

MACHINE LEARNING – A NOVEL APPEAL FOR SUSTAINABLE AGRICULTURE

Abstract

Machine learning is emerging globally in all fields. This chapter provides the information on the basic concepts on machine learning techniques and its applications in agriculture and to manage the crops effectively by giving inputs to the crops in a needed time to avoid wastage of inputs, the yield of crop is also increased and monitored using machine learning techniques.

Keywords: machine learning; agriculture; crop; input; yield

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I. INTRODUCTION

The continuous growth of human population across the globe has paved way for another pressure on agriculture sector. To minimize the environmental impacts and to drive the productivity of crops, the modern tools such as agricultural technology, precision farming is being employed. The data inferred from employing concepts such as operational environment which studies tripartite interaction of soil, crop and weather conditions and machinery data helps to fasten the decision making in agriculture.

Machine learning is concept of employing the machines to learn from experience. Their algorithms don't use the predetermined equations from model instead use learns directly from the data sets (Friedman, 1991, Quinlan, 1992, Cleveland, 1979). As the size of sample increase the algorithms adapts to enhance their performance. The data intensive process in agriculture environment is been studied through the machine learning approaches which paves way to unmask the novel opportunities to unravel, quantify and helps to understand the data intensive process (Samuel, 1959).

II. ABOUT MACHINE LEARNING

Machine learning, a subtype of AI, enables computers to gain knowledge through experience. Its algorithms don't rely on established equations as a model; instead, they use computational techniques to learn straight from datasets. As the quantity of training samples rises, the algorithms gradually modify to improve performance. With the use of sensor data or data from other diverse networked sources, (Christopher M. Bishop, 2006), (David Barber, 2012), (Kevin P. Murphy, 2012). ML techniques are potent instruments capable of addressing large-scale non-linear problems automatically. With the least amount of human involvement, it enables better decision-making and informed actions in practical situations.

The use of ML techniques is constantly evolving. And are often used in nearly all disciplines. However, they are fundamentally constrained in how they can be used. The precision the quality of the data, the appropriate model representation, and the accuracy Establish connections between the inputs and the target parameters. Machine learning algorithms can be divided into two major categories: supervised learning and unsupervised learning. In supervised learning, a model is trained to predict the target variable for out-of-sample data using a known set of labelled data²⁸. Applications of supervised learning that are often used include classification and regression methods. Fig. 1 highlights the list of typical algorithms that come under the various methods. Unsupervised learning, on the other hand, makes inferences from unlabeled data using hidden patterns or inherent data structures. It is beneficial for exploratory applications when there is no defined objective or where the information in the data is ambiguous. Additionally, it works perfectly as a tool for dimension reduction on data with a variety of attributes.

The most prevalent learning model for this kind of learning is clustering, and it can be used for exploratory data analysis tasks like gene sequencing and object classification (Christopher M. Bishop, 2006). The amount, kind, and intended level of insight into the data all influence the algorithm choice. However, there isn't a set rule for choosing an algorithm; most of the time, it's a matter of trial and error. In IoT smart data analysis across numerous

domains, supervised and unsupervised learning approaches are both widely used (Mohammad Saeid *et al.*, 2018).

