Chapter 21
Application of Artificial Intelligence and Machine Learning in Agriculture

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Abstract Artificial intelligence (AI) is the branch of science that deals with the development of machines to mimic human intelligence. Machine learning (ML) is a subdomain of AI where the machine can learn automatically from data without being explicitly programmed. Agriculture is constantly pressed upon to produce more with less resource. AI and ML techniques have the capacity to optimize resource utilization by analysing agricultural data. It has changed the present-day face of farming by predicting various input parameters and forecasting post-harvest life of a crop. This chapter discusses the different AI and ML techniques available and how they have been used in different phases of the agriculture life cycle. This chapter includes vast range areas in agriculture that requires AI and ML. It includes soil, irrigation, and disease managements. Importance of AI in the field of plant phenomics also included in this chapter. The probable use of geographic information system (GIS) and remote sensing coupled with AI are discussed in this chapter.

Keywords Artificial intelligence (AI) · Machine learning (ML) · Agriculture · Recommender system · Phenomics · Geographic information system (GIS) · Remote sensing

21.1 Introduction

Artificial intelligence (AI) is the study of tools and technologies which are used to solve tasks that require human intelligence. Tasks such as natural language understanding, processing, generation, visual perception, decision making, and many more. Machine learning and deep learning are the two most widely used AI approaches. With breakthrough technologies, AI has transformed every aspect of life, including agriculture. With more than 50% workforce employed in agriculture, low expert to farmer ratio requires necessary AI interventions like automatic

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diagnosis and recommendation of proper advisories. The major hurdles in agricultural production are decision making related to crop production, disease pest infestation, weather forecasting, yield prediction, advisory systems for enhanced crop productivity, etc. Agricultural productivity is mostly influenced by temperature, soil fertility, water availability, water quality, etc. For predicting these parameters accurately, improved AI techniques are being applied. While the technological explosion has made farming little easier, small, and marginal farmers still face many obstacles. Unlike other technologies AI has the potential to reach out to individual farmer much more easily and improve the life of farmer. The consideration of two life cycle, namely agriculture and farmers have a gigantic scope to intervene and enormously improve the same.

Agriculture life cycle starts from land preparation for the crop followed by seed sowing, irrigation, weeding, fertilizer application, pest and disease management, harvesting, post-harvest processing, storage, and marketing. Various AI techniques have the potential to affect and improve all the phases of the life cycle, some of which are already available and some still need to be worked on. In an ideal smart ecosystem, a farmer would be guided by an artificially intelligent assistant that would suggest the most appropriate date and method to prepare the land based on the GIS and remote sensing data of that region. Using a block chain and recommender system enabled supply chain, farmer would collect quality seeds to sow after land preparation. Scheduled weeding would be handled by low-cost smart weeding and fertigation (fertilization and irrigation) systems. The identification of pest and disease with their suitable management practices may be handled by AI enabled mobile applications. The yield prediction may be done through drone based smart application and the predicted yield will help in selecting the appropriate market and buyer (Fig. 21.1).

21.2 Artificial Intelligence, Machine Learning, and Deep Learning

The artificial intelligence is a very old field of study and has a rich history. Modern AI was formalized by John McCarthy, considered as father of AI. It was established as a branch of computer science around early 1950s. Primarily, the term artificial intelligence (AI) refers to a group of techniques that enable a computer or a machine to mimic the behaviour of humans in problem solving tasks. Formally, AI is described as 'the study of how to make the computers do things at which, at the moment, people are better' (Rich and Knight 1991; Rich et al. 2009). The main aim of AI is to programme the computer for performing certain tasks in humanly manner such as knowledgebase, reasoning, learning, planning, problem solving, etc. The machine learning (ML) techniques are the subset of AI which makes the computers/machines/programmes capable of learning and performing tasks without being explicitly programmed. The ML techniques are not just the way of mimicking

