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# A Systematic Review on Monitoring and Advanced Control Strategies in Smart Agriculture

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**ABSTRACT** Automation in agriculture nowadays is the main focus and area of development for various countries. The population rate of the world is increasing rapidly and will be double in upcoming decades and the need of food is also increasing accordingly. To meet this rapid growth in demand, agriculture automation is the best solution. Traditional strategies employed by farmers are not efficient enough to fulfill the rising demand. Improper use of nutrients, water, fertilizers and pesticides disturbs the agricultural growth and the land remains barren with no fertility. This research paper presents different control strategies used to automate agriculture such as: IoT, aerial imagery, multispectral, hyperspectral, NIR, thermal camera, RGB camera, machine learning, and artificial intelligence techniques. Problems in agriculture like plant diseases, pesticide control, weed management, irrigation and water management can easily be solved by different automated and control techniques mentioned above. Automation by advance control strategies of agricultural methods have verified to increase the crops yield and also the soil fertility become strong. This research paper reviews and observe the work of different researchers to present a brief summary about the trends in smart agriculture and also provides the work flow and revenue of smart agriculture system in figure 15 using technologies verified by researchers in their research papers.

**INDEX TERMS** Artificial intelligence (AI), diseases, farming, imaging technique, IoT, irrigation, nutrients, pesticides, stress monitoring, smart agriculture, soil.

## I. INTRODUCTION

Agriculture and forestry plays a vital role for food security and property development [1]. Agriculture is one amongst the fundamental sources of keep for folks and plays a key role within the development of the agricultural economy [2]. Smart Agriculture is becoming very important essence for farmers now a days and it will become more important in upcoming era for proper growth of the fields and increase in the productivity of yields. The major issue is that it is very challenging to provide food security to the people in upcoming decades as the population is increasing rapidly. The continuous growth of the globe population at the side of the lowering of resources at disposal create the matter of good usage of resources [3]. With the increasing demand for food, good agriculture and farming applications have gained importance and wide usage because the ancient ways have lost their efficiency [4]. The ancient agriculture production lacks the appliance of the knowledge and technology that has been widely utilized in business, and different aspects of life. [5]–[10] The immediate actions are to be taken to save the crops from pests, lack of nutrients, excess amount of water, need of fertilizers, and light etc.

With rising issues concerning agriculture's role in surface associate in groundwater quality combined with increasing chemical costs and also have to be compelled to meet an expected 50–70% increase in international food demand with restricted resources, there's also a demand to improve agricultural systems into extremely resource-efficient systems that each area unit is profitable [11]. To improve agricultural system, monitoring the stress level and the reason of stress is the main focus to identify. Stress level includes all the factors

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affecting the plants health. Monitoring and identification of the stress level of crops help the aggrotech to produce healthy crops and also increases the yield. Smart agriculture [12] utilizes tools and technologies to identify in-field soil and crop variability for improving farming practices and optimizing agronomic inputs [12].

Stress Monitoring focuses on smart agriculture system in which all the stress levels of plants can be rectified, performing agriculture tasks and communicate autonomously. Different Sensors, actuators, drones and communication medium requires to build an advance stress monitoring mechanism which leads to smart agriculture system. This research paper reveals the complete picture of the perfect use of technology to build smart agricultural environment for future work and inventions. Stress monitoring system increases the yields and allows to grow healthy crops. In [13] a case study on the organic and conventional growth of lettuce is carried out in the year of 2015, author provides experimental results that organic farming yields more than conventional farming.

The authors in [14] provides a systematic literature review on institutional perspectives of climate-smart agriculture by analysing a total of 137 research papers published between the years 2001 and 2017 and few papers from 1996 to 1998. As the quantity of agricultural information will increase considerably, to study, process, and analysing this massive amount of data a capable analytical technique is needed to get reliable information for correct predictions to build smart agriculture environment which can increase the yield. The authors in [15] have done a systematic literature review on data mining methods published between the years 1984 and 2019.

## II. BACKGROUND

Agriculture plays important role within the development of an agricultural country. Problems regarding agriculture are continually impeding the events of countries. The sole resolution to the present drawback is wise agriculture by modernizing the current ancient ways of agriculture. Global studies have revealed that agriculture division is more effective in reducing hunger and poverty than other sectors [16].

In [17] demonstrate that the number of traditional small farms strongly declines, being replaced by modern and larger farms. In [18] they instructed that agriculture is undergoing a fourth revolution triggered by the exponentially increasing use of knowledge and communication technology (ICT) in agriculture. Once the analysis within the agricultural field, researchers found that the yield of agriculture is decreasing day by day. However, use of technology within the field of agriculture plays necessary role in increasing the assembly in addition as in reducing the additional man power efforts. a number of the analysis makes an attempt square measure finished betterment of farmers that provides the systems that use technologies useful for increasing the agricultural yield.

This section focuses on the factors that affects the growth or production of crops, Drones using for monitoring and operations in agriculture, techniques use to form Smart agriculture system architecture and their related work.

Agriculture foundation depends on five basic factors, nutrients, water or humidity level, temperature pesticides and light. The smart agriculture system based on collecting data, decision making and act accordingly as shown in figure 1 [19].

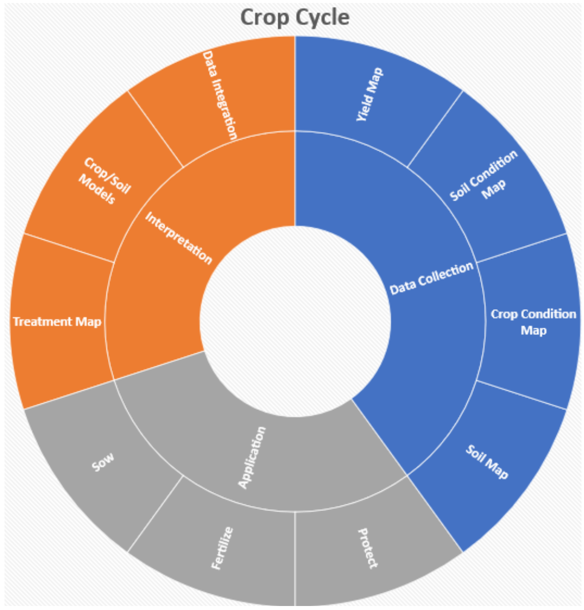


FIGURE 1. Agriculture cycle [19].


FIGURE 2. Things plants need [21].

### A. FACTORS AFFECTING IN AGRICULTURE

Each factor is important and necessary for the growth of crops [20] The main factors that plants need is shown below in figure 2 [21].

#### 1) NUTRIENTS

There are 17 nutrients plants needs to grow. Hydrogen, oxygen and carbon are taken from air water. Other 14 nutrients are divided into two groups Micro nutrients and Macro nutrients [20].

##### a: MICRO NUTRIENTS

Plants need these nutrients in lesser amount than micro nutrient but we cannot eliminate them because they are also playing an important role for plants health. Micronutrients include Iron (Fe) [22], Copper (Cu) [23], Manganese (Mn) [24], Zinc (Zn) [25], [26], Boron (B) [27], Chlorine (Cl) [28], and Molybdenum (Mo) [29]. Silicon (Si) [30], Sodium (Na) [31], Cobalt (Co) [32], Nickel (Ni) [33], [34] are lesser known micro nutrients.

##### b: MACRO NUTRIENTS

Plants growth mostly depends on the macro nutrients because plants need them in larger quantity. Macronutrients include Nitrogen (N) [35], Potassium (K) [36], Calcium (C) [37], Magnesium (Mg) [38], Sulfur (S) [39] [25] and phosphorus (P) [40]. Nitrogen (N), Potassium (K) and Phosphorus (P) are important nutrient from macro nutrients.

#### 2) WATER OR HUMIDITY LEVEL

Plants need water to survive as human being needs water. Human body need 70% water while plants need 90% of water. Cactus in dessert need water too but in little amount. Water break down important minerals in plants. All the nutrients transport to plant cells by absorbing water [41].

Water should be provided in right amount to the plants. Little or too much water can kill the plants.

The author in [42] calculated the water footprint of major crop in Hetao irrigation district, China. Then, it evaluated the influencing factors that caused the variability of crop water footprint throughout the study amount. The results counsel that the water footprint of crop primarily depends on agricultural management instead of the regional climate and its variation. The results indicated that the water footprint of a crop may be controlled at an inexpensive level by higher management of all agricultural inputs and therefore the improvement of water use potency in agriculture.

#### 3) PEST AND DISEASES

Identification of the pest, understanding its biology and seasonal population trends, damaging life stages and their habitats, nature of the harm and its economic significance, the vulnerability of every life stage for one or a lot of management choices, host preference and alternate hosts, sure thing of pesterer incidence supported the surroundings, cropping trends, farming practices, and different influencing factors, and every one the connected data is crucial for distinctive associate effective management strategy [43].

Author in explained [44] many theoretical frameworks available in the literature. Some of them are specifically related to plant pests including insects, pathogens and weeds. These can help researchers, for example, to conceptualize and prioritize planning in climate change biology research in managed and unmanaged ecosystems.

As all living organisms, plants should face infections and diseases following the attacks of a mass of plant pathogens and pests from animal, microbic or infectious agent origin. These diseases may be minor inflicting entirely a discount of plant-growth capacities or may be at the origin of rather more severe harm resulting in plant death within the worst case [45].

#### 4) TEMPERATURE

Plants reacts to temperature as in summer grows faster and in winter growth of plants slow down.

In [46] Climate change has been causing a drastic change in weather patterns both in summer and winter resultantly adversely affecting the crop yields.

#### 5) LIGHT

Intensity of light varies from season to season. In winter, due to shorter day time light time is also less. In spring light time and its intensity both increases. Growth of plants varies season to season and type of plants can be decided on the basis of light as summer light responsible for grow new leaves, fall light responsible for shedding leaves and spring light responsible for grow new leaves [20].

Author defines well in [47] Plants use light parameters, such as spectral composition, light intensity, direction and duration, as a source of information from the environment to modulate growth and control developmental transitions.

### B. SMART AGRICULTURE SYSTEM ARCHITECTURE

The application [48] of (smart) cameras for method management, mapping, and advanced imaging in agriculture has become part of exactness farming that facilitates the conservation of fertilizer, pesticides, and machine time. This method to boot reduces the number of energies needed in terms of fuel. In [49] author describes the existing scenario and instances for the sensors and equipment which are low budget for the monitoring of crops and measurement of the plant's health in agriculture.

Smart agriculture system form by four layers physical layer, network layer, decision layer and application layer well defined in Figure 3 [50]. Each layer performs particular tasks and depends on other's data.

#### 1) PHYSICAL LAYER

Physical layer used for information acquisition process. Information will be collected by means of sensors at ground level, human work and two innovative systems: Multispectral Terrestrial Mobile Mechatronic System and Multispectral Autonomous Aerial Mobile Mechatronic System [50].

#### 2) NETWORK LAYER

Wireless communication is an indispensable technology for precision agriculture [50]. The main function of network layer is to transfer network packets to the destination from the source.

#### 3) DECISION LAYER

This system will create, store, analyses and process spatial information distributed through a computerized process regarding soil type, nutrient levels and correlate them with a certain plot of field. Moreover, will enable viewing, understanding and interpreting data in many ways. In this way, by monitoring inputs and outputs of crop, farmers will determine what areas of the field are profitable or not and what steps can be taken to increase profits in affected areas [50].

