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REVIEW ARTICLE

Survey on Machine Learning and Deep Learning Techniques for Agriculture Land

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Abstract
Agriculture land is playing a vital role in developing the economy of Indian states and contributes ~ 15% of India's gross domestic product (GDP). Moreover, agriculture is a major source of livelihood by engaging two-third (~ 66%) of the nation's population in various activities such as food supply, the raw material to the industries, internal and external trade. Therefore, the continuous monitoring and mapping of agricultural land are crucial for the sustainable life and development of the country. Most of the agriculture monitoring solutions are based on field observations or conventional strategies which are time-consuming and costlier. However, remote sensing delivers a cost-effective solution of acquiring information regarding the healthy or unhealthy vegetation in agricultural land with the help of a diverse range of advanced geospatial techniques such as classification, change detection, and pan-sharpening. In the present paper, we have performed a systematic survey with respect to recent advancements made in the classification algorithm, especially for agricultural land. These emerging methods incorporated in classifiers are machine learning and deep learning to enhance and detect the various features of vegetation parameters. It is expected that such studies will provide effective guidance to the researchers in better understanding the features, limitations, and specific importance of emerging classifiers in the Agriculture domain.

Keywords Agriculture land · Machine learning · Deep learning · Artificial neural network · Remote sensing data

Introduction

Agriculture land is the backbone of the Indian economy and the major source of national income via agriculture and allied activities. Agriculture acts as a supply chain of food products and raw materials for industrial development, commercial activities, and international trade [77]. It has also been observed that in India, since the past few decades, agriculture activities have been continuously decreasing due to urbanization or the growth of other sectors [44]. But it is still high as compared to other countries. It is more important to perform the comprehensive assessment of agriculture with respect to crop production which is essential to meet the demands of the food supply chain [78]. To assess the agricultural land, field observation methods are generally followed which is a time-consuming, expensive and tedious task [3]. Moreover, there is a very rare possibility of continuous monitoring on a daily or weekly basis. Crop mapping and classification are some of the most difficult tasks among agricultural land problems [32]. In agricultural land, the most common approach used for crop monitoring is the digital cameras or field observation for evaluation of the crop yield which may be costly or limited to the small area [12]. Therefore, automatic, consistent and a fast, system are necessary to deliver the precise crop mapping and monitoring over all large scale [4].

Remote sensing via optical or microwave imaging offers a cost-effective way to monitor the land cover changes at a very large scale [29]. The continuous monitoring and assessment of agricultural cropland provide valuable insights into

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the different agronomic parameters [61, 69]. The use of advanced geospatial technologies is necessary to acquire information related to variations in soil, climate, and other physic-chemical changes [49]. The monitoring of agricultural manufacturing systems follows strong seasonal patterns about the biological life cycle of yields. Every part of these factors is highly variable in time and space dimensions [71].

To monitor the agricultural land, various techniques are available such as change detection, classification, and fusion or pan-sharpening [44, 83]. Change detection procedures are generally used to monitor multi-temporal changes and detailed information can be found in different studies [44, 83]. In change detection procedures, classification is an important element to categorize the different land types based on their similarity score and allow the user to extract the meaningful information in the form of a thematic map [45]. The classification techniques can be categorized as (a) supervised/ unsupervised; (b) parametric/non-parametric, (c) hard/soft, (d) per-pixel/sub-pixel, and (e) object-based classification [44]. Due to the limitations of various satellite sensors, it is not possible to acquire the earth imagery at a very high temporal and spatial resolution simultaneously and there is a requirement to perform the pan-sharpening or fusion of high-resolution and low-resolution datasets. In many cases, pan-sharpening is found to be more effective to improve the classification and change detection results [81].

