AGRICULTURE EQUIPMENT'S AND SMART TECHNOLOGY

Abstract

Agricultural production food crops involve every aspect of cultivation, harvesting, processing, storage, and transportation are included in. Agricultural inputs including labor, water, arable land, and other resources (such as energy, fertilizer, etc.) are crucial for agricultural productivity and are significantly affected by the type and scope of farming techniques. agriculture production provides locals with considerable employment possibilities, food security, and opportunities for economic growth in many developing nations. To improve crop yields, efficiency, and sustainability, modernization, automatization, precession in agricultural operation is needed. Smart agriculture and precise agriculture are only getting started, but they might pave the way for far larger use of technology in the farming environment. Technological advancement, IoT development, and mobile application have all contributed considerably to the acceptability of technology in agriculture. The employment of computers, software, sensors, and other information technology in smart farming techniques and methodology can be linked to technological advancement. Evidently, smart farming is a creative agricultural approach that, when implemented correctly, may assist farmers in achieving an array of benefits including increased yield, enhanced quality, and lower costs.

Keywords: Agriculture Equipment, Smart Technology, Precision agriculture, AIoT, Soil management.

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Nomenclature

ANN	Artificial Neural Networks	**IOT**	Internet Of Things
SOM-NN	Self-Organised Map Neural Network	**AIOT**	Agricultural Internet Of Things
CNN	Convolutional Neural Network	**FMS**	Farm Machinery Systems
RGB	Red Green Blue	**ML**	Machine Learning
ENN	Extension Neural Network	**DL**	Deep Learning
AI	Artificial Intelligence	**IP**	Image Processing
UGV	Unmanned Ground Vehicles	**PSI**	Plant Species Identification
UAV	Unmanned Arial Vehicles	**GPS**	Geological Positioning System
RMS	Root Mean Square	**GIS**	Geographical Information System
CHT	Circular Hough Transformation	**IT**	Information Technology
IOU	Intersection Of Union	**WC**	Wireless Communication
SAE-ELM	Self-Adaptive Evolutionary Extreme Learning Machine		

I. INTRODUCTION

Sowing, planting, irrigation, fertilizer spraying, harvesting, and other traditional agricultural techniques have seen considerable advancements as a result of engineering research. However, in order to further enhance our economic status, we must increase agriculture quality and productivity. Agriculture is now facing a workforce shortage. Farmers prefer to use reaper harvesters due of shortage. These reapers are costly and only available for a large-scale field. (Bhabad *et al.*2017).

In practical scenario, diseases were not detected by farmers due to the absence of information and the lack of a local expert. The integration of digital technologies and focused on the future technologies for usage as smart object are the most basic criteria for agricultural progress. (Keller et al., 2014)

Mechanization is the replacement of mechanical energy for biological energy at different phases of the manufacturing process. In the agriculture, mechanization refers to employ suitable machinery to speed up the completion of field tasks and the proper use of numerous agricultural inputs. In other words, appropriate tools and implements, equipment for agriculture, combines, pumping systems and other equipment are introduced at a proper level. (Sarkar, A. 2020).

Mechanization of farms in India is at 40%-45%, which still appears lower when compared to countries such as the United States (95%), Brazil (75%), and China (57%). Although mechanization lags behind a number of other developed countries, it has made remarkable development in the last decade. Agricultural electricity availability on Indian farms grew from 1.47 kW/ha in 2005-06 to 2.02 kW/ha in 2013-14. (Anonymous 2014).

Farm Management Systems (FMSs) are critical for achieving advanced operational farm activities because they include features for planning, coordinating, monitoring, and regulating agricultural activities.

In present FMSs typically depend on specific models, and their functions do not go beyond agricultural data monitoring and the distribution of selected control services via standalone applications that are tightly associated with each system because they consist of closed specifications for commercial infrastructures and address specifically selected clients.

This imposes major limits on the FMSs' interoperability as well as the semantic labeling of the myriad varied agricultural data that they must handle. FMSs should be capable of improving the performance of these tasks in the area of sustainability.

- At reduced costs, carry out efficient and interactive automated agricultural activities (such as cultivation, monitoring, irrigation, and so on) in complicated surroundings and farm structures.
- Ensure effective and secure working circumstances for the environment as well as agricultural stakeholders (such as farmers, agronomic engineers, policymakers, development cooperation experts, and so on).
- Increase synergies among all agricultural stakeholders, allowing them to make choices on issues that are outside their areas of competence.

These goals can be met by promoting a comprehensive approach to from end-to-end farm management, which is based on the coordinated internal and external relationship of technologies as well as farming infrastructures, processes, and applications in an intelligent digitalized the surroundings, in the context of Agriculture's cutting-edge trend. 4.0

Furthermore, data-driven farm management might be used to alleviate production issues. To boost efficiency, data management is required for data/information analysis. This technique illustrates how robots are going to play a major role in farming's future growth. (Saiz-Rubio & Rovira-Ma´s, 2020)

Precision agriculture is "the use of current technological innovations to process, and evaluate multi-source data of high regional and temporal resolution for the purpose of making decisions and operations in farming and crop management." This precision agriculture may result in increased yields of crops, soil degradation, enhanced water use, a reduction in the volume of chemical pesticides and fertilizers used in cultivation, and the adoption of modern farming practices that enhance crop quality, quantity, and cost. The purpose of incorporating Agriculture IoT solutions is to aid farmers in bridging the supply-demand mismatch, which may be done by ensuring high yields, increasing earnings, and protecting the environment.

