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Review article

Empowering vertical farming through IoT and AI-Driven technologies: A comprehensive review

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A R T I C L E I N F O

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A B S T R A C T

The substantial increase in the human population dramatically strains food supplies. Farmers need healthy soil and natural minerals for traditional farming, and production takes a little longer time. The soil-free farming method known as vertical farming (VF) requires a small land and consumes a very small amount of water than conventional soil-dependent farming techniques. With modern technologies like hydroponics, aeroponics, and aquaponics, the notion of the VF appears to have a promising future in urban areas where farming land is very expensive and scarce. VF faces difficulty in the simultaneous monitoring of multiple indicators, nutrition advice, and plant diagnosis systems. However, these issues can be resolved by implementing current technical advancements like artificial intelligence (AI)-based control techniques such as machine learning (ML), deep learning (DL), the internet of things (IoT), image processing as well as computer vision. This article presents a thorough analysis of ML and IoT applications in VF system. The areas on which the attention is concentrated include disease detection, crop yield prediction, nutrition, and irrigation control management. In order to predict crop yield and crop diseases, the computer vision technique is investigated in view of the classification of distinct collections of crop images. This article also illustrates ML and IoT-based VF systems that can raise product quality and production over the long term. Assessment and evaluation of the knowledge-based VF system have also been outlined in the article with the potential outcomes, advantages, and limitations of ML and IoT in the VF system.

Nomenclature

AI	**Artificial Intelligence**	HTTP	**Hypertext Transfer Protocol,**
ML	Machine Learning	TCP	Transmission Control Protocol
DL	Deep Learning	UDP	User Datagram Protocol.
IoT	Internet of Things	IETF	Internet Engineering Task Force
VF	Vertical Farming	OASIS	Organization for the Advancement of Structured Information Standards
M2M	Machine to Machine	DDS	Data Distribution Service
TDS	Total Dissolved Solids	OMG	Object Management Group
DWC	Deep Water Culture	CMOS	Complementary Metal-Oxide-Semiconductor
NFT	Nutrient Film Technique	YOLO	You Only Look Once

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EC	Electrical Conductivity	INC-VGGN	Inception -Visual Geometry Group Network
RH	Relative Humidity	F-RCNN	Fast Regional Convolutional Network
SVM	Support Vector Machine	LDA	Linear discriminant analysis
k-NN	K Nearest Neighbours	NB	Naive Bayes
DT	Decision Tree	SVR	Support Vector Regression
RF	Random Forest	XGB	Extreme Gradient Boosting
RNN	Recurrent Neural Network	RMSE	Root Mean Square Error
DNN	Deep Neural Network	ANFIS	Adaptive Neuro -Fuzzy Inference system
R–CNN	Regional Convolutional Network	ANN	Artificial Neural Network
ELM	Extreme Learning Machine	R^2	Coefficient of Determination
MQTT	Message Queuing Telemetry Transport	MAE	Mean Absolute Error
CoAP	Constrained Application Protocol	LSTM	Long Short-Term Memory
AMQP	Advanced Message Queuing Protocol	MVR	Multivariate Regression Composer
XMPP	Extensible Messaging and Presence Protocol	DKL	Deep Kernel Learning
REST	Representational State Transfer	Res Net	Residual Network
GUI	Graphic User Interface	VGG	Visual Geometry Group
LoRa WAN	Long Range Wide Area Network	DDOS	Distributed Denial of Services
LR- WPAN	Low-Rate Wireless Personal Area Network	LoRa	Long Range
QOS	Quality Of Service	Wi-Fi	Wireless Fidelity
REST	Representational State Transfer	PCA	Principle Component Analysis
IEEE	Institute of Electrical and Electronics Engineers	AMSAM	automated multivariate standard addition method
UAV	Unmanned Aerial Vehicles	YOLO	You Only Look Once
TP	True Positive	FP	False Positive
TN	True Negative	FN	False Negative
TPR	True Positive Rate	FPR	False Positive Rate
ROC	Receiver Operating Characteristic	AUC	Area under the ROC curve
SSE	Sum of Squared Error	MSE	Mean Squared Error

1. Introduction

Over the years there has been a continuous swelling in the population of the world which has a significant impact on the food supply. There is a possibility that world population may reach up to 9.7 billion in 2050 and 10.9 billion in 2100. The situation is more critical for India, as it has surpassed China and become the highest populated nation across the globe with a population of 1.42 billion in 2022. Cultivable and arable land is getting smaller due to a sharp hiking population and rising food demands. According to reports, between 1963 and 2009, the amount of land needed for agriculture increased by 42 percent, while India's per-capita land use decreased by 48 percent [1]. With an estimated population up to 2050, the globe would need to produce 50 % more food, which will require additional arable land that will simply not be accessible. The amount of arable land per person is predicted to be less than 0.20 ha by 2050, which is less than a third of what it was in 1970 as shown in Fig. 1 [2].

The soil's fertility has been negatively impacted by expanding metropolitan, rapid, natural calamities, global warming and indiscriminate utilization of herbicides and pesticides. In addition, each individual now has access to less land, and soil fertility and production have both deteriorated dramatically [3]. The challenges to the water resources in the watershed include a changing climate, surging temperature, continual droughty spells, and the unpredictability of the weather. A few threats to the water resources of the watershed include excessive irrigation water use, unregulated water contamination, and a downward trend in groundwater levels [4].

In recent decades, as seen in Fig. 2, 70 % of the world's water need has been met by agriculture. The expansion of agricultural areas has resulted in water consumption almost doubling from 500 to 2500 cubic kilometres across the globe. It is obvious that the

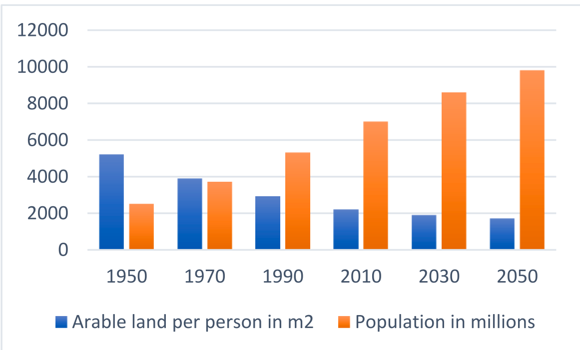

Fig. 1. Growing world population and declining agriculture land.

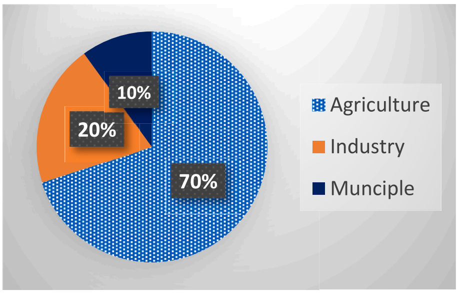

Fig. 2. Water Withdrawals by sector.

agriculture industry needs to modify its current methods of production and adoption in order to favour water and land conservation while reducing the danger of uncertain markets [5].

Therefore, problems like reduced soil production, decreased nutrients in the soil, narrow irrigation feasibility, land depletion as well as climate diversity pose major threats to traditional soil-based agricultural production systems. Thus, food production by conventional agriculture system is today's real challenge [6]. VF technique is one of the substantial solutions that could be used in place of soil-based farming systems as a supplementary approach to address the ongoing scarcity of water and fertile agricultural land. The practice of indoor vertical farming is frequently regarded as a crop-production strategy that is climate-resilient and can be helpful in future climate instabilities. Crops can be reliably grown all year long in indoor growing systems like VF since they are not dependent on regional weather conditions [7]. In comparison to conventional farming, VF is said to use natural resources like land and water more efficiently [8]. In comparison to conventional agriculture, there is very little utilization of pesticides and the use of fertilizers is also minimal in VF, which results in reduced direct on-farm greenhouse gas emissions, such as nitrous oxide (NO) [9]. Over the years, the traditional horizontal expansion of farmed fields into adjacent forest areas significantly harmed the environment by destroying and disrupting other ecosystems. Instead of requiring a lot of horizontal space, vertical farms can fit into urban environments and may reduce the need for regular rural farms to spread out further as shown in Fig. 3. VF enables the cultivation of crops indoors, where variables like light, temperature, and minerals are precisely controlled and applied. By using this ground-breaking technique, less freshwater is needed while preserving the soil and land resources [10]. VF has other advantages for environmental sustainability as well, though when compared to traditional farming techniques, it also makes it possible to significantly lower the volume of freshwater usage while at the same time providing higher yields [11]. One of the benefits of VF is that its products do not have any harmful pesticides and herbicides because the risk of pest infection is greatly decreased in an under-control environment of indoor farming, thus maximizing the overall nutritional value of the cultivated crop [12].

A VF system is typically thought of as an indoor farm inside of any infrastructure with cutting-edge agricultural systems and climate control. Artificial lights, cooling, heating, irrigation mechanism, ventilation nutrition solution, CO_2, soilless means, and grow beds to support the growing units are all included in the system. The automation system and sensor technologies are another essential component of VF. Multiple greenhouses and indoor farms throughout the world are currently using this technology to provide dependable, stable growth conditions all year long. Additionally, automated technologies are used to reduce operational expenses because labour expenditures in farming make up half of the output costs [13]. Fig. 4 provides an illustration of the primary components of VF system [14].

Due to ambiguity in weather, increasing food demand, and high population growth, there is a need to use innovative techniques like IoT, and AI in the VF system. Also, the use of AI solves various issues of farming such as pest detection, disease detection, weed control, and yield prediction. Besides this IoT allows the evolution of new innovations and designs. IoT technology increases the yield of crops and at the same time decreases the demand for irrigation, also system becomes fully digitized and automated with the help of integrated environmental sensors and prediction technologies [15,16].

With the application of sensors, actuators, and IoT farmer's workload can be reduced to a great extent [17]. In modern agricultural

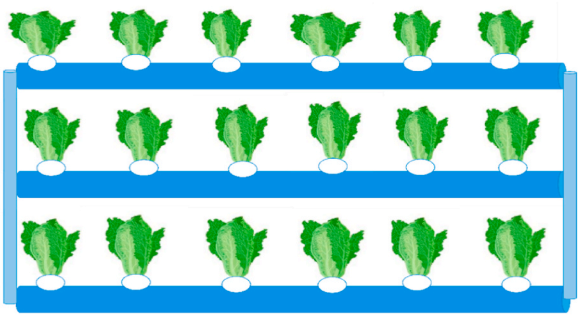

Fig. 3. Vertical Farming system.

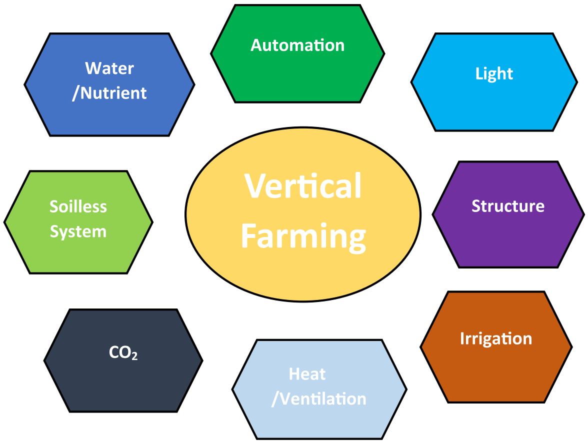

Fig. 4. Vertical farming system primary components.

operations, the use of temperature, light, chemical, moisture, pH, wind, rain, and auditory sensors is widespread. Every sensor has a unique combination of potential and equipment needs that are customized to the circumstances at a particular place. IoT devices, computer vision techniques, capacities of big data, analysis of data, and wireless technology support modern farm management. So, in agriculture, IoT and AI support farmers in their farming tasks at the same time these techniques encourage directed farming, which delivers large production with the best kind and utilizes fewer resources [18].

The IoT paradigm enables a variety of sensors and objects to monitor their surroundings and connects them with the global web in the view of exchanging data or instructions. IoT facilitates communication between things as well as between humans. IoT vertical garden gathers sensor data and keeps track of measured parameters for the optimal plant cultivation conditions on a small amount of ground [19]. IoT can automate the all parameters of farming in order to improve the process of farming [20]. VF paves the way for new smart engineering solutions for agriculture systems that can fulfil the demand for food requirements of the present population [21].

VF can become a more sustainable and productive practice by combining the IoT and AI. In this controlled environment, sensors continuously gather data on plant health and growth. AI algorithms then analyse this data to monitor plant development and optimize resource use, such as water and nutrients. This integration of IoT and AI is a recent advancement that's transforming VF [22]. Soilless VF techniques, which include hydroponics, aeroponic, and aquaponic farming, are potential modern agricultural adaptations that have been shown to increase production while using less water, feed, and other resources. VF techniques are also a possible solution for shrinking farmland. Advanced VF systems will be data-driven, utilizing modern technologies for monitoring the plant life cycle and traits in order to obtain higher yield. Plant trait analysis can involve monitoring growth, disease detection, species recognition, stress detection, and yield estimation. These plant traits can be analysed through image data of plants using machine learning (ML) algorithms. Several methods for analysing the evolution of plant traits have been developed by researchers in response to the increasing application of computer vision. DNN-based analytical methods are currently widely used by researchers for accurate and high-throughput plant traits analysis. In computer vision, DL algorithms analyse images to perform tasks like object detection, image segmentation, classification, and regression. These algorithms become more accurate as they are trained on larger and more diverse datasets of images [23].

Plant trait analysis requires methodologies for accurate identification, classification, and localization of plants. DNN models excel in this area, and YOLO version 3 is a particularly well-suited choice. YOLO v3 is known for its speed and precision in object detection, making it ideal for real-time analysis. It also demonstrates strong performance when working with aerial images, commonly captured by UAVs and field surveillance cameras. This combination of speed, accuracy, and suitability for aerial imagery makes YOLOv3 a valuable tool for real-time plant trait analysis based on data collected from UAVs and other field cameras [24]. A regression method called LCGM-Boost, which is similar to another model called XGBoost was used to monitor the growth and yield prediction of lettuce plant in an aeroponics VF system. The system monitors factors that affect lettuce growth, such as temperature, pH, electrical conductivity (EC), and turbidity of the nutrient solution. By analysing this data, the system can predict crop yield with high accuracy (over 95 %) and minimal errors [25]. ML approaches like SVR and lasso regression were used to find the accuracy of spinach crop growth in hydroponics system [26]. Mobile aquaponics VF combines fish farming and plant growing in one system. Fish tank water nourishes the plants, gets cleaned, and then returns to the fish. The enhanced IoT system generated datasets that, when subjected to training across multiple ML algorithms, attained a test RMSE score of 0.6140 compared to 1.0128 from the previous system, specifically in predicting fish length using Decision Tree Regressor [27]. A secure and intelligent monitoring system for aquaponic environments was designed to analyse data to predict plant and fish growth based on environmental factors. The RF algorithm produced more accurate predictions in this study [28]. Hypophonic represents a comprehensive monitoring system designed for integrated vertical farming. It encompasses areas such as aquaponics, agriculture, and poultry management. Utilizing a variety of sensors, the system is closely monitored, with predictive insights derived from the gathered data through Machine Learning Algorithms. These benefits empower farmers to significantly reduce water and fertilizer consumption while simultaneously increasing profits, thus offering multiple avenues for income generation [29].

Vertical hydroponics farming systems can be significantly improved by combining the IoT and ML. This approach aims to optimize plant growth by automating monitoring and adjustments. The system leverages Azure IoT Hub to collect sensor data. A logistic regression model then analyses this data to predict optimal settings for nutrient delivery, water flow, and light based on upcoming seasonal changes. Cloud-based decision-making identifies potential deficiencies in nitrogen (N), phosphorus (P), and potassium (K) based on sensor readings. Additionally, it calculates a health score for each plant. Compared to traditional soil-based cultivation, vertical hydroponics offers greater efficiency and effectiveness. This is due to reduced water evaporation and the ability to precisely control nutrient delivery. So, by incorporating AI and machine learning (ML), vertical hydroponic farming can be revolutionized. Real-time disease detection and diagnosis empower farmers to take preventive actions, safeguarding their crops and maximizing yield. This technology also opens doors to cultivating a wider variety of exotic and medicinal plants in a sustainable way. This advancement has the potential to bolster food security and promote overall health and wellness [30].

It is crucial to talk about the high energy consumption of vertical farming and its effects on the environment, especially with regard to carbon dioxide emissions, when debating its drawbacks. There is a noticeable increase in greenhouse gas emissions associated with vertical farming when it uses energy from non-renewable sources, including fossil fuels. Additionally, a significant amount of land is needed for the installation of these energy systems, especially when vertical farms are powered by renewable energy sources like wind or photovoltaics [31]. The competition for land that may be utilized for food production and installing renewable energy sources may lead to conflicts [32].

Consequently, although vertical farming presents novel approaches to urban agriculture and food production, its dependence on energy-intensive systems and possible inconsistency with renewable energy installations in terms of land use can present issues with sustainability and ecological effects [33]. Vertical farming approaches will not be viable or sustainable in the long run unless these limitations are addressed through the development of energy-efficient technologies and careful land-use planning [34].

In vertical hydroponics farms, various sensors work together to track and control essential plant growth factors like water level, temperature, and humidity. A special algorithm, called a Random Forest algorithm, analyses this sensor data to decide the best adjustments for these factors. This approach minimizes unnecessary actions by the system, saving energy and reducing the burden on the sensors. As a result, the system responds quickly and uses less power. In fact, system achieved significant power consumption reductions, saving 20.4 % during temperature and water level regulation and a remarkable 82.1 % during light regulation [35].

The key highlights of this review article are as follows.

- The survey addresses different types of VF systems along with their advantages, disadvantages, and applications.
- Detailed overview of IoT and ML in VF is presented along with their practical implications.
- The survey highlights the assessment and performance analysis of AI and IoT in the VF system.
- Challenges and future scope of the VF system is briefly outlined.

The key distinctions between this review paper and other published papers in this area are shown in Table 1.

The layout of the article is just like that of section 2 gives an explanation of various VF systems. Section 3 presents a detailed overview of different ML algorithms. Section 4 provides a brief discussion of architecture, and sensors in IoT systems. Section 5 gives the application of ML and IoT in the VF system. Section 6 makes the assessment and evaluation of a knowledge-based VF system. Sections 7 and 8 present the challenges and future scope of the VF system. Section 9 provides conclusion remarks to summarize the paper.

2. Types of vertical farming

The agricultural methods have many issues like the destruction of animal living in order to increase the agricultural space, soil erosion, and groundwater pollution. These issues of conventional agriculture have pushed the VF as a means of reducing reliance on conventional agriculture [41]. The geologist Gilbert Ellis Bailey initially proposed the word "Vertical Farming" in 1915, but he gave a

Table 1
The article's main differences from previously published articles.

S. No.	Paper	Key Difference
1	[36]	Ref. [36] gives a thorough review about the learnings of the application of ML as well as IoT for precision agriculture, covering the fundamental ML techniques, to identify pests, diseases, yield, weeds, and soil. But this study does not cover any aspect of VF. This research article provides a comprehensive review of the VF system along with the application of ML and IoT in VF.
2	[37]	Ref. [37] discusses the benefits and drawbacks of 5G for the agri-food industry. The author does not discuss the ML application in agriculture. This article provides the detailed application of ML in VF.
3	[38]	Ref. [38] gives a thorough explanation for improvements in IoT and AI techniques in the area of smart agriculture systems. There is no discussion about the VF system. This study discusses various types of VF systems and the use of ML and IoT in VF systems.
4	[39]	Ref. [39] explains important uses of AI in agriculture. The authors do not outline the basics of IoT and classification of ML algorithms. This paper provides a detailed description of IoT architecture and ML algorithms used in VF systems.
5	[40]	Ref. [40] analyses research conducted during the past 20 years in Agriculture 4.0. The author discusses the IoT and AI in agriculture but not in vertical farming. This paper discusses the ML and IoT applications in the VF system in a detailed manner.

completely different definition to VF, proposing farming widely into the soil by reaching extensively to the bottom of root growing [42].

VF makes the cultivation of crops possible indoors where variables like temperature, light, and minerals can be precisely supervised and applied. With this ground-breaking technique, less freshwater is needed, also soil and land are preserved. There are multiple types of VF techniques available, urban farmers can select a suitable VF technique according to their needs. Each VF technique has a distinct level of sophistication and price due to ongoing technological advancements [43]. VF techniques offer an applicable solution with the potential to be sustainable for the growth of agriculture in the future. The traditional horizontal expansion of farming fields over centuries caused significant environmental harm by intruding on forest lands, harming and disrupting other ecosystems [44].

