Machine Learning in Smart Farming

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Machine learning applications are having a great impact on the global economy by transforming the data processing method and decision making. Agriculture is one of the fields where the impact is significant, considering the global crisis for food supply.

crop prediction machine learning feature selection artificial intelligent smart farming

1. Introduction

Agriculture is a vital element that has a significant role in nourishing the world's growing population. To keep pace with the increasing demand for foodstuffs, farmers need to make the best use of them to reap output while minimizing losses. Forecasting and examining reap growth is a serious part of modern agriculture, and machine learning has become a powerful tool to achieve this goal line [1][2]. Smart farming, or precision agriculture, is a modern farming conduct that utilizes recent technology to optimize reap production and minimize waste. Smart farming aims to increase reap output while minimizing using resources such as water, fertilizer, and energy [3].

Figure 1 illustrates IoT and machine learning-based crop analysis and prediction processes. Over the years, numerous elements and technologies have been integrated into the architecture of a smart farm, such as sensing and monitoring systems, Internet of Things (IoT) sensors, data analytics and Artificial Intelligence (AI), precision agriculture techniques, remote monitoring and control, automated systems, livestock management systems, cloud computing and big data storage, energy management, and farm management software, to enhance farming practices and boost productivity [4][5][6]. In smart farming, the Internet of Things is considered one of the key contributing technologies used. IoT sensors can be utilized to monitor soil moisture, temperature, and other environmental aspects [7], and the gathered data from the IoT sensors can be used to define the best time to plant, water, and harvest reaps. By using IoT sensors, farmers can guarantee that the reaps receive the right amount of water and nutrients, which can improve their quality and yield [8][9].

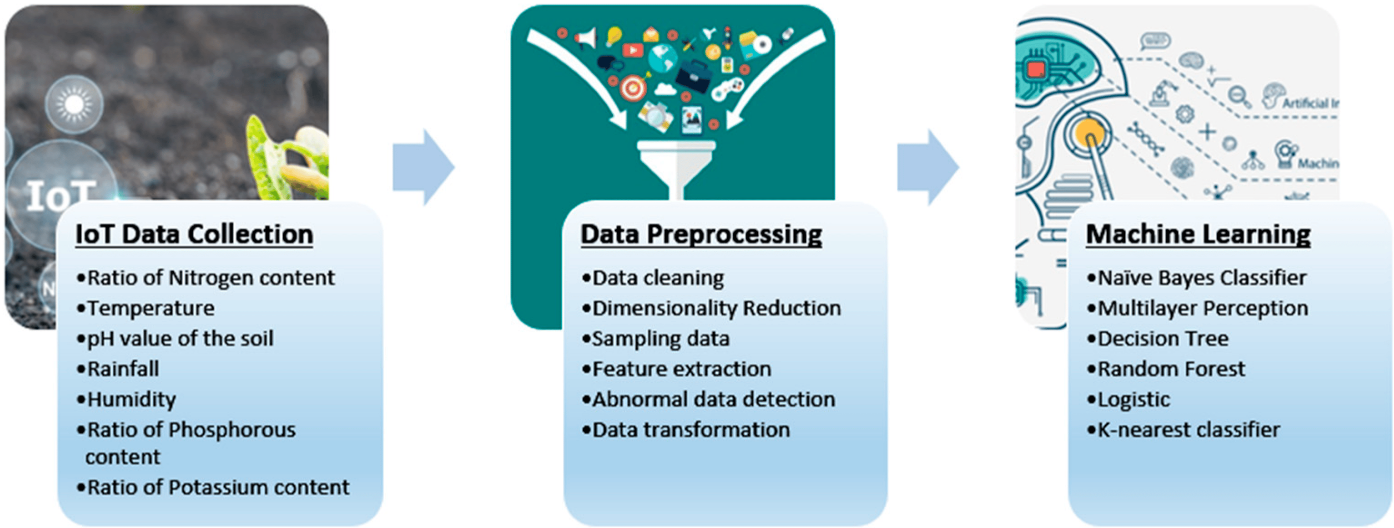

Figure 1. IoT and machine learning-based crop analysis and prediction process.