Precision agriculture refers to techniques that leverage Internet of Things (IoT) technology to ensure effective use of existing resources, with the objective of boosting agricultural output while decreasing operational costs. The IOT has a multitude of applications in precision agriculture, but the most significant among them are crop sowing, crop management of water, management and controlling of insects, precise detection and nutrients management, yield monitoring, and safe storage management. All of the measurements may be obtained using sensors, and the data is subsequently stored in the cloud or on a server connected to the network for further processing, as shown in Figure 1. The modification of sensors over time highlights the advances achieved in the measurement of a wide range of characteristics, which includes temperature, pH, humidity, and analytical data like potassium, phosphorous, and nitrogen readings from a remote site. Temperature, pH, and humidity are examples of all of these variables.

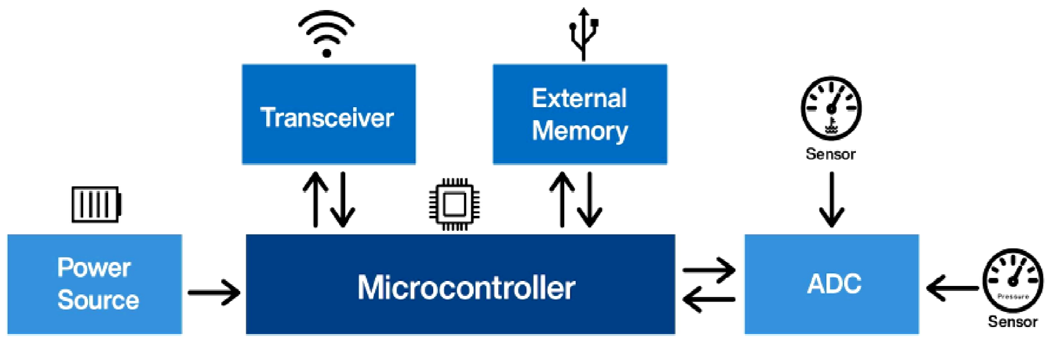

Figure 1: Historical progression of sensor

Agriculture contributes significantly to India's total economy. More than 70% of the rural population relies solely on agricultural earnings for financial security. It employs more than 60 percent of the entire population and provides around 17 percent of the country's overall gross domestic output. From several years, India's agricultural sector has grown at an astounding rate. On the other hand, the reality is that a lot of farmers in India are committing suicide which is quite concerning. Farmers gave them the following reasons for taking their own lives, in order of importance: financial obligations, environment, low food prices, bad irrigation, increased agricultural expenditures, the usage of chemical fertilizers, and failure of crops.

Intuition and other irrelevant problems, such as the need to provide immediate earnings, a lack of demand from the market knowledge, overestimating a soil's capacity for sustaining a particular crop, and so on, have a tendency to cover up a farmer's decision of which crop to grow. This makes the decision challenging for the farmer to choose. An important task that must be completed as soon as possible is the development of a system that can offer Indian farmers with predictive insights and assist them in making accurate choices about what and how to cultivate in order to increase production.

This project must be completed as soon as possible. As a result, there is a growing demand for "smart farming," which is made possible by the IoT. By examining sensor data, farming operations become more transparent, allowing farmers to get critical insights about the well-being of their crops, greenhouses for cultivation, and other facilities. Farming driven by machine learning and employing high-accuracy algorithms is a revolutionary concept that is gaining favour in today's culture. This unique effort makes sustainable product development feasible for everyone involved in the agriculture business. This movement aims to boost both the number and quality of farm goods already cultivated in the fields.

Precision farming and land management, as well as scientific findings from observation of the earth and climate change research, and cutting-edge technologies such as image processing, geographic information systems (GIS), and unmanned aerial vehicles (UAVs), would all help to improve the production of agricultural goods. Farmers may get crop and market information through digital agriculture, which uses information and communication technologies. (Costa et al., 2011).

Geo Farmer is a project tracking and feedback platform for agricultural innovation. Farmers can communicate their positive and negative experiences with one another as well as with professionals (Eitzinger et al., 2019). As shown in Fig. 2, the traditional way of agricultural farming may be changed into smart agriculture by making the necessary modifications to the current method.

