control, early disease detection, crop harvesting and grading [29].

The collected data from agricultural providers will be sent to a centralized data cloud storage through a computerized system. This data will be accessible to all connected farmers, advisors, researchers, and support centres. The system aims to acquire, manage and utilize agricultural data to improve the quality and efficiency of farms and address queries from the farming community. Automated farms will employ distributed computing tools to gather authorized data on farm illnesses, securely storing it to facilitate quick and effective care. Additionally, advancements in wearable agriculture devices, Farm Area Networks, wireless broadband communications and cloud computing enable advanced mobile farm care services, benefiting both farmers and agriculture professionals. This facilitates the development of a system for real-time collection, dissemination and analysis of farm data for managing chronic conditions and detecting emergencies [30].

The advancements in computer vision, mechatronics, AI and machine learning have also enabled the development of remote sensing technologies. These technologies can identify and manage plants, weeds, pests and diseases [31]. Through AI, farmers can now accurately detect and address these issues, leading to improved crop health and increased yields. Furthermore, AI provides an unprecedented opportunity to develop precise seeding techniques for optimal fertilization. By using AI tools, farmers can reduce waste, enhance product quality and gain quicker access to the market [32].

Overall, AI technology gives an array of benefits to farmers, including improved decision-making, increased efficiency, reduced waste, and enhanced crop quality. It has changed the way agriculture is practised and became an essential tool in mitigating the challenges posed by climatic and environmental factors [33]. AI is being used to enhance weed control, determine optimal harvest timing, monitor soil and crop health and even predict yield in advance. While AI and ML have been utilized as development tools across industries in the last decade, it is only recently that their potential to improve decision-making in agriculture has become evident [34].

The advancements in sensor technologies, personal mobile devices, wireless broadband connections and cloud computing have enabled agriculturists and farmers to gather and share agricultural data in real-time, regardless of their location. Personal mobile devices, like PDAs and mobile phones, continue to improve in terms of their processing power and ability to manage information, playing a significant role in people's daily lives. These technological advancements have prompted the development of a scalable and cost-effective system for real-time monitoring and analysis of agricultural data, to cater the necessities of those who regularly optimize the resources in their farms [35]. The sensors installed, are used to measure and transmit data on the parameters like wind speed, soil pH, air humidity, atmospheric pressure, soil temperature, air temperature, soil moisture, solar radiation, wind direction, leaf wetness and rainfall [109]. AI can also gather data about soil quality, recommend fertilizers, monitor the weather, and assess the product's maturity. This helps farmers improve their decisions at each step of the crop production process [36].

AI algorithms can analyse and provide valuable insights from the data facilitating decision-making. The introduction of innovative approaches like Natural Language Processing, ML, Machine Vision, Artificial Neural Networks (ANN), etc. made problem-solving and automation easier. Among these, ML and ANN are the most commonly employed methods in agriculture research for automation [37]. CNN has achieved remarkable advancements and demonstrated outstanding performance in tasks such as image segmentation, classification, detection and retrieval-related tasks, thus reigniting the scientific community's interest in ANNs [38].

Predictive Analytics

Predictive analytics can be a powerful tool. AI enables farmers to gather and handle much more data than they could otherwise, and in a shorter time. Farmers can use AI to deal with important challenges such as assessing market demand, forecasting prices and choosing the optimal time to plant and reap [39].

Crop yield prediction is crucial for marketing strategies and estimating crop costs. In the era of precision agriculture, predictive models can analyse various factors that directly impact yield. An artificial neural network model was utilized with backpropagation learning to predict yield based on soil parameters [40]. A neural model was developed for predicting tomato yield, growth and water usage in a greenhouse setting [41]. AI algorithms can evaluate the performance of hybrid seeds and estimate their potential yields, all wing farmers to make informed decisions before sowing, minimizing the risk of failed harvests and increasing overall productivity [42].

