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Chapter

Internet of Things and Machine Learning Applications for Smart Precision Agriculture

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Abstract

Agriculture forms the major part of our Indian economy. In the current world, agriculture and irrigation are the essential and foremost sectors. It is a mandatory need to apply information and communication technology in our agricultural industries to aid agriculturalists and farmers to improve vice all stages of crop cultivation and post-harvest. It helps to enhance the country's G.D.P. Agriculture needs to be assisted by modern automation to produce the maximum yield. The recent development in technology has a significant impact on agriculture. The evolutions of Machine Learning (ML) and the Internet of Things (IoT) have supported researchers to implement this automation in agriculture to support farmers. ML allows farmers to improve yield make use of effective land utilisation, the fruitfulness of the soil, level of water, mineral insufficiencies control pest, trim development and horticulture. Application of remote sensors like temperature, humidity, soil moisture, water level sensors and pH value will provide an idea to on active farming, which will show accuracy as well as practical agriculture to deal with challenges in the field. This advancement could empower agricultural management systems to handle farm data in an orchestrated manner and increase the agribusiness by formulating effective strategies. This paper highlights contribute to an overview of the modern technologies deployed to agriculture and suggests an outline of the current and potential applications, and discusses the challenges and possible solutions and implementations. Besides, it elucidates the problems, specific potential solutions, and future directions for the agriculture sector using Machine Learning and the Internet of things.

Keywords: Machine Learning, Internet of Things, Agriculture, remote sensors, Land utilisation

1. Introduction

Précised agriculture depends on the utilisation of selective resources like water, fertilisers, seeds, and other necessary things. Sensor technology in the agriculture domain provides excellent support and offers the farmers to map their fields easily. Around the globe, the researchers of the agriculture domain strongly depending

on the sensor technologies for both plant phenotyping and soil quality by using the latest technologies, including multispectral cameras, satellite imagery and drones, with the aid of internet of things (IoT) and cloud computing [1, 2]. The achievement of increment in the production level of agriculture outcome by introducing sensor technologies which offer the improvement in crop and soil quality, safety of food, sustainability, and profitability [2]. It helps farmers to understand the crops on the microscale. Sensors-based techniques used to provide appropriate tools to achieve the goals mentioned above [2]. Different sensing phenomena adopted for the agriculture field, and few of the selective sensors and their functionality.

1.1 Agriculture sensors

The technological advances and development facilities to attain the implementations on the agriculture domain by breaking the barriers to the basic needs of the farmers. Many sensing technologies that were already identified for precision agriculture by monitoring and optimising the crops [2]. Few of the sensors are listed below, which can offer the best solution for this precise farming.

1.1.1 G.P.S. based position or location sensors

This technology supports the proper application of agrochemicals and can safeguard water quality. Around 82 per cent of the implementation of the fertiliser can be uniform and appropriate by using a human resource controlled or lightbar guidance system [3]. Determination of longitude, altitude, and latitude by using the signals received from signals; these sensors can monitor the accurate position or location of the crop (**Figure 1**).

The G.P.S. systems used to measure the distances to the precisely located G.P.S. satellites to find positions on earth. Radio signals broadcasted from the G.P.S. satellites monitored by receivers [3]. A GPS position is usually determined by simultaneously measuring the distance to at least three satellites. The time taken for a radio signal which travels from the satellite to the G.P.S. receiver determines the length. For the calculation of positions, the information collected from the radio signals, which includes broadcasting time and satellite information, has to be processed.

This technology relatively inexpensive and also helps with parallel tracking devices, which assists the operators for the visualisation of the position concerning previous passes and to recognise the need for steering adjustments.



Figure 1.
G.P.S. system.

Commonly, these aids are coming with different configurations. G.P.S. technology was used for monitoring yield or mapping the field and also soil sampling [3, 4]. The G.P.S. navigation system can increase the efficiency of the farm and improve the aspects of agribusiness by reducing environmental impacts. This system can also reduce the operator's fatigue and anxiety regarding fertiliser and pesticide application. The use of this technology can demonstrate to the non-agricultural community that advanced technology used for farming efficiently and safely sampling [4].

1.1.2 IoT sensors

In the last decades, farming implemented by several technological transformations and becoming more industrialised and driven by the latest technology. Introduction of smart agriculture gadgets which helps farmers for gaining best control on the process of crops growth and maintaining livestock as well with excellent efficiency. Internet of Things (IoT), based devices started to occupy every part of our life, from health care, automation, automotive and logistics, to smart cities and industrialisation (**Figure 2**). The Internet of Things creates up an era of precision agriculture sampling [5].

Precision agriculture is a basic term for all the services based on digital systems and inventions on technical things for the fulfilment of the modern farmer's needs for the yield optimisation, reduction of wastage, and maintaining the quality of environment [5, 6]. IoT sensors installed in the crop can support the farmers for allotting the pesticides and fertilisers in the right way along with the following support:

- Harvesting time optimisation
- The health of the crop
- Temperature, light and humidity level monitoring in greenhouses
- Soil quality and moisture level measurement

Many smartphone applications identified to incorporate with the Internet of Things (IoT) ideals, aggregation of data, and speed of the process, which may bring the data up to date, information can be provided to the small farmers like watering, seeding, fertilising and weeding. These applications are collecting the data from these sensors, especially from remote sensors and weather stations [6]. It helps in an in-depth analysis of data and provides valuable recommendations too.

Seeding is not guesswork after the innovation and application of IoT technologies. The programmed smart device can find the exact place for a seed to be planted and grown in a possible way. The collection of crops by the smart tractors with more exceptional efficiency and care when the harvest is ripe. Presently, the percentage of energy needed for the cultivation of crop by repairing the tractor damage itself goes around 80 to 90. By using the G.P.S. controlled steering system and route planning based on the input data, we can:

- Minimising erosion by tracking vehicle path
- Fuel cost reduction
- Improvement in accuracy on the operations



Figure 2.
IoT system.

The applications developed for small-scaled farmers may support them in multiple ways. The diagnosis of the diseases on plants identified and forwarded to the experts to rectify. The number of nutrients needed by the fertilisers by the determination of leaf colour and soil quality [7]. Also, the pH value of the soil and other conditions can be measured. From the observations on leaves, the water needs of the plants determined. The readiness on the crop harvesting with the aid of U.V. and white light-based photos can aid in the prevention of ripeness [7].

1.1.3 Optical sensors

The optical sensors are used to collect and record the data about crop field and soil quality by the collection of light reflected from the growing plants. The application of nitrogen to the plants indicated to the users according to the health of the plants [8]. As this technology is not depending on the atmospheric light, the optical sensors used day and night. It uses external light to analyse the properties of soil. Measurement of light reflectance frequencies is carried out by the sensors in near and mid-infrared and polarised light spectrums. Optical sensors can be easily placed or integrated on vehicles or drones or even satellites too. The aggregation of data, collected from optical sensors, can be processed further. Determination of the organic matter, clay, and soil moisture level content can also be analysed by optical sensors (**Figure 3**).

