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Application of Artificial Intelligence in Horticulture: A Review

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ABSTRACT

India, with its diverse soil and climate conditions and varied agro ecological regions, provides a possibility to grow many horticultural crops, which significantly contribute to the Indian economy by enhancing farm output, generating employment, and providing raw materials to various food-processing businesses. The amount of land allotted for horticulture is minimal, but the demand for the production of horticulture crops is high. Therefore, meeting the demand with minimum resources is a bit challenging, nevertheless can be achieved by the introduction of Artificial Intelligence (AI) to the field. Application of AI in horticultural crop production by predicting adverse climate conditions, providing suitable micro-environment through remote controlled drip irrigation, and its application in providing automated irrigation, determining crop genotype, disease diagnosis, pest and weed management, maturity identification of fruits and vegetables, yield forecasting, automated harvesting using robots, reducing post-harvest losses and its role in fruit quality assessment and in processing industry is elaborated in this review.

Key words: *Artificial Intelligence, Automated irrigation, Disease diagnosis, Yield forecasting*

Introduction

Artificial Intelligence (AI) is a technology which can store, retrieve, manipulate, manufacture, transmit/ receive, analyse a set of digital information, and can instruct machines on how to replicate human physical actions and react like humans. In a computer, AI is achieved through powerful mathematical algorithms and it is implemented with programming tools. It was first introduced by John McCarthy, an American computer scientist in 1956. Nowadays, AI finds a lot of direct applications across sectors and it can also bring a paradigm shift in agriculture, horticulture and farming today.

Every day, farms produce thousands of data points on temperature, soil, usage of water, weather condition, etc. With the help of artificial intelligence and machine learning models, this data can be leveraged on a real-time basis for obtaining useful insights on right time for planting, watering, field management, harvesting, post-harvest handling etc. The use of these latest technological solutions will make farming more efficient with a customized solution for each specific problem and with improved product quality. According to Manaware (2020), AI technologies are helpful to yield healthier crops, provide information on prevailing weather conditions such as temperature, rain, wind speed, wind direction and solar radiation in field, helps in pest control, monitor soil and growing conditions, organize data for farmers, help with the workload and improve food supply chain. The present article high-lights some of the major applications of artificial intelligence based techniques in horticulture.

Application of AI in prediction of soil fertility

Micro and macronutrients, soil pH, soil moisture, soil temperature etc. are critical factors for crop health and yield. Currently, these parameters are estimated by methods which are less accurate and time consuming. At present, drones, Unmanned Aerial Vehicle (UAVs) and computer vision models entered the field with which the former is capable of capturing aerial image data, and later will intelligently monitor the soil conditions. PEAT- a Berlin based start-up developed a deep learning application known as Plantix for finding nutrient deficiencies in soil where algorithms are used which will correlate particular foliage patterns with certain soil defects (Varshitha and Choudhary, 2021). Identification of soil properties using image processing and Artificial Neural Network (ANN) system was developed by Palaniappan *et al.* (2019) which help in recommending suitable crop for that soil.

Application of AI in crop production

Nowadays, horticultural crop production is facing environmental challenges like increase in temperature, occurrence of frost etc. which may lead to crop loss. With the advancement of AI, solutions are available for predicting the changes in environmental parameters which in turn helps the farmers to take necessary measures to protect the crop either by early harvest or by other means. This technology is also applicable in the field of the greenhouse, where variations in the environmental parameters inside the structure can be monitored and controlled.

A company known by the name Sentiment had invented a system that can carefully check the factors such as light intensity, temperature, salinity, and water stress, and can alert for variations if detected which can create favourable condition for growth of basil (Sahni *et al.*, 2021).

A study conducted by Robinson and Mort in 1997, developed a neural network system for the prediction of frost occurrence which may otherwise, damage the crop, resulting in loss of the harvest, trees, or in extreme cases whole orchard. The result also indicated that networks predicted frost more effectively when trained using a range of meteorological parameters like maximum temperature, minimum temperature, precipitation, humidity, cloud cover (clear, partially overcast, overcast), wind speed and direction, rather than past values of a single parameter. Qiu *et al*. (2014) developed an intelligent greenhouse environment monitoring control system with temperature, humidity and light intensity sensors for real-time detection of greenhouse environmental factors, which will be compared with default values and brings back to optimum value by operating greenhouse fans, lights and irrigation equipment. A similar study was carried out by Srbinovska *et al*. (2014) which helped in improving micro-environment for pepper in greenhouse using remote control for drip irrigation and fan facilities which works based on data obtained from the sensor nodes.