Predictive analytics can estimate precipitation and evapotranspiration, when joined with data from soil samples and other sources, ML models can provide precious insights into soil moisture, temperature, and overall soil health. By utilizing this information, farmers can optimize their irrigation practices, leading to improved crop yields and profitability, while also reducing water waste and helping the environment [43].

Storage Systems

Typically tailored for controlled environments, a cold storage management system is specially crafted to function in such controlled conditions. Employing automation through Internet of Things (IoT), automated cold storage systems prove advantageous for prolonged storage of agricultural produce. The system's design, mirrors that of a conventional storage system, with the addition of IoT-driven automation. This includes the integration of an alarm system or a mobile application to facilitate local control and monitoring of the system [44].

Navigation and Monitoring of The Performance of Tractors

Automation also plays a crucial role in modern agriculture. Automated tractors enabled with GPS technology can prepare the fields for planting and harvesting without requiring a human driver [32]. The performance monitors for the tractor measure, record and enable remote visualization of the entire operation. The key parameters include power, fuel consumption, draught and wheel slip. Optimizing these parameters holds significant potential for enhancing tractor performance. Draught was assessed using a strain gauge mounted on a ring transducer at the drawbar's front end. Fuel consumption was measured by a positive displacement flow meter and wheel speed was determined by gears and magnetic pick-ups [45].

Utilizing a data acquisition system is advantageous for monitoring performance by incorporating transducers to measure various operational parameters. The Differential Global Positioning System (DGPS) allows for spatial mapping of tractor-implement performance. The GPS plays a significant role in providing spatial values, enabling it to measure, record and monitor the tractor-implement system's performance relative to its position. Given that the performance is affected by soil condition and land slope, this mapping system is particularly valuable for calculating the cost of crop production within the field boundary, influenced by the architecture of an IoT device [46].

In developed countries, modern farms now feature tractors equipped with integrated navigation systems and sensors that monitor both macroscopic and microscopic elements in the field. The increasing connectivity and internet access on farms have unlocked the full potential of the IoT and related technologies for effectively overseeing tractor performance. A comprehensive system for monitoring tractor navigation and performance consists of both hardware and software components. The hardware segment includes essential sensors to measure geo-location, fuel flow and power consumption, with the collected data transmitted to a processing unit or PCB. Utilizing communication technology such as LPWAN (Low Powered Wide Area Network), the data is then sent to the network. On the software side, web applications connected to a real-time and scalable database are employed for efficient data utilization [47].

Crop Monitoring

AI-powered systems can autonomously monitor farm conditions, leading to a more efficient and less labour-intensive approach to agriculture. By identifying and managing variations in the field, these systems ensure that crops receive precisely the resources they need. This precision response to farmland requirements improves crop yields, fertilizer efficiency and overall profitability. Moreover, precision agriculture promotes sustainability, environmental protection and enhanced productivity and efficiency. Consequently, numerous agricultural companies worldwide are leveraging AI and its various technologies to enhance the efficiency of their operations [48].

Technique	Application	Reference
ANN	Helps in detecting crop nutrition disorder	[49]
FUZZY cognitive map	To predict cotton yield and help in improving decision management	[50]

Soil Management

Soil management plays a critical role in agriculture as it is vital for growth and development of crops. Soil acts as a reservoir for essential nutrients like nitrogen, phosphorus, potassium, micronutrients, enzymes and proteins along with water are required for healthy plant growth [51]. AI technology can be utilized to generate soil maps that reveal the correlation between soil landscapes and the different layers and compositions of soil beneath the surface. This assists in comprehending the distribution and properties of soil across an area, facilitating better soil management decisions [52]. A fuzzy-based system was developed by using farmers' knowledge that recommends crops based on land suitability maps generated by the fuzzy system.

