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Chapter 1

# Smart agriculture: Technological advancements on agriculture— A systematical review

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## 1 Introduction

Agriculture is an important sector of the world economy and a strong foundation for human life; it is the largest source of food grains and other raw materials. Agriculture plays a dynamic role in the growth of a country's economy. It is the primary source of income and very helpful for the development of the economic condition of the country (Abate et al., 2018). Traditionally, most diseases were not diagnosed by farmers because of lack of knowledge and unavailability of a local expert. The most basic requirements for the advancement in agriculture are integration of internet technologies and future-oriented technologies for use as a smart object (Keller et al., 2014; Lasi et al., 2014; Liao et al., 2017; Maynard, 2015; Pivoto et al., 2018). Further, data-driven agricultural management can be used to meet the production challenges. Data management is required to analyze the data/information for better production. This approach defines how robots will play a vital role in the evolution of farming (Saiz-Rubio & Rovira-Más, 2020). The growth of technologies is an excellent initiative toward the development of the agriculture sector (Kapur, 2018; Lytos et al., 2020; Rehman & Hussain, 2016). Smart farming concepts, such as precision agriculture and land management, scientific data, such as earth observation and climate science, and cutting-edge technologies, such as image processing, geographic information systems (GIS), and unmanned aerial vehicles (UAVs), would improve agricultural production. Digital agriculture using information and communication technologies provide crop and market information to the farmer (Costa et al., 2011). GeoFarmer is a type of monitoring and feedback

**1**

**FIG. 1** The transformation from traditional to smart agriculture.

system for agricultural development projects. Farmers can manage their crops and farms better if they can communicate their experiences, both positive and negative, with each other and with experts (Eitzinger et al., 2019). Traditional agricultural farming can be smart agriculture by making suitable improvement in the existing solution, as shown in Fig. 1.

Unluckily farmers still far away from modern technologies and still relying on traditional methods of farming and food supply techniques have low productivity, and countries are producing yields much below their potential (Kumar & Ilango, 2018). To overcome these problems and bring revolution in the agriculture sector, modern technologies can play a vital role and can resolve these problems (Timalsina, 2019). There are various data-driven and data analysis techniques that makes agriculture smart, as illustrated in Fig. 2. The application of these techniques in specific aspects, like data analysis, prediction, estimation, and monitoring, are shown in Fig. 3.

The main objective for preparing the survey discussed in this chapter was to help researchers, farmers, nongovernmental organizations (NGOs), and everyone who associated with the agriculture domain. In this survey, we reviewed about 170 papers that suggested different technological advancements to make agriculture easy, productive, and smart.
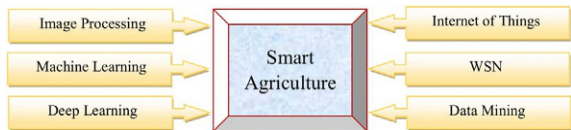


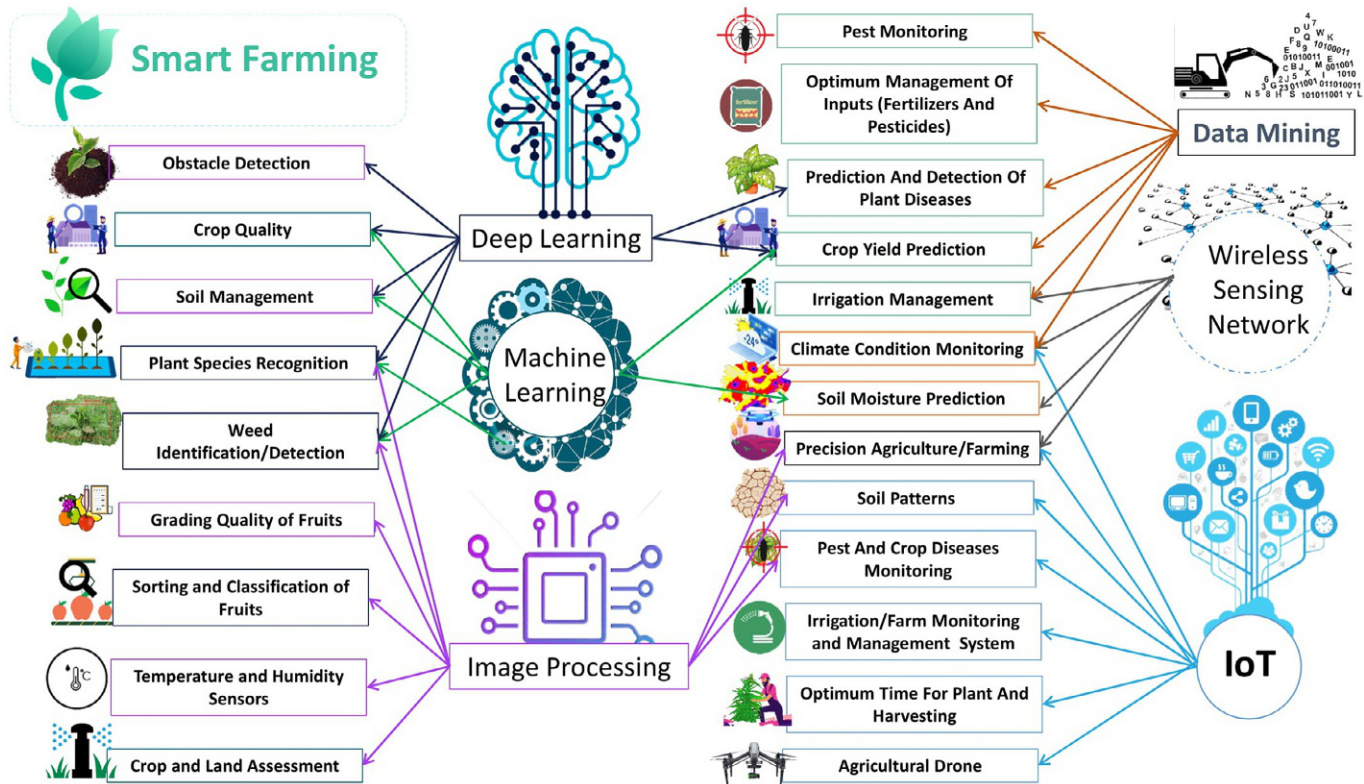**FIG. 2** Technologies used in agriculture.

**FIG. 3** Application of technologies in agriculture domain.

The chapter begins with a brief description of technological advancements and their applications in the agriculture sector. The chapter then goes on to describe methodology, image processing, machine learning (ML), deep learning (DL), the internet of things (IoT), wireless sensor networks (WSNs), and data mining (DM) application for the advancement of farming and improvements in agriculture. Finally, the chapter presents the conclusions of the survey.

## 2 Methodology

The literature within the agricultural domain was analyzed in order to develop this chapter. Initially, a keyword-based search forconference papers or journal articles was performed from the scientific databases ScienceDirect and IEEE Xplore and from the scientific indexing services Web of Science and Google Scholar. The methodology used for doing this survey is show in Fig. 4.

The search terms we used to collect the desired research papers and filter out research papers irrelevant to agriculture were: {Image Processing + Agriculture}, {Image Processing + Farming}, {Machine Learning + Agriculture}, {Machine Learning + Farming}, {Deep Learning + Agriculture}, {Deep Learning + Farming}, {IoT + Agriculture}, {IoT + Farming}, {Wireless Sensor Network + Agriculture}, {Wireless Sensor Network + Farming}, {Data Mining + Agriculture}, and {Data Mining + Farming}. Doing so, we downloaded almost 300 papers, including papers from IEEE Xplore, ScienceDirect, Web of Science, and other sources. After downloading the articles, we screened out the duplicates and separated out almost 234 papers for further consideration. For further scanning and filtering, we performed a full text reading and obtained a final set of 170 papers for the articulation of the survey, which involves 19 papers of image processing, 13 of ML, 33 of DL, 14 of WSN, 23 of IoT, 31 of DM, and 37 (papers + Web Source) of agriculture and farming. The statistical information about the technological advancement in agriculture is shown in Fig. 5.



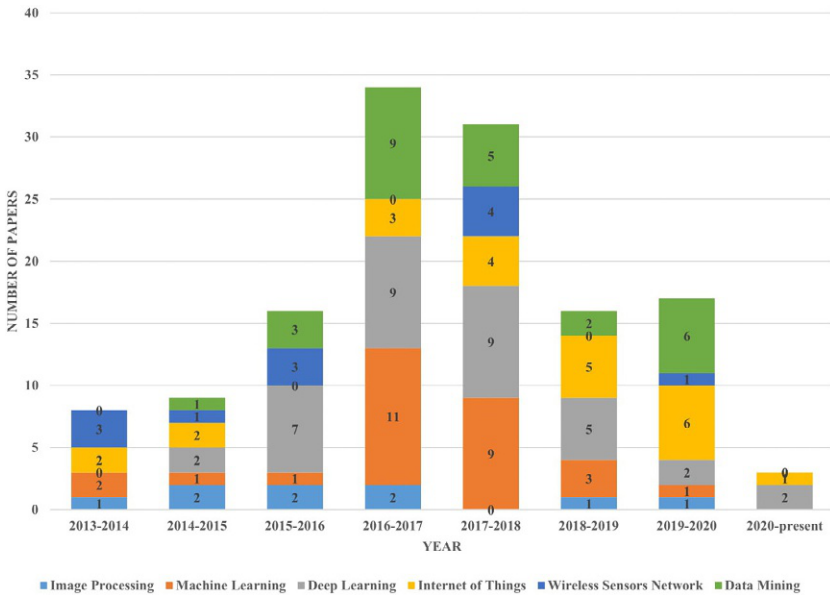**FIG. 4** Flow for obtaining final set for writing review.

**FIG. 5** Number of papers published from 2015 to 2020 on technological advancements in agriculture.

## 3 Role of image processing in agriculture

Image processing in agriculture is a huge step toward the modernization of agriculture. Image processing is a method used to operate an image to get an enhanced image or extract useful information from it. Image processing is a proven, effective process in the agriculture domain to increase the production rate and sustain agricultural demands throughout the world. Image processing with different spectral measurements, such as infrared and hyperspectral X-ray (Feng et al., 2018) imaging, is helpful in identifying crop diseases, weeds, and land mapping, which can help farmers by decreasing labor cost and time. Identifying crop diseases will help farmers tackle infections and prevent them from spreading to the total yield. Imparting image-processing techniques in modern agriculture will uplift the agricultural production to sustain the market demands and provide timely information to farmers through various automated applications in agriculture. The following subsection describes and analyzes the different specific applications of image processing in agriculture.