VF is a multichannel indoor farming system that enables the precise control of essential farming components like light, water, temperature, CO2 consolidation, humidity, and nutrients to harvest a large amount of crop throughout the year. VF is not dependent on sunlight and other outdoor parameters. The use of sensing instruments, digital photography, and AI can make the VF totally automated [45,46].

Currently, across the world, VF has around thirteen distinct methods, and each one is technologically advanced to revolutionize the agriculture sector. In the coming section, a few of the VF techniques which are quickly developing, expanding, and refining are illustrated [47]. VF can be categorized into three different types, namely hydroponics, aeroponics and, aquaponics.

2.1. Hydroponics

William Gericke wrote a book "The Complete Guide to Soilless Gardening" in the 1930s, provided the foundation for hydroponic culture and this book became a landmark for VF. In 1960, Othmar Ruthner an Austrian engineer built more hydroponic systems in a controlled environment [48]. Hydroponics technique can be regarded as a crucial element of VF system. The popularity of the hydroponics technique has increased quite gradually. Using hydroponics, vegetation can be cultivated and harvested in a soilless medium [49].The vegetable plants are put into a medium like coconut coir and in net cups, this is done to supply water and nutrients to the plants with proper support. Water is a scarce quantity, which can be saved by farming with a hydroponics system because this system consumes very little water compared to traditional farming systems [50].

Due to the high quality of the harvested crop, effective resource management, and the ability to preserve proper TDS in water, hydroponics farming is becoming more popular nowadays. TDS of water can be monitored manually, semi-automatically, and in a totally automatic manner [51]. Hydroponics farming has several merits such as simple crop management, no weed growth, and less need for watering. In comparison to soil-based farming, soil-less hydroponics can guarantee a very low water consumption of up to 70–80 %. The top nations that are accepting hydroponics techniques are Netherlands, United Kingdom, United States, Israel, and Canada. Hydroponics can be utilized to harvest a large number of leafy as well as fruit plants. Some of these include strawberries, cucumbers, tomatoes, peppers, and green vegetables [52]. Fig. 5 shows the basic structure of the hydroponics technique of VF.

2.1.1. Types of hydroponics structures

Hydroponics systems can be of multiple types based on the structure used to make the complete hydroponics system. Some of them are being discussed here.

(a) **Wick System:** Vegetables are planted immediately inside vermiculite, coco coir, and rock wool which are absorbing materials. Before being dipped into the fertilizer solution, the plants are wrapped with nylon wicks [53]. This nylon wick engages in

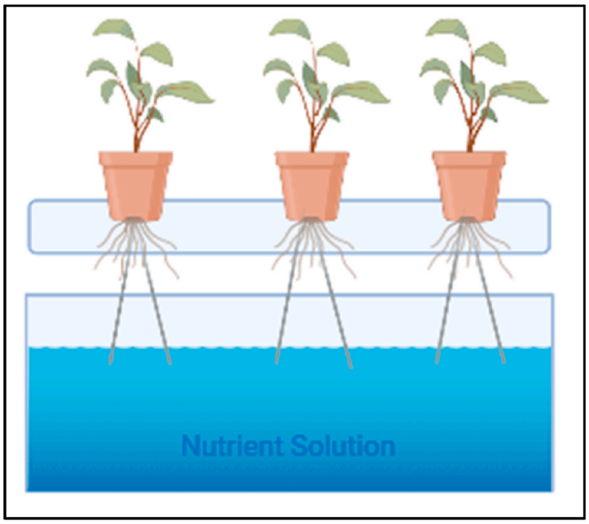

Fig. 5. Hydroponics farming.

capillary action to deliver the required volume of nutrient solution to the plant's roots. In the comparison to other hydroponics techniques, it is the most fundamental technique. Plants like spinach, herbs, etc. are highly suitable for this hydroponics system. However, it struggles to grow herbs that need a lot of nutrient supply. Fig. 6 shows the wick hydroponics system.

(b) **Deep Water Culture (DWC):** This technique is frequently used for large plants, particularly those that produce fruits or vegetables, such as tomatoes and cucumbers. The plant's roots are dipped directly inside the nutrient tank so that oxygen and nutrients are absorbed by the plant easily. An air stone has been fitted for the supply of oxygen directly to the system. However, due to its complexity, this system is not frequently used [54]. There is a possibility that algae will grow in the reservoir and to overcome this problem the essential parameters like oxygen ratio, pH, and nutrient amount should be maintained at a required value. Optimizing electricity usage, low water consumption, providing high oxygen levels for plants, accuracy, and time management in the automation process are also the main issues at DWC [55]. A common illustration of deep-water culture is the hydroponics bucket system. Fig. 7 shows the DWC hydroponics system.

(c) **Ebb and flow system (flood and drain):** This hydroponics technique is well known for its inexpensive initial cost, straight-forward design, and easy operation. Flood and drain concepts were initially deployed economically in this hydroponics system. In this system, plant pots are filled up by media, like rock wool that serves as a provisional nutritional solution tank as well as an anchor for roots. A nutrient solution from the tank is poured into a grow bed by a water pump until this solution reaches a specific level and stays at the grow bed for a particular time interval. Numerous crops can be grown with this hydroponics system, but there can also be some problems like algae, and root rot. In order to overcome these problems this system should be modified with filtration techniques [56]. Fig. 8, shows the Ebb and flow hydroponics technique.

(d) **NFT (Nutrient Film Technique):** This technique was created in the 1960s by Dr. Alen Cooper of England in the interest of addressing the drawbacks that occurred in the ebb and flow technique. The nutrient solution goes into the grow tray using a motor pump and this solution circulates throughout the entire system. The excess nutrients can drain back into the reservoir as the grow tray is designed in a slanted manner. This mechanism is designed with a minimally inclined way to cause the shrub roots to return the mineral-rich solution to the reservoir. However, because plants are frequently submerged in the nutrient tank, algae and fungal infection can create a significant problem. This technique is used for commercial production of mostly green leafy plants, primarily lettuce [57]. A description of the NFT hydroponics system is shown in Fig. 9.

(e) **Drip system:** Both business and residential growers frequently employ the drip hydroponics technique. In a hydroponics system with drip irrigation, drippers at the base of each plant's stem distribute nutrient solution on a set schedule. In continuous drip systems, the used nutrient solution can be turned back to a tank or it can be taken out of the system. These techniques can either be recovery- or non-recovery-based. The nutrient solution is utilized very efficiently in recovery systems, while nonrecovery systems need minimum operating cost due to pH symmetry and nutritional stability sustained in the new solution, which reduces the need for maintenance [58]. If plants are put in a medium that absorbs nutrients slowly then the nutrient solution is consumed moderately by the plants. Numerous crops can be grown in a proper way as there is a water conservation in this system. Fig. 10 shows the drip hydroponics system.

2.1.2. *Components of hydroponics*

(a) **Nutrient Solution:** Both soil and soilless farming systems have the fundamental principle to provide the all-necessary nutrients to the growing plant. For plants to grow and provide fruits various nutrients are required to be supply to the plants. Soilless plants are grown in nutrient, water, and oxygen-rich solutions [59]. Nutrients, oxygen, and vital mineral components are provided to the roots of plants to be grown in a hydroponics atmosphere. Plants need a total of seventeen components to thrive properly. Nine of these components are macronutrients like Potassium(K), Phosphorus (P), Magnesium (Mg), Calcium (Ca),

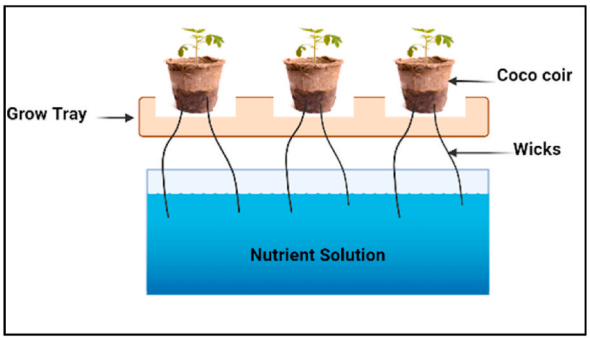

Fig. 6. Wick hydroponics system.

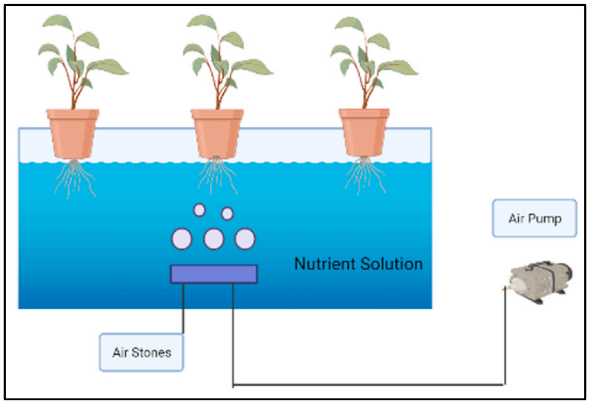

Fig. 7. DWC hydroponics system.

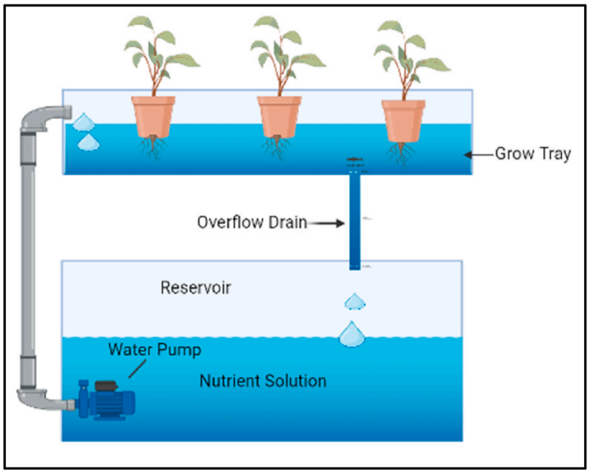

Fig. 8. Ebb and flow hydroponics system.

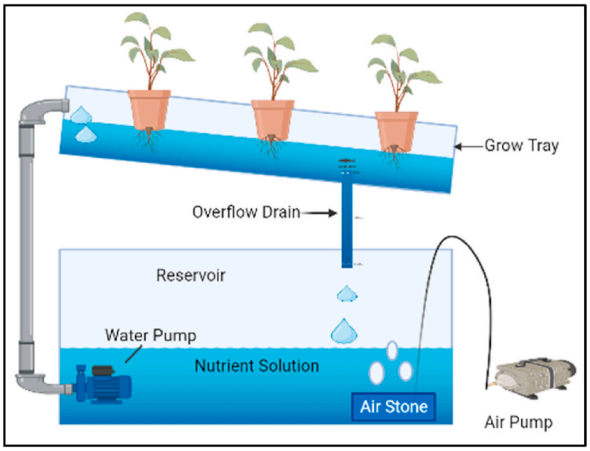

Fig. 9. NFT hydroponics system.

Hydrogen (H), Carbon (C), Oxygen (O2), Sulphur (S), and Nitrogen (N). The other eight components are called micronutrients like manganese (Mn), iron (Fe), chlorine (Cl), copper (Cu), boron (B), zinc (Zn), cobalt (Co), and molybdenum (Mo). Micronutrients are required in small quantity [60]. The majority of nutrient solutions are proposed on the basis of primary work done

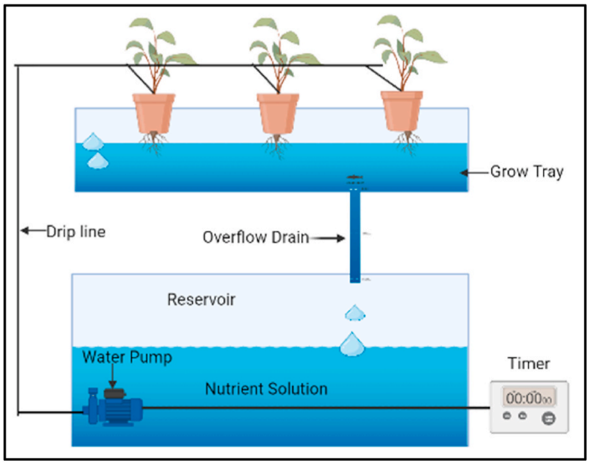

Fig. 10. Drip hydroponics system.

by Hoagland and Arnon (1938). The quality and productivity of leafy and fruit crops are greatly dependent on the utilization of nutrients. Consequently, application of nutrients in a balanced manner is essential for determining the product's quality.

(b) **EC and** pH **monitoring in Nutrient Solution:** The pH level decides the utilization of nutrients in the plants. In vertical eco-farming systems, nutrients are supplied according to the needs of the crop. Plants can absorb the nutrients in a particular pH range and this range can vary according to the type of crop. Daily pH changes are necessary for soilless systems because of their decreased buffering capability. Between 5.0 and 7.5 is the ideal pH range for the hydroponics system. If the pH of the fertilizer solution is higher than the range that is ideal for the plants then there is a greater likelihood of nutrient deficiencies, which can make the plants poisonous. EC also needs to be regularly monitored to verify the proper amount of nutrients in the nutrition tank. EC should be lowered till the plant produces a significant quantity of roots for developing plants from stems [61]. Hydroponics' optimal EC range is from 1.0 to 2.5, with most plants flourishing in the 1.5–2.0 range. While lettuce and celery prefer higher levels of fertilizer salts, some plants, like tomatoes, cucumber, eggplant, and eggplant, thrive at lower EC levels.

(c) **Water:** Reverse osmosis with very low TDS is used in hydroponics systems in order to add salt at various stages of the crops [62]. Recently, hydroponics has used wastewater treatment as a method of reducing environmental pollutants. Despite the fact that wastewater contains micro- and macronutrients, it has been noted that deficient knowledge of the proper supply of minerals can limit plant production because of less or higher amounts of nutrients can be given to plants [63].

(d) **Temperature:** The fluctuating temperature has an impact on the plant's physical features and chemical reactions. The primary environmental component that affects fruit quality, ripening, growth, maturing, and vegetative growth is the air temperature [64]. It has been considered that the growth of a plant is a result of the average 24-h temperature. If the difference between the air temperature of day and night is large, then it is believed that the plant grows taller and has smaller leaves. Vegetable organoleptic properties are directly impacted by low temperatures. A certain indicator of low temperature is tomato having reduced juice and a crumbly taste. High temperatures cause the fruits of the tomato, cucumber, and eggplant to alter in texture, colour, and shape [65]. Therefore, for a healthy plant growth in an indoor hydroponic system, the temperature must be kept within a certain range. This require an ideal temperature range between 19 °C – 28 °C. Fig. 11 depicts an air conditioning

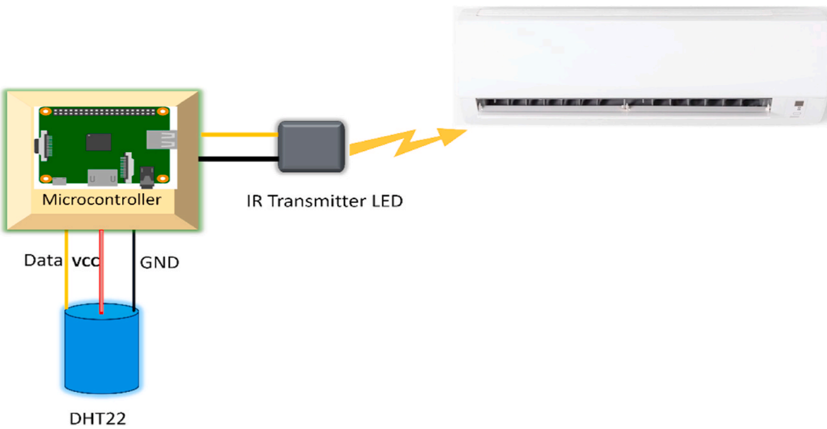

Fig. 11. Air conditioning subsystem.

subsystem that can be installed in an indoor hydroponic system to regulate the room temperature and humidity. The subsystem composes of three important components temperature sensor (DHT22), microcontroller and air conditioner. The temperature sensor monitors the room temperature and continuously sends the signal to microcontroller which regulates the temperature of the air conditioner through an infrared (IR) LED [66].

A commercial power meter, which can be digitalized to retain data for analysis, can be used to monitor the power consumption of air conditioning system. The cooling capacity of a 2-ton unit is around 7.034 kW and the air conditioner power consumption is determined by dividing the cooling capacity by its Energy Efficiency Ratio (EER). A normal two-ton air conditioner uses 2.6 kW, but a typical three-star air conditioner has an EER of 2.7. The air conditioning system is comprised of two distinct units: the evaporator, located indoor, and the compressor, located outdoors. The evaporator uses a very little amount of power in comparison to the compressor. The compressor unit only runs when the interior temperature rises above the set point and shuts off when the target temperature is reached. If we assume the compressor unit is operational 60 % of the total time, the energy consumption per hour of operation amounts to 1.56 kWh. However, the overall monthly consumption varies depending on daily usage patterns [67].

(e) **Light:** Crop growth is affected by light, which influences photosynthesis, photorespiration, and photoperiodism. Generally, vegetable crops grown in a greenhouse require light within the intensity of 50,000 to 70,000 lux. In the summer season, the greenhouse plants can avail the light intensity of 100,000 lux and in winter days 3200 lux light intensity is exposed to the crops. Photosynthesis is impacted by light, water, temperature, CO_2, and the availability of nutrients. Plants capture light energy to convert carbon dioxide (CO_2) into carbohydrates. This process, called photosynthesis, requires a significant amount of energy. The captured light energy gets stored within the carbohydrate molecule. Light intensity plays a crucial role in photosynthesis. If the light is too weak, the process slows down, limiting plant growth. On the other hand, excessively strong light can damage chloroplasts, the structure responsible for photosynthesis and therefore hinders the growth of the plant. In addition, light also influence the plant response during the day-night cycle (photoperiodism). Many responses, such as leaf shape, stem elongation, and flowering, are controlled by the relative temperatures of the day and night periods [68].

Another crucial factor in the process of photosynthesis is the wavelength of the light. Plants don't need the entire light spectrum to grow; they only absorb the specific light wavelengths necessary for their growth. This essential light falls within the range of 400–700 nm, known as photosynthetically active radiation (PAR), which is within the visible spectrum. Photosystem I (PSI) work best with light around 700 nm (nm), while Photosystem II (PSII) prefers light around 680 nm. So, light sources with more concentrated energy at these wavelengths will boost the rate of photosynthesis. Furthermore, flowering plants require a high intensity of red and blue light, but non-flowering plants just require a high intensity of red light [69].

Several artificial LED light such as 6K3R4 and K6 (Guangdong China) can be used in indoor hydroponics system to provide necessary light intensity to the plants. The light spectrum of 6K3R4 is characterized by a high intensity of red light, making it ideal for growing leafy vegetables. In contrast, K6 features high intensities of both blue and red lights, rendering it well-suited for growing flowering plants [70].

(f) **Relative Humidity:** Since relative humidity has an impact on a plant's quality, controlling it inside the greenhouse is crucial. The RH range for most of the crops is 60–75 %. A range of RH between 25 % and 80 % is necessary for normal plant growth [71].

2.1.3. *Advantages of hydroponics System*

Brazil, Mexico, and Latin America and many other nations have embraced hydroponics farming systems to meet their food needs. By using vertically stacked trays to create additional space, the production technique of hydroponics is upgraded and encourages large-scale growing without the need for soil. This increases the production of several crops with much greater yields. Benefits of this approach include improved control over the supply of nutrition, highly effective utilization of available areas as well as the potential to use less fertilizer. With a smaller environmental effect and less greenhouse gas emissions, hydroponics produces environment-friendly, sustainable, and cutting-edge crops [72]. Table 2 shows the advantages of hydroponics system.

Table 2
Advantages of Hydroponics system.

S. No.	Sector	Advantage of Hydroponics
1	Plant Growth	In comparison to soil cultivation, a crop's production ratio in hydroponics is 30–50 % fast. For instance, lettuce grown hydroponically grows at a rate 11 times faster than lettuce grown traditionally [73]
2	Use of land	10 % less land is needed for hydroponic cultivation [74].
3	Water utilization	Compared to traditional agricultural methods, the management of water resources is better, and just 10 % of the available water is consumed [75]. Hydroponics system consumes seven times less water as compare to greenhouse farming and four times less to the traditional farming [76].
4	Low impact on the environment	There is 0.23 kg of CO_2 equivalent gas emission from soil-based crops and 0.11 kg of CO_2 equivalent gas emission from hydroponics crops respectively [77].

