Chapter

Use of machine learning and IoT in Smart Farming: Future of Agriculture

TanushreeSanwal[1], Sandhya Avasthi[2], Meenakshi Tyagi[3], Sapna Yadav[4], Ankita Sharma[5], Suman Lata Tripathi

[1,3,4,5]KIET Group of Institutions, Delhi-NCR, Ghaziabad, India
[2]ABES Engineering College, Ghaziabad, India
[6]Lovely Professional University, Phagwara, India
Email: *tanushreesanwal12@gmail.com, sandhya_avasthi@yahoo.com, meenakshi.tyagi125@gmail.com, Sapna.yadav11@gmail.com, ankitasharma2293@gmail.com

Abstract

Agriculture is backbone of Indian economy, that is why India is known as an agro-based economy. The exponential growth of population has created the situation of in equilibrium between demand and supply of agriculture products. To obtain equilibrium is not possible through tradition way of agriculture, that is to meet demand, India needs to shift from Traditional farming to Smart farming. Machine learning and IoT, which is a category of artificial intelligence, can help a lot in smart farming by setting up knowledge-based farming systems. The goal of this study is to give more information about machine learning in agriculture by doing a thorough review of secondary literature. The results showed that this topic is important in many areas that are good for international convergence research. Precision agriculture, also called "smart farming," has been introduced to solve the problem of disequilibrium in demand and supply and make sustainability in agriculture. Artificial Neural Network techniques are the best of the machine learning methods that are used for smart farming. To get accurate data for analysis, sensors were put on satellites and unmanned ground and air vehicles were used. Everyone would benefit from this study because they would learn about the important uses of machine learning and will be able to help with future research in agriculture.

Keywords: IoT, Machine learning, Artificial Intelligence, Smart Farming

1. Introduction

In recent times agriculture sector is going through a major shift due to potential growth in the market and the use of the latest information technology tools. Much research is going on agriculture, machine learning, IoT for optimizing smart farming, and rationalization of the use of natural resources and good sustainable practices. With the growth in IoT-based applications and data analysis, agro-industrial and smart farming systems are largely altered and using these information technology tools for making optimum utilization of resources in agriculture sector. In this section, a review of ML algorithms, IoT, and their application are reviewed. The estimation forgrowth in market size according to the various application is shown in Figure 1(as accessed on12th April'2022 on statistica.com).