However, the main focus of the present study is to make a comparative study on various emerging land-use and land-cover classifiers. Generally, supervised classification requires having adequate knowledge about prior information or training data to generate classified images. Whereas, in unsupervised classifiers, there is no requirement of prior information or training data because it classifies the input dataset based on similarity or in the form of clusters [86]. Moreover, semi-supervised classifiers are more preferable due to their less dependency on user's skills and handling more complex problems [81]. Nowadays, some machine learning or deep learning-based classifiers have become more popular due to their effectiveness in extracting critical information from remotely sensed data. Table 1 summarizes some of the basic and advanced classifiers, especially for agricultural land.

In the present paper, we address the major developments made into the field of classifiers based on satellite datasets, epically for agricultural land. The aim of the present analysis is on: (a) the recent advancements made in classification methods; and (b) comparative analysis of different strategies to monitor agricultural land. This paper also highlights the different types of satellite sensors available or previously used in agriculture applications and various steps involved in satellite dataset pre-processing as explained in the second section. Afterward, a detailed review of conventional as well as advanced classification models for agriculture applications. At last, we have made the summary and future recommendations for optimal ways to use satellite datasets of agricultural land in sections.

Classification Models

The supervised classification requires the training data to classify the input dataset [34] such as decision tree, minimum distance [39], nearest neighbor (NN) [102], and maximum likelihood classifier (MLC) [14]. Whereas, the unsupervised classifiers divide the spectral information into specified class categories based on statistical information acquired from an image itself [15, 16]. Such as ISO [89] and K-mean [15, 16]. The parameters classifiers like mean-vector and covariance matrix are often generated from training samples [63]. In the case of complicated landscapes, parametric classifiers generate undesirable results such as linear discriminant analysis [63] and MLC [15, 16]. Non-parametric classifiers are generally based on the exclusion of statistical parameters and free to learn with the help of training dataset such as support vector machine (SVM) [74], NN [21], decision tree [21].

Conventional classifiers are generally based on the signatures generated from the training dataset (Table 2). These classifiers generally ignore the mixed pixel information and provide the result based on maximum likelihood [33]. Such as MLC [24], NN, decision tree [14, 36].

Whereas, subpixel classifier offers the combination of partial membership of multiple class categories within a specific pixel [86] such as Fuzzy-set [80, 84], spectral mixture analysis [63] and linear mixture model [87]. The OBC classifiers involved the categorization of pixels based on the spatial relationship with the surrounding pixels [39]. In this paper, we have reviewed different approaches (neural networks, machine learning, and deep learning) with highlighting various features like classification techniques, classifier, sensor category, crop/parameters, and performance accuracy. NN (Neural Networks) are smart tools to derive thematic maps from satellite datasets (Table 2).

Machine Learning-Based Classifiers

The machine learning approach is used to solve large nonlinear problems using datasets from various sources. It enables improved decision-making and knowledgeable procedures in a real-world scenario with minimum dependency on the user's skill. It provides a flexible and powerful structure for the integration of expert information into the system. The machine learning approaches are broadly used for the accurate measuring of biotic stress for weed detection as well as plant disease in the crop (Table 3). Cai et al. [7] described the utilization of Landsat series spectral data to solve the