2.2. Aeroponics system

Growing the plant in the absence of soil or a base component is known as aeroponics. In this system, the plant uses artificial support to grow in the air and doesn't need soil or substrate to maintain itself, as shown in Fig. 12. In essence, it is an air and water culture growth method where plant roots get suspended in the open air, are exposed to the atmosphere, and receive atomized nutrients and water. The crop's crown and uppermost leaf rise beyond the moist area. The synthetically made structure divides the crop's root from its shade. With the help of pressure nozzles or foggers, an aeroponics VF system can spray nutrients in the air to maintain hypergrowth under controlled circumstances. A major benefit of aeroponics is its superior aeration [78]. Additionally, studies have shown that using this high-density planting technique results in easier harvesting and larger yields.

2.3. Aquaponics system

This is a merger of aquaculture (farming with fish) with hydroponics (plant growth without soil). Between the fish and the plant, there is a closed-loop freshwater recycling system. Following the nitrification process, fish wastes are converted into nutrients for plants. Biofilter is used to clean the water before these return to the fish tank. Aquaponics systems can mitigate the problem of food scarcity but their operation can be difficult because aquaponics facilities must constantly be monitored to get the healthful development of fish and herbs. An aquaponics system is shown in Fig. 13 [79].

3. Machine learning

Machine learning is a subset of computer science engineering where computer systems learn without being programmed explicitly [80]. Alan Turing proposed the concept of machine learning concept in 1950 and wrote a research article "The Turing test for Machine Intelligence". By performing tests Alan Turing tested the ability of machine's intelligent behaviour identical to humans [81]. Machine learning finds the hidden pattern in historical data and based on this pattern a prediction model is framed, and output is predicted when new data is given to this model. Precision in the prediction of output depends on the size of data used to make the prediction model, a model trained with larger size data predicts the output more accurately. Fig. 14 outlines the workflow of machine learning algorithms.

In order to make a prediction for a complex problem, the ML algorithm processes the raw data and finds the pattern from this data, finally, a prediction model is made which can predict the outcome for new data given to the model. ML algorithms can be categorized into three different categories supervised, unsupervised, and reinforcement learning. Fig. 15 shows the categorization of ML algorithms. In supervised ML the machine gets trained by labelled data in which some input data is entitled with output. In supervised ML, there exist a supervisor which instructs the machine about the accurate prediction. This follows the concept of students learning under the supervision of a teacher. There is no supervisor in unsupervised learning and the model uses unstructured data to find the hidden patterns in the dataset by putting similar objects into separate groups. An unstructured dataset has input data but there is no output specified priorly. Pattern recognition from the training data is a more challenging task in unsupervised ML in comparison to supervised ML. This process of unsupervised ML can be understood by the process of how the human brain learns about new things. Reinforcement ML is based on the feedback concept. In reinforcement learning an agent performs the actions and deduces the outcomes from these actions, finally, the agent determines how to operate in an environment. This agent gets the award for each positive action and punishment or negative feedback for each negative action. Reinforcement learning was used by DeepMind's chess-playing game AlphaGo to defeat the finest chess-playing computer programme in the world [82].

One of the main advantages of ML is its capability to use datasets from several connected resources to automatically answer the most challenging non-linear problems. In real-world situations, ML enables decision-making and intelligent conduct with comparatively little human intervention. For generating data-driven decisions, ML offers a strong and adaptable framework that also

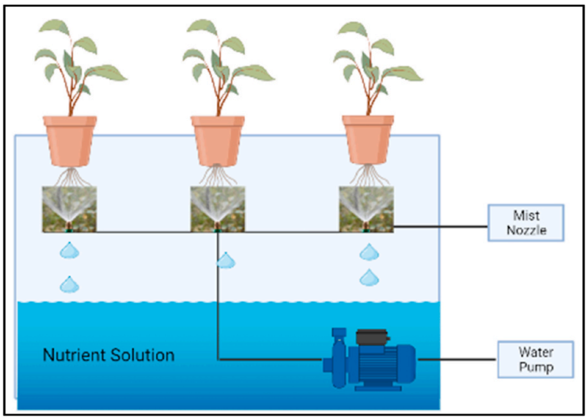

Fig. 12. Aeroponics system.

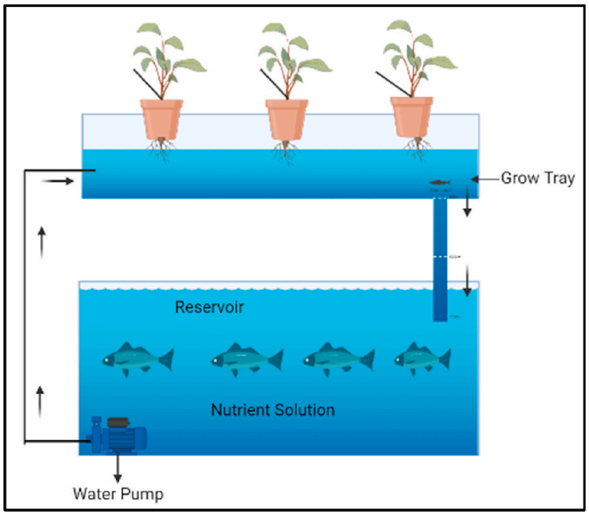

Fig. 13. Aquaponics system.

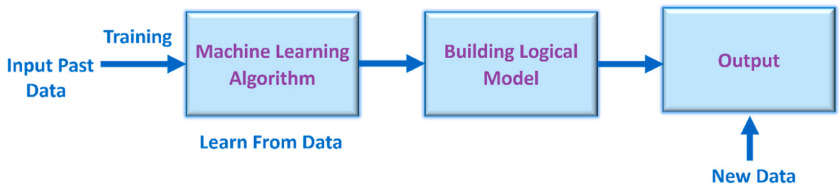

Fig. 14. Machine learning algorithm workflow.

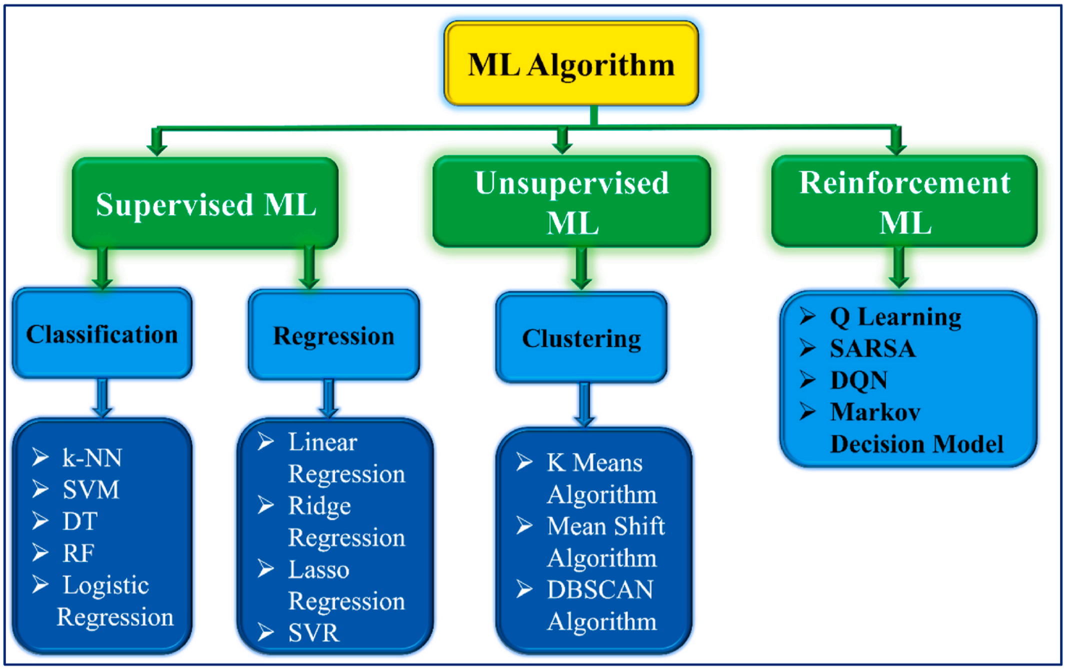

Fig. 15. Categorization of ML algorithms.

Table 3
Machine learning algorithms.

Name of ML Algorithm	Description	Advantage	Disadvantage
Linear Regression	This is a very simple and genuine algorithm. In this algorithm, the relationship among continuous variables is shown by the regression process.	Implementing and understanding the results of linear regression are both simple.	Underfitting problems can occur in this algorithm and outliers can also damage the performance.
Logistic Regression	Supervised ML is used in this type of binary classification method. Logistic regression provides the best prediction of the dependent variable.	The training in logistic regression is very effective and easy to execute and analyse.	Only discrete functions can be predicted with it.
Decision Tree	This ML algorithm follows the tree structure of classification. The data's characteristics are shown by internal nodes. Branch and leaf nodes show the decision-performing action and the result of classification respectively.	This process is very simple to learn because this resembles the logic used by humans in daily life to solve a problem.	With different layers present, the complexity is high in this algorithm.
RF	Ensemble learning is used in this type of ML algorithm. In ensemble learning, various classifiers are put together to find the solution of a problem with higher accuracy.	This ML algorithm processes the big datasets with lots of dimensions.	Classification as well as regression can be done by this algorithm but regression is not suitable for this ML algorithm.
DNN	An ANN having several hidden layers between the input and output layers is called a DNN.	High accuracy due to its ability to find complex patterns in data.	This algorithm requires large training data and computational power.
SVR	This algorithm is used for regression analysis. This predicts continuous target variables with minimum prediction error.	SVR is less vulnerable to the impact of data outliers.	This is not efficient for non -linear problems.
XGB	This is a type of ensemble method, which builds a single, more powerful prediction model by combining several weaker models (usually decision trees).	This algorithm excels at producing accurate results across various ML tasks.	Hyperparameter tunning and overfitting problems can exist in this algorithm.
CNN	Convolutional neural networks are DL models are used to process and analyses visual input, such as images and movies.	This is capable of extracting features automatically	High computational demands

incorporates professional skills.

ML models can be considered as black-boxes as they take data as input and understand the relationship between input and output to predicts either a numerical value or a categorial value based on the nature of problem. The dataset has various features, and each feature has different relevance towards predicting the target variable. Therefore, it is necessary to evaluate and interpret how these models make accurate predictions and which feature are more informative and plays a significant role in these predictions. There are different agnostic methods such as feature importance, partial dependence plots (PDP), SHAP (SHapley Additive exPlanations), feature interaction and surrogates which interprets all these models [83]. However, there are also certain model specific methods such as decision trees and Random Forest which have built-in methods to interpret the model performance and compute the feature importance. Other than these two models feature importance can be evaluated by analysing the model performance with the addition or deletion of each feature. PDP provides an alternative way to examines the individual or group of feature marginal effect by evaluating the model performance keeping all the other features constant. This method assumes that the features are correlated with each other and is useful in both regression and classification problems. SHAP is based on game theory and assigns a Shapley value to each feature by considering its contribution in all possible combinations with other features. Although, it is computationally expensive but presents a unique graphical representation to understand the contributions of different features by decomposing the prediction based on each feature. Surrogates is another approach where an alternative simple model is explored to get insight of the methodology of the complex model. However, for improving the accuracy of ML models influence of each feature on one another should be examined. There are different ways to examines the feature interaction which includes correlation matrix, association matrix, etc.

Once the important features have been extracted from the dataset thereafter the data is divided into training and testing set. The training data is used to train the model and the model identifies hidden relationship between independent and dependent variables. Once the model is trained thereafter testing data is used to examines the performance of the trained model. There are different approaches to divide the data into these two sets which include hold-out approach where a certain percentage of data either in 80-20, 70-30 or any other ratio can be split into training and testing sets. Cross-validation is another technique to split the data into training and testing where instead of a single split data is divided in multiple subsets or folds. The model is trained and tested multiple times with different subsets of data and lastly the results from different models are averaged. The uniqueness of this approach is that all the data samples are used to train the model once therefore this is a robust approach to evaluate the performance of model. Table 3 presents widely explored supervised, unsupervised, and reinforcement machine learning algorithms.

3.1. Performance metrics in ML

A crucial stage in creating a successful ML model is assessing the model's performance. Various metrics are utilized to assess the performance of the ML model, these metrics are referred to as evaluation metrics or performance metrics. A performance metric is a mathematical and logical construct that quantifies how closely the actual results match the expectations or predictions. Thus, by adjusting the hyper-parameters, we can enhance the model's performance. All ML models are designed to generalize well on new or unknown data, and performance metrics are used to assess the model's generalization ability on the new dataset.

In actual use, a single ML model's suitability is evaluated using one, more, or a mix of metrics. Nevertheless, it appears that there is no systematic understanding of which scenarios call for the application of particular metric. To overcome this knowledge gap, this section gathers the most widely used performance metrics and emphasizes how to utilize them to assess the performance of regression and classification ML models.

Performance metrics are used in ML regression experiments to assess how well the trained model predicts the actual (observed) data from the testing data set. The outcomes of these comparisons can have a direct impact on the choices made about the kinds of machine learning algorithms to be used. Various performance metrics, such as the correlation coefficient (R) and RMSE, have been documented in the open literature Table 4 lists the popular performance metrics for ML regression models that have been compiled from public literature [84].

Table 4
Commonly used performance metrics for ML regression models.

Metric	Formula	Performance measurement
Error(E)	E = A- P	Measures the difference between an observation and its true value.
MAE	$\text{MAE} = \frac{\sum_{i=1}^{n} \lvert E_i \rvert}{n}$	This metric measures the absolute difference between actual and predicted values
SSE	$\text{MSE} = \sum_{i=1}^{n} E_i^2$	This gives the sum of the squared differences between the predicted values and the actual values in the dataset.
MSE	$\text{MSE} = \frac{\sum_{i=1}^{n} E_i^2}{n}$	It calculates the average of the squared difference between the model's actual value and the values that were predicted.
RMSE	$RMSE = \sqrt{\frac{\sum_{i=1}^{n} E_i^2}{n}}$	This metric gives root square of average squared error.
Coefficient of Determination (R^2)	$\text{R2} = 1 - \sum_{i=1}^{n} (P_i - A_i)^2 / \sum_{i=1}^{n} (A_i - A_{mean})^2$	R^2 is a statistical measure used to evaluate how well a regression model fits the data. R^2, value near to 1.0 indicate strong correlation.
Adjusted R_a^2	$1 - [(n-1)/(n-k-1) \times (1-R^2)]$ Where n is number of observations, k is number of independent variables	This metric is used to solve the issues of R^2.

In classification tasks, the classification or grouping of data into specific categories is determined using training data. The ML model gains insights from the provided dataset and subsequently categorizes new data into predefined classes or groups based on its training. It produces predictions in the form of class labels, such as "Yes" or "No," "0″ or "1," "Spam" or "Not Spam," etc. Various metrics are employed to assess the performance of a classification model, Table 5 lists the popular performance metrics for ML classification models that have been compiled from public literature [85].

4. Internet of things

Kelvin Ashton first used the term Internet of Things in 1999 during his tenure as executive director of MIT's Auto-ID Labs. Kelvin Ashton introduced IoT for the first time in a presentation for Procter & Gamble [86]. IoT is a network of interconnected devices that can interact together and can transfer data over the internet without human interaction. A global research platform did a survey and found that there is a hike of 8 % in IoT-connected devices in 2021 and it is assumed that in 2025 the IoT equipment will be increased by 22 % which is around 27 billion units in number. An IoT includes firstly hardware device such as sensor collects the data from the surrounding environment. Data collected by sensors is given to the gateway which acts as a wireless access point for IoT connected equipment to interface to the internet or cloud. Through the gateway sensor's data is given to the cloud in order to be processed by the software or model. The software after analysing this data, sends it to the end user through an application or website. Fig. 16 shows the complete working of IoT.

A sensor is an electronic device that interacts with the environment and gathers some input from it then converts this input into data that can be understood by a machine. Numerous types of sensors are used in vertical farming depending on the particular application. Fig. 17 shows the various types of sensors used in the IoT system. Table 6 describes different sensors with their specifications and applications in vertical farming. A gateway is a network node that makes communication between two networks like sensors and cloud which operate with dissimilar transmission protocols. Whole data traveling between IoT devices and sensors will pass through IoT gateways. Some gateways may accumulate, correlate, synchronize, and preprocess the received data using various communication protocols before sending it to the cloud, this is called edge computing. Gateway also performs protocol transformation. Ethernet, Bluetooth, Wi-Fi, Zigbee with other wireless technologies can be utilized by gateways to communicate with sensors. Gateway can then gather information and send it to the cloud using protocols like MQTT, CoAP, AMQP, XMPP, REST, etc.

Table 7 provides a comparison of various gateway models, highlighting their specifications and suitable applications [87].

4.1. IoT architecture

The basic principle of IoT data processing and architecture is the same for all IoT systems. Fig. 18 depicts the five-layer architecture of the IoT system with the associated components [88].

The perception layer includes various sensors and actuators. A sensor is a hardware device that gathers physical inputs like temperature, light, and humidity and then converts this information into electrical signals in order to send these signals to the IoT system [89]. Sensors used in IoT networks are small and absorb less amount of power. Actuators can transform the data produced by intelligent things into instantaneous actions that are closely related to the sensors. These are often tiny devices with little power, and in the simplest circumstances, one low-size microcontroller using no operating system can provide the necessary computing power. Small operating systems created especially for these types of systems, include Contiki, TinyOS, and FreeRTOS, and are utilized when more

Table 5
Commonly used performance metrics for ML classification models.

Metric	Formula	Performance measurement
Accuracy	$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}$	This metric shows the overall percentage of accurate predictions.
Precision	$Precision = \frac{TP}{(TP+FP)}$	The percentage of positive predictions that were truly accurate is determined by precision.
Recall or TPR	$Recall = \frac{TP}{(TP+FN)}$	It indicates the extent to which model is able to capture all pertinent positives.
F1-Score	$F1 - Score = \frac{2TP}{(2TP+FP+FN)}$	This is used to assess a binary classification model based on predictions for the positive class. This is calculated as the harmonic mean of both precision and Recall
TNR	$\mathrm{TNR} = \frac{TN}{(TN+FP)} = 1 - FPR$	This explains the percentage of real negatives that are properly recognized.
FPR	$\mathrm{FPR} = \frac{FP}{(FP+TN)} = 1 - TNR$	This explains the percentage of negative cases that were mistakenly classified as positive cases.
ROC	ROC curve is plotted with TPR on the vertical axis and FPR on the horizontal axis	Indicates how sensitivity and specificity are related. Suitable for categorical data.
AUC	$\mathrm{AUC} = \frac{1}{2} w(h + h')$, where, w = width, and h and h' = heights of the sides of a trapezoid histogram	It finds the model's ability to discriminate between positive and negative cases.
Log *Loss Error*	$LLE = -\sum_{c=1}^{M} A_i\ log\ P_i$ where, M: number of classes, c: class label, y: binary indicator (0 or 1) if c is the correct classification for a given observation.	This metric is generally used for optimization during training. This has probability between 0 and 1 and works for categorical data.

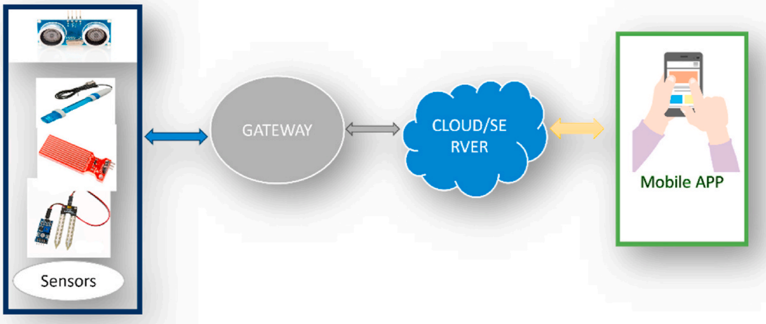

Fig. 16. Working of IoT.

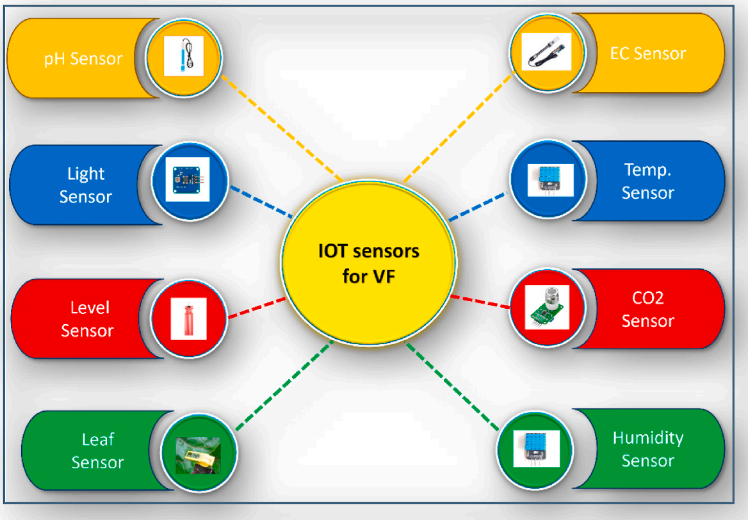

Fig. 17. IoT sensors.

complicated capabilities are required.