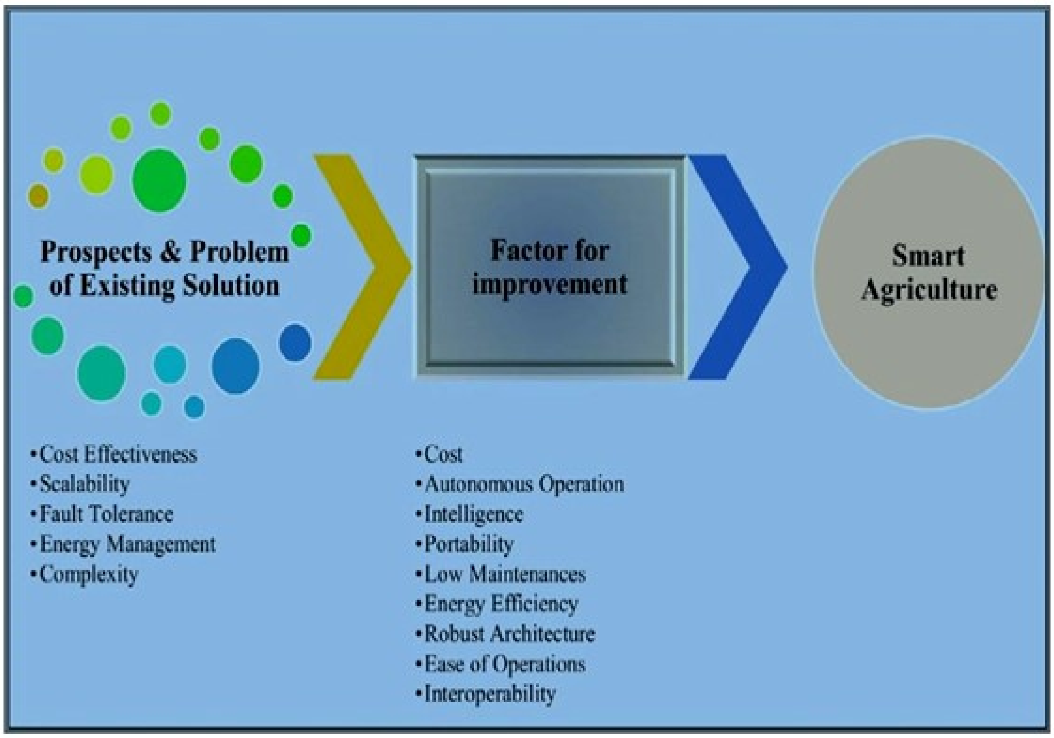

Figure 2: The transformation of traditional agriculture to smart agriculture practice

Unfortunately, farmers who are orthodox doesn't practice modern innovations and food supply systems have a low rate of productivity. Where others produce yields that are much lower than their potential (Kumar & Ilango, 2018). Modern technology can play a critical part in overcoming these issues and bringing about a revolution in the agricultural industry. (Timalsina, 2019).

II. SMART TECHNOLOGIES AVAILABLE IN AGRICULTURAL FIELDS

1. **Agricultural Internet of Things (AIoT):** The IoT is vast network connected to individual objects that are connected using industry-standard protocols like the Internet. Due to the virtual object representations on the Internet that combine relevant information with actual objects, it serves as a storage and communication infrastructure. In this situation, computer programmes function as central information hubs for objects, continuously updating and combining data from many sources to carry out any required tasks remotely over the Internet (Botta *et al.* 2016).

Industry 4.0 and Agriculture 4.0 will connect physical and virtual objects to intelligent networks. By the idea, the virtual object is inextricably linked to the IoT, which can be expressed by specific characteristics in both the agricultural and industrial sectors, such as heterogeneity due to an extensive range of gadgets, interrelationships a high degree of adaptability, object-related services, and, finally, dynamic changes because the state of a device may shift continuously at any moment (Lakhwani *et al.* 2018).

Agriculture 4.0 guidelines state that the AIoT offers a promising framework for the collection, processing, management, and transmission of a variety of farm data as well as a means for the seamless integration of a number of systems and services into FMSs (Ma J *et al.* 2012). Such systems can:

- Handle a variety of data that is incomplete and, in some situations, conflicting;
- Real-time data acquisition, correlation, and fusion
- Change network behavior dynamically to vary data gathering,

Employ diffuse cognitive ability and multi-agent technologies that enable particular system locations to evaluate, function, and interact within a communal structure while acknowledging the contemporaneous involvement of both an individual and a communal goal.

2. **Artificial Intelligence (AI) and Machine Learning (ML):** Due to uncertainty surrounding several agricultural activities like sowing, intercultivation, plant protection, irrigation and drainage and storage agriculture faces a number of challenges. AI and ML techniques create the systems that are capable of carrying out knowledge-based tasks that require deft judgements and unstructured commands in order to facilitate effective risk management, reduce prediction costs associated with making decisions, and ultimately improve the accuracy and efficiency of intelligent agriculture (Rieder and Patrcio, 2018).

   Multiple feature selection procedures, including as clustering and classification of heterogeneous data in agriculture. With the aim of combining and aggregating data from various supplied heterogeneous sensors (such as those used in agricultural farms), data fusion methods for classification in particular can be widely applied in multisensory environments.