Technique	Application	Reference
DSS	To reduce erosion	[53]
Fuzzy Logic: SRC-DSS	To classify according to risks	[54]
ANN	To predict, soil texture soil enzyme activity	[55-59]
MOM	Minimizes nitrate leaching	[60]

Water Management

Water management in agriculture has a major impact on hydrological, climatological and agronomic balance. In regions with pronounced water scarcity, irrigation relies heavily on underground water sources. The operation of pumps is contingent upon the water level within wells, necessitating careful regulation to prevent damage, especially for water-cooled diesel engine pumps. Consequently, monitoring the well's water level becomes crucial, integrating it with irrigation planning. In areas facing both water scarcity and power shortages, the development of an IoT-based solar energy system for intelligent irrigation becomes feasible. These systems leverage solar energy to charge batteries during sunlight hours. Similar to conventional irrigation setups, they incorporate sensors to measure temperature, humidity, soil moisture and a flow rate sensor for precise control. The emphasis in designing these systems is on energy conservation, incorporating a fuzzy logic-based control algorithm that enhances the existing irrigation approach. By employing diverse combinations of input values, the water pump can be efficiently operated as needed. The systems also offer remote monitoring through mobile or web applications, ensuring accessibility from any location [61].

ML-based applications have made vital progress in estimating evapotranspiration on a daily, weekly, or monthly basis, leading to more efficient irrigation system utilization. Additionally, ML models can predict the daily dew point temperature, aiding in the identification of expected weather patterns and providing estimates for evapotranspiration and evaporation [62]. Highlighted research using artificial intelligence techniques in irrigation management are discussed. A Takagi Sugeno Kang fuzzy inference system to estimate the stem water potential of plants using meteorological and soil water content data [63]. An artificial neural network-based system to estimate soil moisture in paddy fields was designed [64]. Additionally, the fluctuating levels of soil moisture are described and estimated using a remote sensing device embedded in higher-order neural network (HONN) [58].

Fertilizer Application

In addition to presence of weed, improper application of fertilizers stands out as a significant factor contributing to low agricultural yields. Hence, it is essential to conduct soil testing before applying fertilizers to estimate the crop's nutrient requirements. However, due to the complexity of traditional laboratory procedures, many farmers tend to skip this crucial step. Presently, organizations are encouraging farmers to embrace digital practices and adopt technology-enabled farming methods. IoT technology offers a smart solution for fertilizer application. An NPK sensor, utilizing components like light-emitting diodes (LED), light-dependent resistors, and resistors, can measure nitrogen (N), phosphorus (P) and potassium (K) levels. Operating based on colorimetric and photoconductivity principles, the NPK sensor provides values directly to a processing unit or system-on-chip. Subsequent analysis can be conducted through either fog computing, where the processor directly interacts with the sensors or edge computing, facilitated by an edge server connected to the internet. Fuzzy logic aids in analysing and determining the optimal fertilizer quantity for application. Leveraging cloud services such as Google Cloud Platforms ensures scalable, timely and uninterrupted service, enabling the delivery of recommended fertilizer quantities to farmers via SMS [65].

Plant Disease Detection

To achieve high yields in agriculture, it is crucial to have effective disease control measures in place. Diseases affecting plants and animals can significantly reduce yield potential. Various factors contribute to the development of these diseases, including genetics, soil type and weather conditions such as rain, dry weather, wind and temperature, among others. Managing the impacts of these diseases is a major challenge, particularly in large-scale farming, because of the unpredictable nature of disease causation [51]. AI utilizes ML algorithms to extract valuable insights from the vast and complex big data that standard data-processing systems struggle to handle. This enables the understanding of crop growth patterns, identification of potential crop diseases and recommendations for specific fertilizers or pesticides based on disease patterns. Disease prediction can also be made by analysing factors such as leaf growth, size or colour. To gather data, various sensors such as field sensors, weight sensors, soil sensors, temperature sensors, intensity sensors and different camera types are employed. These sensors can be installed on machines such as low-flying drones or small robots that can navigate the agricultural fields [66].