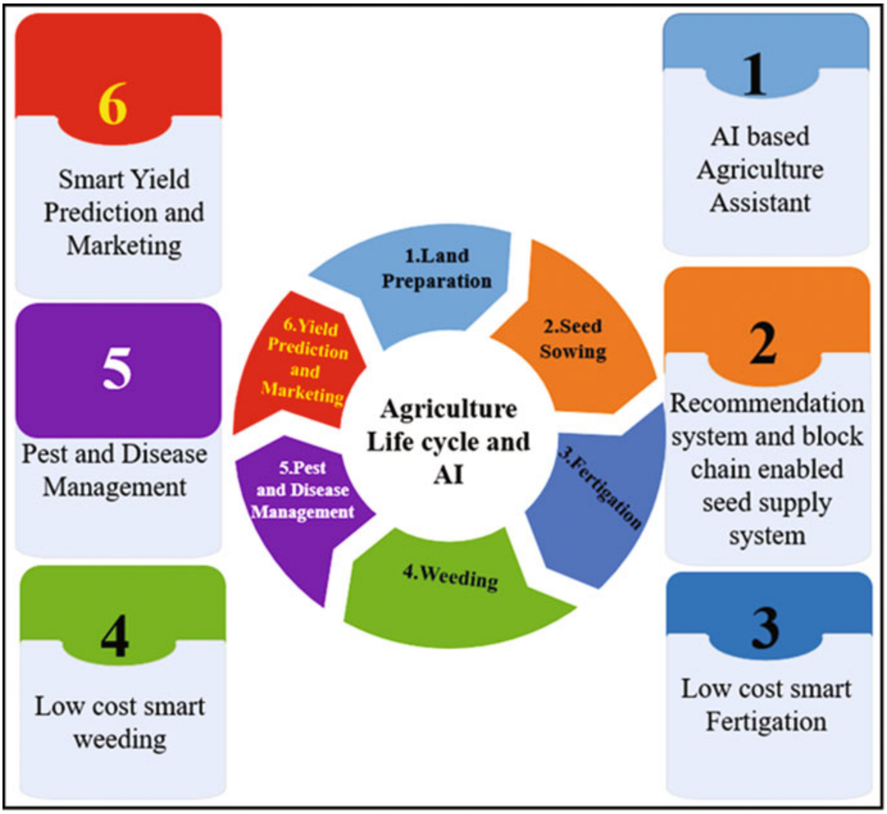

Fig. 21.1 An ideal smart ecosystem for farmer

human behaviour but the way of mimicking how humans learn things. The main characteristics of machine learning are 'learning from experience' for solving any kind of problem. The methods of learning can be categorized into three types: (a) supervised learning algorithm is given with labelled data and the desired output, whereas (b) unsupervised learning algorithm is given with unlabelled data and identifies the patterns from the input data, and (c) reinforcement learning algorithm allows the ML techniques to capture the learnable things on the basis of rewards or reinforcement. Nowadays, deep learning (DL) techniques are the advanced version of machine learning algorithms gained huge popularity in the area of artificial intelligence based applications. The artificial neural networks (ANNs) clubbed with representation learning are the backbone of the deep learning concepts. These techniques allow a machine to learn patterns in the dataset with multiple levels of abstractions. The DL models are composed of a series of non-linear layers where each of the layer has the capability of transforming the low-level representations into higher-level representations, i.e. into a more abstract representations (LeCun et al. 2015). There are several DL algorithms available now-a-days such as deep