In recent years, machine learning applications have entered our lives in many areas, from health to defense industries and education to urbanization, and have taken an effective way in decision-making situations. At the same time, it started to produce information and technology solutions by forming the basis of the newly emerging search engine infrastructure, such as ChatGPT (Chat Generative Pretrained Transformer from the OpenAI [10], Google Bard [11], and similar AI-based chatbots and some other tools). Many research companies reveal that new trends will grow even more in various platforms. In this respect, the effect of machine learning-oriented systems and solutions in the technology field will increase its effectiveness as a huge multiplier, and many sectors, such as chip design [12] and traffic estimations [13], would be changed by enforcing machine learning models.

Generally, it is essential to collect and analyze accurate data using machine learning algorithms. The data collection is critical in both quality and size to obtain accurate results and make high predictions. In general, big data have size, speed, and various characteristics. Their large size helps eliminate randomness and allows the data to provide detailed results. In addition, large-scale analysis data could be more structured. Using more than one dataset from different sources in the analysis will provide a higher success rate. Many sources, such as sensors, social media, digital networks, physical devices, the stock market, and health centers, are sufficient data sources. This data can be accessed through APIs, web collection, and direct access paths. Data can be in two forms: static datasets or stream data. Data from different platforms are incorporated into the data processing operations. Analysis using these collected data makes data cleaning and preprocessing more critical while using machine learning algorithms.

Machine learning algorithms can analyze vast amounts of data from IoT sensors and other sources. It is a rapidly growing field that has the potential to transform the way researchers predict and analyze crop growth and output. Machine learning algorithms use statistical/mathematical models and algorithms to analyze data and make predictions, enabling computer systems to learn and improve from experience without being explicitly programmed [14]. In agriculture, especially in the cultivation area, machine learning algorithms can be trained on comprehensive data collected from farms, such as weather patterns, soil properties, crop growth stages, and pest and disease outbreaks. By evaluating the collected data, machine learning models can forecast reap growth, output, and quality with high accuracy [15].

A noteworthy application of machine learning in agriculture is precision farming, which includes employing data and technology to optimize agricultural conducts such as fertilization, irrigation, and pest control to improve reap output and quality. Machine learning models can examine bulky amounts of data from several sources, such as satellite imagery, drone footage, and soil sensors, to craft comprehensive maps of reap growth, nutrient levels, and moisture content. Farmers can utilize these maps to regulate their farming conducts, such as applying fertilizer or watering specific field areas, to maximize reap output and minimize waste [16]. Machine learning can also help farmers identify the most profitable crops to plant based on market demand and environmental factors. By analyzing historical market data and weather patterns, machine learning models can predict the demand for different crops and suggest optimal planting times and locations [17]. This can help farmers maximize their profits while minimizing the risk of crop failure. In addition to predicting crop growth and output, machine learning can also analyze the quality of the harvested crops. Machine learning models can analyze the color, texture, and shape of fruits and vegetables to determine their ripeness and quality. This information can be used to optimize the harvesting process and ensure that only high-quality produce is sold to consumers [18][19].

There are several encounters for deploying machine learning in agriculture, such as the lack of data groundwork, high cost of sensors and other technology, and need for specialized proficiency to develop and maintain the different solutions. However, as more farms implement precision agriculture and gather data, the potential profits of deploying machine learning in agriculture will become more evident. It is worth mentioning that machine learning in agriculture is still in its early stages, and more research needs to be conducted in this area to realize this technology’s potential fully. So far, the results are promising, and machine learning will likely become increasingly important [20].

2. Machine Learning

Innovative farming methods have profoundly transformed agriculture using advanced technologies to increase productivity, enhance sustainability, and lessen environmental harm. Machine learning (ML), a vital component of this change, has enabled various applications that simplify farming operations and better inform decision-making processes.