Table 1 Agricultural land with machine learning and deep learning

Techniques	Category	Characteristics	Advantages	Disadvantages	Examples
CNN	Hybrid/ Semi-supervised	Computer vision and visual object recognition are based on the dataset [18, 91] Bioinformatics based on microarray data	Learns the filters automatically without mention them explicitly [23] Captures the spatial features from an image	Overfitting and the need for large training datasets [41–43] The high computational cost of training [75, 76]	[34, 62, 76, 90]
RNN	Hybrid/ Semi-supervised	Determine patterns and other significant features present in the dataset [15, 16] Predict future developments [22]	It remembers each piece of information through time [27] RNN is even used with convolutional layers to extend the effective pixel neighborhood [97]	Training an RNN is a very difficult task [62] Gradient vanishing and exploding problems [98]	[5]
SVM	Supervised	The concept of decision plans defines decision boundaries [50] To supports both regression and classification tasks and can handle multiple continuous and categorical variables [52]	It works relatively well when there is a margin of separation between classes[100] It is effective in cases where the number of dimensions is greater than the number of samples [55]	It does not perform very well when the data set has more noise [77] It is not suitable for large data sets [57]	[14–16, 74, 77]
MLC	Supervised	Based on maximum belongingness, pixels are allocated to the class category [65] It considers both variances and covariances of the class signatures [68]	Robust method and applicable for distributed datasets [41–43] Classifies each pixel without considering the dissimilarity [85]	Undesirable outcomes in non-normal distributed data [60] Requires the number of computational steps to classify [94]	[84, 86, 88, 101]
ISO	Unsupervised	Euclidean distance used to cluster pixels into different classes It preserves within data	It is automatically adjusting the clusters during the iteration process There is no need for reference data beforehand	More power if data are unstructured Spiral out of control leaving only one class	[89]
K-mean	Unsupervised	Pixels with a similar spectrum [48] Follows the non-fuzzy logic	In the cluster, variability becomes decreased Simplicity in operation	Consumes additional memory and time as the band is increasing User must have information on the number of classes	[15, 16, 21, 53, 103]
DT	Supervised	It is quite robust to the presence of noise [40] It can handle both discrete and continuous features [68]	It can handle both categorical and numerical data [48] It can be used to build larger classifiers by using ensemble methods [92]	Require some kind of measurement as to how well they are doing [60] It can create biased learned trees if some classes dominate	[14, 21, 39]
KNN	Supervised	It is based on the Euclidean distance between a test sample and the specified training samples [19] Classification typically involves partitioning samples into training and test categories	It is a versatile algorithm as we can use it for classification as well as regression It is very useful for nonlinear data	It is computationally a bit expensive algorithm because it stores all the training data It is very sensitive to the scale of data as well as irrelevant features	[10, 39]
NN	Supervised	It extracts features from the input image [35] It learns the values of the filters on its own during the training process [51]	It can be trained with any number of inputs and layers (J. [41–43] NN work best with more data points [52]	It is computationally very expensive and time-consuming to train with traditional CPUs [72] It depends a lot on training data. This leads to the problem of over-fitting and generalization	[15, 16, 34, 95, 103] [85]

CNN convolution neural network, *RNN* recurrent neural network, *SVM* support vector machine, *MLC* Maximum likelihood classification, *ISO* international classification for standards, *DT* decision tree, *KNN* K-nearest neighbors, *NN* nearest neighbour problem of clouds while implementing the machine learning model and more accurate analysis of the classification process. Coopersmith et al. [10] reported the landowner to hesitant to place sensors due to financial cost, difficulty, and sometimes infeasibility physical visit to the remote location which may be limited by modeling the wetting or drying process through machine learning algorithms. Duro et al. [14] selected a subset of a large amount of drainage basin select for a long-term study land-use and land-cover monitoring.

Deep Learning-Based Classifiers

The deep learning further extends machine learning applications into more depth as well as transforms the dataset using the different function that hierarchically allows data representation, through several levels' abstractions. A strong benefit of deep learning is feature-based learning that includes the automatics extraction of different features from input dataset Table 4, represents the various deep learning approaches including CaffeNet and convolution neural network (CNN). Kussul et al. [33] utilized the multilevel deep learning architecture for the classification of different land use and land cover types from remotely sensed datasets. In this section, we briefly review relevant deep learning-based models that were originally proposed for visual dataset processing and that are widely used for state-of-the-art research into deep learning in Remote Sensing Dataset. In addition, we mention the latest deep learning developments, which are not yet widely applied to remote sensing but may help create the next generation of its algorithms. Figure 1 gives an overview of the deep learning models we discuss in this section.