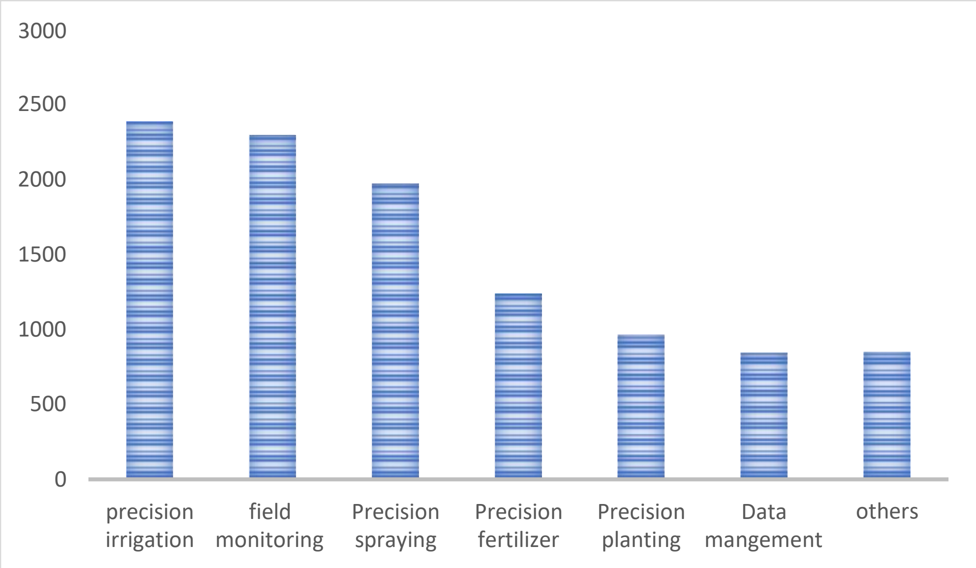

Figure1. Growth market for various applications in smart farming

1.1. Machine Learning and its use in Agriculture

The world population will increase to 10 billion approximately by the end of the year 2050, sothe demand for food will increase but due to urbanization, available resources for agriculture are diminishing. In this modern world, agriculture is confronted with many challenges, including rising food consumption due to global population growth, climatechange [1, 2], natural resource depletion [2, 3], changing dietary preferences [3, 4], and safetyand health issues [5, 6]. There is a crucial need to increase agricultural efficiency while reducing environmental impact to address the challenges, which put pressure on the agricultural sector. These two factors have augmented agriculture's shift to precision agriculture. This agricultural modernization has the potential to improve sustainability, productivity, and environmental health significantly [5]. To meet increasing demand, smart farming is built on four key pillars: (a) natural resource management, (b) efficient use of naturalresources, (c) development of suitable services, and (d) application of modern technologies [6].The most populated country will be India by the year 2050, the country is already falling shortof meeting its current demand for food.

The adoption of ICT is an unavoidable requirement of modern agriculture, as urged by governments all over the world. Farm management information systems, wireless sensor networks, cameras, drones, humidity and soil sensors, low-cost satellites, accelerometers, internet services, and automated guidedvehicles are examples of information technology. [7]. Additionally, enormous storage space is required for editing, analyzing, and interpreting the massive amounts of data generated by digital technologies, which is frequently referred to as "big data." The latter has the potential to have a sizable positive impact on society, the environment, and policymakers [8]. On the other hand, big data presents challenges as a result of its "5-V" requirements: (a) value, (b) variety, (c) velocity, (d) veracity, and (e) volume [9]. Outdated data processing methods are not able to keep up with the ever-increasing needs of of smart farming, posing a barrier to extracting needful information from field data [10]. Machine Learning (ML), a subset of artificial intelligence, was developedto accomplish this goal as a consequence of the exponential progress in processing power capacity [11].

Machine learning has a huge of applications in agriculture. A recent review of the literature from 2004 to 2018 revealed four distinct categories, according to Liakos et al. [12]. (Figure 1). Crop, water, soil, and livestock/ animal management are the four categories. Crop management articles accounted for the majority of articles (61 percent of total articles) and were further classified as follows:

• Prediction of yield;
• Disease identification;
• Detection of weeds;
• Crop identification;
• Crop quality

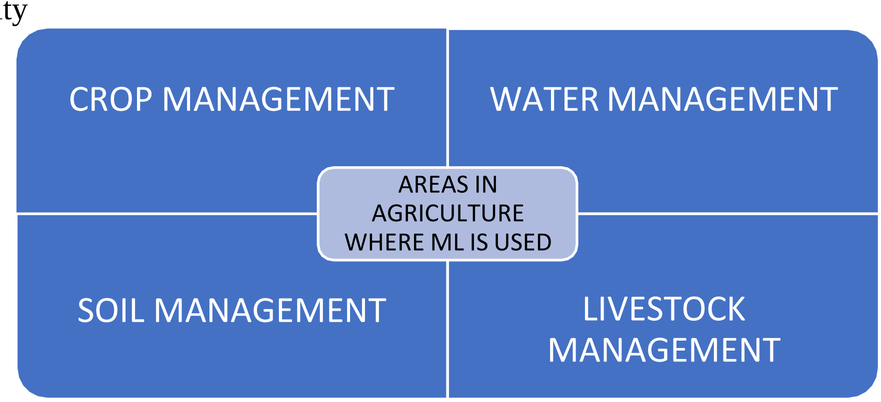

Figure2. Four groups in agriculture that are used by machine learning algorithms, as mentioned in [12].

1.2. Agriculture Machine Learning Problems That Haven't Been Solved

This academic subject has been subjected to numerous evaluations because of the breadth of machine learning applications in agriculture. Detection of crop disease [13–16], detection of weed [17,18], prediction of yield [19,20], recognition of crop [21,22], water management [23,24], welfare of animal [25,26], and livestock production [27,28] have been the primary topics of these studies. Another study looked at the use of machine learning technologies in major grain crops, examining a variety of factors such as quality and disease detection [29]. Finally, large-scale data analysis using machine learning has gained popularity, to identify real-world challenges related to modern farming [30] or methods for analyzing data [31].

