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Internet of Things and Machine Learning for Smart-Agriculture: Technologies, Practices, and Future Direction

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Abstract: Smart agriculture has quickly gained popularity due to the tremendous introduction, growth, and integration of modern techniques with conventional agriculture, including the internet of things (IoT), computer vision (CV), machine learning (ML), big data, edge computing, and cloud computing. With the use of inexpensive sensors, smart agriculture aims to improve the effectiveness and sustainability of agriculture. These comprise airflow, location, optical, and mechanical sensors. Along with the real-time monitoring, identification, and categorization of objects, these sensors can be used to gather information about the position of crops and assess the condition of the soil. Furthermore, because IoT and open wireless communication networks are used in smart-agriculture ecosystems, these channels are vulnerable to a variety of cyber threats and security concerns. It has been stated that these actions could have a significant negative impact on the economy of a wide range of nations due to the rise in harmful assaults on the agricultural industry. Without the necessity for a centralized authority, AI and blockchain can be utilized to address a number of difficulties related to the deployment and management of smart agriculture. The benefits of cloud computing include its capacity to manage enormous amounts of data while offering a range of storage alternatives. Edge computing, on the contrary hand, provides a faster response time and less latency. The technique smart agriculture systems are created is anticipated to change as a result of this interaction. As a consequence, the way these techniques are applied is changing paradigmatically.

Keywords*—Agricultural sensors, Smart Agriculture, Wireless technologies, Internet of things, Machine learning.*

1. Introduction

In terms of population, India is a vast nation that is close to overtaking China. Up from the present estimate of 1370 million, the population is projected to reach 1.64 billion by 2050. (UN, 2019). The nation also produced more food grains, increasing its output from 55 million tonnes in 1960 to 281.37 million tonnes (2019). To fulfill the increased demand for food by the year 2050, India will need to expand its food output by an additional 20% during the next 30 years. Given the uncertainty surrounding agricultural productivity and farm revenue, meeting the rising need for food will create a variety of significant challenges. The economy of India depends heavily on agriculture. The agricultural sector accounts for more than 60% of employment in India and 17% of its GDP. Over the last several decades, India's agricultural sector has seen substantial growth.

The extensive usage of the internet over the past 20 years has helped individuals and companies in a variety of ways, both locally and internationally. The ability to immediately provide and consume services was this discovery's key benefit. Internet of Things, or IoT, recently said that it might deliver the same benefit via its cutting-edge technology and provide a way to boost the user's perception and skills by changing the working environment. The potential applications of IoT technology span a number of sectors. Since agriculture needs ongoing monitoring and administration, IoT adoption is seen

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as the ideal solution. Various layers and the whole output chain of the agriculture business employ IoT. (Medela et al., 2013). Precision agriculture, livestock, and greenhouses are the three major Internet of Things (IoT) applications in agriculture, which are divided into several monitoring domains. To monitor all of these applications, a range of IoT-based sensors and devices are employed, including wireless sensor networks (WSNs), which help farmers get essential data via sensing devices. Researchers and farmers may be able to make wiser decisions by employing IoT-based devices that leverage cloud services to monitor and analyse remote data. The management and decision-making choices offered by environmental monitoring systems have increased as a result of recent technological developments. A particularly designed, low-human input landslide risk monitoring system has been developed to allow quick deployments in difficult locations (Giorgetti et al., 2016). What distinguishes the developed system from other systems is its capacity to resist node failures and self-repair the network's broken communication links. The provider offers an IoT management system that keeps track of factors including wind, soil, atmosphere, and water (Zheng et al., 2016). Their sub-domains have also been used to find IoT-based agricultural monitoring systems. Environmental monitoring, which encompasses soil, air, and water monitoring as well as temperature, water quality, sicknesses, locations, and environmental conditions, is one of the sub-domains that is being explored. The Internet of Things paradigm also improves face-to-face contact by using low-cost technology and communication protocols. The real-time monitoring of various environmental data through IoT also enables the creation of realistic maps of temperature, noise level, air, water, and harmful radiation. (Torres-Ruiz et al., 2016) In addition to informing authorities, message alerts or trigger warnings are used to notify consumers of numerous environmental conditions (Liu et al., 2013; Hachem et al., 2015).

The number of research on IoT-based agriculture that have been published over the previous several decades has been quite small. The most current research on this topic need to be gathered, listed, broken down, and arranged. The primary objective of this research is to carry out a empirical research of the literature in the field of smart agriculture.