Further, [76] provided a better understanding of the capability of Sentinel-1 dataset radar dataset or images for agricultural land mapping. Ndikumana et al. [53] developed the deep learning model efficiently and perfectly classify cloud, shadow, and land cover in different high-resolution satellite datasets. Moreover, Zhou et al. [102] investigated the suitability and potential of DCNN in the supervised classification of POLSAR (Polarimetric Synthetic Aperture Radar) dataset. Spatial information was naturally employed to terrain classification due to the properties of convolutional networks (Table 5).

Sowing and Harvest of Summer and Winter Crops

Figure 2 represents the Sowing and harvesting of different crops during the summer season (May–October) and winter (October–April) [41]. The phonological stages for each crop's and Botanical names such as wheat (*Triticum aestivum*), Barley (*Hordeum vulgare*), Mustard (*Brassica nigra*), Berseem (*Trifolium alexandrinum*), Paddy (*Oryza sativa*), Corn (*Zea mays*), Millet (*Pennisetum typhodium*), Sorghum (*Sorghum bicolor*) and Sugarcane (*Saccharum officinarum*) have been acquired from growth guides provided by Punjab State's Department of Forestry, Agriculture, and established by interviews with neighborhood farmers [33].

Traditionally, mapping the vegetation of an entire area is a matter of time and requires a demanding field survey. Remotely sensed datasets, especially such as sentinel-2, Landsat-8, and MODIS dataset the classification and monitoring of vegetation can be accomplished more cost-effectively with more detail in less period with the help of machine learning and deep learning approaches (Table 6). Three stages play an important role for vegetation monitoring or mapping of Punjab state's region such as plantation, growth, and harvest time of crop cycle. In the past, classifiers have proved useful for finding different crop classes such as SVM [77] and KNN [34] for wheat; RF, SVM [77] and NN [101] for barley; RF, KNN and DCNN [34] for mustard; DT, RF and SVM [26] for Berseem and paddy; KNN [7] for corn; RF [4] for millet and sorghum and MLP [33] RF and DCNN [34] for sugarcane.

Summary and Conclusion

The main focus of the present analysis is on the recent advancements made in classification methods and comparative studies on different strategies to monitor agricultural land [28]. Agriculture monitoring via remote sensing offers a cost-effective and rapid way. Nowadays, a significant contribution has been in the field of agriculture monitoring via satellite images due to the free data access policy offered by most space organizations [36]. With continuous development in space technology such as high spectral, spatial, and temporal resolutions, more or unexplored information can be warranted in the future [46]. Advanced geospatial classification techniques such as machine learning and deep learning can be more significant to extract important information from agricultural land [58].

From the previous literature, it is apparent that pixel-based methods have certain limitations such as not considering the variations within a pixel which can be effectively solved with the help of sub-pixel-based approaches up to a great extent. There is further existence of variation within a pixel [9]. Most studies on satellite datasets highlighted the performance of object-based classification approaches for different regions such as agriculture areas, urban areas, forests, and wetlands [47]. In the past various years, different studies have been carried out using different emerging classifiers in remote sensing-based agriculture applications [91]. Worked on NN and concluded that NN spontaneously selects

Table 2 General convention in agricultural land

Category	Classifier	Sensor	Crop/parameter	Performance	References
Hierarchical Classification	RF	Landsat 7, Landsat 8, Sentinel 2-A, 2-B	Soy, maize, cotton, beans, carrot, onion, potato, millet, sorghum	–	[4]
Supervised	MLC, RF	TerraSAR-X, Radarsat-2, Envisat, FORMOSAT-2	Maize, pumpkin, rice, soya	85%	[24]
OBIA and Pixel-based	RF	Sentinel-2	Carrots, maize, onions, soya, sugar beet, sunflower		[26]
Pixel-based and Parcel-based	MLP	Landsat-8, Sentinel-2	Wheat, rapeseed, maize, sugar beet, sunflower, soybeans	89.40%	[33]
Supervised	RF, SVM	Radarsat-2, Formosat-2	Wheat, barley, rapeseed, grassland	70%	[77]