The network layer or connectivity layer consists of various connecting devices Wi- Fi, ZigBee, Bluetooth, cellular networks, gateways, etc. The task of this layer is data transfer among the equipment like sensors, and actuators as well as from the devices to the cloud server and vice versa [90]. The connection between devices and the cloud is made either directly using TCP/IP, UDP stack, or via a gateway. It guarantees the orderly and secure receipt of data between the networks.

The data processing layer or middleware layer gathers, stores, and processes data that is sent to it from the previous layer. This layer gets raw data from sensors without processing and uses cloud and big data modules in order to convert raw data into meaningful information.

All these tasks are executed by the IoT platform or cloud in two steps namely data gathering stage and the data extraction stage. In the data gathering stage, an API is used to capture data in real time such that this data is held in rest mode to satisfy the needs of non-real-time applications. This stage also determines data pertinent to the business requirements and at which location it should be put down, among other things. In the extraction stage, data processing is done to enable consumer applications to produce insights with this data. Similar to this, data received by the application layer is redesigned here so that devices can understand it at the physical level. This layer also makes the system responsible for taking decisions and actions according to the received data. This layer also gives predictions and insights using information collected in the perception stage.

The application layer consists of the mobile app, smartwatch, and home applications, etc. Software analysis is done in this layer to solve the business tasks based on the data captured by the sensors. If the output of any sensor crosses a certain threshold, then the business tasks are activated automatically. Some examples of tasks are given below [91].

Table 6
List of IoT Sensors with specification.

Name of Sensor	Type	Measuring Range	Temperature Range	Accuracy	Power Consumption	Supply Voltage	Application
pH *sensor*	Vernier pH Sensor	0–14 pH	5–80^0 C	±0.2 pH units	2 mW	5 V	Check and adjust the nutrition solution's pH value.
Leaf Sensor	LWS-200	0–70 % humidity	−20°Cto 60 °C	±0.5 °C.	5 mW	2.5–5 Volts	Measure leaf moisture
Water level sensor	Ultrasonic level sensor	0.4–9 m	−40 to 75^0 C	±%0.2 FS	2,4Watt max.	16 … 30 VDC	Regulate the water level in the water tank
EC sensor	EC 250	0–1000 μs/cm	0–50^0 C	1 % FS@ 25^0 C	40 t0 90 mA	10–14 V	Regulate electrical conductivity in nutrient solution
CO2 sensor	CO2 sensor	0–5%, 0–20 %, 0–100 %	0–50^0 C	±70 ppm/ ±5 % of reading	3.5 mW	3.3 V	Measure and regulate CO2 levels to promote photosynthesis
Temperature sensor	LM 35	−55 to 150^0 C	−55 to 150^0 C	0.5^0 C accuracy at 25^0 C	60 μA	4 to 30Vot	Regulate the temperature for optimal growth of the plant
Light sensors	BH1750	1–65535lx	−40 to 85^0 C	±20 %	0.12 mA	2.4V–3.6V	Establish the proper lighting levels and make the necessary adjustments to the artificial lighting.
Humidity Sensor	DHT 11	20 %–90 % RH	0 °C–50 °C	humidity + -5%RH; temp + - 2^0 C	0.3 mA in active mode,60 μA in standby mode	3.5V–5.5V	Regulate humidity levels in order to avoid excessive moisture or dryness.

Table 7
List of different IoT Gateways.

Gateway	CPU/PROCESSOR	Operating Frequency	Operating Temperature	Application
Raspberry Pi 4	64 bit quad-core ARM cortex A72 processor	1.5 GHZ	0–85^0 C	IoT Gateway
LEC 6041	Intel Atom x7-E3950 or x5-E3930	1.6 GHZ	−40 to 70^0 C	Industrial IoT Gateway
LEC -7230	Intel® J1900 Quad-core Processor	2 GHZ	0–55^0 C	Healthcare Sector
V3S	Intel® Atom™ x7-E3950	1.6 GHZ	−40 to 70^0 C	Vehicle Area Network
CPS 50-N01	NXP i. MX8M plus cortex R -A 53 Quad core processor	1.6 GHZ	−20 to 70^0 C	ML inference at the industrial and IoT

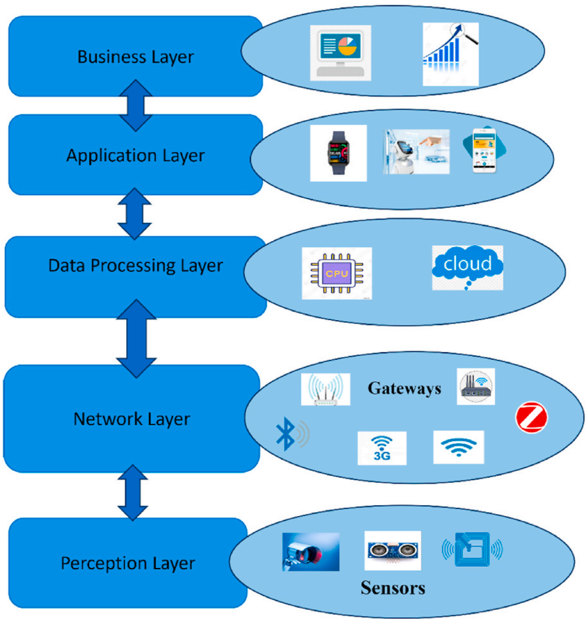

Fig. 18. Five layer architecture of IoT.

Table 8
List of different IoT Protocols at the perception/link layer.

Protocol Name	IEEE Standard	Latency	Data Rate	Frequency band	Range	Network/ Topology	Power use	Advantage	Application
Bluetooth	IEEE 802.15.1	6 ms	1 Mbps	2.4 GHz	10–100m	PAN/Star	Low	Low latency Robustness Scalability	Network for data exchange headset
Wi-Fi	IEEE 802.11	50 ms	1 Mbps −2.4 Gbps	2.4–5 GHz	100m	LAN/Star	Low-High	Scalability Data Security Fast data transfer Privacy Protection	Any device with cellular connectivity
Lora WAN	Lora WAN R1.0	234+-4 ms	0.3–50kbps	868/900 MHz	<30 km	WAN/Star	Very Low	Bidirectional Range is high High capacity	smart agriculture smart environment
Zigbee/(LR-WPAN)	IEEE 802.15.4	20–30 ms	250 Kbps	865–915 MHz 2.4 GHz	10–100m	LAN/Star, Mesh, Tree	Very Low	Long battery life Randomization	Senor networks Industrial automation
Cellular 2G/3G/ LTE	_	300–1000 ms, 100–500 ms, <100 ms	1 Gbps	700–2500 MHz	GSM (35 km) HSPA (200 km)	MAN /Mesh	HIGH	Battery life is good. Highly reliable	Use in wi-fi, ADSL, broad band, digital TV& Radio
Z Wave	_	1000 ms	40 Kbps	900 MHz	30m	LAN /Mesh	Very Low	simple installation reliable and secure communication	Residential lighting & automation
Ethernet	IEEE 802.3	120μs	25 Gbps	2000 MHz	100m	LAN/Star	Low	Speed resistant to noise secure and reliable efficiency	To connect wi-fi router to end point To connect devices like PC

- The user can turn on or off a particular device with the help of a GUI button.
- Activation or deactivation of the device based on the output from different sensor
- ML-based analytical approaches
- A graphical user interface chart showing sensor data with different time interval

The business layer provides a way by which users can see the working of the whole IoT architecture. Here based on the data business layer makes the decisions. This layer ensures the success of IoT device in terms of profitability, technology, and how it is delivered to the consumer. It produces many business models for successful business strategies [92].

IoT Protocols: These protocols enable data transmission within the IoT devices and cloud-based servers over the internet. Protocols send the commands to the IoT devices and receive data from these devices over the internet. As there are various IoT equipment accessible nowadays, many protocols have been developed. Table 8 gives the description of various IoT protocols used in the perception/link layer in IoT architecture [93–95].

Table 9 describes the various IoT protocols used at the application layer. Protocols of the IoT application layer are helpful to connect things and also used to interface user applications to the internet [96–98].

5. ML and IoT in vertical farming

VF techniques like hydroponics and aeroponics may be used to cultivate different vegetable plants, fruit plants, and herbs. Farmers using IoT may now automate VF cultivation. IoT can utilized to monitor and automate the control of pH, water level, temperature, and light intensity. For instance, during the winter, water has a tendency to freeze in some places, which might completely impede the process of cultivation. The hydroponics farm's water temperature sensors can detect temperature decline and notify the farmer appropriately. In the same manner, EC and pH sensors can detect deficiency of mineral levels so that with the help of a pump minerals are circulated in suitable amounts. So, IoT may be used to monitor and control several variables like pH, temperature, water level, and light intensity. Though IoT is capable of automating the VF system some intelligence is also needed in order to control the system. At this point, ML which is a subset of AI comes into the picture. ML enables the computers to do actions on their own after getting trained for a particular work. ML in VF has enabled the farmer to automate plant growth and supervise and regulate the pH and EC values in the nutrient tank [99]. So, by using ML with IoT the cultivation of crops will be more productive and of higher quality. Fig. 18 shows the block diagram of ML and IoT-based VF systems consisting of three sections input, ML system, and output. The input section has various IoT sensors to collect various input data. The received data from IoT sensors and manually entered is pre-processed in the output section then this data is split into training and testing. Now suitable ML algorithm is applied to the data, and finally output section gives the predicted result. This result is used for further improvement in the system [100].

It is important to mention that IoT and Machine learning algorithms are applied in a similar manner in both vertical as well as traditional farming in terms of data collection, disease identification, yield prediction and automation. IoT sensors collect data which monitors different environment parameters and machine learning algorithms analyse that data which helps in making intelligent decisions for optimized crop production and management. The only difference for execution of these two technologies is in terms of scalability and precision as traditional farming works on wide agriculture lands and requires large number of IoT sensors and complex machine learning models while vertical farming system is mostly implemented on a smaller scale in indoor environment and therefore requires a smaller number of IoT sensors with precise and simple machine learning models. Fig. 19 shows the working of a fully automated VF system using ML algorithms and IoT technologies.

Fig. 20 depicts an intelligent hydroponics system with IoT where an ML algorithm has been deployed at the edge for making the prediction with suitable action depending on the input gathered by sensors connected in the hydroponics system. Hydroponics system

Table 9
List of different IoT Protocols at the application layer.

Protocol Name	Transport Protocol	Architecture	*Security& QOS*	*REST full* support	Standard	Advantage	Application
HTTP Restful	TCP	Response/Request	Both	YES	IETF	Maintaining of application is easy	Integration with Web services
CoAP	UDP	Response/Request	Both	YES	IETF	Multicast support Low overhead Low latency	In M2M application
MQTT	TCP	Publish/Subscribe Request/Response	Both	NO	OASIS	Lightweight Low cost Low B.W. Remote connection is easy Implementation is easy	Messaging to IOT application
AMQP	TCP	Publish/Subscribe	Both	NO	OASIS	High routing reliability Security	In banking, IoT devices
Web Socket	TCP	Publish/Subscribe	Security	NO	IETF	Simply the web communication and co- network compatibility	Real-time application
DDS	TCP/UDP	Publish/Subscribe	QOS	NO	OMG	Real-time monitoring of quality of service	Distributed application

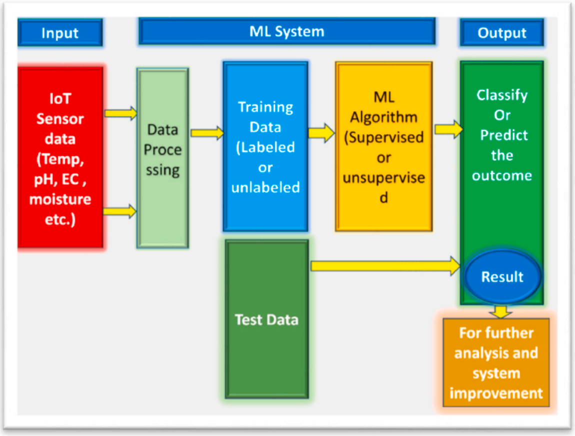

Fig. 19. ML and IoT enabled VF system.

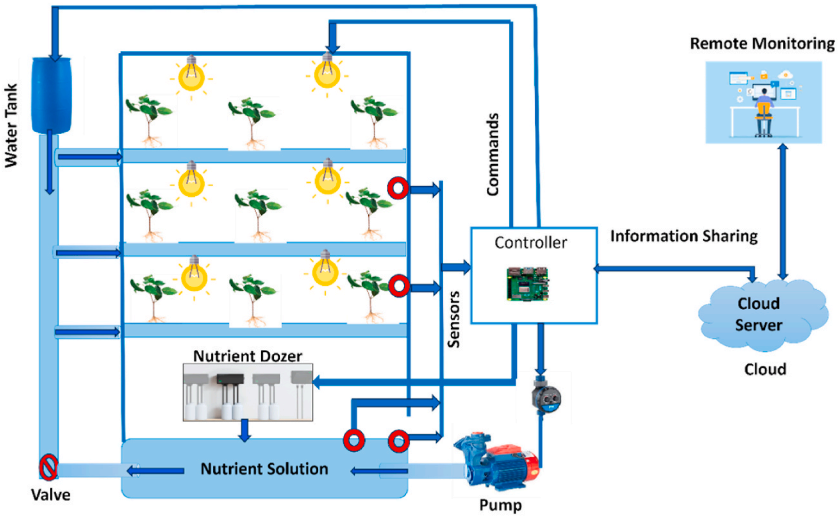

Fig. 20. Architecture of ML and IoT-enabled hydroponics VF system.

requires the monitoring and controlling of humidity, light, pH, EC, and temperature in order to produce a good quality crop. In Fig. 20 system has a water tank, water pump, pipes, artificial lights, and nutrient tank with pH, EC, temperature, and water level sensors. EC, pH, and water level controlling make the management of nutrients in solution easy [101]. Sensors forward the collected data to the Raspberry Pi microcontroller which is connected to the Raspberry Pi board. Raspberry Pi has been fitted with a ML model which is trained in the cloud by the data gathered from all sensors and equipment of the system. This trained ML model makes intelligent predictions which is the final output of the system. The final output result is given to Raspberry Pi in order to activate the concerned actuator like the water pump, switch of the light or fan, etc. Application of ML and IoT can be categorized into various activities that can be handled using ML and IoT. Fig. 21 shows the various applications of ML and IoT in VF systems. In further sections, the detailed description of ML and IoT in VF systems along with the research work done by various researchers are discussed.

5.1. Disease detection

To increase a farmer's profit from the crop's production and growth, it is important to identify plant disease. Disease-causing fungus, microbes, and pathogens derive food power for their survival from the crop where they live, this has an impact on agricultural crop yield. Farmers may suffer significant financial loss if this problem is not discovered in time. Pesticides, which are used to get rid of plant leaf illnesses and get crops working again, come with a heavy cost burden for farmers. In addition to harming the environment, overuse of pesticides also affects the agricultural land's water and soil cycles. Plant disease manual monitoring will not provide accurate results. Farmers are also unable to afford the monitoring and diagnosis done by the disease expert all the time of crop season. For autonomous plant disease detection and diagnosis with minimal human labour, numerous artificial intelligence systems are now suggested [102]. Utilizing an AI system such as ML and DL with the best possible design during the growing season of crops

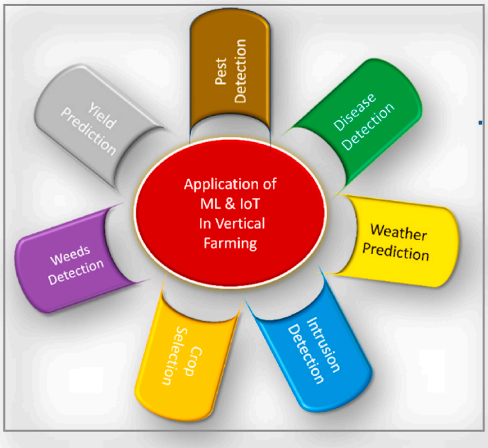

Fig. 21. Application of ML and IoT in VF system.

lowers the danger of plant infestation as well as its effect on financial sources. ML also reduces the destructive impact of unplanned farming on the atmosphere. So, ML-based techniques are playing an important role nowadays in detecting the disease present in a crop based on leaf image. The complete steps of the process for the detection of diseases in a plant leaf occurring in hydroponics, aeroponics, and aquaponics VF system has been shown in Fig. 22. The leaf image is taken by a camera device that is fitted into an IoT system in a real-time scenario which is used to train ML algorithm. This trained model is fitted to Raspberry Pi for the purpose of classifying the diseases occurring in the plant leaves. In the last step, this information on leaf disease detection is given to the farmer's mobile app connected to an IoT environment. Farmers may keep an eye on sensor data and the state of plant leaf disease and can take appropriate action like spraying pesticides, supplying nutrients, etc. Using a smartphone app, the farmer may do this to continually monitor the state of the land.

In [103] author explored the random forest technique for the segmentation of images and the classification of illness in apple fruit by using the SVM algorithm which gives total accuracy of 94.1 %. In Ref. [104] author proposed a CNN model having less power by utilizing the knowledge distillation technique to detect plant diseases in a smart hydroponics system. This model makes use of the shallow neural networks by knowledge distillation in which teacher-student model is practiced. Here teacher model is used for high computational resources for training purposes and student model used for learning from teacher model with less computational resources. The proposed model reduces the number of parameters and minimized the computation. Low power deep learning model achieved an accuracy of 99.4 % and consumed a low power of 6 W. In Ref. [105] the author developed an AI-based smart hydroponics expert system based on the integration of Raspberry Pi, IoT system and mobile application. The system has two models namely Classification – DLCNN as well as Prediction -DLCNN, fitted to IoT servers at cloud. The DLCNN model is used for prediction of an appropriate nutrient value that depends on standard data while the DLCNN model detects the different plant infestations in the

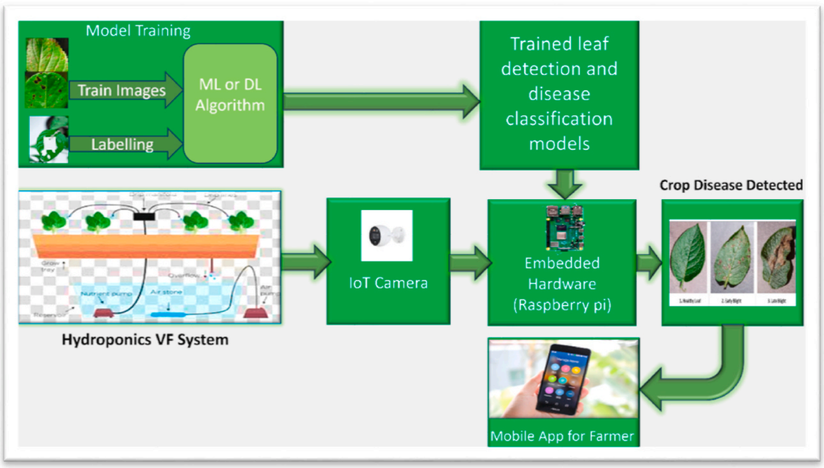

Fig. 22. Block diagram of plant disease detection in hydroponics VF system.

hydroponics system. Once the classification model finds the type of the disease then predicted model finds a new mineral value that depends on the data. In last step, this detailed input is shared with the framer by mobile application such that he can take a suitable course of action. Both models attained an accuracy of 99.82 and 99.297 % respectively. A robotic-based hydroponics system was proposed by the author in Ref. [106]where an intelligent robot was designed for making navigation towards every plant in any greenhouse hydroponics system. A robotic arm equipped with a camera has been utilized for the purpose of capturing lettuce images. This system is capable of detecting diseases in the lettuce and can monitor the plant growth. In this system, a light weight, low latency, and low power neural network architecture MobileNet V2 has been utilized to train and test the ML model. An accuracy of 98.19 % has been achieved for disease detection by this system. In Ref. [107] author proposed a SVM based lettuce disease identification model for hydroponics system, two types of lettuce disease namely leaf roll and brown blotch disease were identified. In this approach, the shape, colour and texture features of lettuce were extracted in order to train the SVM model. A total of 2400 images were captured by CMOS camera, and this model achieved an accuracy of 93.45 % in disease identification. In Ref. [108] author proposed an automatic leaf sorting system based on deep learning for the hydroponics systems. The hydroponics system of lettuce crop contains some abnormal leaves that should sorted out before final packaging. Abnormal leaves of lettuce in the system were divided into yellow, withered, and decay, decay leave is more harmful due to the presence of bacteria on it. Healthy and abnormal leaves are sorted out on the basis of colour and texture. In this system, DeepLabV3+ model was used with some pillar techniques namely ResNet-101, ResNet-50, Xception-65, and Xception-71. The ResNet-101 presents the finest pixel accuracy of 99.24 % in segmentation while ResNet-50 has fast speed of segmentation. In Ref. [109] author proposed a lightweight object detector U^3 YOLOWs model to detect subhealth regions in the rape plant at a bolting stage in the hydroponics system. Due to the irregularity in the nutrient solution of the hydroponics system there could be white spots and yellow leaves on the rape plant which are referred to as the abnormalities in the rape plant. U^3 YOLOWs model achieved average precision of 99.09 % in mark classification, 98.67 % in the category of yellow, and 94.38 % in mAP. In Ref. [110] researcher demonstrated the benefits of backward propagation neural networks and image purification to find the mildew disease present at the root part of mulberry plant cutting grown in aeroponics propagation procedure. This system achieved an accuracy of 80 % in identifying the mildew disease that occurred on the root part of mulberry cuttings. In Ref. [111] author proposed a technique based on computational intelligence and computer vision to identify good shape and greensick lettuce leaves in revolving hydroponic systems. SVM proved to be the best model which achieves an accuracy of 100 % with the quickest forecast processing time. In Ref. [112] author used faster R–CNN along with the Inception V2 algorithm to find the illness with in the hydroponically grown vegetables with DL model for objection detection. In the view of creating the object detection model, the author gathered photos of hydroponically grown lettuce (Lactuca sativa) plants that have the disease. A total of 873 images were searched and taken from internet sources. Faster R–CNN achieved an accuracy of 70 % and YOLO achieved 75 % accuracy. In Ref. [113] author proposed an agriculture detection farmwork based on INC-VGGN as well as deep learning network depending on kohonen. This framework was used to find severity level of diseased plant and to classify the diseases in the plant. The model gave the accuracy of 96.88 % using the

Table 10
Different ML algorithms for the detection of diseases in VF system.