Application of AI in assisting pollination

One-third of all food consumed by humans relies on animal pollination and currently, due to shrinking population of natural pollinators food supply reduction is reported. Several researches are going on in this field to integrate AI for assisting pollination in crops.

Researchers at Monash University recorded the individual movements of pollinators like honey bees, hover flies, moths, butterflies and wasps using Computer Vision and AI to build a database of over 2000 insect tracks at a commercial strawberry farm in Victoria, to understand the contributions of different species to pollination, thereby to improve pollination and crop yield. This will enable the farmers to alter hive numbers and locations to boost pollination to optimum levels. A prototype of robotic micro air vehicle pollinators with flapping wings was designed and manufactured by Chen and Li (2016) for intelligent autonomous pollination. Small size, energy efficiency and agility are the characteristics which makes it suited for the job. It works by capturing real-time field data of crop and flowers, using cameras and thermal sensors, which will be transferred to the central control system via wireless signal connections and thereby controlling the robotic swarm.

Application of AI in automated irrigation

About 70% of the world's fresh water is consumed by agriculture and water application efficiencies are low. To cope with the scarcity of water, nowadays there is a critical need for smart irrigation systems that can irrigate more areas with a lesser quantity of water. There is an availability of various low water consumption-based irrigation techniques, viz, sprinkler systems and drip irrigation systems; but these systems need human intervention to a great extent. These irrigation systems can be made smart by incorporating features of AI technology that can automatically starts sprinklers or drips as per water requirements of crop.

Fully automated on-farm irrigation system, which works based on real-time feedback of soil moisture detected using sensors was developed by Ooi *et al*. (2010) in apple variety Pink Lady with increased economic water use efficiency of 73% compared with manual irrigation. Proximal Soilsens Technologies Pvt. Ltd had developed a smart soil monitoring system called soilsens, which have sensors for soil moisture, soil temperature, ambient humidity and ambient temperature and based on the readings, farmers are advised about optimum irrigation to be provided to the crop through a mobile app (Manaware, 2020). Santesteban *et al*. (2016) reported that thermal images obtained from drone mount high-resolution camera provides accurate results on water status in the vineyard. Use of electrotensiometers for automation of irrigation in greenhouse was studied by Contreras *et al*. (2021) in which demand-based fertigation dosage was supplied to sweet pepper, resulting in increased yield, water productivity and nutrient productivity without drainage. Recent studies have pointed that according to soil water availability and atmospheric demand, stem diameter increases or shrinks daily and these trunk variations can be measured using dendrometers, which is helpful for scheduling irrigation (Hahn *et al*., 2021).

Application of AI in crop phenotype determination

Evaluation of different breeding methods in horticultural crops requires phenotypic data to explore the correlation between genomic and phenotypic information. Field surveys and field phenotyping are the two traditional methods relied upon for this now, which are time consuming and labour intensive. Recently, UAVs equipped with various sensors were used for field phenotyping of citrus rootstocks by Ampatzidis *et al*. (2019) to determine the phenotypic characteristics of sweet orange trees grafted on 25 rootstocks. They concluded it as a cost-efficient tool that can be used for monitoring phenotypic changes of plants at spatial and temporal resolution with 99.9% accuracy for tree count. Images from UAVs combined with deep learning convolutional neural networks were used by Wu *et al*. (2020) to measure the crown width, perimeter, and crown projection area of apple trees which helps grower's to efficiently manage processes such as precision spraying, machine harvesting, and monitoring of tree growth during the growing season.

Application of AI in disease diagnosis

According to Food and Agriculture Organization estimates, up to 40% of global agriculture production loss is due to plant pests and diseases (Fenu and Malloci, 2021). Therefore, finding new ways to identify plant diseases can significantly improve food yield and turn the losses into profit. Automatic plant disease detection techniques can assist farmers in improving crop quality while also reducing disease occurrence through early identification, timely and appropriate treatment.

Images captured using drone-mounted camera were used to create a vegetation indices map by Patel *et al*. (2013) which helps in differentiating healthy and unhealthy plants and for crop disease detection. These indices works based on the image spectrum of crops, which will be different for healthy and unhealthy sample.

