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A Survey on Applications of Machine Learning in Agriculture

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Abstract - *The population is increasing daily with fast speed and most of the people depend on agriculture for their livelihood. Although agriculture provides a huge contribution in the Indian Economy. In spite of significant advances in the service sector, agriculture remains the foremost supplier of employment and source of revenue in Asian countries. The process of modernization of agriculture reduces the laborious work and motivates the farmers for doing smart farming. Artificial Intelligence plays a vital role in the smart farming concept. Artificial Intelligence is a trending topic for the advancement of the agriculture field. Machine Learning is one of the subareas of Artificial Intelligence. Machine Learning would ensure the increase of crop quality and quantity by using supervised and unsupervised techniques. Some of the application areas of machine learning are given i.e. automated irrigation systems, agricultural drones for field analysis, crop monitoring systems, precision agriculture, animal identification and health monitoring, etc. This paper gives an overview of crop disease identification, weed detection, yield prediction, soil management.*

***Key Words*: Artificial Intelligence, Machine Learning, crop disease identification, weed detection, yield prediction, soil management.**

1. INTRODUCTION

India is the 7th largest country in the world and more than 50% population depends on agriculture and allied activities. As India has diversified region different varieties of crops are cultivated. So the agrarian economy plays a vital role in the Indian economy. Because of frequently changing climate farmers are facing many problems related to crop quality and quantity. Thus sufficient yield has not been produced. Due to the rapidly increasing of population, agricultural land is converting to urbanized and commercial area which reduces land availability for crop production. Now it's a necessity of society to cultivate qualitative and quantitative cop in the limited field area.

Nowadays the modernization of agriculture is on the priority list of the government. Modernization of agriculture is a process of transforming agriculture from traditional labor-based agriculture to technology-based agriculture [1]. This process makes a profit for farmers as well as the Indian economy. The Ministry of Human Resource Development has launched a program called Unnat Bharat Abhiyan which is inspired by the vision of transformational change in rural development processes. The mission of Unnat Bharat Abhiyan is to enable higher educational institutions to work with the people of rural India in identifying development challenges and evolving appropriate solutions for accelerating sustainable growth [2].

A new concept of Smart Farming is a hot topic worldwide. Smart farming is a farming management concept using modern technology to increase the quantity and quality of agricultural products [3]. In this concept, artificial intelligence, automation and robotics, sensing technologies, agricultural drones, IoT applications, positioning technologies are widely used. Artificial Intelligence is an area of computer science that accentuates the formation of intelligent machines that work and behave like humans. AI has many subfields such as Machine Learning, Neural Networks, Robotics, Expert System, Natural Language Processing, etc.

Machine Learning is an application of artificial intelligence that provides systems the ability to automatically learn and take the decision from experience without being explicitly programmed. Nowadays, Machine Learning is playing a vital role in the improvement of agriculture. ML techniques are categorized in supervised, unsupervised and reinforcement. The daily life farmer's problems from seed sowing to harvesting of crops can be resolved by using machine learning algorithms.

The rest of this paper is organized as follows. The various application areas of machine learning are presented in section 2. In this paper crop monitoring system is focused which gives an overview of crop disease identification, weed detection, yield prediction and soil management. The conclusion of this paper is provided in section 3.

2. APPLICATIONS OF MACHINE LEARNING

Machine Learning is the future key to precise farming. The various algorithms of machine learning are effectively helping in agricultural problems. The use of machine learning in agriculture a hot topic for researchers from all over the world. Here, some of the application areas of machine learning are given i.e. automated irrigation systems, agricultural drones for field analysis, crop monitoring systems, precision agriculture, animal identification and health monitoring, etc. The crop monitoring system includes crop disease identification, weed detection, yield prediction, soil management.

2.1 Crop Disease Identification

Crop disease is outlined as “anything that stops a plant from performing routine activity to its most potential.” Crop disease involves any harmful deviation or alteration from the traditional functioning of the physiological processes. The various diseases occur on various plants and fruits. Due to crop diseases annually farmer faces crop yield losses of 20-40%.

ML techniques achieved a better success rate higher than 95% in plant disease detection with different algorithms [4]. Sankaran and Ehsani detected the citrus leaves infected by Huanglongbing disease by victimization the spectral options extracted from the fluorescence imaging under both laboratory and field conditions. The results showed that fluorescence spectral options with NB have a capability to properly classify the 90.1% of observations (infected and healthy both) within the laboratory dataset, whereas the accuracy was dropped to 68.3% for field dataset [5]. Bandi used textural options extracted from HSI color co-occurrence matrices (CCMs) with NB to spot three common diseases on citrus leaves with an overall accuracy of 95% [6].

