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Application of Machine Learning in Agriculture: A Review

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Abstract: In the world economy, agriculture plays a vital role. With the ongoing growth of the human population, stresses on the agricultural sector will intensify. With big data innovations and high-performance computing, machine learning has evolved to create new prospects for data-intensive research in the area of multi-disciplinary agro-technology. This paper provides a systematic analysis of studies on machine learning technologies in agricultural production systems. The evaluated works were classified into (a) crop control, including introduction of yield estimation, disease detection, crop quality weed detection, and recognition of species; (b) Livestock Management and (c) water management. The filtering and sorting of the papers discussed illustrate how machine learning technology can support agriculture. Farm management systems are transforming into real-time artificial intelligence powered programmes by implementing machine learning to sensor data that offer rich recommendations and observations for farmer decision support and intervention that contribute to more detailed and quicker decision-making.

Keywords: artificial intelligence, crop management, livestock management, water management.

INTRODUCTION

In the world economy, agriculture plays a vital role. With the ongoing growth of the human population, stresses on the agricultural sector will intensify. As new research areas have evolved, agri-technology and precision farming, now often referred to as digital agriculture, use data-intensive methods to drive agricultural production while minimising its effects on the environment. A number of different sensors provide the data produced in modern agricultural operations, providing a better understanding of the operating environment and the process itself (data from machinery), contributing to more detailed and faster decision-making.

Together with big data technology and high-performance computing, Machine Learning (ML) has arisen to generate fresh ways to unravel, measure, and grasp data-intensive processes in agricultural operating environments [2]. ML is known as the scientific area that gives machines the ability to learn without it being specifically configured, among other meanings. Year after year, ML is increasingly used in research fields such as bioinformatics, biochemistry, medicine, meteorology, economics, robotics, aquaculture, food safety and climatology. A systematic analysis of the application of ML in agriculture is provided in the current report. A variety of related papers that emphasise main and special features of common ML cases are discussed [1].

LITERATURE REVIEW

At the first step, the reports examined were categorised into four general categories: crop management, Livestock management, and water management. ML applications in the seed segment is classified into sub-categories, including yield estimation, disease identification, efficiency of crop weed detection, and recognition of organisms.

Yield Prediction

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For yield mapping, yield calculation, balancing crop supply with demand, and crop management to maximise productivity, yield prediction, one of the most important subjects in precision agriculture, is of high importance. Instances of ML applications provide an effective, low-cost, and non-destructive process that automatically counts coffee fruit on a division of those in the projects. The system measures the three types of coffee fruits: harvestable, not harvestable, and fruits with a maturation period that is not taken into account. In addition, the process measured the weight of the coffee fruits and the proportion of growth and development [4]. The objective of this paper is to provide the coffee growers with knowledge to maximise the economic advantages and schedule their agricultural work. Another research used for yield estimation is that of the authors, in which a machine vision device was developed to automate shaking and collecting cherries during harvest. And where these are discrete, the machine segments and detects occluded cherry trees with full foliage. In physical harvesting and handling procedures, the main purpose of the system was to eliminate labour requirements. In another research, the authors built an early yield mapping method to classify immature green citrus in outdoor conditions in a citrus grove. Like all other comparative research, the purpose of the analysis was to provide yield-specific knowledge to growers to help them maximise their yield in terms of benefit and improved yield.

In another report, the authors created a methodology focused on ANNs and multitemporal remote sensing data for grassland biomass estimation (kg dry matter/ha/day). Another research was discussed in another study devoted to yield prediction, and especially to wheat yield prediction [5]. For a more reliable forecast, the established method used satellite imagery and obtained crop growth characteristic fusion with soil data. The author proposed an EM-based system for detecting tomatoes and remotely sensed Red Green Blue (RGB) photographs collected by unmanned aerial vehicles (UAV). In addition, the authors developed a system for the prediction of the rice production stage based on SVM and simple geographical details collected from weather stations in China in their work. Ultimately, in another report, a generalised framework for agricultural yield forecasts was presented. The method is based on an ENN implementation on agronomical information gathered over a long period (1997-2014). The study focuses on regional forecasts (specifically in Taiwan) to help farmers prevent market supply and demand imbalances triggered or accelerated by the nature of crops harvested.

Disease Detection

The sub-categories with the larger number of publications discussed in this review are disease diagnosis and yield estimation. Pest and disease management in open-air (arable farming) and greenhouse environments is one of the most important issues in agriculture. In pest and disease control, the most commonly used method is to spray pesticides evenly over the cropping area. This practise has a high financial and substantial environmental expense, although it is successful. Residues of agricultural goods, side effects on pollution of ground water, effects on local wildlife and habitat, and so on, may have environmental effects. ML is an integrated part of the management of precision farming, where the input of agrochemicals is directed in terms of time and location. A technique for the diagnosis and classification of healthy Silybum marianum plants and those contaminated by the smut fungus Microbotyum silybum during vegetative growth is described in the literature. In their work, the authors created a new system for real-time control based on the image analysis protocol for the classification of parasites and the automated identification of thrips in the strawberry greenhouse environment. A system for identification and screening of Bakanae disease in rice seedlings was proposed by the authors. More precisely, the goal of the analysis was to reliably detect the pathogen Fusarium fujikuroi

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in two rice varieties. Compared to naked eye inspections, the automatic identification of contaminated plants increased crop yield and was less time consuming.