Even though machine learning has made tremendous progress in agriculture, certain points remain unresolved. The primary barriers to sensor deployment on farms, according to [23,24,28,32], are high ICT costs, old practices, and a deficiency of information. Additionally, the existing datasets do not replicate accurate conditions, as they are generated by individuals collecting specimens over a short period and from a small area [15,21–23]. Thus, a higher number of datasets are needed [18,20]. Also, the requirement for additional and efficientmachine learning approaches and scalable computer architectures, which can aid in data processing speed, has been recognized [18,22,23,31]. Lighting changes [16,29], camera blind spots, ambient noise, and concurrent vocalizations have all been identified as barriers to obtaining audio and video recordings. Also, most farmers aren't experts in machine learning, so they can't see the patterns that algorithms find. This is an important problem that needs to be addressed. Thus, more intuitive systems are required. Simple, easy-to-use solutions, such asa visualization device with a people-friendly edge for proper data presentation [25,30,31], would be extremely beneficial. Given farmers' increasing comfort with cell phones, smart mobile phone applications is seen as a potential solution to the aforementioned challenge [15,16,21]. Finally, and perhaps most importantly, the development of effective machine learning techniques based on professional knowledge from stakeholders should be encouraged as a means of constructing accurate solutions, particularly in agriculture, computing science, and the private sector [19,22,24,33]. As highlighted in [12], current effortsare concentrated on individual solutions that are rarely related to decision-making processes, as demonstrated in other areas.

1.3 Use of IoT in Agriculture and AI

In 1956, John McCarthy invented the term AI, which he defined as the study of creating intelligent machines with human-like intellect. Such AI-based machines can learn, understand, and imitate a given situation. Some subfields of AI are Machine learning, Computer Vision, Expert systems, Text mining, and machine translation. In various real-life situations, AI-based applications have been in use. In the sectors of agriculture, robotics, health care, finance, e-commerce, and automation, intelligent AI systems are being extensively investigated. Samsung, Apple, and other electronics behemoths have stated that shortly, they would include this technology in every item they create. Another emerging technology is the ‘Internet of Things’ (IoT), which connects smart sensors and devices over the internet.

Farming uses IoT-based solutions for monitoring soil condition and soil moisture, such collected data can be used in training ML models. The ML model provides the best prediction for the optimum use of fertilizers for a crop. Another useful IoT-based application comes from drones, they are used to monitor fields and crops, spray pesticides, and drip irrigation. In drip irrigation, drones use AI-powered water irrigation method trained on weather pattern and reduces wastage of water. The use of AI-enabled robots in harvesting crops is fast-paced and performs a task in large volume. IoT-based sensors are being used in livestock management for monitoring the health of cattle.

1.4. The Purpose of the Research

As previously stated, numerous review papers have recently been published in response to theuses of machine learning in agriculture. However, the majority of these studies are narrow in scope, focusing exclusively on one component of agricultural productivity. Figure 1 summarizes the categories described in [12]. A complete bibliographic analysis is offered on the spectrum of these categories. Machine learning improvements, increased worldwide interest, and the potential impact on a wide range of agricultural fields all served as impetuses for this project. A new viewpoint on machine learning applications in agricultural systems is provided by focusing on material released in the recent three years (2018–2020). With the same inclusion criteria, this study represents a continuation of [12]. There are severalcritical features that can be used to accurately capture current progress and trends, such as (a) the areas that are most interested in machine learning in agriculture (b) efficient machine learning models
(c) the most researched crops and animals (d) the most employed features and technology.

As said further below, the quantity of journal articles published in the last few years has increased by 745 percent [12], indicating the necessity for an innovative review on the subject. Crop managing was also the most researched sector, with a variety of machine learning algorithmsused to manage the heterogeneous data supplied by agricultural areas. In comparison to [12], a broader range of agricultural and animal species have been investigated, with a diverse set of input parameters derived primarily from remote sensing techniques such as satellites and drones. Furthermore, researchers from a variety of scientific disciplines have applied machine learning to agriculture, contributing to the field's remarkable success.