Reference	Attribute	Source of Dataset	Crop Name	Name of VF Technique	ML Algorithm	Accuracy Measure
[103]	Leaf detection, Disease identification	Publicly available dataset at Kaggle	Apple	Hydroponics	SVM Classifier	Accuracy 94.11 %
[104]	Plant disease detection	Publicly available dataset at Plant village (54306 instances)	Tomato, Potato, Pepper	Hydroponics	Knowledge distribution based on DCNN	99.4 %
[105]	Plant disease detection	Agricultural Collaborative Research Outcomes System (AgCROS), Plant village dataset	Tomato, Apple, Grape	Hydroponics	DLCNN	99.82 (Prediction model) 99.297 (Classification model
[106]	Disease detection	Self-generated 2150 images dataset	Lettuce	Hydroponics	MobileNet V2, Neural Network Architecture	98.19 %
[107]	Disease detection	Self-generated 2400 images taken by CMOS camera	Lettuce	Hydroponics	SVM	93.45 %
[108]	Abnormal Leaves segmentation	Publicly available dataset at PASCAL VOC 2012	Lettuce	Hydroponics	DeepLabV3+ model	99.24 %
[109]	Detect subhealth region	Publicly available dataset at PASCAL VOC 2007	Rape	Hydroponics	U^3 YOLOWs model	94.38 % in mAP
[110]	Disease detection	Self-generated 16 images dataset	Mulberry	Aeroponics	Backward propagation Neural Network	80 %
[111]	Disease detection	Self-generated 533 images dataset	Lettuce	Hydroponics	SVM. LDA, KNN, NB	SVM = 100 %, NB = 92 % KNN = 100 %, LDA = 85 %
[112]	Disease detection	Publicly available dataset (873 instances)	Lettuce	Hydroponics	Faster RCNN, YOLO	R–CNN = 70 %, YOLO = 75 %

dataset of plant village and plant document. In Ref. [114], researchers developed deep learning CNN models for finding the disease in plants. Author trained his model with 87,848 images of training data available on open-source website. This research showed that among various DLCNN models, the VGG-CNN performed well by achieving a high accuracy of 99.53 %. Thus, the author proved that CNN models are most efficient in plant disease classification and detection. In Ref. [115] author developed a less complex deep CNN model for the purpose of leaf disease detection in apple fruit by lower computing procedure. The author developed a CNN model with 3 convolutional layers named as Conv3-DCNN model. Dataset has been taken from plant village website for the training of model to identify three diseases in apple leaf which are Scab, Black rot and Cedar rust. The proposed model presents 98 % accuracy and outperforms other deep learning and ML models to detect leaf disease. In Ref. [116] author developed PCA DeepNet model for detecting the tomato leaf diseases. PCA DeepNet is the mixture of PCA ML algorithm and DNN. The author used F-RCNN model for detection purpose and PCA DeepNet for training purposes. With 10 CNN layers this model gave the accuracy of 99.60 %. In Ref. [117] author detects the presence or absence of blight disease in tomatoes and potatoes. The author used ResNet-9 model with the plant village dataset for training purposes. This model achieved the accuracy of 99.25 % and 99.67 % overall precision. In Ref. [118] author builds S-Agric-IoT which is a combination of IoT as well as DL for the smart agriculture fields. In this system, IoT made the agriculture system fully automatic and DL performed the disease detection in the plants. The author took the 20,600 images of tomato plants by accessing the plant village dataset in order to train and test CNN models. This was evident from the result that S-Agric-IoT achieved an accuracy of 95 % in disease detection, also this model was energy efficient. Table 10 compares several ML algorithms for the detection of disease in plant in vertical farming system.

5.2. *Yield prediction*

Predicting crop yields is a crucial part of any type of farming industry. Also, in the production of food, crop yield prediction is extremely important. In order to increase national food security, policymakers must make timely choices on import and export based on the prediction. It entails calculating the expected yield of crops in a certain location using a range of variables, such as the type of pesticide used, the weather as well as crop management techniques. ML has become a robust technique for predicting crop yields. ML model needs a large dataset of crop yield in order to make yield predictions. This dataset may include the type of crop, weather conditions, location, fertilizers or nutrients information, amount of pesticide, crop management techniques and date of planting. Now ML algorithm is trained with this data to learn the corelation between input and output. Trained ML model is useful to make the prediction about crop yield in new location by inputting the required data such as weather condition and nutrient data. Fig. 23 shows the working of ML model for crop yield production. First crop data is collected from various sources then this data is put in a central data storage where ML algorithms are applied for feature extraction and to train the model. In the last step yield is predicted according to new dataset for a particular crop [119].

In [120] author explored four ML approaches SVR, XGB, DNN, and RF to predict the lettuce crop yield, grown of a hydroponics system. Cultivation of lettuce crop was done within the three types of hydroponics system and samples were taken after 50 days of transplanting for each system in a span of two years. Crop yield was predicted on the basis of crop parameters such as number of leaves, utilization of water, and dry weight. Among all ML algorithms, XGB performed well with the highest R^2 of 0.94 and the lowest RMSE of 8.88. In Ref. [121] authors developed an automated system of aquaponics in which the growth rate and weight of lettuce are monitored with DL techniques. ML model is trained with the parameters of size of crop and crop fresh weight. The system calculated the crop amount and natural weight with an error of 0.5 g (8.3 %) and 30 mm (18.7 %) respectively. In Ref. [122] author proposed two models for tomato yield prediction in aquaponics systems. These two models are ANN and ANFIS with a feed-forward back propagation network. With this model, tomato fruit production in the aquaponics system can be predicted by a simple and cost-effective manner

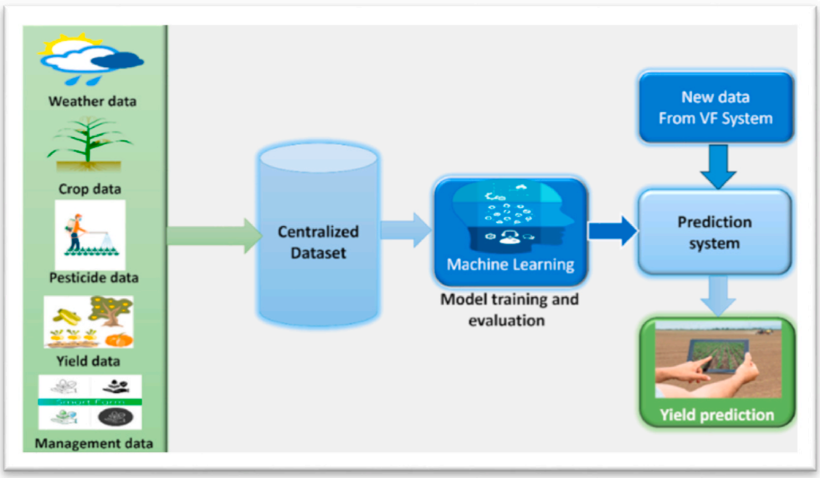

Fig. 23. Block diagram of yield prediction using machine learning algorithm.

and farmers can make a proper balance between demand, market supply and, economy management. In this system, the author used a dataset for model training from a tomato fruit growth mathematical model for aquaponics. This dataset has information on recirculating water temperature, dissolved oxygen, nitrate, and pH as input data and tomato biomass as output data. The result showed that the ANFIS model is highly accurate with an RMSE of 0.4582, R^2 of 0.9918, and MAE of 0.1079. In Ref. [123] authors developed a CNN model of two stages to predict the dry weight, fresh weight, area of leaf, height, and diameter of lettuce grown within the hydroponics system. This dual-step CNN model depends on ResNet50V2 layers. CNN model with RGB -D images can give accurate, faster, and non-destructive results of the growth parameters. This model is efficient by achieving R^2 of 0.88–0.95 and RMSE of 6.09 % on an unknown lettuce image. In Ref. [124] researcher proposed a MASK R–CNN dependent model for the monitoring of lettuce growth rate. The growth rate was monitored based on the identification of the leaf area of lettuce and verification of area estimation. The image of lettuce was taken at the interval of each 30 min 6 a.m. to 6 p.m. in the complete cycle of lettuce growth. The model's mean accuracy for estimating leaf area was 97.63 %. In Ref. [125] authors illustrated that yield in hydroponic system is more in comparison to traditional agriculture systems. With the utilization of a full greenhouse, crops may be cultivated that are lush green, mature more quickly, and are less vulnerable to pests and illnesses. This hydroponics system used organic coconut coir medium for germination as this is bio-degradable. Also, this proved that the NFT technique of hydroponics along with organic coconut coir medium is highly accurate. NFT technique with KNN ml algorithm gave the 93 % accuracy. In Ref. [35] authors presented a yield prediction model for various crops in a controlled environment aeroponics system. Three supervised ML algorithm like DNN, SVM and RF are used in this work. The author did ensemble of two ML models DNN and RF as these models did not show good results individually in the validation test. Ensembled models, DNN and RF achieved a good coefficient of determination value R^2 of 0.81. In Ref. [126] authors explored several machine and deep learning techniques like SVM, K means, RF, Decision Tree, Naïve Bayes, LST and RNN for predicting the crop yield. Yield was predicted for four crops rice, ragi, gram, potato, and onion based on features such as temperature, humidity, pH, and rainfall. The dataset for training purposes of ML algorithms was collected from Andhra Pradesh and Kaggle repository. Among all ML algorithms, Random Forest achieved 99.27 % accuracy in crop prediction. In Ref. [127] author explored two ML algorithms namely Multi-Variant Regression Network and ResNet-50 CNN network in order to predict the growth rate and biomass production for a plant in an aeroponics system. The estimation of the growth rate of a plant needs numerous data per plant and there is also a strong relation between the growth rate of biomass and the leaf area of a plant. The dataset for ML networks was taken by the camera module and from ImageNet. Multi-Variant regression network achieved biomass estimation with RMSE of 0.0466 g and ResNet-50 achieved growth rate with RMSE of 0.1767 g. In Ref. [128] authors discussed numerous regression models for the prediction of crop yield. Linear regression predicts the correlation between a continuous dependent variable and different independent variables. The author used datasets of kharif as well as rabi crops for the past 18 years from the Indian agriculture website with various parameters. The result showed that among all regression models LSTM has the highest accuracy of 86.3 %. In Ref. [129] authors explored DNN for predicting the yield, yield differences, and check yield that depends on the environment as well as genotype data. DNN successfully learned the relationship between genes and environmental conditions which are nonlinear and complex. DNN predicts the yield with high accuracy and RMSE of 12 %. In Ref. [130] authors explored four ML algorithms for prediction of yield about four crops namely Potato, Wheat, Rice, and

Table 11
Different ML algorithms for yield prediction and growth monitoring of plants in the VF system.

Reference	Attribute	Source of Dataset	Crop Name	Name of VF Technique	ML Algorithm	Accuracy Measure
[120]	Yield Prediction	Self-generated dataset	Lettuce	Hydroponics	SVR, XGB, DNN, and RF	R^2 of 0.94, RMSE of 8.88 for XGB
[121]	Yield Prediction	Self-generated 2250 images by webcam	Gem Romaine Lettuce	Aquaponics	MASK RCNN	Error of 0.5 g (8.3 %) and 30 mm (18.7 %)
[122]	Yield Prediction	Self-generated dataset	Tomato	Aquaponics	ANN and ANIFS	RMSE of 0.4582, R^2 of 0.9918, and MAE of 0.1079. For ANFIS model
[123]	Growth Prediction	Publicly available dataset at https://data.4tu.nl/articles/_/15023088	Lettuce	Hydroponics	CNN with ResNet50V2	R^2 of 0.88–0.95 and RMSE of 6.09 %
[124]	Growth Prediction	Self-generated 128 images by webcam	Lettuce	Hydroponics	MASK RCNN	97.63 %
[125]	Yield Prediction	Self-generated dataset at University of Agriculture Science GKVK, Bangalore	Spinach	Hydroponics	KNN	93 %
[35]	Yield Prediction	Self-generated, 200 sample dataset	Garlic, Basil, Chives, Red card etc.	Aeroponics	DNN, RF, SVM	R^2 of 0.81
[126]	Yield Prediction	Andhra Pradesh, Kaggle Repository	Rice, ragi, gram, potato and onion	Hydroponics	Random Forest, SVM, K means, Decision Tree, Naïve Bayes, LSTM and RNN	Random Forest Accuracy 99.27 %
[127]	Growth rate and Yield Prediction	ImageNet and Self-generated image dataset	Leafy crop	Aeroponics	MVR, ResNet-50	RMSE for MVR 0.0466 g RMSE for ResNet-50 0.1767 g

Maize. Four ML algorithms SVM, Decision Tree Regressor, and Gradient Boosting Regressor were used with training datasets taken from FAO and World Data Bank. Among these four ML models, Decision Tree Regressor obtained the highest R^2 of 96 % and accuracy of 96 %. The potato crop had the best prediction score among the four crops. In Ref. [131] authors explored one ML model RF and three DL models such as DNN, 1D-CNN, and LSTM for predicting the winter wheat crop yield of China region. The dataset for training the models was taken from the publicly available platform of Google Earth Engine with the features of climate information, soil properties, and spatial information. All four models predict the yield at the country level with R^2 of ≥ 0.85 and RMSE ≤ 768 kg/ha but on ground level, only DNN and RF models performed well with R^2 of 0.71,0.66, and RMSE of 1127 kg/ha and 956 kg/ha respectively. Table 11 compares several ML algorithms for the prediction of yield and growth monitoring for a plant in vertical farming system.

5.3. Nutrition and irrigation control automation

The use of control systems in VF has grown in popularity as a result of the fusion of AI with the sensors and gadgets made possible by IoT. One aspect that both agriculture and AI have in common is the use of recommendation systems to boost production by spotting nutritional shortages in plants, spending resources wisely, minimizing environmental harm, and avoiding financial losses. Fig. 24, shows the complete process of automation in VF using IoT and ML. Once sensors connected to the VF system observe any deficiency of nutrients, water, light, etc. immediately this information goes to cloud through microcontroller. At cloud ML algorithm works and predicts the course of action. Now actuators like water pumps, artificial light, and nutrient pumps are activated. The user is also getting this information and can initiate any suitable action.

In [132] authors explored four CNN models such as DenseNet 201, ResNet101V2, MobileNet, and VGG16 in order to detect N, P, and K nutrient deficiency in hydroponics systems. The author created his own dataset for the ML model by camera and a total of 1757 images were taken, by data augmentation and preprocessing the total images were converted to 10000. Among all CNN models, VGG16 achieved the highest accuracy of 93.82 %. In Ref. [133] researchers developed a sensor-fusion based smart and energy-efficient hydroponics system that can monitor and regulate the environmental conditions to produce a good crop yield. The system was made intelligent by using an RF ML algorithm to regulate ambient temperature on a priority basis. The system also monitors and regulates the concentration of nutrients in the water solution. With this hydroponics saved 20.4 % of peak power by regulating the water level as well as temperature automatically. Light supervision by this system also saved 82.1 % of peak power. In Ref. [134] authors proposed an intelligent hydroponics system with the application of ML DNN algorithm. The hydroponics system environment was controlled by various parameters like pH, lighting, humidity level, temperature, and water level. A real dataset of 5000 related to five parameters was taken in order to train DNN. The Model was trained over 10,000 epochs in the cloud so that it could take suitable action. The system achieved 88.50 % accuracy in the prediction of output action. In Ref. [135] authors demonstrated the automation of hydroponics system in lettuce production using IoT and ML algorithms. The system uses some sensors and a k-NN algorithm for making the prediction of the value of TDS, pH, and nutrient temperature in the NFT technique of hydroponics. Based on the prediction of the result the controller system activated the actuators. With this model, it was possible to turn on and off the actuators simultaneously according to classified labels. Results showed that the K-NN ML algorithm achieved 93.3 % accuracy with a k value of 5. In Ref. [136] the researcher developed an IoT and ML-based hydroponics system in which environmental parameters are controlled automatically. The authors used the DNN algorithm to predict the suitable control action in the system. In starting 4000 control datasets were collected in IoT-based operating NFT hydroponics system, this dataset is used to train DNN model. The trained DNN model achieved 81 % accuracy in prediction of control action for the system. In Ref. [137] authors prepared a small dataset which is used to predict the appropriate concentration of nutrients in aquaponics for the optimal rise of fish and plants within the closed setup. A small sample dataset of 201 was recorded at Texas University, which is boosted synthetically by Monte- Carlo (MC) technique. Three ML classifiers such as linear SVM, Adaboost, and Gradient Boosting were employed to make predictions of the nutrients. Linear SVM achieved 75 % accuracy in prediction of appropriate nutrients. In Ref. [138] authors proposed a methodology to control the aquaponics system automatically through the cloud using Auto ML machine learning technology. Auto ML was performed by the TPOT Python library. XGB method, whose k-10 validation result is 0.98, has been chosen by TPOT as the best algorithm. The event of automatic circulation of water by pump triggering had an accuracy of 0.9795. There was an accuracy of 0.9690 for UV light turns on/off events. Fan control has an F1 score of 0.9473 and has low false positives. In Ref. [139] authors explored Bayesian network for advanced agriculture to build and execute an IoT-built NFT hydroponics farm. To automate the system, this Bayesian Network model uses sensor input to categorize as well as forecast the levels of actuators. The system also provides an internet interface using a cloud platform to access, manage as well as monitor the farm from a distance. After model validation, the prediction model's accuracy was 84.53 %. In Ref. [140] author explored RNN algorithms to estimate the EC of nutrient solutions in root-zone in a soilless system. EC can be predicted by historical environment parameters in a soilless system to enhance EC-based nutrient management in varied climatic situations. The experiment was done on the sweet pepper plant. The results showed that by training the LSTM algorithm nutrient solution can be controlled in a soilless system by making the prediction of future value for EC. LSTM achieved the best test accuracy ($R^2 = 0.72$) among all RNN algorithms. In Ref. [141] an advanced setup was developed to identify three ions (phosphate, calcium and magnesium) using the AMSAM and DKL models. This model offered good performance in on-site detection and measurement of ions in lettuce hydroponics by securing RMSEs of 12.5, 12.1, and 7.5 mg per litre for calcium, phosphate, and magnesium respectively. Measured data was uploaded on a cloud computer which made it easier for gardeners to readily check the nutrients in their plants. In Ref. [142] author created a hydroponics system that is automated using sensors and microcontrollers without human interference. Two Arduino boards were used in the system for controlling and analysing the data that is received. A Raspberry Pi board namely Domoticz was also utilized in order to run the open-source automation programme. Remote monitoring and control were done by incorporating an IoT network in the automated hydroponic system, this also maintains the necessary conditions for growing the test plant. In Ref. [143] authors used

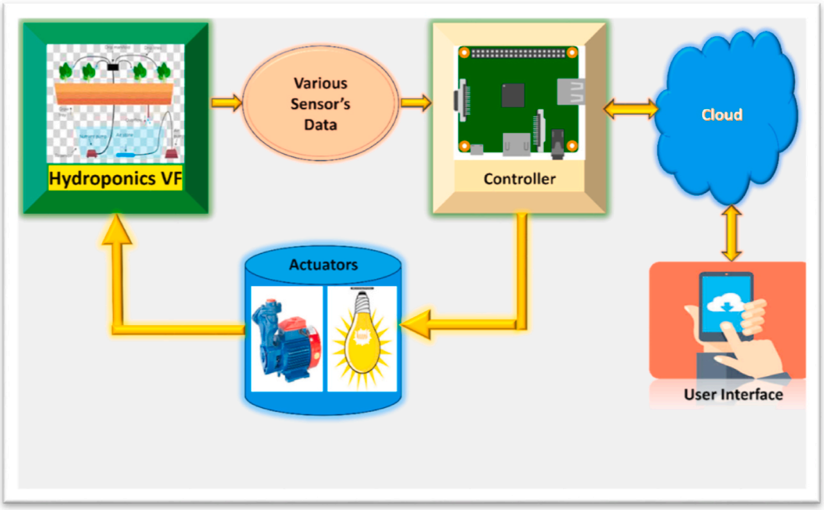

Fig. 24. Block diagram of automation in VF with IoT and machine learning algorithm.