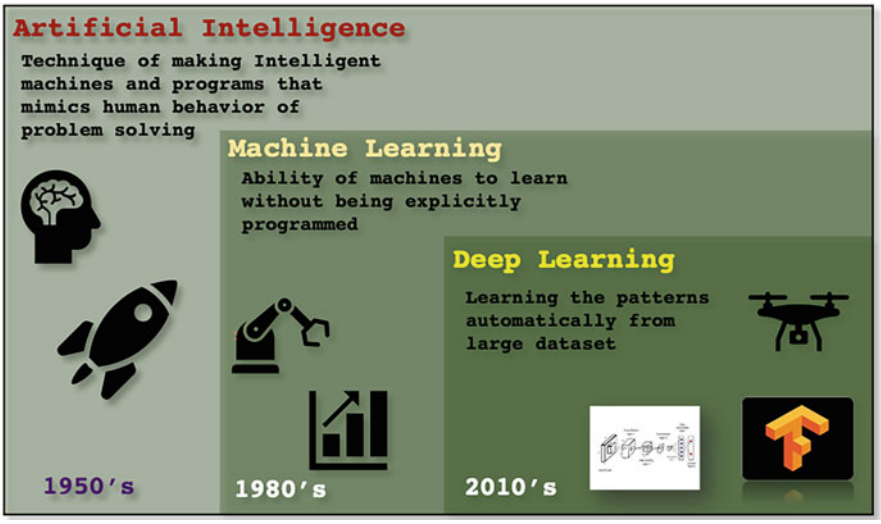

Fig. 21.2 Chronology of artificial intelligence, machine learning, and deep learning concepts

convolutional neural networks (aka CNNs or convnets), recurrent neural networks (RNNs), long short-term memory (LSTM) networks that are being applied to different areas of engineering, bioinformatics, agriculture, medical science, and many more (Fusco et al. 2021) (Fig. 21.2).

21.3 Major Applications of AI and ML Techniques in Agriculture

In the present scenario, AI and ML techniques are being exponentially applied in the various areas of the agricultural domain. These areas can be categorized into the following groups: soil and water management, crop health management, crop phenotyping, recommender-based systems for crops, semantic web and ontology driven expert systems for crops and Geo-AI. The applications of AI, ML, and DL based techniques on these areas are discussed in the following sections.

21.3.1 Soil and Irrigation Management

Soil and irrigation are the most viable components of agriculture. The soil and irrigation are the determinant factors for the optimum crop yield. In order to obtain enhanced crop yield and to maintain the soil properties, there is a requirement of appropriate knowledge about the soil resources. Irrigation scheduling becomes crucial when water resources are scarce. Therefore, the soil and irrigation related issues should be managed properly and cautiously to ensure a potential yield in crops. In this regard, AI and ML based techniques have shown potential ability to resolve soil and irrigation related issues in crops. A range of machine learning models such as regression-based models, support vector machines (or regressors), artificial neural networks, and random forest algorithm are being used. Many researchers have used remote-sensed data with the machine learning techniques for determining soil health parameters. Few significant studies in this area have been highlighted in the following sections.

21.3.1.1 Soil Management

Besalatpour et al. (2012), Aitkenhead et al. (2012), and Sirsat et al. (2017) used different machine learning techniques such as multiple-linear regression (MLR), support vector regressors (SVR), random forests regressors (RFR) for the prediction of the physical and chemical properties of soil. Rivera and Bonilla (2020) and Azizi et al. (2020) worked on estimation and classification of aggregate stability of soil using conventional machine learning techniques as well as deep learning techniques from the publicly available soil properties datasets. Jha and Ahmad (2018) worked on prediction of microbial dynamics in soils using regression-based techniques which is very significant in improving the soil fertility. Patil and Deka (2016) and Taghizadeh-Mehrjardi et al. (2016) worked on predicting the evapotranspiration rate in crops using several machine learning techniques. Researchers worked on mapping the soil properties digitally using machine learning techniques as well as deep CNN techniques (Taghizadeh-Mehrjardi et al. 2016; Kalambukattu et al. 2018; Padarian et al. 2019; Taghizadeh-Mehrjardi et al. 2020). In these soil property mapping works, researchers have used several remotely sensed data and historical weather-based data. More details of these works are provided in Table 21.1.

