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Machine Learning in Agriculture

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Abstract:

Agriculture has undergone a digital revolution that has transformed many managerial functions into artificially intelligent systems in an effort to extract value from the growing amount of data coming from diverse sources. Machine learning, a branch of artificial intelligence, offers a great deal of promise for addressing many difficulties in the development of knowledge-based agricultural systems. By carefully evaluating recent academic literature using the keywords "machine learning" combined with "crop management," "water management," "soil management," and "livestock management," the current study intends to shed light on machine learning in agriculture.

Keywords: Machine learning, Precision agriculture, crop management, livestock production.

Introduction:

General Context of Machine Learning in Agriculture

The increasing demand for food brought on by the world's population boom, climate change, resource depletion, altered dietary preferences, and safety and health concerns are just a few of the difficulties that modern agriculture must overcome. There is an urgent need to maximize the efficiency of agricultural methods while concurrently reducing the environmental load in order to solve the problems, which put strain on the agricultural sector. These two components have fueled the transition from agricultural to precision agriculture. The modernization of agriculture has a huge potential to provide environmental safety, maximum productivity, and sustainability (Lampridi et al., 2019). The use of Information and Communication Technology (ICT), which is supported by policymakers across the world, is unquestionably a necessary requirement for contemporary agriculture. Farm management information systems, soil and humidity sensors, accelerometers, wireless sensor networks,

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cameras, drones, inexpensive satellites, internet services, and autonomous guided vehicles are only a few examples of ICT (Sørensen et al., 2019).

The management of crops, water, soil, and animals is covered by these categories as shown in Figure 1. In instance, crop management comprised the bulk of articles across all categories (61% of all articles), and it was further broken into: • Yield prediction; • Disease detection; • Weed detection; • Crop recognition; • Crop quality

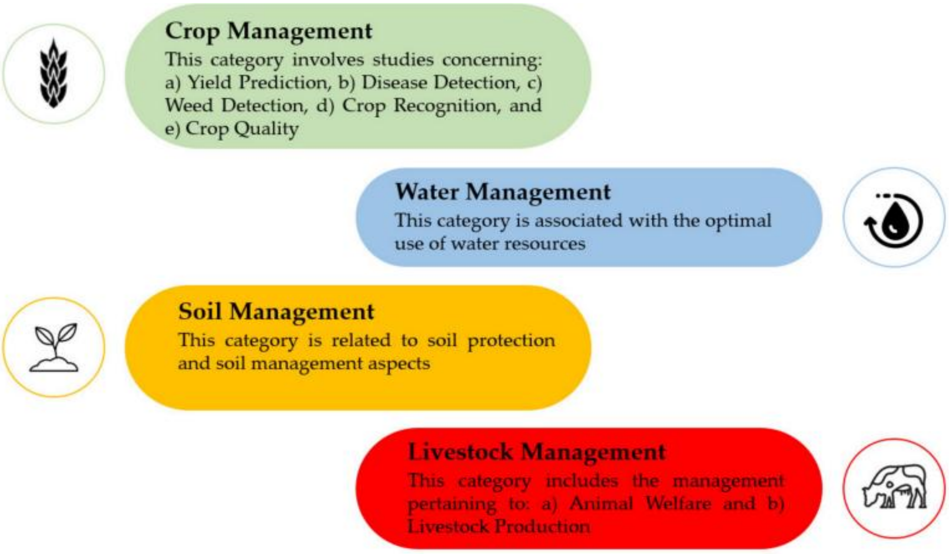

Figure 1. The four generic categories in agriculture exploiting machine learning techniques, as presented in (Liakos et al., 2018).

Crop Management: Crop management is a broad category that includes a variety of elements that result from the blending of agricultural methods in the direction of regulating the biological, chemical, and physical crop environment with the goal of achieving both quantitative and qualitative objectives. Utilizing cutting-edge methods for crop management, such as yield forecasting, disease and weed detection, crop identification, and crop quality assessment, helps to boost production and, as a result, monetary income (Yvoz et al., 2020).

Yield Prediction: One of the most significant and difficult subjects in modern agriculture is yield prediction. Numerous variables, including the environment, management techniques, crop genotypic and phenotypic traits, and their interactions, might affect yield prediction. A fundamental understanding of the connection between these interacting parameters and yield is thus required (Van Klompenburg et al., 2022).