3. **Agricultural Robotic and Autonomous Systems:** Robotics and autonomous machinery are inherently complex since they are made up of numerous interconnected subsystems that must work in harmony to carry out tasks flawlessly as an entire and effectively communicate any data that is required. The timing and length of accounting cycles, as well as the communication patterns between all subsystems, depend on this kind of integration [45]. These Systems are more complex and sophisticated because they must function in unstructured agricultural conditions in order to reduce farmer workload, increase production rates, improve soil health as well as the quality of yields, and manage resources. These tasks include the planting process, trimming, phenotyping, intended fertilising, harvesting, and sorting in autonomous or nearly autonomous modes. (Reiser *et al.* 2019)

The major challenges that must be addressed in order to effectively incorporate robotic technology into agricultural operations:

- To achieve success, it is necessary to make advancements in suitable machinery and intelligent mechanisms. Issues like the variable output and environment of agriculture, as well as difficult conditions (such as dust, vibration, extreme temperatures, and humidity), must be overcome.
- To be fit for functioning unattended in open fields, autonomous systems must overcome inherent safety and dependability challenges, as safeguarding persons, the environment, crops, and machinery is still required today.

III. APPLICATION OF IMAGE PROCESSING (IP) IN AGRICULTURE

Agriculture processing images represents a key advancement in agricultural modernization. IP is a method for improving images or getting useful information out of them. For boosting productivity and satisfying global agricultural demand, IP is a well-established technique in agriculture. In order to diagnose agricultural diseases, weeds, and land mapping, IP utilising different spectrum measurements, such as infrared and hyperspectral X-ray imaging, is helpful. This may help farmers save money and time. Finding crop diseases early on can help farmers treat infections and stop them from spreading to the entire crop. Introducing image-processing technology into contemporary agriculture will increase agricultural productivity to satisfy market demands and provide farmers with timely updates via a variety of automated agricultural applications. The paragraph that follows explains and examines the various specialized uses of processing of images in the agriculture sector (Feng et al., 2018).

1. **Plant Disease Identification:** IP is commonly utilized for identifying plant diseases in a variety of agricultural crops. Farmers confront significant dangers as a result of the growth of numerous pests and diseases in crops. Some of the most prevalent causes of illness infections are fungi, bacteria, viruses, and nematodes. Most infections were previously not identified or suspected by farmers because they lacked understanding about crop diseases and needed assistance and advice from professionals. However, early detection of diseases can help to reduce crop loss. IP is vital for identifying plant diseases since disease identification and detection are only possible with visual information. For disease identification and analysis, a neural network-based technique is proposed (Jhuria et al., 2013).

   An intelligent system will be used to identify the disease utilising the diagnostic technique. On apple and grape plantations, the work is completed. Two distinct databases were used by the system. The authors created a study on the classification and mapping of illnesses based on their morphology, colour, and texture. Better findings were given to the writers, and grading was finished. Farmers will use the grade to determine how much insecticide they require. Additional research (Chahal & Anuradha, 2015) suggested a system for classifying plant diseases and identifying plant and leaf diseases.

   The study's authors also proposed a broad paradigm for image processing. Among the efficient categorization systems investigated were the use of support vector machines (SVMs), deep neural networks with k-means, and the analysis of principal components

(PCA). IP technology, several researchers developed a variable-rate chemical application system. The primary goal of the project was to discover diseases on rice crops. To detect the unhealthy zone of rice plants, an image segmentation approach based on chromatic aberration was applied. The author created a prototype that consumes fewer chemicals and has a diagnostic technique for variable rate application. This strategy is both environmentally and economically advantageous (Tewari et al., 2020).

2. **Fruit Sorting and Classification:** Many fruits were available in markets for eating as routine activities increased consumer demand. Because there are so many fruits to pick out by hand and in such a short amount of time, the process is skewed, time-consuming, and stressful (Butz et al. 2006). Researchers have found that using processing images in combination with other strategies can increase output (Surya & Satheesh, 2014). The proposed model provides a platform for further IP research while categorising and displaying applications of image analysis in agriculture. These techniques support the development of the automaton model and the gathering of more precise data.

3. **Plant Species Identification (PSI):** PSI is another helpful use for botanists, researchers, and even the average person. In the identification of species from a collection of species photos, content-based image retrieval is utilized. Plants can be identified by their morphological characteristics, which include the shape, dimensions, colour, and roughness of their petals and leaves. An experienced and qualified botanist is necessary for species identification. This issue can be resolved with information technology, such as real-time image photographing tools. Critical steps in recognising plant species from a set of species photographs include feature extraction and image analysis. Researchers claim that form analysis of leaves may be done using the leaf border (Farmer & Jain, 2005). The two types of leaf analysis are boundary-based and region-based. Boundary signatures can be used to identify plant species by applying them to the leaf's boundary regions (Femat-Diaz et al., 2011). Other characteristics, such as leaf color and texture, are considered for categorization. When the color feature is paired with the form feature, the accuracy of the findings may be improved.

4. **Precision Farming (PF):** By IT in agricultural research has enabled the merging of these two industries, resulting in the growth of precision agriculture. This can help farmers make more informed judgments about crop output. It entails good comprehension and efficient exploitation of natural resources available in the field. It provides optimum profit and output with little input and best resource use. Farmers must have prior understanding of technology and how it works. Farmers must be properly trained in order to learn about precision agriculture. Precision agricultural equipment uses the GPS and GIS. GIS is used to identify all accessible data, while GPS assists in determining the position of an object on the globe via signals from satellites. Images obtained remotely by satellite may be retrieved and analyzed in digital form. Remote sensing, like GIS, has advanced independently due to advances in IP techniques. To improve PF system that combines remote sensing equipment and software for IP is employed.