ML applications are widely used in livestock, water, soil, and crop management. ML improves animal welfare for livestock and boosts production, increasing sustainability via predictive modeling and real-time health monitoring [21]. ML is exploited to optimize irrigation and water usage for water management by analyzing various parameters. The application of newly emerging ML technologies and large amounts of available weather and water data makes it easier to manage water resources. This is especially helpful because natural events can be unpredictable, and the relationships between them can be complicated [22].

In soil management, ML helps analyze soil health, predict nutrient needs, and conclude the factors affecting soil distribution controls [23]. As in crop management, ML detects diseases and weeds, evaluates crop quality, recognizes species, and predicts crop yield.

Crop yield prediction is immensely important for farmers and policymakers, governments concerned with food security, and food marketing organizations [24]. These stakeholders can use yield prediction models to make data-driven decisions and develop strategies for efficient resource allocation, food distribution, and price stabilization. This leads to a more resilient food system that can be assured by anticipating crop production changes. However, predicting crop production is a complex task, as it is affected by many factors, such as weather conditions, the kind of fertilizer used, soil type, and the variety of seeds. Consequently, tackling this task necessitates the incorporation of diverse datasets and a range of attribute types.

Supervised learning techniques benefit crop yield prediction among the numerous ML categories. This is due to their robust predictive capabilities and ability to handle different attribute types. These methods employ labeled data to forecast outcomes based on specific inputs. For example, they project crop yields based on weather conditions and soil quality data.

Forecasting crop yield can be achieved using a broad spectrum of ML techniques, including Artificial Neural Networks (ANNs), Support Vector Machines, and Random Forests [25][26][27][28]. These algorithms' ability to process historical and up-to-date information regarding weather, soil conditions, and crop health facilitates precise crop yield predictions. The resulting insights enable farmers to make educated decisions about planting, irrigation, and fertilization, ultimately leading to optimized yields and less resource wastage.

Machine learning is already playing an important role in providing farmers with information to make agriculture more efficient and productive, hence maximizing their profits. Therefore, farmers are highly encouraged to apply ML algorithms and techniques efficiently, especially while collecting, processing, and analyzing data. ML technology can provide a solution to most challenges farmers face [29]. It can help them predict the weather more accurately, decrease waste, boost output, and increase profit margins. In this regard, farmers are motivated to use the advanced technology to collect data, such as autonomous vehicles, variable rate technology, GPS-based soil sampling, automated hardware, telematics, software, sensors, cameras, robots, drones, GPS guidance, and control systems [30].

According to [31], two-thirds of the farmers worldwide struggle to use technology, and more than 50% are unaware of the existing solutions. Teaching farmers to work with machine learning can be a transformative step in modernizing agriculture and improving productivity. While AI technology may seem daunting to some, there are ways to educate farmers about the benefits of smart farming and the usage of machine learning algorithms. Farmers need to be aware of the great benefits they may achieve if they use automation and AI on their farms. Training and informative workshops are the fastest ways to do so. This training needs to include foundation knowledge of ML, identifying use cases in agriculture, the importance of data collection and preparation for better prediction, ML algorithms and their best applications, and addressing concerns or misconceptions related to ethical and privacy considerations. They should be introduced to success stories of smart farms and encouraged to increase collaboration and share knowledge with their peers. A very important point is to introduce them to user-friendly tools and platforms that do not require programming skills for easy adaption. Since ML is a rapidly evolving field and new techniques and tools emerge frequently, researchers should encourage farmers to continue learning and stay updated with the latest developments in the field.

Despite the optimistic outlook of ML in agriculture, similar to any ML issue, the quality of the results is predominantly influenced by the quality of the input data. The efficacy of crop yield prediction depends heavily on the quality and availability of data. Crop prediction requires wide-ranging data, including weather, soil, historical yield, and satellite imagery. Guaranteeing data quality through efficient collection, preprocessing, and feature selection is critical in model development.

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