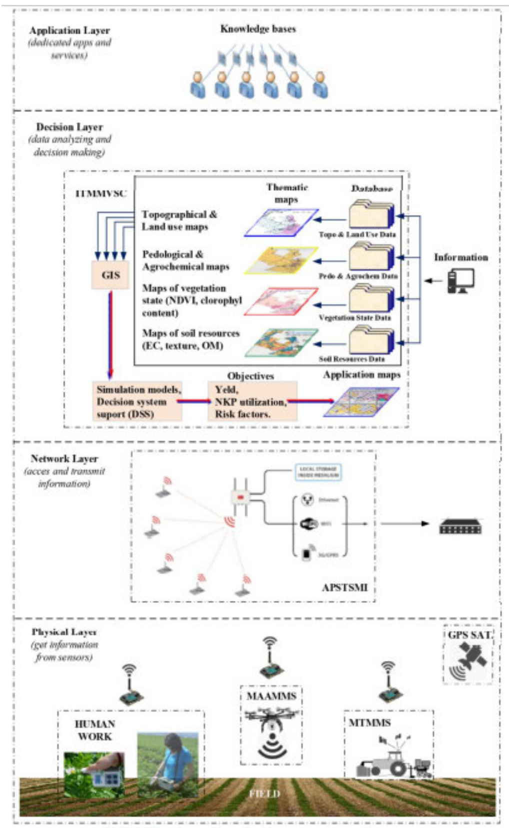


**FIGURE 3.** Layers for smart agriculture architecture [50].

#### 4) APPLICATION LAYER

This layer provides solution to the problem based on spectral data or sensors data and its learning. It is also capable of providing solutions to other similar problems [50].

Farmers can use this system for monitoring stress level, identification of the actual cause of stress, optimizing the use of assets and for performing any agricultural desired tasks.

## III. RELATED WORK

The world is moving towards smart agriculture system because to meet the market demand is becoming challenging from last decades. Increase yields and healthy crops is the targeted research work for the researchers, which focus their interest to develop smart monitoring and operations system for agriculture. Monitoring crops, finding stress areas and their levels of stress and to perform actions based on the stress data is big task. Therefore, this review emphases and deliberates the existing methods and techniques using in agriculture which help researchers to find gap for future advancements.

The author Sankaran *et.al.* [51] proposed the system design that features following major units

1) Sensor unit
2) Zigbee transceiver unit
3) Platform
4) Internet server
5) Wi-Fi module
6) Rf module

Here raspberry pi as server used. to amass the sensing element knowledge Arduino is employed to interface with the various sensors like Dht11, soil wet, Image sensing element, Ph. sensor, illumination sensing element and plenty of additional that is employed in agriculture field. To monitor the plant growth according to circumstances and environment in comparison to actual growth is very important to accomplish. For this problem the author in [52] used imaging technique to monitor and proposed an architecture which is module based architecture and the use of MATLAB standard functions enables the flexibility, stability, and expandability of the software. Using this package, all processes involved in camera configuration, image acquisition, image pre-processing and analysis, and decision making are done without the need of programming knowledge.

Similarly, Imaging based monitoring of crops is also attracting researchers' interest as it is very reliable method. In [53] author concluded that Overall, UAS-based multispectral data successfully quantified winter wheat survival and spring stand, and crop necrosis in potato production.

Agriculture sector where the parameters like shelter, yield, quality of product were the necessary measures from the farmers' purpose of read. Many times, skilled recommendation might not be reasonable, majority times the supply of skilled and their services could consume time. To address this problem authors in [54] on the basis of survey suggest that Image processing with communication network will modify things of obtaining the expert recommendation well among time and at reasonable price since image processing was the effective tool for analysis of parameters. In [55] image processing with MATLAB is done or identifying weed areas in agriculture.

By using Artificial Intelligence (AI) algorithms we can easily train our system by providing all the necessary data for future similar sort of project. In the field of agriculture, we can train model for identifying diseases, pests water level and much more. In [56] the use of AI in agriculture challenges and ideas are explained for the researchers to gr direction.

Authors [57] in their work proposes an expert system by integrating sensor networks with Artificial Intelligence systems such as neural networks and Multi-Layer Perceptron(MLP) for the assessment of agriculture land suitability.

Author in [58] demonstrated that the application of a machine learning regression to digital color image data enables the accurate prediction of the anthocyanin content of detached. In [59] authors reviewed many articles on monitoring agriculture using imaging technique and biochemical methods to measure plants growth.

Authors in [60] highlights the importance of remote sensing for different applications in agriculture sector and recent practices. They review articles from 1990 to 2015 which are mainly focused on remote sensing and agriculture.

Authors in [61] focused on irrigation system for agriculture. They review articles of last 10 years and divided articles according to applications like advance control, Artificial intelligence, convolution irrigation application areas, IoT monitoring and precision irrigation.

Authors in [62] review paper describes intelligent sensors techniques which is used for monitoring and control operations in agriculture.

Authors in [63] reviewed research articles from year 2010 to 2017 and describes the use of IoT, recent works, future trends and challenges of IoT in agriculture.

Authors in [64], [65] highlight the use of IoT in agriculture. A survey is done by authors in [66] explains the major components of IoT based smart farming, network technologies, network architecture and layers, network topologies, and protocols. Cloud computing, big data storage and analytics role and use in the field of agriculture and open research issues and challenges also provided.

Importance of autonomous vehicles and drones are becoming very important from last two decades because of its human friendly technology which allows user to perform their desire tasks easily. Drones are using almost in all fields for example military, surveillance, rescue, monitoring, delivery, construction etc. Drones are also very famous in agriculture as in [67], [68] authors investigated and highlight the importance of using drones in agriculture their application and technical specifications. Availability of top drones in market for yielding better crop quality and preventing fields from any sort of damage is also explained.

Drones, Imaging technique, IoT and Artificial Intelligence are todays trend of research. Utilizing these techniques in a smart way enhance the research scope and advancements in agriculture to meet market demand.

In the next session questions are stated which explains and clear the confusions regarding smart agriculture along with the collaboration of stated technologies which define future directions.

## IV. METHODOLOGY

This methodology of doing systematic literature review is present in this section. The researchers in [69] have done a focus SLR in the field of image capturing, image processing and machine learning approaches in the field of agriculture (plant diseases). In this section research questions and the factors of motivation are mentioned which is a part of systematic literature review. The articles are taken from many data sources, as listed below. For precise searching and reviewing inspection has been adopted to focus on articles needed to perform systematic literature review considering the criteria of inclusion and exclusion. The articles which is considered for review in this paper are from quality and famous publishers such as IEEE, Elsevier, MDPI, Springer, Frontiers, Research gate and google scholar mentioned in table 1.

The research questions and the motivations for such questions are listed in Table 2. New developments within the past 8-10 years have created large enhancements to the trade that create trailing and managing agriculture and farm animal abundant easier and data-driven. This technology will be available the shape of biological process technologies, genetics, digital technology, and more. The review in this article considered from last five years. i.e. 2015.

Articles chosen for review are on the basis of complete study of articles shown in figure 4.

**TABLE 1. Sources of data review in this paper.**

| | |
|---|---|
| IEEE | https://ieeexplore.ieee.org/search/advanced |
| ELSEVIER | https://www.elsevier.com/ |
| MDPI | https://www.mdpi.com/ |
| SPRINGER | https://www.springer.com/gp |
| FRONTIERS | https://www.frontiersin.org/ |
| Research gate | https://www.researchgate.net/ |
| Google Scholar | https://scholar.google.com/ |

**TABLE 2. Research questions and their motivations.**

| | |
|---|---|
| Q1: What factors are considered and how they calculated during farming? | It helps to study the factors affecting in growth of crops or plants. |
| Q2: What are the challenges in traditional farming methods that highlights the importance of advancement in agriculture? | Advance Agriculture system reduce human efforts and let the operations done very precisely. |
| Q3: What are the existing control strategies used in smart agriculture? | Many techniques and algorithms are used in advancement and monitoring plant stress which discussed in detail |
| Q4: What are the research trends and open issues challenges or advancement need in technology to identify and solve agriculture problems precisely? | This Systematic literature review helps the reader to know the recent trends and future work to modernize the traditional agriculture system. |

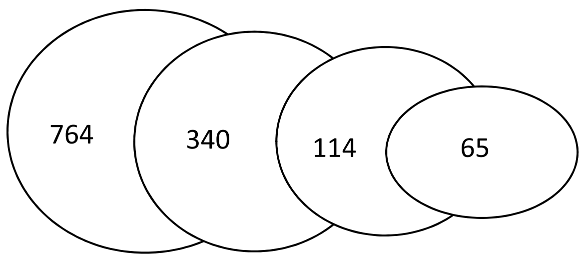


**FIGURE 4. Criteria of articles selection.**

### A. ARTICLES SELECTION CRITERIA

The methodology used in the article's selection criteria begins from the research questions. Keywords helps in the selection and search process. The articles published in the English language are considered.

This review provides the complete knowledge of the use of technology and advancement needed in agriculture to make life easier and control wastage of assets. The articles mostly were not selected because their titles did not match the determination criteria, or in contrary, abstracts were not appropriate to be considered in this survey.

## V. DISCUSSION

In this section the research questions are answered with facts and results.

Q1: What factors are considered and how they calculated during farming?

Climate, land relief, soil and vegetation are the main factors which influence agricultural activity. The growth of plants depends on the temperature, nutrients, pesticides and humidity of the land and the amount of light it receives [70] The above-mentioned factors can easily be monitored by modernizing Soil, water, fertilizers, pesticides and weather changes are mainly considered in plants health. To monitor these factors and act according to the requirement is necessary. There are many different ways of using technology to take control strategies for the better growth of plants, increasing yield productivity, agriculture system using technologies and predictions can be made by AI models on the basis of previous data and monitoring weather conditions which can alert and suggest what steps should be taken. optimum use of water, reduce harmful effects of chemical fertilizers and pesticides.

In table 3 the factors involve in plants health their impact, reason and solution with technology is presented which helps the reviewer to find direction according to requirements.

Q2: What are the problems and challenges in traditional farming methods that highlights the importance of advancement in agriculture?

### A. MAJOR PROBLEMS

Agriculture being the most significant contributor towards the national GDP has always been the most critical economic domain for Pakistan. However, despite its criticality, the sector suffers from various types of challenges. Figure 5 highlights these challenges.

Some of these are challenges are techno-economic in nature which highlights in figure 5 and are explained below.

A high performing agriculture sector is the key to economic growth & poverty alleviation especially in developing countries yet it remains a significantly under developed sector of the economy.

a Low per Hectare Yield.

Developed nations are getting higher yield per hectare due to use of modern technology and trained labor. However, in developing countries, even employment of ~40.0% of the national labor force in this sector (as compared to $<$ 5% in developed countries) cannot produce better yield due to obsolete methods and technologies.

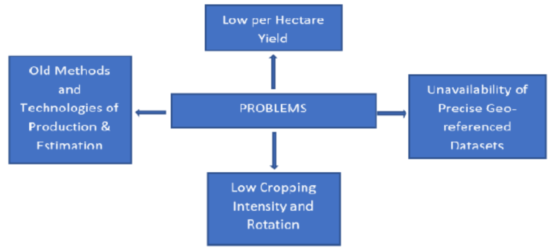


**FIGURE 5. Problems arises in agriculture sector.**

b. Old Methods and Technologies of Production & Estimation Processes.