Bayesian Network and IoT in order to make NFT hydroponics system fully automatically operational. Bayesian networks employ probability theory for prediction and anomaly detection. Data generated by various sensor is given to the Bayesian Network which processes this data and generates appropriate output decisions to control the actuators. The results show that the crops produced by automatic control are superior to the crops produced by human control, with computed gain differences ranging from 20 % to 60 % for all criteria used to assess high-quality crops.

In [144] authors explored the analysis of big data with an IoT network for making an automated hydroponics system. The microcontroller gets the input from the sensor and makes a decision based on the threshold value that farmers have chosen. When the threshold value is reached, water will flow to the plants for a specific amount of time before the automatic closure of the setup. Nutrition is provided from the nutrition tank at the same time. In the last all values are sent to a centralized mobile application and server for additional analysis. Table 12 compares several ML techniques for the automation of VF system.

6. Assessment and evaluation of knowledge-based VF System

This part of the article analyses the ML algorithms and IoT utilized in various research of the hydroponics, aeroponics, and aquaponics VF systems. ML algorithms were utilized to detect disease, yield prediction, and automation of nutrient and irrigation

Table 12
Different ML algorithms for automation of VF system.

Reference	Attribute	Source of Dataset	Crop Name	Name of VF Technique	ML Algorithm	Accuracy Measure
[132]	Nutrient Deficiency	Self-generated 1757 images by webcam	Basil	Hydroponics	DenseNet 201, ResNet101V2, MobileNet, VGG16	93.82 % for VGG16
[133]	Nutrient Deficiency, Water level	Self-generated dataset	Spinach	Hydroponics	Random Forest	82.1 % of peak power saved
[134]	Automation the system	Self-generated 5000 sample real-time dataset	Tomato	Hydroponics	DNN	88.5 %
[135]	Nutrition management	Self-generated dataset	Lettuce	Hydroponics	k-NN	93.3 %
[136]	Automation the system	Self-generated 4000 sample dataset	Lettuce	Hydroponics	DNN	81 %
[137]	Nutrition management	Self-generated 201 datasets recorded at Texas University	Leafy Plant	Aquaponics	Linear SVM	75 %
[138]	Automation of water, light, fan	Self-generated sample dataset	Leafy Plant	Aquaponics	XGB	97.9 %,96.9 %
[139]	Automation of pH, EC, light,	Self-generated 6881 sample dataset	Lettuce	Hydroponics	Bayesian	84.53 %,
[140]	Control of Nutrient solution	Self-generated 1416 sample dataset	sweet pepper	Hydroponics	LSTM	Test accuracy (R^2 = 0.72), Test RMSE = 0.08.
[141]	Ion Concentration recognition	Self-generated 100 sample dataset	Lettuce	Hydroponics	DKL	(RMSEs) of 12.5, 12.1, and 7.5

control in the VF systems. IoT was used to capture the data like images of leaf, stem, vegetables and readings of temperature, EC, pH, humidity and light in the VF systems. IoT was also responsible to put the captured data to the cloud and user's mobile application, so that disease detection, yield prediction and automation of nutrient can be done smartly. In this review paper, several research papers related to vertical farming systems were analysed and discussed, among them 31 research articles were based on ML algorithms and 14 on IoT technology. Fig. 25 classifies the research articles studied for applications of ML algorithms and IoT technology in the VF systems.

Fig. 26 shows the division of ML as well as DL models with their application to the hydroponics, aeroponics, and aquaponics VF systems. It has been noted that the researchers used a variety of ML techniques for parameter prediction and classification in the bulk of the literature. DL-based CNN model was used mostly in all aspects of VF such as detection of disease, prediction of yield, nutrients automation, and irrigation. Object detection techniques like YOLO and RCNN were used in disease detection and yield prediction. Regressors like SVR were explored in the prediction of yield for the VF system. Different classification techniques like SVM, KNN, RF, K- Means, DT, LSTM, and RNN were utilized in disease detection, yield prediction, and automation of nutrients and irrigation in hydroponics, aeroponics, and aquaponics VF system.

Fig. 27 shows CNN, DNN, and RCNN algorithms used in hydroponics, aeroponics, and aquaponics VF systems. Around 16 distinct DL/NN algorithms were employed by authors for prediction and classification, as shown in Fig. 27 while the remaining 2 (LST, and Deep kernel) algorithms were used in yield prediction and automation. Fig. 26 also illustrates several microcontrollers exercised in IoT applications for VF systems, such as the Raspberry Pi and Arduino boards.

6.1. Comparison of ML algorithms and IoT in vertical farming

In this section, the authors examine the benefits as well as drawbacks of various machine and deep learning algorithms that are employed in the vertical farming system.

6.1.1. Disease detection

The advancements in image processing are principally responsible for the use of AI approaches in disease identification in hydroponics, aeroponics, and aquaponics VF systems. The most popular tool for creating a system to detect diseases is CNN. CNN is a powerful type of neural network, a subfield of DL, excelling at image recognition. Unlike standard neural networks that require heavy pre-processing, CNN can handle raw images with minimal preprocessing work. In essence, CNNs are built for classification or detection tasks. They differ from regular neural networks by using convolutions instead of matrix multiplications in at least one layer. This allows them to work with entire images as input, rather than flattened vectors. The magic behind CNN lies in their pyramid-like architecture. This structure combines convolutional layers and pooling layers to shrink the image's width and height while extracting increasingly complex features. These features are then fed into a classifier at the top of the pyramid for final analysis. So, the core of a CNN lies in its convolutional and pooling layers, which work together to automatically extract meaningful features from images. DCNN models can provide 99 % accuracy in disease detection in hydroponics VF system, whereas MobileNet V2 model achieved 98.18 % accuracy in disease detection.

While DL holds immense potential to revolutionize ML and AI applications, its advancement is currently hindered by three main obstacles: overfitting, training time, and the risk of getting stuck in local minima. Overcoming these challenges will unlock breakthroughs across all facets of ML and AI in the field of VF [145]. These obstacles can be overcome by using techniques such as regularization, data augmentation, early stopping, drop out, and advanced optimization algorithms like Adam optimizer.

IoT devices with camera are used to capture the images of plant's leaf in VF, these images are sent to cloud hub for further preprocessing. ML algorithms can be used to detect the disease in these leaves. By constantly monitoring the plants, IoT-based devices can detect diseases at early stages, allowing for rapid intervention and minimizing crop loss. However, it can be expensive to set up and maintain an IoT system, particularly for smaller farms. Security of the gathered data, including photographs and sensor readings, is

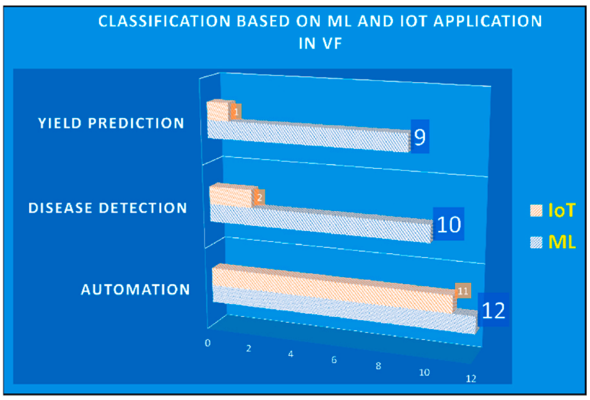

Fig. 25. Classification of research papers on the basis of ML and IoT application in the VF systems.

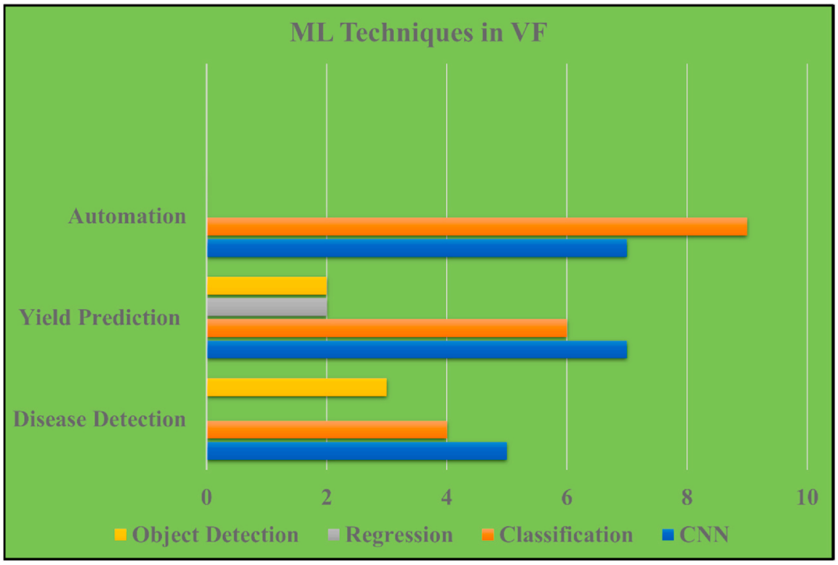

Fig. 26. Machine learning techniques in VF system.

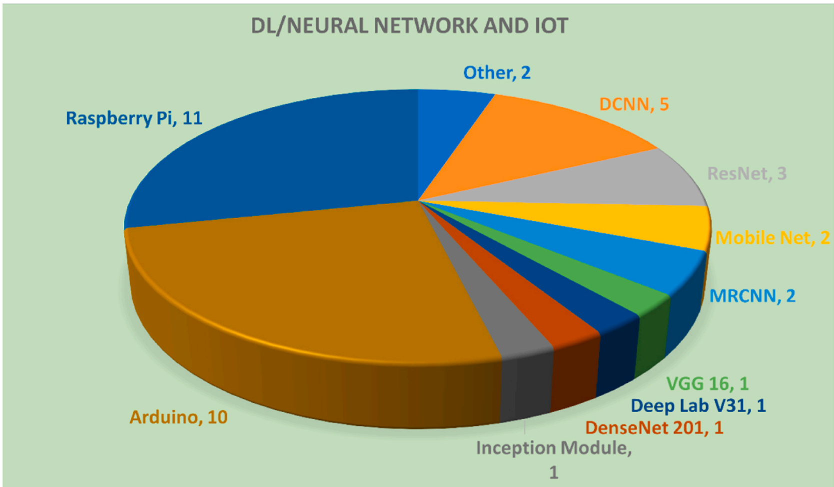

Fig. 27. Classification of ML algorithms and IoT microcontrollers in VF systems.

also critical. There is another crucial limitation of using IoT in VF is that IoT devices consume large power due to high computational requirements in real-time data collection. However, IoT devices can reduce power consumption and computational strain by processing data locally through edge computing.

6.1.2. Crop yield prediction

Crop yield prediction is very crucial task in VF. Yield forecasting require a large dataset collected from different IoT sensors which depends on various factors that influence plant growth, such as light intensity and spectrum, temperature and humidity, nutrient solution levels (pH, EC) and images of plant health. This data is used to train various ML models like RF, SVR and MVR regression that can identify patterns and relationship between these factors to predict the crop yield. By utilizing trained ML algorithms crop yield predictions may be generated more quickly and accurately. SVR and MVR regression algorithms are the most promising crop yield prediction methods as they have the lowest RMSE values as compared to other ML algorithms. RF algorithm also performed well by achieving accuracy of 99.27 % in yield prediction for hydroponics VF system. The accuracy of these ML models heavily relies on the quality and quantity of data collected by various sensors. Several data preprocessing techniques like data normalization, outlier detection, and missing value identification are required to get fruitful results from the ML algorithms. With proper monitoring and control, VF has the potential for high yield production. IoT empowers the farmers for managing the essential conditions for growing plants hydroponically, along with the ability for remote monitoring [146].

6.1.3. Nutrient and irrigation control

Nutrition circulation and water supply are crucial in any type of VF system. An intelligent IoT based VF system can be developed by employing DNN or any ML algorithm. This system monitors several factors that affect plant growth in a VF system. These factors include pH level, temperature, light intensity, humidity, and nutrient solution level. Sensors capture this data, which is then analysed by a ML algorithm. ML algorithm predicts the most suitable control action like nutrition and water supply for the VF system. The captured data, along with the corresponding control action labels, are stored in the cloud. This system can be implemented using a ML trained microcontroller.

The ML trained microcontroller effectively monitors the optimal growth environment in real-time in terms of temperature, humidity, light intensity, and nutrient levels. Nutrient and irrigation control using a ML algorithm can assist in resource management by reducing over-fertilization and water runoff by accurately controlling fertilizer and water supply based on plant demands. The XGB ML algorithm has achieved an accuracy of 97.9 %, while automating the light and water supply in aquaponics VF system. VGG-16 and k-NN algorithms have also achieved an accuracy of 93.82 % and 93.3 %, respectively for nutrition management in hydroponics VF system. Real-time automation of nutrients and irrigation is possible using IoT-connected actuators in VF as it enables the broadcasting of the sensor's information to the farmer on a mobile application and can provide valuable feedback to the farmers. Internet connectivity is essential throughout the day and night to make automation of nutrients and irrigation possible in the VF system. However, this issue can be resolved by optimizing data collection intervals in which frequency of data collection is adjusted based on the specific requirements of VF system.

7. Challenges in the vertical farming System

IoT and ML technologies are becoming the most fruitful techniques in VF in order to meet the food requirements of society. While being popular these techniques are having various challenges in operating with VF systems which are discussed as follows.

- **High Investment Cost:** The cost of the first investment in hydroponics, aeroponics, and aquaponics VF systems is relatively expensive due to the great complexity of creating a viable facility [147].
- **High Power Consumption:** It is necessary to artificially provide all of the light if a vertical farm is operated entirely inside. Electricity will thus be quite expensive, even with LED bulbs. Complex computing and other components of VF also consume large power [148].
- **Crops grown are limited:** The number of species that can be planted in VF is less at the current time.
- **Security and Privacy issues:** A significant obstacle to IoT-enabled VF systems is a lack of security and privacy. As a result, managing the information gathered on VF environmental elements is difficult. The system has a small vulnerability, which might result in the loss of sensitive data [149].
- **Connectivity Issue:** Because of the inadequate 2G, 3G, and 4G covering range, the connection is the biggest obstacle for IoT in the VF system. Although few low-power broad area techniques, such LoRa and Sigfox are helpful in resolving these problems, they are unable to manage very massive datasets [150].
- **Community Acceptance:** For non-technical people, putting smart and new technology into practice will be a difficult undertaking. Therefore, it is crucial to provide users and farmers with training and instruction so they can learn how to use new technology [151].
- **Technological failures:** Because of its extensive reliance on technology, VF has another issue. The plants might sustain severe harm if the electricity or irrigation system goes out [152].
- **Interoperability is Limited:** A number of devices must be able to communicate with one another using data protocols and IoT communication standards [110]. So, the problem here is not a lack of standards or their unavailability; rather, the main problem is the availability of an infinite number of standards [153].
- **Precision Monitoring:** VF setups like hydroponics, aeroponics, and aquaponics need proper monitoring of nutrition management, pesticide spraying, and irrigation to plants [154].
- **Vague Output:** IoT systems are able to predict the yield based on the sensor's data but actual profit can also depend on market conditions and cost savings etc**.**
- **High maintenance:** Components used in VF systems will degrade during their useful lives and require replacement or maintenance due to the high level of complexity and continuous operation of the plant [155].
- **Data Accuracy and Reliability**: IoT sensors can generate unreliable data because IoT system is vulnerable to malfunction. This wrong data can predict inaccurate yield and decisions related to monitoring the system.

8. Future trends of IoT and ML in VF System

Systems for producing food provide people work as well as food. Several potential study areas in VF are summarized below.

- More consideration is needed for agri-food supply chain traceability, which has enormous IoT potential.
- While LoRa, ZigBee, and Wi-Fi are the most often employed technologies in these publications, new high-speed data transfer technologies like 5G and NB-IoT can also be adopted to improve the VF system's speed and accuracy.
- To better predict various VF metrics, future researchers should look at durable and adaptable ML and DL algorithms that have been optimized using swarm intelligence algorithms such as SVM-PSO and ANN-GWO algorithms.

- Future research should continue to focus on the system's ability to identify plant diseases at various disease stages and plant locations in VF systems. Furthermore, depending on the illness stage, such systems must be able to suggest particular treatments. Additionally, it may be developed to include a mobile application for detecting plant diseases in real time, which would undoubtedly increase farmer confidence.
- Future robots, artificial intelligence systems, and smart sensor technologies should be explored to automate the harvesting and packing of fruits and vegetables in VF systems.
- An effective and realistic intrusion detection system must be adopted in the VF system in order to prevent IoT networks from cyber-attacks.

9. Conclusion

This article presents a comprehensive review of IoT and ML techniques used in VF systems. Many established VF strategies like hydroponics, aeroponics, and aquaponics are discussed to aid farmers in understanding the technological foundation of a VF system. The article explores how effectively VF parameters EC, PH, humidity, temperature, and irrigation can be monitored remotely using IoT devices. Also, it has been studied that how ML and IoT techniques empowered the farmer to predict disease and yield of crops in all types of VF systems. The paper also outlines five layers of IoT architecture, sensors, devices, and various protocols which act as the backbone of the IoT system. The fundamental concepts of ML algorithms and their types are also covered in the article. This paper includes a review of the effectiveness of ML algorithms employed in VF systems for managing nutrition, crop yield prediction, and disease detection. This study also takes into account several security risks and open problems with IoT and ML-enabled VF systems along with potential future research opportunities. Finally, it is anticipated that this review article will produce a wealth of information that will be extremely helpful to agriculturists, academics, policymakers, and technologists that are engaged in the development of intelligent VF systems.

Data availability statement

No data was used for the research described in the article.

CRediT authorship contribution statement

Ajit Singh Rathor: Writing – original draft, Visualization. **Sushabhan Choudhury:** Writing – review & editing, Conceptualization. **Abhinav Sharma:** Writing – review & editing, Investigation. **Pankaj Nautiyal:** Supervision, Formal analysis. **Gautam Shah:** Visualization, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] G. Kaur, P. Upadhyaya, P. Chawla, Comparative analysis of IoT-based controlled environment and uncontrolled environment plant growth monitoring system for hydroponic indoor vertical farm, Environ. Res. 222 (Apr) (2023), https://doi.org/10.1016/j.envres.2023.115313.

[2] N.B. Naikoo, R. Kanth, M.A. Bhat, A. Nazir, Vertical farming: the future of agriculture: a review [Online]. Available: http://www.thepharmajournal.com, 2022.

[3] R.M. Lehman, et al., Understanding and enhancing soil biological health: the solution for reversing soil degradation, Sustainability 7 (1) (2015) 988–1027, https://doi.org/10.3390/su7010988.