According to the data collected using various platforms, like satellites, aerial (aeroplanes, UAVs and drones) and ground-based, the reflectance recorded. The collection of images from satellites, aircraft, and UAV's using cameras where the optical sensors installed in the ground are able to collect the reflectance data as a text file. According to the operation, these ground sensors classified either active or passive. The passive sensors are in need of an external source of light, like the sun. However, the active sensors are operated by their source of view of different wavelengths or a specific wavelength [9]. The relationship between the visible light and the chlorophyll content provides plant details. From this analysis, we could identify healthy plants as green. The mesophyll cells are reflecting the near-infrared light, which is invisible to the human eye, found that more than chlorophyll content, the quantity in a plant, results in the highest reflectance than the visible lights. Biomass production and evaluation of colour classified by analysing both wavelengths. Sensor position may affect the field measurements, like the crop distance, light



Figure 3.
Optical system.

source dependency, leaves may cover by snow dews, and also because of other factors that may cause the plant stress. The moderated distance between the target and the sensor kept avoiding noise in the captured signal. It will lead to overcoming the limitations of the sensor output. It is essential to monitor the leaves, which should not be covered by water molecules or dews, which may change the reflectance [9].

1.1.4 Electrochemical sensors and mechanical sensors

Among different domains and their development like the Internet of Things (IoT) supported farming, the electrochemical sensor system is playing a vital role by detecting single or multiple soil components effectively, selectivity, and efficiently for soil quality measurements. It can be done either remotely by sharing the data and in-situ like the direct point of care on soil health. This perspective is aimed for the description of the state of art sensor technology based on the electrochemical mechanism for the measurement of soil quality by considering present scenarios. The electrochemical sensing mechanism explored its applications in many fields and even for a point of use. Mainly, lab-based methods like an ion-selective membrane, impedance spectroscopy, and amperometric sensors are in use to detect the nutrients of the soil and other parameters of agriculture (**Figure 4**) [10].

One of the attractive methods is to combine the electrochemical sensing technique by using ion-selective membrane transducers, which can easily monitor the parameters of soil like phosphate, nitrate, potassium, and others. Electrochemical sensing techniques are not so complicated like spectroscopy or any optical complexity and deployed directly to measure soil nutrients. These sensors are consisting of two electrodes of a working electrode, which can detect the target and another one of a reference electrode, which supplies a constant potential. The difference in potential between these two electrodes is either proportional or inversely proportional to the target according to its nature, either anions or cations. The working principle of this sensor governed by the Nernst equation. By relating the change in working electrode potential, which is compared with the potential of a reference electrode, based on the linearity of the activity of the sensed ion. The electrochemical sensors to deploy for in-situ measurements are expecting the electronic circuits embedded with the sensor (**Figure 5**) [11].

The microelectromechanical system (MEMS) based sensors embedded with electrochemical sensing units, which gains excellent potential for the analysis of soil quality because of their portability, rapidity, real-time measurement, and in-field deployability [12]. The ability of electrochemical soil sensors to sense different soil



Figure 4.
Amperometric sensor.

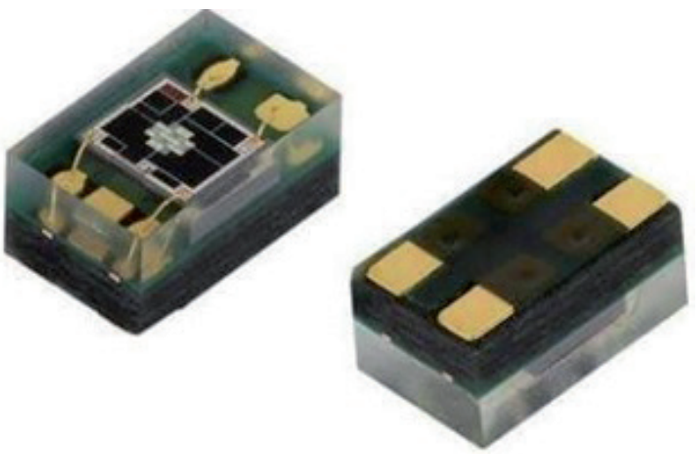


Figure 5.
Electromechanical system.

parameters, needed to be present in those systems as a basic and essential part for smart farming. This micro-scaled sensing system with the high potential for soil analysis is the much need for next-generation agriculture. MEMS-based sensors can save the data easily due to their affordability & sharing, on-time analysis, and accuracy in the decision [12].

1.1.5 Mechanical sensors

These sensors used to estimate the mechanical resistance of the soil. The penetration or cutting through the land to measure the force using individual devices like strain gauges or load cells is the basic phenomenon of these sensors (**Figure 6**).

The developed prototypes by the researchers can map the soil resistance continuously in a feasible way. Unfortunately, these prototypes are not available commercially. A new technique called the "traction control" system on tractors based on drift sensors is using a similar method to control the three-point hitch on the way [13].

1.1.6 Dielectric sensors

Dielectric sensors are used for measuring the soil moisture levels by the utilisation of the dielectric constant of the material. It defined as the electrical property, which is getting changed according to the content of soil moisture (**Figure 7**).

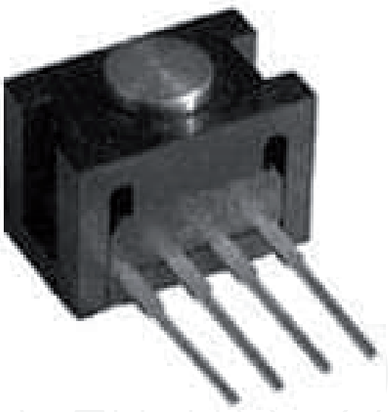


Figure 6.
Mechanical sensor.

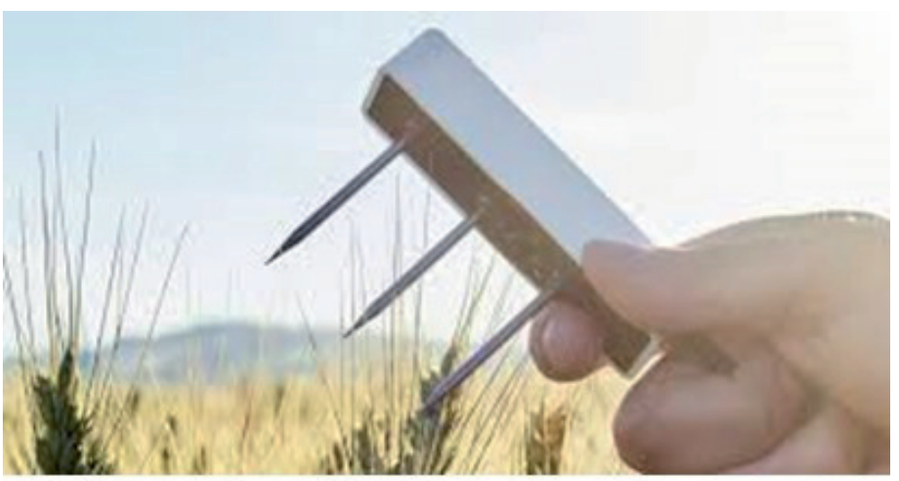


Figure 7.
Dielectric sensor.