21.3.1.2 Irrigation Management

Zema et al. (2018) applied data envelopment analysis (DEA) with multiple linear regression (MLR) based techniques to improve the irrigation performance of the Water Users Associations. Ramya et al. (2020) and Glória et al. (2021) worked on IoT-based smart irrigation systems in which machine learning techniques were used to analyse the data. Agastya et al. (2021) and Zhang et al. (2018) applied deep CNN-based models for detection of irrigations using remote sensing (RS) data. Jimenez et al. (2021) worked on estimating the irrigation schedules based on the soil matric potential using a LSTM-based neural networks. More details are provided in Table 21.2

Table 21.1 Soil management using AI and ML techniques

Area of work	Techniques used	Remarks	Citation
Prediction of physical properties of soil	Support vector machines with simulated annealing	SVM obtained R^2 of 0.98 and MSE of 0.06	Besalatpour et al. (2012)
Prediction of chemical properties of soil	Artificial neural network (ANN) model	Highest r^2 value obtained for clay property of 0.89	Aitkenhead et al. (2012)
Classification of soil data	Random forest	More than 90% accuracy obtained	Sirsat et al. (2017)
Prediction of aggregate stability property of soil	ANN and GLM	ANN achieved highest performance with R^2 of 0.82 on test dataset	Rivera and Bonilla (2020)
Classification of soil aggregate stability	Deep learning models	ResNet50 Model obtained accuracy of 98.72%	Azizi et al. (2020)
Estimation of crop evapotranspiration	Extreme learning machine (ELM) algorithm	ELM performed better than the ANN and Hargreaves model	Patil and Deka (2016)
Estimation of mean reference evapotranspiration on monthly basis	SVM, multivariate adaptive regression splines (MARS), algorithms	MARS and SVM-RBF algorithms performed better	Taghizadeh-Mehrjardi et al. (2016)
Modelling the soil salinity variation in Arid Region	Genetic algorithm-based machine learning techniques	Obtained R^2 was 0.87	Taghizadeh-Mehrjardi et al. (2016)
Digital mapping of soil nutrients in the hilly watersheds of Indian Himalayan region	ANN algorithms	For SOC R^2: 0.83 and MSE: 0.05 For available nitrogen R^2: 0.62 and MSE: 0.0006	Kalambukattu et al. (2018)
Mapping of soil properties digitally	Deep learning techniques	30% of error reduction observed	Padarian et al. (2019)
Digital soil mapping for predicting the particle size fractions	CNN and random forest algorithm	CNN model out-performed the random forest algorithm	Taghizadeh-Mehrjardi et al. (2020)
Microbial dynamics prediction	Regression-based techniques	R^2 of 0.99	Jha and Ahmad (2018)

21.3.2 Crop Health Management

Every year a significant amount of yield is damaged due to the attack of disease-causing pathogens and insect-pest infestation. In order to manage the spread of the

Table 21.2 Irrigation management using AI and ML techniques

Area of work	Techniques used	Remarks	Citation
Improved irrigation scheduling	Data envelopment analysis (DEA) was integrated with multiple linear regression (MLR) analysis	This approach potentially helpful for the irrigation decisionmakers	Zema et al. (2018)
IoT based system for smart irrigation in fields	SVR and bagging	Ensemble based techniques achieved 90% accuracy	Ramya et al. (2020)
IoT-based adaptive irrigation management system	Random forest, ANN, DT, and SVM	Random forest obtained best results with accuracy of 84.6%	Glória et al. (2021)
Irrigation detection using satellite images	CNN models with IoT based systems	Proposed CNN model was nine times better than traditional supervised models	Agastya et al. (2021)
Image-based recognition of center pivot irrigation systems	CNN-based model	Precision: 95.85% and recall: 93.33%	Zhang et al. (2018)
Estimate of irrigation schedules	LSTM network	R^2 ranges from 0.82 to 0.98	Jimenez et al. (2021)

diseases and insect pests, proper management practices should be applied at the earliest. Therefore, there is requirement of automatic diseases, pest identification system. In this regard, image-based diagnosis of diseases and pests have become de facto standard of automatic stress identification. This kind of automated detection methodology use sophisticated deep learning-based AI techniques that reduces the intervention of the human experts. There have been several attempts to diagnose the diseases as well as insects-pests in crops using deep learning techniques. In this section, some of the significant works in this field have been discussed briefly.