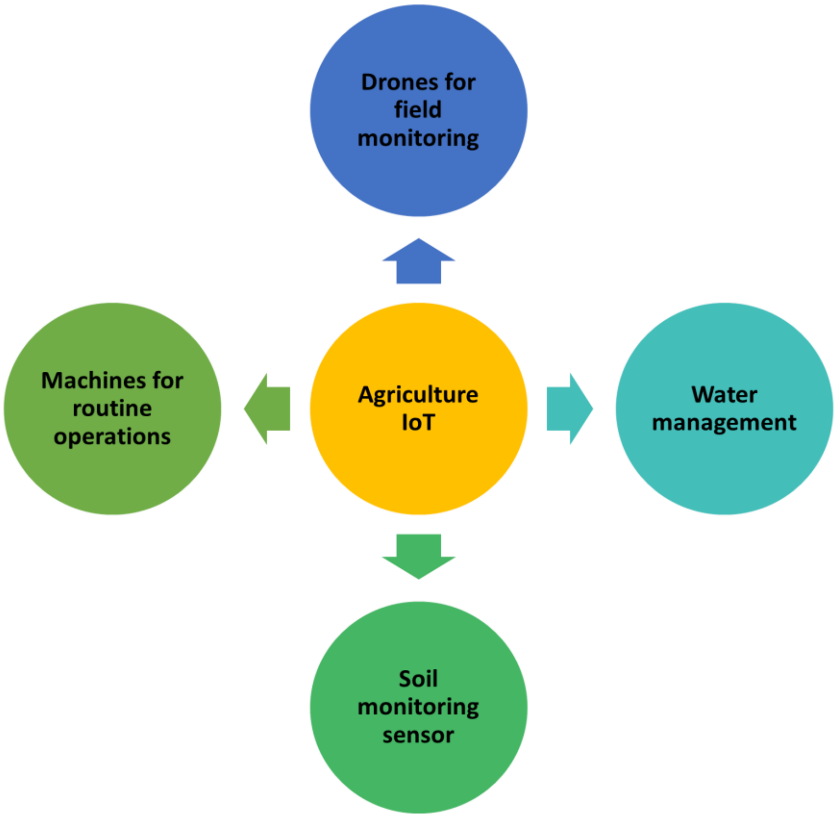

Fig. 1. Role of IoT in Agriculture

(Source: Udhaya N. et al., 2018.)

2. Background

Researchers have proposed a number of Internet of Things (IoT)-based agricultural innovations that would boost output while needing less labour. To increase agricultural quality and productivity, researchers have created a number of IoT-based agriculture projects. Carnegie Mellon University used wireless sensor technologies to develop the plant nursery (Junaid, 2009). Researchers developed a WSN-based system for monitoring polyhouses that incorporates modules for CO2, humidity, temperature, and light (Song et al., 2012). It has been shown that a WSN-based system may use GPS and the ZigBee protocol to monitor a number of agricultural metrics (Satyanarayana and Mazaruddin, 2013). To boost output, a real-time monitoring system for rice crops has been developed (Sakthipriya, 2014). To reduce crop loss and increase agricultural output, the crop monitoring system described in (Rajesh, 2011) gathers and analyses temperature and rainfall data. In order to monitor various agricultural data, including temperature, Shaobo et al. (2010) developed a budget-friendly Bluetooth-based technology that utilizes a microcontroller that also functions as a weather station. The recommended strategy is effective in tracking recent field data. Haefke et al. (2011) developed a smart sensor platform by using ZigBee to monitor environmental factors including humidity, temperature, daylight, and pressure. The suggested design has many characteristics that make successful communication between nodes possible, including a mesh network, fast data rate, inexpensive technology, and an accurate sensor. An Android app is used by a GSM-based irrigation monitoring system to monitor and regulate a number of environmental factors (Pavithra and Srinath, 2014). A system based on GSM and Field Programmable Gate Array was developed to measure greenhouse properties like humidity and temperature (FPGA). The suggested approach offers affordable, simple tools for monitoring crop and soil data (Dinesh and Saravanan, 2011). A straightforward, low-cost fuzzy control system that can monitor different greenhouse conditions is described by researchers (Castaeda-Miranda et al., 2006). The operational and design methodologies for WSN were used to construct a more intricate monitoring and control system for the greenhouse (Ferentinos et al., 2014).

3. Need And Necessities Of New Technologies In Indian Agriculture

Access to agricultural extension services has long been a problem for farmers in India, especially marginal and small farmers. The beginning of the Green Revolution and the following advancements in agricultural technology made it clear that farmers lacked access to adequate agri-extension services. While some of them "led" the way in embracing new technology, others lagged behind for a variety of reasons. In addition to the accessibility issue, the cost of technology investment was steadily rising to the point where even significant ground-level credit-flow growth and bank expansion were unable to make agricultural technology "ubiquitous" and "pervasive" to all farmers across various regions. In addition, agricultural technology, which comes in electrical, mechanical, and chemical forms, has detrimental environmental effects that have rendered it unsustainable over time. As a result, it is now only used as "traditional technology" in agriculture throughout the developing world, including India.