Patil and Thorat (2016) developed a monitoring system using Hidden Markov statistical model for early and accurate detection of disease in grape vineyards. The system consists of temperature, relative humidity and leaf wetness sensors kept in vineyard which will generate data at continuous intervals and will be compared with the dataset, having factors provided by National Research Centre for Grapes (NRCG), found responsible for spreading of diseases. This system is found to be beneficial to the farmers in improving the quality, quantity and profit of grapes, along with accurate identification of diseases and providing correct sprays of pesticides. Mohanty *et al*. (2016) developed a smartphone-assisted crop disease diagnosis which is demonstrated to have an accuracy of 99.35%. In this approach, diseased and healthy plant leaves were collected under controlled conditions well before and a dataset of 54,306 images was generated, which was used to train a deep convolutional neural network to identify 14 crop species and 26 diseases.

Berlin-based agricultural technology startup PEAT developed a deep learning application called Plantix which can identify plant diseases with 95% accuracy, by correlating particular foliage patterns with software algorithms (Manaware, 2020).

Application of AI in field management

Manual spraying of pesticides have several shortcomings like extra chemicals use, farm labour shortage, lower spray uniformity, environmental pollution, less area coverage etc. However, high-definition images from airborne systems (drones) will provide real-time estimates of areas in the field which requires pesticide spray. In addition, drones which carry 40 litres of pesticide tanks are available currently with the ability to follow pre-mapped routes to spray crops according to the requirements.

Hafeez *et al*. (2022) elaborated the use of UAV for pesticide spraying in fields. The study pointed that the application of drone-mounted sprayers in the field has enhanced the coverage, increased the chemical effectiveness, and made the spraying job easier and faster.

Vitirover solar robot which could cut grass and weeds, to within 2-3 cm of grape vine with a speed of 500 meters per hour was reported by Bhavana and Bhagwan (2021). It could work in slopes of 15% and sensors attached to the robot helps keep the grass cutting blades away from vines and protect it from damage. A California based startup company developed a robot called 'See & Spray' which reportedly leverages computer vision to monitor and precisely spray on weeds, which can help prevent herbicide resistance and could save about 90% of herbicide that would be needed to spray in the entire field. Debnath (2020) developed an autonomous agriculture robot named Agrobot Srishti, capable of identifying and destroying weed.The system uses weed detection algorithm which provides the X, Y and Z coordinates of the weed and data is passed to the delta robot and later felicitate for weed removal or spraying of pesticide.

Application of AI in identification of produce maturity

Harvesting of horticultural produce at correct maturity stage is important for attaining acceptable eating quality for the consumer and for enhancing the shelf life. This will also aids in warding off the development of physiological disorders during storage which may otherwise exhibit poor dessert quality. Maturity index can be determined by observing physical parameters like skin colour, by measuring chlorophyll pigment and by analyzing chemical parameter like sugar and also by detection of fruit firmness, sweetness etc. Implementation of AI in this field to judge the maturity of horticultural produce will give an accurate estimation within no time than manual assessment.

Yossy *et al.* (2017) developed a system using computer vision and ANN to distinguish maturity in mango variety 'Gincu' based on colour, with 94% accuracy. The computer vision used in this study can extract the fruit information from the image and will sort mango fruits into four category, large size ripe mango fruit, small size ripe mango fruit, large size unripe mango fruit and small size unripe mango fruit whereas, the neural network can make the system process the information like a human. Guzman *et al*. (2015) devised machine vision supported image analysis for determination of maturity index of olive in which colour based segmentation algorithms are employed. QiBing *et al*. (2015) identified hyperspectral imaging in the range of 500 - 950 nm as an effective method for the classification of tomato ripeness based on skin colour since, Sun Bright tomatoes at six ripeness grades (i.e., green, breaker, turning, pink, light-red, red) had shown changes in optical absorption and scattering properties.

Hyperspectral imaging based optical system was developed by Saputro *et al*. (2018) to detect the ripening of banana by predicting the amount of chlorophyll pigment in the peel of fruit. Cho *et al*. (2021) identified 400 - 1700 nm as the suitable wavelength range for hyperspectral imaging of strawberry fruits to predict anthocyanin content at different stages of maturity. A non-destructive method of hyperspectral imaging in lettuce was developed by Simko *et al*. (2016) to determine chlorophyll and anthocyanin content. Torkashvand *et al*. (2017) studied the potential for using AI systems in predicting fruit firmness. The study pointed that ANN model can be employed for predicting six month-fruit firmness in kiwifruit with different input datasets like nitrogen and calcium concentrations. Ma *et al*. (2021) developed a multifiber-based spatially resolved spectra collection to measure the firmness of apple fruits. In this method, a number of optical fibers were employed at certain distances from the point of entry of light into the samples, which will transfer the returned photons from inside the fruit to the hyperspectral imaging system, which thereby indicates the fruit firmness.