OBIA object-based image analysis, *RF* random forest, *MLC* maximum likelihood classification, *MLP* multi-layer perceptron's, *SVM* support vector machine

Table 3 Agricultural land with machine learning (ML)

Category	Classifier	Sensor	Crop/parameter	Performance	References
Supervised	KNN	Landsat 5,7 and 8 for 2000 to 2015	Corn, soybean	95%	[7]
Supervised	Boosted Perceptrons, Regression Trees, KNN	Situ Sensors	Statistical soil dryness	91–94%	[10]
Supervised	DT, RF, SVM	Online GeoBase spatial Data portal (www.geobase.ca)	Mixed grassland, crop, wetland, exposed rock/soil, water, riparian,	DT (88.84%), RF (93.39%), SVM (94.21%)	[26]
Unsupervised / Supervised	K-means, SVM, MLP BRF	MODIS (MOD09GA) satellite sensor	Cropland grids		[15, 16]
Supervised	DT, KNN, SVM, RF	Landsat-8	Wheat, grape, canola, lucerne, lupine, olive, pasture	96.2%	[21]
Supervised	Adaboost.M1, DT KNN, naiveBayes, PLDA, RF, SVM	Digital Orthophoto Map (DOM)	Crop, bare land, woodland, water, building, road	Object-Based	[39]
Supervised	ANN, RF, SVM	Sentinel-2	Agricultural land, water, urban, bare soil, grassland, forest, cloud	90%	[37]
Supervised	DT, RF SVM	SPOT-6 and RADARSAT-2	Palm oil, grass, vegetation, paddy, water, bare and flooded soil	88.08%	[20]
Supervised	DT, RF, SVM, Xgboost	Sentinel-2	Agriculture, deciduous, water, wetland, clearcut, coniferous, artificial, open land	75.8%	[1]

KNN K-nearest neighbors, *DT* decision tree, *RF* random forest, *SVM* support vector machine, *MLP* multi-layer perceptron's, *BRF* bias-corrected random forest, *PLDA* probabilistic linear discriminant analysis, *ANN* artificial neural network, *Xgboost* extreme gradient boosting

the training samples on the contextual information extracted from the target area [34]. Moreover, the spatial distributions of the objects have also been improved and strengthened as it uses multi-scale contextual information [34, 76]. The accuracy in class-category and boundary information has also been improved in NN classified maps [18].

Moreover, the machine learning classifiers such as DT [26], SVM [20], RF [1], MLP [15, 16] and KNN [7] has the potential to improve the classification results in agriculture regions as compared to conventional classifiers [37]. Moreover, machine learning techniques directly study information from small data samples through their features and successively construct a difficult statistical model to make predictions on larger ones [15, 16]. These features come from variables that are involved in classification, namely predicting variables [7]. Such data-driven approaches can

Table 4 Agricultural land with Deep Learning

Category	Classifier	Sensor	Crop/parameter	Performance (%)	References
Unsupervised	RF, KNN, DCNNs	Landsat-8 and Sentinel-1A	Water, forest, grassland, bare land, winter wheat, winter-spring cereals, rapeseed, soybeans, sunflowers, maize, and sugar beet	88.7, 92.7, 93.5, 94.6	[34]
Supervised	KNN, RF, SVM	Sentinel-1A/1B SAR dataset	Rice, sunflower, lawn, irrigated grassland, wheat, alfalfa, tomato, melon, clover, swamps, vineyard	96	[53]
Supervised	CNN	Planet-Scope and Sentinel-2	Cloud labels: clear, haze, partly cloudy, cloudy. shade labels: un-shaded, partly shaded, and shaded. land cover label: agriculture, water, bare ground, habitation, forest,	84	[76]
Supervised	NN	POLSAR	Find the 14 classes like Forest, Peas, Lucerne, Beet, Wheat, Potatoes, Grasses, Bare soil, Rapeseed, Wheat2, Wheat3, Barley, Water, Buildings	92.46	[101]