Although mechanization of agriculture processes is increasing in Pakistan, in most of the areas, the old implements are still being used for agricultural production. Old and orthodox techniques of yield and production estimation do not present the real picture and are hence incapable of bringing any significant change.

c. Low Cropping Intensity and Rotation.

At present, the level of cropping intensity in developing countries is very low as compared to advanced countries. Cultivable areas under double or multiple cropping is inadequate in developing countries. Moreover, due to ill-definition of agro-ecological zonings, constant cultivation of ill-suited crops exhausts the fertility of soil. No formal mechanism has been adopted to eradicate the soil erosion and even after harvesting nothing is done to restore the soil energy. Hence, the fertility of soil is decreasing day by day.

d. Unavailability of Precise Geo-referenced Datasets Non -availability of precise and accurate geo-referenced datasets (up to farm levels) e.g., soil mapping, water availability, crop suitability, crop risk predictions etc. creates a huge information gap for both decision makers and farmers.

The challenges facing in traditional farming methods are as follow.

### B. CHALLENGES

- The traditional farming system or methods are facing challenges due to not produce targeted and valuable yield in less acres to fulfill the demand of market as it is increasing rapidly. The rapid growing population of the world at the side of the minimal of resources at disposal cause the matter of sensible usage of resources [3] This can be vital particularly within the area of food production and soil misuse.
- Use of pesticides [75]in adequate amount is one of the challenges in conventional method as these chemicals are very harmful and can causes many health risks when human beings and animals eat crops [45].
- Producing more foods in lesser acres to fulfill the demand of increasing world population is also a big challenge in traditional farming [76].

**TABLE 3.** Factors considered during farming, their impact, solution and technique.

| FACTORS | REASON | IMPACT | SOLUTION | TECHNIQUE |
|---|---|---|---|---|
| SOIL EROSION [71] | Less knowledge about land and crop to grow in that particular soil to prevent the soil from erosion. | • Environment and property damage<br>• Loss of livelihoods and services<br>• Social and economic disruption.<br>• Lowers soil quality | Soil assessment. | Monitor soil health using imagery data or sensors. |
| CHEMICAL PESTICIDES and FERTILIZERS[72] | Improper identification of pests is and spray | • Affect humans and animals' health<br>• Air, water and soil pollution | Proper use of chemical substances in adequate amount. | Prescription mapping using AI model. |
| CLIMATE CHANGE [73] | Changes in wind, sunny weather, unpredicted rainfall etc | • Reduced agricultural productivity<br>• Reduce access to food<br>• Affect food quality | Monitoring and record weather updates to predict weather updates and takes safety measures accordingly. | Train model for weather prediction using previous data |
| WATER USAGE [74] | The actual need of crops is unknown which leads to wastage of water or improper use of water. | • Wastage of water<br>**Excess water:**<br>• **Water** logging<br>• Soil may be ill<br>• Additional **water** chokes the air spaces<br>• Roots absorbs toxic salts<br>• Damage **crops**<br>**Less Water:**<br>• Vital nutrients cannot travel through the **plant.**<br>• Effect in yield and quality | Provide water when and where it is needed and in a right amount. | Humidity sensors. |

- Improper use of nutrient are the reason of soil and water pollution which can harm the crop and causes health risks of the farmers or exposure with living things [77].
- In conventional method estimation of requirement of water to the crops cannot predict accurately and the area where is needed and the amount of water needed [78].
- Lack of information and knowledge about climate and environmental issues and farming crops according to market demand on the same soil by making it compatible for the crop [79].
- Prediction of the requirement of assets which help crops to grow is usually not comes true due to the change of market demand and unavailability of resources.

Smart agriculture System addresses the above challenges, and the following are the advantages of the use of technology in agriculture and the reasons for its fast acceptability.

### C. ADVANTAGES OF THE USE OF TECHNOLOGIES IN AGRICULTURE

- Reduce Waste: The key components or factors affecting in growth of agriculture can be monitored, predicted and automated by using sensors, robots, GPS technology and aerial images which can reduce waste of nutrients, water and pesticides etc.
- Improve Productivity: Smart agriculture system can increase the production rate of crops sowing by mechanical plantation, testing soil, monitoring growing rate of

crops from beginning till the stage of harvesting and provide targeted necessary contents on particular regions according to requirement using data from aerial images and different sensors.
- Enable Management using remote sensing: Remote sensing in agriculture helps to provide the data of important factors like; yield estimation, vegetation indexes and water stress monitoring, assessment of crop development, estimation of crop land (acer) and cropland mapping.
- Decision making support: This can help to estimate or provide the necessary content to the crops according to requirement based on AI.

### D. REASONS FOR MOVING TOWARD SMART TECHNOLOGIES IN AGRICULTURE

#### 1) CONVENTIONAL METHODS IN AGRICULTURE

Conventional farming includes an ordinary methods or approach to farming. This practice is trailed by human from ancient time.

In [17] authors presented a case study in which they discussed decline impacts of traditional farming on landscape mountains and compare modern farms with traditional farms.

In [80] authors reviewed articles and suggest the advance us of technology in the field of agriculture.

The use of smart technologies such as image processing, robots, IoT, Artificial intelligence makes life in agriculture very easy by increasing yield production including the time safety, reducing human efforts, protecting living things from direct exposure with chemical and fertilizers and grow maximum crops in lesser acers with minimal resources.

Q3: What are the existing control strategies used in smart agriculture?

This paper discusses articles in detail as Image processing, IoT and AI techniques in agriculture based on the approaches used in the articles carefully chosen for assessment from different sources to make agriculture smart and reliable.

In this review, we explored the IoT, robots, image processing techniques and algorithms implemented by various researchers and sorted them based on the methodologies. The agriculture related problems are monitoring soil moisture, water level detection, nutrient amount, identification of diseases and pests, identification and memorizing the area of stress in fields and requirements to cure stress.

Based on the above criteria, 65 articles are carefully chosen for the review. The estimated variable or research area along with its technique, achievements and limitations or future work of each article is addressed. In this section, the findings are reviewed to give detail information of techniques such as IoT, Image processing and AI along with robot which can identify, specify and solve the agriculture related problems. We provided the use of these technologies in different factors of agriculture to monitor and control them.

Following methods and control strategies are reviewed from different articles to modernize traditional agriculture trends.

### E. IoT IN SMART AGRICULTURE

Sensors (Soil pH, light, water volume, humidity, Air temperature, etc.) forms a system which automates the agriculture.

Authors in [81] performs survey and examines to merge IoT with Robots which enhance performance of both and also discuss challenges occurs by merging these technologies.

Field health can be monitored from anywhere using IoT which are very efficient technique as compared to conventional methods.

In [82] authors develop smart agriculture using IoT, big data and also proposed K means clustering algorithms.

### F. DRONES IN AGRICULTURE

Modifications in technology over time and drones in agricultural are a good model of this.

Authors in [83] reviewed many articles on robotics and highlights the applications, trend of using robots in upcoming years, advantages, and achievement stories of using drones for farming.

Now a days, agriculture is including in the key industries which uses drones. Drones in agriculture are being employed so as to boost traditional agricultural practices. The ways that Unmanned Ground Vehicle (UGVs) and Unmanned Aerial Vehicles (UAVs) are being employed in agriculture are assessment of crop health, irrigation, monitoring and assessment of crops, crop spraying, planting, analysis of soil and field.

In [84] authors reviewed many articles and provide the details of using agriculture robots which are practically implemented and sustainable. Authors in [85] provides review on Path planning ground robots in agriculture.

### G. LIMITATIONS OF EXISTING CONTROL STRATEGIES

By implementing or adopting control strategies in agriculture remote sensing plays a vital role which saves human efforts, time and assets.

A major limitation included in remote sensing for crop growth models are as under
- lack of spatial information on the actual conditions of each field or region [86].
- low vegetation signal-to-noise ratios [87], [88].
- High soil background reflectance [89], [90].
- High spatial heterogeneity from plot to regional scales [91].
- Irregular growing seasons due to unpredictable seasonal rainfall and frequent periods of drought [91].
- The data which are needed to estimate crop yield are insufficient most of the time due to many problems such as climate conditions (% of clouds), and low temporal resolution [92].

The data from drones helps in concerning plant health indices, prediction of yield, counting crops or plants, measuring crops or plants height, survey reports, pigment measure, identifying nutrient, pests or diseases and so on.

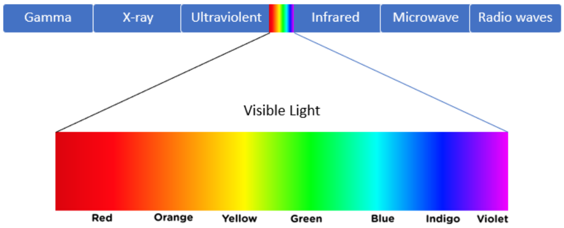


**FIGURE 6.** RGB bands [94].

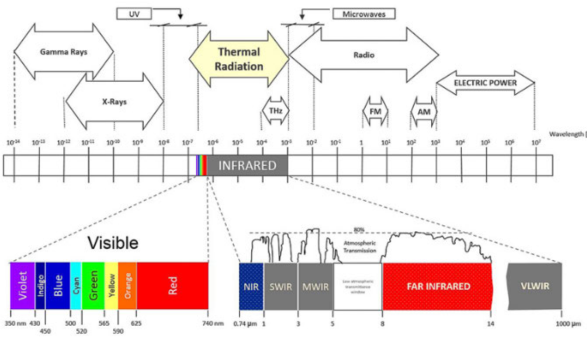


**FIGURE 7.** Infrared bands [95].

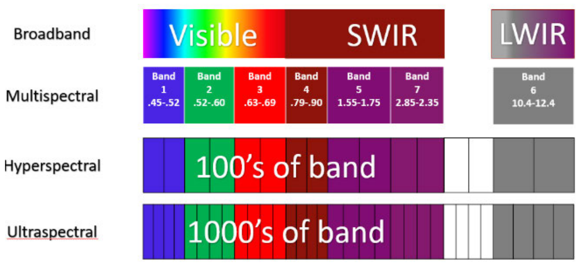


**FIGURE 8.** Spectral bands [96].

### *H. IMAGING TECHNIQUE IN SMART AGRICULTURE*

Image capturing from agriculture to find different hidden parameters accurately is possible now. Capturing images through suitable camera according to findings and process the pictorial data you may have your desired information to work with. In [93] authors reviewed imaging techniques and machine learning algorithms for detecting plat diseases.

The cameras are RGB, Multi spectral, Near Infra-Red (NIR), Thermal Camera, Hyperspectral cameras which are mostly use in agriculture nowadays according to the data required.

Figure 6 [94] shows Red, Green and Blue (RGB) bands and their ranges.

Infrared bands and their ranges are shown below in figure 7 [80] shows.

Spectral bands (Broad band, Multispectral, Hyperspectral and Ultra bands) and their ranges are shown below in figure 8 [81].

Authors in [97] shows techniques of finding fruits grading and diseases in agriculture. Image processing applications helps to identify nutrient content, humidity, pests and many others.

In this article a review on the cameras used in the field of agriculture and for the purpose of use is present to develop the interest of reader and find a path way for future work.

### *I. AI BASED SMART AGRICULTURE SYSTEM*

AI in field of agriculture is promoting a lot as it helps the farmers to know the environmental information's like temperature, precipitation, wind speed, and radiation.

In [98], [99] authors reviewed articles on AI techniques in agriculture which helps in different sectors of agriculture to make tasks automated, precise and easy.

AI is being employed in applications like machine-controlled machine changes for meteorology, diseases or pest's identification and others.

