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Artificial Intelligence based Models for Plant Protection

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ABSTRACT

Computational models have been an important contributor to growth in agriculture. Artificial Intelligence (AI) has revolutionized agriculture by efficiently disseminating information to achieve food security. Plant Protection plays a significant role in achieving targets of crops production. AI has begun to modify the plant protection environment around us. AI-based equipment and machines like robots and drones have been designed for disease and weed detection (Liakos et al., 2018). Machine Learning (ML) coupled with computer vision have potential to help farmers in protection of crops.

This paper presents a brief review of Artificial Intelligence based models for Plant Protection some significant research efforts in crop protection using AI with followed by some potential applications. Some machine learning techniques for Big data analytics are also reviewed. The outlook for Big data and machine learning in crop protection is very promising.

Keywords: Artificial Intelligence, Machine Learning, Plant Protection, Food Security

Introduction

Computational models have been an important contributor to growth in agriculture. Artificial Intelligence (AI) has revolutionized agriculture by efficiently disseminating information to achieve food security. Plant Protection plays a significant role in achieving targets of crops production. AI has begun to modify the plant protection environment around us. AI-based equipment and machines like robots and drones have been designed for disease and weed detection (Liakos et al., 2018). Machine Learning (ML) coupled with computer vision have potential to help farmers in protection of crops.

Traditionally, crop and weed inspection were identified by farmers or experts which was not feasible continuously for the large fields. Computer vision empowered with ML promises to monitor crops for occurrence and diagnosis of disease and weeds at large scale. The four phases namely image acquisition, image pre-processing, features extraction, and classification are used in computer vision based models.

Image based disease and weed identification methods are of two types i.e. (i) image processing and (ii) machine learning. For disease and weed identification, image processing techniques are necessarily followed by some machine learning methods. On the other hand, machine learning methods can work on both image-based dataset as well as textual attribute based data. Egmont et al. (2002) identified various image processing algorithms. Clipping, smoothing and enhancement of images enable detection of plant diseases (Khirade and Patil 2015).

Machine learning methods improve disease detection and diagnosis in comparison to conventional techniques

(Jain et al. 2005). Jain et al. (2009) compared ML models to traditional logistic regression method and showed better performance over traditional approach in case of forewarning powdery mildew disease of mango. The support vector machine, k-nearest neighbours and Artificial Neural Network (ANN) are some other commonly used ML algorithms for plant disease identification.

Weed management and control are important given that crop yield losses caused by weeds are high. Farmers control the weeds either by manual operations or through herbicide control. To escape huge losses, herbicides are applied liberally in the field causing indiscriminate use of chemicals. AI based approaches can help in weed identification at an early stages so as to focus the efforts to eliminate weeds at the identified points. Such identification will also lead to development of AI based machines which reduce human labour as well as chemical applications in weed control. This work first presents a brief review on different techniques of some significant research efforts in plant protection using AI followed by some potential applications.

AI based Flowchart for Plant Protection

The outlook for machine learning and deep learning techniques in plant protection is very promising. The basic steps for plant protection using these techniques mainly contains four phases that are image acquisition, image pre-processing, feature extraction and classification as shown in Figure 1. Each step is discussed in detail further.

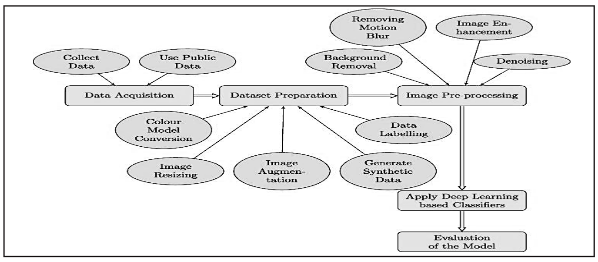

Figure 1.Basic Steps Involved for Plant Protection

Data Acquisition and Preparation

The foremost step in plant disease classification or identification includes image acquisition. It is the process in which acquired images are converted to the desired output format for further processing. Images may be self-acquired by authors or may be any bench marking dataset such as Plant village database (Hughes and Salathe, 2015).