These sensors embedded with rain gauge stations and arranged around the farm. While the vegetation level goes down, the observation on soil moisture conditions can be performed by them. Also, the soil moisture sensors used the soil's dielectric constant to justify the content of the volume of water and the transmission of electricity based on the soil's capability depending on its dielectric constant. The dielectric constant land's water is larger compare with air, so that, if the water content of the soil increases, the increment of the dielectric constant of the soil will also be recorded. So, the constant dielectric measurement provides a fair observation of water content.

1.1.7 Airflow sensors

Airflow sensors used to measure the permeability of air of the soil. The amount of pressure needed to pressurise a certain volume of air to some depth on the land, which is used to compare the multiple properties of soil (**Figure 8**).

From multiple experiments, it is possible to distinguish between various soil types and soil structure, moisture levels and compaction. These measurements can be made not only at a single location, while in motion too dynamically. The expected outcome is the need for pressure to allow a particular amount of air to the



Figure 8.
Airflow sensor.

ground in the wanted level of depth. By using such unique sensors, we can study various types of soil properties, including soil type, compaction, moisture level and structure, which produces unique identified signatures.

1.2 Benefits of agriculture sensors

Agriculture sensors can increase the food demand because of the utilisation of minimum resources like water, seeds, and fertilisers. These sensors fulfil the above basic requirements by resource conservation and field mapping. Also, these sensors easily installed and used efficiently. They are cost-effective too. Along with the usage in agriculture, these sensors can also serve for the prevention of pollution and global warming. With the advantages of communication protocols, these sensors controlled remotely.

1.3 Limitations of agriculture sensors

Precision agriculture and IoT technology are expecting flawless internet connectivity, which is a significant constraint and not available in many of the developing countries like I.N.D.I.A. there is a presumption among the customers that they may not be ready to utilise the present IoT devices integrated with agriculture sensors. Another significant impact on the infrastructure requirements like traffic systems, smart grids, and communication towers is not available everywhere, which also hinders the growth of the use of agriculture sensors.

Challenges and ideas to overcome limitations:

According to the expert's vision, precision agriculture has a standard potential to meet the increment in food demand around the globe. Even though the field has good growth and scope, still this has not robust as expected earlier. This domain has several challenges that we need to overcome.

a. The technology following the standards is not uniform and the same, which gets changed often. Precision agriculture expected, to a large extent.

The challenge depends on converting smart devices like sensors and gateways to farmer-friendly platforms.

b. Setting up the architecture for IoT technology is needed to be implemented. Knowledge of precision farming must be reached the farmers and enrich them to operate the sensors/tools independently so that the loss of the workforce prevented.

c. Providing continuous internet connectivity is mandatory, and network performance like the speed of bandwidth closely monitored.

d. All the crops are not going to produce the same products. So the product functioning must be defined correctly. Dividing their land as small zones for proper management may also derive the right results.

e. To prevent the mechanical damage of the sensor/device, continuous monitoring of the operation of these devices is a must. So, food safety cant is compromised. Upgradation of the tools is also essential. E-waste of these devices should adequately evacuate.

2. Soil quality identification for precision agriculture

One of the formidable global challenges is to feed the huge population soon. It predicted that the population could increases to 9.73 billion people by 2050 and estimated that it would require 70% additional food production in comparison to the present scenario [14]. The conventional agriculture practices resulted in a decline in the total productivity, causing poor ecological diversity, reduce the pollination services, affects carbon sequestration, causes soil and water pollution, soil erosion and food security [15, 16]. It is in dare need to use newly emerged modern sensing and controlling digital technology for effective agriculture. The agricultural sector is not just about maximising productivity it has shifted to the spectrum of other activities like optimising landscape management, development of rural, protection of the environment and social justice outcomes [17, 18]. Precision farming is one of the innovative methods practised, it incepted in the early 1980s, and with the past few years, it has become more common. It is a concept of "right practice at the right location at the right time at the right intensity". Precision agriculture uses electronic information and other digital technologies to collect data and analyse spatial/temporal data to improve the efficiency, productivity, and sustainability of agricultural operations [19]. Site-specific crop management practised from earlier decades like grid soil sampling and spot application of fertiliser and lime to optimise soil nutrient levels [20]. Global positioning systems (G.P.S.) initiated for civilian use in 1983, and in 1990's Global Navigation Satellite Systems (GNSS) enabled to develop equipment for variable rate fertiliser application for soil sampling and yield monitoring [21]. Incorporating digital management and surveillance technologies in farming automates the farming with integrated crop management to maximise the effectiveness of crop and yield [22–24]. The mechanical digitisation encompasses farm machinery for the sowing of seedling, fertilisers, cultivation, harvesting and the implication of satellites and tractors to drones, using Geographic Information Systems (G.I.S.), Global Positioning System includes yield mapping,



Figure 9.
Precision farming cycle.

remote sensing, variable rate irrigation, automatic tractor navigation, and robotics, proximal sensing of soils and crops, and profitability and adoption of precision farming (**Figure 9**). The details of the machinery discussed in the below sections. It is essential to understand the soil quality, functions and the role of indicators.

2.1 Soil quality

Soil is a vigorous component for crop production, and it plays a critical role in delivering ecosystem services. Like water and air, soils contribute a major carrier for biodiversity. The concept infers the capacity of soil to perform a specific function as a store, recycle and energy balance, that reflects the living and dynamic nature of the soil within the ecosystem boundary for multiple uses [25, 26]. The diverse potential of land uses to understand the quality of soil for ensuring the sustainability of the environment [27]. In the context of agriculture, good quality of soil has the fitness to support crop growth with enhanced productivity resulting in abundant and high quality of crops [28]. Generally, the soil has two parts viz., intrinsic, and dynamic. Intrinsic soils have the nature or inherent capacity for crop growth, which depends upon the parent material and topography. These soils are almost static, and the characteristics of these soils are permanent and do not change easily [29, 30]. Dynamic soil quality depends on its agronomic practices managed. The soil property encompasses soil texture, depth, permeability, soil organic matter, biological activity, water-and nutrient-holding capacity and soil structure. The organic matter changes from years to decades, pH changes from months to years, few properties can change from hours to days like microbial biomass and populations, soil respiration, nutrient mineralisation rates, and macroporosity [29, 31].

