J. Agric. Res. Technol., Special Issue (1) : 126-129 (2022) DOI: https://doi.org/10.56228/JART.2022.SP120

Machine Learning Applications in Agriculture

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Abstract

Agriculture plays a vital role in the economic growth of the country. To meet out the food requirement of the increase of population is a challenging task with frequent changes in climatic conditions and limited resources. Smart farming have emerged as an innovative tool to address current challenges in agricultural sustainability. The mechanism that drives this cutting edge technology is machine learning (ML). It gives the machine has the ability to learn without being explicitly programmed. Machine Learning together with IoT (Internet of Things) enabled farm machinery are key components of the next agriculture revolution. Machine Learning applications in the field of agriculture are explained in this article. The areas that are focused are prediction of soil parameters such as moisture content, crop yield prediction, disease and weed detection in crops, Identify water stress in plant, Crop mapping , Crop selection prediction , Ground water level prediction: Groundwater is the largest storage of freshwater resources, which serves as the and species detection. Intelligent irrigation which includes drip irrigation and intelligent harvesting techniques are also discussed to reduces human labour to a great extent. This article demonstrates how knowledge-based agriculture can improve the sustainable productivity and quality of the product.

Key words : Machine Learning, IoT.

The population of the world will increase to 9.1 billion approximately 34% as of today by the end of 2050. Food requirement will increase by 70 percent and due to rapid urbanization, land availability for agriculture will decrease drastically in the coming years. India will be the most populated country by 2050 and presently it is already lagging the domestic food production. The main reason for reduced food production is the lack of planning, unpredictable weather conditions, improper harvesting and irrigation techniques and livestock mismanagement. In the last few years, nature has experienced a drastic change in weather conditions due to global warming. The average temperature of the earth has been increased due to which there is uncertainty in climatic conditions. Frequent droughts, heavy rainfall are the biggest challenge for poor farmers. According to the government of India annual economic survey, adverse climatic conditions, reduce the farmer's income by 20-25%. Precision agriculture [1-2] is one of the solutions to ensure food security for the entire world [3]. Precision agriculture also abbreviated as digital agriculture is a technology-enabled data-driven sustainable farm management system. It is basically the adoption of modern information technologies, software tools, and smart embedded devices for decision support in agriculture [4]. Precision farming is an important part of the third agriculture revolution [5]. Digital technologies such as IoT [6], AI, data analytics, cloud computing, and block-chain technology play a key role in precision agriculture. In precision farming, IoT based smart sensors are deployed in the agriculture land for collecting data related to soil nutrients, fertilizers, and water requirements as well as for analysing the crop growth. Autonomous and semi-autonomous devices such as an

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unmanned aerial vehicle (UAV) [7] and robots are used for identifying weed and disease in the plants using computer vision techniques. Satellite images are also used in precision agriculture for monitoring the field and identifying the diseases in the plants. The data obtained from the deployed sensors [8] are processed and analyzed using ML algorithms to make farming practice more controlled and optimized.

Machine Learning Applications

Plants and crops disease detection : In 2050, human agricultural crop yield will need to increase by an estimated 70 percent to sustain the expected population size. By a particular statistics, crop diseases currently reduce the yield of the six most important food crops by 42 percent, and some farms are wiped out entirely on an annual basis. Thus, it becomes of utmost importance to find methods by leveraging technology for accurate crop disease detection. This is where machine learning techniques can help. Deep learning algorithms can be trained on crops and plants images with good accuracy for crop disease detection. The challenge is to get the plant/crop images and then labelled images. One of the prevalent techniques used currently is Unmanned Aerial Vehicles (UAVs) paired with large-scale backend systems involving machine learning models for detecting crop diseases. In order to address the challenge associated with data collection, modeling technique such as generative adversarial network (GAN) can be used to generate synthetic data using the crop disease images. One of the other challenge for training models having high accuracy is class imbalance in the collected data. This is where DC-GAN (Deep convolutional GAN) plays a great role to alleviate the class imbalance issue by generating synthetic images. A deep convolutional neural network (CNN) model (such as EfficientNet) can then be trained to classify and detect crops / plants diseases. The CNN model can be trained to identify ailments that made their physical presence on the leaf and/or stem of the crop and detect diseases. Recall that generative adversarial networks are pairs of neural networks that are divided into two roles: generator and discriminator. The generator learns to develop synthetic images of some class, while the discriminator learns to discern between real and synthetic images. The models train off of each other to improve results.

Crop yield prediction : Predicting the crop yield accurately will help farmers know when they should start harvesting so that they can maximize their profits by selling it at an appropriate price. Crop yield prediction is about forecasting the expected yield of agriculture crops in a given period. Crop yield prediction is extremely challenging due to its dependence on multiple factors such as crop genotype, environmental factors, management practices, and their interactions. The machine learning models are built to predict crop yields by taking into consideration different factors that affect it such as weather data (temperature, rainfall), soil moisture sensors, astronomy images etc., thus predicting accurate yield values for an agriculture field before harvest time. These techniques can be used by farmers on daily basis with high accuracy which enable them to make decisions on when to harvest crops, how much pesticide needs to be applied and what fertilizers need to be used. Deep learning models can be used to predict agriculture production in large scale with an accurate estimation of the yield. This will help farmers make important decisions related to cropping patterns and crop management leading to better yields during harvest season. Algorithms such as multi-linear regression, Lasso regression, LightGBM, random forest, XGBoost and deep neural networks (CNN, LSTM etc) have been used for crop yield predictions.