Image Pre-Processing

Image pre-processing is the technique of enhancing some image features and suppressing unwanted distortions for further processing. Initial captured images are in various formats along with different resolutions and quality. In order to get better feature extraction, there is a need for pre-processing final images intended to be used as dataset in order to gain consistency. Furthermore, procedure of image pre-processing aims at highlighting the region of interest (disease infected area) in plant leaves (Hanson et al., 2017). Image pre-processing commonly involves process for image segmentation image enhancement and colour space conversion firstly image digital image is enhanced by filter. Leaf image is filtered form the background image. Then filtered image's RGB colours are converted into colour space parameter. Further image is segmented to a meaning full part which is easier to analyse. Unfortunately, removing background is quite difficult, and sometimes needs the intervention of the user, which decreases the automation of the system (Le et al. 2015). MATLAB is most widely used tool for image pre-processing. Image Pre-processing is followed by feature extraction.

Feature Extraction

Feature extraction is the process done after segmentation phase in pre-processing. Features proposed by experts are extracted from the image for constructing feature vectors. This extraction could be the any of statistical, structural or signal processing. For example, colour moments are used to extract colour statistics (Semary et al. 2015), in which Gabor Transform (GT) and Wavelet Transform (WT) are combined (GWT) for the extraction of multiscale features. Gray Level Co- occurrence Matrix (GLCM) is used in many previous works to extract texture features.

Classification

The last phase identifies the plant disease existing in leaf using a classification model. The model should be trained using learning algorithms and examples with a known disease images. The Support Vector Machine, K-Nearest Neighbors (KNN), Artificial Neural Network (ANN) and deep learning architectures represent the most commonly used learning algorithms in the literature reviewed. The SVM algorithm maximizes the margin between classes in linearly separable cases. The KNN algorithm classifies an image by voting between the K closest examples in the features space. The ANN is a model organized in layers, in which each layer is connected to the next one starting from the input to output. Table 1 and 2, present some recent studies in plant disease identification and weed management.

Different Techniques for Plant Protection

Image Processing Techniques

Image processing techniques were widely and successfully used for accurate detection and classification of the plant. Categorization is achieved with as a two-dimensional taxonomy. One dimension of which specifies object recognition, data reduction/ feature extraction, pre-processing, segmentation, optimization and image understanding. In an alternative dimension, inputs are received and tasks at different levels are completed e.g. pixel level, object set level etc.

The various pre-processing techniques such as image clipping, image smoothing, image enhancement is carried out for increasing the efficient detection of diseases (Khirade and Patil 2015). Image segmentation can be done using various methods like Otsu' method, k-means clustering, converting the RGB image into HIS model etc. The various image pre-processing techniques were done using the Fourier filtering, edge detection, and morphological operations in MATLAB for the feature extraction and image recognition.

Machine Learning (ML)

Machine learning focuses on algorithms capable of learning on their own from a given set of input data according to the objective. Its high-performance computing creates new opportunities in the agriculture domain. Machine learning and statistical pattern recognition have been the subject of tremendous interest in the agriculture domain because they offer promise for improving the sensitivity of disease detection and diagnosis. Liakos et al. (2018) presented a comprehensive review of research dedicated to applications of machine learning in agricultural systems and demonstrated how agriculture will benefit from machine learning technologies over time. The machine learning enabled techniques provide rich recommendations and insights for farmer decision support and action.

Artificial Neural Networks (ANN)

Among the different approaches used for detecting plant diseases and one of the reliable approaches is artificial neural networks (ANNs). Neural networks are combined with different methods of image pre-processing in favour of better feature extraction. ANN works on the principle of biological neurons in human nervous system. However, ANN can infer meaning from complicated data and find patterns that are too difficult to detect by humans or conventional computers. Adaptive learning, self-organization, real-time operations, and so on are some of the other benefits of ANNs.