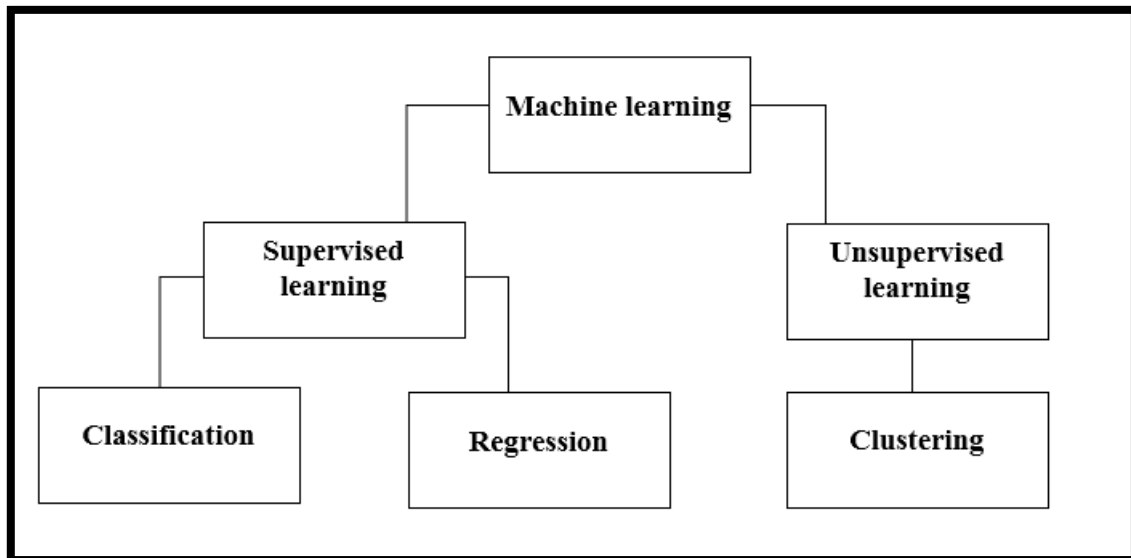


Figure 1: Machine Learning Algorithms

ML approaches often incorporate a learning process with the goal of learning from "experience" (training data) to carry out a task. In ML, the input is a collection of examples. Typically, a set of properties often referred to as features or variables, are used to characterise a specific example. A characteristic can be numeric, binary, ordinal, or nominal (enumeration, such as A+ or B) (integer, real number, etc.). A performance indicator that gets better with practice over time is used to assess how well the ML model performs in a particular activity. Several statistical and mathematical methods are used to determine how well ML models and algorithms function. Once the learning process is complete, the trained model can be used to categories, forecast, or cluster fresh instances (testing data) based on the knowledge gained during the training process. Figure 2 displays a typical ML strategy.

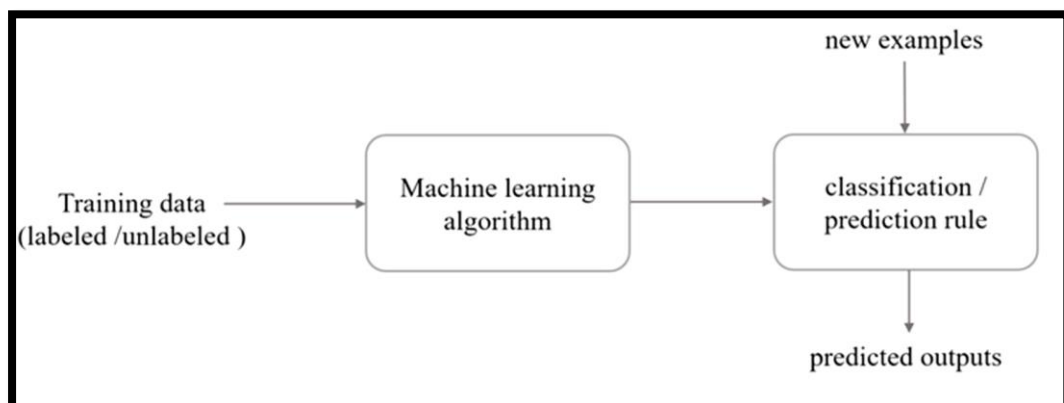


Figure 2: A Common Machine Learning Strategy

III. LEARNING MODELS

1. **Regression:** Regression is a type of supervised learning model that seeks to produce an output variable prediction based on known input variables. The most popular algorithms are stepwise regression (Efroymson, 1960), logistic regression (Cox, 1958), and linear regression. Additionally, more sophisticated regression methods have been created, including cubist (Quinlan, 1992), multiple linear regression (Quinlan, 1992), multivariate adaptive regression splines (Friedman, 1991) and locally calculated scatterplot smoothing (Cleveland and W.S. Robust 1979).
2. **Clustering:** Finding natural groups of data using clustering (Tryon, 1957), is a common use of an unsupervised learning technique (clusters). The k-means approach (Lloyd, 1982), the multilevel approach (Johnson, 1967), and the expectation maximizing technique (Dempster, 1977) are well known clustering algorithms.
3. **Bayesian models:** In Bayesian models (BM), the analysis is carried out in the framework of Bayesian inference. BMs are a class of probabilistic graphical models. This model type can be used to address classification or regression issues and falls under the domain of supervised learning.
4. **Instance based models:** Memory-based models called "instance-based models" (IBM) learn by contrasting fresh examples with examples from the training database. They do not keep a set of abstractions; instead, they build hypotheses directly from the data at hand, and they only use specific instances to produce classification or regression predictions. These models' drawback is that as data accumulates, their complexity increases.
5. **Decision trees:** Decision trees (DT) are regression or classification models that are constructed using a tree-like topology (Belson, 1959). With DT, the dataset is gradually divided into smaller, homogenous subsets (sub-populations), and a corresponding tree graph is also produced. Each branch of the tree - like structure represents the result of this comparison, whereas each internal node represents a distinct pair - wise comparison on a chosen attribute. After going from root to leaf, leaf nodes indicate the ultimate judgement or forecast made (expressed as a classification rule). The classification and regression trees (Breiman *et. al.*, 1984) the chi-square automatic interaction detector (Kass, 1980) and the iterative dichotomiser (Quinlan, 1992), are the most popular learning methods in this category.
6. **Artificial neural networks:** ANNs are modelled after the operation of the human brain, simulating intricate processes including pattern creation, cognition, learning, and decision - making process (McCulloch and Pitts, 1943). The human brain is made up of billions of neurons that communicate with one another and process any information that is sent to them. Similar to a biological neural network, an ANN is a simplified representation of its structure made up of interrelated processing units arranged in a certain topology. The following nodes are among those arranged in many layers:
 - An output layer where the decision or prediction is made.
 - An input layer where the data is supplied into the system.
 - One or more hidden units where the learning occurs.

