The Journal of Computational Science and Engineering (TJCSE)
ISSN 2583-9055 (Media Online)
Vol 3, No 2, February 2025
PP 180-188

Digital Agriculture: Transforming Farming with ML and IOT

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Abstract

The agricultural industry is being constantly challenged by several factors including the growth in the population globally, the environment, and unsustainable practices in farming. Smart agriculture is a promising solution when it comes to integrating elements of Internet of Things (IoT) and Machine Learning (ML). Thus, the monitoring of real-time environmental and crop conditions is facilitated by IoT through the interlinkage of sensors and devices. Machine learning enables data-driven insights, predictive analytics, and automation capacities in agriculture. This paper takes a journey through how the applications of IoT and machine learning could be developed into precision irrigation, crop health monitoring, pest and disease management, yield prediction, and farm automation in agriculture. We analyze through key use cases how technologies will improve decision-making, enhance resource utilization, and bring down impacts on the environment.

Keywords: Transforming Farming with ML and IOT ,Prediction

Introduction

This unprecedented pressure that the world is going through regarding growing population, climate change, scarcity of resources, and producing more food without destroying nature leads to increased demand for improved farming practices. As farming is being carried out under such diverse and pressing issues, there is an urgent requirement to design new systems that promote both productivity, sustainability, and efficiency in agricultural farming. This is precisely the motivation for adopting innovations using IoT and ML as new paradigms that might change agriculture in recent times leading to Concept of Smart Agriculture.

Smart agriculture is the use of modern technology in monitoring and analyzing farming practices to optimize agriculture for the improvement of crop yield, resource usage, and environmental impacts. The combination of the IoT and machine learning thus present a strong synergy that leads to data-driven decisions in real-time, thereby enhancing the precision and efficiency of operations in agriculture.

Research Objectives and Methodology

Both IoT and ML have revolutionized agriculture by offering innovative solutions for monitoring, analysis, and automation of various aspects of farming in order to enhance efficiency, reduce costs, and increase sustainability.

1.The main purpose of implementing real-time data for the optimization of irrigation is the efficiency of water use, waste reduction, and providing crops with the proper amount of water at the appropriate time.

2.With the help of IoT sensors and Machine Learning, it can make irrigation systems more intelligent, responsive, and highly adaptive to environmental conditions.

3.The aim is to enhance agricultural productivity while advocating sustainability by conserving the available water resources, mainly in areas where water is scarce.

4.Empower farmers with the tools and insights needed to make better irrigation decisions, enhancing crop productivity while minimizing water waste.

2. Literature Survey

In this paper we discuss the integration of Internet of Things and Machine learning in smart agriculture, looking at the applications, benefits, and the challenges. We will look into some of the most interesting applications, such as precision agriculture, pest and disease management, crop health monitoring, and yield prediction, and briefly discuss the technological frameworks enabling these innovations. We hope to understand the synergy between IoT and machine learning and show how the technologies have the potential to transform the future of agriculture

1.PRECISION AGRICULTURE

One of the answers to food security for everyone in the world is the precision agriculture. Precision agriculture can also be referred to, as digital agriculture; these are data-driven technologies to support sustainable farm management, wherein primarily there involves the adoption of modern information technologies, software tools and embedded smart devices for decision-support in agriculture . Mechanized agriculture and the Green Revolution are the two principal revolutions that form the first and second revolutions of agriculture, and precision farming falls under the third agriculture revolution.

John Deere came up with this technology in 1990 for seed sowing and fertilizer spraying using GPS controlled tractors. The primary objective of precision farming is to minimize production cost and environmental impacts thereby increasing the profitability of a farm. Digital technologies that are the backbone of Precision Agriculture include IoT, AI, data analytics, cloud computing, and block-chain technology. Precision Farming: Deploy IoT-based smart sensors within your farm's agricultural lands in order to collect data on the field, including amount of fertilizers and nutrients used in the soil, amount of water being used, and analytics of crop growth. Computers and robots, with a device like an UAV, use computer vision in order to identify weed and disease within the plant. These are satellite images in precision agriculture to monitor the field and find the diseases in the plants.