Despite these technological advancements, India's agriculture still confronts difficulties including poor profitability, a lack of labour, and restrictions on energy and other inputs. New technology ideas like the "Internet of Things", "Digital Technology," and "Precision Farming," which have improvised agriculture in industrialized nations, are anticipated to dominate the future of agriculture. India has to join the international movement to modernize agriculture along new technical lines, starting with IoT. In actuality, technologies like IOT provide tremendous potential to solve current and future problems encountered by Indian farmers in order to transform the agricultural sector into a profit-generating company.

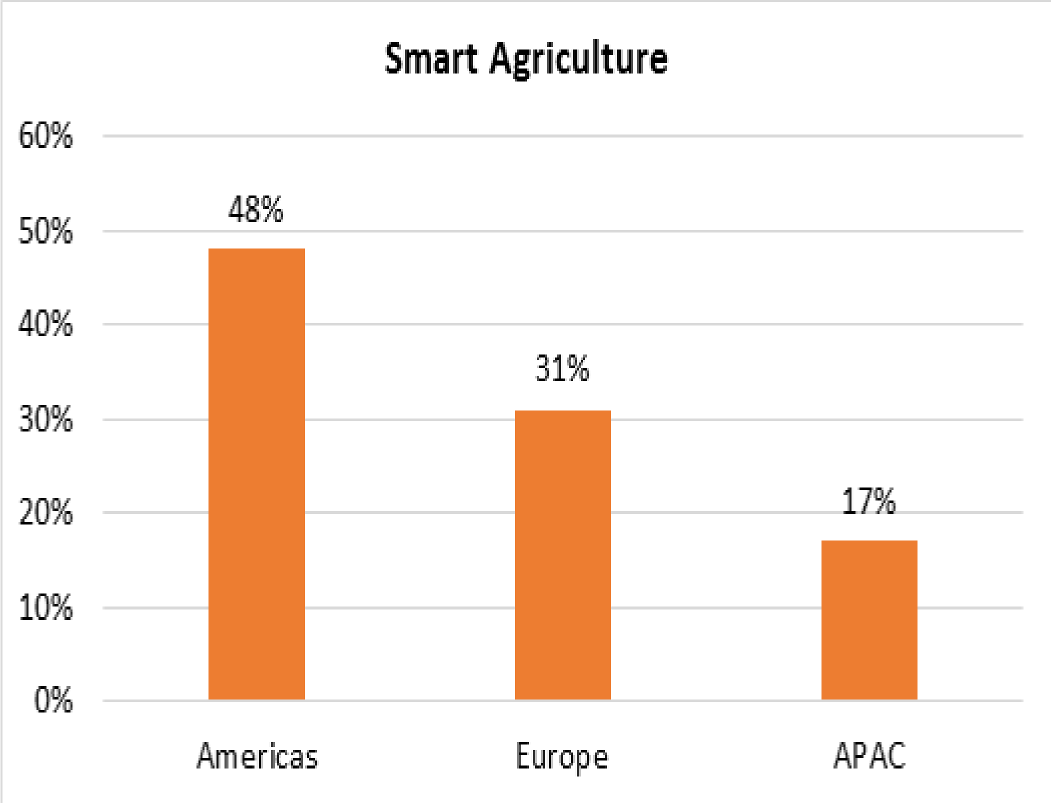

Fig. 2. Global Share of IoT projects in Agriculture

(Source: IoT Analytics 2016 Global overview of IoT use in Agriculture)

Agriculture IoT

A. The Importance of Agriculture Automation

More than 70% of Indians depend on agriculture for their living (Arunlal and Rajkiran, 2018). Due to the extensive use of traditional farming practices that lead to subpar crop yields and plant growth, agricultural automation in operations like irrigation, plowing, planting, and harvesting, as well as pesticide treatment, is now feasible. IoT may be highly helpful in the agricultural industry, especially for managing soil and crops as well as regulating the usage of pesticides and insecticides.

B. IoT in Agriculture

According to research, a wide range of technologies—from manual to automated, from tractors and machines to computers, to mobile devices and database software, to artificial intelligence, the IoT, and big data—have advanced between the years before 1990 and the present (Basnet and Bang, 2018). IoT and other technologies are used by farmers and agricultural businesses to do this and boost production (Business Insider, 2016). Therefore, farmers may be able to meet this growth in food demand via smart agriculture and improved crop yield.

By 2025, there will be 75.44 billion more connected gadgets on the planet, predicts Statista. Additionally, Nayyar and Puri provide evidence of the expansion of IoT use in agriculture in the form of current and future IoT-related agricultural enterprises. (2016). Between 2000 and 2016, there will be an estimated 540 million farm connections, and between 2035 and 2050, there will be an estimated 780 million connections.