By implementing these integrated measures, farmers can enhance disease management and optimize their overall yield potential [67]. Therefore, there is a growing need to apply AI approaches in disease control and management, as they can help overcome the challenges of time consumption and cost-effectiveness. The Explanation Block (EB) provides a transparent explanation of the logical reasoning used by the core of the expert system. In this particular system, a unique method of rule promotion that incorporates fuzzy logic is employed. This innovative approach enables the system to make intelligent inferences and recommendations for managing crop diseases [68, 69]. A system utilizing a rule-based and a forward chaining inference engine has been employed to create a solution that identifies diseases and offers treatment recommendations.

Disease Management

Technique	**Application**	**Reference**
Computer vision system (CVS), genetic algorithm (GA), ANN	Can multi-task and detect the diseased leaves	[63]
Rule-based expert, Data Base (DB)	Helps in detecting diseased leaves in tested environments	[63]
Fuzzy Logic (FL)	Eco-friendly, Cost effective	[70]
FL Web-Based, Web-Based Intelligent Disease Diagnosis System (WIDDS)	Response fastly to the nature of crop diseases	[71]
FL & TTS converter	Solves plant pathological problems quickly	[66]
Expert system using rule-base in disease detection	Faster treatment as diseases are diagnosed faster. Cost-effective based on its preventive approach	[69]
ANN, GIS	95% accuracy	[40]
FuzzyXpest provides pest information for farmers. It is also supported by internet services.	High precision in the forecast	[72]
Web-Based Expert System	High performance	[73]

Detection of Weeds and Pests

Herbicide sprays used to inhibit weeds may affect the health of consumers and in addition, it may pollute the environment. So, weed detection systems with the help of artificial intelligence have been tested in laboratories to quantify the exact amount of spray to be used and also with spatial accuracy, which also lowers costs and the risk of damaging crops [74]. A study was conducted on identifying crops and weeds accurately to effectively target herbicide application. Plant morphology, including leaf characteristics and shape was identified to be a reliable method for species recognition through image analysis [17]. However, challenges such as varying lighting conditions, leaf distortion and the variability of young plants due to different growth factors and environmental conditions make distinguishing between crops and weeds difficult. It also suggested the use of neural network approaches for device to learn important features and improve its functionality. Additionally, the selectivity of herbicides used in fields helps reduce overall usage and minimizes herbicide pollution in water sources.

The machine vision combined with a back propagation-trained neural network to identify weeds of five different species was used. In a comparison study, three neural network models (back propagation, counter propagation and radial basis function) with the same inputs and found that the back propagation network outperformed the others, achieving 97% accuracy [75]. A different approach by using image analysis and neural networks for weed management. Developing a site-specific weed control system through IoT, Robotics and advanced imaging (RGB and IR) allows efficient weed detection [76]. Pre-processing, segmentation, feature extraction and classification, employing techniques like SVM and neural networks, optimize herbicide use and reduce environmental impact. For weed identification in maize crop SVMs have been successfully used [77]. AI technology helps in identifying the main plant on the farm and supports pest management. It determines the appropriate pesticides for use, along with their required quantities. Additionally, AI enables the use of drones to spray pesticides on crops, which saves time and increases efficiency [78].

TEAPEST, an expert system for pest management in tea, using an object-oriented approach to frame a rule base was developed. When the researchers used a sticky trap to collect six different kinds of flying insects and photograph them in real-time. They used YOLO object recognition for detection and rough counting and support vector machines (SVMs) with global features for the data and fine counting. Then, the computer vision model precisely detected and counted moths, flies, mosquitoes, bees, chafers and fruit flies with 92.5% and 90.18% accuracy, respectively [79]. Addressing concerns over chemical dependency in pest control, IoT offers solutions through remote monitoring of pests, precise weather tracking and AI-driven crop health assessment. Early warning models, utilizing big data and neural networks, predict pest occurrences based on real-time field data. Object detection technologies like Faster R-CNN (faster region-based convolutional neural network) prove effective in identifying pests in large farms, while innovative spraying equipment minimizes pesticide usage, reducing environmental impact on soil and groundwater [80].