Crop row detection : Crop row detection is a key element in developing vision based navigation robots in agricultural robotics. Recent work on crop row detection has used deep learning based methods thereby overcoming the major challenges in implementing a real world vision based navigation system. Some of the key aspects in crop row detection are weed density, growth stages, shadows and discontinuities etc. CNN architectures can be used for crop row detection based on weed density, growth stages, shadows etc.

Identify water stress in plant : Plant water stress may occur due to the limited availability of water to the roots/soil or due to increased transpiration. These factors adversely affect plant physiology and photosynthetic ability to the extent that it has been shown to have inhibitory effects in both growth and yield. Early identification of plant water stress status enables suitable corrective measures to be applied to obtain the expected crop yield. It is necessary to identify potential plant water stress during the early stages of growth to introduce corrective irrigation and alleviate stress. This is where machine learning techniques come into picture. Machine learning techniques can be used to estimate leaf water content (LWC) which is then further used to estimate water stress in the plants. Leaf water content (LWC) is a measure that can be used to estimate water content and identify stressed plants. LWC during the early crop growth stages is an important indicator of plant productivity and yield. Different techniques can be used for data collection. They include usage of sensors or UAVs. Usage of sensors can, however, prove to be very expensive. Ensemble and regressor methods can be used to predict the LWC value. And, classification models can be used to classify the water stress based on LWC and other parameters.

Crop mapping : Crop type mapping at the field level is critical for a variety of applications in agricultural monitoring. Crop type mapping at the field resolution is a prerequisite to mapping farm management and yield outcomes at large spatial scale. This task is all the more urgent in a time when populations in food-insecure regions continue to increase and climate change is predicted to adversely affect global agriculture. Traditionally, crop type information has been obtained from field surveys and censuses, but such surveys are expensive and time consuming to conduct. This is where machine learning techniques are applied on the satellite data for crop type maps. Classification algorithms such as LDA, random forest can be used for crop classification and mapping.

Crop selection prediction : Machine learning techniques can be used to help the farmers select the crop efficiently and maximize crop yield with minimal cost. The machine learning models can be trained to predict most appropriate crop selection and yield for different regions. One will be required to select different types of crops, identify features and then train model to classify the crop selection for different regions. Algorithms such as SVM, random forest, logistic regression, deep neural networks etc, can be used to train such models. Features used in such models can be related to weather parameters (rainfall, temperature etc.), fertilizers used, land type, soil-related information etc.

Irrigation detection : Detecting irrigation is critical to understand water usage and promote better water management. Such data will potentially enable the study of climate change impact on agricultural water sources, monitor water usage, help detect water theft and illegal agriculture and inform policy decisions and regulations related to water compliance and management. Machine learning techniques can be used for irrigation detection. However, this is a complex problem to solve with the help of ML techniques due to the lack of curated and labelled data available that are centered around irrigation systems. This is where pre-trained models can help. This will be classification models and the target label is a binary variable indicating whether the land in the image is permanently irrigated or not. CNN models can be trained to classify the land as irrigated or otherwise.

Ground water level prediction : Groundwater is the largest storage of freshwater resources, which serves as the major inventory for most of the human consumption through agriculture, industrial, and domestic water supply. Deep neural networks can be trained to forecast ground-water levels. Deep learning methods are known to produce accurate results even with the limited information available in this case, which is mostly satellite data and hydro-meteorological parameters.

Machine learning applications are more prevalent in agriculture than you might think. The agriculture industry has a lot of data, but they may not know how to leverage it with machine learning models for better crop selection and yield prediction.

Iot Applications In Precision Agriculture : Precision agriculture refers to a system with minimizing direct involvement of the caretaker/farmer except when there is an urgent need or an emergency i.e. when there is a failure in the system. IoT helps in maintaining the defined standards of parameters needed for day to day work in agriculture. The parameters can be measured using the required sensors and can be uploaded to an IoT cloud for remote monitoring so that the direct involvement of farmers is minimized. The IoT cloud can be used for control purposes also, say for example in detecting and avoiding animal intrusion in the agriculture field. Sensors are an integral part of IoT for precision agriculture without which the monitoring and controlling becomes next to impossible task. Figure 6 shows the trend search of keywords “IoT in agriculture” and “sensor in agriculture” on google in the last 10 years. Apart from monitoring and controlling, IoT in agriculture is also used as datastorage technology. Parameters like properties of soil, crop yield, seasonal behaviour data, temperature changes, etc can be stored on the IoT cloud which will be helpful in analyses, prediction, and deciding on estimated crop production.

Conclusion

Precision agriculture is empowering the farmers with technology intending to get optimum outputs with precise inputs. IoT enabled smart sensors, actuators, satellite images, robots, drones are some of the key technological revolutions that boosted the agriculture industry. These components play a vital role in collecting real-time data and accordingly making decisions without human support. Artificial intelligence which is the automation of intelligent behaviour is continuously benefiting our planet and helping humans in various aspects of life. The impact of AI and IoT in smart farm management is discussed with a brief introduction to ML application in agriculture.

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