Disease Detection: In agricultural production systems, crop diseases pose a serious risk because they reduce yield quality and quantity at the production, storage, and transportation levels. An essential component of effective management is the prompt diagnosis of plant diseases. Different types of bacteria, fungus, pests, viruses, and other agents can cause plant illnesses. Agronomists with advanced training used to do field scouting to find diseases. Recent technical developments have enabled commercially accessible sensing devices to recognize afflicted plants before the symptoms manifest. Additionally, a sizable dataset of photos of healthy and sick plants is required for precise image classifiers for disease identification. Such automated procedures can be coupled with autonomous vehicles in the context of large-scale cultivations in order to undertake routine inspections that promptly identify Phyto pathological issues. Maps showing the regions of the farm where the infection has spread can also be made to show the geographical distribution of the plant disease (Anagnostis et al., 2021).

Weed Detection: Weeds typically develop and spread invasively across huge areas of the field very quickly due to their prolific seed production and lifespan, competing with crops for resources like space, sunshine, nutrients, and water availability. Additionally, since they don't have to contend with natural enemies, weeds usually emerge earlier than crops, which negatively impacts crop growth (Su 2020). Herbicide application is the most popular procedure because mechanical treatment is sometimes challenging to carry out and ineffective if done incorrectly. However, using a lot of herbicides ends up being expensive and bad for the environment, especially if they're applied uniformly without taking the weeds' geographical distribution into consideration.

Crop Recognition: In a number of scientific disciplines, including plant taxonomy, botanical gardens, and the discovery of new species, automatic recognition of crops has drawn a lot of interest. Analysis of a variety of plant parts, such as leaves, stems, fruits, flowers, roots, and seeds, can be used to identify and categorize different species of plants (Zhang et al., 2020). The most popular method appears to be leaf-based plant recognition, which looks at individual leaf properties including colour, shape, and texture. Crop categorization by remote sensing has grown in popularity as a result of the increased usage of satellites and other aerial vehicles to detect crop attributes. Similar to the aforementioned subcategories, automatic crop detection and categorization have been made possible by advancements in computer software, image processing hardware, and machine learning (ML).

Crop Quality: The market heavily depends on crop quality, which is often influenced by factors like soil and climatic conditions, cultivation techniques, and crop features, to name a few. Agricultural producers often make more money when selling high-quality products because they can command higher prices. Both high-value crops (tree crops, grapes, vegetables, herbs, etc.) and arable crops have quality characteristics that are highly influenced by the date of harvesting. Furthermore, crop quality is intimately related to food waste, which presents another difficulty for modern agriculture to overcome since crops that don't conform to the ideal shape, colour, or size may be discarded. Similar to the aforementioned part, ML algorithms in conjunction with image technology can yield promising results (Papageorgiou et al., 2018).

Water Management

On a worldwide scale, the agricultural industry is the primary consumer of fresh water since plant growth is heavily dependent on water availability. More effective water management is required in order to better save water in order to achieve sustainable agricultural production, taking into consideration the high depletion rate of many aquifers with limited recharge (Neupane and Guo, 2019). Effective water management can also result in increased water quality, less pollution, and lowered health concerns. Variable-rate irrigation may be used to achieve water savings, according to a recent study on precision farming. Instead of employing a consistent rate throughout the field, this may be achieved by conducting irrigation at rates that vary based on field variability and the unique water requirements of various management zones. To achieve both water conservation and yield optimization, the success and viability of the variable rate irrigation system depend on agronomic parameters, including topography, soil characteristics, and their impact on soil water.

Soil Management: The mechanisms and activities that go on in soil, a diverse natural resource, are extremely complicated. Regionally specific soil data is essential for improving soil management in line with the potential of the land and, more generally, for sustainable agriculture (Lampridi et al., 2019). Due to problems like soil erosion, soil nutrient imbalance brought on by excessive fertiliser usage, and land degradation (loss of biological productivity), better soil management is also very important (as a result of vegetation overcutting, improper crop rotations rather than balanced ones, livestock overgrazing, and

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unsustainable fallow periods). Texture, organic matter, and nutrient content are a few examples of useful soil characteristics. Traditional soil evaluation techniques include laboratory analysis and soil sampling, which are typically costly and require a lot of time and effort. For the investigation of soil spatial variability, remote sensing and soil mapping sensors can offer a simple, low-cost approach. When using conventional data analysis techniques, data fusion and the handling of such heterogeneous "big data" may have significant disadvantages. A dependable, affordable solution for this problem can be found using ML approaches.