2.INTEGRATED PEST MANAGEMENT(IPM) WITH IOT

Integrated Pest Management (IPM) is an ecosystem-based strategy that focuses on long-term prevention of pests through biological control, habitat manipulation, and minimal use of chemical pesticides. The integration of IoT (Internet of Things) into IPM systems brings greater efficiency and precision, enabling real-time monitoring and data-driven decision-making. IoT-based solutions for integrated pest management were developed as part of smart agriculture projects. K.-C. Chen and Y.-K. Chen (2014) described an IoT-based pest monitoring system, which emphasized the collection of data from sensors deployed in fields to identify environmental conditions that favor pest outbreaks. These systems are now widely used to send real-time alerts to farmers.

Real-Time Pest Monitoring IoT Devices: In fields, sensors are placed to capture environmental conditions, including temperature, humidity, soil moisture, and light, all which affect pest activity, then connect these to a cloud system; the farmer can access the farm from anywhere using either smartphone or computer.

Sensor data: Pest monitoring systems based on IoT extract data that is collected from traps or cameras placed in the field through sensors. Sensors may record data on the number of pests captured, their movement pattern, or temperature and humidity that impacts the pest.

Geographical Pest Dispersion: Datasets will need to involve a wide range of geographical areas so that the different pest species are accounted for, and their behavior is accordingly different in different regions. For example, locusts are a severe problem in the desert regions of Africa, and aphids are more typical of temperate climates.

3.CROP HEALTH FARMING

The development of crop health monitoring applications has been cross-disciplinary, involving the different fields such as agriculture, computer science, remote sensing, and data science. No single individual "discovered" the crop health monitoring applications. Instead, several researchers and institutions, as well as companies, have contributed toward the evolution of these technologies.

Applications of machine learning and computer vision in crop health monitoring have been prominent in recent years. Among these are the contributions of David P. Hughes and Marcel Salathe with their paper in 2016 entitled "Using Deep Learning for Image-Based Plant Disease Detection." They showed how CNNs can identify crop diseases from images of plant leaves.

Luis G. Barbedo, in turn, has devoted a great deal of research to applying image processing to the task of plant disease detection and classification, from seminal papers issued in 2013 and 2018. Another significant area is IoT-based monitoring of environmental conditions that affect crop health directly, developed by K.-C. Chen and Y.-K. Chen in 2014. Their work is in the development of smart farming systems, including sensors, data analytics, and wireless networks to monitor and manage crop growth conditions. Many startups and companies have also played a crucial role in applying IoT to agriculture. For example, firms such as John Deere and CropX have developed IoT platforms and sensors to monitor soil moisture, plant health, among other key variables in real time.

3. Methodology

In smart agriculture, the integration of Internet of Things (IoT) and Machine Learning (ML) enables the development of intelligent systems that optimize farming processes. Here's an outline of the methodologies used in IoT and ML for smart agriculture.

IoT Methodologies in Smart Agriculture:

Sensor Networks for Data Collection:

Sensors are strategically located in fields to measure several parameters such as soil moisture, temperature, humidity, pH levels, light intensity, and nutrient levels. The moisture level in the soil is detected by soil moisture sensors, which then activate irrigation systems to optimize water use.

Wireless Communication and Data Transmission:

IoT devices rely on wireless communication technologies, such as Wi-Fi, Bluetooth, Zigbee, LoRaWAN, NB-IoT, for transmitting data from sensors to cloud-based servers for analysis and decision-making. LoRaWAN is used for long-range, low-power communication in rural agricultural environments to monitor crops and soil conditions in real-time.Edge computing reduces latency because it processes sensor data at or near the source, or edge, rather than waiting for cloud processing.