### 3.1 Plant disease identification

Image processing is widely used for the identification of plant diseases in various agriculture crops. Farmers face major threats due to the emergence of various pests and diseases in the crops. Fungi, bacteria, viruses, and nematodes

are some of the common reasons for disease infections. Traditionally, most diseases were not diagnosed or suspected by farmers, as they lacked knowledge about crop diseases and required support and suggestions from specialists. However, the diagnosis of infections in their early stages can mitigate crop damage. For identification of plant diseases, image processing plays an important role as the detection and identification of diseases is only done through visual information. A neural network-based methodology is suggested for disease detection and classification (Jhuria et al., 2013). The diagnostic approach is proposed to identify the disease under an intelligent system. The work is carried out on apple and grape plants. The system used two different databases. The authors defined a work on classification and mapping of disease based on color, texture, and morphology. The authors obtained better results, and grading was done. The grade will help farmers determine the requirement of insecticide to be applied. Other researchers (Chahal & Anuradha, 2015) defined a framework for plant disease classification and recognition of plant and leaf disease. The authors also proposed a broad model to perform image processing. The study on some of the effective classification approaches, including support vector machines (SVMs), neural networks, k-means, and principal component analysis (PCA), were also discussed. Some researchers (Tewari et al., 2020) worked on a variable rate chemical spraying system considering the image processing technique. The main motive of the work was to identify diseases on paddy crops. The chromatic aberration-based image segment method was used to detect the diseased region of paddy plants. The author developed a prototype with a diagnostic approach for variable rate application, which uses less chemical. This method is beneficial for the environment and the economy.

## 3.2 Fruit sorting and classification

Varieties of fruits are distributed in markets for consumption as day-to-day activity increased demand from consumers. These fruits received from the market are sorted out manually, which is a biased, time-consuming, and tiresome process as large quantities of fruits must be sorted out in a short time (Butz et al., 2006). Researchers (Surya & Satheesh, 2014) developed a technology in which image processing combined with other techniques can be used as expert advice to enhance production. The proposed model classifies and illustrates the application of image processing in agriculture and presented an approach for further study in image processing. These methods are supportive in the development of the automation model and in obtaining higher accuracy of information. Automatic sorting and classification of fruits is a postharvest process where the application of image processing is introduced for automation. This method is more advantageous than human labor with more accuracy, reliability, speed, and consistency. The industrial sector is benefited by the automated sorting of fruits and vegetables by applying this nondestructive method of classification (Bogue, 2016). Fruits with different size, color, shape,

and texture can be easily identified and separated. Damaged fruits and vegetables can also be easily identified and removed. This automation helps the industries, supermarket stores, and other wholesale fruit stores to sort the fruits in a shorter period with high accuracy.

### 3.3 Plant species identification

Plant species identification is also an important application useful for botanist, researchers, and even the common man. Content-based image retrieval is used in the species identification from the collection of species images. Plants are identified by their morphological characteristics like texture, size, shape, and color of leaves and flowers. The support of a trained and experienced botanists is needed for species recognition. To conquer this issue, information technology, such as real-time image capturing devices, can be deployed. Feature extraction and image analysis are a vital parts of plant species identification from the collection of species images. Researchers (Farmer & Jain, 2005) suggest that shape analysis on leaves can be done based on the leaf boundary. There are two basic approaches to leaf analysis: region-based and boundary-based. Boundary signatures can be applied over the boundary regions of the leaf to identify the plant species (Femat-Diaz et al., 2011). Other features, such as are color and texture of leaves, are taken into consideration for classification. The accuracy of results can be greater when the color feature is combined along with the shape feature.

### 3.4 Precision farming

Development in information technology and agriculture science has made it possible to merge these two sectors, leading to the rise of precision farming. This can assist farmers in making better decisions regarding optimal crop production. It involves proper understanding and efficient use of natural resources found within the field. It gives maximum profit and production with minimum input and optimal use of the resource. Farmers need preacquired knowledge about technology and their workings. Proper training is required for farmers to acquire information about precision agriculture. The global positioning system (GPS) and GIS are the technologies used in agriculture equipment in precision agriculture. GIS is used to identify all available data, and GPS supports in identifying the object position on the globe using satellite signals. Remotely acquired images through satellites can be accessed and analyzed in their digital form. The advancement in image processing techniques has made remote sensing, along with GIS, progress independently. For better precision farming, an integrated system is used that consists of combining the remote sensing devices and image processing software package.

### 3.5 Fruit quality analysis

Consumer awareness and demand for qualitative products in the market has demanded the development of an automation system for quality assessment. This insists on the inspection of fruit quality to have qualitative fruits in the market. Fruit quality is analyzed by characteristics like color, shape, flavor, texture, and size (Freixenet et al., 2002). This computer vision task involves activities like image acquisition, processing, and interpretation for analysis. Extracting the fruit region became a necessary step for analyzing the major characteristics to determine the fruit quality from the background. The fruits are graded into different categories based on quality. Different patterns and classifiers are used for grading. Color, size, texture, and shape are considered some of the important features for grading (Mendoza & Aguilera, 2004). Manual inspection is time-consuming, biased, and prone to errors. To overcome these issues, a nondestructive quality assessment method developed, in contrast to certain destructive assessment methods, could determine the fruit quality with higher accuracy and speed. Nowadays, in many industries, these computer vision-based automated quality assessment tools replace traditional manual inspection (Gao et al., 2010). Classifiers like neural network, SVMs, Bayesian decision theory, k-nearest neighbors (KNN), and PCA are used to grade the quality of fruits (Mans et al., 2010). Decisions of the automated system in the quality assessment are proved to be effective and supportive for numerous food industries. For quality estimation, color, shape, and size are the primary parameters to be considered (Moreda et al., 2012; Prabha & Kumar, 2013). Some research (DePalma et al., 2019) offers essential knowledge and a way of producing pea-based, tofu-free soybeans.

### 3.6 Crop and land assessment

Remote sensing is one of the important data sources used in GIS for accessing data acquired through satellites. The factor considered important in remote sensing is reflectance of visible light energy from an external source. The external source of energy for passive systems is the sun. Information gathered through satellites has been increased through the use of image sensors. Remotely acquired images through satellites can be accessed and analyzed in their digital form. Advancement in image processing techniques like image enhancement, restoration, and analysis have made remote sensing progress independently in advance of GIS. The main aim of remote sensing is to monitor the Earth's surface and thereby measure geographical, biological, and physical variables to identify the materials on the land cover for further analysis.

### 3.7 Weed recognition

Weeds are a threat to farmers in that they reduce crop production and quality. Hence, more attention is needed to monitor weeds. The use of herbicide is one

of the standard method used to control the growth of weeds. With the latest innovations, weed recognition is automated such that the system automatically distinguishes weeds from crops. The automated system monitors weed growth regularly and decides the time of weed control. Classifiers, along with image-processing methods, make it an easier job to identify weeds and destroy them in their earlier stages (Lamb & Brown, 2001). Researchers (Vibhute & Bodhe, 2012) proposed image processing for analyzing agricultural parameters and describing how image processing on different spectrums, such as infrared and hyperspectral X-ray, can be useful in determining the vegetation indices, canopy measurement, irrigated land mapping, and more. The authors define a work on image porosity with algorithms that can be used for surveying and weed classification. The classification accuracy can be obtained up to 96% with correct imaging techniques and algorithms. Researchers (Poojith et al., 2014) considered image processing to identify weeds in the field. In the proposed model, the images are captured and processed using MATLAB to identify the weed areas in the field. A defined algorithm approach can also identify and spray weedicide on the weeds. For two different types of weeds, the threshold value should be selected carefully.

By adopting this methodology, the usage of weedicides can be reduced, thus saving the environment. The wide-ranging variety of applications on the subject of counting objects in digital images makes it difficult for someone to prospect all possible useful ideas. One article (Pandurng, 2015) defined a work surveying the application of image processing in the agriculture field, such as imaging techniques for crop management. Researchers (Prakash et al., 2017) implemented image processing using MATLAB to detect the weed areas in images that are taken from the fields, which can cause potential solutions for problematic issues to be missed. Again, for the detection and classification of crops and weeds, one study (Bosilj et al., 2018) suggested a method based on SVM with the support of morphology of attributes that classify the detected regions into three classes, namely weed, crop, and mixed. The study's result showed effective and completive classification rates. The proposed method was implemented and evaluated on sugar beets and onions.

Table 1 shows the most popular methods and models based on image processing in smart agriculture.

## 4   Role of Machine Learning in Agriculture

ML is a promising technology in modern farming. With the help of robots, ML can be used for spraying pesticides, fertilizers, and other chemicals in agricultural fields. The combination of ML and IoT makes it possible to monitor the status of a farm and estimate the exact damage severity. This would decrease the use of fertilizers by 70% by targeting only the effective areas. That will be beneficial for the economy and the environment. These applications of ML would decrease agricultural waste by 60%, which will help reduce the carbon footprint

**TABLE 1** Summary of role of image processing in agriculture.

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| Classification and mapping of disease on fruits | Jhuria et al. (2013) | Neural network-based work implemented using MATLAB | Obtained better results and grading has been done. | The grade help farmers determine the required insecticide to be applied |
| Plant disease classification and recognition | Chahal and Anuradha (2015) | The recognition model with a broader view | An excellent result was achieved | Ability to work in a variety of crops and environments |
| Identification of diseased crop | Tewari et al. (2020) | Chromatic aberration-based image segment method | The field testing results showed a minimum 33.88% reduction in applied chemicals | This is beneficial for the environment and the economy |
| Supportive in the development of the automation model | Surya and Satheesh (2014) | Image enhancement and image segmentation method are inevitable methods in varied applications. | Higher accuracy in the higher-level process for decision-making | Higher accuracy of information |
| Automatic sorting and classification | Bogue (2016) | Nondestructive method of classification | More accuracy, reliability, speed, and consistency | Sorting of the fruits in a shorter time with high accuracy |
| The detection and classification of crops and weeds | Bosilj et al. (2018) | SVM with the support of morphology of attributes | The results showed effective and completive classification rates | Implemented and evaluated on sugar beets and onions |
| To identify the plant species | Farmer and Jain (2005) | Region-based and boundary-based approaches for shape analysis | An excellent result was achieved | This approach can be applied over the boundary regions of the leaf |

| | | | | |
|---|---|---|---|---|
| Accuracy of result can be higher when the color feature is combined with the shape feature. | Femat-Diaz et al. (2011) | Same as above, and color and texture features of the leaves were considered. | Accuracy of result can be greater when the color feature is combined along with the shape feature | Better analysis is possible |
| An automation system for quality assessment | Freixenet et al. (2002) | Image process-based method | Better results obtained | Consumer awareness and demand for qualitative products in the market is possible |
| For fruit grading | Mendoza and Aguilera (2004) | Model based on image processing with support of computer vision | High classification accuracy | Helps in fruit quality assessment |
| To determine fruit quality | Gao et al. (2010) | Nondestructive quality assessment method | Higher accuracy and speed | Cost-effective |
| Automated fruit quality assessment | Mans et al. (2010) | SVM, Bayesian decision theory, KNN | Effective and supportive | Reduce error of manual inspection |
| Improve fruit quality assessment tools | Moreda et al. (2012), Prabha and Kumar (2013) | Fourier descriptors, shape signatures, and skeleton operator from the morphological operation | Better results were obtained | Increased the efficiency of the existing method for fruit quality assessment |
| To monitor the weeds | Lamb and Brown (2001) | Classifiers along with image processing methods | Gain more satisfactory results | This approach identifies weeds and destroys them in their earlier stage of growth |
| Surveying and weed classification | Vibhute and Bodhe (2012) | Image processing on different spectrums, such as infrared and hyperspectral X-ray | Vegetation indices, canopy measurement, and irrigated land mapping were obtained | This approach helps save the environment and reduce cost |