2. Overview of Machine Learning Techniques

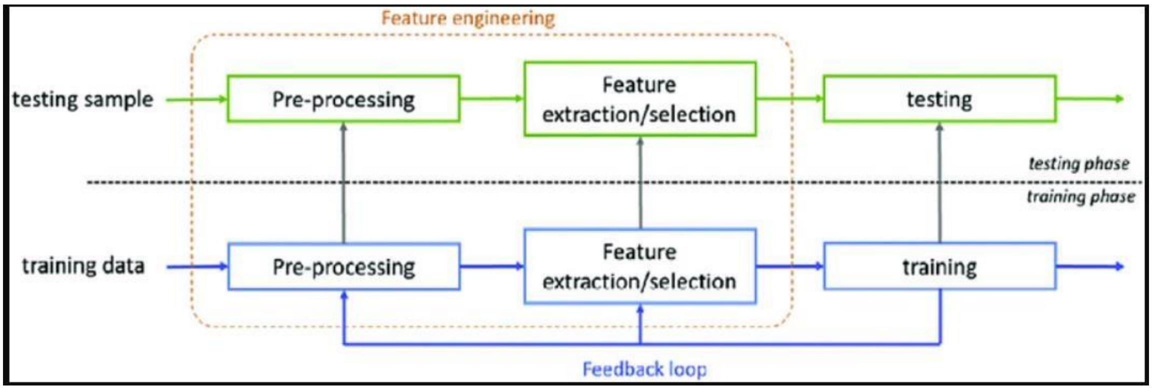

Figure 3: Example of machine learning system in its entirety.

In general, machine learning algorithms try to improve how well a task is done by using examples or past data.Machine learning, for example, can be used to optimize data input relationships and reconstruct a knowledge architecture. The more data there is in this data-driven process, the better machine learning performs. This is equivalent to the degree to which a human performs a task well as their experience grows [34]. The primary result of machine learning is a measure of generalizability, which is the machine learning algorithm's ability to produce accurate predictions when new data is presented using previously learned rules derived from similar data [35]. The term "data" refers to a set of characteristics that describe a collection of samples, which are sometimes referred to as features. In general, machine learning systems use two processes: learning (for training) and testing. These featuresare frequently merged into a feature vector, which can be binary, numeric, ordinal, or nominal[36]. During the learning phase, this vector is used as an input. In summary, during the learningperiod, the computer gains experience performing the task by relying on training data. It's over when the student's performance in learning is good enough (as measured by mathematical and statistical relationships). After the model has been trained, it can be used to sort, group, or predict data.

To convert the collected data to a usable state, pre-processing is compulsory. When multiple data sources are used, (a) data cleansing to eliminate inconsistencies, missing objects, and noise, (b) data integration, and (c) data transformation, such as normalization and discretization, are frequently required [37]. During the training phase, the extraction/selection feature is used to create or recognize the informative subset of structures that will be used to implement the learning model [38]. As shown in Figure 2, the feedback loop is used to modify thefeature extraction/selection unit as well as the pre-processing unit, thereby improving the learning model's overall performance. Previously unknown bugs were discovered during the testing phase.

The trained model sometimes referred to as a feature vector, is fed samples. Finally, the modelmakes an appropriate decision depending on the features of each sample (classification or regression, for example). Deep learning, a field of machine learning, delegated the duty of converting raw data into features to the learning system (feature engineering). By doing away with the feature extraction/selection unit we are left with a trainable system that starts with unstructured input and ends with the desired output [39,40]. Figure 3 depicts a distinctive machine learning system. Based on the type of learning, machine learning may be grouped into the following categories, according to the associated research [41,42]:

- Supervised learning: Given the input and output, the machine attempts to find the shortest path between them.
- Without labels, unsupervised learning requires the learning system to generate structure from the data on its own.
- Semi-supervised learning is a type of machine learning in which both labeled and unlabelled data are accepted as input.
- Reinforcement learning: Rather than relying solely on trial and error and a delayed outcome, decisions are made to determine which behaviors will result in a more favorable outcome.

To name a few applications, these include recognition of image [43], recognition of speech [44], independent driving [45], fraud detection of credit card [46], forecasting of stock market [47], fluid mechanics [48], malware filtering, spam and email [49], medical diagnosis [40], detection of contamination in city water networks [50], and recognition of activity [51].