[4] S.N. Bhanja, A. Mukherjee, M. Rodell, Groundwater storage change detection from in situ and GRACE-based estimates in major river basins across India, Hydrol. Sci. J. 65 (4) (Mar. 2020) 650–659, https://doi.org/10.1080/02626667.2020.1716238.

[5] V.A. Natarajan, M. Sunil Kumar, R. Patan, S. Kallam, M.Y. Noor Mohamed, Segmentation of nuclei in histopathology images using fully convolutional deep neural architecture, in: 2020 International Conference on Computing and Information Technology, ICCIT 2020, Institute of Electrical and Electronics Engineers Inc., Sep. 2020, https://doi.org/10.1109/ICCIT-144147971.2020.9213817.

[6] T. Gomiero, Soil degradation, land scarcity and food security: reviewing a complex challenge, Sustainability 8 (3) (2016), https://doi.org/10.3390/su8030281. MDPI.

[7] Y. Kobayashi, T. Kotilainen, G. Carmona-García, A. Leip, H.L. Tuomisto, Vertical farming: a trade-off between land area need for crops and for renewable energy production, J. Clean. Prod. 379 (Dec) (2022), https://doi.org/10.1016/j.jclepro.2022.134507.

[8] F. Orsini, et al., Features and functions of multifunctional urban agriculture in the global north: a review, in: Frontiers in Sustainable Food Systems, vol. 4, Frontiers Media S.A., Nov. 16, 2020, https://doi.org/10.3389/fsufs.2020.562513.

[9] M. Rufí-Salís, M.J. Calvo, A. Petit-Boix, G. Villalba, X. Gabarrell, Exploring nutrient recovery from hydroponics in urban agriculture: an environmental assessment, Resour. Conserv. Recycl. 155 (Apr) (2020), https://doi.org/10.1016/j.resconrec.2020.104683.

[10] G.N. Yuan, et al., A review on urban agriculture: technology, socio-economy, and policy, Heliyon 8 (11) (Nov. 01, 2022) e11583, https://doi.org/10.1016/j.heliyon.2022.e11583. Elsevier Ltd.
[11] F. Kalantari, O.M. Tahir, R.A. Joni, E. Fatemi, Opportunities and challenges in sustainability of vertical farming: a review, Journal of Landscape Ecology(Czech Republic) 11 (1) (Jan. 2018) 35–60, https://doi.org/10.1515/jlecol-2017-0016.
[12] K. Al-Kodmany, The vertical farm: a review of developments and implications for the vertical city, Buildings 8 (2) (2018), https://doi.org/10.3390/buildings8020024. MDPI AG.
[13] P. Sengodan, An overview of vertical farming: highlighting the potential in Malaysian high-rise buildings, Pertanika Journal of Science and Technology 30 (2) (Apr. 01, 2022) 949–981, https://doi.org/10.47836/pjst.30.2.06. Universiti Putra Malaysia Press.
[14] L.S. Hallock, B. Buscher, M. Spoor, Vertical Farms, Urban Restructuring and the Rise of Capitalist Urban Agriculture, 2013.
[15] O. Matei, T. Rusu, A. Petrovan, G. Mihuţ, A data mining system for real time soil moisture prediction, in: Procedia Engineering, Elsevier Ltd, 2017, pp. 837–844, https://doi.org/10.1016/j.proeng.2017.02.475.
[16] M. Pathan, N. Patel, H. Yagnik, M. Shah, Artificial cognition for applications in smart agriculture: a comprehensive review, in: Artificial Intelligence in Agriculture, vol. 4, KeAi Communications Co, Jan. 01, 2020, pp. 81–95, https://doi.org/10.1016/j.aiia.2020.06.001.
[17] D.J. Mulla, Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps, in: Biosystems Engineering, vol. 114, Academic Press, 2013, pp. 358–371, https://doi.org/10.1016/j.biosystemseng.2012.08.009, no. 4.
[18] T. Ayoub Shaikh, T. Rasool, F. Rasheed Lone, Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming, in: Computers and Electronics in Agriculture, vol. 198, Elsevier B.V., Jul. 01, 2022, https://doi.org/10.1016/j.compag.2022.107119.
[19] M.N. Halgamuge, A. Bojovschi, P.M.J. Fisher, T.C. Le, S. Adeloju, S. Murphy, Internet of Things and autonomous control for vertical cultivation walls towards smart food growing: a review, in: Urban Forestry and Urban Greening, vol. 61, Elsevier, GmbH, Jun. 01, 2021, https://doi.org/10.1016/j.ufug.2021.127094.
[20] A.A.R. Madushanki, M.N. Halgamuge, W.A.H.S. Wirasagoda, A. Syed, Adoption of the Internet of Things (IoT) in agriculture and smart farming towards urban greening: a review, Int. J. Adv. Comput. Sci. Appl. 10 (4) (2019) 11–28, https://doi.org/10.14569/ijacsa.2019.0100402.
[21] R.R.A. Siregar, K.B. Seminar, S. Wahjuni, E. Santosa, Vertical farming perspectives in support of precision agriculture using artificial intelligence: a review, Computers 11 (9) (Sep. 01, 2022), https://doi.org/10.3390/computers11090135. MDPI.
[22] B. Fasciolo, A. Awouda, G. Bruno, F. Lombardi, A smart aeroponic system for sustainable indoor farming, in: Procedia CIRP, Elsevier B.V., 2023, pp. 636–641, https://doi.org/10.1016/j.procir.2023.02.107.
[23] A.J. Hati, R.R. Singh, AI-driven pheno-parenting: a deep learning based plant phenotyping trait analysis model on a novel soilless farming dataset, IEEE Access 11 (2023) 35298–35314, https://doi.org/10.1109/ACCESS.2023.3265195.
[24] University of Dhaka, Faculty of engineering and technology and institute of electrical and electronics engineers, in: ICIET 2019 : 2nd International Conference on Innovation in Engineering and Technology (ICIET), University of Dhaka, Dhaka, Bangladesh, 2019.
[25] G. Rajendiran, J. Rethnaraj, Smart aeroponic farming system: using IoT with LCGM-boost regression model for monitoring and predicting lettuce crop yield, International Journal of Intelligent Engineering and Systems 16 (5) (2023) 251–262, https://doi.org/10.22266/ijies2023.1031.22.
[26] M. D. Tambakhe, V. S. Gulhane, and Y. M. Rajgure, “International journal of intelligent systems and applications in engineering machine learning based approach for crop growth monitoring in hydroponics cultivation.” [Online]. Available: www.ijisae.org.
[27] C.N. Udanor, N.I. Ossai, B.O. Ogbuokiri, O.E. Nweke, P.O. Ugwoke, U.K. Ome, A pilot implementation of a remote IoT sensors for aquaponics system datasets acquisition, Journal of Computer Science and Its Application 28 (2) (Aug. 2022) 1–8, https://doi.org/10.4314/jcsia.v28i2.1.
[28] D. Ekanayake, P. De Alwis, P. Harshana, D. Munasinghe, A. Jayakody, M.N. Gamage, A smart aquaponic system for enhancing the revenue of farmers in Sri Lanka, in: 9th International Conference on ICT for Smart Society: Recover Together, Recover Stronger and Smarter Smartization, Governance and Collaboration, ICISS 2022 - Proceeding, Institute of Electrical and Electronics Engineers Inc., 2022, https://doi.org/10.1109/ICISS55894.2022.9915162.
[29] st R. Vadivel, nd R. Parthasarathi, rd A. Navaneethraj, rd P. Sridhar, th K. Muhammad Nafi, and th S. Karan, “Hypaponics-Monitoring and Controlling Using Internet of Things and Machine Learning.”.
[30] G.L. Priya, C. Baskar, S.S. Deshmane, C. Adithya, S. Das, Revolutionizing holy-basil cultivation with AI-enabled hydroponics system, IEEE Access 11 (2023) 82624–82639, https://doi.org/10.1109/ACCESS.2023.3300912.
[31] M. Cossu, M.T. Tiloca, A. Cossu, P.A. Deligios, T. Pala, L. Ledda, Increasing the agricultural sustainability of closed agrivoltaic systems with the integration of vertical farming: a case study on baby-leaf lettuce, Appl Energy 344 (Aug) (2023), https://doi.org/10.1016/j.apenergy.2023.121278.
[32] Y. Kobayashi, T. Kotilainen, G. Carmona-García, A. Leip, H.L. Tuomisto, Vertical farming: a trade-off between land area need for crops and for renewable energy production, J. Clean. Prod. 379 (Dec) (2022), https://doi.org/10.1016/j.jclepro.2022.134507.
[33] M. Kumar, D. Haillot, S. Gibout, Survey and evaluation of solar technologies for agricultural greenhouse application, in: Solar Energy, vol. 232, Elsevier Ltd, Jan. 15, 2022, pp. 18–34, https://doi.org/10.1016/j.solener.2021.12.033.
[34] A.F. Soofi, S.D. Manshadi, Carbon-aware operation of resilient vertical farms in active distribution networks, IEEE Trans. Smart Grid 15 (1) (Jan. 2024) 431–443, https://doi.org/10.1109/TSG.2023.3284752.
[35] IEEE Circuits and Systems Society and Institute of Electrical and Electronics Engineers, 2020 IEEE International Symposium on Circuits and Systems (ISCAS) : Proceedings : ISCAS 2020 : Virtual Conference, October 10-21, 2020.
[36] T. Saranya, C. Deisy, S. Sridevi, K.S.M. Anbananthen, A comparative study of deep learning and Internet of Things for precision agriculture, in: Engineering Applications of Artificial Intelligence, vol. 122, Elsevier Ltd, Jun. 01, 2023, https://doi.org/10.1016/j.engappai.2023.106034.
[37] M. van Hilten, S. Wolfert, 5G in agri-food - a review on current status, opportunities and challenges, Comput. Electron. Agric. 201 (Oct. 2022), https://doi.org/10.1016/j.compag.2022.107291.
[38] S. Qazi, B.A. Khawaja, Q.U. Farooq, IoT-equipped and AI-enabled next generation smart agriculture: a critical review, current challenges and future trends, in: IEEE Access, vol. 10, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 21219–21235, https://doi.org/10.1109/ACCESS.2022.3152544.
[39] M. Javaid, A. Haleem, I.H. Khan, R. Suman, Understanding the potential applications of artificial intelligence in agriculture sector, Advanced Agrochem 2 (1) (Mar. 2023) 15–30, https://doi.org/10.1016/j.aac.2022.10.001.
[40] A. Yousaf, V. Kayvanfar, A. Mazzoni, A. Elomri, Artificial intelligence-based decision support systems in smart agriculture: Bibliometric analysis for operational insights and future directions, Frontiers in Sustainable Food Systems 6 (2023). https://doi.org/10.3389/fsufs.2022.1053921, 1053921.
[41] R.N. Lubowski, A.J. Plantinga, R.N. Stavins, Land-use change and carbon sinks: econometric estimation of the carbon sequestration supply function, J Environ Econ Manage 51 (2) (Mar. 2006) 135–152, https://doi.org/10.1016/j.jeem.2005.08.001.
[42] D. Waldron, Vertical farms: historic development, current state and future directions [Online]. Available: https://www.researchgate.net/publication/330738805, 2017.
[43] M.K. Gupta, S. Ganapuram, VERTICAL FARMING USING INFORMATION AND COMMUNICATION TECHNOLOGIES, 2019.
[44] C, Carlos, A.J. Corvalán, (Anthony J) McMichael, Simon. Hales, and World Health Organization., *Ecosystems And Human Well-Being : Health Synthesis : a Report of the Millennium Ecosystem Assessment*, World Health Organization, 2005.
[45] M. SharathKumar, E. Heuvelink, L.F.M. Marcelis, Vertical farming: moving from genetic to environmental modification, Trends Plant Sci. 25 (8) (Aug. 01, 2020) 724–727, https://doi.org/10.1016/j.tplants.2020.05.012. Elsevier Ltd.
[46] A.M. Beacham, L.H. Vickers, J.M. Monaghan, Vertical farming: a summary of approaches to growing skywards, J. Hortic. Sci. Biotechnol. 94 (3) (May 04, 2019) 277–283, https://doi.org/10.1080/14620316.2019.1574214. Taylor and Francis Ltd.
[47] A.M. Beacham, L.H. Vickers, J.M. Monaghan, Vertical farming: a summary of approaches to growing skywards, J. Hortic. Sci. Biotechnol. 94 (3) (May 04, 2019) 277–283, https://doi.org/10.1080/14620316.2019.1574214. Taylor and Francis Ltd.
[48] T. Van Gerrewey, N. Boon, D. Geelen, Vertical farming: the only way is up? Agronomy 12 (1) (Jan. 01, 2022) https://doi.org/10.3390/agronomy12010002. MDPI.
[49] D. Despommier, “Field Actions Science Reports Vertical Farms, Building a Viable Indoor Farming Model for Cities”.

[50] P. M. P, "Vertical farming: a concept carbon-di-oxide capturing using biochar and converting biomass into biochar view project liner material to removal of pollutant form landfill leachate view project." [Online]. Available: http://www.ijetjournal.org.
[51] M. Martin, S. Poulikidou, E. Molin, Exploring the environmental performance of urban symbiosis for vertical hydroponic farming, Sustainability 11 (23) (Dec. 2019), https://doi.org/10.3390/su11236724.
[52] M. Kannan, G. Elavarasan, A. Balamurugan, B. Dhanusiya, D. Freedon, Hydroponic farming – a state of art for the future agriculture, Mater Today Proc 68 (Jan. 2022) 2163–2166, https://doi.org/10.1016/j.matpr.2022.08.416.
[53] G. Student and B. Dunn, "Oklahoma cooperative extension service arjina shrestha." [Online]. Available: http://osufacts.okstate.edu.
[54] B.M. Eldridge, L.R. Manzoni, C.A. Graham, B. Rodgers, J.R. Farmer, A.N. Dodd, Getting to the roots of aeroponic indoor farming, New Phytol. 228 (4) (Nov. 2020) 1183–1192, https://doi.org/10.1111/nph.16780.
[55] K.R. Venugopal, Institute of electrical and electronics engineers. Bangalore section, and institute of electrical and electronics engineers, in: 2019 Fifteenth International Conference on Information Processing (ICINPRO) : Theme: Internet of Things : Proceedings, 2019 (Bengaluru, India).
[56] N. Sharma, S. Acharya, K. Kumar, N. Singh, O.P. Chaurasia, Hydroponics as an advanced technique for vegetable production: an overview, J. Soil Water Conserv. 17 (4) (2018) 364, https://doi.org/10.5958/2455-7145.2018.00056.5.
[57] M. Kannan, G. Elavarasan, A. Balamurugan, B. Dhanusiya, D. Freedon, Hydroponic farming – a state of art for the future agriculture, Mater Today Proc 68 (Jan. 2022) 2163–2166, https://doi.org/10.1016/j.matpr.2022.08.416.
[58] S. Khan, A. Purohit, N. Vadsaria, Hydroponics: current and future state of the art in farming, J. Plant Nutr. 44 (10) (2020) 1515–1538, https://doi.org/10.1080/01904167.2020.1860217. Bellwether Publishing, Ltd.
[59] S. Sato, S. Sakaguchi, H. Furukawa, H. Ikeda, Effects of NaCl application to hydroponic nutrient solution on fruit characteristics of tomato (Lycopersicon esculentum Mill.), Sci. Hortic. 109 (3) (Jul. 2006) 248–253, https://doi.org/10.1016/j.scienta.2006.05.003.
[60] V.A. Kumar, J. Singh, Trends in hydroponics practice/technology in horticultural crops: a review, Int J Plant Soil Sci 35 (2) (Feb. 2023) 57–65, https://doi.org/10.9734/ijpss/2023/v35i22759.
[61] M.E.H. Chowdhury, et al., Design, construction and testing of iot based automated indoor vertical hydroponics farming test-bed in Qatar, Sensors 20 (19) (Oct. 2020) 1–24, https://doi.org/10.3390/s20195637.
[62] W. Suwaileh, D. Johnson, N. Hilal, Membrane desalination and water re-use for agriculture: state of the art and future outlook, in: Desalination, vol. 491, Elsevier B.V., Oct. 01, 2020, https://doi.org/10.1016/j.desal.2020.114559.
[63] S.T. Magwaza, L.S. Magwaza, A.O. Odindo, A. Mditshwa, Hydroponic technology as decentralised system for domestic wastewater treatment and vegetable production in urban agriculture: a review, in: Science of the Total Environment, vol. 698, Elsevier B.V., Jan. 01, 2020, https://doi.org/10.1016/j.scitotenv.2019.134154.
[64] C. Maucieri, C. Nicoletto, E. van Os, D. Anseeuw, R. Van Havermaet, R. Junge, Hydroponic technologies, in: Aquaponics Food Production Systems, Springer International Publishing, 2019, pp. 77–110, https://doi.org/10.1007/978-3-030-15943-6_4.
[65] Y. Rouphael, M.C. Kyriacou, S.A. Petropoulos, S. De Pascale, G. Colla, Improving vegetable quality in controlled environments, in: Scientia Horticulturae, vol. 234, Elsevier B.V., Apr. 14, 2018, pp. 275–289, https://doi.org/10.1016/j.scienta.2018.02.033.
[66] M. Al-Azba, Z. Cen, Y. Remond, S. Ahzi, An optimal air-conditioner on-off control scheme under extremely hot weather conditions, Energies 13 (5) (2020), https://doi.org/10.3390/en13051021.
[67] 2017 9th IEEE-GCC Conference and Exhibition (GCCCE), IEEE, 2017.
[68] M. SharathKumar, E. Heuvelink, L.F.M. Marcelis, Vertical farming: moving from genetic to environmental modification, Trends Plant Sci. 25 (8) (Aug. 01, 2020) 724–727, https://doi.org/10.1016/j.tplants.2020.05.012. Elsevier Ltd.
[69] D. Fernandez, Choosing a LED grow light for your hydroponic crop, Available online: https://scienceinhydroponics.com/2010/05/choosing-a-led-grow-light-for-your-hydroponic-crop.html.
[70] Create your ecological world," Available online: http://www.koraylight.com/.
[71] N. Khammayom, N. Maruyama, C. Chaichana, M. Hirota, Impact of environmental factors on energy balance of greenhouse for strawberry cultivation, Case Stud. Therm. Eng. 33 (May 2022), https://doi.org/10.1016/j.csite.2022.101945.
[72] D.I. Pomoni, M.K. Koukou, M.G. Vrachopoulos, L. Vasiliadis, A review of hydroponics and conventional agriculture based on energy and water consumption, environmental impact, and land use, Energies 16 (4) (2023), https://doi.org/10.3390/en16041690. MDPI, Feb. 01.
[73] G.L. Barbosa, et al., Comparison of land, water, and energy requirements of lettuce grown using hydroponic vs. Conventional agricultural methods, Int J Environ Res Public Health 12 (6) (Jun. 2015) 6879–6891, https://doi.org/10.3390/ijerph120606879.
[74] J.S. Barbosa, et al., Live imaging of adult neural stem cell behavior in the intact and injured zebrafish brain, Science 348 (6236) (1979) 789–793, https://doi.org/10.1126/science.aaa2729. May 2015.
[75] A. Alshrouf, "Hydroponics, Aeroponic and Aquaponic as Compared with Conventional Farming," American Scientific Research Journal for Engineering 27(1), 247-255, 2017, [Online]. Available: http://asrjetsjournal.org.
[76] D. Romeo, E.B. Vea, M. Thomsen, Environmental impacts of urban hydroponics in europe: a case study in lyon, in: Procedia CIRP, Elsevier B.V., 2018, pp. 540–545, https://doi.org/10.1016/j.procir.2017.11.048.
[77] M.A. Martinez-Mate, B. Martin-Gorriz, V. Martínez-Alvarez, M. Soto-García, J.F. Maestre-Valero, Hydroponic system and desalinated seawater as an alternative farm-productive proposal in water scarcity areas: energy and greenhouse gas emissions analysis of lettuce production in southeast Spain, J. Clean. Prod. 172 (Jan. 2018) 1298–1310, https://doi.org/10.1016/j.jclepro.2017.10.275.
[78] I.A. Lakhiar, J. Gao, T.N. Syed, F.A. Chandio, N.A. Buttar, Modern plant cultivation technologies in agriculture under controlled environment: a review on aeroponics, J. Plant Interact. 13 (1) (Jan. 2018) 338–352, https://doi.org/10.1080/17429145.2018.1472308.
[79] T.Y. Kyaw, A.K. Ng, Smart aquaponics system for urban farming, in: Energy Procedia, Elsevier Ltd, 2017, pp. 342–347, https://doi.org/10.1016/j.egypro.2017.12.694.
[80] A. L. Samuel. "Some Studies in Machine Learning Using the Game of Checkers.".
[81] A.M. Turing, COMPUTING MACHINERY AND INTELLIGENCE, 1950.
[82] A. Sharma, A. Jain, P. Gupta, V. Chowdary, Machine learning applications for precision agriculture: a comprehensive review, in: IEEE Access, vol. 9, Institute of Electrical and Electronics Engineers Inc., 2021, pp. 4843–4873, https://doi.org/10.1109/ACCESS.2020.3048415.
[83] M.Z. Naser, An engineer's guide to eXplainable Artificial Intelligence and Interpretable Machine Learning: navigating causality, forced goodness, and the false perception of inference, Autom Constr 129 (Sep) (2021), https://doi.org/10.1016/j.autcon.2021.103821.
[84] M.Z. Naser, A.H. Alavi, Error metrics and performance fitness indicators for artificial intelligence and machine learning in engineering and sciences, Architecture, Structures and Construction 3 (4) (Dec. 2023) 499–517, https://doi.org/10.1007/s44150-021-00015-8.
[85] A. Botchkarev, A new typology design of performance metrics to measure errors in machine learning regression algorithms, Interdiscipl. J. Inf. Knowl. Manag. 14 (2019) 45–76, https://doi.org/10.28945/4184.
[86] J. Gubbi, R. Buyya, S. Marusic, M. Palaniswami, Internet of Things (IoT): a vision, architectural elements, and future directions, Future Generat. Comput. Syst. 29 (7) (2013) 1645–1660, https://doi.org/10.1016/j.future.2013.01.010.
[87] G. Beniwal, A. Singhrova, A systematic literature review on IoT gateways, Journal of King Saud University - Computer and Information Sciences 34 (10) (Nov. 01, 2022) 9541–9563, https://doi.org/10.1016/j.jksuci.2021.11.007. King Saud bin Abdulaziz University.
[88] N. Chandnani, C.N. Khairnar, An analysis of architecture, framework, security and challenging aspects for data aggregation and routing techniques in IoT WSNs, Theor. Comput. Sci. 929 (Sep. 2022) 95–113, https://doi.org/10.1016/j.tcs.2022.06.032.
[89] M.U. Farooq, M. Waseem, S. Mazhar, A. Khairi, T. Kamal, A Review on Internet of Things (IoT) 113 (1) (2015) 1–7, https://doi.org/10.5120/19787-1571.
[90] Communication in the OSI-Model (Example with Layers 3 to 5) OSI Model.".
[91] T. Domínguez-Bolaño, O. Campos, V. Barral, C.J. Escudero, J.A. García-Naya, An overview of IoT architectures, technologies, and existing open-source projects, in: Internet of Things (Netherlands), vol. 20, Elsevier B.V., Nov. 01, 2022, https://doi.org/10.1016/j.iot.2022.100626.