Modern agriculture has been significantly impacted by the expanding body of technology that has automated tasks and adopted a variety of system designs for smart agriculture. For smart farms, Jirapond et al. (2019) suggested IoT and agricultural data analysis. The author examined agricultural practices, crop yields, and real-time water management in the three villages using Internet of Things (IoT) gadgets, such as sensors. A web application sends data about an agricultural field to a mobile device. An ultrasonic sensor, a DHT22 sensor, and a soil moisture sensor make up the system's three sensors. The cost of the program is fair. In India, Das et al. (2019) created an intelligent farm system using the Internet of Things. Poor agricultural harvests and unpaid debts are the main causes of farmer suicides. Smart agricultural systems built on the IoT and using a range of sensors and Raspberry Pi boards provide one answer to this problem. Successful food businesses in India are now needed to grow intelligent seeds and maintain a careful eye on pests and soil moisture in order to boost yields. The design of the system is rather expensive yet quite reliable. Naresh et al. presented a smart farm system utilizing the Internet of Things (2019). In order to assess the moisture content of the soil, water level, etc., the author illustrated how a smart agricultural system may employ a variety of sensors. The data will be provided by the ARM 7 (LPC2148) Processor and uploaded to a cloud service like Things peak through a number of sensors it is connected to. The farmer's mobile device's data can only be accessed through the Wi-Fi module. A more powerful ARM 7 CPU than the ones on preceding boards is connected to four sensors. The three tiers used in the research by Ravindranath et al. (2019) on the usage of the cloud of things for smart agriculture were the back-end layer, gateway, and front-end layer. This software provides in-depth details to help locate rodents that reduce agricultural productivity. Sensors that monitor a variety of factors and provide their results to the ship include those that measure temperature, humidity, and wetness. The three-story structure was constructed in stages, but it was expensive. In 2019, Sai Prasanna and collaborators developed a hypothesis based on embedded electronics to regulate and monitor plant development conditions. The method promotes agriculture by offering top-notch working conditions, being reasonably priced, and assessing the efficiency of plant development. The Raspberry Pi Model B is a costly gadget that is connected to all of the sensors. The usage of additional sensors is the system's main advantage.

Lavanya et al. (2019) created an IoT-based fertilizer notification system for smart agriculture. Utilizing LDR and LEDs, construct a cutting-edge calorimetric NPK sensor. The data that has been gathered is evaluated using the internal software of the NPK sensor. Daily data from the Internet of Things is sent to the farmer's Android phone, including information on NPK levels. A temperature-compensated intelligent nitrate sensor was created by Alahi et al. for use in agriculture (2017). One of the author's main areas of interest in terms of research is the development of intelligent, temperature-adjustable nitrate-N detecting sensors. It may leverage the IoT to function as a sensor network. Data is immediately received by a cloud-based web server or an IoT platform. Smart farming and an Internet of Things-based method for measuring soil nutrients were suggested by Badhe et al (2018). The only sensors about which the author went into great detail were the DHT 11, pH value, NPK sensor, light intensity, and soil moisture. These sensors are connected to the Raspberry Pi using the MCP3204 A/D converter, which subsequently sends position information about the sensors to the internet. Let's finish by determining which crop will thrive in a certain soil characteristic. Raut et al. (2018) created a system for monitoring, watering, and fertilizing soil via the Internet of Things. An ARM CPU, a relay, a temperature sensor, a soil moisture sensor, a colour sensor, an LCD, and other sensors have all been utilized in studies (LPC 2148). Farmers will get Gmail messages with updates on factors impacting soil health as a result of the IoT. Agro-sensors were used by Fenila Naomi et al. (2019) to identify the best watering technique for a soil quality evaluation. Clarifying the challenges farmers face, such as bug control, a lack of water resources, inadequate irrigation, and a dearth of fertilizer, is the author's main objective. The DHT 11 weather sensor is one of several sensors used by the IoT to determine the optimal fertilizer rates for plant development. In order to determine which crops required the application of pesticides, the author used machine learning. To satisfy a sensor need, Mekala and Viswanathan (2019) created an IoT system based on the THAM Index.