Support Vector Machines (SVM)

Support vector machine is a supervised learning system and used for classification and regression problems. In case of SVM, hyperplane is used to separate the classes. Hyperplane in N- dimensional space is analogous to a line in two dimensional space. This hyperplane is a line that divides a plane into two halves in two-dimensional space, with each class on either side The SVM algorithm searches for the best hyperplane to categorise new examples from given labelled training data. Thus SVM finds the hyperplane to categorise the data points individually.

Support Vector Machine (SVM) has been also found to be very promising to achieve an efficient classification of leaf diseases.

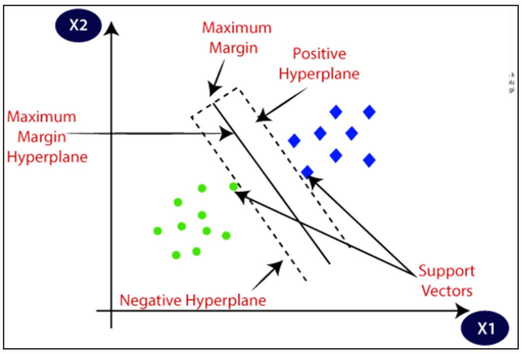

Figure 2.Support Vector Machines

Random Forest (RF)

Random forest algorithm is a supervised classification and regression algorithm and this algorithm randomly creates a forest with several trees. Generally, the more trees in the forest the more robust the forest looks like. Similarly, in the random forest classifier, the higher the number of trees in the forest, greater is the accuracy of the results.

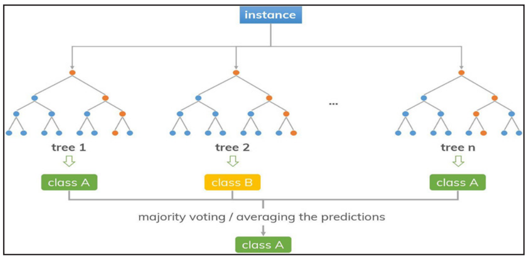

Figure 3.Random Forest Algorithm

Random forest builds multiple decision trees (called the forest) and glues them together to get a more accurate and stable prediction. The forest it builds is a collection of decision trees, trained with the bagging method. Random forest is an ensemble of decision trees, it randomly selects a set of parameters and creates a decision tree for each set of chosen parameters. Each decision tree predicts the outcome based on the respective predictor variables used in that tree and finally takes the average of the results from all the decision trees in the random forest.

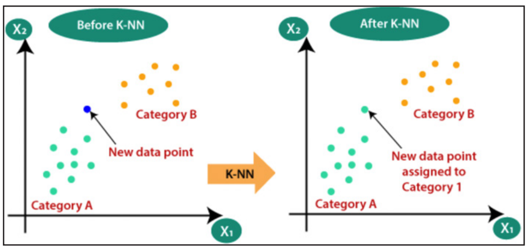

Figure 4.K-Nearest Neighbour

K-Nearest Neighbour (KNN)

K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique. K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories. K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm (Figure 4).

Deep Learning (DL)

With the development of computational systems, in particular, Graphical Processing Units (GPU) embedded processors, the Machine Learning-related Artificial Intelligence applications have achieved tremendous growth in recent years, leading to the development of prominent methodologies and models especially Deep Learning (DL) (Le Cun et al. 2015). DL is deep neural network that refers to the addition of more depth or complexity into the model as well as transforming the data using various functions that allow data representation in a hierarchical way, through several levels of abstraction (Schmidhuber, 2015, LeCun and Bengio, 1995). Deep Learning (DL) is quickly becoming one of the most important tool that can be applied for solving various agricultural problems involving classification or prediction, related to computer vision and image analysis, or more generally to data analysis. Kamilaris and Boldú, (2018) reviewed 40 research efforts that employ deep learning techniques, applied to various agricultural and food production challenges. They examined the particular agricultural problems under study, the specific models and frameworks employed. Nigam and Jain (2020) explored computer vision based DL for automating the identification of yellow rust disease and achieved accuracy up to 97.3%.