2.2 Soil functions

The primary function of soil is to nurture and sustain crop growth. Due to the dive's potential of land use, each soil performs a specific function for sufficient crop growth. Regulation of partition of water flow and storage helps for plant root penetration, and water infiltration for the crop growth [27, 32, 33]. The natural fertility of the soil increases by nutrient availability and has the adequate cation-exchange capacity, decreases acidity, maintains a proper buffer, and helps to remove the toxicants [34]. It also reduces the compaction risk like water retention, water infiltration, cohesion workability/trafficability [35–37]. The soil also reduces the contamination risk, leaching potential, toxic absorption, and toxic mobility. However, overuse exploitation of the earth can deteriorate the soil quality temporarily or permanently based on its usage. Soil erosion is widespread and estimated that approximately 75 billion tons of fertile soil is lost from world agricultural systems every year, consequently reduces the productivity of all-natural ecosystems [38–41]. Soil organic carbon (S.O.C.) observed and depleted 30–40% in cropland soils when compared to natural or semi-natural vegetation due to cultivation [42, 43]. Other threats like soil compaction, salinisation, waterlogging, nutrient imbalance, floods, and landslides and soil sealing, have both natural and human-induced causes [40, 41, 44–46]. This threat posses both agricultural production and terrestrial ecosystem. It reported that nearly 11.9–13.4% of the global agricultural supply lost due to soil degradation. Hence it is essential to protect soil degradation at different levels to safeguard food security, ecological health, and also for global sustainable development [47].

2.3 Soil indicators

Soil indicators fill the gap of traditional soil testing because merely measuring and reporting individual parameters is no longer sufficient; it requires an in-depth understanding of soil quality by inferring various parameters. U.S.D.A. classified the soil into four classes, such as visual, physical, chemical, and biological indicators. Visual was mostly observed to be a conventional type and mainly analysed by farmers through local knowledge and also obtained through photographic interpretation, subsoil exposure, erosion, presence of weeds and colour. The physical indicators connected to the organisation of the particles and pores like particle-size distribution, aggregate stability, max. Root depth, penetration resistance, hydraulic conductivity, infiltration rate, water holding capacity, water content, porosity, soil depth, particle density, water-dispersible clay, shear strength, stone content, clay mineralogy, total surface area, soil odour [48–56]. The chemical property such as pH; T.O.C. or organic matter, Nutrient Availability electrical conductivity; selected heavy metals, organic pollutants, particulate matter [55–66] Soil respiration; N. mineralisation, earthworms, nematodes respiration, urease activity enzyme activities, total species number, fungal biomass functional diversity, bacterial biomass, potential denitrification activity, potential amonium oxidation, mycorrhiza populations root health, soil fauna diversity, phosphatase activity, microbial diversity are the biological indicators that measure the quality of soil [49, 54, 67–74]. The selection of these indicators needs to ensure that they are sensitive and responsive to pressure and change in land use management. **Table 1** infers that indicators measured for different countries (**Table 1**). Soil indicators refer to the capacity of soil to perform crop production that used in response to the dynamic changes in an agroecosystem.

Indicators	Values	Description	References
pH ($CaCl_2$)	4.0 ± 0.37	Physical and chemical properties of soil in Araucaria forest (N.F.), Brazil	Pereira et al. [75]
Organic-C (g kg^{-1})	33 ± 12.9		
Bulk density (g cm^{-3})	1.08 ± 0.2		
Macroporosity (m^3 m^{-3})	0.16 ± 0.07		
Microporosity (m^3 m^{-3})	0.41 ± 0.06		
Sand (g kg^{-1})	459.0 ± 157		
Silt (g kg^{-1})	87.3 ± 40		
Clay (g kg^{-1})	453.8 ± 136.5		
Organic matter	10–20 g kg^{-1}		Lal [76, 77]
Nitrogen	1.6–2.4 g kg^{-1}		Adeoye and Agboola [78]
Active carbon	6–15 g kg^{-1}		Adeyolanu [79]
Cation exchange capacity	3.5–6.0 c mol kg^{-1}		Adeoye and Agboola [78]
Wet stable aggregate	0.40–0.75 kg kg^{-1}		Adeyolanu [79]
Mean weight diameter	0.53–2.00 mm		Adeyolanu [79]
Available moisture content	8–20%		Lal [76, 77]
Bulk density	1.3–1.5 g cm^{-3}		Lal [76, 77]
Macroporosity	0.15–0.18 m3 m^{-3}		Lal [76, 77]
Soil strength	60–120 kPa		Adeyolanu [79]
Infiltration capacity	7–21 cm $hr.^{-1}$		Adeyolanu [79]
Saturated hydraulic conductivity	0.2–3 cm $hr.^{-1}$		Adeyolanu [79]
Organic matter content(%)	4.3	Benchmark soil, for natural Pampa Region, Argentina	de la Rosa and Sobral
Respiration rate (kg C ha^{-1} d^{-1})	83		
Aggregate stability (%)	70		
Infiltration (mm h^{-1})	44		
Compaction (Mpa)	3.7		
O.M. (%)	2.65 ± 0.96	Soil water retention and soil resistance to penetration curves of Argentina	Imhoff et al.
Clay (%)	27 ± 10		
Sand (%)	18 ± 18		
Silt (%)	55 ± 15		
Bd (g cm^{-3})	1.37 ± 0.09		
B.D. (g cm^{-3})	1.5	Soil quality indicators, baseline limits used for in northern Ethiopia.	Harris et al. [80]
MWHC (%)	30		Gregory et al. [81]
OC^e (%)	3.5		Kay and Anger [82]
SAS (%)	30		Harris et al. [80]
Zn (mg kg^{-1})	18		Mausbach and Seybold [83]
Fe (mg kg^{-1})	40		Harris et al. [80]

Table 1.
Different types of indicators used for different countries.

3. Comprehensive machine learning models in agriculture

Ml is a technology that aims to build an intelligent model that makes an accurate prediction without the intervention of human beings. The conventional machine learning approach depicted in **Figure 1**. It constructs various algorithms to make effective decisions in the problem domain. The primary step is to select the data on the problem under investigation and to select the parameters for the examination. The model is trained by a sample set of data (termed as training data) to gain experience in the environment and make the model fit. Later, the model evaluated using a sample set of data (termed as test data). So this is the primary step involved in any machine learning model, i.e., Train-Test-Predict. Usually, the data set was divided into two viz., training (70%) and testing (30%). Testing data is kept separate and not used in the preparation. The conventional machine learning approach depicted in **Figure 9**.

The dataset with many alternatives is collected and pre-processed using any normalisation or standardisation methods. The pre-processed data set was divided as train and test data set. The machine algorithms take the train data as input to train the model or to learn for the historical information. The trained model is evaluated with test data. The data visualisation tools are used for visualising the prediction or classification results. Algorithms involved in machine learning are supervised and unsupervised learning. In supervised learning, the model is trained with input data and mapped it into the known results whereas, in unsupervised learning, the model is trained, validated with input data and finds all type of unknown patterns.

The most familiar learning models that fall under these two categories are clustering, regression, classification, and dimensionality reduction. Machine learning utilises a secondary dataset (termed as validation data) for training the model further to avoid the overfitting of the model by the trained data. If the model generates more error on validation data, that means the model overfitted with the prepared data so that training stopped. Now the data split can be done like 60, 10, and 30 per cent of training, validation, and testing, respectively. Machine learning employed in almost all scientific applications such as health care, home automation, smart city, robotics, aquaculture, digital marketing, financial solutions, enterprises, climatology, food safety, agriculture, and more.