21.3.2.1 Disease Identification

Mohanty et al. (2016) worked on disease diagnosis problem using deep CNN models. They used an open-source dataset named Plant Village (Hughes and Salathe 2016) containing 54,306 colour images of 26 diseases from 14 crops. Ferentinos (2018) worked on developing deep CNN-based models for recognizing 56 diseases from different crops. Barbedo (2019) applied transfer learning approach for diagnosis of diseases of 12 different crops. Too et al. (2019) applied pre-trained deep CNN models for the identification of diseases of 18 crops using the Plant Village data. Chen et al. (2020) applied a pretrained VGG Net network for classifying the diseases of Rice and Maize crop. Chen et al. (2020) and Rahman et al. (2020) worked on identifying the major diseases of Rice crop using deep learning approach. Lu et al. (2017), Johannes et al. (2017), Picon et al. (2019), and Nigam et al. (2021) applied

Table 21.3 Disease identification using deep learning techniques

Crop	Number of diseases	Techniques used	Remarks	Citation
14 crops	26 (diseased and healthy)	Pre-trained GoogleNet and AlexNet model	GoogleNet obtained 99.35% testing accuracy	Mohanty et al. (2016)
25 crops	58 (diseased and healthy)	AlexNet, VGGNet, GoogleNet	Highest accuracy: 99.53%	Ferentinos (2018)
14 crops	79 diseases	Transfer learning on GoogleNet	Average accuracy around 82%	Barbedo (2019)
18 crops	26 diseases	VGG 16, Inception V4, ResNet and DenseNet	DenseNet achieved the highest accuracy of 99.75%	Too et al. (2019)
Rice and maize	Rice: 4 Maize: 4	Pre-trained VGGNet	Accuracy: 91.83%	Chen et al. (2020)
Rice	5 diseases	Modified DenseNet	Accuracy: 98.63%	Chen et al. (2020)
	5 diseases	Custom two-stage small CNN architecture	Accuracy of 93.3%	Rahman et al. (2020)
Wheat	7 (diseased and Healthy)	Modified VGGNet model with localisation	Recognition accuracy: 97.95%	Lu et al. (2017)
	3 diseases	Image processing techniques with deep learning model	AuC metrics higher than 0.80	Johannes et al. (2017)
	3 diseases	Deep CNN model	Accuracy more than 96%	Picon et al. (2019)
	3 diseases	Custom CNN based model	Accuracy: more than 90%	Nigam et al. (2021)
Maize	4 (diseases and healthy)	Modified LeNet model	97.89 % accuracy on test dataset	Ahila Priyadharshini et al. (2019)
	4 (diseases and healthy)	Custom CNN model	92.85% accuracy	Sibiya and Sumbwanyambe (2019)
	2 (MLB and healthy)	Base-line training or Inception model	Classification accuracy: 99.14%	Haque et al. (2021)

deep CNN models for recognizing the most important diseases of wheat crop. Ahila Priyadharshini et al. (2019), Sibiya and Sumbwanyambe (2019), and Haque et al. (2021) used deep learning-based models for identifying images of diseases of maize crop. More details about the disease diagnosis work are discussed in Table 21.3

21.3.2.2 Pest Identification

Pest identification problem is inherently different from disease identification problem. As compared to disease detection comparatively lesser studies have been reported in pest identification. Most of the works on insect-pest detection are based on localization and object detection concept. Some significant research works on the pest identification have been discussed in this section.