5. **Fruit Quality Analysis:** Awareness among consumers and market demand for quality products have resulted in the creation of a quality evaluation automation system. This requires fruit quality inspection in order to have high-quality fruits on the market. Fruit quality is assessed using attributes such as color, shape, flavor, texture, and size

(Freixenet et al., 2002). Image capture, processing, and interpretation for analysis are all part of this computer vision activity. Extracting the fruit region from the backdrop became a critical step for examining the primary features to evaluate the fruit quality. The fruits are classified into distinct quality groups. Grading is done using various patterns and classifiers. Color, size, texture, and form are regarded as essential grading characteristics (Mendoza & Aguilera, 2004).

Manual examination is slow, biassed, and vulnerable to errors. In order to overcome these difficulties, a non-destructive quality evaluation method was developed that, in contrast to some destructive processes, could more accurately and quickly determine fruit quality. In many industries nowadays, automated quality evaluation systems based on computer vision are replacing traditional manual inspection methods (Gao et al., 2010). Classifiers like neural networks, SVMs, Bayesian decision theory, k-nearest neighbours (KNN), and PCA can be used to rate the quality of fruits. Numerous food enterprises have found the automated system's quality evaluation decisions to be helpful and advantageous. When evaluating quality, the three main factors to consider are colour, form, and size. (Prabha & Kumar, 2013). Some study as provide critical knowledge as well as a method for generating pea-based, tofu-free soybeans.

6. **Crop and Land Assessment:** Remote sensing has become one of the most important data sources that are used in GIS for getting information from satellites. The reflection of visible light energy from an external source is a significant aspect in remote sensing. The sun is an external supplier of energy for passive systems. The adoption of image sensors has boosted the amount of information acquired by satellites. Images obtained remotely by satellite may be retrieved and analyzed in digital form. Due to improvements in ways to process images including picture improvements remediation, and assessment, satellite imagery has developed independently of GIS. Scanning the surface of the Earth is the main objective of satellite imagery, which evaluates geographical in nature, genetic, and physical characteristics to determine the types of ground cover for further study.

7. **Weed Recognition:** Weeds are a concern to farmers because they affect agricultural yield and quality. As a result, greater effort is required to monitor weeds. Herbicides are one of the most used methods for controlling weed growth. Weed recognition is now controlled automatically so that the system can tell the difference between weeds and crops. The automatic system analyzes weed growth on a regular basis and determines when to control it. Classifiers, in conjunction with IP approaches, make it simpler to identify and eradicate weeds in their early stages (Lamb & Brown, 2001). Researchers proposed IP to evaluate agricultural parameters and explaining how IP for various spectrums, such as infrared and hyperspectral X-ray, may be useful in identifying vegetation indices, canopy estimation, irrigated land map tracking, and other applications. The authors define an image porosity work that includes algorithms for surveying and weed categorization. With the proper imaging methods and algorithms, classification accuracy may reach up to 96%. IP was examined by the researchers to recognise weeds in the field (Poojith et al., 2014). The suggested method uses MATLAB to process images of the field to locate weed locations. Additionally, weeds may be identified and treated with weedicide using a well-defined algorithm technique.

The value of the threshold should be carefully determined for two distinct sorts of weeds. Weedicide consumption may be minimized by using this practice, saving the environment. The huge range of uses for counting items in digital photographs makes it impossible to foresee all possible helpful ideas. Identified a piece of research looking at how image processing is used in the agriculture sector, such as imaging techniques for crop management. In order to discover weed patches in field pictures, researchers (Prakash et al., 2017) employed MATLAB IP. This can result in the failure to identify effective solutions for critical problems. Again, one study (Bosilj et al., 2018) suggested an approach based on SVM with the aid of attribute morphology that divides the detected areas into three groups, namely weed, crop, and mixed. This method classifies the detected areas into these three groups: crop, mixed, and weed. The results of the investigation showed successful and full classification rates. The proposed method was tested and used to sugar beets and onions.

IV. APPLICATIONS OF MACHINE LEARNING IN AGRICULTURE

With the use of robots, ML might be used to spray pesticides, fertiliser, and other chemicals in agricultural areas. Monitoring a farm's condition and determining the level of damage are made possible by the integration of ML and IoT. This would use 70% less fertiliser by focusing on the most prosperous areas. That will benefit both the economy and the welfare of the planet. By reducing agricultural waste by 60%, these ML applications would reduce their carbon footprint and preserve the ecosystem. This offers farmers customised and affordable agricultural solutions. ML has a wide range of applications and can be used for things like disease diagnostics, crop forecasting, and crop management (Liakos et al., 2018). The section that follows covers and examines the many specialized uses of ML in the agricultural sector.

1. **Yield Prediction:** Yield prediction has become one among the most significant research areas in precision agriculture. Crop management, crop supply matching with customer demand, yield estimation, yield mapping, and yield mapping are crucial for increasing productivity. A citrus orchard with premature green citrus can be located using an early yield mapping method that was developed based on open-air environmental parameters. The farmers who use this information can also improve the yields and profits from their orchards. A system for machine vision that rattles and collects cherries on its own during harvesting was developed in a different study that also provided a methodological approach.