As Agriculture forms the major economy for most of the countries, better assistance speeding up each stage of agricultural crop production is mandatory. ML and the Internet of Things (IoT) serve this platform more effectively. IoT devices such as sensors, actuators through wireless communication protocols continuously monitor the crop, soil, water and communicate their health to remote devices either by message or log data or buzzer to alert the agriculturalist to take necessary actions. The data from these devices will make meaningful predictions and recommendations to the user exclusively farmers through machine learning algorithms.

Machine learning models trained by the historical data of the agricultural field through which it gains experience and makes wise decisions for the data signals received from the IoT devices. The data collected from these IoT devices must be secured and ensure confidentiality for accurate prediction results. Precision Agriculture is a strategy adopted to integrate heterogeneous information (Spatio-temporal data) for making precise and effective managerial decisions for global sustainable agricultural practices. Most of the parts of our country are adopting this strategy to improvise agrarian production in a brief span. Application of machine learning in precision agriculture has reshaped the plan such as field-based crop suggestion, fertiliser recommendation, water supply prediction, harvest prediction, thereby controlling the water usage by assisting the agriculturalists or farmers for better yield in a smart way.

Digital agriculture (a term coined by use of Precision Agriculture and Remote sensing) evolved to increase agricultural productivity with a minimised impact on environmental factors. Digital agriculture uses the data (crop, soil, and weather) sensed from the IoT devices to make effective decisions on nutrient demand-based fertiliser recommendation, water supply through proper irrigation, soil nourishment, pest or weed control, and crop protection from intruders. Digital agriculture focuses on the best-of-breed optimisation algorithms fro crop production and its protection during growth. Multi-cropping is a technique adopted in Digital agriculture or smart farming, which allows the cultivation of more than one crop in a single cultivable land.

Digital agriculture has to take more precautionary steps while feeding these different crops with weeds and fertilisers as the mixed plant has a different nutritional requirement and water supply. So it takes into account inter-variability and intra-variability among the crops before feeding the fertilisers. It adopts the techniques like in-row treatment to spray fertiliser for each plant separately, sensor-equipped drones to track the weed, automated sensing of fertiliser details from the barcode label for a correct proportionate mix of pesticides, drift reduction techniques and integration of these applications with global positioning system and comprehensive information system for periodic relay to the agriculturalists.

The application of Machine learning in different stages of agricultural crop production are depicted in **Figure 10**. The necessary steps involved in crop cultivation are Land suitability analysis, appropriate crop selection, crop production, crop protection, nutrient supply, water supply, crop health monitoring (pest and weed control), human and animal attack detection, yield management, and post-harvesting.

Although these steps are common for all types of crops, soil nourishment value and chemical composition determine the techniques adopted in each level. Also,

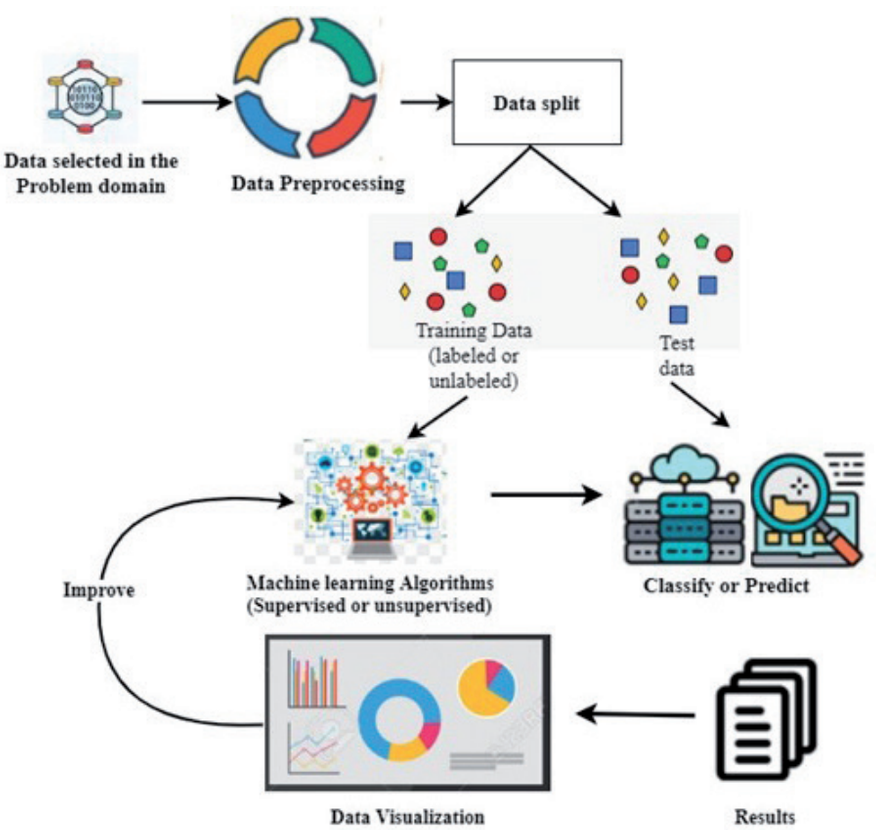


Figure 10.
Machine learning approach.

this paves a significant consideration of fertiliser supply when multi-cropping is selected. This multi-cropping technique has been in evolution decades back and done explicitly in the hill areas with meagre farming areas yielding better productivity.

3.1 Machine learning in land suitability analysis

Land suitability analysis has done for any barren land before permitting any residential plots to be constructed on that land. By ensuring better land use analysis, most of the agricultural land not converted into residential buildings or industrial areas. It will reduce the cultivable land area and air pollution. Cultivating a crop without suitability analysis may lead to an enormous waste of time, more fertiliser supply, abnormal and water requirements. Therefore, Land suitability analysis for the cultivation of crops is an essential factor in ensuring sustainable agriculture yielding better production. Geographic Information System (G.I.S.) provides more significant support in aiding the suitability analysis of the land. Multiple factors considered for analysing the land suitability attained from advanced G.I.S. systems. Some of the factors considered for land suitability analysis are soil quality parameters (pH, organic carbon content, salinity, texture, slope), topography, water availability, essential nutrients, socio-economic factors.

Mokkaram et al. have implemented an ensemble classifier method, namely RotBoost, an integration of Rotation forest and AdaBoost algorithms for land suitability analysis. Benjamin et al. have assessed the suitability of land for cultivation of a different variety of rice crops in rural Thailand using species presence only prediction method. They proved that the MaxEnt model outperforms and provides better crop suitability on particular land. A land with a higher suitability index for the cultivation of a crop selected for farming. Support Vector Machines (SVM) preferred for classifying the suitable area for agriculture of rainfed wheat based on thirteen factors relating to property, topography, climate, and soil.