Machine Learning In Agriculture

C. Management of Crop

a) Yield Prediction

The ability to map and estimate yields, match crop supply and demand, and manage crops for maximum productivity are the important elements of precision agriculture. Examples of ML applications that might automatically count the coffee fruits on a tree are given by Ramos et al (2017). Coffee fruits may be divided into three categories using this method: those that can be plucked, those that cannot, and those whose stage of growth is ignored. The size and pace of fruit maturity for coffee were also impacted by the equipment. To help coffee growers better manage their crops for profit, this program was established. In order to anticipate production, Ramos et al. (2015) created a machine vision system for cherry picking that automatically shakes and gathers the cherries. If there is enough foliage, the algorithms can separate and differentiate even invisible cherry branches. A method for identifying immature green oranges in an outdoor citrus orchard was presented in separate research (Sengupta and Lee, 2014). The goal of this research, like many others that came before it, was to provide farmers with knowledge about specific yields to help them optimize their grove for more yield and profit. In prior research, the authors used multitemporal remote sensing data and ANNs to create a model for computing grassland biomass (kg dry matter/ha/day) (Ali et al., 2016). Another test aimed to predict wheat output (Pantazi et al., 2016). Utilizing soil information, crop growth indicators, and satellite images, a more precise estimate was given. Using remotely detected electromagnetic (EM) and RGB pictures, the authors of devised a method for identifying tomatoes (Senthilnath et al., 2016). Research work has created a method for forecasting the development stage of the rice crop utilizing SVM and crucial geographical data (Su et al., 2017). The preceding research offered a comprehensive method for assessing agricultural productivity (Kung et al., 2016). The method is based on an ENN application that utilizes prior agronomical data. The study's regional estimates were created to help farmers prevent supply and demand imbalances that may be worsened by harvest-time crop quality issues, especially for Taiwan.

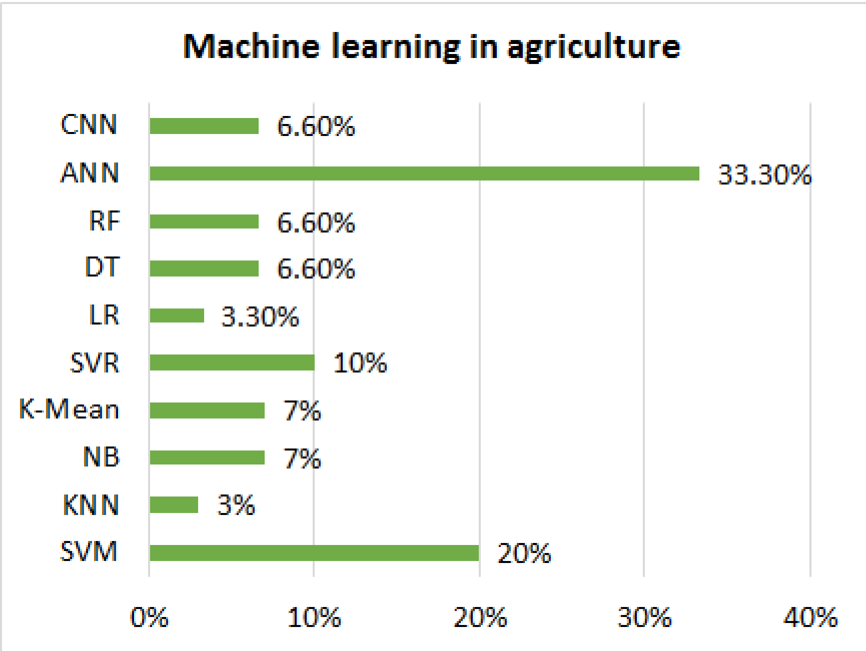

Fig. 3. Machine learning algorithms used in agriculture

(Source: Raju, K. Lova & Veeramani, Vijayaraghavan, 2020)

b) Weed Detection

Weed identification and management are important concerns in agriculture. Farmers often see weeds as the greatest threat to agricultural output. Given how difficult it is to tell weeds from crops, weed identification is crucial for sustainable agriculture. Once again, the integration of sensors and machine learning algorithms may be able to provide precise weed classification and identification at a low cost and without endangering the environment. Thanks to machine learning for weed detection, using robots and other technologies to eradicate weeds may result in a decrease in the need for pesticides. Machine learning has been used in two published studies to address weed identification issues in agriculture. In a study, Pantazi et al. (2017) developed a unique method for recognizing Silybum marianum, a hard-to-remove weed that significantly lowers agricultural productivity, using counter propagation (CP)-ANN and multispectral pictures obtained from unmanned aircraft systems (UAS). Using machine learning and hyperspectral data, another study (Pantazi et al., 2016) developed a unique approach for classifying crop and weed species. To identify weed species, the researchers utilized an active learning strategy. For both economic and environmental reasons, the main goal was to accurately identify and classify these species. A technique for weed detection based on SVN was created by the researchers of a second study (Binch and Fox, 2017) for cropping grasslands.

c) Crop Quality

The last part of the crop category is research aimed at identifying crop quality traits. Agricultural quality features that are correctly identified and classified have the power to raise product prices while lowering waste. The first study's authors (Zhang et al., 2017) devised a special method for recognizing and classifying alien botanical and non-botanical components trapped in cotton lint during harvesting. The goal of the research was to increase quality while minimizing fibre damage. A strategy for identifying and classifying Korla aromatic pears into deciduous-calyx and persistent-calyx categories were created in the second research on the production of pears (Hu et al., 2017). Hyperspectral reflectance images and machine learning were employed in the approach. A method for predicting and identifying the geographic origin of rice samples was also offered by Maione et al. (2016) in their most recent work on this topic. The idea was to sample chemical components using ML algorithms. According to the study, the four essential chemical elements for differentiating samples are Cd, Rb, Mg, and K.