Cheeti et al. (2021) proposed insect-pest detection approach using advanced deep learning techniques for four pests of crops. They used YOLO (You Only Look Once) algorithm for detection and localisation of the pests in the image and AlexNet model as classifier to classify the images. Chen et al. (2021) employed three object detection models such Faster R-CNNs, SSDs, and Yolo-v4 for detecting and localizing the scale pest from the images. Their proposed approach achieved more than 89% accuracy for detecting and classifying the pest images. Fuentes et al. (2017) worked on combining the object detection based meta-architectures with deep CNN models for detecting the diseases crop pests of tomato crop. In this work, their proposed Faster R-CNN with VGG-16 model outperformed all the other models with mean average precision (mAP) of 83%. Li et al. (2020) proposed a deep learning-based disease and pest detection approach of rice crop using video dataset. They employed different state-of-the-art deep learning models such VGG16, ResNet-50, ResNet-101 with YOLO-v4 for the object detection purpose. Liu and Wang (2020) applied theYOLO-v3 object detector model for detecting and classifying the images of disease and pests of tomato crop.

21.3.3 *Plant Phenotyping*

Non-destructive phenotypic measurement with high throughput imaging technique becoming extremely popular. High throughput imaging system produces a large number of images. Deduction of the phenotypic characteristics through image analysis is quick and accurate. A wide range of phenotypic study can be done using phenomics analysis. High throughput imaging system coupled with sophisticated AI technology like deep learning make this field more efficient and accurate. Phenomics has been used for studying several phenotypic characters like spike detection and counting, yield forecasting, quantification of the senescence in the plant, leaf weight and count, plant volume, convex hull, water stress, and many more as presented in Table 21.4.

Table 21.4 Plant phenotyping using AL and ML techniques

Area of working	Technology used	Country	Remarks	Citation
Spike detection	Neural network-based method using laws texture energy	Australia	Can identify spikes with an accuracy of over 80%	Qiongyan et al. (2014)
Forecasting of yield	Auxiliary information	India	Evaluation of different machine learning models	Elavarasan et al. (2018)
In field spike detection	Faster R-CNN	Australia	Average detection accuracy ranging from 88 to 94%	Hasan et al. (2018)
Spikelet counting	FCN	Norwich	Mean absolute error (MAE) and mean square error (MSE) of 53.0, 71.2 respectively, in counting	Alkhudaydi and Zhou (2019)
In-field counting of spikes	Context-augmented local regression networks	China	91.01% counting accuracy	Xiong et al. (2019)
Spike detection and counting	U-Nets	India	Precision detection—99.93%, counting—99%	Misra et al. (2020)
Plant senescence	Colour thresholding	Australia	Quantifying the onset and progression of senescence	Cai et al. (2016)
Water-deficit stress	Spectral imaging	India	PLSR was the best model for prediction of RWC	Das et al. (2017)
Water status in plant	Hyperspectral reflectance	India	The models based on water band index (WBI), MSI, NDWI 1640, and NMDI become best	Ranjan et al. (2017)
NDVI	RGB image processing	USA	Simpler to use and more cost efficient than traditional dual-image NDVI or hyper-spectral imaging	Beisel et al. (2018)
Leaf fresh weight	ANN	India	Enhanced the fresh biomass prediction as compared to the conventional regression technique	Misra et al. (2020)
Water deficit stress	Thermal imaging and hyperspectral remote sensing	India	Optimal wavebands related to water deficit stress were evoked	Krishna et al. (2021)