*Continued*

**TABLE 1** Summary of role of image processing in agriculture—cont'd

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| Identification of weeds in the fields | Poojith et al. (2014) | Image processing with supports of MATLAB | Acceptable accuracy | We can reduce the usage of weedicides, thus saving the environment. |
| Weed identification, plant pest identification, machine vision, navigation | Prakash et al. (2017) | Text sym4 function series and bior3.7 wavelet are adopted. | Gain more satisfactory results | Agricultural image denoizing, enhancement processing, and image compression |

and protect the environment. This provides farmers with cost-effective and targeted solutions on their farm. ML with its huge applications can be used to perform an activity like crop prediction, crop management, and disease identification. ML models have been applied in multiple applications, such as crop management, yield prediction, and disease detection (Liakos et al., 2018). The following subsection describes and analyzes the different specific applications of ML in agriculture.

## 4.1 Yield prediction

Yield prediction is one of the most significant research areas in precision agriculture. To increase productivity, there is the high importance of yield estimation, yield mapping, matching of crops supply with the demand, and crop management. One study (Sengupta & Suk, 2013) developed an early yield mapping system that identifies the immature green citrus in a citrus grove under open-air environmental conditions. This study also helps farmers optimize their orchard in terms of profits and increased yields. Another study (Amatya et al., 2015) proposed a methodology strategy and developed a machine vision system that automatically shakes and catches cherries during harvesting. The framework separates and identifies blocked cherry branches with foliage in any situation, even when these are unnoticeable. The objective of the framework was to reduce labor requirements. Another study (Senthilnath et al., 2015) uses expectation maximization (EM) and remote sensors to develop a framework that detects tomatoes. The proposed system senses Red Green Blue (RGB) images, which were captured by a UAV. Based on artificial neural networks (ANNs) and multitemporal remote sensing data, the study (Ali et al., 2016) proposed a model that estimates the grassland's biomass (in kg dry matter/ha/day). In another study, researchers (Pantazi et al., 2016) introduced a technique based on satellite imagery. The proposed method is specifically for wheat yield prediction. The system receives crop growth characteristics fused with soil data, which enhances the system performances and makes the forecast more accurate.

A generalized method was introduced in one study (Kung et al., 2016) for agriculture yield predictions. The method is based on extension neural network (ENN) application on long-period generated agronomical data (1997–2014). The study was a regional prediction, specifically in Taiwan. The study supports farmers in maintaining the market supply, demand, and crop quality. Another study (Ramos et al., 2017) presented an efficient, nondestructive, cost-effective method that automatically counts fruits, in this case, coffee on a branch. The proposed method classifies the coffee fruits into three categories: nonharvestable, harvestable, and fruits with a disregarded maturation stage. This work helps coffee growers plan their work and optimize economic benefits. Other researchers (Ying-xue et al., 2017) provided a model based on SVM and basic geographical data collected from a weather station in China for the rice development stage prediction. Another study (Chlingaryan et al., 2018) defined the

ML approach for crop yield prediction and nitrogen status estimation. A proposed method is about combining ML with other technology to get a hybrid system for cost-effective and compressive solutions for farming. At last, rapid advances in sensing, techniques, and ML will provide cost-effective and compressive solutions for better crop and environmental state estimation. One study (Murugesan et al., 2019) defined work on ML in three platforms: Python, R, and Seaborn for soil management. A prototype of unmanned ground vehicle (UGV) (Aravind et al., 2017; Ribeiro, 2016; Roldán et al., 2017) was also developed to take soil parameters and predict crop yield.

One study (Gonzalez Viejo et al., 2018) adopted a novel approach to food research utilizing computer modeling approaches that could allow a major contribution to accelerated screening of food and brewing items for the food industry and to the application of artificial intelligence (AI). The usage of RoboBEER to evaluate beer content has proven to be an effective, impartial, precise, and time-saving tool for forecasting sensory descriptors relative to professional sensory panels. This approach may also be useful as a fast screening technique for determining the consistency of beer at the end of the manufacturing line for industrial applications.

## 4.2   Disease detection

The most broadly utilized practice in irritation and disease control is to shower pesticides over the cropping area consistently. This practice, albeit powerful, has a high financial and significant ecological expense. ML is a coordinated piece of precision agriculture management, where agro-synthetic compound input is focused as far as time and spot. One study (Moshou et al., 2004) proposed a methodology strategy for the detection of healthy wheat and yellow rust-infected wheat through the support of an ANN model and spectral reflectance features. A real-time remote sensing model proposed (Moshou et al., 2005) detects yellow rust-infected or healthy wheat based on a selforganizing map (SOM) neural network and data fusion of hyperspectral reflection and multispectral fluorescence imaging. Researchers (Moshou et al., 2013) proposed a system that automatically discriminates between healthy and infected winter wheat canopies in terms of water-stressed Septoria trici. The recommended is based on least square (LS)-SVM classifier along with multisensory optical fusion. Another study (Chung et al., 2016) suggested a methodology for detecting and screening of Bakanae disease in rice seeding. The main motive of the study was to detect the pathogen, namely Fusarium fujikuroi, with more accuracy for two rice cultivars. The proposed method uses less time and increases grain yield. Wheat crops were also examined under the same automated detector. Other researchers (Pantazi et al., 2017b) proposed a tool that is capable of detecting and discriminating between healthy *Silybum marianum* plants and those that are infected by smut fungus Microbotyum silybum. Another study (Pantazi et al., 2017) presented a system that detects nitrogen-stressed and

healthy winter canopies and yellow rust-infected based on a hierarchical self-organizing classifier and hyperspectral reflectance image data. The useful usages of fertilizers and fungicides as per the plant's requirement was the main objective achieved in the study.

### 4.3 Weed recognition

It is also one of the first problems in agriculture. The detection and discrimination of weeds are quite difficult from the crops. ML algorithms can be a useful tool that can be integrated with sensors for more accurate detection and discrimination, which can minimize the need for herbicides. One study (Pantazi et al., 2016) proposed a methodology strategy and developed a model for crop and weed species recognition. The proposed model is based on ML and hyperspectral imaging. The main objective of the study is to detect and discriminate various types of maize (*Zea mays*) as crop plant and Tarraxacum officinale, *Sinapis arvensis*, *Ranunculus repens*, *Medicago lupulina*, and Urtica dioicaas, a weed species. Based on counter propagation (CP)-ANN, one study (Pantazi et al., 2017a) proposed a method with the support of multispectral images captured by unmanned aircraft systems that can identify *Silybum marianum*. This weed causes significant losses to the crop yield, and it is quite difficult to isolate it.

### 4.4 Crop quality

The identification of features connected with crop quality is important to increase product price and reduce waste. Researchers (Maione et al., 2016) suggested a method based on ML techniques used in the chemical composition of samples for predicting and classifying the geographical origin of rice samples. The study's result showed that Rb, K, Cd, and Mg are the most relevant chemical components for the classification of the samples. One study (Zhang et al., 2017) proposed a methodology strategy and developed a model that detects and classifies botanical and nonbotanical foreign matter embedded inside the cotton lint during harvesting. The main objective of the study was to improve the quality by minimizing fiber damages. Another study (Hu et al., 2017) considered the ML method supported with hyperspectral reflectance imaging to identify and differentiate Korla fragrant pear into deciduous-calyx or persistent-calyx categories.

### 4.5 Species recognition

Researchers ( Jha et al., 2019) proposed methodology on agricultural automation practices like IoT, wireless communication, ML, AI, and DL. Automation is the key to gain productivity and strengthen soil fertility. The proposed system is for leaf and flower identification and plant watering.

### 4.6 Soil management

ML is used in predicting and identifying agricultural soil properties like soil conditions, temperature, soil drying, and moisture content available in the soil. Researchers (Coopersmith et al., 2014) proposed a method for the evaluation of soil drying through the support of evapotranspiration and prediction data from Urbana, Illinois, in the United States, which helps in agricultural planning. The main motive of the proposed method was the provision of remote farm management decisions. One study (Morellos et al., 2016) proposed a methodology strategy and developed a model that predicts soil conditions. In the study, the author adopted a visible-near-infrared (Vis-NIR) spectrophotometer to collect soil spectra from 140 unprocessed and wet samples of the top layer of Luvisol soil types. The samples were collected from an arable field in Premslin, Germany, in August 2013. One study (Nahvi et al., 2016) presented a model based on a self-adaptive evolutionary extreme learning machine (SAE-ELM) with the support of weather data. In the study, estimation of daily soil temperature took place at six different depths, that is, 5, 10, 20, 30, 50, and 100 cm, in two different climate condition regions of Iran: Bandar Abbas and Kerman. A different study (Johann et al., 2016) proposed a novel method to estimate soil moisture primarily based on the ANN model with the support of a dataset from force sensors on a no-till chisel opener.

Table 2 shows the most popular methods and models based on ML in smart agriculture.

## 5 Role of deep learning in agriculture

DL is a promising technology for the agricultural sector. DL is a subset of ML where ANNs, algorithms inspired by the human brain, learn from large amounts of data (Lecun et al., 2015; Schmidhuber, 2014). DL can be used for crop management, prediction, and more. DL technology in modern farming with evolved algorithms is efficient and effective in the agroindustry. DL in data analysis helps farmers analyze crops to get the desired output. DL, with its selflearning capability, is capable of using IoT for the advancement of water and soil management to empower yield production healthily. In regards to adverse effects of climate change and various environmental and economic factors affecting crops, DL helps farmers tackle these problems by species breeding to get specific genes for plants to adapt to climatic changes and become disease resistant. DL technology is a game changer in modern agriculture that can help sustain the agriculture sector. Algorithms makes crop prediction and crop management models much more precise and effective. The following subsection describes and analyzes the different specific application of DL in agriculture.