3 Machines Learning and IoT in Smart Agriculture

Cropping Management

Crop management is a wide term that refers to different characteristics that result from a mixture of agricultural practices aimed at regulating the crop's biological, chemical, and physical situation to achieve quantitative and qualitative areas and goals [52]. Using modern crop management techniques such as prediction of yield, disease diagnosis, weed identification, crop recognition, and crop quality results in increased production and, as a result, financial benefit. Precision agriculture's primary objectives are as described above. Figure 4 illustrates various smart agriculture domains and smart farming solutions in each one of them.

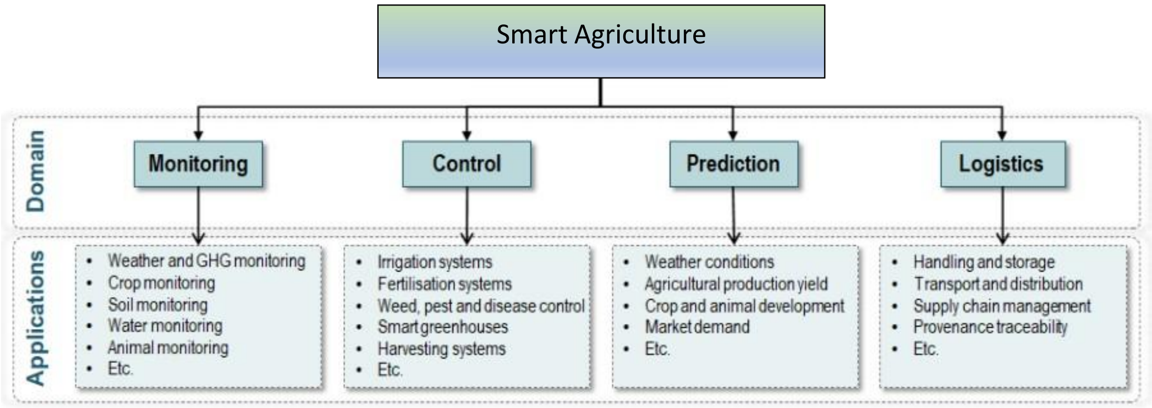

Figure 4. Smart Agriculture Domain and various solutions for smart farming

Prediction of Yield

Yield estimation becomes the most critical and hardest, if major portion of agriculture depends on monsoon. For instance, an accurate model can aid farm owners in making informed management decisions about yield and market demand [20]. However, this is not a simple task; it necessitates several steps. Numerous variables, like the environmental conditions, practices of management, and crop characteristics, all have an impact on yield prediction. As a result, an understanding of the relationship between these interacting characteristics and yield is required. Machine learning helps to establish such relationships necessitates large datasets and complex algorithms [53].

The detection of disease

Agricultural production systems are under threat from crop diseases, which can reduce the quality and quantity of crops produced as well as their shelf life and transportation costs. Plantdisease-related output losses are frequently reported by farmers [54]. A substantial threat to global food security is posed by crop diseases, as well. Early detection and management of plant diseases are crucial. Plant infections can be caused by a variety of organisms, including bacteria, fungi, parasites, and viruses. Weeds, withering leaves and fruits, leaf curling, and other disease symptoms are all physical signs of pathogen presence and phenotypic changes in plants. Professional agronomists have always carried out field reconnaissance to identify disease. It's a laborious process that relies on visual judgement and takes a lot of time. Commercially available sensor systems that can detect unhealthy plants before symptoms appear have been made possible thanks to recent technological advances. It's worth noting that computer vision has made considerable strides recently due mostly to the application of deep learning. As proven by Zhang et al. [56] utilizing deep learning to recognize cucumber leaf diseases, it is useful to decrease background before model training due to the shifting environmental context. For accurate disease detection image classifiers, a huge library of healthy and diseased plant photos is also necessary. Automatic approaches can be used in large-scale farming with autonomous vehicles to detect problems sooner and build maps of the plant disease's spatial distribution, indicating the zones of infection in vast farms [57].