D. Water Management

Effective water management is necessary to maintain the hydrological, climatological, and agronomic components of water in balance in order to achieve excellent agricultural yields.

The four pieces of research that make up this section's major focus was calculating evapotranspiration on a daily, weekly, or monthly basis. It may be challenging to calculate evapotranspiration accurately when designing and managing irrigation systems. A computer technique was developed by the authors of the second research to determine the monthly mean evapotranspiration in areas (Mehdizadeh et al., 2017). Another study utilized temperature information collected over a prolonged period of time from six meteorological stations to calculate daily evapotranspiration in an area (between 1961 and 2014). (2017) Feng et al. The authors of previous work, Patil and Deka (2016), created a technique for determining weekly evapotranspiration for two meteorological weather stations using an ELM model that received temperature data. The objective was to accurately forecast weekly evapotranspiration using a scenario with little data for agricultural water management in dry regions of India.

But anticipating climatic occurrences and figuring out evapotranspiration and evaporation are significantly influenced by the daily dew point temperature. Another experiment discovered a machine learning (ML) prediction model for the daily dew point temperature (Mohammadi et al., 2015).

E. Soil Management

Soil performs a broad variety of complex functions. Soil characteristics may help researchers comprehend how agriculture influences ecosystem dynamics. A detailed evaluation of the soil's state might lead to better soil management. The soil's temperature is the single major factor in determining how successfully a region's eco-environmental conditions and the effects of climate change are studied. It is a crucial meteorological variable because it regulates the interaction between the earth's atmosphere and the planet. Crop yield volatility is significantly influenced by soil moisture. However, as soil measurements may sometimes be expensive and time-consuming, the application of computer analysis based on ML techniques may provide a trustworthy and affordable option for accurate soil evaluation (Coopersmith et al., 2014). This research developed a method for precisely calculating soil dryness for agricultural planning. Using data on evapotranspiration and precipitation, the approach accurately calculates soil dryness in a location near to Urbana, Illinois, in the United States. This invention was intended to enable remote agricultural management. A study discovered that precise forecasts of soil properties may enhance soil management (Morellos et al., 2016). In a related investigation, Nahvi et al. (2016) created a unique method for calculating the daily soil temperature in Bandar Abbas and Kerman, the country of Iran's two distinct climate zones. Agricultural management requires a precise estimation of soil temperature. A unique method for measuring soil moisture was provided in the most current study (Johann et al., 2016), which combined ANN models with data from force sensors on a no-till chisel opener.

F. Future Technologies for Agriculture

The following agricultural technologies will be employed in the future (Emerging Agriculture Technologies, 2019).

a) Weather Tracker

The weather monitoring system is made up of online weather services, most of which are focused on agriculture. Using this technology, farmers may utilize mobile devices to get early notice of hail, frost, and other weather-related information. They may also take precautionary steps to conserve agricultural crops.

b) Vertical Agriculture

This method produces food in vertically stacked layers. It may thrive in urban areas, where fresher foods are more easily and cheaply available. Farmers use this strategy to grow crops generally unsuited for certain locations to make the best use of the available area.

c) Satellite Imaging

Satellite imaging technologies are used to get real-time crop images. The pixels in the images have a resolution of more than five meters. Farmers may save time and money by using this technology. Farmers will be able to get alerts on their agricultural methods relating to water, soil, and crop sensors by using this technology.

d) RFID Sensors and Tracking

RFID sensors might be used to track food from farm to merchant. Using this technology allows for the distribution of recently manufactured items. This technique makes it easy to discover and reduce harmful germs. Barcodes on the commodities may be scanned with a smartphone to allow the farmer to safely market their products.

e) Usage of Robots in Agricultural

This technique can also be called as abbot. This is a type of technology created for automated agricultural procedures such as weeding, planting, irrigation, picking of fruit, harvesting, and other similar tasks.

5. Conclusion

In particular, the notion of the Internet of Things as it applies to agriculture is well explained in this study. Future agricultural sensors, actuators, and equipment will be able to make basic decisions and communicate with one another through the internet. By creating effective procedures, these advances may aid agricultural management systems in organizing the processing of farm data and enhancing agribusiness. Academics may employ ML and IoT to assist farmers now that these technologies have matured. These would aid in pest management, increase throughput, and help farmers use their land better. In order to highlight some of the most relevant and recent uses of modern sensor technologies utilized in precision agriculture, this research will present a synopsis of these technologies.

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Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all the aspects of this work.

Declaration of Conflicts of Interests

Authors declare that they have no conflict of interest.

Consent for Publication

All authors read and aware of publishing the manuscript in xxxxxxxx

Data Availability Statement

The database generated and /or analysed during the current study are not publicly available due to privacy, but are available from the corresponding author on reasonable request.