In this article a review on use of sensors, cameras, drones, AI techniques in the field of agriculture and their purpose is present to develop the interest of reader and find a path way for future work.

Table 4 presented below in which monitoring and control strategies are present to form smart agriculture systems.

The table 4 below covers the areas like pests, diseases, nutrients contents and levels, soil moisture, water level and humidity in agriculture areas.

Q4: What are the research trends and open issues challenges or advancement need in technology to identify and solve agriculture problems precisely?

Agriculture is becoming more important by the increasing in population to meet the demand of market and fulfil their needs. Agriculture sector faces many challenges from sowing to harvesting. It is necessary to resolve issues because agriculture plays significant role in country's economy.

Smart Agriculture enables farmers to provide a quality product that is profitable using technology. With drone-based aerial intelligence, farmers can collect and analyses data from their crops that, until now, have been inaccurate and incomplete.

In the field of agricultural intelligence, introducing technology elements into farm management, such as monitoring and tracking of the whole process from the production of crops, processing, transportation, to sales and other procedures, can effectively overcome the aforementioned problems. Such non-structural interventions are knowledge driven and are very high yielding and efficient as compared to conventional correctional measures.

a. Sensing, Collection and Estimation

Development of farm level crop parameters (like health, yield, production, crop fertility needs and pest and disease pressure etc.) estimation techniques, methodologies and software tools based on international practices using satellite and / or aerial mounted multi & hyperspectral sensors and ground-based data collections.

b. Computation of Actionable Information

Development of easy-to-use interfaces for complex software applications based on AI techniques and agro-ecological modelling do as to provide farmers and policy makers with precise farm level actionable information.

**TABLE 4.** Characteristics of monitoring and control strategies in agriculture.

| Ref Author's name and year | Crops/Orchards | Model/TECHNIQUE/ SOFTWARE | Technologies/Sensors | Estimated Variables/Research Approaches | Achievements |
|---|---|---|---|---|---|
| [100] T. Islam et al.,2018 | Rice | Image classification | RGB | disease classify | 1. Efficient technology 2. Faster and minimum computation time |
| [101] Z. P. D. Marston et al.,2020 | soybean | Linear regression model | Multispectral | Pest | Stress identified by NDVI |
| [102] X. Zheng *et al.*,2019 | | Regression model | ASD Field Spec® 3 Spectroradiometer | Locusta calculate VIs (NDVI, RVI, SAVI, GNDVI) | Designed loss estimation model |
| [103] A. A. Sarangdhar et al.,2017 | Cotton | SVM (Support Vector Machine) | Sensors RGB images | leaf disease | detect 5 diseases successfully |
| [104] T. Henmi et al,2016 | | SVM (Support Vector Machine | Sensors | early detection of fault in plants | Proposes a new fault detection method |
| [105] V. Partel etal.,2018 | Weed | Convolutional neural network (CNN) and deep learning | graphics processing unit (GPU), RTK GPS | weed sprayer and detect | cost efficient system |
| [106] J. Priyadarsini et al., 2019 | | sound frequency | ultrasonic sounds (33K-48KHZ), ph SENSOR | PEST CONTROL | Usage of pesticides decrease |
| [107] A. Srivastava *et al.*,2019 | BRINJAL | View Spec Pro (Software) | Hyper spectral remote sensing | Monitor crop stress growth and disease | bandwidths shows strong positive correlation |
| [108] R. H. Al Shidi et al.,2019 | Date | SUPERVISED LEARNING | Multispectral | O. lybicus infestations | detect the early infestation levels and location |
| [109] W. Yang et al., 2019 | CORN | CNN | Hyperspectral camera | Plant cold damage | Detect cold damage in corn seedlings. |
| [110] N. Gorretta et al.,2019 | APPLE | PLS-DA classification model | SWIR Hyperspectral | Fungal disease apple | effective region to separate infected and healthy leaves. |
| [111] J. Behley et al.,2019 | BARLEY | GAN | Hyper spectral | Powdery mildew | MODEL PREDICT OVER 7 DAYS |
| [112] H. Niu et al.,2019 | ALMOND | DEEP LEARNING NEURAL NETWORK | UGV, SWARM | intelligent bugs mapping and wiping (iBMW) robot | cost efficient system |
| [113] W. Liao *et al.*,2019 | BANANA | MACHINE LEARNING | Hyperspectral | Banana disease | 1. Feature representation banana disease 2. Detection Accurate system |
| [114] Y. C. Ouyang *et al.*,2019 | | SVM, spectral information divergence (SID) Sequential N-FINDER CEM (constrained energy minimization) | Hyperspectral, RGB | Inspection of phalaenopsis | Time saving Work in real time |

**TABLE 4.** ***(Continued.)*** **Characteristics of monitoring and control strategies in agriculture.**

| Ref Author's name and year | Crops/Orchards | Model/TECHNIQUE/ SOFTWARE | Technologies/Sensors | Estimated Variables/Research Approaches | Achievements |
|---|---|---|---|---|---|
| [115] M. Balota et al.,2016 | Peanut | Linear regression | RGB, UAV | Late leaf spot/Hue angle, greener area | Leaf drop (disease indicator) |
| [116] L. M. Dang *et al*.,2018 | RADISH | CNN (Convolution Neural Network) | RGB, UAV | Fusarium wilt/ CNN | 1.Color and texture features 2.Disease severity |
| [117] S. K. Sarkar et al.,2016 | CITRUS | SVM | RGB, UAV | Disease detection | PIXELS/Classify healthy and diseased |
| [53] L. R. Khot etal.,2016 | POTATO | LINEAR REGRESSION | Multispectral | GNDVI/DISEASE SEVERITY | GNDVI/DISEASE SEVERITY |
| [118] A. Patrick et al.,2017 | PEANUTS | LINEAR REGRESSION | Multispectral | SPOT WILT | 1.Vis 2.Disease severity |
| [119] E. C. Tetila etal.,2017 | soybean | Several classifiers | RGB | Target spot, powdery mildew | 1.Color 2.Texture 3. Shape features 4.Classify healthy and 2 diseases |
| [120] T. Zhao et al.,2015 | Almond | Image processing | UAS, RGB/NIR Camera pair | NDVI and SWP | Detect water stress levels in shaded and without shaded conditions |
| [121] S. S. Raghavan et al.,2018 | | Sensor based system | Arduino UNO, turbidity sensor, pH sensor, temperature sensor, GSM SIM900 module, Amazon Web Services (AWS), DynamoDB, Athena | Water contamination levels | system designed to detect the contamination levels in water bodies. |
| [122] A. L. Sumalan et al.,2017 | | Image processing, Supervised Learning | UAV Multiple descriptors, | Flooded and Vegetation areas | Algorithm developed for the detection and discrimination of flooded and vegetation areas. |
| [123] D. Long et al.,2017 | Cotton | Thermography | UAV Thermal IR Camera | Water level detection | Algorithm developed for overhead imagery |
| [79] I. Conference et al.,2020 | | Sensor based system | Arduino UNO, IoT (turbidity sensor, pH sensor, temperature sensor, GSM module ph. sensor, TDS sensor, LCD display.) | Waste Water Monitoring | System is in working condition and implemented. |
| [124] D. B. Lindell et al.,2016 | | AVE algorithm | Advanced Scatter meter (ASCAT) sensor | soil moisture level | 1. soil moisture |
| [125] D. Kale et al.,2019 | | Sensor based system | Wi-Fi, Raspberry Pi 3b+, IoT (Ultrasonic sensor, PIR sensor, DHT sensor, Water Quality, Turbidity Sensor, PI camera, soil sensor) | saves water, check water quality, secure ground water and measure water level. | Water Crises are solved |

**TABLE 4.** *(Continued.)* **Characteristics of monitoring and control strategies in agriculture.**

| Ref Author's name and year | Crops/Orchards | Model/TECHNIQUE/ SOFTWARE | Technologies/Sensors | Estimated Variables/Research Approaches | Achievements |
|---|---|---|---|---|---|
| [126] S. Sayanthan et al.,2018 | egg plant | Sensor based system | Soil moisture sensor, Arduino (UNO), LCD and SD card. | soil moisture | low cost technique |
| [127] Wang Yu et al.,2019 | | Sensor based system | Soil moisture sensor, Zigbee, WIFI and mobile app, WSN. | soil moisture | Experiment shows the humidity levels (high/low) from persists value |
| [128] Z. Yu et al., 2018 | | Sensor based system | Soil moisture probes | soil moisture | Design algorithm and test soil moisture |
| [129] N. Roussel *et al.*,2016 | | Sensor based system along with antenna | GNSSR, remote sensing and antenna. | soil moisture variations | amp, phase and frequency |
| [130] M. Ha et al.,2018 | | Phase wrapping method | GNSS-R and SNR | 1.soil moisture 2.Effective height changes | Soil moisture and effective height changes monitored satisfied. |
| [131] X. Zhang et al., 2017 | Citrus | Sensor based system | Iot(Air temp, Air humidity, Soi temp and Soil humidity) sensors | soil moisture and nutrients | 1. Early warning and decision-making 2.Provide a reference solution for citrus large-scale cultivation. |
| [132] L. Cuina et al.,2019 | | Quality control system | QC process | can detect data by fault instruments and QC method for detecting abnormal data | QC successfully attempted |
| [133] I. F. García-Tejero *et al.*,2017 | Almond | infrared thermography | Thermal camera | 1.Tc and CWSI with Ψleaf 2. TC and CWSI with gs | monitor the almond water status |
| [134] I. F. García-Tejero *et al.*,2018 | Almond | non-invasive technique | Thermal Imaging camera | water status/ CWSI | 1.water resources management 2.irrigation scheduling 3.crop-water status |
| [135] . Gutiérrez-Gordillo *et al.*,2020 | Almond | Imagery analysis | Thermal Imaging camera | crop water status | 1.materialize other WSB for different cultivars 2.tree ages for alternative irrigation programming, |
| [136] A. Bonfante *et al.*,2019 | Maize | Decision support system | LCIS DSS tools | Water detection | the maximum obtainable maize production |
| [137] K. Wu *et al.*,2019 | | Path tracking and mapping to point out stress areas | 1.Drone-bornegrou+H22nd-penetrating radar (GPR) 2.Light weight UAV 3.Transmitting and receiving antenna 4.Power bank and smartphone.H30 | Soil moisture | Presented new lightweight, drone-borne frequency-domain GPR for soil moisture mapping |