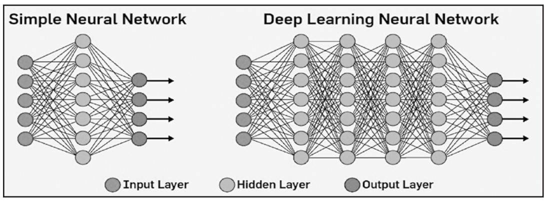

Figure 5.Difference between Simple Neural Network and Deep Neural Networks

Case Studies on use of AI in Plant Protection

Plant Leaf Disease Identification

Methods based on conventional machine learning techniques and image processing techniques have been relatively successful under limited and constrained setups, but many of the difficulties associated with the intrinsic characteristics of the problem could not be properly handled. Husin et al. (2012) captured the chilli plant leaf image and processed to determine the health status of the chilli plant to ensure chemicals should be applied to the diseased chilli plant only. Yao et al. (2009) explored an application of image processing techniques and Support Vector Machine (SVM) for detecting rice diseases such as bacterial leaf blight, rice sheath blight and rice blast. The results showed that SVM could effectively diagnose and classify disease spots to an accuracy of 97.2 percent. Rumpf et al. (2010) developed a system for the early detection and differentiation of sugar beet diseases (Cercospora leaf spot, leaf rust, and powdery mildew) based on Support Vector Machines (SVM) and spectral vegetation indices. The classification of brown spot and the leaf blast diseases in rice, radial distribution of the hue from the centre to the boundary of the spot images has been done using Bayes' and SVM Classifier. An automated classification system based on the morphological changes caused by rice diseases was also developed (Phadikar et al. 2012). With the SVM based classifier and algorithm, unhealthy region and classification using texture features on ten species of plants namely banana, beans, jackfruit, lemon have been proposed by Arivazhagan et al. (2013).

Menukaewjinda et al. (2008) tried another ANN, i.e., Back Propagation Neural Network (BPNN) for efficient grape leaf colour extraction with a complex background and proposed a diagnostic system for grape leaf diseases. BPNN is a back-propagation of error back-propagation algorithm for a learning process. Another system was proposed for classifying the healthy and diseased part of rice leaves using BP neural network as a classifier (Liu and Zhou, 2009). Bashish et al. (2010) introduced image processing-based work consisting acquired image segmentation using the K-means techniques and then training through a pre-trained neural network classifier based on the statistical classification that detects and diagnose the diseases with approximate precision of 93%. Classification with identification accuracy up to 91% has been achieved through ANN based classifier (Kulkarni and Patil 2012). Husin et al. (2012) processed chilli plant leaf image to determine the health status and ensured chemicals should be applied to the diseased chilli plant only.

With the inception of deep learning concepts, most of them were solved and higher accuracy were achieved by the researchers. DL models are able to recognize different plant diseases out of healthy leaves with the ability to distinguish plant leaves from their surroundings (Brahimi et al. 2017, Cruz et al. 2017, Ferentinos, 2018, Liu et al. 2018, Mohanty et al. 2016). According to Le Cun et al., 1998, one of the most powerful and basic DL tools for modelling complex processes and performing pattern recognition is Convolutional Neural Networks (CNNs). CNN has achieved an impressive result in the field of image-based plant disease classification (Amara et al. 2017, DeChant et al. 2017). The severity identification models can be further worked upon to provide automatic advisory services to the overloaded extension experts. Plant Village database (publically available) is most preferred database used by the authors for training of their models in most of the case studies.

Weed Management

Over the past century, weed control has been a long-standing issue in the field of agriculture. The weed infestations, pests and diseases reduce the yield and quality of food, fibre and biofuel value of crops. Weeds are undesired plants which compete against productive crops for space, light, water and soil nutrients and propagate themselves either through seeding or rhizomes. Weed management is a challenging tasks for farmers as without adequate technical support, it results in poor weed control and reduced crop yield. Hence, weed control is an important aspect of horticultural crop management, as failure to adequately control weeds leads to reduced yields and product quality.