Phadikar identified different types of diseases on rice leaves using the Fermi energy-based segmentation method followed by the extraction of color and shape features. The shape of the infected region was used to determine the shape of the spot based on two steps genetic algorithm consisting of locating the center of spot followed by positioning the set of primitive shapes at the center of the spot. The NB classifier trained on the extracted color and shape features indicated a maximum classification accuracy of 91.39% [7].

Mondal identified the okra and bitter gourd leaves infected by the yellow vein mosaic virus using a combination of color and textural features along with the NB classifier. The success rates for the right identification of diseases were found to be 95% and 82.67% for okra and bitter gourd, severally [8].

Dubey and Jalal used the K-means clustering technique for defect segmentation at the side of a multiclass SVMs classifier to classify among different types of diseases common to apple fruit. The results showed that their system was ready to properly classify 93% of apple diseases [9].

Zhang used the K-means clustering algorithm for segmenting the diseased portions of the cucumber leaves followed by training five multiclass classifiers to differentiate among seven diseases. The results showed that the very best classification accuracy (91.25%) was achieved for grey mold [10].

The SVMs based ML technique is successful and applied different areas of agricultural machine vision systems like plant disease detection [11]. Naive Bayes classifier, Decision Tree (DT), Random Forests (RF), Support Vector Machine (SVM), AdaBoost and Logistic Regression (LR) were accustomed create choices concerning insecticide application for leaf roller pest monitoring on kiwifruit [12].

2.2 Weed Detection

A weed could be a plant thought-about undesirable in a very specific scenario, "a plant within the wrong place". Some traits of weedy species are the flexibility to breed quickly, disperse wide, sleep in a spread of habitats, establish a population in strange places, achieve disturbed ecosystems and resist demolition once established. Weed management is very important in agriculture. Weed management strategies vary in line with the expansion habit of the weeds in queries. Crop weeds will inhibit the expansion of crops, contaminate harvested crops and infrequently unfold speedily. They will conjointly host crop pests like aphids, plant life rots and viruses.

The naive Bayes, k-means clustering, support vector machines (SVMs) and kNN based ML algorithms were utilized for weed detection at the side of the machine vision system and yielded as a successful solution having a higher success rate for all cases [13].

Mursalin and Mesbah-Ul-Awal identified four different weeds in capsicum fields using nine different shape features in conjunction with NB. The typical accuracy rate was found to be 98.9% [14]. In addition to the HSI color space, the concept of CCM was conjointly enforced on the luminance color space for the identification of various weeds within the wild blueberry cropping system. The highest classification accuracy of the reduced feature set (94.9%) was achieved by HSI color space [15].

In recent decades there has been rising interest in pest and disease detection [16][17][18] and within the automation of weed sprayers [19]. A sensible sprayer system has to be able to find weed spots in real-time and manage to spray the specified chemical solely on the exact location. Song analyzed numerous sensors and techniques for weed detection as machine vision, spectral analysis, remote sensing and thermal images [20].

Kargar and Shirzadifar developed a machine vision weed spot-sprayer on corn crops. The system used image segmentation and feature extraction to identify the grass leaves apart from corn plants on over 90% accuracy. It is to be noted that in this case, the corn leaves are much wider than the grass, that will increase the detection accuracy [21].

A precision spray technology will considerably cut back the number of weed killers needed, compared with traditional broadcast sprayers that typically treat the complete field to control pest populations, which probably leads to the unnecessary application to areas that do not need treatment. Applying weed killer solely wherever weeds occur could cut back prices, risk of crop damage and excess pesticide residue, as well as potentially reduce environmental impact [22].

In this paper, a low-priced and smart technology for precision weed management (for specialty crops) is given and evaluated. This technology utilizes Artificial Intelligence (aka. deep and transfer learning) to differentiate between target and non-target plants in real-time, and spray solely on a particular target (e.g. specific weed). The utilized deep learning neural network analyzes rather more advanced properties than an image segmentation alone, thus, it may be used to distinguish weeds from crop plants on a variety of situations (e.g. open field environment) [23].

2.3 Yield Prediction

The agriculture yield prediction is that the toughest task for agricultural departments across the world. The agriculture yield depends on varied factors. In India, the majority of agriculture growth depends on rainwater, which is very unpredictable. Agriculture growth depends on completely different parameters, specifically water, nitrogen, weather, soil characteristics, crop rotation, soil wetness, surface temperature, and rainwater etc.