   In each instance, even though the obstructions are imperceptible, the structure distinguishes and recognises cherry branches with leaves. The structure aimed to reduce the demand for labour. (2015) Amatya et al. In this study, a framework for detecting tomatoes utilising satellites and anticipation optimising is developed. The proposed method can identify RGB images that were captured by a UAV. Ali et al., 2016, proposed a model that uses ANNs and multitemporal imagery from satellites to forecast grassland. Pantazi et al., 2016, suggested satellite photography. The provided strategy is intended only for forecasting wheat production.

   A generalized technique for predicting agricultural yields was developed. The approach is based on the use of ENN to long-term agronomic info from 1997 to 2014.

Taiwan was the primary region of emphasis for the research. Kung et al., 2016 stated an excellent, non-destructive, and affordable method for counting fruits. The suggested method classifies fruits into three groups: fruits that can be harvested, fruits that are harvested, and fruits whose maturity stage is unknown. This strategy aids coffee growers in organising their labour and maximising financial advantages (Ramos et al., 2017). Ying-xue et al., 2017, established a model for rice development stage prediction based on SVM and basic geographical data obtained from a meteorological station in China. Another work developed the ML technique for predicting crop output and estimating nitrogen status. Combining ML with other technologies to develop a hybrid system for economical and compressive agriculture solutions is one suggested tactic.

At the very foremost, significant progress in detecting, techniques and AI are opening the door to further affordable and integrative approaches for improved crop and environmental condition assessments. For the management of soil. Murugesan et al., 2019 deeply worked on ML on three systems, including Python, R, and Seaborn. Additionally, a working model of an UGV was developed to collect information on soil characteristics and forecast agricultural output. (Aravind et al., 2017).

A single investigation employed to food research that could significantly advance the usage of AI and faster food and beverage product vetting for the food industry. In comparison to expert sensory panels, Robo BEER has shown to be an efficient, objective, precision and timeliness of operation for anticipating sensory descriptions. The uniformity of beer at the final stage of the manufacturing process might potentially be assessed using this technique as a rapid screening approach for industrial uses (Gonzalez Viejo et al., 2018).

2. **Disease Detection:** Spraying pesticides across the cropped zone on a regular basis is the strategy that is most commonly employed to manage irritability and disease. Despite being effective, this strategy has a high cost in terms of money and the environment. Agro-synthetic compound input is taken in terms of time and place using ML, a coordinated component of precision crop planning. An ANN model and spectral reflectance data were used in one study to create a methodical method for differentiating between wheat that is healthy and wheat that has been affected with yellow rust. Using a SOMNN with information fusion from multidimensional fluorescence photography and hyperspectral contemplation, a real-time remote sensing model was created to determine if wheat was healthy or diseased with yellow rust (Moshou et al., 2005). Experts (Moshou et al., 2013) proposed a system for detection of wholesome and infected wintertime wheat crowns in order to address water-stressed Septoria trici. The suggested classifier is based on multisensory optical fusion and least square (LS)-SVM. A method for detecting and screening Bakanae disease during rice seedling development was suggested in a subsequent study (Chung et al., 2016). The main objective was to enhance the detection of Fusarium fujikuroi in two rice types. The suggested strategy increases grain yield while saving time. The same automatic detecting technology was also used on wheat crops.

Other researchers suggested a technique for identifying and distinguishing between the marianum Silybum plants that are wholesome and those which have the smut fungus Microbotyum silybum contaminated. Another study (Pantazi et al., 2017) used hyperspectral absorbance pictures to create a system based on a hierarchical self-organizing classifier that recognizes nitrogen-stressed and healthy winter canopy as well as yellow rust-infected canopy. The study's major goal was to obtain useful fertilizer and fungicide usages based on plant requirements. 4.3 Weed identification It is also one of the earliest agricultural challenges. Weed identification and differentiation from crops is quite challenging.

When combined with sensors, ML algorithms can be a useful tool for improving detection and classification while lowering requirement for herbicides. For identifying crop and weed species, an investigation (Pantazi et al., 2016) offered a methodological strategy and produced a template to follow. The suggested strategy is based on spectral imaging and computational learning. The main objective is to detect and separate several species of weeds including Tarraxacum officinale, Ranunculus repens, and Urtica dioicaas from agricultural crops like maize (Zea mays).

A research using counter propagation (CP)-ANN (Pantazi et al., 2017a) developed a technique for identifying Silybum marianum using multispectral images obtained by unmanned aircraft systems. This weed significantly reduces agricultural output and is extremely difficult to identify.

3. **Crop Quality:** It is critical to identify crop quality characteristics in order to improve product pricing and decrease waste. Researchers (Maione et al., 2016) proposed a syatem for predicting and identifying the geographic location of rice samples based on ML methods utilized in sample chemical composition. Findings of the investigation demonstrated that the most relevant chemical elements for sample categorization are Rb, K, Cd, and Mg. Zhang et al., 2017, foreign botanical and nonbotanical elements found in cotton lint during harvest were identified and categorised using a scientific technique. The main objective of the study was to improve quality by reducing fibre damage. Hu et al. 2017, investigated the use of ML to identify and classify the fragrant Korla pear into persistent-calyx and deciduous-calyx categories.