### 5.1 Leaf disease detection

For detecting cucumber leaf diseases, especially zucchini yellow mosaic virus and melon yellow spot virus, researchers (Kawasaki et al., 2015) proposed a

**TABLE 2** Summary of role of machine learning in agriculture.

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| Identifies the immature green citrus | Sengupta and Suk (2013) | An early yield mapping system | Acceptable accuracy | Also helps growers/farmers in optimizing their grove in terms of profits and increased yields |
| Reduce human resources labor requirements | Amatya et al. (2015) | Machine vision system | Effective and supportive | Help farmers in reducing human resources |
| To detect tomatoes | Senthilnath et al. (2015) | User-defined framework based on EM and remote sensors | Gain more satisfactory results | Cost-effective and can also apply to other vegetables |
| Estimates the grassland's biomass | Ali et al. (2016) | User-defined model based on ANNs and multitemporal remote sensing data | Acceptable accuracy | This approach helps save the environment and reduce cost |
| For wheat yield predictions | Pantazi et al. (2016) | A technique based on satellite imagery | Prediction is more accurate | Enhances the existing system performances |
| For agriculture yield predictions | Kung et al. (2016) | The user-defined method based on ENN | Acceptable accuracy | The study supports farmers in maintaining the market supply, demand, and crop quality |
| To classifies the coffee fruits. | Ramos et al. (2017) | Nondestructive method | High classification accuracy | Helps coffee growers in optimizing economic benefits |

*Continued*

**TABLE 2** Summary of role of machine learning in agriculture—cont'd

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| For the rice development stage prediction | Ying-xue et al. (2017) | A model based on SVM and essential geographical data | Prediction is more accurate | Enhances farming performances |
| Crop yield prediction and nitrogen status estimation | Chlingaryan et al. (2018) | Hybrid system-combining ML with other technology | Cost-effective and compressive solutions for farming | Provides cost-effective and compressive solutions for better crop and environmental state estimation |
| To take soil parameters and predict crop yield | Murugesan et al. (2019) | UGV | Better accuracy in crop prediction | Ability to work in a variety of crops and environments |
| For detection of yellow rust-infected or healthy wheat | Moshou et al. (2004) | ANN model and spectral reflectance features | Better results obtained | This approach can also be implemented in other crops. |
| To discriminate between healthy and infected winter wheat canopies | Moshou et al. (2013) | LS-SVM classifier along with multisensory optical fusion | High classification accuracy rate. | Cost-effective |
| For detecting and screening of Bakanae disease in rice seedling | Chung et al. (2016) | A user-defined method based on ML | Detected pathogen namely Fusarium fujikuroi with more accuracy for two rice cultivars | The proposed method uses less time and increases grain yield |

| | | | | |
|---|---|---|---|---|
| Detecting and discriminating the healthy *Silybum marianum* plants | Pantazi et al. (2017b) | User-defined tool based on ML | High accuracy obtained | Greater efficiency |
| To detect nitrogen-stressed and healthy winter canopies and yellow rust-infected | Pantazi et al. (2017) | Hierarchical selforganizing classifier and hyperspectral reflectance image data. | Gain more satisfactory results | Also provides useful usages of fertilizers and fungicides as per the plant's requirement |
| To detect and discriminates various types of maize | Pantazi et al. (2016) | User-defined model based on ML and hyperspectral imaging | High accuracy obtained | Cost-effective |
| To identify Silybum marianum | Pantazi et al. (2017a) | The method based on CP-ANN | Effective and supportive | Helps identify and isolate Silybum marianum, which causes major loss to crop yield |
| For predicting and classifying the geographical origin of rice samples | Maione et al. (2016) | User-defined based on ML techniques | The result showed that Rb, K, Cd, and Mg are the most relevant chemical component for the classification of the samples. | Higher prediction rate |
| To improve the quality by minimizing fiber damages | Zhang et al. (2017) | User-defined model | The effect is ideal. | Cost-effective |
| For identifying and differentiating Korla fragrant | Hu et al. (2017) | The method based on ML and hyperspectral reflectance imaging | Gain more satisfactory results | Higher classification rates |

*Continued*

**TABLE 2** Summary of role of machine learning in agriculture—cont'd

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| Agricultural automation | Jha et al. (2019) | IoT, wireless communication, ML, AI, and DL | Gain productivity and strengthen soil fertility | Botanical farm for flower and leaf identification and watering using IoT |
| For the evaluation of soil drying | Coopersmith et al. (2014) | User-defined method support with evapotranspiration and prediction data from Urbana, IL, USA | Improve smart farming | Greater efficiency |
| For predicting soil conditions | Morellos et al. (2016) | User-defined model based on ML supported with adopted Vis-NIR spectrophotometer | Acceptable and effective results | Improve smart farming |
| For estimation of daily soil temperature taken at six different depths | Nahvi et al. (2016) | SAE-ELM with the support of weather data | Supportive and effective results obtained | Greater efficiency |
| To estimate soil moisture | Johann et al. (2016) | ANN model | Highly accurate compared to existing techniques | Improve the agriculture environment |

methodology strategy and developed a convolutional neural network-based (CNN-based) system. The proposed method utilizes square crop and square deformation strategies as a preprocessing step with the overall accuracy of 94.90%. Another study (Sladojevic et al., 2016) proposed a DL model that uses CaffeNet for leaf disease detection. The proposed method is created with the database containing 4483 images that include 13 various types of healthy leaves and plant diseases. The proposed method has an accuracy of 96.30% (classification accuracy), which is better than the SVM. Researchers (Chen et al., 2020) planned to acquaint a framework on deep convolutional neural network (DCNN) for plant leaf disease identification and data used by a pretrained model for doing specific tasks. The proper approach presents a substantial performance improvement concerning other state-of-the-art methods. This would be extremely beneficial in preventing massive crop damage and increasing production. The average accuracy of the proposed approach reaches 92.00% for the class prediction of rice plant images. Experimental results demonstrate the validity of the proposed approach, and it is accomplished efficiently for plant disease detection.

## 5.2   Plant disease detection

One study (Mohanty et al., 2016) presented a framework based on CaffeNet and supported by AlexNet and GoogleNet. The authors' proposed model identified 26 diseases and 14 crop species using the PlantVillage public data set of 54,306 images of diseased and healthy plant leaves. The 0.9935 F1 score indicates the precision of the proposed method. Another study (Lu et al., 2017) considered DL and developed a model that identifies paddy crop disease. The developed CNN model is an upgraded version of AlexNet CNN architecture and LeNet-5. The trained CNN model has an average recognition precision of 95.48% for 10 paddy crop diseases. To prevent overfitting and to enhance the capability of the proposed model, stochastic pooling is preferred. One study (Amara et al., 2017) classified banana leaf diseases using the support of a DL model that uses LeNet and achieved the precision of 96% and an F1 score of 0.968. The image dataset comprises of 3700 images of banana disease acquired from PlantVillage. Another study (Lu et al., 2017) proposed a framework based on supervised DL that diagnoses the wheat diseases. The proposed framework considered 50,000 images of the wheat crop, including infected leaves and healthy leaves. In the proposed framework, four different CNN models performed recognition of seven wheat disease classes. The maximum average recognition accuracy of 97.95% was achieved with the support of the VGG16 model, which has fully connected layers. In a different study, researchers (Brahimi et al., 2017) classified nine tomato diseases based on CNN models, especially GoogleNet and AlexNet, with the support of the visualization method to visualize and detect symptoms. The dataset used for the study comprises of 14,828 images. The study's result showed that the CNN model is a better choice

compared to the SVM and random forest (RF). For the identification of plant disease, researchers (Ferentinos, 2018) proposed five different deep CNN models that include Google Net, AlexNetOWTBn, AlexNet, Overfeat, and VGG. The proposed framework considered 87,848 individual leaf images from 58 different classes of plant disease combinations of 25 different plant species. The highest classification accuracy achieved using the VGG-CNN model was 99.53%. Based on DL, researchers ( Jiang et al., 2019) developed an INAR-SSD model to detect five apple leaf diseases. The dataset consisted of 26,377 images. The INAR-SSD performance was about 78.80% mAP along with a detection speed of 23.13 FPS.

## 5.3  Land cover classification

One study (Chen et al., 2014) developed a framework based on a hybrid of PCA, autoencoder, and logistic regression that is capable of producing the precision result of 98.00%, which is 1% more precise than RBF-SVM. In the study, the authors identified 13 different land cover classes at the Kennedy Space Center (KSC) and nine different classes in Pavia. The database used in the framework was collected from the KSC, Florida, USA, and an urban site in the city of Pavia, Italy. Another study (Luus et al., 2015) developed a framework based on Theano. The proposed framework supports land cover classification with an average accuracy of 93.48% (classification accuracy). Land owned by the University of California, Merced, was used as a dataset in the study in which the authors identified 21 land-use classes that contain a variety of spatial patterns. Other researchers (Lu et al., 2017) proposed a methodology strategy based on deep CNN that is used to extract information about cultivated land with the help of a dataset comprised of images from UAVs at the Sichuan province, China, Guanghan country, Pengzhow country.

## 5.4  Crop type classification

One study (Kussul et al., 2017) proposed a methodology to classify crops like wheat, soybean, maize, sugar beet, and sunflower. The study uses a database comprised of 19 multitemporal scenes collected by Landsat-8 and Sentinel-1A RS satellites from a test site in Ukraine. The overall classification accuracy of the proposed method is 94.60%, which is better than the RF (i.e., 88%) and multilayer perception (MLP) (i.e. 92.7%). Another study (Ghosal et al., 2018) considered a deep machine vision-based methodology that identifies, classifies, and measures plant stresses, including abiotic and biotic, using a database comprised of 25,000 images of healthy and stressed leaflets in the fields. Deep CNN model accomplishes the classification accuracy of 94.13%.