Cloud Computing and Data Storage:

Data is sent from IoT devices to cloud platforms where it aggregates, stores, and analyses. Cloud computing ensures scalability so that farmers can access the data from anywhere

Automated Actuators and Control Systems:

IoT systems integrate with actuators (e.g., automated irrigation systems, drones, fertilizer dispensers) and take actions based on the real-time data. Soil moisture below a certain level will trigger an automatic system of irrigation to water those crops.

Data Visualization and Remote Monitoring:

Through mobile apps or web dashboards, farmers can access real-time data and control the farm system, making remote monitoring of farm conditions possible.

IoT with Environmental Data:

Usually, IoT devices are combined with weather stations for real-time environmental data such as temperature, humidity, wind speed, and rainfall. Managing crops efficiently requires all that, so it is better if the weather station could connect to the farm's IoT system and predict how soon

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the rain will pour, hence improving the timing of the irrigation schedule.

ML Methodologies in Smart Agriculture:

Data Preprocessing and Feature Engineering:

Data Cleaning: Raw data from IoT sensors need to be cleaned and preprocessed to handle missing values, outliers, and noise.

Predictive Modeling and Forecasting:

Regression Models: Machine learning algorithms such as Linear Regression, Random Forests, Support Vector Machines (SVM) - predict continuous variables such as crop yield, soil moisture, or temperature.

Clustering for data grouping:

Identifying patterns in data: Unsupervised learning techniques such as K-Means or DBSCAN could be applied to identify the clusters of similar conditions or regions within a farm, which might need different management strategies (for example, irrigation scheduling for different zones).

4. Experimental Setup and Implementation

Challenges in Implementing IoT and Machine Learning Technologies in Resource-Constrained Settings

In IoT-based surveillance for smart agriculture, data privacy raises important ethical concerns, especially as technology increasingly monitors farm activities, environmental conditions, and machinery performance. Key ethical implications include:

Data Ownership and Control:

The farmers will produce a lot of data with the help of IoT devices, such as soil sensors, drones, and smart irrigation systems. It creates questions regarding who owns the data: the farmer, the company providing IoT services, or third-party data aggregators. Farmers might lose control over their data usage, which might result in exploitation.

Data Security:

IoT systems are prone to hacking and unauthorized access, which can expose sensitive information about farm operations. Inadequate security protocols can lead to breaches that compromise a farmer's competitive edge or financial standing.

Informed Consent:

Farmers may not be aware of the exact amount of data that the IoT devices are collecting, and how they will use that information. Hence, transparent policies and clear terms of service ensure informed consent in data collection practices.

5. Result Analysis

Table I. Sensors' readings at different time instants

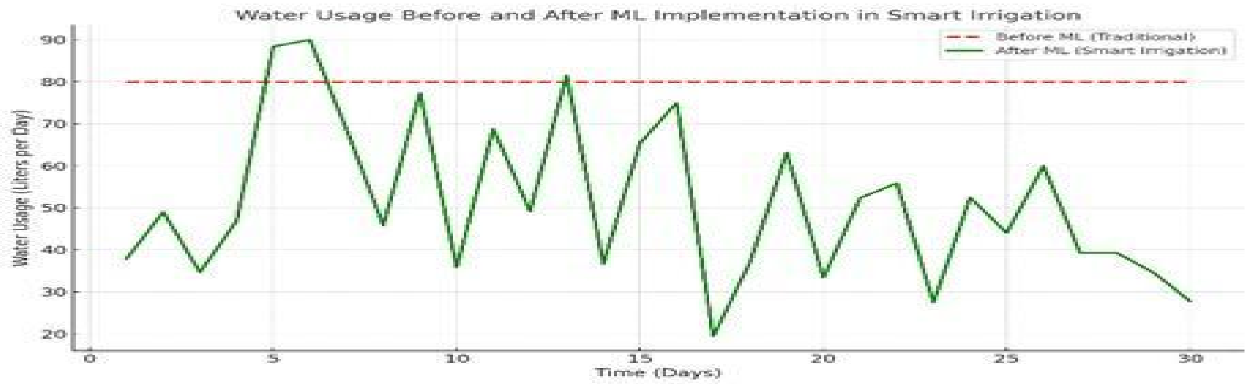
Instants	Temperature (^{0}C)	Humidity (%)	Soil Moisture	Acetone (PPM)
1	30.8	78	1024	0.0
2	30.9	78	1024	356
3	22.0	68	971	373