Sweetness is an excellent indicator of fruit maturity and prediction of orange fruit sweetness based on image processing technology was studied by Al-Sammarraie *et al*. (2022). In image processing, information is being stored in a three plane and each plane represents three colours that are red, green and blue (RGB). These three colour combination makes up all the colour which could be seen as an RGB images. The study elucidated the relationship between the RGB values of orange fruits and the sweetness of those fruits. The results showed that the value of the red colour has a greater effect than the green and blue colours in predicting the sweetness of orange fruits, as there is a direct relationship between the value of the red colour and the level of sweetness.

The amount of sugar content increases in fruits as it ripens and it can be a valuable maturity indicator also. Gutierrez *et al.* (2018) identified hyper spectral imaging using portable Near InfraRed (NIR) spectrophotometer at a wavelength range of 400-1000 nm as a successful real time non-destructive method to measure total soluble solids in the vineyard of grapes.

Application of AI in yield forecasting

Fruit count is important for forecasting yields and for planning harvesting schedules to attain more productivity. Manual counting of fruits and vegetables which is practised at present has many drawbacks as it is time consuming and requires plenty of labours. In this context, Lomte *et al*. (2019) developed an automated and efficient fruit counting system using Image Processing. It works with an image as input and when a snap is made, tiny bits of information are gathered by the camera's sensor, and a set of features of the image is generated as output. Maheswari *et al.* (2021) elaborated different steps involved in developing an intelligent yield estimation system using Deep Learning (DL), which include tree sampling followed by data capturing using different sensing technologies, data augmentation, fruit detection, counting and yield estimation using DL-based semantic segmentation architectures.

Application of AI in harvesting

Manual harvesting of horticultural crops contributes to 60% of production costs. The dual labour challenges of shortages and high costs can be overcome by the introduction of AI in harvesting. Automated harvester wheeled through rows of plants can reduce the cost of picking, which otherwise is a labour-intensive operation.

Kitamura *et al.* (2005) developed a fruit picking robot which can distinguish between fruits and leaves by using video image capturing. Robot arm is supported by a camera which can detect colours and compare with properties stored in the memory and if a match is found, the fruit is picked. The pressure applied to the fruit is only sufficient for removal from the tree, but not enough to crush the fruit.

An automated apple harvesting robot which is capable of detecting the two-dimensional position of fruits with 90% accuracy in two seconds using colour camera and a Single Shot MultiBox Detector was found to work efficiently by harvesting one fruit in approximately 16 seconds using a robot arm (Onishi *et al*., 2019). Xiong *et al*. (2020) developed an autonomous robot capable of picking strawberries in clusters continuously in polytunnels. The study also presented a novel obstacle separation path planning algorithm installed in the system which allows the successful harvest of strawberries that are surrounded by other strawberries, as well as by leaves and other obstacles. The research also added a new feature to the gripper, which is a component of robot, to pick a market punnet and harvested berries are fed straight into the container. Birrell *et al.* (2019) developed a robotic harvesting system 'Vegebot' for iceberg lettuce which had overcome the shortcomings like poor visibility and mechanical damage occurs during manual harvesting of crop. Navas *et al*. (2021) mentioned the soft robotics and soft gripper approach using silicone elastomers for the harvest of delicate commodities. Soft grippers were identified as the most befitting solution for the harvesting of high value crops, so that mechanical damage is minimised and the products can fetch maximum value in the market.

Application of AI in fruit grading

High costs, tediousness and inconsistency associated with manual sorting and grading have been forcing the post harvest industry to apply automation in these postharvest operations. Chopde *et al.* (2017) identified computer vision technology as an emerging technique in sorting and grading of fruits and vegetables that will improve productivity of industry and will also help to provide better quality produce to consumers. Kavdir and Guyer (2003) exploited the use of high-tech sensors or machine vision for apple grading and making the final grading decision using Fuzzy Logic, a computer based approach. The study reported that Fuzzy Logic grading result was in 89% general agreement with the results from the human expert, providing good flexibility and grading standards into the results. Similarly, Mustafa *et al*. (2009) developed an automated system for sorting and grading of apple, banana and mango. This system starts the grading process by capturing the fruit's image using a regular digital camera or mobile phone camera which is then transmitted to the processing level where feature extraction, classification and grading is done using Fuzzy Logic. In feature extraction, image processing of commodity is done and features such as area, major axis length, minor axis length, and perimeter are extracted which will be used as measures for grading. Olaniyi *et al*. (2015) developed a machine vision based grading system for banana, with 97% effectiveness, which will reduce human errors such as individual perception differences in determining whether the produce is healthy or defective for use.