## 5.5  Plant recognition

A study (Reyes et al., 2015) proposed a model based on CaffeNet and supported by AlexNet. The dataset is comprised of 91,759 images distributed in 13,887

plant observations collected by LifeCLEF in 2015. In the study, the authors recognize seven different views of various plant: branch, entire plant, flower, stem, fruit, and scans. The overall LifeCLEF metric is about 48.60%, which is worse than the local descriptors in representing images and KNN. Another study (Lee et al., 2015) developed a model based on CaffeNet and supported by AlexNet with a maximum classification accuracy of 99.60%, which is better than SVM (95.1%) and ANN (58%). In the study, the authors recognize 44 different plant species using the Malaya Kew Leaf dataset that is comprised of 44 classes collected at the Royal Botanic Garden, Kew England. Another group of researchers (Grinblat et al., 2016) presented a framework based on Pylearn2 that supported the identification of plants from vein patterns of white, soya, and red beans and has a classification accuracy of 96.90%. The dataset was comprised of 866 leaf images provided by INTA Argentina, that is, 172 white bean, 272 red bean, and 422 soybean leaves. Another study (Anami et al., 2020) introduced a technique based on DCNN with VGG-16 CNN model for the identification of crops using field images. The proposed framework was for automatic recognition and classification of biotic and abiotic paddy crop stress using field images. The trained models achieved an average accuracy of 92.89%. The generality of the proposed approach can make it applicable to a wide range of field crops, such as wheat, maize, barley, soybean, and more.

## 5.6   Segmentation of root and soil

One study (Douarre et al., 2016) proposed a methodology strategy based on CNN with SVM supported by MatConvNet for identification of roots from soils with a quality measurement of 0.23 (simulation) and 0.57 (real roots). The soil images used in the study were generated from X-ray tomography.

## 5.7   Crop yield estimation

Researchers (Kuwata & Shibasaki, 2015) presented a work based on CaffeNet to estimate maize yield with a root mean square error of 6.298, which is better than support vector regression (8.204). The dataset is downloaded from the climate research unit, and moderate resolution imaging spectroradiometer-enhanced vegetation index comprised data of maize yield from 2001 to 2010. Another study (Kamilaris & Prenafeta-Boldú, 2018) defined work on a CNN and presented the advantage and disadvantages of the CNN. This approach is for the implementation of the CNN in a sugarcane plantation in Costa Rica, and future potential of DL is also discussed in the other areas.

## 5.8   Fruit counting

At present, DL-based approaches are dominating the field of image segmentation and object detection (Badrinarayanan et al., 2017). The overwhelming

success of these techniques is often attributed to the huge amount of training data from which the networks learn features that ideally generalize across environments. Previously, fruit counting is dominated by circular Hough transformation (CHT) (Pedersen & Kjeldgaard, 2007). CHT requires extensive parameter tuning and fails to handle occlusions. These issues led to the development of more sophisticated methods for fruit counting. One study (Chen et al., 2017) suggested a data-driven approach for counting oranges and apples based on DL. First, they introduced a labeling platform to label the fruits on input images. Then, with the use of a blob detector neural network, the candidate region was extracted. Again, another neural is utilized for counting the number of fruits within the image. Finally, regression analysis is applied between algorithmic count and manual count to evaluate the performance. This method is used for oranges and apples with the intersection of union (IoU) 0.813 and 0.838, respectively. Another study (Häni et al., 2018) addressed the problem of accurately counting fruits directly from images. They presented a solution that uses AlexNet CNN, which modified and fine-tuned their training data. The methodology achieved accuracy in the range of 80% to 94%. The detection and counting of fruits got more attention after the development of faster R-CNN. In another study, researchers (Hashim et al., 2018) demonstrated a quick, simple, and reliable method of nondestructive identification of the impact of cold storage on mango. The proposed method may be used to effectively distinguish separate fruits after low temperature preservation.

## 5.9   Obstacle detection

One study (Steen et al., 2016) considered a framework on CaffeNet based on AlexNet in the area of obstacle detection with a high classification accuracy of 99.9% in row crops and 90.8% in grass mowing. The study is about identifying ISO barrel-shaped obstacles in row crops and grass mowing using a total of 437 images as a dataset for the framework. Another study (Christiansen et al., 2016) suggested a model based on AlexNet and VGG supported by CaffeNet, which has 0.72 F1 score to detect obstacles.

## 5.10   Identification of weeds

In one study, researchers (Xinshao & Cheng, 2016) developed a model based on PCANet and LMC classifiers that classify 91 weed seed types with an average classification accuracy of 90.96%, which is better than the other features extraction techniques. The dataset used in the framework contains 3980 images, including 91 different types of weed seed. A different study (Dyrmann et al., 2016) proposed Theano-based Lasagne library for Python supported by variation in VGG16 to classify weed from crop species with 85.20% classification accuracy using the dataset of 10,413 images collected from BBCH 12–16, including 22 weed and crops species at early growth stages. Another study

(Sørensen et al., 2017) proposed a method based on DenseNet to identify thistle in winter wheat with a classification accuracy of 97.00%. Based on CNN supported with crop lines algorithm, researchers (Bah et al., 2018) presented work for identification of weeds in bean, beet, and spinach fields. The dataset comprises of vegetable images captured by drone at about 20 m. In the study, the best accuracy was obtained in the beet field. Finally, one study (Yu et al., 2019) proposed a model based on DCNN with the support of GoogleNet, VGGNet, and DetectNet for weed detection in turfgrass using images captured using digital cameras. The study's result showed that DCNN is most suitable for weed detection.

### 5.11 Prediction of soil moisture

To predict soil moisture content over an irrigated cornfield, researchers (Song et al., 2016) developed deep belief network-based macroscopic cellular automata (DBN-MCA) with root mean square error of 6.77. The soil data was collected from an irrigated cornfield (an area of 22 km$^2$) in the Zhangye oasis in northwest China.

### 5.12 Cattle race classification

A study (Santoni et al., 2015) suggested a model based on gray level cooccurrence matrix CNN (GLCM–CNN) supported by DL MATLAB Toolbox for cattle race classification with an average classification accuracy of 93.76%.

Table 3 shows the most popular methods and models based on DL in smart agriculture.

## 6 Role of IoT in agriculture

To connect objects with a network for information exchange and communication, IoT technology is used. IoT is capable of making billions of interconnected devices that are also termed smart objects. These smart objects are proficient at collecting environmental information and communicating with other systems through the internet (Meiklejohn et al., 2013). IoT-based applications enable devices to monitor and control in different domains, including processes, home appliances, health monitoring applications, smart homes, smart cities, smart agriculture, and more (Chang & Lin, 2018). IoT applications have unique importance throughout the lifespan of the agriculture sector, such as cultivate yields, irrigation, harvesting, postharvesting, crop storage, processing, transportation, and sales. For agriculture applications, there are a variety of specialized sensors available, for instance, soil moisture sensor, humidity, leaf moisture, solar emissions, infrared radiations, rain predictor, and more. In the scenario of IoT, sensors can be installed in different fields like greenhouses, seed storages, cold storages, agriculture machinery, transportation system, and livestock;

**TABLE 3** Summary of role of deep leaning in agriculture.

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| For detecting cucumber leaf diseases | Kawasaki et al. (2015) | A CNN-based system | Overall accuracy of 94.90% | Help farmers increase productivity |
| For leaf disease detection | Sladojevic et al. (2016) | DL model with the support of CaffeNet | Classification accuracy of 96.30% | The proposed model is better than the SVM |
| Plant leaf disease identification | Chen et al. (2020) | DCNN | High accuracy about 92.00% | Great efficiency |
| To identify 26 diseases and 14 crop species | Mohanty et al. (2016) | CaffeNet, AlexNet, and GoogleNet | 0.9935 as F1 score | Cost-effective |
| To identify paddy crop diseases | Lu et al. (2017) | Trained CNN model. | Average recognition precision of 95.48% | The developed CNN model is an upgraded version of AlexNet CNN architecture and LeNet-5 |
| For classification of banana diseases | Amara et al. (2017) | DL model with the support of LeNet | Classification accuracy of 96.00% and 0.968 as F1 score | Better performance among existing models |
| For recognition of seven wheat disease classes | Lu et al. (2017) | VGG16 model | The maximum average recognition accuracy of 97.95% | Enhances farming performances |
| To classify 9 tomato diseases | Brahimi et al. (2017) | CNN model, GoogleNet, and AlexNet | Higher accuracy | CNN model is a better choice compared to the SVM and RF |
| For the identification of plant disease | Ferentinos (2018) | GoogleNet, AlexNetOWTBn, AlexNet, Overfeat, and VGG | VGG-CNN model achieved the highest classification accuracy of 99.53% | Enhances farming performances |

| To detect five apple leaf diseases | Jiang et al. (2019) | INAR-SSD model | 78.80% mAP and detection speed of 23.13 FPS | The system can be improved more |
|---|---|---|---|---|
| To identify 13 different land cover classes at KSC and 9 different classes in Pavia | Chen et al. (2014) | Framework based on hybrid of PCA, autoencoder, and logistic regression | 98.00% classification accuracy | This framework was 1% more precise than RBF-SVM |
| For land cover classification | Luus et al. (2015) | User-defined model based on Theano | The average accuracy of 93.48% | Capable of identifying 21 land-use classes that contain a variety of spatial patterns |
| To extract information about cultivated land | Lu et al. (2017) | Deep CNN | Satisfactory results | Better performance |
| To classify crops like wheat, soybean, maize, sugar beet, and sunflower | Kussul et al. (2017) | A user-defined model with the support of by Landsat-8 and Sentinel-1A RS satellites | Classification accuracy of 94.60% | Better than RF and MLP |
| To identify, classify, and measure plant stresses | Ghosal et al. (2018) | Deep machine vision-based system | Classification accuracy of 94.13% | Great efficiency |
| To recognize seven different views of various plant: branch, entire plant, flower, stem, fruit, and scans | Reyes et al. (2015) | A model based on CaffeNet supported by AlexNet | Average accuracy | The overall LifeCLEF metric is about 48.60%, which is worse than the local descriptors in representing images and KNN |
| To recognize 44 different plant species using the Malaya Kew Leaf dataset | Lee et al. (2015) | A model based on CaffeNet supported by AlexNet | Maximum classification accuracy of 99.60% | The proposed method was better than SVM (95.1%) and ANN (58%) |