Senagi et al. have applied Parallel Random Forest (PRF), SVM, Linear Regression (L.R.), K.N.N., Linear Discriminant Analysis (LDA), and Gaussian-Naïve Bayesian to ensure the land suitability for sorghum crop cultivation. PRF provides better accuracy than others when evaluated using ten cross-fold validation. One of the most important attributes that contribute to suitability analysis is soil quality. The moisture content in the soil helps to determine the suitability of growing a particular crop in a land. Typically the dryness or wetness level of the earth can be determined by considering the same at other locations, which has similar soil type and hydroclimate.

Coopersmith et al. recommend that land suitability analysis will be more accurate in the sandier soil (with more drainage) than poorly drained soils. They have used K.N.N., Boosted perceptron, and classification tree for soil dryness estimate at a site in Urbana. Perhaps, K.N.N. shows best results than Boosted Perceptron when evaluated with farmer's assessments. Soil fertility levels should be periodically monitored and maintained at appropriate levels for the continuous nourishment of crop production in agricultural land. Gholab applied the decision tree classification model for building the predictive model. All these approaches use the data obtained through remote sensing and IoT devices. A better understanding of the land suitability of the agricultural field under consideration will assist in selecting suitable crops as well as supplying fertiliser to make it better nourished for growing the required plants. It followed by crop production, water supply, and Nutrient management.

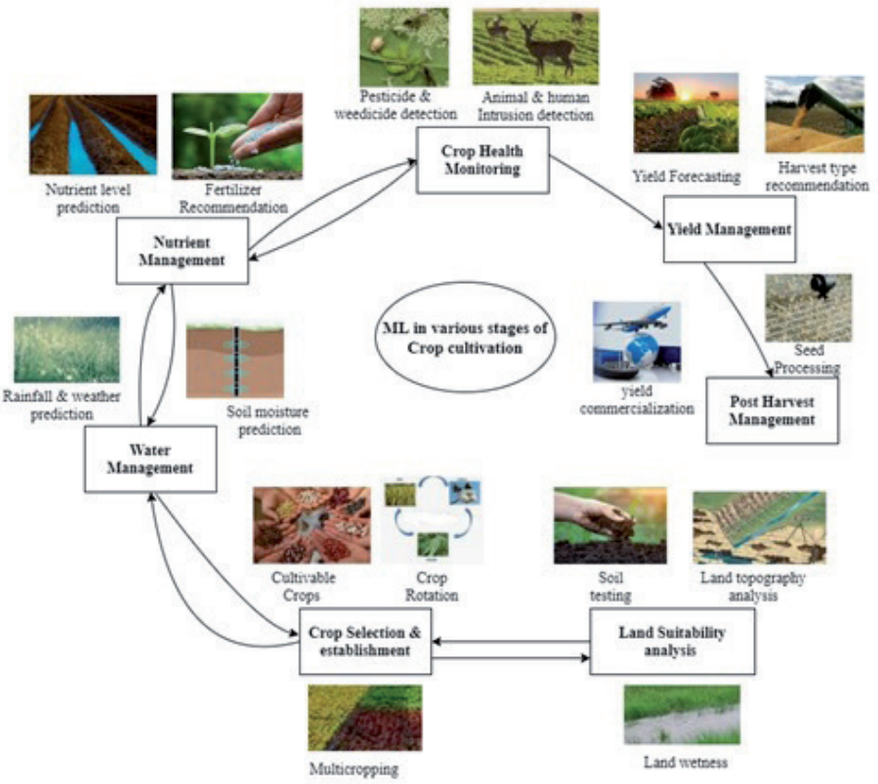


Figure 11.
Machine learning in agricultural crop cultivation.

3.2 Machine learning in crop production

Crop Production and management include crop selection, soil preparation based on suitability analysis, sowing seeds, application of manure & fertiliser, water management through proper irrigation mechanisms, and harvesting. Machine learning in agriculture crop production links various participants in the food chain or agricultural chain. Machine learning helps the agriculturalists in making better decisions in crop quality determination, yield prediction, plant species determination, crop disease prediction, and harvesting techniques (**Figure 11**).

The machine learning algorithms data acquired from IoT sensors in the agricultural field. Once the data feed, ML algorithms train the model using history and can make predictions at any stage of production to determine the different features required to predict the yield. It will help to improve the nutritional value (if deficient in the current return predicted) in the next production. Consequently, the crop production price will show a dramatic improvement in the upcoming yield. Application of A.I. in agriculture will enable the farmers to get up to minute information about current production, suggestions on next production, plant species identification, and quality improvement.

Once Land suitability analysis for cultivation is done, crop species selection has to be done based on suitability. Based on the nourishing factor in the soil and nutrient capability, a crop can be selected appropriately. Multi-criteria decision-making models used to get land suitability analysis. Image processing techniques integrated with machine learning suggested for plant species identification for the given crop image. Patil et al. analysed the various ML techniques used for crop selection based on environmental parameters and live market. They have used the K.N.N. classifier for the data obtained through multiple IoT sensors and prices based on entries in National Commodity and Derivative Exchange.

Land specific yield prediction by considering Crop yield prediction using topological algorithms like ANN, backpropagation, and Multi-layered perceptron through the implementation of a neural network. Support vector regression (S.V.R.) a variant of SVM used for crop yield prediction. As nitrogen is an essential component for photosynthesis, nitrogen management is mandatory as the yield prediction. The various decision support systems provide agricultural decisions, the agriculturalist has to deal with enormous heterogeneous data for making wise decisions, so Machine learning plays a vital role. Chlingaryan et al., 2018 have analysed the various ML approaches and signal processing methods used for crop yield prediction and optimised techniques for nitrogen management. They reviewed that B.P.N.N. provides best accurate crop yield estimation (by considering the importance of vegetative indices), CNN with Gaussian Process is best for feature extraction, best Multi-class crop estimation by M5 Prime R.T., Least Squares SVM for Nitrogen management and Fuzzy cognitive map for representing the expert's opinion.

A comparative analysis of ML algorithms M5-Prime, K.N.N., S.V.R., ANN, and Multi-linear regression model was carried out on prediction of crop yield and suggested that M5-Prime outperforms others followed by K.N.N., S.V.R., ANN, and the last Multi-Linear Regression. It was evaluated based on the accuracy metrics (Normalised Mean Absolute Error, Root Relative Squared Error, Root mean square error, and Correlation Factor). Corn yield prediction predicted by Back Propagation Neural Network whose efficiency tested on green vegetation index, Normalised Difference Vegetation Index, perpendicular vegetation index, and soil adjusted vegetation index. Also, Deepa learning showed the most stable results on corn yield prediction at the particular region (Iowa state) when compared with Estimated Randomised Trees, Random Forest, and SVM. Deepa learning overcomes the overfitting problem prevalent in most of the ML algorithms.