The wheat yield was classified and expected by J48, K-nearest neighbors (KNN), One-R and Apriori classifier methods using phenotypic plant traits as inputs [24]. Using supervised Kohonen and counter-propagation neural networks, the wheat yield has been quantified as low, medium and high [25]. Gndinger and Schmidhalter explore the digital count of maize plants using DIP methodologies, first isolating the corn plants of collected aerial images through color spectral variations and so correlating the number of green pixels present in the image with manual counting of the plants [26].

Fan proposed a brand new algorithm based on deep neural networks to sight tobacco plants in images captured by UAVs. Three stages were assumed during this approach: first, the extraction of many candidate tobacco plants using morphological operations and the watershed segmentation.

Then, the classification of candidate tobacco and nontobacco plants was created employing a deep convolutional network, followed by a step of post-processing to boost the exclusion of nontobacco plant regions [27]. In this research work, with the assistance of UAVs field images are captured. The images can be used to evaluate the quality of plants, consistency of the planted crop. The overall no. of plants is counted from these aerial images [28]. The various ML techniques are available for this purpose. The similar work is also carried out by these authors [29][30][31].

This paper proposes a totally automatic system for grapevine yield estimation, comprised of strong shoot detection and yield estimation based on shoot counts made from videos. Experiments were conducted on four vine blocks across two cultivars and trellis systems over two seasons. A completely unique shoot detection framework is presented, including image processing, feature extraction, unsupervised feature selection, and unsupervised learning as a final classification step. Then a procedure for converting shoot counts from videos to yield estimates is introduced. In this paper, a totally automatic system for grapevine yield estimation by visual shoot detection has been conferred. It combines a robust shoot detection framework with an algorithm and method for converting the image processing results to actual shoot counts using only a GoPro camera, backing board and vehicle [32].

The author used ML to estimate the yield of Sorghum. Here, a drone flies from the field of sorghum & capture the images. This system is already trained to detect ears of sorghum on images. The weight estimation is done in order to calculate total yield with the help of deep learning. This system has an average accuracy of 74.5% [33].

2.4 Soil Management

The technological enhancement of the treatment of soil acidity, multiple nutrient deficiencies, and plant health management helps to revive the agriculture sector. This, in turn, produces a rise in productivity from the present levels. The most reason for an important loss in soil quality is because of the inaccurate soil and crop management strategies. Also, excess use of chemical fertilizers has created imbalances within the availability of soil nutrients.

The interest in predicting the amount of these soil parameters with ML techniques helps in reducing the unneeded defrayment on fertilizer inputs and analyses soil health and environmental quality. Extreme Learning Machine (ELM) methods are one of the second generation neural network methods, which are appropriate for classification issues similarly to get instant classification and prediction results. Incorrect soil and crop management practices throughout cultivation have given rise to an important loss in soil quality [34]. Chemical fertilizers employed in excess have created imbalances with the availability of soil nutrients.

Enhanced productivity may well be achieved through effective soil resource management and corrective measures to use micronutrients. These days the prediction and classification problems are effectively handled by Machine Learning (ML) techniques. In earlier days of ML techniques, the Levenberg-Marquardt based back-propagation method in the Artificial neural networks (ANNs) was used to predict the soil fertility [35]. Partial least squares regression was additionally used to forecast the soil fertility using the available water capacity, electrical conductivity (EC), clay loam, silt loam, sandy loam soils, soil OC and soil bulk density [36].

An unbiased linear predictor was used to predict soil organic carbon [37]. The organic carbon on Sicilian soils was foreseen by using the boosted regression trees [38]. The random forest has been combined with the feature choice methodology of genetic algorithms to predict organic carbon in soils of eastern Australia [39]. Totally different machine learning approaches were used to predict the soil nutrient content, soil type and soil moisture [40].

Machine Learning techniques facilitate within the domain of agriculture and will support data analysis for creating predictions. In the future, the classification of soil nutrients N2O, P2O5, and K2O using efficient and fast ELM methods or any advanced neural network techniques are often used for fertilizer recommendation for the specified crop.

3. CONCLUSIONS

The modernization of agriculture will improve the situation of Indian farmers which will boost the agrarian economy as well. Artificial Intelligence can play the role of an expert person which will be beneficial in daily routine operations in the field. The problems faced by farmers from sowing the seeds until harvesting will be resolved by the machine learning. Many algorithms based on the supervised and unsupervised techniques of machine learning playing a major role in various sectors of agriculture. The various algorithms of machine learning can perform tasks such as identifying fruit disease, damages caused by insects, counting of fruits, to determine soil, texture, color, slope, plant recognition, crop management, fruit grading, nutrition deficiency, plant phenotyping, etc. This paper gives an idea about crop management system which includes crop disease identification, weed detection, yield prediction, soil management.

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