**TABLE 3** Summary of role of deep leaning in agriculture—cont'd

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| For identification of plants from vein patterns of white, soya and red beans | Grinblat et al. (2016) | A framework based on Pylearn2 | Classification accuracy of 96.90% | Better performance |
| The identification of crops using field images | Anami et al. (2020) | DCNN Framework with VGG-16 CNN model | The trained models achieve an average accuracy of 92.89% | Applicable to a wide range of field crops |
| For identification of roots from soils | Douarre et al. (2016) | CNN with SVM supported by MatConvNet | Quality measure of 0.23 (simulation) and 0.57 (real roots) | Great efficiency |
| To estimate maize yield | Kuwata and Shibasaki (2015) | User-defined model based on CaffeNet. | Root mean square error of 6.298 | Better than SVR |
| Sugarcane plantation in costa rice | Kamilaris and Prenafeta-Boldú (2018) | CNN | Better results obtained | This approach can also be implemented in other areas |
| For counting of oranges and apples | Chen et al. (2017) | A data-driven approach based on DL | This method is applied for oranges and apples with the IoU 0.813 and 0.838, respectively | Applicable to a wide range of field crops |

| | | | | |
|---|---|---|---|---|
| For accurately counting fruits directly from images | Häni et al. (2018) | AlexNet CNN | The accuracy in the range of 80% to 94% | Faster R-CNN is better than the proposed method |
| In the area of obstacle detection | Steen et al. (2016) | CaffeNet based on AlexNet | High classification accuracy of 99.9% in row crops and 90.8% in grass mowing | Great efficiency |
| To detect obstacles | Christiansen et al. (2016) | AlexNet and VGG supported by CaffeNet | 0.72 F1 score | Better performances |
| To classify 91 weed seed types | Xinshao and Cheng (2016) | PCANet and LMC classifiers | Average classification accuracy of 90.96% | Better than the other feature extraction techniques |
| To classify weed form crop species | Dyrmann et al. (2016) | Theano-based Lasagne library for Python supported by variation in VGG16 | 85.20% as classification accuracy | Enhances farming performances |
| To identify thistle in winter wheat | Sørensen et al. (2017) | DenseNet | Classification accuracy of 97.00% | Great performances |
| For identification of weeds in bean, beet, and spinach fields | Bah et al. (2018) | CNN supported with crop lines algorithm | Best accuracy was obtained in the beet field | Can improve more |
| For weed detection in turf grass using the images | Yu et al. (2019) | DCNN with support of GoogleNet, VGGNet, and DetectNet | Better performances | DCNN is most suitable for weed detection |
| To predict soil moisture content over an irrigated cornfield | Song et al. (2016) | DBN-MCA | Root mean square error of 6.77 | Can improve more |
| For cattle race classification | Santoni et al. (2015) | GLCM–CNN supported by DL MATLAB Toolbox | Average classification accuracy of 93.76% | Better performances |

and their data can be stored in the cloud for monitoring and control (Sawa, 2019). Researchers (Farooq et al., 2020) conducted a survey of IoT technology and its application in the agricultural domain. Using supervised learning, the authors presented the main issue and challenges in the field of agriculture. The framework and contextualization of a range of solutions in agriculture were also discussed. The following subsection described the progress of IoT in smart farming.

## 6.1   Climate condition monitoring

In one study (Brandt et al., 2017), the Food and Agriculture Organization of the United Nations introduced an approach related to the weather/climate, namely climate-smart agriculture, which identifies the climate conditions and helps in improving the agriculture system to a great extent. IoT had been deployed with the support of WSN to monitor weather conditions by using sensors and devices (Martín et al., 2017).

## 6.2   Crop yield

One study (Ayaz et al., 2019) was intended to apply wireless sensor and IoT in the agriculture domain. The development of the ventilate, wireless sensor, VAVS, cloud computer, and a new method for improving the crop yield and handling were also discussed. The IoT-based sensors and communication is mandatory in agriculture to maximize crop production.

## 6.3   Soil patter

To monitor soil moisture content, humidity and moisture sensors were deployed in one study (De Morais et al., 2019). The soil monitoring test is one of the most delicate tests that increases crop productivity and also suggests the best suitable fertilization technique. However, IoT technology supports identification of contaminated soil, which protects the field from crop loss and over fertilization.

## 6.4   Pest and crop disease monitoring

A study (Zang & Wang, 2014) proposed a system for monitoring wheat diseases, pests, and weeds based IoT technology with the support of ZigBee network. The dataset was collected by IoT. The proposed system is easy to operate, and users can even monitor using a PC or hand-held terminal. One of the major issues is crop raiding, which is generally due to contraction of the cultivated field into the different wildlife haunts. A different study (Giordano et al., 2018) had developed a methodology based on IoT application with the support of low-power devices and an open-source system for crop protection from both weather conditions and wild animal attacks. Another study (Awan et al., 2019)

considered blockchain technology for the development of smart farming. A smart farming model is developed to uplift the traditional agriculture using blockchain technology and IoT. The proposed technique can be used to reduce food waste and the cause of foodborne diseases.

### 6.5 Irrigation monitoring system

With the installation of various sensing devices, irrigation monitoring systems aid farmers by reducing monthly bills for irrigation and limited water resources (Keswani et al., 2018). A more generalized, advanced system was proposed by researchers (Hellin et al., 2014) that uses cellular technology for controlling the process of irrigation. In the proposed method, sensor data can be transferred to the system database using mobile technology. One study (Mohanraj et al., 2016) suggested a framework consisting of KM-knowledge base and monitoring modules for field monitoring and automation using IoT in agriculture domain. A knowledge data flow model was constructed connecting scattered sources to the crop structures, and a comparison between the development system and the existing system was presented. The system overcomes the limitations of traditional agricultural procedures by utilizing water resources efficiently and also reducing labor cost. For monitoring water quality, researchers in one study (Ikhwan & Thamrin, 2017) proposed a model based on IoT using sensor nodes for empowering the wireless communication to measure physical and chemical constraints of water, such as temperature, pH, oxygen, and conductivity. For supervision of the collected database about water management system on the internet, cloud computing services were utilized. The proposed system also controls the water consumption in the field. Another study (Nawandar & Satpute, 2019) designed and developed a low-cost irrigation system based on an IoT with the support of HTTP and MQTT protocols. The proposed system's results promises to be beneficial with its intelligence, portability, and low cost.

### 6.6 Optimum time for plant and harvesting

A study (Kamilaris et al., 2016) proposed an IoT-based framework applying real-time collection processing and analysis of data. This will provide real-time provisions or smart solutions and decision support by experts to researchers and farmers. Also, this smart farming framework increases productivity and protects the environment by using fewer resources like water, fertilizer, and so on.

### 6.7 Tracking and tracing

One study (Satyanarayana, 2013) developed a model that monitors soil condition with the support of the ZigBee network along with other devices, such as GPRS, CMS, and GPS. However, the proposed technique is expensive but highly utilized in the field of agriculture because of its accurate location

monitoring and tracking property. Another study (Farooq et al., 2019) proposed a framework on technologies involving IoT in the agriculture domain. The author also presented a discussion on network technologies involving network architecture and layers and the connection of IoT-based agriculture system to relevant technologies.

## 6.8  Farm management system

A farm management system is a crucial element for processing, planning, and decision-making in smart farming (Gardasˇevic et al., 2017). One study (Elijah et al., 2018) considered the integration of IoT with data analytics for enabling smart agriculture. The author classified all the advantages and challenges in the implementation of IoT in the agricultural sector. The main aim is to draw attention to research in the development of LPWA communications. Also, as the cost of IoT devices, data storage, processing, and transfer reduces with time, small- and medium-scale farmers will be able to deploy the IoT systems.

## 6.9  Agricultural drone

Agricultural drones, that is, UAVs, are used to improve different practices and process of smart farming. Agricultural processes include screening, scouting reports, crop health assessment, nitrogen measurement, spraying, and monitoring soil conditions. One study (Bodake et al., 2018) proposed a methodology based on the integration of IoT and GIS to map and capture the image of crop health with the support of drones. The proposed method is specially deployed for monitoring bacteria and fungus on the farm.

Table 4 shows the most popular methods and models based on IoT in smart agriculture.

## 7  Role of wireless sensor networks in agriculture

For sensing and analyzing the various parameters that are required in the agriculture domain, WSN technologies are available. To utilize sensors in agriculture, many applications have been developed. Sensor networks are the best options to make a strong bond between cyberspace and the real world. By design, sensors are appropriate for connecting agriculture to the IoT. WSN are cheap devices capable of working in specific environments for an extended period without battery replacement (Louis & Dunston, 2018). The concept of precision farming is made clear, and the study of vital elements of precision and smart farming is done. The concept of GIS, a distinct information system, is discussed in one study (Yanxia et al., 2007) in detail. The system utilizes GIS techniques, agro-techniques, scientific research results, expert experience, and computer technique in creating a comprehensive precision farming expert

**TABLE 4** Summary of role of internet of things in agriculture.

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| To identify climate conditions | Brandt et al. (2017) | User-defined, model based on IoT and WSN | Satisfactory results obtained | Can improve more |
| For improving the crop yield and handling | Ayaz et al. (2019) | Ventilate, wireless sensor, VAVS, and cloud computing | Better performance | IoT-based methods are essential to maximizing crop production |
| To monitor soil moisture | De Morais et al. (2019) | Humidity and moisture sensors and IoT technology | Higher efficiency | Most excellent test that increase crop productivity |
| For monitoring wheat diseases, pests, and weeds | Zang and Wang (2014) | Monitoring system based on IoT technology and ZigBee network | Acceptable accuracy | Easy to operate; users could monitor using PC |
| For crop protection from weather conditions and wild animal attacks | Giordano et al. (2018) | IoT application with the support of low-power devices and an open-source system | Great efficiency | Also solves the issue of crop raiding |
| Uplift the traditional agriculture | Awan et al. (2019) | Smart farming model | Improve smart farming | Reduce food waste and the cause of foodborne diseases |
| For controlling the process of irrigation | Hellin et al. (2014) | Cellular technology | Better results obtained | Performance of the existing system increases |

*Continued*

**TABLE 4** Summary of role of internet of things in agriculture—cont'd

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| Field monitoring and automation | Mohanraj et al. (2016) | KM-knowledge base monitoring module | The trained models achieve high accuracy and utilizing water resource efficiently | Requires less labor cost |
| For empowering irrigation monitoring system | Ikhwan and Thamrin (2017) | The user-defined system based on IoT | The effect is ideal | The proposed system also controls water consumption in the field. |
| For monitoring water quality | Nawandar and Satpute (2019) | Low-cost irrigation system based on IoT with the support of HTTP and MQTT protocols | System's results promises to be beneficial with its intelligence | Portability and low cost |
| Increases the productivity | Kamilaris et al. (2016) | Real-time data collection and analysis | DL is better than existing AI technologies | High accuracy, reliability and robustness |
| To monitor and soil condition | Satyanarayana (2013) | ZigBee network, along with other devices such as GPRS, CMS, GPS | The results showed exact location monitoring and property tracking | The proposed technique is expensive. |
| Agricultural challenges and security requirements | Farooq et al. (2019) | IoT-based network architecture | Improve smart farming security | Cost-effective |
| To draw attention to research in the development of LPWA Communications | Elijah et al. (2018) | Integration of IoT with data analytics | Satisfactory results | Helps in enabling smart agriculture |
| For monitoring bacteria and fungus on the farm | Bodake et al. (2018) | IoT, GIS, and drones | Better performances | Helps in enabling smart agriculture |

system that is of great intelligence. This section reviews the progress of image processing in the agricultural and food processing.