TOMRA sorting food is an artificial intelligence based sensor machine, used for sorting of tomato. It uses features such as cameras and near-infrared sensors to visualize products with human perception and sorts the good quality tomatoes from defected tomatoes during harvesting or/and during the postharvest phase (Sahni *et al*., 2021).

Application of AI in reducing postharvest loss

Postharvest loss in horticultural produce occurs due to physical, physiological and biological factors. Moisture loss, mechanical bruising, postharvest diseases, physiological disorders etc. are few among them. Nowadays, with the introduction of AI to identify this deteriorating factors at an earlier stage, postharvest loss can be reduced to a level which is lowest possible.

Depending on the type of produce, fresh fruit contains 80 - 95% water and water vapour is transferred from the intercellular space of fruit tissue to the surrounding air, during transpiration. Decreasing moisture leads to wilting and lack of brittleness of fruit with adverse effects on the appearance, taste, and volume of the product. Kader (2002) suggested reduction in moisture content as a primary cause of postharvest damages in horticultural produce. Siregar *et al*. (2017) identified 700 - 1200 nm as suitable wavelength in hyperspectral imaging for prediction of moisture content in fruit tissue of banana.

Mechanical bruising, which is a major cause of postharvest loss in strawberry fruits, occur during manual harvesting as well as during post harvest operations. Identification of these bruises using human eyes is challenging because the damage occurs beneath the peel. Nagata *et al*. (2006) identified a combination of near infrared (NIR) hyperspectral imaging and ANN as an efficient method for detecting a wider extent of bruising in strawberry variety Akihime and this method is found to be better because of its capability to linearly and non-linearly map input variables to output results in classifying pixels.

The most significant damage during storage of fruits and vegetables is found to be the spoilage caused by fungi and bacteria under high humidity, or the wilting of the fruit surface under low humidity. Thus, relative humidity in the fruit storage environment have a greater role in enhancing the shelf life, without affecting the fruit quality. Morimoto *et al*. (1997) used neural networks and genetic algorithms for effective control of relative humidity in fruit storage atmosphere.In this study, neural network was used for identifying relative humidity as affected by ventilation, and optimal functions to modify the relative humidity were sought through simulation using genetic algorithms. Mishra and Chakshu (2019) developed a cost-effective, user friendly system for food supply chain management which consists of sensors to detect the temperature, moisture, humidity and ethylene in the cold storage conditions. This system uses python as a programming language and AI to predict the future values of parameters like temperature, moisture and humidity in order to avoid the further deterioration of food crops stored in cold storages. Apart from this, the system is capable of controlling and monitoring the cold storage environment automatically without any human intervention.

Postharvest diseases due to microbial infection is another major contributing parameter for postharvest loss. Identifying and removing the infected and decayed fruits from other in a lot will helps protect the remaining from decay. Sun *et al*. (2017) identified a significant reduction in chlorophyll content as a result of fungal infection in Honey peach. The study pointed out that hyperspectral imaging at wavelengths 617, 675 and 818 nm, which correspond to the absorption of light by chlorophyll pigment, will helps distinguish diseased peaches from healthy ones. Mehl *et al*. (2002) found that in the visible area of the electromagnetic spectrum, there is significant differences between the reflectance spectra of healthy and infected apples.

Physiological disorders which occur as a result of dysfunction of physiological processes within fruit tissues will reduce the shelf life of horticultural produce and thereby adds to the postharvest loss.Low temperature breakdowns, chilling injury and freezing injury are the most common physiological disorder in horticultural commodities. Lu *et al.* (2018) and Pan *et al.* (2016) investigated the detection of low temperature breakdowns in jujube and peach respectively using hyperspectral imaging and found a wavelength range of 400-1000 nm useful.