4. **Species Recognition:** Jha et al., 2019, offered techniques for agricultural autonomous activities such as IoT, WC, ML, AI, and DL. The suggested method is for identifying leaves and flowers as well as watering plants.

5. **Soil Management:** Agricultural soil metrics like soil conditions, temperature, soil dryness, and moisture content are forecasted and detected using ML. In order to assist in agricultural planning. Coopersmith et al., 2014, assessed soil dryness using evapotranspiration and prediction data from Urbana, Illinois, in the United States. The main objective was to offer options for remote farm management. Morellos et al., 2016, offered a methodological strategy and created a model that predicts soil conditions. They collected soil spectra from 140 raw and wet extracts of the top layer of distinct Luvisol soil types using a Vis-NIR spectrophotometer. The samples were collected in August 2013 from a farm field close to Premslin, Germany. Nahvi et al., 2016, provided a model based on a SAE-ELM with meteorological data. An innovative method for predicting soil moisture was provided by a third study (Johann et al., 2016), which primarily used the ANN model and a dataset from force sensors put on a no-till chisel opener.

6. **Crop Type Classification:** Kusul et al. (2017) developed an approach for classifying crops such as wheat, soybean, maize, sugar beet, and sunflower. The study makes use of a database that contains 19 multitemporal scenes taken by Landsat-8 and Sentinel-1A RS satellites from a Ukrainian test site. The suggested technique has an overall classification accuracy of 94.60%, which is higher than the RF (88%) and multilayer perception (MLP) (92.7%). Ghosal et al., 2018 used a collection of 25,000 photographs of wholesome and affected petals in the field to examine an in-depth computer vision-based approach to recognising, categorising, and measuring plant stressors, both abiotic and biotic. The classification rate for the deeper CNN model is 94.13%.

7. **Crop Yield Estimation:** Kuwata & Shibasaki (2015) used CaffeNet to estimate crop yields of maize with an estimated RMS error of 6.298, which is lower than the RMS error of support vector regression (8.204). The dataset, which used a moderate resolution image spectroradiometer enhanced vegetation index to calculate maize production data from 2001 to 2010, was obtained from the climate research unit. Kamilaris & Prenafeta-Boldu 2018, described working for CNN and covered its advantages and disadvantages. This approach is used to put CNN into practise on a Costa Rican sugarcane field, and the future application of DL is also investigated.

8. **Fruit Counting:** Picture segmentation and object identification are presently dominated by DL-based approaches (Badrinarayanan et al., 2017). The large amount of data utilized for training, from which the networks gain traits that ideally generalize across circumstances, is widely attributed with these technologies' overwhelming success. Previously, the fruits count was dominated by the CHT (Pedersen & Kjeldgaard, 2007). CHT requires significant parameter tweaking and is unable to handle occlusions. These difficulties inspired the creation of more complicated fruit-counting systems.

   Based on DL, one study proposed a data-driven strategy for counting oranges and apples. They began by introducing a labeling platform for classifying the fruits on input image files. The candidate region was then extracted using a blob detection neural network. Another neuron is used to count the number of fruits in the image once more. Finally, regression analysis is used to compare the performance of algorithmic and manual counts. This approach is applied to oranges and apples with the IoU values of 0.813 and 0.838, respectively.(Hani et al., 2018) looked at the issue of reliably counting fruits from photographs. They demonstrated a system that makes use of AlexNet CNN to modify and fine-tune the data they use for training. The approach attained an accuracy of 80% to 94%. Fruit detection and counting gained popularity with the introduction of faster R-CNN. Researchers developed a rapid, easy, and reliable way of non-destructive detection of the influence of cold storage on mango. After low temperature preservation, the suggested approach may efficiently differentiate individual fruits.(Hashim et al., 2018).

9. **Obstacle Detection:** CaffeNet-based AlexNet structure for finding obstacles was examined by Steen et al. (2016). It has an impressive identification accuracy of 99.9% in row crops and 90.8% in meadow mowers. The research uses 437 pictures as a dataset to build the framework and focuses on recognising ISO barrel-shaped barriers in meadow mowing and row crops. Using AlexNet and VGG with CaffeNet assistance, Christiansen et al. (2016) proposed a barrier identification strategy with a 0.72 F1 score.

10. **Irrigation Monitoring System:** Irrigation monitoring techniques assist farmers by minimizing monthly irrigation expenditures and restricted water resources through the installation of different sensing devices (Keswani et al., 2018). Hellin et al., 2014, presented a more broad, sophisticated method that employs cellular technology to regulate the irrigation operation. Sensor data may be sent to the system database utilizing mobile technology in the suggested technique. Mohanraj et al., 2016, proposed a framework for field monitoring and automation utilizing IoT in agriculture, consisting of KM-knowledge base and tracking modules. A knowledge-based data flow model was built to connect different sources to crop structures, and an analysis of the development system and the current setup was shown. The technology overcomes the limits of conventional agricultural techniques by efficiently using water resources and lowering labor costs.