ANNs are supervised models that are frequently applied to classification and regression issues. Radial base function networks (Broomhead and Lowe, 1988) perceptron algorithms (Rosenblatt, 1958), back-propagation (Linnainmaa, 1976), and robust back-propagation (Riedmiller and Braun, 1993) are some of the learning methods frequently employed in ANNs. Many ANN-based learning algorithms have also been reported, including counter propagation algorithms (Hecht-Nielsen, 1987) adaptive-neuro fuzzy inference systems (Jang, 1993) autoencoder, XY-Fusion, and supervised Kohonen networks (Melssen, Wehrens and Buydens, 2006) as well as Hopfield networks (Hopfield, 1982) multilayer perceptrons (Pal and Mitra, 1992) self-organizing maps (Kohonen, 1990) extreme learning machines (Huang, Zhu, and Siew, 2006) generalised regression neural network (Specht, 1991) ensemble neural networks or ensemble averaging, and self-adaptive evolutionary extended networks (Cao *et. al.*, 2012) Deep neural networks (DNNs) or deep learning (DL) are the most used names for deep ANNs (LeCun, Bengio, and Hinton, 2015) They are a relatively recent area of ML research that enables multi-processing layer computer models to learn complex data representations utilising several degrees of abstraction. The fact that the feature extraction stage is occasionally carried out by the model itself is one of the key benefits of DL. The state-of-the-art in many various fields and businesses, including agriculture, has significantly improved because to DL models. DNNs can be supervised, only partially supervised, or even unsupervised. They are basically ANNs with additional hidden layers between the input and output layers.

- 7. Support vector machines:** SVMs were first used in the work of (Vapnik, 1995) on the theoretical underpinnings of statistical learning theory. In order to categorise data instances, SVM is fundamentally a binary classifier that builds a linear separating hyperplane. The "kernel technique" can be used to turn the initial feature space into a feature space of a greater dimension, greatly improving the classification skills of conventional SVMs. SVMs have been applied to grouping, regression, and classification. SVMs are appealing in a variety of applications because they handle overfitting issues that arise in high-dimensional spaces thanks to global optimization (Suykens and Vandewalle, 1999, Chang and Lin, 2013). The most popular SVM methods are successive projections algorithm-support vector machine (Galvao *et. al.*, 2008) least squares SVM (Suykens *et. al.*, 2002) and support vector regression (Smola, 1996).

IV. ML IN ASSESSING CROP MANAGEMENT

- 1. Yield prediction:** The ML technique assist the farmers to optimize the grove in term of enhancing the yield and profit through exhibiting the yield specific information,

Since the yield of crops is ultimate destination in farming journey and so the yield prediction plays crucial role for yield mapping, yield estimation, correlating the supply and demand in crop supply and other crop management techniques to increase the productivity.

Ramos *et al.*, 2017 employed the ML method which are non-destructive, low cost technique to count the coffee fruits of three categories such as harvestable fruits, non-harvestable fruits, disregarded maturation fruits and in addition helps to estimate the

maturation percentage, weight of coffee fruits. The ML technique helped the farmers to plan their work and optimize the economic benefits.

Another ML technique, an automatic shaking and catching of cherries during the harvest. The system is programmed in order to detect the cherry branches and another ultimate aim is to reduce the dependency of human labors in harvesting (Amatya *et al.*,2015).

Through the ANN concept, Ali *et al.*,2016 developed a model to estimate the grassland biomass by employing multi-temporal remote sensing data. The yield prediction in wheat was developed through satellite imagery which received crop growth characters fused with soil data (Pantazi *et al.*,2016).

Through the Unmanned Aerial Vehicle (UAV) the detection of tomatoes through EM and red green blue (RGB) images (Senthilnath *et al.*, 2016). With the help of SVM and basic geographic information from weather stations Su *et al.*, 2017 developed a method to predict development stage in rice cropping system.