Ariana *et al*. (2006) developed an integrated model of reflectance and fluorescence imaging for detection of different disorders in apple variety Honeycrisp. This ANN classification models will accurately categorize fruits into normal, and ones with bitter pit, black rot, decay, soft scald and superficial scald tissues which is promising for accurate recognition of different types of disorder in apple.

Application of AI in quality assessment

To ensure a steady supply of high-quality fruits for meeting market demands, determination of fruit quality during cold storage is critical. Mohammed *et al.* (2022) developed a nondestructive method of detection of food safety and predicting quality attributes in dates using an ANN model. The study identified it as a powerful tool to efficiently predict the pH, total soluble solids, water activity, and moisture content of date fruits based on their electrical properties at 10 kHz.

Sonwani *et al*. (2022) designed a prototype with sensors for detection and monitoring of food spoilage. It consists of camera sensor and sensors for humidity, gas and heat which can notify the user about the food spoilage using voice-activated commands or via display and works with an accuracy of 95%. Megalingam *et al*. (2019) presented a novel idea for detecting food spoilage using image classification with artificial intelligence, deep convolutional neural networks, computer vision and machine learning algorithms. In this system, testing and processing of images are done in a computer which will then perform image classification and machine learning algorithms for getting the colours in the image and spoilage is detected by Hue Saturation values and percentages of each colour.

Altaf *et al*. (2020) exploited Wireless Sensor Networks for real-time monitoring of banana fruit quality during storage. It is by sensing the gases in the storage atmosphere, training was given to an ANN through the Back Propagation algorithm and diagnosis of the current condition of banana (healthy/ rotten) fruits will be done.

Banana fruits release different volatile compounds during different stages of ripening and detection of that aroma volatiles will shed light on the shelf life of fruits. Sanaeifar *et al*. (2014) demonstrated electronic nose (e-nose) as a non-destructive instrument to discriminate the volatile odours produced by banana during shelf-life process.

Nowadays, AI is been used in detection of adulteration in horticultural produce also. Image processing and Deep Learning techniques were used by Jahanbakhshi *et al*. (2021) to detect chickpea powder adulteration in ginger powder with 99.70% accuracy. Images captured by smartphones were used for grading and fraud detection in saffron by Convolutional Neural Network (Momeny *et al*., 2023) with an accuracy of 99.5%. This was achieved with the help of a dataset created and categorized into six classes including: dried saffron stigma using a dryer; dried saffron stigma using pressing method; pure stem of saffron; sunflower; saffron stem mixed with food colouring; and corn silk mixed with food colouring.

Traceability of organic vegetables by Radio Frequency Identification (RFID) technology using wireless non-contact two-way communication method to exchange data on breeding, growing, fertilizing, farming, inspecting, harvesting, logistics and distribution was elaborated by Yong and Xiuping (2014).

Application of AI in processing industry

Recently researches are going on about a system called self-optimizing clear-in-place (SOCIP), which uses the AI technology with ultrasonic sensing and optical fluorescence imaging to detect the tiniest amount of food left over and microbial debris present in the food processing equipment. This can improve the cleaning time and drastically reduce resources used for cleaning including water (Sahni *et al.*, 2021).

AI with augmented vision and sensors capable of sensing sight and scent and can detect products that are not appropriate for processing and can replace employees on the production line for this sole purpose are available nowadays (Sahni *et al*., 2021).

Application of AI in aeroponics

Priyanka *et al*. (2020) developed a prototype for digital farming using aeroponics with two chambers, one each for shoots and roots. The dark chamber for enclosing roots was supplied with different sensors for temperature, humidity, light, pH and water level sensor, whereas shoot chamber hosts sensors and exhaust fans for temperature and humidity regulation. The mobile application developed in the study called 'Aeroponics' will compares the real-time data with firebase database and any variation from normal will immediately alerts the application.

Limitation of artificial intelligence in horticulture

Though AI offers vast opportunities for application in horticulture, there still exists a lack of familiarity with high-tech machine learning solutions on farms across most parts of the world.

Conclusion

Automation of farming achieved by implementing artificial intelligence in different farm operations helps shift to precise cultivation for higher crop yield and better quality while utilizing fewer resources. AI can also reduce the cost of cultivation by regulating the use of labour, efficient use of fertilizers and pesticides, and reducing crop losses by harvesting at a correct time and maturity. Moreover, technological innovations may attract the young generations who are tech-savvy to opt for horticulture as a preferred profession rather than distracting them to migrate towards urban belts.

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