Weed Management

Technique	Application	Reference
Saloma expert system for evaluation, prediction and weed management	High adaptation rate and prediction level.	[81]
Mechanical Control of Weeds ROBOTICS. Sensor machine learning	Saves time and removes resistant weeds.	[82]
Digital Image Analysis (DIA), GPS	Has above 60% accuracy and success rate.	[83]
Support Vector Machine (SVM), ANN	Quickly detects stress in crops that will prompt timely site-specific remedies.	[84]
Learning Vector Quantization (LVQ), ANN	High weed recognition rate with short processing time.	[85]

Intelligent Spraying

Farmers prefer hand spraying, harmful. We can avoid this by using UAVs with computer vision AI, pesticides and fertilizers can be applied evenly across a field. The computer vision system can spray so accurately that it prevents damage to crops or the environment [86].

Observing Crop Maturity

This vision-based idea was developed to surpass human objective observation in properly recognizing crop (wheat) growth stages, eliminating the requirement for farmers to visit the fields regularly to monitor their crops [28]. Farmers used the ripeness of tomatoes by visiting the field every day and checking them with their hands to see how they were developing, but today they can check the maturity of fresh tomatoes on an industrialized level [87].

Harvesting

An Autonomous Fruit Picking Machine (AFPM) was developed specifically for harvesting apples. Machine design included a flexible gripper that allowed for the precise picking of individual apples, reducing economic losses from damaged fruit. In a similar vein, a fruit-picking robot developed in 2013 utilized an automatic extraction method for its vision system, which was effective even in varying agricultural backgrounds [88].

Livestock Health Monitoring

In livestock management, IoT-based systems utilize sensors like accelerometers and temperature sensors to detect oestrus and calving events, employing AI models to analyse activity patterns for timely identification, emphasizing parameters like ruminating time, feeding time and resting time obtained from accelerometer data [89]. Cow health and activity are tracked using overhead cameras and computer vision algorithms which means a cattle farmer does not have to be always near the cow to spot a problem. Welfare monitoring systems incorporate non-invasive technologies such as digital imaging and vocalization analysis, supported by sophisticated big data analytics [90]. Analysing cattle behaviour offers an enhanced understanding of their health and early detection of diseases, as well as monitoring feed intake, heat and oestrus events. The labour-intensive task of closely observing all farm cattle can be alleviated through the use of animal attached sensors, offering an automated monitoring solution suitable for both small and large-scale cattle farms [91].

The current automation system for behaviour monitoring and analysis employs sensors on animal body parts, sensor nodes for data processing and an AI-enabled model for status updates. Machine learning models, utilizing time-series data from sensors, employ feature selection techniques, such as LOOA and SCV, for effective decision-making [92].

Precision poultry farming includes three core components: environment monitoring, precision feeding systems and poultry welfare. Environmental monitoring involves multi-sensors to track temperature, humidity and gases like CO_2 and ammonia, which are crucial for bird health. Advanced prediction models based on deep learning can forecast broiler weight up to 72 hours in advance. Robotics plays a pivotal role in efficiently managing various poultry activities [93].

Utilizing autonomous robots can improve bird well-being by encouraging bird movement and efficiently aerating the poultry floor litter. This practice reduces infection risks and safeguards against diseases such as salmonella. Precision feeding systems play a crucial role in accurately regulating feed intake, with recent studies demonstrating that broiler breeders subjected to precision feeding yield more fertile eggs [94].

Weather Prediction

AI enhances the flexibility of the agricultural sector by introducing advanced technologies. Traditional linear regression models are being replaced with more sophisticated methods, where raw data is collected and processed [95]. Neural networks are capable of calculating and predicting past weather patterns, taking into consideration non-linear dependencies. This enables optimal timing of planting seeds for important crops like rice, wheat and maize, as they heavily rely on adequate rainfall for growth and are typically cultivated.