21.3.4 Recommender Systems

Recommender systems (RS) help online users in decision making regarding products among a pile of alternatives. In general, these systems are software solutions which predict liking of a user for unseen items. RSs have been mainly designed to help users in decision making for areas where one is lacking enough personal experience to evaluate the overwhelming number of alternative items that a website has to offer (Resnick and Varian 1997). Recommender systems have proved its worth in many different applications such as e-commerce, e-library, e-tourism, e-learning, e-business, e-resource services, etc. by suggesting suitable products to users (Lu et al. 2015). RSs are used to introduce new/unseen items to users, to increase user satisfaction, etc. Recommendations are generated by processing large amount of historical data on the users and the products to be suggested. Most popular way of gathering users liking on a particular product is in terms of rating either in numerical scale (1–5) or ordinal scale (strongly agree, agree, neutral, disagree, strongly disagree). Other techniques of more knowledge-based recommendation are the use of Ontologies (Middleton et al. 2002) of user profiles or item descriptions, etc. The core task of a recommendation system is to predict the usefulness of an item to an individual user based on the earlier history of that item or by evaluating the earlier choices of the user. Collaborative way of user modelling (Konstan et al. 1997) is where ratings are predicted for $<user, item>$ pair, $\overline{R}<u, i>$ based on a large number of ratings previously gathered by the system on individual $<user, item>$ pairs. Another way of recommendation is to suggest items that are similar to the ones previously liked by the user, called Content based filtering (Wang et al. 2018; Smyth 2007). In a hybrid method of prediction, limitations by the earlier mentioned processes are tackled in various ways.

Agriculture has used recommender systems since 2015 and continues to do so. RSs have been explored to develop crop recommendation strategies based on soil and weather parameters, crop rotation practices, water management, suggestions on suitable varieties, recommendations for management practices, etc. It is absolutely essential for the farmers to receive recommendations on the best crop for cultivation. Kamatchi and Parvathi (2019) proposed a hybrid RS in combination with collaborative filtering, case-based reasoning, and artificial neural networks (ANNs) to predict future climatic conditions and recommendation of crops based on the predicted climate. Crop recommendations have been developed based on season and productivity (Vaishnavi et al. 2021) area and soil type (Pande et al. 2021) by using several machine learning algorithms such as support vector machine (SVM), random forest (RF), multivariate linear regression (MLR), K-nearest neighbour (KNN), ANN, etc. Ensemble techniques have been used to develop a collaborative system of crop rotation, crop yield prediction, forecasting, and fertilizer recommendation (Archana and Saranya 2020) to classify soil types into recommended crop types Kharif or Rabi based on specific physical and chemical characteristics, average rainfall and surface temperature (Kulkarni et al. 2018). Naha and Marwaha (2020) presented an Ontology driven context aware RS that can recommend land preparation methods, sowing time, seed rate, fertilizer management, irrigation scheduling and harvesting methods to Maize cultivators. Application of RSs has also penetrated in the e-agriculture domain by suggesting parts of agricultural machineries in online ordering (Ballesteros et al. 2021).

21.3.5 Semantic Web, Knowledge Base, and Natural Language Processing

The agricultural industry is a vast source of information. But most of it is stored in an unstructured way. That unstructured knowledge is merely understandable for machine. It is also having low accessibility for human too. The main objectives of the semantic web and knowledge base system is to make unstructured data into structured one. Semantic web and the knowledge base mainly facilitated by the ontology in the back end. Ontology is a formal, explicit specification of a shared conceptualization (Gruber 1991). Making of Ontology that facilitated the semantic web and knowledge base can be made across the agricultural domain to make the unstructured data into structured one. Many ontologies have already been developed in accordance with the Bedi and Marwaha (2004) in the agricultural domain. Saha (2011) developed an ontology on dynamic maize variety selection in different climatic conditions, Sahiram (2012) developed an ontology on rapeseed and mustard for identification of the variety in multiple languages; Das et al. (2017) developed an ontology for USDA soil taxonomy and another ontology was extended by Deb et al. (2015). Biswas et al. (2013) developed an ontology on microbial taxonomy and was extended by Karn (2014).