Weed detection

Weeds generally proliferate and spread invasively across large areas of the field quickly as a result of their productive production and huge life span, competing with crops that need resources such as space, sun, nutrients, and water. Furthermore, weeds emerge earlier than crops and lack natural enemies, which hurts crop growth [18]. Weed control, whether mechanical or chemical, is critical for preventing agricultural yield decline. Since mechanical treatment is time-consuming and inefficient if done incorrectly, the application of herbicide is the most commonly used method. Using huge quantities of herbicides, on the other hand, prove to be both costly and environmentally damaging, especially when applied consistently without regard for the spatial distribution of weeds. Surprisingly, long-term pesticide use is likely to breed weed resistance, making weed control more difficult and expensive. Based on smart agriculture, significant progress has been made in recent years in distinguishing weeds from crops. Sensors attached to satellites, and unmanned vehicles along with aerial and ground vehicles can be used to achieve this differentiation. Converting data collected by UAVs into useful information remains a difficult task, as both collection and classification of data, require time and effort [58]. Combining machine learning algorithms with imaging technology or non-imaging spectroscopy enables real-time weed differentiation and localization, enabling precise herbicide application to specific zones rather than spraying entire fields [59-60] and path planningfor weeding.

Crop Identification

Automatic recognition of crops has sparked significant interest in a wide range of scientific fields, including plant taxonomy, botanical gardens, and the discovery of new species. Plant organs and parts can be used to identify and categorize species. The most common technique appears to be leaf-based plant recognition, which involves assessing specific leaf characteristics such as color, shape, and texture. Classification of crops using remote sensing has become common as unmanned aerial vehicles and satellites have been used to collect data on crop properties more extensively. As with the previously mentioned subcategories, advancements in computer software and image processing technologies, combined with machine learning, have led to advancements in the automatic recognition of crops and their classification.

Managing quality of crop

Crop quality has a substantial market influence and is determined by a variety of elements, including soil and climatic conditions, cultivation procedures, crop features, and so on. When farmers offer high-quality agricultural products at a higher price, they make more money. The most often used harvesting markers for fruit quality, for example, are flesh hardness, soluble solids content, and skin colour. In both high-value crops (such as grapes, vegetables, and herbs)and arable crops, the harvesting date has a considerable impact on the quality of harvested products. As a result, establishing decision support systems can assist farmers in making better management decisions, which will result in higher-quality food. Selective harvesting is a management strategy that can improve product quality dramatically. Crops of poor quality also result in food waste, posing a new difficulty for contemporary agriculture, as crops that do not meet the acceptable shape, quality, colour, or size may be rejected. As seen in the prior section, combining machine learning algorithms with picture technology might yield intriguing outcomes.

Water and Rainfall Management

The industry of agriculture is the world's largest consumer of readily available freshwater, as plant development is dependent on the availability of water. Given the rapid depletion of manyaquifers with little or no replenishment, more effective water management is critical for achieving long-term crop production. Proper water management can lead to good water qualityas well as a reduction in pollution and health issues. Variable-rate irrigation has the potential to save water, according to recent precision agricultural research. Rather than implementing irrigation at a constant rate across the field, this can be accomplished by implementing irrigation at rates that vary based on field variability and the unique water requirements of discrete management zones. Variable-rate irrigation's performance and viability are influencedby agronomic considerations.

When attempting to save water while optimizing yields, topography, soil properties, and their effect on soil water are all factors that must be considered. Irrigation scheduling and water management can be improved by closely monitoring soil water levels, crop development conditions, temporal and spatial trends, and weather monitoring and forecasting. Remote sensing is one of the ICTs that can give pictures that show how the soil is wet and how crops are growing so that water can be managed well. In dry areas, it is hard to manage water because irrigation needs groundwater and rainfall only meets a small part of crop evapotranspiration (ET) needs. A good way to manage water resources and figure out how bad floods are is to be able to predict rain accurately.

Soil Management

Soil, as a diverse natural resource, implies a plethora of systems and processes. Accurate regional soil knowledge is critical for better soil management that is compatible with land potential and, more broadly, for sustainable agriculture [5]. Land degradation, soil nutrient imbalance (as a result of excessive fertilizer use), and erosion of soil (as a result of excessive vegetation cutting, unbalanced crop rotations, livestock overgrazing, etc) are all issues that must be addressed. Texture, organic matter, and nutrient concentration are just a few of the beneficial soil properties. Traditional soil evaluation methods frequently involve soil sampling and laboratory analysis, which are both expensive and time-consuming consuming. On the other hand, remote sensing and soil mapping sensors can give a low-cost and straightforward method for researching soil spatial variability. When conventional data analysis techniques are used, data fusion and management of such diverse "big data" can provide substantial challenges. Machine learning approaches have the potential to provide a dependable, low-cost solution for this activity.