Declarations

Author(s) declare that all works are original and this manuscript has not been published in any other journal.

References

[1] Alahi, M. E. E., Xie, L., Mukhopadhyay, S., & Burkitt, L. (2017). A temperature compensated smart nitrate-sensor for agricultural

industry. IEEE Transactions on Industrial Electronics, 64(9), 7333-7341. https://doi.org/10.1109/TIE.2017.2696508

[2] Ali, I.; Cawkwell, F.; Dwyer, E.; Green, S. Modeling Managed Grassland Biomass Estimation by Using Multitemporal Remote Sensing Data-A Machine Learning Approach. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2016, 10, 3254-3264. https://doi.org/10.1109/JSTARS.2016.2561618

[3] Amatya, S.; Karkee, M.; Gongal, A.; Zhang, Q.; Whiting, M.D. Detection of cherry tree branches with full foliage in planar architecture for automated sweet-cherry harvesting. Biosyst. Eng. 2015, 146, 3-15. https://doi.org/10.1016/j.biosystemseng.2015.10.003

[4] Arunlal, K. S., & Rajkiran, S. N. (2018). Smart agriculture: IoT based precise and productive farming approach. International Journal of advanced Research, Ideas and Innovations in Technology, 4(6), 771-775.

[5] Badhe, A., Kharadkar, S., Ware, R., Kamble, P., & Chavan, S. (2018). IOT based smart agriculture and soil nutrient detection system. International Journal on Future Revolution in Computer Science & Communication Engineering, 4(4), 774-777.

[6] Basnet, B., & Bang, J. (2018). The state-of-the-art of knowledge-intensive agriculture: A review on applied sensing systems and data analytics. Journal of Sensors, 2018, 1-13. https://doi.org/10.1155/2018/3528296

[7] Binch, A.; Fox, C.W. Controlled comparison of machine vision algorithms for Rumex and Urtica detection in grassland. Comput. Electron. Agric. 2017, 140, 123-138. [Google Scholar] [CrossRef][Green Version] https://doi.org/10.1016/j.compag.2017.05.018

[8] Business Insider. https://www.businessinsider.com/inter net-of-things-smart-agriculture-2016-10/.

[9] Castañeda-Miranda, R.; Ventura-Ramos, E., Jr.; del RocíoPeniche-Vera, R.; Herrera-Ruiz, G. Fuzzy greenhouse climate control system based on a field programmable gate array. Biosyst. Eng. 2006, 94, 165-177. https://doi.org/10.1016/j.biosystemseng.2006.02.012

[10] Coopersmith, E.J.; Minsker, B.S.; Wenzel, C.E.; Gilmore, B.J. Machine learning assessments of soil drying for agricultural planning. Comput. Electron. Agric. 2014, 104, 93-104. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2014.04.004

[11] Das, R. K., Manisha, P., & Dash, S. S. (2019). Smart agriculture system in india using internet of things. Springer Nature Singapore Pte Ltd, 758, 247-255. https://doi.org/10.1007/978-981-13-0514-6_25

[12] Dinesh, M.; Saravanan, P. FPGA based real time monitoring system for agricultural field. Int. J. Electron. Comput. Sci. Eng. 2011, 1, 1514-1519.

[13] Emerging Agriculture Technologies. https://www.ayokasystems.com/news/emerging-agriculture-technologies/. Accessed April 05, 2019.

[14] Feng, Y.; Peng, Y.; Cui, N.; Gong, D.; Zhang, K. Modeling reference evapotranspiration using extreme learning machine and generalized regression neural network only with temperature data. Comput. Electron. Agric. 2017, 136, 71-78. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2017.01.027

[15] Fenila Naomi, J., Theepavishal, R. A., Madhuaravindh, K. S., & Tharuneshwar, V. (2019). Soil quality analysis and an efficient irrigation system using agro-sensors. International Journal of Engineering and Advanced Technology (IJEAT), 8(5), 703-706.

[16] Ferentinos, K.P.; Katsoulas, N.; Tzounis, A.; Kittas, C.; Bartzanas, T. A climate control methodology based on wireless sensor networks in greenhouses. In Proceedings of the XXIX International Horticultural Congress on Horticulture: Sustaining Lives, Livelihoods and Landscapes (IHC2014), Brisbane, Australia, 17-22 August 2014; pp. 75-82. https://doi.org/10.17660/ActaHortic.2015.1107.9

[17] Giorgetti, A.; Lucchi, M.; Tavelli, E.; Barla, M.; Gigli, G.; Casagli, N.; Dardari, D. A robust wireless sensor network for landslide risk analysis: System design, deployment, and field testing. IEEE Sens. J. 2016, 16, 6374-6386. https://doi.org/10.1109/JSEN.2016.2579263