    In order to analyse the physical and chemical limits of water, including the pH level, temperature, oxygen content, and conductivity, Khwan & Thamrin introduced an IoT paradigm based on nodes filled with sensors in 2017. The record of information about the water control system that was gathered was monitored using cloud-based services. The proposed technology also controls how much field water is used. Nawandar & Satpute, 2019 innovated a cheap system for irrigation based on the IoT with support for the HTTP and MQTT protocols. The outcomes of the proposed system, with their intelligence, mobility, and low costs, promise to be favourable.

11. **Optimum Time for Plant and Harvesting:** Kamilaris et al., 2016, offered an IoT-based system for data collecting, processing, and analyzing in real time. This would deliver real-time provisioning or smart solutions, as well as expert decision assistance to researchers and farmers. Furthermore, by utilizing fewer resources such as water, fertilizer, and so on, this smart agriculture framework boosts production while protecting the environment.

12. **Tracking and Tracing:** A system that tracks soil condition utilising the ZigBee system and additional gadgets like GPRS, CMS, and GPS was created by Satyanarayana in 2013. Despite being expensive, the suggested approach is popular in agriculture because to its ability to precisely monitor and track positions. A framework for IoT-enabled agriculture solutions was provided by another study (Farooq et al., 2019). An IoT-based farm system's connectivity to key technologies was also covered by the author, along with network technologies including network structure and layers.

13. **Farm Management System:** For sensible processing of crops, strategy, and deciding, a farm management system is essential (Gardasevic et al., 2017). Elijah et al. (2018) examined how IoT and data analytics might be combined to enable intelligent farming. The author categorized all of the benefits and obstacles of using IoT in the agriculture industry. The primary goal is to raise awareness of research in the design and development of LPWA communications. Furthermore, as the cost of IoT devices, data storage, processing, and transport decreases over time, small and medium-sized farms will be able to install IoT systems.

14. **Agricultural Drone:** UAVs, or agricultural drones, are utilized to enhance various farming methods and processes. Selection, scouting reports, crop health evaluation, nitrogen measuring, spraying, and soil condition monitoring are all agricultural

procedures. Bodake et al., 2018, developed a system for mapping and capturing crop health images using drones that is based on the combination of IoT and GIS. The suggested technology is designed specifically for tracking bacteria and fungi on farms.

V. PRECISION FARMING

Bencini et al., 2012, developed a feasible solution for agro-food chain tracking and supervision through design, optimization, and development. VineSense's primary characteristics have been discussed. Furthermore, several significant agronomic outcomes obtained through the use of VineSense in various instances was pointed out, highlighting the advantageous effects of WSN technology for the agricultural environment. An extensible and adaptive architecture for integrity WSN with cloud computing was presented in Piyare & Lee, 2013, for collecting information and dissemination using REST-based web services. Consumers can access the data from any place and on any mobile device with internet connectivity, according to the test results. The suggested approach is an energy-effective way to increase the lifespan of sensory nodes. An agricultural monitoring system was developed and built in a different study (Bhanu et al., 2014) to reduce manual labour. This system measures the variables and informs farmers of the findings. Parameter modifications of any size can be found.

With the continuous monitoring of numerous environmental indicators, the WNS system design and data architecture were addressed; the producer may assess the best environmental conditions for attaining maximum crop productivity and amazing energy savings. According to Gangurde and Bhende (2015), the WSN has completely changed the landscape of precision agriculture. The proposed WSN system has the capacity to control agricultural variables and promote growth. In their evaluation of several wireless technologies or protocols published in 2017, Jawad et al. suggested a system that makes use of the ZigBee and Lora wireless protocols, which are advantageous for their low power requirements and extensive communication range. Energy harvesting and strategies, as well as an algorithm for categorising energy-efficient ways, were also presented. In 2019, Siva Rama Krishnan and Arun Kumar developed a strategy for smart agriculture application that makes use of WSN-recommended routing. An RF transmitter gathers the information and sends it to a single server, which processes it and produces more information.

VI. CONCLUSION

In the future decades, farming will be more important than ever. Smart agriculture and precise agriculture are only getting started. However, they might open the door for a much more widespread use of innovation in farming environments. The goal of innovative agriculture is to close the disparity amongst farmers in industrialised and poor nations. Mobile applications, IoT development, and technological innovation have all made significant contributions to the acceptance of electronic devices in farming. It's no surprise that most traditionally performed agricultural activities have changed drastically. The employment of machines, applications, instruments, and other information technology in intelligent farming practises and methodology can be linked to technological advancement. Evidently, sustainable agriculture includes innovative farming. concept that, when correctly implemented, may help farmers gain a variety of benefits, including higher output, improved quality, and lower expenses. Such innovative thinking requires the use of resources, knowledge, and technical abilities. You need more than simply a passion for farming to assess your farm's data, account for and follow advancements, and forecast demand and price fluctuations. This chapter seeks to offer a concise summary to agricultural and smart farming researchers. Almost all peer-reviewed quality publications over the previous years were examined. Because each publication examined uses a unique collection of datasets, metrics, preprocessing methods, models, and parameters, it is impossible to generalize and compare the articles. The final line is that, while smart farming is important in agriculture and promises higher yields, study on best practices that meet your agricultural goals and needs is recommended.

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