One or more stages of crop cultivation will give information to other steps and vice versa. Depending on soil test results done during land suitability and crop health monitoring, the fertilisers will be recommended. Consequently, water and nutrient management carried out. The ML approaches work best for fertiliser recommendation. Water management is M.L.P. neural network with Backpropagation algorithm based on soil nutrient content, Gradient boosting and Random forest for soil nutrient assessment and Multivariate Relevance Vector Machine and Multilayer Perceptron for estimating the water requirement based on evapotranspiration and climatic data. Periodic Drought assessment is essential for crop maintenance and water management. Machine learning approaches used for drought assessment are Random Forest, Cubist, boosted regression trees, support vector regression, coupled wavelet ANNs, and ANN. Drought assessment is done based on the drought factors (land surface-related) and drought index.

3.3 Machine learning in crop protection

Crop protection implies the protection of crops from weeds (unwanted plants that grow in the land), pests (insects, bugs), and intruders (an animal which intends to graze the crops and human for theft). K-Means clustering, Support vector machines, and Neural networks are more prominent machine learning techniques employed in Precision Agriculture for crop protection. The weeds may cause a significant loss to the crop yield. Weedicides are applied (weeding) before the crop seeding stage and flowering stage. The weedicides, instead of any common herbicide, have to be explicitly asked to avoid the devastation of the desirable

crop in the field. Accurate detection of weeds is more significant and done using Machine learning algorithms integrated with sensor data.

One of the most undesirable weeds, which causes a significant loss to crop and very difficult to detect and abolish, is Silabynum marianum. Pantazi XE et al., have suggested a weed detection method by multispectral imagery obtained through a camera mounted on Unmanned Aircraft Vehicle (UAV) using Counter Propagation ANN, XY-Fusion Network and Supervised Kohonen Network (S.F.N.) to detect Silabynum marianum from other crops. Furthermore, a weed detection system that accurately classifies the weeds was designed based on hyperspectral images through the camera mounted on a robot using an active learning machine learning model. This model designed using a class neural network classifier (one class mixture of Gaussians) for novelty detection and one self-organising class map. This active learning model provides 100% accuracy on the classification of the crop, whereas different weed species detection accuracy varied from 34 to 98%.

The different weed species detected using this model are *Taraxacum officinale*, *Ranunculus repens*, *Poa annua*, *Cirsium arvense*, *Stellaria media*, *Urtica dioica*, *Sinapis arvensis*, *Oxalis europaea*, *Polygonum persicaria*, and *Medicago lupulina*. The model outperformed when compared with the autoencoder network and one-class SVM classifiers. Some of the other weeds detected through images from cameras on UAV using machine learning techniques are: identification of broadleaf and grass from soybean using Convolution Neural Network (CNN) in comparison with SVM, Random Forest and Adaboost; weeds classified in sugarbeet fields with sugarbeet shape features using SVM and ANN are Pigweed, Turnip weed, Lambsquarters and Hare' s-ear mustard.

Some pests may infect weeds, and that might be contagious to the crops, so pest detection is one of the essential stages in crop protection. Thus weeds serve as hosts for pests and diseases consuming all the resources supplied to the plants. It is done using machine learning algorithms and followed by the recommendation of pesticides for pests. The images acquired through the optical sensors attached to UAV help in detecting the pests. CNN provides better results in this classification of pests from images. D. C. Corrales et al. have suggested a list of supervised machine learning algorithms used for crop protection in terms of diseases and pests. The are SVM, K.N.N., ANN, Decision trees, and Bayesian Network. Decision trees, SVN, and ANN, are best for prediction and classification of pests, whereas Bayesian Networks and K.N.N. are excellent in training. These pests have a devastating effect on the crop storage, precautionary measures taken by identifying the categories of pests and their nature of the occurrence. Crop Image analysis used to categorise the type of pests using computer vision.

Cheng et al., have implemented a deep residual learning model for classifying the pest image and it outperforms the Back-Propagation Neural Network and SVM in the accuracy of the pest image recognition. Also, it provides better performance than deep CNN (Alexnet). Tomato Whitefly classification using deep CNN, Paddy crop pests classification using deep CNN [84] and banana pest and disease detection using deep CNN are some of the successful CNN based crop pest classification models outperforming the traditional approaches. Therefore integration Image processing or computer vision and machine learning CNN algorithms provide the best classification of crop pests and diseases.

Animal intrusion detection is one of the threats to the agricultural crop. These intrusions identified and detected to avoid loss of crop production. IoT sensors provide periodic alerts on the detection of an animal object like rats, cow, sheep, elephant, and other wild animals. It can be detected effectively and prevented through wireless sensors alerts to farmers mobile and machine learning algorithms

can be used for object classification. Also, Machine learning algorithms used to predict the animal or human object entry apriori by training the model with past data from IoT sensors.

3.4 Machine learning in livestock management

Livestock management is essential for animal husbandry, and wellbeing of rural people as this frames a significant economic factor for rural beings and sustainable agricultural practices. Livestock species used for varied purposes such as employment for the community, food supply, nourishing the family nutrition, significant income to few families, soil enrichment, believed ritual events. Livestock management includes vaccination for cattle species, health monitoring of livestock, managing livestock during drought, feed schedule, grazing, milk quality management, ketosis for dairy animals, ear tagging, production, and castration. The machine learning approaches used for animal welfare are Bagging with decision trees for classification of cattle behaviour-based features like grazing, walking, sleeping, ruminating, classification of chewing patterns in calf using decision tree/C4.5 based on chewing signals while dieting ryegrass, supplements, hay, rumination and during sleep, behavioural changes monitoring and tracking of pigs using Gaussian Mixture Model based on 3D motion information, ANN for determination of rumen fermentation, CNN for face recognition of pigs, estimation of beef's carcass weight using S.V.R. models, SVM models for early evaluation of egg production in hen and bovine weight estimation in cattle.

3.5 Considered machine learning approaches for agriculture

Several machine learning approaches have become popular for achieving superior and precision agriculture [85, 86]. The following sub-section discusses certain machine learning approaches that have been deployed for achieving enhanced agricultural benefits. In the perspective of machine learning, supervised learning is a phenomenon that encompasses both the input and the sought after target values. Besides, both the input and target data are in labelled form, which offers a learning platform for processing data in the future. Further, when this model is offered a new test dataset (with a similar background) since the model is already trained, it generates the accurate output for the test data. Kaur et al. review the scheme of plant disease diagnosis and taxonomy employing leaf images with the aid of computer vision technologies [87].

3.5.1 Belief Networks

Belief Networks also referred to as Bayesian Networks, are probabilistic graphical models, which are utilised for building models from data or through specialists' outlook. Further, these networks can be a beneficial approach for evaluation and effective decision-making process in the case of agrarian problems. The Belief Networks are built using the Bayes theorem, which in turn supports in computing the input data's posterior likelihood. Belief Networks are more suitable for agrarian applications owing to their capability to reason with inadequate data, and further, they also add new evidence data. Further, Aguilera et al., [88] evaluate the quality of the groundwater by deploying the probabilistic clustering supported by the hybrid Bayesian networks via Mixtures of Truncated Exponentials. Huang et al. [89] established a Bayesian driven averaging technique for offering a trustworthy forecast of maise yields in China. Besides, Cornet et al. [90] established a Bayesian network model for identifying the initial growth and yam yield interactions.