Management and production of Livestock

It is accepted that livestock production techniques have been enhanced in terms of productivityper animal. This intensification includes social concerns about animal welfare and human health, which may influence consumer perceptions of food safety, security, and sustainability.To optimize production processes, it is critical to consider both animal welfare and total productivity. All of the aforementioned domains are part of precision livestock farming, whichaims to increase early-stage output by utilizing engineering methodologies to monitor animal health in real-time and recognize danger signals. Precision livestock farming is becoming increasingly important in assisting livestock owners in making decisions and redefining their roles. It can also help with product traceability and monitoring product quality and animal living conditions, as specified by policymakers. Non-invasive sensors such as cameras, radio-frequency identification systems, and optical or temperature sensors are used in precision livestock husbandry [25]. Sensors in the Internet of Things monitor temperature, sound, humidity, and other variables using physical quantities. IoT sensors, for example, can notify users in real-time if a VPQ is unusually high or low, providing critical information on specificanimals. As a result, the cost of examining each animal on a regular and laborious basis can bereduced. To use massive amounts of data, machine learning techniques have become ingrained in modern livestock husbandry. Models capable of specifying how a biological system works,relying on causal relationships, and using this biological understanding to make predictions and suggestions can be created.

Sensor technologies combined with advanced machine learning algorithms have the potential to significantly increase the efficiency of cattle production. Given the impact of animal management practices on productivity, livestock owners are becoming more conservative in their investment decisions. However, as livestock herds grow larger, it becomes increasingly difficult to care for each animal. From this vantage point, the above-mentioned farmer assistance through precision livestock farming is a positive step toward economic efficiency and the creation of sustainable workplaces with a smaller environmental footprint. Numerous animal production methods have been used in the past, with the majority of them aimed at increasing the efficiency with which animals are raised and fed. However, machine learning techniques are required due to the massive amounts of data involved.

4. Methodologies

Various secondary literature was used to identify studies that examined machine learning aboutvarious aspects of agricultural management. Furthermore, the term "machine learning" was associated with the following keywords: "crop management," "water management," "soil management," and "livestock management." The authors aimed to conduct a literature search using the same methods as [12], but just for the period 2018–2020.

5. Challenges in smart farming and use of information technology tools

As a means of supplying the world's growing population with food, artificial intelligence (AI)holds great promise. A number of obstacles to its widespread use in the agricultural sector havebeen described as follows:

- According to a recent survey conducted by the Indian government, the literacy rate of Indian farmers is extremely low, making it difficult to close the technological gap between farmers and technology.
- Farmers have a lower level of motivation to learn new digital skills in order to improve their farming practices.
- Rural areas tend to be home to the majority of agricultural land. It is difficult to implement IoT architecture and WSN in rural locations without dependable internet connectivity since cloud services are required for data storage and processing.
- It is challenging to make accurate predictions and classifications using computers' cognitive abilities when the geographical conditions differ.
- Digital farming's initial setup, which involves both hardware and software, necessitates a significant financial commitment.
- When smart sensors and other electrical gadgets are installed, they consume a lot of power.
- In order to create an intelligent harvesting system, an accurate training dataset is essential.
- Farmers lose money if their harvesting is delayed or rejected because of an inaccuracy in the system's detection of ripe or overripe crops.

6. Main Conclusions and Discussion

The current systematic review study focuses on machine learning in agriculture, which is becoming increasingly popular as new technologies are developed around the world. To achieve this goal, Liakos et al. [12] conducted a comprehensive assessment of the current situation of the four generic groupings described in their previous research. Plant, water, soil, and livestock management are all included in this category. As a result, after reviewing relevant literature from the previous three years (2018–2020) and applying the findings, various elements were analyzed using an integrated approach. Finally, the following key findings can be drawn from this research:

• Crop management accounted for the vast majority of journal publications, with the other three broad topics accounting for roughly equal shares of the total. Using [12] as a reference study, it is possible to conclude that the above picture has remained largely unchanged, except for a decrease in the percentage of articles about livestock from 19% to 12% in favor of articles about crop management, which has increased from 1% to 2%. This, however, only depicts one side of the building's façade. When the massive increase in the number of related papers published in the last three years is considered, it is estimated that 400% more publications on livestock management were discovered. Another significant discovery was an increase in interest in crop identification research.