Livestock Management: It is generally acknowledged that livestock production methods have become more intensive in terms of productivity per animal. This intensification incorporates societal issues that have the potential to affect how consumers perceive the security, safety, and sustainability of their food supply in relation to human health and animal welfare. For example, monitoring both animal welfare and total productivity is crucial for enhancing production systems (Fournel et al., 2017). The aforementioned areas are part of precision livestock farming, which aims to use engineering approaches to monitor animal health in real time, identify warning signs, and enhance productivity in the early phases. As livestock owners' decision-making processes are supported and their roles are altered, the importance of precision livestock farming grows. In addition to monitoring the goods' quality and animal welfare as needed by policymakers, it can also make the products' tracability easier. Non-invasive sensors, including cameras, accelerometers, gyroscopes, radio-frequency identification systems, pedometers, and optical and temperature sensors, are essential for precision livestock production. IoT sensors use variable physical quantities (VPQs) to detect things like humidity, sound, and temperature. For instance, real-time alerts from IoT sensors can provide important information on specific animals if a VPQ exceeds normal bounds. As a result, it will be less expensive to inspect each animal one by one, repeatedly and laboriously. Modern cattle husbandry now uses ML approaches on a regular basis to benefit from the abundance of data. It is possible to create models that can describe how a biological system behaves by depending on causal linkages and utilising this biological knowledge to produce predictions and suggestions.

Animal Welfare: Since animal health is closely linked to product quality, which in turn has a major impact on consumer health and, indirectly, on increasing economic efficiency, there is

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a persistent concern for animal welfare (Wathes et al., 2008). Animal wellbeing may be assessed using a variety of metrics, such as behavioural and physiological stress markers. Animal behaviour, which may be influenced by illnesses, emotions, and living situations and may reveal physiological problems, is the most often used indication.Commonly used sensors for detecting behavioural change include microphone systems, cameras, accelerometers, etc. (examples include changes in water or food consumption or decreased animal activity). Animal Production Advanced machine learning techniques used in conjunction with sensor technologies can boost the productivity of cattle. Owners of cattle are becoming more protective of their investment due to the effects of animal management techniques on productive aspects. However, as livestock holdings grow, it becomes increasingly challenging to properly evaluate each animal.According to this viewpoint, the above-mentioned support for farmers through precision livestock farming is a positive development for factors related to economic efficiency and the creation of sustainable workplaces with little environmental impact. Animal production has historically employed a variety of approaches, with the general goal of raising and feeding animals as efficiently as possible. Again, though, the sheer amount of data involved necessitates the use of ML techniques.

Open Problems Associated with Machine Learning in Agriculture

Numerous evaluations have been published in this area of study because of the wide range of ML applications in agriculture. The detection of agricultural diseases, weeds, yield prediction, crop identification, water management, animal welfare, and livestock production have received the bulk of attention in these review studies (Ellis et al., 2020;Lovarelli et al., 2020). In addition, several studies focused on the application of ML techniques to the primary grain crops by examining various factors, such as quality and disease detection. Last but not least, attention has been given to large data analysis using ML with the goal of identifying practical issues resulting from smart farming or addressing approaches to analyse hyper spectral and multispectral data. Despite the fact that machine learning in agriculture has advanced significantly, there are still a number of unresolved issues that share some common ground. Additionally, it has been noted that scalable computing architectures and more effective machine learning (ML) techniques are required for rapid information processing. The difficult backdrop has also been highlighted in relation to capturing photos, videos, or audio recordings because of variations in illumination, camera blind spots, background noise, and simultaneous vocalizations. Another significant unresolved issue is that most farmers lack ML expertise, making it difficult for them to properly understand the underlying patterns discovered by ML algorithms. More user-friendly systems should be created as a result. Specific Smartphone applications have been suggested as a potential way to solve the aforementioned difficulty, taking into consideration that farmers are becoming increasingly used to smart phones. Last but not least, in order to build practical solutions, it is important to promote the development of effective ML approaches by merging expert knowledge from many stakeholders, notably in computer science, agriculture, and the commercial sector (Patrício et al., 2018).

The main benefit of machine learning:

i. Its ability to automate and improve the accuracy of complex tasks.
ii. Machine learning algorithms can be used to identify patterns in large datasets, make predictions, and automate decision-making processes.
iii. This can help businesses save time and money, as well as improve customer service and satisfaction.
iv. Machine learning can also be used to detect fraud, improve cyber security, and optimize marketing campaigns.

Conclusion:

Machine learning has the potential to revolutionize agriculture by increasing efficiency and productivity while reducing costs. The application of machine learning in agriculture can be divided into two main categories: precision agriculture and agri-food analysis. Precision agriculture involves the use of machine learning algorithms to gather data from various sources such as weather, soil, and yield sensors to make informed decisions about farm management. For example, machine learning algorithms can be used to optimize irrigation systems, predict crop yields, and identify disease outbreaks. The goal of precision agriculture is to maximize yield while minimizing inputs such as water, fertilizer, and pesticides.

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