- 2. Crop protection aspects:** Pest, diseases and nematodes causes a considerable amount of yield loss if unnoticed in early stages of infection which hinders the crop yield. The usage of insecticides, fungicides and nematicides though helps to get rid of pathogens but causes severe after math such as residual settlement in crops, environment which has serious ill effects to humans and other organism in ecosystem. With the help of ML the agro-chemical input is targeted in time and space.

Chung *et al.*,2016 developed a model for detecting the rice bakanae disease and concluded that ML helps in accurate detection of pathogen *Fusarium fujikuroi* which helped to increase the yield of grains when compared to naked eye detection. The image processing method of detection of thrips in strawberry *Frankliniella occidentalis* were developed (Ebrahimi *et al.*, 2017). The detection of smut fungal pathogen, *Microbotyum silybum* in healthy milk thistle plant *Silybum marianum*, during vegetative stage (Pantazi *et al.*,2017).

The use of ANN and auto-reflectance features helps to detect yellow rust infected and healthy wheat seedlings accurately which paves way for targeted application of fungicides in field (Moshou *et al.*,2004). The guidance based on self-organising map (SOM) neural network and data fusion of hyper-spectral reflection and multi-spectral fluorescence imaging (Moshou *et al.*,2005) detected the wheat yellow rust in field conditions. This helps the farmers to detect the presence of pathogen before the expression of symptoms. Through the simple method of using leaves images with sufficient accuracy helps to classify the diseased and healthy plants through CNN.

- 3. Weed management:** ML algorithms along with sensors leads to accurate detection of parasitic plants in field conditions. This technique is simple, low cost with no harmful effects to environment and also helps to deter the dependency on herbicides to deter the weeds from fields. ML technique using counter propagation (CP)-ANN and multispectral images captured by unmanned aircraft systems (UAS) for detection of *Silybum marianum* (Pantazi *et al.*, 2017). The usage of hyperspectral imaging technique for recognising the

crop and weeds. This model was developed to detect maize crop, *Zea mays* and wide range of weed species which includes *Ranunculus repens*, *Cirsium arvense*, *Sinapis arvensis*, *Stellaria media*, *Tarraxacum officinale*, *Poa annua*, *Polygonum persicaria*, *Urtica dioica*, *Oxalis europaea*, and *Medicago lupulina* (Pantazi *et al.*, 2016).

4. **Crop quality:** The accurate detection of crop quality decides the economic value of produce. The method of detecting the cotton quality and minimizing the fiber damage and detection of botanical and non- botanical foreign matters by SVM approaches. The results were 95% accuracy for spectra and images (Zhang *et al.*, 2017). The twenty chemical components in rice samples were detected through coupled plasma mass spectrometry. This helps to differentiate the rice samples based on their origin of rice samples and results obtained through this method was found to be 93 % accurate in differentiating the rice samples (Maione *et al.*, 2016).
5. **Species recognition:** The main aim of utilizing the ML approaches in species recognition is to avoid error raised during the human classification of species and also helps to reduce the time needed by humans for classification of large number of samples. Classification of three different plant species such as red beans, white beans and soybean with vein images of leaves through CNN algorithm showcased accuracy of about 90-98% depending upon the crops (Grinblat *et al.*, 2016).
6. **Soil management:** Soil is a heterogeneous natural resource with several properties such as soil pH, temperature, moisture, soil drying which allows the researchers to understand the dynamics of ecosystem. The accurate estimation of soil properties helps to improve the soil quality. In general, the soil parameter estimation is time consuming and high cost for which an alternate key is the usage of ML for accurate estimation of soil properties.

Measurement of soil moisture by observing the parameters such as dataset of forces acting on chisel and speed through from force sensors ANN/ MLP and RBF approaches (Johann *et al.*, 2016). The estimation of soil temperature at six different depths varying from 5 -100 cm at two different agro climatic conditions was observed using ANN/ self-adaptive evolutionary-extreme learning machine (SaE-ELM) model (Nahvi *et al.*, 2016).

Soil drying property is observed through IBM/KNN and ANN/BP by taking features such as precipitation, potential evapotranspiration data which helps to evaluate soil drying for agricultural planning (Coopersmith *et al.*, 2016). Prediction of soil organic carbon, moisture content and total nitrogen of 140 soil samples from cultivable land gave best results for soil condition properties (Morellos *et al.*, 2016)

7. **Water management:** Irrigation management plays crucial role in hydrological, climatological and agronomical balance. Mehdizadeh *et al.*, 2017 developed ML concept to estimate the evapotranspiration by observing various parameters such as maximum, minimum and mean temperature, solar radiation, relative humidity (RH) and wind speed using MARS concept. The daily dew point temperature is measured employing ANN/ELM technique which includes parameters such as average air temperature, relative humidity, atmospheric pressure, vapour pressure, and horizontal global solar radiation (Mohammadi *et al.*, 2015)

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