**TABLE 4.** *(Continued.)* **Characteristics of monitoring and control strategies in agriculture.**

| Ref Author's name and year | Crops/Orchards | Model/TECHNIQUE/ SOFTWARE | Technologies/Sensors | Estimated Variables/Research Approaches | Achievements |
|---|---|---|---|---|---|
| [138] L. S. Pereira et al.,2020 | | dual Kc approach | FAO56 | Soil water balance | FAO56 methodology adopted in SWB is very accurate. |
| [139] L. Nhamo *et al.*,2020 | | Machine learning | Multispectral remote sensing | Ground water | |
| [140] N. Bono Rossello et al.,2019 | hazelnut | Machine learning | Multi spectral, Thermal spectral | Water management in large scale | novel model proposed for water dynamics. |
| [141] A. Goap et al.,2018 | | Supervised and un supervised machine learning algorithm | IoT devices | 1. Soil moisture 2. Soil temperature 3.Air temperature 4. Ultra violet (UV) 5.Light radiation Relative humidity. | IoT based architecture and ML algorithm proposed. |
| [142] D. Grados et al.,2020 | Tomato | Image processing | Multispectral imagery | NDVI | 1. On-ground plant measurements 2. Evaluate canopy characteristics |
| [143] H. E. Brown *et al.*,2020 | | Image processing | infra-red | NDVI | System can identify less irrigation without loss of yield |
| [144] D. Thakur et al.,2020 | | Sensor based system | IoT (Arduino, python, cloud application, soil moisture sensor, PIR, Water pump) | Intrusion detection and moisture of soil for irrigation | cost effective and reliable devices for irrigation |
| [145] P. Sihombing et al.,2019 | | Sensor based system | IoT | Monitor nutrient of hydroponic plants | novel approach system Sensor and microcontroller monitor and control by smartphone |
| [146] H. Zheng *et al.*,2018 | Rise | Machine Learning | Multispectral, Hyperspectral | Nitrogen concentration | 1.Moderate accuracy 2. Image estimation |
| [147] S. Li et al.,2018 | | Random forest estimator | RGB | N Status | great feasibility for N-status prediction |
| [148] D. Walshe et al.,2019 | Spruce | Spring random forest model | Multispectral | nutrient deficiency | determine the areal extent of nutrient deficiency |
| [149] J. He et al.,2020 | Sugar beet | SLI imagery processing technology | scanner | nitrogen rate | Discriminating and monitoring sugar beet N status |
| [150] N. Lu *et al.*,2019 | Wheat | IMAGE PROCESSING, ML | Multispectral | nitrogen content | ML based algorithm proposed |
| [151] H. Zheng et al.,2019 | Rice | IMAGE PROCESSING | Multispectral | N Status | Textural indices performed |
| [152] A. Badhe et al.,2018 | Wheat, Rice, Orange, Sugarcane, Tomato, Apple | Sensor based system | IoT (soil moisture sensor, ph sensor and NPK sensor) | nutrients and soil health | system performance is quite reliable and accurate. |

**TABLE 4.** *(Continued.)* **Characteristics of monitoring and control strategies in agriculture.**

| Ref Author's name and year | Crops/Orchards | Model/TECHNIQUE/ SOFTWARE | Technologies/Sensors | Estimated Variables/Research Approaches | Achievements |
|---|---|---|---|---|---|
| [153] G. Sun et al.,2019 | Tomato | IMAGE PROCESSING | Hyperspectral, Multispectral | Chlorophyll | 3D point cloud model |
| [154] M. C. F. Lima et al.,2020 | Tomato | Robotic platform | Multispectral UAV | organic fertilization status | System developed for precision organic fertilization robotic platform. |
| [155] G. Sun et al.,2019 | Tomato | MACHINE LEARNING | Multispectral | NPK | 3-DIMENSIONAL IMAGING |
| [156] B. H. Shraddha et al.,2018 | MAIZE | Spectral analysis | NIR (Near Infra Red) | N, P | Spectral analysis separately for identification of nitrogen and phosphorus content |
| [157] R. G. Regalado et al.,2017 | | Colorimetry | chemical soil test kit (Colorimetry) | n,p,k ph of soil | no significant difference b/w proposed and human resource readings |
| [158] C. Ballester et al.,2017 | Cotton | Linear Regression | Multispectral | Several Vis | Nitrogen concentration and uptake |
| [159] P. Benincasa *et al.*,2018 | Wheat | Linear Regression | Multispectral | NDVI | Nitrogen concentration and uptake |
| [160] L. Caturegli *et al.*,2016 | Turfgrass | spectral analysis | Multispectral | NDVI | nitrogen content |
| [161] Martina Corti et al.,2018 | Maize | Machine learning | CIR (color infra-red) | Several Vis | Nitrogen concentration and uptake |
| [162] J. Geipel et al.2016 | Wheat | Spectral analysis | Multispectral | NDVI, REIP | Nitrogen concentration and uptake |

c. Availability, Accessibility and Dissemination

Development of an online Crop Information Portal on a web based, open-source platform conceived and designed to support the analysis and dissemination of Pakistan's crop data and related climatic, agronomic, hydrologic and economic variables.

d. Capacity Building

Component I. Joint research studies and academic projects with national and international academia, researchers and research & development institutes

Component II. Seminars, workshops and training for farmers and policy makers on use of technologically advanced solutions and systems.

The table 4 and table 5 provides you the existing trends and achievements in agriculture through which you can easily find the pathway for future work.

In figure 9 analysis of technologies are provided which are used in selected articles.

Characteristics of Existing Control Strategies:

In this section we will discuss the advantages and limitations of models and techniques discussed in this review paper present in table 4.

### 1) RGB CAMERA

The RGB color band is a stabilizer color band in which red, green, and blue light are merge together in numerous ways to produce a wide-ranging colors array. In RGB, a color is well-defined as a combination of pure red, green, and blue lights of many strengths.

The RGB bands of light is sensitive to human eye. Most drones escort cameras that capture a similar RGB bands therefore the pictures they manufacture recreate nearly specifically what our eyes see. To begin with RGB cameras in farm is good at beginning stage. As they are low cost and consumer drones. RGB cameras are sensible for making maps of Orthomosaic that display your whole field directly,

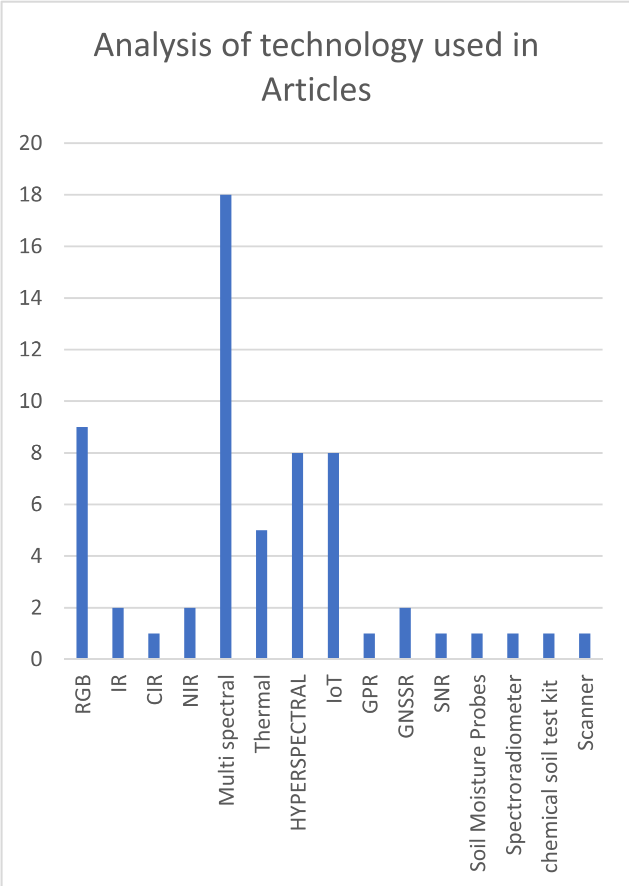


**FIGURE 9.** **Analysis of technology used in articles.**

and RGB can capture aerial videos. Individually the red, green and blue levels of light is encoded between 0 to 255, with 0 that means lowest level and 255 that means highest level [163]

The values of RGB are usually not transferable among devices, cannot identify differentiate and determine specific colors perfectly, and are not uniform perceptually [164]

### 2) IR CAMERA

Infrared energy emitted by all objects, called heat signature. The camera translate that infrared data into an electronic image that express measured temperature of objects on the apparent surface and also measures the infrared energy of objects [165].

Thermal imaging with a wide range of more features is capable of increase resolution, automate functions, record and stream video, permit voice annotations, support analysis and reporting [165].

The range of transmission is quite short compared to wired transmission. The performance will drop off if the distance to the receiver is out of range for the infrared device [166].

### 3) CIR AND NIR

To understand CIR imagery, you first must understand To understand CIR representational process, you initially should perceive what we will and can't see with our eyes. The human eye will see high-frequency electromagnetic radiation (a.k.a. light) from solely a really tiny portion of the spectrum. To 'see' on the far side this vary, we'd require cameras and instruments that may sight then translate invisible radiation into the familiar colours of the rainbow. Color-infrared (CIR) representational process uses a little of the spectrum called close to infrared (NIR) that lies simply on the far side the visible wavelengths for the colour red [167]

CIR imaging (representational process) is imagery created from a mix of colours among the spectrum with the addition of NIR light that present by another, distinct color among the spectrum [167]

Infrared Cameras give false readings on surfaces which are reflective and shiny [168].

### 4) MULTISPECTRAL CAMERA

A Multispectral camera in agriculture use for sensing elements, captures multiple pictures within the visible ranges of ultraviolet visible and infrared. It permits skilled farmers to manage farms or crops, yields, fertilizing process and irrigation precisely. Every imagery data captures by Multispectral camera for preciseness in agriculture is passed through a filter to limit light to a particular color or wavelength. There square measure provides advantages of Multispectral sensors for each to the farmer and to the environment by minimizing the utilization of pesticides, fertilizers, wastage of water and at an equivalent time increasing the yields at harvesting.

It is helpful to understand the working of monochrome and color. Monochrome Cameras contains a picture sensing element that is comprised of a two-dimensional array of sensitive pixels. These pixels area unit sensitive to incoming light across a broad spectral vary as an example during a monochrome CMOS image sensing element. Every pixel is sensitive to light from four hundred nanometers to one thousand nanometers [169].

A color camera contains a picture sensing element with a two-dimensional array of pixels but during a color camera. The multispectral camera remote sensing is coated with a mosaic arrangement of pigments that transmit red, green or blue. These pigments frame what's known as the Colour Filter Array (CFA) well-known from common RGB cameras [169].

### 5) HYPERSPECTRAL CAMERA

Spectral imaging in agriculture is the light detection which is reflected by crops using specialized sensors. It measures in spectral bands. The accuracy is higher by higher number of bands. Spectral imaging currently using widely in agriculture and smart farming.

Gamaya used Hyperspectral technology, which is capable of higher detection because it consists of higher number of spectral bands. It is the solution of almost every problem encountered in the field. Hyperspectral imaging in agriculture permits to considerably extend the range of farming problems and applications that may be self-addressed by remote sensing [170].

The main distinction between multispectral and hyperspectral imaging is that the variety of wavebands being imaged and how narrow the bands are. Multispectral imagery refers to three to ten distinct "broader" bands. Hyperspectral mental imagery consists of a lot of narrower bands (10-20 nm). A hyperspectral imagery have many thousands of bands [171].

### 6) THERMAL CAMERA

Thermal imaging is a technique of the use of infrared light radiations and thermal energy to collect data and information regarding objects, so as to express pictures of them, even in the environments with low visibility [172].

All objects release infrared energy, referred to as a heat signature. An infrared camera or thermal imager detects and measures the objects of infrared energy. The camera converts that infrared data or information into image (electronic) which measures the surface temperature of objects [173].

### 7) IoT

The (IoT) internet of things, is a system which connect and relate computing devices, digital and mechanical machines, animals or people, objects that are providing with unique identifiers (UIDs) and also the ability to transfer information over a network while not requiring human-to-human or human-to-computer interaction [174].

Smart farming based on IoT, is a system designed for observance the crop field with the assistance of sensors (light, humidity, temperature, soil wet, etc.) and automate the system of irrigation. In IoT-based sensible farming, a system is made for observance the crop field with the assistance of sensors (light, humidity, temperature, soil wet, etc.) and automating the irrigation system. The farmers can easily monitor their fields conditions from anyplace. IoT-based farming is very economical when put next with the traditional approach [175].