[92] R. Khan, S.U. Khan, R. Zaheer, S. Khan, Future internet: the internet of things architecture, possible applications and key challenges, in: Proceedings - 10th International Conference on Frontiers of Information Technology, FIT 2012, 2012, pp. 257–260, https://doi.org/10.1109/FIT.2012.53.
[93] C.C. Sobin, A survey on architecture, protocols and challenges in IoT, in: Wireless Personal Communications, vol. 112, Springer, 2020, pp. 1383–1429, https://doi.org/10.1007/s11277-020-07108-5, no. 3.
[94] N. Chamara, M.D. Islam, G, Frank, Bai, Y. Shi, Y. Ge, Ag-IoT for crop and environment monitoring: past, present, and future, in: Agricultural Systems, vol. 203, Elsevier Ltd, Dec. 01, 2022, https://doi.org/10.1016/j.agsy.2022.103497.
[95] K. Lova Raju, V. Vijayaraghavan, IoT technologies in agricultural environment: a survey, Wireless Pers. Commun. 113 (4) (Aug. 01, 2020) 2415–2446, https://doi.org/10.1007/s11277-020-07334-x. Springer.
[96] D. Glaroudis, A. Iossifides, P. Chatzimisios, Survey, comparison and research challenges of IoT application protocols for smart farming, Comput. Network. 168 (Feb) (2020), https://doi.org/10.1016/j.comnet.2019.107037.
[97] S. Elhadi "Comparative study of IoT protocols." [Online]. Available: https://ssrn.com/abstract=3186315.
[98] H.D. Kotha, V. Mnssvkr Gupta, IoT application, a survey, Int. J. Eng. Technol. 7 (2018) 891–896, https://doi.org/10.14419/ijet.v7i2.7.11089.
[99] M.I. Alipio, A.E.M. Dela Cruz, J.D.A. Doria, R.M.S. Fruto, On the design of Nutrient Film Technique hydroponics farm for smart agriculture, Engineering in Agriculture, Environment and Food 12 (3) (Jul. 2019) 315–324, https://doi.org/10.1016/j.eaef.2019.02.008.
[100] E. Elbasi, et al., Artificial intelligence technology in the agricultural sector: a systematic literature review, in: IEEE Access, vol. 11, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 171–202, https://doi.org/10.1109/ACCESS.2022.3232485.
[101] W.J. Cho, H.J. Kim, D.H. Jung, D.W. Kim, T.I. Ahn, J.E. Son, On-site ion monitoring system for precision hydroponic nutrient management, Comput. Electron. Agric. 146 (Mar. 2018) 51–58, https://doi.org/10.1016/j.compag.2018.01.019.
[102] S. Sankaran, A. Mishra, R. Ehsani, C. Davis, A review of advanced techniques for detecting plant diseases, Comput. Electron. Agric. 72 (1) (Jun. 2010) 1–13, https://doi.org/10.1016/j.compag.2010.02.007.
[103] K. Lisha Kamala, S. Anna Alex, Apple fruit disease detection for hydroponic plants using leading edge technology machine learning and image processing, in: Proceedings - 2nd International Conference on Smart Electronics and Communication, ICOSEC 2021, Institute of Electrical and Electronics Engineers Inc., 2021, pp. 820–825, https://doi.org/10.1109/ICOSEC51865.2021.9591903.
[104] A. Musa, M. Hassan, M. Hamada, F. Aliyu, Low-power deep learning model for plant disease detection for smart-hydroponics using knowledge distillation techniques, J. Low Power Electron. Appl. 12 (2) (Jun. 2022), https://doi.org/10.3390/jlpea12020024.
[105] S.V.S. Ramakrishnam Raju, B. Dappuri, P. Ravi Kiran Varma, M. Yachamaneni, D.M.G. Verghese, M.K. Mishra, Design and implementation of smart hydroponics farming using IoT-based AI controller with mobile application system, J. Nanomater. 2022 (2022), https://doi.org/10.1155/2022/4435591.
[106] C. Jayasekara, S. Banneka, G. Pasindu, Y. Udawaththa, S. Wellalage, P.K. Abeygunawardhane, Automated crop harvesting, growth monitoring and disease detection system for vertical farming greenhouse, in: 3rd International Conference on Advancements in Computing (ICAC) , IEEE, 2021, pp. 228–233, https://doi.org/10.1109/ICAC54203.2021.9671074.
[107] W. Deng, F. Zhou, Z. Gong, Y. Cui, L. Liu, Q. Chi, Disease feature recognition of hydroponic lettuce images based on support vector machine, Trait. Du. Signal 39 (2) (Apr. 2022) 617–625, https://doi.org/10.18280/ts.390224.
[108] Z. Wu, R. Yang, F. Gao, W. Wang, L. Fu, R. Li, Segmentation of abnormal leaves of hydroponic lettuce based on DeepLabV3+ for robotic sorting, Comput. Electron. Agric. 190 (Nov) (2021), https://doi.org/10.1016/j.compag.2021.106443.
[109] X. Gong, et al., U3-YOLOXs: an improved YOLOXs for Uncommon Unregular Unbalance detection of the rape subhealth regions, Comput. Electron. Agric. 203 (Dec) (2022), https://doi.org/10.1016/j.compag.2022.107461.
[110] Y. Guo, J. Gao, M.H. Tunio, L. Wang, Study on the identification of mildew disease of cuttings at the base of mulberry cuttings by aeroponics rapid propagation based on a BP neural network, Agronomy 13 (1) (Jan. 2023), https://doi.org/10.3390/agronomy13010106.
[111] H. Aquino, et al., On-demand healthy and chlorotic Lactuca sativa leaf classification using support vector machine in a rotating hydroponic system, in: 2022 IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management, HNICEM 2022, Institute of Electrical and Electronics Engineers Inc., 2022, https://doi.org/10.1109/HNICEM57413.2022.10109533.
[112] I. Yudha Pratama, A. Wahab, M. Alaydrus, Deep learning for assessing unhealthy lettuce hydroponic using convolutional neural network based on faster R-CNN with Inception V2, in: 2020 5th International Conference on Informatics and Computing, ICIC 2020, Institute of Electrical and Electronics Engineers Inc., Nov. 2020, https://doi.org/10.1109/ICIC50835.2020.9288554.
[113] A. Pal, V. Kumar, AgriDet: plant Leaf Disease severity classification using agriculture detection framework, Eng. Appl. Artif. Intell. 119 (Mar) (2023), https://doi.org/10.1016/j.engappai.2022.105754.
[114] K.P. Ferentinos, Deep learning models for plant disease detection and diagnosis, Comput. Electron. Agric. 145 (Feb. 2018) 311–318, https://doi.org/10.1016/j.compag.2018.01.009.
[115] V.K. Vishnoi, K. Kumar, B. Kumar, S. Mohan, A.A. Khan, Detection of apple plant diseases using leaf images through convolutional neural network, IEEE Access 11 (2023) 6594–6609, https://doi.org/10.1109/ACCESS.2022.3232917.
[116] K. Roy, et al., Detection of tomato leaf diseases for agro-based industries using novel PCA DeepNet, IEEE Access 11 (2023) 14983–15001, https://doi.org/10.1109/ACCESS.2023.3244499.
[117] A.O. Anim-Ayeko, C. Schillaci, A. Lipani, Automatic blight disease detection in potato (Solanum tuberosum L.) and tomato (Solanum lycopersicum, L. 1753) plants using deep learning, Smart Agricultural Technology 4 (Aug) (2023), https://doi.org/10.1016/j.atech.2023.100178.
[118] J. Contreras-Castillo, J.A. Guerrero-Ibañez, P.C. Santana-Mancilla, L. Anido-Rifón, SAgric-IoT: an IoT-based platform and deep learning for greenhouse monitoring, Appl. Sci. 13 (3) (Feb. 2023), https://doi.org/10.3390/app13031961.
[119] L.S. Cedric, et al., Crops yield prediction based on machine learning models: case of West African countries, Smart Agricultural Technology 2 (Dec. 2022) 100049, https://doi.org/10.1016/j.atech.2022.100049.
[120] A. Mokhtar, et al., Using machine learning models to predict hydroponically grown lettuce yield, Front. Plant Sci. 13 (Mar) (2022), https://doi.org/10.3389/fpls.2022.706042.
[121] A. Reyes-Yanes, P. Martinez, R. Ahmad, Real-time growth rate and fresh weight estimation for little gem romaine lettuce in aquaponic grow beds, Comput. Electron. Agric. 179 (Dec) (2020), https://doi.org/10.1016/j.compag.2020.105827.
[122] P. Debroy, L. Seban, A tomato fruit biomass prediction model for aquaponics system using machine learning algorithms, in: IFAC-PapersOnLine, Elsevier B.V., 2022, pp. 709–714, https://doi.org/10.1016/j.ifacol.2022.04.116.
[123] M.S. Gang, H.J. Kim, D.W. Kim, Estimation of greenhouse lettuce growth indices based on a two-stage CNN using RGB-D images, Sensors 22 (15) (Aug. 2022), https://doi.org/10.3390/s22155499.
[124] J.Y. Lu, C.L. Chang, Y.F. Kuo, Monitoring growth rate of lettuce using deep convolutional neural networks, in: 2019 ASABE Annual International Meeting, American Society of Agricultural and Biological Engineers, 2019, https://doi.org/10.13031/aim.201900341.
[125] V. Mamatha, J.C. Kavitha, Machine learning based crop growth management in greenhouse environment using hydroponics farming techniques, Measurement: Sensors 25 (Feb) (2023), https://doi.org/10.1016/j.measen.2023.100665.
[126] S. Kumar Apat, J. Mishra, K. Srujan Raju, N. Padhy, The robust and efficient Machine learning model for smart farming decisions and allied intelligent agriculture decisions 10 (2) (2022) 139–155. http://pubs.iscience.in/jist [Online]. Available:.
[127] O. Åström, H. Hedlund, A. Sopasakis, Machine-learning approach to non-destructive biomass and relative growth rate estimation in aeroponic cultivation, Agriculture (Switzerland) 13 (4) (Apr. 2023), https://doi.org/10.3390/agriculture13040801.
[128] S. Iniyan, V. Akhil Varma, C. Teja Naidu, Crop yield prediction using machine learning techniques, Adv. Eng. Software 175 (2023), https://doi.org/10.1016/j.advengsoft.2022.103326.
[129] S. Khaki, L. Wang, Crop yield prediction using deep neural networks, Front. Plant Sci. 10 (Apr) (2019), https://doi.org/10.3389/fpls.2019.00621.
[130] J. Pant, R.P. Pant, M. Kumar Singh, D. Pratap Singh, H. Pant, Analysis of agricultural crop yield prediction using statistical techniques of machine learning, in: Materials Today: Proceedings, Elsevier Ltd, 2021, pp. 10922–10926, https://doi.org/10.1016/j.matpr.2021.01.948.

[131] J. Cao, et al., Wheat yield predictions at a county and field scale with deep learning, machine learning, and google earth engine, Eur. J. Agron. 123 (2021), https://doi.org/10.1016/j.eja.2020.126204.
[132] Z. Gul, S. Bora, Exploiting pre-trained convolutional neural networks for the detection of nutrient deficiencies in hydroponic basil, Sensors 23 (12) (Jun. 2023) 5407, https://doi.org/10.3390/s23125407.
[133] Y.V. Bhargava, P.K. Chittoor, C. Bharatiraja, R. Verma, K. Sathiyasekar, Sensor fusion based intelligent hydroponic farming and nursing system, IEEE Sens J 22 (14) (Jul. 2022) 14584–14591, https://doi.org/10.1109/JSEN.2022.3177777.
[134] M. Mehra, S. Saxena, S. Sankaranarayanan, R.J. Tom, M. Veeramanikandan, IoT based hydroponics system using Deep Neural Networks, Comput. Electron. Agric. 155 (Dec. 2018) 473–486, https://doi.org/10.1016/j.compag.2018.10.015.
[135] View of Hydroponic Nutrient Control System Based on Internet of Things".
[136] E.D. Nugroho, A.G. Putrada, A. Rakhmatsyah, Predictive control on lettuce NFT-based hydroponic IoT using deep neural network, in: Proceeding - 2021 International Symposium on Electronics and Smart Devices: Intelligent Systems for Present and Future Challenges, ISESD 2021, Institute of Electrical and Electronics Engineers Inc., Jun. 2021, https://doi.org/10.1109/ISESD53023.2021.9501402.
[137] S.B. Dhal, M. Bagavathiannan, U. Braga-Neto, S. Kalafatis, Can Machine Learning classifiers be used to regulate nutrients using small training datasets for aquaponic irrigation?: a comparative analysis, PLoS One 17 (8 August) (Aug. 2022), https://doi.org/10.1371/journal.pone.0269401.
[138] C.S. Arvind, R. Jyothi, K. Kaushal, G. Girish, R. Saurav, G. Chetankumar, Edge computing based smart aquaponics monitoring system using deep learning in IoT environment, in: 2020 IEEE Symposium Series on Computational Intelligence, SSCI 2020, Institute of Electrical and Electronics Engineers Inc., Dec. 2020, pp. 1485–1491, https://doi.org/10.1109/SSCI47803.2020.9308395.
[139] M.I. Alipio, A.E.M. Dela Cruz, J.D.A. Doria, R.M.S. Fruto, On the design of Nutrient Film Technique hydroponics farm for smart agriculture, Engineering in Agriculture, Environment and Food 12 (3) (Jul. 2019) 315–324, https://doi.org/10.1016/j.eaef.2019.02.008.
[140] T. Moon, T.I. Ahn, J.E. Son, Forecasting root-zone electrical conductivity of nutrient solutions in closed-loop soilless cultures via a recurrent neural network using environmental and cultivation information, Front. Plant Sci. 9 (2018), https://doi.org/10.3389/fpls.2018.00859.
[141] V.N. Tuan, et al., A smart diagnostic tool based on deep kernel learning for on-site determination of phosphate, calcium, and magnesium concentration in a hydroponic system, RSC Adv 11 (19) (Feb. 2021) 11177–11191, https://doi.org/10.1039/d1ra00140j.
[142] V. Palande, A. Zaheer, K. George, Fully automated hydroponic system for indoor plant growth, in: Procedia Computer Science, Elsevier B.V., 2018, pp. 482–488, https://doi.org/10.1016/j.procs.2018.03.028.
[143] Institute of Electrical and Electronics Engineers and IEEE Consumer Electronics Society, in: IEEE 6th Global Conference on Consumer Electronics (GCCE), 2017, 24-27 Oct. 2017.
[144] A. Shrivastava, C.K. Nayak, R. Dilip, S.R. Samal, S. Rout, S.M. Ashfaque, Automatic robotic system design and development for vertical hydroponic farming using IoT and big data analysis, Mater Today Proc (Jan. 2021), https://doi.org/10.1016/j.matpr.2021.07.294.
[145] A. Shrestha, A. Mahmood, Review of deep learning algorithms and architectures, in: IEEE Access, vol. 7, Institute of Electrical and Electronics Engineers Inc., 2019, pp. 53040–53065, https://doi.org/10.1109/ACCESS.2019.2912200.
[146] A. Munandar et al., "Design and Development of an IoT-Based Smart Hydroponic System.".
[147] O. Elijah, T.A. Rahman, I. Orikumhi, C.Y. Leow, M.N. Hindia, An overview of internet of things (IoT) and data analytics in agriculture: benefits and challenges, IEEE Internet Things J. 5 (5) (Oct. 2018) 3758–3773, https://doi.org/10.1109/JIOT.2018.2844296.
[148] I. Lee, K. Lee, The internet of things (IoT): applications, investments, and challenges for enterprises, Bus. Horiz. 58 (4) (2015) 431–440, https://doi.org/10.1016/j.bushor.2015.03.008.
[149] F. Kalantari, O.M. Tahir, R.A. Joni, E. Fatemi, Opportunities and challenges in sustainability of vertical farming: a review, Journal of Landscape Ecology(Czech Republic) 11 (1) (Jan. 2018) 35–60, https://doi.org/10.1515/jlecol-2017-0016.
[150] M.S. Farooq, S. Riaz, M.A. Helou, F.S. Khan, A. Abid, A. Alvi, Internet of things in greenhouse agriculture: a survey on enabling technologies, applications, and protocols, IEEE Access 10 (2022) 53374–53397, https://doi.org/10.1109/ACCESS.2022.3166634.
[151] R. Rayhana, G. Xiao, Z. Liu, Internet of things empowered smart greenhouse farming, IEEE Journal of Radio Frequency Identification 4 (3) (Sep. 2020) 195–211, https://doi.org/10.1109/JRFID.2020.2984391.
[152] H. Ibrahim, et al., A layered IoT architecture for greenhouse monitoring and remote control, SN Appl. Sci. 1 (3) (Mar. 2019), https://doi.org/10.1007/s42452-019-0227-8.
[153] K. Patel, C. Mistry, R. Gupta, S. Tanwar, N. Kumar, A systematic review on performance evaluation metric selection method for IoT-based applications, Microprocess. Microsyst. 101 (Sep. 2023) 104894, https://doi.org/10.1016/j.micpro.2023.104894.
[154] C. Giua, V.C. Materia, L. Camanzi, Smart farming technologies adoption: which factors play a role in the digital transition? Technol. Soc. 68 (2022) 101869 https://doi.org/10.1016/j.techsoc.2022.101869.
[155] A. Lytos, T. Lagkas, P. Sarigiannidis, M. Zervakis, G. Livanos, Towards smart farming: systems, frameworks and exploitation of multiple sources, Comput. Network. 172 (May 2020), https://doi.org/10.1016/j.comnet.2020.107147.