RF random forest, *KNN* K-nearest neighbors, *DCNN* deep convolutional neural networks, *SVM* support vector machine, *CNN* convolutional Neural Network, *NN* nearest neighbour

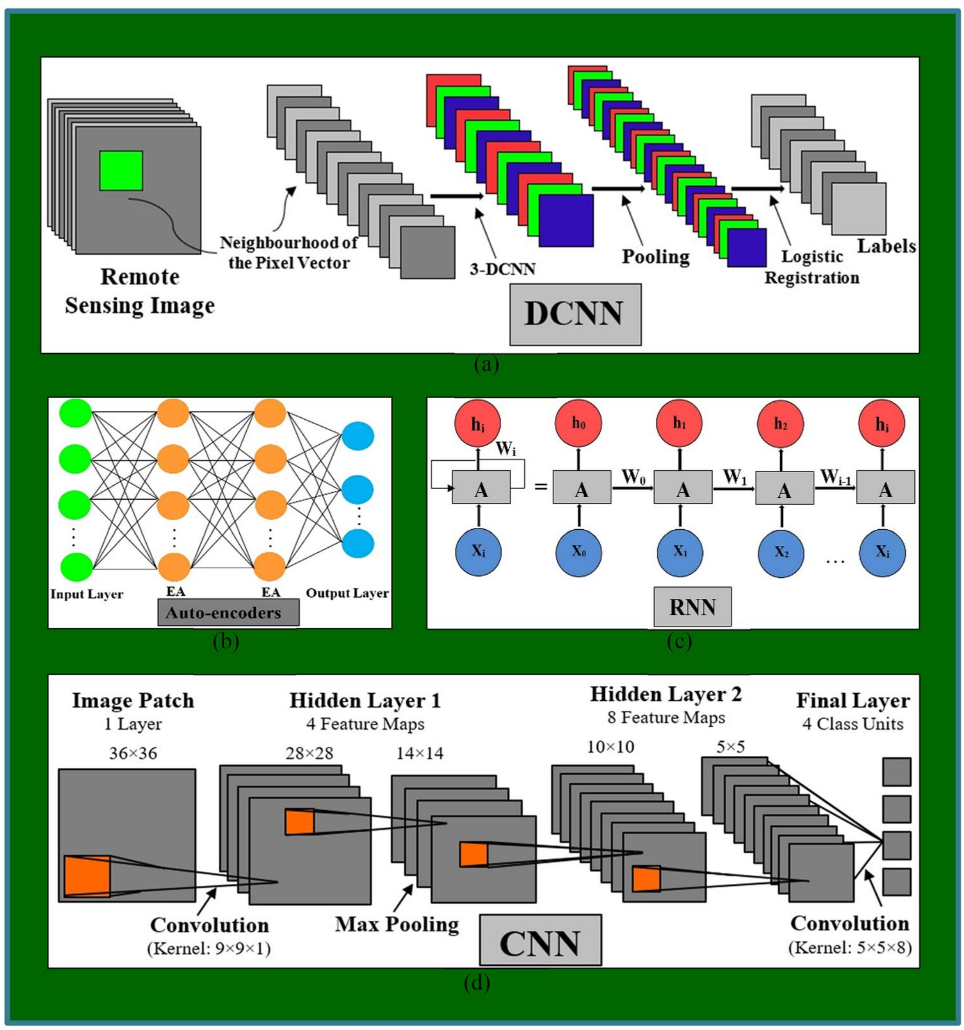

Fig. 1 An overview of various deep learning classifiers: **a** deep convolution neural network (DCNN), **b** autoencoders, **c** recurrent neural network (RNN), and **d** convolution neural network (CNN)