- To deal with the heterogeneous data collected from agricultural areas, several machine learning techniques have been developed, including These algorithms can be divided into MLmodel families, which can then be further subdivided. In a similar vein to [12], ANNs were discovered to be the most efficient ML models. Although this is not the case, there has been a shift in emphasis away from [12] and toward EL, which can aggregate predictions from a variety of models. SVM completes the collection of the three most accurate machine learning models in agriculture due to a variety of advantages, including its excellent performance whenworking with image data.
- When it comes to the most extensively researched crops, maize and, later, wheat, rice, and soybean have all been thoroughly investigated using ML techniques. Cattle, sheep, and goats were the most extensively studied animals in livestock management, accounting for approximately 85% of all research. More species have been added since [12], but wheat and rice, as well as cattle, remain important specimens for machine learning applications.
- The visualization of the input data used in the ML algorithms, as well as the sensors that provided the data for the algorithms, was a significant outcome in the current review study. RGB images were the most common, which explains the widespread useof CNNs, which have a greater capacity for dealing with this type of data due to their superior processing speed. A wide range of indicators for climatic, soil, water, and cropquality conditions were also included in the study. Remote sensing, like images from satellites, unmanned aerial vehicles (UAVs), and unmanned ground vehicles (UGVs), was the most common way to get data for ML applications, but measurements were also taken in the field and in a lab. As was already said, unmanned aerial vehicles (UAVs) are steadily gaining ground on satellites because they are more flexible and can take high-resolution photos in any weather. Satellites, on the other hand, can give information about large areas over time. Lastly, animal welfare research relied a lot on technology like accelerometers to find out what the animals were doing, while livestock production research relied a lot on the animals' core physical and growth characteristics to figure out how happy they were.
- The use of machine learning applications to facilitate many aspects of agricultural management is a major concern on a global scale, as evidenced by the geographical distribution (shown in Figure 6) and the wide range of research topics. Indeed, due to its adaptability, it is an excellent choice for convergence research. While convergence research is a relatively new method, it is based on a shared understanding among researchers from various fields and has the potential to benefit the general public. Reduced environmental impact and human health protection are two examples of what is meant by this phrase. In this regard, the application of machine learning in agriculture holds a lot of promise for value generation.
- It is also worth noting that as a result of the study's findings, there is a growing interest in subjects related to machine learning in agricultural applications. When comparing 2018 and 2019, the total number of relevant studies increased by approximately 26%, according to Figure 13. When comparing the findings from 2018 to 2020, the equivalent increase increased by 109 percent, for a total increase of 164 percent. A variety of factors, including significant advances in agricultural information and communication technology systems, are contributing to the increased interest in machine learning in agriculture. Enhancing the competence of agricultural practices while reducing their environmental impact is also critical. To present a complete picture of agricultural

processes, it is necessary to use both precise measurements and data management techniques capable of handling massive amounts of data. The current technological revolution has the potential to significantly boost agriculture in the direction of improving food security and meeting rising consumer demands. This is particularly true in agriculture.

To summarise, information and communications technology (ICT) combined with machine learning, seems to be the finest option for dealing with new challenges. Given the current rate of data acquisition and the development of numerous technologies, farms will need to advance their management practices by implementing Decision Support Systems (DSSs) personalized to the needs of each agricultural system. These DSSs employ algorithms capable of dealing with a greater number of cases while taking into account a huge amount of data that farmers would find difficult to manage. Even though most information and communications technology (ICT) requires upfront fees, such as high infrastructure investment costs, many farmers are hesitant to use these technologies. This will be a pressing problem, particularly in developing countries where agriculture plays a significant economic role. Having a visible impact, on the other hand, is a long-term goal that necessitates hard work. To develop innovative skills, we must be aware of the profits of processing large amounts of data and assert appropriate financial resources, all stakeholders must adopt a new way of thinking. Machine learning will undoubtedly become a behind-the-scenes enabler for the development of agriculture which is productive and sustainable due to the increasing use of artificial intelligence in agriculture. Scientists, policymakers, engineers, ICT system developers, manufacturers, and farmers are all expected to benefit from the current systematic effort, which is expected to result in more systematic machine learning research in agriculture.

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