Table II. Decisions based on soil moisture sensor's readings

Soil Moisture		Pump status	Remarks
Value	Percent		
1024	100	Can't start ("0")	A value of 1024 means soil moisture is at saturation (very wet)
> 819.2	> 80	OFF ("0")	Values above 80% indicate excess moisture stress
552.9	54	OFF ("0")	A value of 54% means near optimum soil moisture for plant growth
< 204.8	< 20	ON ("1")	Values below 20% indicate drought
0.0	0.0	ON ("1")	A value of 0 means soil moisture is at the wilting point (very dry)

The image contains two tables that give information on sensor readings and their corresponding decisions for a soil moisture management system. Table I shows the sensors' readings at three different time instants, including temperature (°C), humidity (%), soil moisture, and acetone levels (PPM). For example, at Instant 1, the temperature is 30.8°C, humidity is 78%, soil moisture is at its maximum value of 1024, and acetone levels are 0.0 PPM. Similarly, at Instant 2, the temperature is 30.9°C with the same humidity and soil moisture values but acetone increases to 356 PPM. At Instant 3, the temperature decreases to 22.0°C, humidity to 68%, soil moisture reduces to 971, and acetone increases by a small margin to 373 PPM.

Table II depicts the decisions made on the basis of readings from the soil moisture sensor. It correlates the sensor values with percentages of soil moisture and also indicates the status of the pump's operation. A reading of 1024 (100%) represents a saturated soil where the pump will not start. A reading of above 819.2 (above 80%) means there is too much moisture, and the pump will stay off. A reading of 552.9 (54%) means that the soil is almost optimal for plant growth, and the pump will stay off. Readings below 204.8 (20%) represent drought conditions and the pump will turn on. At 0.0 (0%), the soil is at the wilting point (very dry), and the pump is also turned on. This system ensures proper management of water by adjusting the operation of the pump according to the moisture content in the soil.



The graph with the implementation of ML would present water consumption at reduced and efficient amounts that correlate closer to the actual amounts and weather forecast.

Here is a graph showing water usage before and after the implementation of machine learning in a smart irrigation system:

*The red dashed line is the water usage before the implementation of ML, where irrigation follows a fixed schedule, leading to consistent and often high water usage.

*Green line represents the water usage after ML implementation, where the system dynamically adjusts irrigation based on real-time data (e.g., soil moisture, weather conditions), leading to more efficient water usage with adjustments for rain or temperature variations.

As you can see, the after-ML line is more variable and reduces water consumption when the conditions are favorable-for example, during rain or cooler weather. It has an efficient and adaptive approach toward irrigation.

Conclusion

The integration of ML with IoT in smart agriculture has transformed traditional farming methods to allow for more efficient, data-driven, and sustainable crop management. IoT devices such as sensors and weather stations provide real-time data on soil moisture, temperature, humidity, and environmental conditions. This allows the ML algorithms to predict and optimize crucial agricultural processes like irrigation, pest control, and fertilization.

For example, ML-driven irrigation optimization has shown marked improvements through reductions in water usage, dynamic response to weather conditions, and right supply of water at the right time to crops. This not only results in reduced water waste but also leads to improved crop health and yield. In addition, automation and precision by ML and IoT result in reduced labor and operational costs while encouraging resource conservation.

The combination of IoT and ML in smart agriculture creates a powerful system which enhances precision, efficiency, and sustainability in farming. The real-time data from environmental and crop conditions is provided by the IoT sensors, while ML algorithms analyze this data to optimize irrigation, predict crop yields, and prevent problems like disease or water stress. Together, these technologies lead to increased productivity, a reduction in resource consumption, lower costs, and a more sustainable approach to farming, thereby helping improve the resilience and profitability of agricultural operations.

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