21.3.6 GIS and Remote Sensing Coupled with AI

GIS and remote sensing are helping agricultural community since long. The land use planning, land cover analysis, forest distribution, water distribution, water use pattern, crop rotation, and crop calendar analysis can be done by GIS and remote sensing. But when AI and machine learning are coupled with this technology it becomes more powerful. Machine learning and AI efficiently used for correct land classification and phonological change detection. From digital soil mapping to yield forecasting, from phenology detection to leaf area index a vast range of the area in agriculture can be handled by GIS and Remote sensing.

21.4 Framework for Phenology Study Using Artificial Intelligence

Based on the critical analysis of the reviews on the topic, one framework (as shown Fig. 21.3) has been deducted which depicts the mode of working of the methodologies of AI and Machine learning models used in agriculture. The whole framework can be subdivided into three distinct layers. The description of the layers are as follows:

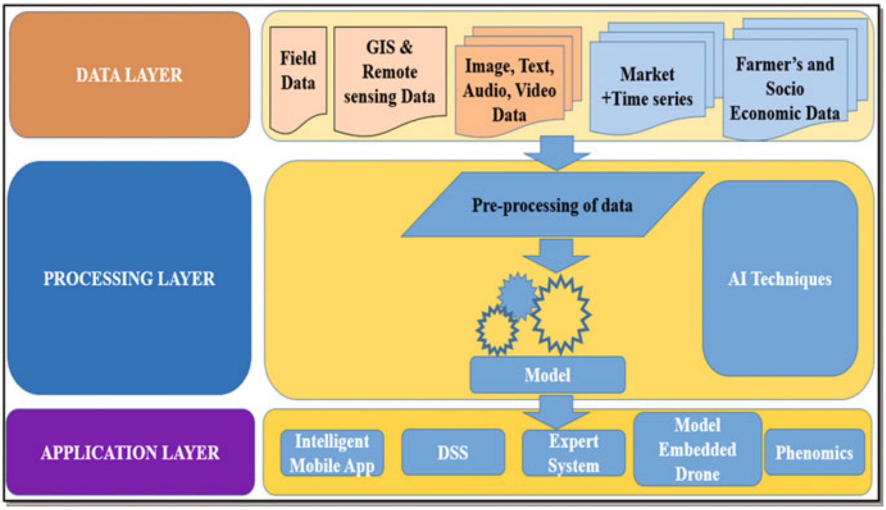

Fig. 21.3 Framework depicting mode of working of the methodologies of AI and machine learning models used in predictive modelling of phenology

21.4.1 Data Layer

This layer of the framework deals with the relevant data. As we know agriculture is a vast source of data with a wide range type. The remote sensing data with a longer period of time also has an importance along with the climatic data. With improvement of the technology, the image data coupled with time series data from Unmanned Aerial Vehicle (UAV) has been used in many studies. This layer is also used for any kind of pre-processing and making the data ready to use for the study.

21.4.2 Processing Layer

This layer of the framework deals with the core part AI. It takes the input, i.e. the ready to use data from the data layer. It also takes care of the model development part of the framework. The ultimate product of the layer is a model that has promising result in the training and testing framework of the machine learning.

21.4.3 Application Layer

This layer has a countless number of uses for the end users. Model which is developed in the previous layer has a great potential to be embedded and can be used in many platforms. The followings are the applications that supports model embedding. In the present discussion Sect. 21.3 covers the application layer of this framework.

21.5 Conclusion

The application of AI and ML can provide viable solutions to major problems in agriculture such as soil health management, irrigation scheduling, crop health management, disease/pest identification, crop phenomics, etc. The utility of artificial intelligence and machine learning techniques in the agriculture domain and survey of different AI related technologies discussed in this chapter will help in deducing a generic framework towards precision agriculture that will improve the overall crop productivity. AI is a powerful tool in the field of agriculture for accurate weather prediction, disease/pest forewarning and assisting the stakeholders in accurate and real-time prediction of various related parameters to obtain maximum yield at minimum cost. AI tools will transform the agriculture industry with better agricultural practices which in turn will benefit the farmers and aid in improving the economy of the country.

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