Having a comprehensive understanding of weather patterns is crucial in making informed decisions that can lead to increased crop yield and improved crop quality [96]. AI and machine learning models utilize vast amount of data generated daily by farms, including temperature, soil conditions, water usage, weather patterns and more. This data is analysed in real-time to provide valuable insights, such as determining the optimal timing for planting seeds, suggesting the most suitable crops to cultivate and selecting hybrid seeds for higher yields. These AI systems enhance precision agriculture by improving the accuracy and quality of the harvest [62].

APPLICATIONS OF ROBOTICS IN AGRICULTURE

Immobile robots and automatic devices are already efficiently used for some indoor farm activities, being capable of identifying animals and feeding them according to their nutritional needs and expected production, selectively milking the cows, weighing and separating them, sheep shearing, cleaning up the shelters. In some crops, there are commercially available and fully autonomous robots dealing with the whole cultivation process, from sowing to harvesting and packing in a greenhouse.

Important progress can also be noticed regarding outdoor activities, both in the establishment of crops, plant care and selective harvesting. For almost all kinds of fruits, available autonomous mobile robots are capable of selective harvesting (strawberries, pears, grapes, watermelons) legumes and flowers. Automatic guidance systems that can be installed on conventional tractors are already in use, considerably reducing the effort of drivers and are also credited with improvement of technical and economic efficiency [97].

Weeding

An innovative agricultural robot was developed for crop and weed management for horticulture crops [98]. EcoRobotix, a fully automated robot sprayed the herbicide with an efficiency of 95% and above at the right spot. Physical weed removal not only saves farmer time but also decreases the need for chemicals, making entire agricultural process more ecologically friendly and sustainable [99].

Harvesting

The implementation of artificial intelligence in cucumber harvesting involves various hardware and software elements of the robot. The components are an autonomous vehicle, a manipulator, an end-effector, two computer vision systems for detecting and creating 3D images of cucumbers and the surroundings and a control system that ensures the manipulator moves without any collisions during the harvesting process. For cotton ball detection and harvesting GRobomac, a commercial robot was developed by a Bengaluru-based robot firm and a robotic arm for cotton picking based on 3D machine vision techniques by IIT Kharagpur [100].

Aerial Imaging Robots (Drones)

Though initially developed for military purposes, drones have progressively found applications in agriculture, representing a significant advancement in automating tasks like pesticide spraying and land monitoring. Agricultural drones, categorized as Unmanned Aerial Vehicles (UAVs), operate without a human pilot and typically consist of a ground station for communication using protocols like Mavelink. Equipped with actuators, motors, and a range of sensors such as lasers, radars, cameras, and GPS receivers, UAVs efficiently monitor large agricultural areas using thermal and multi-spectral cameras during single flight [101].

A system can utilize an unmanned aerial vehicle (UAV) - to optimize parameters, compute and convert to binary the vegetation indexes, imagery to divide images, detect crop rows, and learn a classification model. The crop row detection algorithm helps to distinguish weed and crop rows through wed and crop pixels [84].

To detect infected plants, drones equipped with cameras can capture images using both RGB (Red Green Blue) and infrared light. By analysing these multispectral images, it becomes possible to identify individual clusters of infected plants in different areas of the field. This enables targeted treatment and intervention to be provided to the affected plants simultaneously [102].

Planting Seeds

Demeter is an automated machine designed for speed-rowing, equipped with video cameras and a global positioning sensor to navigate. It can plan and carry out harvesting operations for a whole field, precisely cutting crop rows, turning to cut subsequent rows, adjusting its position in the field, and detecting any unexpected obstacles [103].

CONCLUSION

In today's agriculture digital farming plays an important role in facing different challenges in the farming sector. In smart farming techniques, robotics and AI are vital game-changing technologies. The automation in crop monitoring, irrigation scheduling, and disease and pest detection makes farmers more precise in decision-making. It might take time and way forward research to collect and upload data on different parameters in agriculture and allied sectors. The adoption of robotics and AI in agriculture has a high potential to revolutionize the industry.

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