## 7.1 Irrigation management

A study (Rawidean et al., 2014) proposed a framework on WSNs for resource optimization and monitoring in agriculture. The proposed approach is for gathering real-time information about crops. The implementation of WSNs will optimize the uses of water and fertilizer and maximize the yield of crops. Another study (Ojha et al., 2015) reviewed the WSN application, issues, and challenges in the implementation of WSN. The authors presented various case studies proposed in the literature to discuss WSN deployment for farming applications. The current use of WSN in irrigation, crop management, and more as well as an approach for further implementation of WSNs in agriculture were the main points in the presented article.

## 7.2 Soil moisture prediction

The open-source feature of Tiny OS is discussed by ( Jao et al., 2013) in detail. The detailed design and implementation of WSNs, both hardware and software, was presented. An experiment was conducted to validate the performance of MDA300CA driver. A single node experiment and a multiple node experiment were shown, and the readings were analyzed. The readings helped in knowing the soil type, that is, whether it was dry, moist, or water-saturated soil. ( Joshi et al., 2017) had defined work on soil monitoring systems. The proposed WSN system is for controlling parameters of soil, and this system is embedded on a web server uses Raspberry Pi and IoT for monitoring and controlling soil parameters.

## 7.3 Precision farming

One study (Bencini et al., 2012) came up with the design, optimization, and development of a practical solution for application to the agro-food chain monitoring and control. The main features of VineSense were described. Moreover, some critical agronomic results achieved by the use of VineSense in different scenarios were sketched out, thus emphasizing the positive effects of the WSN technology in the agricultural environment. Another study (Piyare & Lee, 2013) proposed an extensible and flexible architecture for integrity WSN with cloud computing for data collection and sharing using REST-based web services. The evaluation illustrates that the data can be accessed by users anywhere and on any mobile device with internet access. This proposed methodology is an energy-efficient approach to increase the lifetime of senses nodes. A different study (Bhanu et al., 2014) designed and developed an agricultural monitoring

system to reduce manual work. This system measures the parameters and provides the information to farmers. Detects even minor changes in parameters.

The WNS system architecture and data architecture were discussed with the continuous monitoring of many environmental parameters; the grower can analyze the optimal environmental conditions to achieve maximum crop productiveness and to achieve remarkable energy savings. In one study, researchers (Gangurde & Bhende, 2015) defined the WSN as a game changer in precision agriculture. The proposed WSN system can be used to control agricultural parameters and enhance growth. One study ( Jawad et al., 2017) presented a comparison among different wireless technologies or protocols and proposed a system that uses ZigBee and Lora wireless protocols, which are convenient because of low-power consumption and high communication range. Also introduced a classification of energy-efficient techniques algorithm and energy harvesting and techniques. Another study (Siva Rama Krishnan & Arun Kumar, 2019) suggested a strategy for the practical implementation of smart farming using routing recommended in the WSN. The data is taken and sent through the RF transmitter and received by a single server that processes the data, and further details are generated. The authors define the approach to control some parameters for the effective utilization of available resources.

## 7.4 Climate condition monitoring

WSNs trace down climate conditions to automate and analyze the corresponding parameters. Web and smartphone applications show real-time parameters, like temperature, humidity, and CO2, and give access for farmers to remotely open their greenhouse (Roham et al., 2015). Researchers (Rodríguez et al., 2017) proposed a methodology and developed a system for the monitoring and predicting of data in precision agriculture in a rose greenhouse based on WSNs. The roses in a greenhouse were taken for this case study. The proposed design of WSNs can measure parameters like temperature, humidity, and light. Integrated with API for monitoring and predicting.

Table 5 shows the most popular methods and models based on IoT in smart agriculture.

## 8 Role of data mining in agriculture

"Big data" refers to a huge quantity of data gathered from the different channels for extended periods. Data collected from sensors, social networking, and business data is called big data. The big data have many challenges, like capturing, storage, investigation, and research. To cut production costs, big data is useful in the agriculture domain for maintaining supply chain management of agricultural products (Chen et al., 2019). DM and data analysis are key to increasing production at a low rate and getting maximum yield with maximum profit. DM uses existing technologies to bring a revolutionary change in the field of

**TABLE 5** Summary of role of wireless sensor networks in agriculture.

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| Precision and smart farming | Yanxia et al. (2007) | GIS technique | The trained models help in precision farming | Sustainable farming |
| Resource optimization and monitoring in agriculture | Rawidean et al. (2014) | WSN-based techniques | Optimization increased to a great extent | Also maintains the moisture level and healthiness of plants |
| Comparison among different wireless technologies or protocols | Ojha et al. (2015) | WSN, ZigBee, LoRa, and IoT | Low-power consumption and high communication range | Energy-efficient |
| Study of soil state or soil type | Jao et al. (2013) | Tiny OS along with WSN | An experiment was conducted to validate the performance of MDA300CA driver | Also able to define whether soil is dry, moist, or water-saturated |
| Controlling of soil parameters | Joshi et al. (2017) | Soil monitoring with WSN systems | Better results obtained | Cost-effective |
| Food chain monitoring and control | Bencini et al. (2012) | VineSense | More accurate than existing techniques | Improves the agriculture environment |
| For precision farming | Piyare and Lee (2013) | WSN, cloud computing, and REST-based web services | The trained models helps in precision farming | The proposed methodology is energy-efficient approach to increase the lifetime of senses nodes |

**TABLE 5** Summary of role of wireless sensor networks in agriculture—cont'd

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| To reduce manual work in farming | Bhanu et al. (2014) | Agricultural monitoring system based on WSN | Improve smart farming | Reliable, cost-effective, and maximum crop productiveness |
| For control of agricultural parameters and to enhance growth | Gangurde and Bhende (2015) | User-defined module based on WSN | Great efficiency | Performance of the existing system increases |
| Cloud computing with WSN | Jawad et al. (2017) | Integrated WSN, cloud REST-based web services | The effect is ideal | Easily access from anywhere |
| Optimization of crop supervision | Siva Rama Krishnan and Arun Kumar (2019) | Recommendation routing in WSN | Better results obtained | Effective utilization of available resources |
| To trace down climate conditions | Roham et al. (2015) | Web and smartphone application based on WSN | This method show low cost and high portability | Easily controllable for farmer |
| Support and management tools for the agricultural sector | Rodríguez et al. (2017) | WSN technology integrated with API | The results show that SVMs seem to provide the best prediction model | Enhances greenhouse environmental conditions forecasting |

agriculture (MiloviC & Radojevic, 2011). One study (Vanitha et al., 2019) intended to highlight some of the common DM techniques and presented their application in the field of agriculture. The further use of DM to predict crop yield in agriculture sector were discussed. The following subsection addresses the progress of DM in the smart farming and agricultural industry.

## 8.1  Irrigation management

To manage the irrigation system called FITRA, researchers (Kokkonis et al., 2017) presented a fuzzy neural network algorithm. This algorithm uses sensor information. Many soil moisture sensors were being used to limit utilization and increment production. The framework naturally embraces the changing ecological conditions. Another study (Padalalu et al., 2017) proposed an automated irrigation system so that proper supervision and management of water required in the field is filled. To monitor the field, different sensors were installed in the field so that different parameters, such as soil temperature, humidity, and soil type (pH) can be monitored. Naïve Bayes algorithm was adopted for a specific amount of water according to the crop needs. By adopting this proposed method, proper water management can be achieved. In a different study, researchers (Xie et al., 2017) suggested a framework to support irrigation systems. The framework includes irrigation demand estimation, solar energy prediction based on SVR technique, and scheduling optimization.

The framework utilizes hourly numerical weather prediction (NWP) and the time of use (ToU) model. The study's results are quite promising, as 7.97% of water resources and energy can be saved and even amortized cost reduced by 25.34% as compared to the method based on soil moisture. One study (Goldstein et al., 2018) proposed a methodology that predicts irrigation by applying DM methods. In the study, various models were adopted and applied using classification and regression algorithms. For better performance, gradient boosted regression trees (GBRTs) and boosted trees classifiers (BTCs) were used instead of a linear regression model. The main advantage of this model is that its irrigation action helps keep the soil moisture within the suitable limits and helps the system in saving water. One group of researchers (González Perea et al., 2019) proposed a model that predicts occurrences in the irrigation process. The proposed model is based on a decision tree that is combined with an NSGA II. This is also used to optimize the different parameters of the decision tree. Various datasets are being used like crop type data, climatic data, phonological plant, and so forth. Results of this model are quite promising.

## 8.2  Prediction and detection of plant diseases

One study (Padol & Yadav, 2016) suggested that the discovery of a few plant illnesses could be possible using a blend of DM strategies and picture handling to beat the absence of human perception and even to diminish costs. Based on

the manipulator, researchers (Schor et al., 2016) developed a robotic disease detection system with the features of different detection poses. The main objective of the work was to develop a method that can overcome the drawback of PCA-based and coefficient variation-based (CV-based) models, which were generally used in the detection of tomato spotted wilt virus (TSWV) and powdery mildew (PM) that threaten greenhouse bell peppers. Based on the hidden Markov model (HMM), researchers (Patil & Thorat, 2016) suggested a framework for early disease detection in grapes. The proposed model analyzes the input data, like leaf moisture, temperature, and relative humidity, which enable the model to classify grape diseases such as bacterial leaf cancer, rust, anthracnose, downy mildew, and PM. The proposed method was better than the statistical method as per the results of the study. To deduce the probability of Cd stress in rice, one study (Liu et al., 2019) considered a Bayesian method based on temporal characteristics and satellite data and to verify the Cd stress probability soil Cd concentration was used. The overall accuracy of the proposed method was 81.57%.

## 8.3 Pest monitoring

For mapping pests and disease risks, one study (Marques da Silva et al., 2015) suggested an algorithm that can be used for calculating "accumulated degree-days" with the support of land surface data collected by meteorological satellite. In the study, linear regression was also adopted to deal with the missing data and logistic regression that was used to analyzes the results of land surface temperature in monthly degree-days data. Another study (Boniecki et al., 2015) suggested a neural classifier based on MLP neural network topology that can identify likely parasites in apple orchards, such as apple moth, apple aphid, apple blossom weevil, apple clearwing, and apple leaf sucker. The proposed classifier includes 16 color characteristics, 7 form factors, and a total of 23 parameters.