The issues are Compatibility, Complexity, Privacy/Security, Safety can be arise using IoT in agriculture [176].

#### *a: ARTIFICIAL INTELLIGENCE (AI)*

AI is the incorporation of numerous technologies, it has encompassing capabilities such as machine learning, natural language processing, and knowledge management.

In figure 10 and figure 11 AI and areas related to AI are expressed.

Artificial intelligence and related industries are expressed in figure 12 below.

AI models like regression model, SVM, Deep learning, supervised learning, PLSDA classification model, GAN, machine learning, AVE algorithm, un supervised learning and random forest model are explained below used in articles.

The above stated models are used by authors in their articles reviewed in this review paper. The analysis of AI models is presented in figure 12.

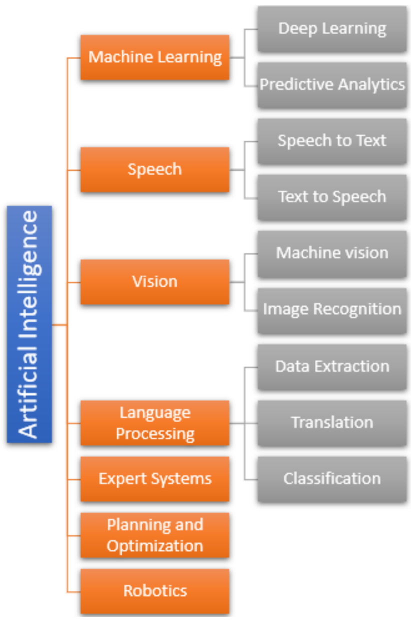


**FIGURE 10. AI models [177].**

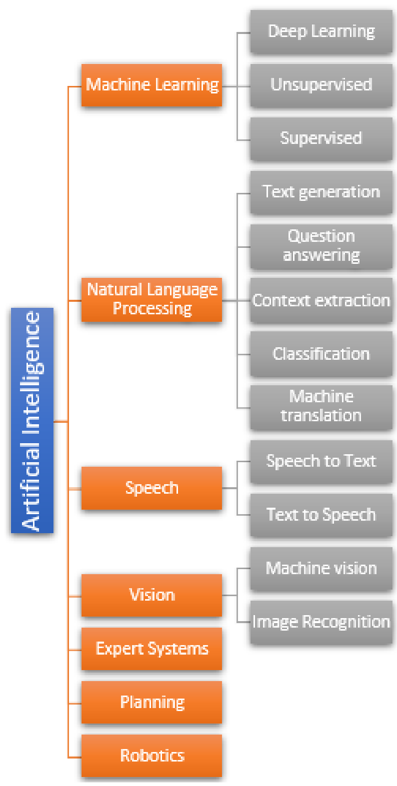


**FIGURE 11. Umbrella of AI [178].**

### 8) REGRESSION MODEL

Analysis of regression in statistical modelling is a set of statistical processes for estimates the relation between a dependent variable and one or more independent variable. Regression analysis is basically used for prediction and forecasting,

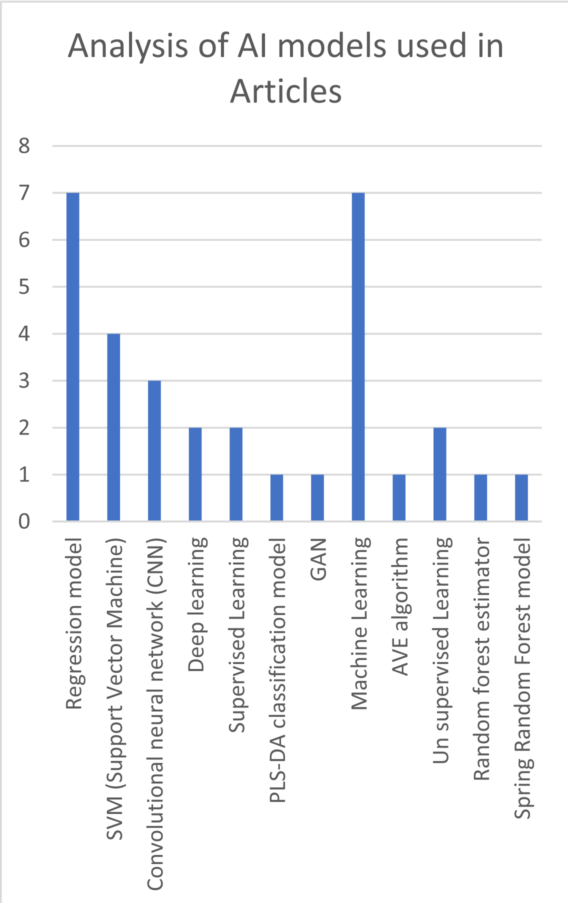


**FIGURE 12.** **Analysis of AI models used in articles.**

where its use has substantial overlap with the field of machine learning. Significantly, regressions only reveal relationships between a dependent variable and a collection of independent variables in a fixed dataset [179]

- Linear Regression
- Logistic Regression
- Polynomial Regression
- Stepwise Regression
- Ridge Regression
- Lasso Regression
- ElasticNet Regression

The general equation is $Y = a + bX$ [180]

Where

Y is the dependent variable

X is the independent variable

b is the slope of the line and a is the y-intercept.

Despite the above-mentioned utilities, the regression analysis has limitations. The relationship of cause and effect between the variables assumed remains same. Due to this assumption may not obtain correct data and estimation using of equation may lead to erroneous and misleading results. It has very long and complex method of calculations and analysis and cannot be used in case of qualitative phenomenon [181].

#### 9) SUPERVISED LEARNING

Supervised learning is a powerful tool to categorize and process data or information using machine language. With supervised learning labeled data used, which is a classified data set, to infer a learning algorithm. The data set is used as the basis for expecting the arrangement of other unlabeled data using machine learning algorithms [182].

#### 10) SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) is basically a supervised machine learning algorithm which is capable of regression, classification and even outlier recognition. Drawing straight line between two classes is working of linear SVM classifier [183]

SVM algorithm is not suitable, does not perform very for large data sets and noisy for noisy data [184].

#### 11) CONVOLUTION NEURAL NETWORK

A Convolutional Neural Network (CNN) is the basis of maximum computer vision technologies. Dissimilar to conventional multilayer perceptron architectures, it uses two operations 'convolution' and pooling' to decrease an image into its vital features, and uses those features to comprehend and categorize the image [185] CNN is widely used in many interesting areas like agriculture, healthcare, surveillance and self-driving cars.

CNN do not encode the location, position and orientation of object or thing. CNN haven't built-in understanding of 3D space so, need tens of thousands of examples to achieve very good performance [186].

#### 12) DEEP LEARNING

Deep Learning is a branch of machine learning concerned with algorithms inspired by the purpose and structure of the brain called (ANN) artificial neural networks. Deep learning is a function of AI that imitate the works of the human brain in data processing for use in objects detection, speech recognition, translating languages, and decisions making. It is capable to learn without human directions and supervision, drawing from data that is both unstructured and unlabeled [187].

Lack of common sense and general intelligence. Deep learning always requires large number of data set and unable to learn from limited examples. It only performs well on benchmark dataset and can badly fail on images not in dataset [188].

#### 13) UNSUPERVISED LEARNING

Unsupervised learning is a subfield of machine learning used to draw inferences from datasets consisting of input data without labeled responses. The foremost common unsupervised learning methodology is analysis of cluster, that is employed for exploratory data analysis to find hidden patterns or grouping in data [189].

Unsupervised learning can't provide precise data or information regarding sorting of data, and the output as data is not labeled and unknown which results in less accuracy because in advance data is not labelled by people [190].

#### 14) GAN

The architecture of a GAN consists of two elements: the discriminator network and the generator network. Each network belongs to any neural network. They can generate good results if the input is mapped into the learned subspace. By learning complete representations, the proposed CR-GAN can generate realistic, identity-preserved images from a single-view input [191].

#### 15) RANDOM FOREST ESTIMATOR (SPRING RANDOM FOREST)

Random forests are a mixture of tree predictors such every tree depends on the values of a random vector sampled severally and with identical distribution for all trees within the forest. The generalization error for forests converges to a limit because the variety of trees within the forest becomes massive. The generalization error of a forest of tree classifiers depends on the strength of the individual trees within the forest and therefore the correlation between them [192].

#### 16) PLSDA CLASSIFICATION MODEL

Partial least squares-discriminant analysis (PLS-DA) is a versatile algorithm that can be used for predictive and descriptive modelling as well as for discriminative variable selection. However, versatility is both a blessing and a curse and the user needs to optimize a wealth of parameters before reaching reliable and valid outcomes [193].

#### 17) AVE ALGORITHM

Automated visual evaluation (AVE) is a machine-learning based algorithm that assesses digital images. All versions of the automated visual evaluation algorithm follow the same basic formula, first developed as a proof-of-concept using the Faster R-CNN approach to deep learning object detection [194].

The strategies used in agriculture are defined and expressed as metrices according to their use in below table 6.

AI models discussed by authors in their articles are reviewed and presented below in table 7.

## VI. RESULTS

The articles are chosen after scrutiny of articles. Total of 764 articles selected from 2015 to 2020 from reputed publishers mentioned in Table 1. On the basis inclusion and exclusion criteria present in table 8, 470 articles are selected. On the basis of studying abstract and conclusion 113 articles are selected. Finally, we consider 65 articles on the basis of complete study of articles.

The publishers of selected articles categorized in figure 13.

The articles published yearly are presented below in figure 14.

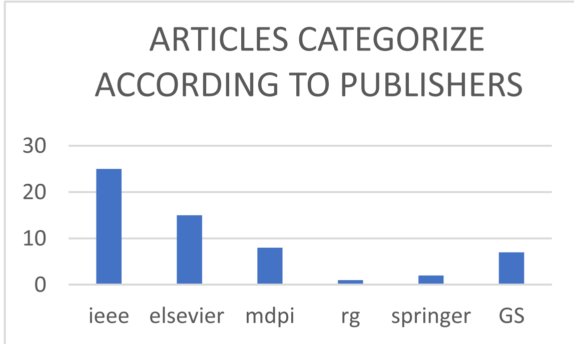


**FIGURE 13.** Articles categories according to publishers.

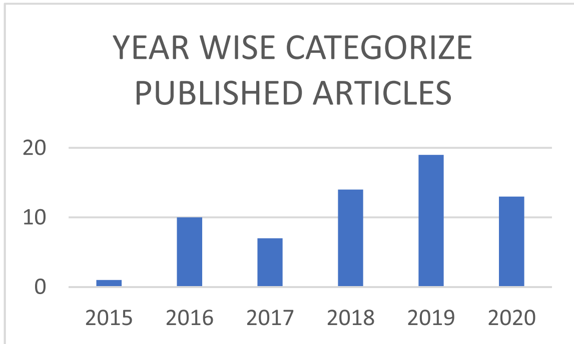


**FIGURE 14.** Articles published year wise for review.

### A. INCLUSION AND EXCLUSION CRITERIA

From the articles which are selected for review, Figure 4 shows the number of articles published year-wise, which are selected for the study. Figure 5 shows the articles which were published by well-known scholarly publishers between 2015 and 2020. The articles are selected on the main areas in agriculture. The main areas are water, soil, irrigation, nutrients, pest and diseases in agriculture. The review present in this paper by involving advance control strategies in main areas of agriculture and to automate agriculture. These strategies are IoT, Imageries cameras, Drones and AI. Figure 6 shows the articles on the basis sensors and technology. Figure 13 shows the articles on the basis of AI models.