Table 5 Deep learning models and its application

Techniques	Advantages	Disadvantages	Applications
DCNN	Once trained, the predictions are pretty fast DCNN can be trained with any number of inputs and layers [79, 82]	It is computationally more expensive and time-consuming to train with traditional CPUs [53]	Agricultural land, plantations [70]
Auto-encoders	It can be trained with any number of inputs and layers [2] Auto-encoders work best with more data points [38]	It depends a lot on training data. This leads to the problem of over-fitting [56]	Agriculture, cotton, mulberry, sugarcane [6, 13]
RNN	It remembers each information through time [27] RNN is even used with convolutional layers to extend the effective pixel neighborhood [97]	Training an RNN is a very difficult task [62] Gradient vanishing and exploding problems [98]	[15, 16, 22,, 25]
CNN	Learns the filters automatically without mention them explicitly [23] Captures the spatial features from an image	Overfitting and the need for large training datasets [41–43] The high computational cost of training [75, 76]	[25, 64, 78]

DCNN deep convolution neural network, *RNN* recurrent neural network, *CNN* convolution neural network

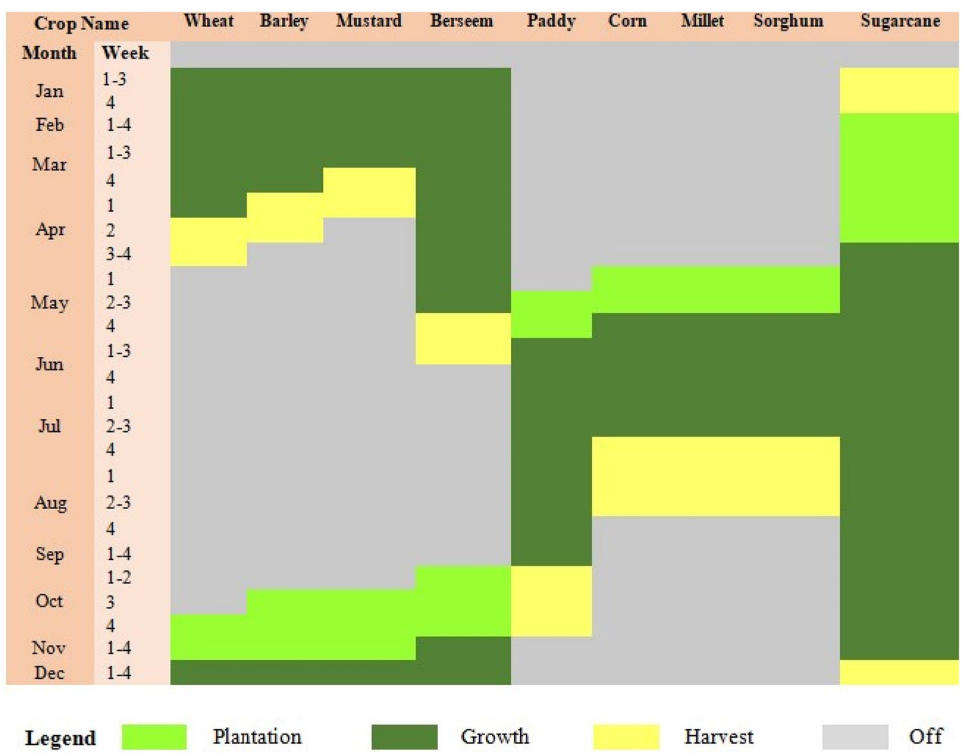

Fig. 2 An overview of various agricultural production phases

enhance the possibilities to adaptively improve the performance of a model by avoiding the problem of over-fitting or under-fitting [1].