## 8.4 Optimum management of inputs (fertilizer and pesticides)

One study (Lottes et al., 2016) presented a system for detection of sugar beet plants based on RF classification and a Markov random field (MRF). The study was carried out on three different sugar beet fields. By implementing the method, the robot was able to perform necessary spraying and remove weeds. Another study (Viani et al., 2016) proposed a novel fuzzy logic to predict the dose of the pesticides to be applied. The fuzzy logic was also used for the management of pests, weeds, and diseases by studying various data like weather data, risk of infection, and stage of the development of the plant. Finally, a study (Chlingaryan et al., 2018) surveyed research literature about the accurate prediction of crop yield and the estimation of nitrogen status in the field of precision agriculture using DM.

### 8.5 Crop yield prediction

One study (Ruß, 2009) showed how data collection, from precise geo-tagging to climate study, will help a lot to farmers. It is an excellent way to use data in the prediction of yield. The author talks about techniques like vector regression, which is immensely helpful in predicting the yield. And likewise, many other methods can be implemented as the author says, which indeed brings a revolutionary change in the agricultural field. Another study (Kaur et al., 2014) proposed a system based on finding a suitable data model that helps in achieving high accuracy and price prediction. Genetic, algorithm-based neural networks can be constructed for price prediction. The Coimbatore market was selected for the price of a tomato as an example and simulated the results using MATLAB. One researcher (Geetha, 2015) defined work on DM from the perspective of the agricultural field. The author also discussed different DM techniques for solving different agrarian problems. The author, in his work, integrates the work of various authors so that it is useful for researchers to get information on the current scenario of DM techniques and their applications in the context of agriculture. The author also presented a subarray to provide a survey of various data money techniques used in agriculture. Other researchers (Kung et al., 2016) suggested the use of cloud computing and IoT, which encompassed with big data and robots can genuinely encourage farm work and increase production with reduced labor or workforce. The use of cloud computing and big data are the keys in the coming future to enhance the agricultural field and increase production.

One study (Gandhi & Armstrong, 2016) presented work on DM for decision-making in agriculture. The various DM techniques, like AI, neural network, and Bayesian networks, improve existing agriculture systems. The authors also propose an approach to use complex agriculture data sets for crop yield prediction with an integration of both seasonal and special using GIS technology. Another study (Bhagawati et al., 2016) proposed a strategy for making agriculture sustainable and resilient and finding a wide application of DM in agriculture. The proposed system depends on translation and a multidisciplinary approach. The suggested approach illustrates how precision agriculture can increase production and productivity. In another study, researchers (Patel & Kathirya, 2017) focused on yield prediction of crops and proposed methodology while considering the uses DM in agriculture. DM in agriculture is a rising research field in crop yield analysis. The IT sector, like DM techniques, play a crucial role in smart farming in agriculture domain. Another set of researchers (Majumdar et al., 2017) proposed a methodology for analyzing agriculture data and finding optimal parameters to maximize the crop production using DM techniques like PAM CLARA. The proposed system is capable of analyzing soil and other factors for increasing crop production under different climatic conditions. There are various DM techniques, such as k-means, KNN, ANNs, and SVMs, being used for very recent applications of DM techniques in the domain of agriculture

for prize prediction of the crop. Other researchers (Cai et al., 2019) presented various ML methods (such as RF, SVM and NN) and regression methods, like least absolute shrinkage and selection operator (LASSO). Before using ML methods, exploratory data analysis was carried out with the satellite and climate data, which enrich the performance of the proposed framework. Finally, one study (Tian et al., 2019) proposed a method to identify the corn cultivated area, especially in Hebei Province based on cloud computing technology with the support of high-resolution images (about 10 m). Input for RF classifier, metric composite for sentinel 1 and sentinel 2 images were calculated. An overall accuracy of 89.89% was obtained.

## 8.6 Climate condition monitoring

For the analysis of various environmental parameters such as Food Price Index, area under cultivation, and annual precipitation (AP), researchers (Sellam & Poovammal, 2016) proposed a method and analysis that establishes the relationship between them. The study was carried out in rice cultivation in India. One study (Balakrishnan & Muthukumarasamy, 2016) developed a forecast model based on time series analysis with the support of AdaSVM and AdaNAIVE, which were far better than the SYM and Naïve Bayes models in terms of accuracy and classification error. For smart farming and performing intelligent irrigation, it can be possible to predict soil temperature, air temperature, and humidity, and one study (Varman et al., 2017) suggested different sensors likely temperature and humidity sensors, including with invariant data. Another study (Rajeswari et al., 2018) proposed a model that helps the farmer by providing the analysis for the best crop sequence; it also suggests the next crop that will grow for better production and the total production in an area of interest. C5.0 classification algorithm and association rule DM method were adopted to collect some valuable information from the input data. The proposed model also monitors real-time soil samples.

Table 6 shows the most popular methods and models based on DM in smart agriculture.

## 9 Conclusion

Farming will become more essential than ever in the coming decades. Smart agriculture and precision farming are beginning, but they may be the precursors for much greater usage of technology in the farming environment. Smart farming is supposed to close the divide between farmers in both emerging and industrialized countries. Technological progress, development in IoT, and mobile implementation have significantly led to the acceptance of technology in agriculture. It is no wonder that most historically practiced agricultural operations have modified dramatically. Smart farming methods and methodologies such as the usage of computers, software, sensors, and information technologies can be

**TABLE 6** Summary of role of data mining in agriculture.

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| To manage irrigation system called FITRA | Kokkonis et al. (2017) | Fuzzy neural network algorithm | Highly efficient | The framework naturally embraces changing ecological conditions |
| For proper supervision and management of water | Padalalu et al. (2017) | An automated irrigation system based on Naïve Bayes algorithm | Proper water management achieved | Improve the existing system |
| To support irrigation system | Xie et al. (2017) | SVR, NWP, and ToU | The results are quite promising as 7.97% of water resources and energy can be saved | Also, cost is reduced by 25.34% as compared to other methods based on soil moisture |
| Predict irrigation | Goldstein et al. (2018) | DM techniques, GBRT, BTC, and regression algorithm | Average prediction rate | The result showed better performances in saving water |
| To predict the occurrences irrigation process | González Perea et al. (2019) | User-defined model based on decision tree combined with a NSGA II | Maximum prediction accuracy | Also used to optimize the different parameters of decision tree |
| For discovery of a few plant illnesses. | Padol and Yadav (2016) | User-defined system based on DM technique | Results showed handling to beat the absence of human perception and even to diminish costs | Better performances |
| For different detection pose | Schor et al. (2016) | Robotic disease detection system | Better results obtained | Improve PCA, CV, and PM used for TSEVdetection |

*Continued*

**TABLE 6** Summary of role of data mining in agriculture—cont'd

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| For early disease detection in grapes | Patil and Thorat (2016) | User-defined model based on HMM | Highly efficient | The proposed method was better than the statistical method |
| To deduce the probability of Cd stress in rice | Liu et al. (2019) | Bayesian method based on temporal characteristics and satellite data | 81.57% was the overall accuracy | Can be improved |
| For mapping pests and disease risks | Marques da Silva et al. (2015) | User-defined model based on land surface data and logistic regression | Better mapping | Better performance |
| To identify parasites in apple orchards | Boniecki et al. (2015) | Neural classifier based on MLP | Results are promising and cost-effective | Performance of the existing system increases |
| For detection of sugar beet plants | Lottes et al. (2016) | User-defined model based on RF classification and MRF | Better performance | Also able to perform necessary spraying and remove weeds |
| For the management of pests, weeds, and diseases | Viani et al. (2016) | Fuzzy logic | Highly efficient | Improve the existing system |
| The prediction of yield | Ruß (2009) | Vector regression | Immensely helpful in predicting the yield | Precision farming is possible |
| Prediction of crop | Kaur et al. (2014) | K-Means, KNN, ANN, SVM | High accuracy and, generally, for price prediction | Effective utilization of available resources and cost-effective |

| For price prediction of tomato | Geetha (2015) | Genetic, algorithm-based neural networks and MATLAB | High accuracy | Better performances |
|---|---|---|---|---|
| DM for decision-making in agriculture | Gandhi and Armstrong (2016) | AI, neural network, Bayesian networks, and GIS technology | Better results obtained | Improve the agriculture environment |
| For increasing production and productivity | Bhagawati et al. (2016) | Translation and multidisciplinary approach | Results are promising and cost-effective | Sustainable and resilient |
| Crop yield analysis | Patel and Kathirya (2017) | Big data and DM | High accuracy on yield prediction of a crop | Cost-effective |
| Optimal parameters to maximize the crop production | Majumdar et al. (2017) | PAM CLARA | More accurate than existing techniques | Increasing crop production under different climatic conditions |
| For crop yield prediction | Cai et al. (2019) | RF, SVM, NN, and LASSO | Uses satellite and climate data, which enrich the performance of the proposed framework | Better performance |
| To identify the corn cultivated area especially in Hebei Province | Tian et al. (2019) | Cloud computing technology and RF classifier | 89.89% was obtained as overall accuracy | Can be improved |
| For the analysis of various environmental parameters | Sellam and Poovammal (2016) | User-defined method based on DM techniques | Satisfactory results obtained | The study was carried out in rice cultivation in India |

**TABLE 6** Summary of role of data mining in agriculture—cont'd

| Application goals and scenarios | Author and year | Method adopted | Results obtained | Advantages and disadvantages |
|---|---|---|---|---|
| For climate condition monitoring | Balakrishnan and Muthukumarasamy (2016) | Forecast model based on time series analysis with the support of AdaSVM and AdaNAIVE | High accuracy and low classification error | Better than the SYM and Naïve Bayes model |
| For prediction of soil temperature, air temperature, and humidity | Varman et al. (2017) | Different sensor with invariant DM techniques | Results are promising and cost-effective | Precision farming is possible |
| For the best crop sequence and suggestion about next crop to be grow | Rajeswari et al. (2018) | C5.0 classification algorithm and association rule DM method | Better production and the total production in an area of interest | The proposed model also monitors real-time soil samples |

linked to technical development. Evidently, smart farming is a brilliant farming idea that can help farmers reap several benefits, including increased production, enhanced quality, and decreased costs if properly applied. Such creativity needs resources, expertise, and technical skills. You need more than just farming passion; you need the right technology and expertise to analyze your farm's data, account and track developments, and predict demand and price changes. This chapter aims to provide a brief summary to researchers working in field of agriculture and smart farming. Almost all the peer-reviewed quality articles of the past 5 years were reviewed. Because each article reviewed involves different datasets, metrics, preprocessing method, models, and parameters, it is difficult to generalize and perform comparison between the papers. The bottom line is that while smart farming is relevant in agriculture and promises improved yields, research on best practices that match with your farming goals and needs is advisable.

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