The identification of weeds in crops is a challenging task that has been addressed through the performances of several machine learning algorithms, ANN, Random Forest (RF), Support Vector Machine (SVM) and K-Nearest Neighbours (KNN), deep learning are analysed to detect weeds. Overview of recent works on artificial intelligence based approaches for weed detection.

Table I.Comparative Analysis of AI based Methods for Disease Identification

Algorithms	Crops and Accuracy (%)	References
KNN	Grape (90)	Krithika and Selvarani (2017)
	Groundnut (80)	Vaishnnaveet al. (2019)
Image Processing	Rice (90 and 97)	Liu and Zhou (2009)
		Yao et al. (2009)
	Chilli (90)	Husinet al. (2012)
	Rice	Khirade and Patil (2015)
	Cotton	Revathi and Hemalatha(2012)
ANN	Rice (90)	Liu and Zhou, (2009)
	Cotton (93)	Bashishet al. (2010)
	Grape (97)	Menukaewjindaet al. (2008)
SVM	Rice (68.1)	Phadikaret al. (2012)
	Sugarbeet (92.6)	Rumpfet al. (2010)
	Rice (97.2)	Yao et al. (2009)
	Fruits (95)	Arivazhaganet al. (2013)
Deep Learning	Tomato (99)	Brahimi et al. (2017), Fuentes (2017), Ashqar and Naser (2019),
	Horticultural Crops (99)	Ferentinos (2018)
	Banana (96)	Amara et al. (2017)
	Mango (96)	Arivazhaganet al. (2018)
	Horticultural Crops (99)	Mohantyet al. (2016)
	Maize (96.7 & 98.9)	DeChantet al. (2017), Zhang et al. (2018)
	Wheat (99& 97.3)	Piconet al. (2018), Nigam et al.(2021)

Table 2.Comparative Analysis of AI based Methods for Weed Management

Algorithms	Crops and Accuracy (%)	References
KNN	Chilli (63)	Islam et al. (2021)
Random forest	Sunflower (87.9)	Castro et al.(2018)
	Chilli (96.0)	Islam et al. (2021)
	Maize (81)	Gao et al. (2018)
ANN	Potato (98.4)	Sabjiet al. (2018)
	Soyabean (96.6)	Abouzahiret al. (2018)
	Sugarbeat (93)	Bakhshipouret al. (2017)
SVM	Soyabean (95.1)	Abouzahiret al. (2018)

	Chilli (94.0)	Islam et al. (2021)
	Sugarbeat (95)	Bakhshipouret al. (2017)

In this section, we explore relevant works conducted in recent years that use machine learning and image analysis for weed detection. Recent studies in the literature present a variety of classification approaches. However, as evidence in the recent state-of-art works shows machine learning algorithms make more accurate and efficient alternatives than conventional parametric algorithms, when dealing with complex data. We observe that performance varies across algorithms and crops. For example, in case of Chilli KNN provided 63% accuracy but SVM and random forest provided 94% and 96% accuracy respectively. In case of high performing deep learning algorithm accuracy varies from 69% for bean to 99.4% for lettuce. Also, the variations depend on experimental design and selection and hyper parameters. Hence, the use of appropriate technique for leaf disease or crop weeds identification requires serious attempt in data selection and model building. Among these algorithms, the deep learning performs better with higher accuracies than others.

Conclusion

This paper explores the potential of artificial intelligence based algorithms for weed and disease identification. The implementation of artificial intelligence based approaches to plant protection and specifically on leaf image classification, plant disease identification and weed management has been presented. In agriculture, plant diseases and weeds cause substantial economic and environmental losses, thus careful and expertise monitoring is must for early detection and consequent application of control measures in order to improve the quality and quantity of crop yield.

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