Zhu et al. [91] established the Bayesian networks based model to characterise the connections between the symptoms and harvest maladies. De Rainville et al. [92] devised the naive-Bayesian classifier combined with the Gaussian mixture clustering approach for classifying the weeds from the actual row crops. Stanaway et al. [93] discussed the hierarchical Bayesian framework for the early diagnosis of exotic plant pests attacks and infectious plant diseases. Russo et al. [94] established a Bayesian model for estimating the hydrologic characteristics and irrigation needs in order to devise a sustainable water management scheme for the agrarian lands in Punjab, India.

3.5.2 Classification and regression trees

The classification and regression trees (CART) are usually referred to as decision trees. Besides, they act as a decision support tool, which deploys a tree-like graph or a decision model and their probable consequences. In a decision tree, each internal node signifies a test on a feature, each branch characterises a result of the test, and each terminal node embraces a class label. There are several applications of the decision tree in agriculture, such as disease diagnosis and classification, crop monitoring and weed classification. Waheed et al. [95] devised a CART algorithm for categorising hyper-spectral information of the corn plots into different classes based on water stress, weeds' existence, and nitrogen application rates. Xueli Liu et al. [96] established a decision tree model for assessing grain loss due to various factors involved in grain storage. Bosma et al. [97] discussed the decision tree model for estimating and modelling the decision-making process of the agriculturists on assimilating aquaculture into agronomy in Vietnam. Moonjun et al. [98] concerted on deploying the G.I.S. assisted decision tree and artificial neural network-based model for assessing the landscape-soil relationship in inaccessible areas of Thailand. Kim et al. [99] established the decision-tree assisted model combined with the geographical information system for forecasting and mapping the variety of bacteria in the soil. Rossi Neto et al. [100] elucidated a decision tree-based approach for categorising the biometric attributes with the highest impact on the sugarcane productivity under the distinct arrangement of plants and edaphoclimatic settings.

3.5.3 Connectionist systems

Connectionist systems also referred to as an artificial neuron network (ANN) is a computation based archetypal relying on the structure and functions of the human brain. Moreover, the connectionist systems are known to possess the neurons that are interconnected to one another in numerous layers of the networks. Also, such neurons are referred to as nodes. Connectionist systems consist of input and output layers, as well as a hidden layer comprising of units, which converts the input into unique values that the output layer can use. Besides, such systems are exceptional methods for determining complicated patterns. Also, brain-inspired systems have an arithmetical value that can accomplish more than one task, concurrently. Priyanka et al. [101] discussed the deployment of the neural networks combined with satellite imageries for monitoring crops and also for estimating the agricultural produce. Daniel et al. [102] established a review on ANN modelling for Agroecology application. Jha et al. [103] investigated various the usage of ANN/Artificial intelligence techniques combined with the internet of things and wireless systems for classifying plants and flowers, in order to accomplish sustainable development in the agricultural domain. Kaul et al. [104] deliberated about the deployment of the ANN models for forecasting the corn and soybean produces

under distinctive climatic settings in Maryland, U.S.A. Thomas et al. deployed the multilayer neural networks along with genetic algorithms for detecting the viruses in plants via data collected using biosensors. Were et al. [105] employed the ANN approach for forecasting and mapping soil organic carbon stocks in Kenya. Besides, this model was validated by means of independent testing data. Nahvi et al. [106] deployed a self-adaptive evolutionary model for forecasting the everyday temperatures of the soil, at six diverse depths and validated the results through genetic programming and ANN models.

3.5.4 Random forest

Random forests (R.F.) algorithm is a supervised learning approach that is deployed for real-world or simulated applications (both classification and regression problems). Besides, it is similar to the bootstrapping algorithm combined with the CART model. Moreover, in this algorithm, the decision trees on data samples get created, followed by the forecast from each of these trees, and lastly, chooses the best solution via voting. Further, it is an ensemble technique that performs superior to a solitary decision tree, since it lessens the over-fitting by averaging the outcome. Fukuda et al. [107] devised an R.F. model for forecasting the yield of the mangoes in retort to the supply of the water in diverse irrigation systems. Philibert et al. [108] designed an R.F. model for forecasting the N2O discharge depending on local data for ranking environmental and crop management attributes. Further, they also established the impact of these attributes on N2O emission. Rhee et al. [109] elucidated an RF-based high-resolution drought estimation system for ungauged expenses by deploying the long-range climate estimation and remote sensing information. Inacio et al. [110] developed a system for identifying weeds in sugarcane fields by deploying the Unmanned Aerial Vehicle for capturing images and later classifying these images via an RF-based classification scheme. Saussure et al. [111] demonstrated the harms caused in maise crops due to wireworms in several agricultural fields across France. Besides, they deployed the R.F. technique for imputing the missing values. Everingham et al. [112] devised an R.F. model for categorising the different types of sugarcane and crop cycle with the aid of imagery acquired via hyperspectral sensors.

3.5.5 Support vector machine approach

A support vector machine (SVM) is a comprehensive supervised learning approach, which is generally deployed for mostly solving two-class categorisation problems. Besides, the SVM can also be utilised for analysing the data for classification and regression scenarios. Further, SVM employs the kernel phenomenon for transforming the data and then depending upon these transformations; it determines an optimal borderline among the likely outcomes. Moreover, the decision boundary between the two classes on a graph needs to be widespread. SVM builds an optimal borderline that splits the new data point and assigns it to the correct category. Therefore, this optimal borderline is also known as the hyperplane. Misra et al. [113] investigated the deployment of SVM techniques for stimulating run-off and sediment produces from the watersheds, via the support of the monsoon-period information. Kovačević et al. [114] developed an SVM model for classifying soil types based on the assessment of the physical and chemical characteristics of the soil. Huang et al. [115] devised a machine vision-driven SVM system for diagnosing the borer diseases in the sugarcane plant. Kawamura et al. [116] devised an SVM model for classifying the diverse inflorescence types by making use of an artificial

dataset. Liu et al. [84] developed an SVM-based system for classifying the urban soil based on quality attributes, such as the soil toxicity due to heavy-metals, soil richness, and potency. Singh et al. [11] reviewed the deployment of SVM based model for the assessment of the plants undergoing high-throughput stress phenol-typing, with the aid of sensors.

4. Conclusions

In this chapter, smart sensor-based approaches are presented for precision agriculture. The use of remote sensors like temperature, humidity, soil moisture, water level sensors and pH value, will provide an idea to on productive farming, which will show accuracy as well as practical agriculture to deal with challenges in the field. This advancement could empower agricultural management systems to handle farm data in an orchestrated manner and increase the agribusiness by formulating effective strategies. The evolutions of Machine Learning (ML) and the Internet of Things (IoT) established methods offered to help researchers to implement these methods in agriculture to support farmers. These will support farmers to improve throughput, effective utilisation of field and manage pests. This paper presents to contribute to an overview of the modern sensor technologies deployed to precision agriculture and suggests an abstract of the present and essential applications and presents the challenges and feasible solutions and applications.

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