Weed Detection

Another critical issue in agriculture is weed identification and control. Most farmers refer to weeds as the most serious obstacle to the production of crops. For sustainable agriculture, effective identification of weeds is of high significance, as weeds are difficult to identify and discriminate against crops. Again, in combination with sensors, ML algorithms can lead to precise identification and classification of low-cost weeds without environmental concerns and adverse effects. ML for weed detection can allow instruments and robots to be built to kill weeds, reducing the need for herbicides. Two experiments have been reported on ML applications in the fields for weed detection problems [7]. A new approach based on counter propagation (CP)-ANN and multispectral images taken by unmanned aircraft systems (UAS) for the detection of Silybum marianum, a weed that is difficult to eliminate and causes large crop yield losses, was proposed by the authors in the first report. In the second research, the authors created a new approach for crop and weed species identification based on ML techniques and hyperspectral imaging. More specifically, the writers built an adaptive learning method to identify maize (Zea mayas) as a crop plant species and as weed species, Ranunculus repens, Cirsium arvense, Sinapis arvensis, Stellaria media, Tarraxacum officinale, Poa annua, Polygonum persicaria, Urtica dioica, Oxalis europaea, and Medicago lupulina. Precise identification and discrimination of these animals for economic and environmental reasons was the main target. The researchers designed a weed detection system based on SVN in grassland cultivation in another study.

Crop Quality

Studies formed for the recognition of features linked to crop quality are the penultimate sub-division for the crop category. Precise identification and classification of the characteristics of crop quality will improve the price of goods and minimise waste. A new method for the identification and classification of botanical and non-botanical foreign matter embedded within cotton lint during harvesting was introduced and established in the first analysis by the authors. Quality enhancement thus mitigating fibre damage was the goal of the analysis. Another research involves the development of pears and, more precisely, a system for the identification and differentiation of Korla fragrant pears into groups of deciduous-calyx or persistent-calyx has been developed. ML techniques with hyperspectral reflectance imaging were used in the approach. The final research for this sub-category was undertaken by the authors of the study, who proposed a tool for predicting and classifying the geographical origin of rice fields. The method was based on ML technologies available to sample chemical components. More precisely, the key purpose was to classify the geographical sources of rice for Brazil's two distinct climatic regions: Goias and Rio Grande do Sul. The findings revealed that the four most important chemical components for sample classification are Cd, Rb, Mg, and K [2].

Species Recognition

Recognition of plants is the last sub-division of the seed category. The primary aim is to automatically recognise and label plant species in order to prevent the use of human experts, and to minimise the time for classification. A method was proposed for the recognition and characterization of three species of legumes, namely white beans, red beans, and soybeans, through leaf vein patterns. The anatomy of veins holds detailed knowledge regarding the properties of the leaf. In relation to colour and type, it is an excellent method for plant identification [3].

LIVESTOCK AND WATER MANAGEMENT

The division of livestock consists of two subcategories, namely animal care and the development of livestock. Animal care is concerned with animal health and well-being, with the primary use of ML to track animal activity for early disease identification. In the other hand, animal farming deals with problems in the processing industry, where the key scope of ML applications is the exact calculation of the producers' economic balances based on the tracking of the production line [10].

In agricultural development, water conservation involves considerable efforts and plays an important role in hydrological, climatological, and agronomic equilibrium. This segment consists of four reports, most of which were produced to estimate evapotranspiration daily, weekly, or monthly. The exact calculation of evapotranspiration is a dynamic process and is of great significance for resource management in the cultivation of crops, and also for irrigation system architecture and operational management. In another research, for arid and semi-arid areas, the authors created a computational tool for estimating monthly mean evapotranspiration. Over the period 1951-2010, it used monthly average temperature data from 44 meteorological stations. Two scenarios for estimating daily evapotranspiration from temperature data obtained from six meteorological stations in an area over a long duration were proposed in another study devoted to ML applications for agricultural water management. Eventually, the researchers designed a program based on an ELM model fed with temperature data for the weekly calculation of evapotranspiration for two meteorological weather stations in another report. The goal was to correctly predict weekly evapotranspiration in arid regions of India based on a scenario of minimal data for the conservation of crop water.

CONCLUSION

Farm management systems are transforming into actual artificial intelligence systems by implementing machine learning to sensor data, giving richer suggestions and observations for future decisions and activities with the ultimate reach of change in development. With this scope, the use of ML models is expected to become much more common in the future, increasing the possibility of integrated and applicable devices. At the present, both methods consider individual approaches and strategies and, as seen in other implementation areas, are not sufficiently related to the decision-making process. This incorporation of automatic recording data, data processing, application of ML and decision-making or assistance would include realistic payments, compatible with so-called knowledge-based farming, to improve production levels and the efficiency of bio-products.

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