On the other hand, the deep learning classifier such as CNN [76], RNN [5] and DCNNs [34] or object-based classification techniques improve the extraction of the agricultural land classes [76]. Within the deep learning approach, convolutional and pooling layers are connected alternatively to simplify the features towards deep and intellectual representations. Typically, the convolutional layer

Table 6 Different machine learning and deep learning approaches related to agriculture informatics

Techniques	Classifiers	Agri. information	Examples
Machine learning	KNN	Grassland	[93]
	DT	Fertile cultivated land, green pasture	[31, 59]
	RF	Grassland, farmland, tropical crops, herb. dry, olive grove, green- lands	[31, 66],
	SVM	Vegetation, grassland, farmland	[31, 73],
	MLP	Fertile cultivated land, green pasture	[59]
	K-mean	Grassland, farmland	[54]
Deep Learning	RNN	Summer and winter crops, vegetation, vineyards, sugarcane crops	[25]
	CNN	Vegetation, plantations	[25, 64, 79]
	DCNN	Agricultural land, plantations	[70]

KNN K-nearest neighbors, *DT* decision tree, *RF* random forest, *SVM* support vector machine, *MLP* multilayer perceptron's, *RNN* recurrent neural network, *CNN* convolution neural network, *DCNN* Deep convolution neural network

improves the learning procedure through a set of samples or image patches across the dataset [91]. Those weights are shared by different feature maps, in which multiple features are learned with a reduced number of parameters, and an activation function, e.g., rectified linear unit is followed to strengthen the non-linearity of the convolutional operations [62]. The pooling layer involves max-pooling or average-pooling, where the summary statistics of local regions are derived to further enhance the generalization capability.

The advanced methodologies (ML and DL) have the potential to become very important to the monitoring of agricultural land using satellite datasets. To apply these technologies for plant diseases, weed detection, real-time field operations, and soil analysis may become routine operations in close to future agriculture [17, 53]. Moreover, the development and integration of advanced algorithms in classification or change detection procedures may be beneficial to acquire information regarding the different vegetation types over agricultural land. Further, the machine and deep learning-based techniques can also be tested for vegetation monitoring over rugged terrain where remote sensing is highly affected with differential illumination effects in the form of shadow [79].

In this paper, we have systematically reviewed the state-of-art machine learning and deep learning techniques in remote sensing data analysis [67]. The deep learning techniques were originally rooted in machine learning fields for classification and recognition tasks, and they have only recently appeared in the remote sensing and geoscience community [30]. From the five perspectives of (a) supervised/ unsupervised; (b) Parametric/non-parametric, (c) hard/soft, (d) per-pixel/sub-pixel, and (e) object-based classification, we have found that deep learning techniques have had significant successes in the areas of target recognition and scene understanding, i.e., areas that have widely accepted as challenges in recent decades in the remote sensing community because such applications require us to abstract the high-level semantic information from the bottom level features, while the traditional remote sensing methods of feature describing feature extraction classification are shallow models, with which it is extremely difficult or impossible to uncover the high-level representation [8].

In agricultural land, which is an SVM-based technique, the testing on the automatic extraction of human-made objects is not made, and the segmentation accuracy limitation is not resolved [50]. The developed SVM classifier is not suitable for the applications, such as change identification and monitoring of the environment [100]. The classification accuracy is not achieved to the expected limit in the developed multi-spectral dataset by utilization of the SVM and RF classifiers [53]. The classification result is not improved by the DT classifier as the training dataset, and the testing area is limited. The research challenges in the DNN-based classification are, DCNN is not advisable for the classification of multi-sensor and multi-resolution satellite datasets (Singh, Sethi, and Singh, 2021). The developed ANN classifier [79, 82] cannot achieve the expected accuracy in massive distinct region databases and suffer from high computational complexity. However, the research in deep learning is still young and many queries remain unsolved. They are some potentially interesting topics in machine learning and deep learning for remote sensing data analysis such as (a) the total number of training samples [99]; (b) the complexity of remote sensing images [11]; (c) transfer between data sets [96]; (d) depth of deep learning model [104].

Author Contributions GS, as the first author, had responsibility for conducting the research, including a writing task. Dr. GKS and Dr. SS, supervised the work, including a re-writing task and visualization,

supervised the work. All authors have read and approved the final manuscript.

Declarations

Conflict of interest The authors declare that there are no conflicts of interest regarding the publication of this paper.

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