## VII. OUR CONTRIBUTION

This review paper presents background, recent works and future trends of the use of technologies in agriculture. This paper achieved the following objectives:

- To identify the factors involved in agriculture and how technically find them.
- To identify the challenges in traditional farming and importance of advance technologies in agriculture.
- To study the existing control strategies in agriculture.
- To identify and highlight the research gap and future trends for reviewers in the agriculture.

By achieving the research objective, on the basis of review paper, research papers and articles we present our block diagram for smart agriculture system.

**TABLE 5.** Highlights of imaging techniques and AI models in agriculture.

| | |
|---|---|
| **RGB** | Red, green, and blue light are merge together in numerous ways. The red, green and blue levels of light is encoded between 0 to 255. |
| **IR** | Infrared energy emitted by all objects, called heat signature. The performance will drop off if the distance to the receiver is out of range for the infrared device. |
| **CIR AND NIR** | Color-infrared (CIR) representational process uses a little of the spectrum called close to infrared (NIR) that lies simply on the far side the visible wavelengths for the colour red. Infrared Cameras give false readings on surfaces which are reflective and shiny. |
| **MULTISPECTRAL** | A Multispectral camera in agriculture use for sensing elements, captures multiple pictures within the visible ranges of ultraviolet visible and infrared. |
| **HYPERSPECTRAL** | Spectral imaging in agriculture is the light detection which is reflected by crops using specialized sensors. It measures in spectral bands. The accuracy is higher by higher number of bands. |
| **THERMAL** | The camera converts that infrared data or information into image (electronic) which measures the surface temperature of objects. |
| **IoT** | Smart farming based on IoT, is a system designed for observance the crop field with the assistance of sensors (light, humidity, temperature, soil wet, etc.) and automate the system. The issues are Compatibility, Complexity, Privacy/Security, Safety can be arise using IoT in agriculture |
| **REGRESSION MODEL** | Regressions only reveal relationships between a dependent variable and a collection of independent variables in a fixed dataset. It has very long and complex method of calculations and analysis and cannot be used in case of qualitative phenomenon |
| **SUPERVISED LEARNING** | With supervised learning labeled data used, which is a classified data set, to infer a learning algorithm. |
| **SUPPORT VECTOR MACHINE** | Support Vector Machine (SVM) is basically a supervised machine learning algorithm which is capable of regression.<br>SVM algorithm is not suitable, does not perform very for large data sets and noisy for noisy data |
| **CONVOLUTION NEURAL NETWORK** | A Convolutional Neural Network (CNN) is the basis of maximum computer vision technologies. it uses two operations 'convolution' and pooling'. CNN do not encode the location, position and orientation of object or thing. |
| **DEEP LEARNING** | Deep Learning is a branch of machine learning concerned with algorithms inspired by the purpose and structure of the brain called (ANN) artificial neural networks.<br>Deep learning always requires large number of data set and unable to learn from limited examples. |
| **UNSUPERVISED LEARNING** | Unsupervised learning is a subfield of machine learning used to draw inferences from datasets consisting of input data without labeled responses.<br>Unsupervised learning can't provide precise data or information regarding sorting of data. |
| **GAN** | The architecture of a GAN consists of two elements: the discriminator network and the generator network. Each network belongs to any neural network. |
| ***RANDOM FOREST ESTIMATOR (spring random forest)*** | Random forests are a mixture of tree predictors such every tree depends on the values of a random vector sampled severally and with identical distribution for all trees within the forest. |
| **PLSDA CLASSIFICATION MODEL** | Partial least squares-discriminant analysis (PLS-DA) is a versatile algorithm that can be used for predictive and descriptive modelling as well as for discriminative variable selection. However, versatility is both a blessing and a curse and the user needs to optimize a wealth of parameters before reaching reliable and valid outcomes |

Our product is the complete use of technologies including IoT, Imaging techniques, Drones and AI. It may also call as a smart cropping model. Implementation of this technology is our future goal. The revenue of product is also present in the paper for reviewers who wants to implement it.

### *A. TRENDS AND OPEN ISSUES*

Today's main focusing areas in agriculture are as follows:

- To save water and use in optimal way.
- To find out the actual reason of stress in crops.
- Provide targeted operations.
- Increase Yield

**TABLE 6.** Metrices of control strategies (imaging technologies and sensors) used in agriculture.

| REF Author's name and year | RGB | IR (CIR and NIR) | Multi spectral | Thermal | HYPER SPECTRAL | IoT | GPR | GNSSR | SNR | Soil Moisture Probes | Spectroradio meter | chemical soil test kit | Scanner |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [84] S. S. H. Hajjaj et al.,2017 | * | | | | | | | | | | | | |
| [85] L. C. Santos et al.,2020 | | | * | | | | | | | | | | |
| [86] F. Yandun et al.,2017 | | | | | | | | | | | * | | |
| [101] Z. P. D. Marston *et al.*,2020 | | | | | * | | | | | | | | |
| [102] X. Zheng *et al.*,2019 | | | * | | | | | | | | | | |
| [103] A. A. Sarangdhar et al.,2017 | | | | | * | | | | | | | | |
| [104] T. Henmi et al,2016 | | | | | * | | | | | | | | |
| [105] V. Partel etal.,2018 | | | | | * | | | | | | | | |
| [107] A. Srivastava *et al.*,2019 | | | | | * | | | | | | | | |
| [108] R. H. Al Shidi et al.,2019 | * | | | | * | | | | | | | | |
| [109] W. Yang et al., 2019 | * | | | | | | | | | | | | |
| [110] N. Gorretta et al.,2019 | * | | | | | | | | | | | | |
| [111] J. Behley et al.,2019 | * | | | | | | | | | | | | |
| [47] A. S. Fiorucci et al.,2017 | | | * | | | | | | | | | | |
| [112] H. Niu et al.,2019 | | | * | | | | | | | | | | |
| [113] W. Liao *et al.*,2019 | * | | | | | | | | | | | | |
| [114] Y. C. Ouyang *et al.*,2019 | * | * | | | | | | | | | | | |
| [115] M. Balota et al.,2016 | | | | | | * | | | | | | | |

**TABLE 6.** *(Continued.)* **Metrices of control strategies (imaging technologies and sensors) used in agriculture.**

| REF Author's name and year | RGB | IR (CIR and NIR) | Multi spectral | Thermal | HYPER SPECTRAL | IoT | GPR | GNSSR | SNR | Soil Moisture Probes | Spectroradio meter | chemical soil test kit | Scanner |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [117] S. K. Sarkar et al.,2016 | | | | * | | | | | | | | | |
| [65] N. Gondchawar et al.,2020 | | | | | | * | | | | | | | |
| [119] E. C. Tetila etal.,2017 | | | | | | * | | | | | | | |
| [120] T. Zhao et al.,2015 | | | | | | * | | | | | | | |
| [121] S. S. Raghavan et al.,2018 | | | | | | * | | | | | | | |
| [122] A. L. Sumalan et al.,2017 | | | | | | | | | | * | | | |
| [123] D. Long et al.,2017 | | | | | | | | * | | | | | |
| [124] D. B. Lindell et al.,2016 | | | | | | | | * | * | | | | |
| [125] D. Kale et al.,2019 | | | | | | * | | | | | | | |
| [110] Wang Yu et al.,2019 | | | | * | | | | | | | | | |
| [127] Z. Yu et al., 2018 | | | | * | | | | | | | | | |
| [128] N. Roussel *et al.*,2016 | | | | * | | | | | | | | | |
| [129] X. Zhang et al., 2017 | | | | | | | * | | | | | | |
| [129] I. F. García-Tejero *et al.*,2017 | | | * | | | | | | | | | | |
| [133] I. F. García-Tejero *et al.*,2018 | | | * | * | | | | | | | | | |
| [135] . Gutiérrez-Gordillo *et al.*,2020 | | | | | | * | | | | | | | |
| [136] A. Bonfante *et al.*,2019 | | | * | | | | | | | | | | |
| [137] K. Wu *et al.*,2019 | | * | | | | | | | | | | | |

**TABLE 6.** *(Continued.)* **Metrices of control strategies (imaging technologies and sensors) used in agriculture.**

| REF Author's name and year | RGB | IR (CIR and NIR) | Multi spectral | Thermal | HYPER SPECTRAL | IoT | GPR | GNSSR | SNR | Soil Moisture Probes | Spectroradio meter | chemical soil test kit | Scanner |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| [138] L. S. Pereira et al.,2020 | | | | | | * | | | | | | | |
| [139] L. Nhamo *et al.*,2020 | | | | | | * | | | | | | | |
| [140] N. Bono Rossello et al.,2019 | | | * | | * | | | | | | | | |
| [141] A. Goap et al.,2018 | * | | | | | | | | | | | | |
| [142] D. Grados et al.,2020 | | | * | | | | | | | | | | |
| [143] H. E. Brown *et al.*,2020 | | | | | | | | | | | | | * |
| [144] D. Thakur et al.,2020 | | | * | | | | | | | | | | |
| [145] P. Sihombing et al.,2019 | | | * | | | | | | | | | | |
| [146] H. Zheng *et al.*,2018 | | | | | | * | | | | | | | |
| [147] S. Li et al.,2018 | | | * | | * | | | | | | | | |
| [148] D. Walshe et al.,2019 | | | * | | | | | | | | | | |
| [149] J. He et al.,2020 | | | * | | | | | | | | | | |
| [150] N. Lu *et al.*,2019 | | * | | | | | | | | | | | |
| [151] H. Zheng et al.,2019 | | | | | | | | | | | | * | |
| [152] A. Badhe et al.,2018 | | | * | | | | | | | | | | |
| [153] G. Sun et al.,2019 | | | * | | | | | | | | | | |
| [154] M. C. F. Lima et al.,2020 | | | * | | | | | | | | | | |
| [155] G. Sun et al.,2019 | | * | | | | | | | | | | | |
| [156] B. H. Shraddha et al.,2018 | | | * | | | | | | | | | | |

**TABLE 7.** Metrices of AI models used in agriculture.

| REF | Regression model | SVM (Support Vector Machine) | Convolutional neural network (CNN) | Deep learning | Supervised Learning | PLS-DA classification | GAN | Machine Learning | AVE algorithm | Un supervised Learning | Random forest estimator |
|---|---|---|---|---|---|---|---|---|---|---|---|
| [77] | * | | | | | | | | | | |
| [78] | * | | | | | | | | | | |
| [79] | | * | | | | | | | | | |
| [80] | | * | | | | | | | | | |
| [81] | | | * | * | | | | | | | |
| [84] | | | | | * | | | | | | |
| [85] | | | * | | | | | | | | |
| [87] | | | | | | * | | | | | |
| [88] | | | | * | | | * | | | | |
| [89] | | | | | | | | * | | | |
| [90] | | * | | | | | | | | | |
| [91] | * | | | | | | | | | | |
| [92] | | | * | | | | | | | | |
| [93] | | * | | | | | | | | | |
| [47] | * | | | | | | | | | | |
| [94] | * | | | | | | | | | | |
| [95] | | | | | * | | | | | | |
| [100] | | | | | | | | | * | | |
| [115] | | | | | | | | * | | | |
| [116] | | | | | | | | * | | | |
| [117] | | | | | | | | * | | * | |
| [122] | | | | | | | | * | | | |
| [123] | | | | | | | | | | | * |
| [124] | | | | | | | | | | | * |
| [134] | * | | | | | | | | | | |
| [135] | * | | | | | | | | | | |

**TABLE 8.** Inclusion and exclusion criteria.

| Inclusion Criteria | Exclusion Criteria |
|---|---|
| The review emphasizes on smart agriculture or stress monitoring techniques (image processing, IoT and Machine learning) in agriculture. | The study based on these technologies but on different applications |
| The articles are considered, published by above mentioned publishers in Table 1 which are well reputed indexed conferences and journals. | The articles which are not published, speeches and editorials are not considered |
| The English language written articles are considered. | The article written on any other language except English are not considered. |

Monitoring humidity or water level from crops and provide water accordingly using humidity sensors or thermal imaging. Provide water according to climate condition is another way of save water. Temperature sensor is available for such cause.

There are only methods of calculating water from soil surface. To calculate water from inner layers using or modifying some sensors and cameras.

Land levelling can also help to optimal use of water. But the existing methods are time taking and not much efficient.

Aerial imagery and sensor's data help to identify actual cause and design prescription maps by training AI models through which targeted operations can perform which saves resources and increase yield.

Safety matters arise on many levels of IoT-based architecture in agriculture, which need to be solved. Due to less safety, operators face different problems like data loss and other on-field parameters. These issues have been presented in [195]–[197] deeply. Furthermore, due to low power and limited memory, it is difficult to implement sophisticated and complex algorithms.

While installing technology-based devices like sensors, capturing aerial images in agriculture sector, numerous cost-related problems arise like hardware cost and running costs. Authors in [5] discussed this issue and present a review paper.

Unfortunately lack of knowledge of technology is the core barrier amongst the farmers living in countryside areas. In developing countries. this problem is very common because of uneducated [198]. The application of smart setups in agriculture is a great challenge, because farmer's training is required along with a lot of investment.

One of the greatest challenges is short range of BLE. The extreme range of modern BLE is 100 meters which is relatively low for a large area. To solve this challenge, master slave concept arises in agriculture in which farmer controls master UAV and other UAVs act like slaves maintaining distance from others [199].

**TABLE 9.** Comparative analysis of imaging technique.

| RGB Imaging | Thermal Imaging | Multispectral Imaging | Hyperspectral Imaging |
|---|---|---|---|
| detect, represent and display of images in electronic systems. | Lies in multi spectral bands (band 10 and 11) | 3 TO 10 bands | Hundreds or thousands of bands |
| Color perception is based on human beings. | Near infrared illumination | Wider bands | Narrow bands |
| | 100 meters. | Each band has 30m of three-dimensional resolution excluding band 8, 10 and 11. | For all 242 spectral bands it produces 30-meter resolution images. |
| | Use in dark to improve visibility | Not having higher level spectral details | higher level of spectral detail |
| | | Less complex | More complex |

Future agriculture will include technologies such as robots, temperature and humidity sensors, aerial images, AI and GPS technology. These advanced strategies and smart agriculture and robotic systems can enable farms to be a lot profitable, well-organized, effective, secure, and nature friendly. The Comparative analysis of Imaging Technique is presented below in table 9 which can be use according to requirements.

### B. FUTURE DIRECTIONS

In this section a block diagram is presented which shows our future direction or practical approach for adapting and implementing technology in agriculture to do smart farming.

This block diagram is resultant of reviewing research papers, articles and review papers. We sketch or design figure 15 according to our understanding on the basis of research articles.

Figure 15 below shows every step of smart farming from operations and data acquisition to final deliverables.

### C. REVENUE

Our revenue model is simple although we have multiple customers:

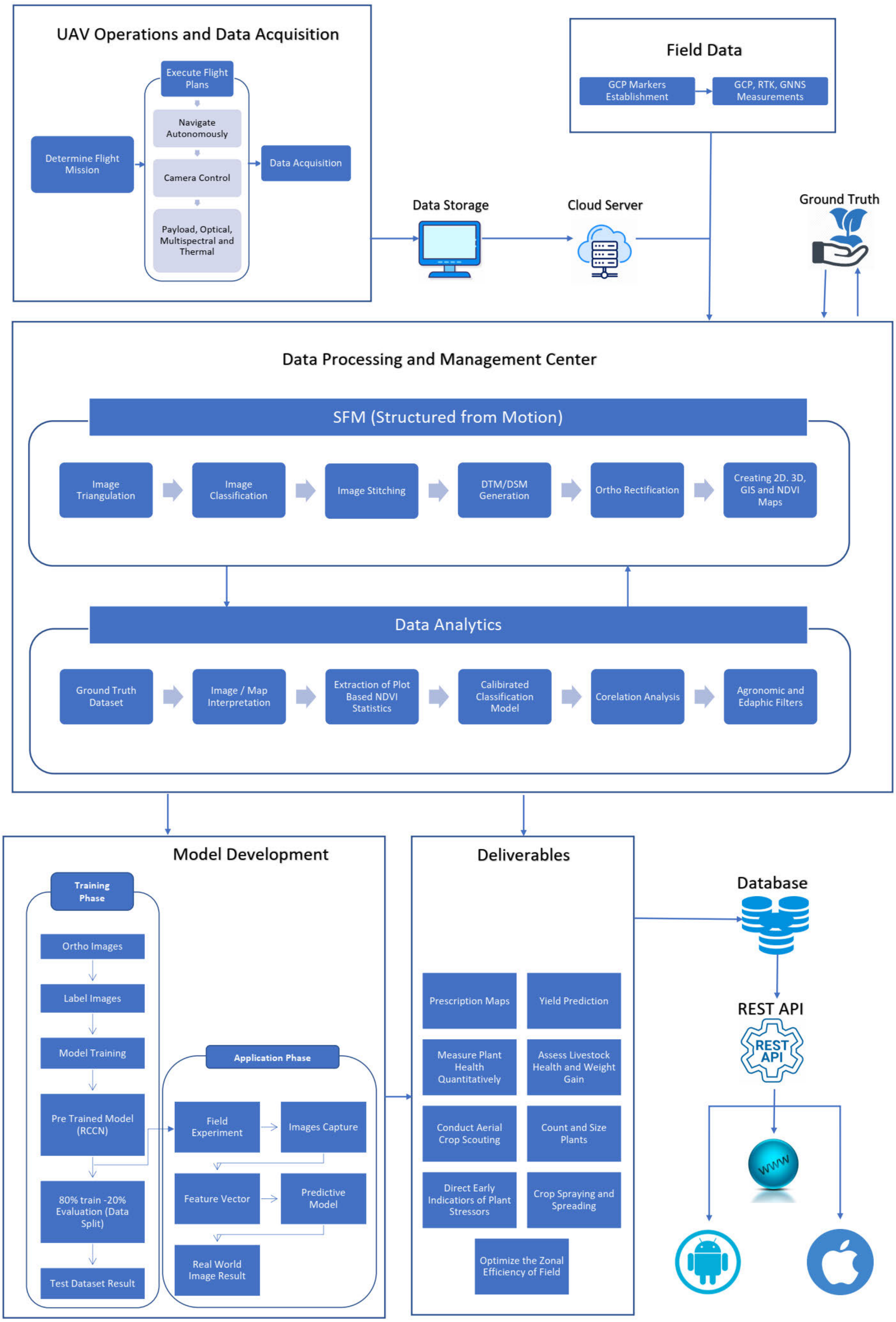


**FIGURE 15.** Block diagram of our technology for agriculture.

### D. FARMERS
We will have a subscription-based model for farmers for giving them insights about their fields, counting the population of the plants to predict the yield, providing them prescription maps and actionable information with timelines to increase the yield and save it from getting damaged. On demand imagery and air scouting will be individually charged as well.

### E. INSECTICIDE, PESTICIDE AND FERTILIZER COMPANIES
These companies struggle for the insights about the frequency of diseases and requirements which in turn hurt their supply chain. Information such as frequency of diseases or requirements of their products in various areas of the country will be really valuable and Engro Fertilizers and Jaffer Agro Services is already showing interest in such insights and yield maps.

### F. SEEDS SUPPLIERS
Different land, different soil needs different seeds accordingly, seed supplier similar to above mentioned companies struggle with the supply chain and adding real value at the right time and at the right place. We will be able to give them insights too after a few years of our operations and data acquisition in the market.

### G. INSURANCE COMPANIES
In Pakistan, natural disasters such as flooding, locusts attack, earthquakes are observed at times leaving the insurance companies bewildered and farmers can't precisely claim the value of their field either. Our imagery-based solution can predict the yield as well as precisely confirm how the farm looks like with time stamped data helping both the farmers and insurance companies.

### H. BANKS
Even large banks even after the digitised Punjab land record struggle with precisely valuing the field farmer is offering in mortgage. Accurate Land Parcels can help them do that with ease and besides that insights around how that capital was used and how it could be more efficiently used can be given to both banks and farmers where both can get benefit. We are almost about to implement this model with HBL which is the largest bank of Pakistan really soon.

### I. DATA COMPANIES
For prescription mapping we will train their Machine Learning algorithm for different crops, diseases, pests and other such issues. This data is really valuable for companies like Bayer who are into research about crops sciences. Cost: Our biggest cost bucket in the initial set up is for the equipment that has to be bought to provide the aforementioned services. The sensors or specialized agri-drones are expensive but help us provide a range of smart solutions. Competitor Analysis: Currently, there is no company in Pakistan providing 360-degree smart agriculture solutions. Globally, there are a number of competitors mostly in Europe and America like Precision Hawk, Terra Drone, Bearag etc.

### J. LIMITATIONS OF THIS REVIEW
This paper consists of limited Conferences and Journals. Additionally, a few varieties of keywords are used for the literature review. Mainly, this review focuses on advance control strategies in agriculture.

## VIII. CONCLUSION AND RECOMMENDATIONS
Agriculture plays vital role in country's economy. This paper helps researcher to cope up with the pressure due to the changes in climate, erosion of soil, biodiversity loss and from end users.

The paper delivers a review of advance control strategies in smart agriculture used by different researchers. The selected papers are on advance control strategies including Spectral imaging, Sensors (IoT) and techniques based on artificial intelligence used to solve the agriculture related problems such as increasing yield, stress detection, targeted operations and so on.

The major edges of exploitation drones embrace crop health imaging, integrated GIS mapping, simple use, saves time, and also the potential to extend yields. With strategy and coming up with supported time period information assortment and process, drone technology can provide a sophisticated remodeling to the agriculture business.

The applications of advance strategies-based farming not solely target typical, giant farming operations, but may even be new farms to transform alternative growing or common trends in agricultural like organic farming, family farming and enhance extremely clear and strong farming.

Small farms also contact to service provider companies who technically manage farms in spite of installing smart system.

This study allows aggrotech, researcher, farmers, fertilizers companies to modify or enhance their systems and prepare themselves for future endeavor. Artificial Intelligence based architectures make systems more efficient. This review purposes to deliver a possible pathway for future study in advance control strategies to modernize agriculture.

UAV is an essential element to replace a massive number of IoT devices, especially in controlling traffic and agriculture, which will help in energy efficiency and to limit pollution.

By serving banks and insurance companies by easing out agricultural loans and keeping farms insured from disasters we plan to reach most of the farmers in Pakistan and from there onwards we believe word of mouth will play its role to help us scale exponentially. Growth potential globally is massive especially in Asia and Africa where still such precision farming is not being observed.

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