[18] Hachem, S.; Mallet, V.; Ventura, R.; Pathak, A.; Issarny, V.; Raverdy, P.G.; Bhatia, R. Monitoring noise pollution using the urban civics middleware. In Proceedings of the 2015 IEEE First International Conference on Big Data Computing Service and Applications, Redwood City, CA, USA, 30 March-2 April 2015; pp. 52-61. https://doi.org/10.1109/BigDataService.2015.16

[19] Haefke, M.; Mukhopadhyay, S.C.; Ewald, H. A Zigbee based smart sensing platform for monitoring environmental parameters. In Proceedings of the 2011 IEEE International Instrumentation and Measurement Technology Conference, Binjiang, China, 10-12 May 2011; pp. 1-8. https://doi.org/10.1109/IMTC.2011.5944154

[20] Hu, H.; Pan, L.; Sun, K.; Tu, S.; Sun, Y.; Wei, Y.; Tu, K. Differentiation of deciduous-calyx and persistent-calyx pears using hyperspectral reflectance imaging and multivariate analysis. Comput. Electron. Agric. 2017, 137, 150-156. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2017.04.002

[21] Jirapond, M., Nathaphon, B., Siriwan, K., Narongsak, L., Apirat, W., & Pichetwut, N. (2019). IoT and agriculture data analysis for smart farm. Computers and Electronics in Agriculture, 156, 467-474. https://doi.org/10.1016/j.compag.2018.12.011

[22] Johann, A.L.; de Araújo, A.G.; Delalibera, H.C.; Hirakawa, A.R. Soil moisture modeling based on stochastic behavior of forces on a no-till chisel opener. Comput. Electron. Agric. 2016, 121, 420-428. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2015.12.020

[23] Junaid, A. Application of Modern High Performance Networks; Bentham Science Publishers Ltd.: Oak Park, IL, USA, 2009; pp. 120-129.

[24] Kung, H.-Y.; Kuo, T.-H.; Chen, C.-H.; Tsai, P.-Y. Accuracy Analysis Mechanism for Agriculture Data Using the Ensemble Neural Network Method. Sustainability 2016, 8, 735. https://doi.org/10.3390/su8080735

[25] Lavanya, G., Rani, C., & Ganeshkumar, P. (2019). An automated low cost IoT based fertilizer intimation system for smart agriculture. Sustainable Computing: Informatics and Systems, 1, 1.

[26] Liu, Z.; Huang, J.; Wang, Q.; Wang, Y.; Fu, J. Real-time barrier lakes monitoring and warning system based on wireless sensor network. In Proceedings of the 2013 Fourth International Conference on Intelligent Control and Information Processing (ICICIP), Beijing, China, 9-11 June 2013; pp. 551-554. https://doi.org/10.1109/ICICIP.2013.6568136

[27] Maione, C.; Batista, B.L.; Campiglia, A.D.; Barbosa, F.; Barbosa, R.M. Classification of geographic origin of rice by data mining and inductively coupled plasma mass spectrometry. Comput. Electron. Agric. 2016, 121, 101-107. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2015.11.009

[28] Medela, A.; Cendón, B.; González, L.; Crespo, R.; Nevares, I. IoT multiplatform networking to monitor and control wineries and vineyards. In Proceedings of the 2013 Future Network Mobile Summit, Lisboa, Portugal, 3-5 July 2013; pp. 1-10.

[29] Mehdizadeh, S.; Behmanesh, J.; Khalili, K. Using MARS, SVM, GEP and empirical equations for estimation of monthly mean reference evapotranspiration. Comput. Electron. Agric. 2017, 139, 103-114. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2017.05.002

[30] Mekala, M. S., & Viswanathan, P. (2019). (t, n): Sensor Stipulation with THAM index for smart agriculture decision-making IoT system. Wireless Personal Communications. https://doi.org/10.1007/s11277-019-06964-0. https://doi.org/10.1007/s11277-019-06964-0

[31] Mohammadi, K.; Shamshirband, S.; Motamedi, S.; Petković, D.; Hashim, R.; Gocic, M. Extreme learning machine based prediction of daily dew point temperature. Comput. Electron. Agric. 2015, 117, 214-225. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2015.08.008

[32] Morellos, A.; Pantazi, X.-E.; Moshou, D.; Alexandridis, T.; Whetton, R.; Tziotzios, G.; Wiebensohn, J.; Bill, R.; Mouazen, A.M. Machine learning based prediction of soil total nitrogen, organic carbon and moisture content by using VIS-NIR spectroscopy. Biosyst. Eng. 2016, 152, 104-116. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.biosystemseng.2016.04.018

[33] Nahvi, B.; Habibi, J.; Mohammadi, K.; Shamshirband, S.; Al Razgan, O.S. Using self-adaptive evolutionary algorithm to improve the performance of an extreme learning machine for estimating soil temperature. Comput. Electron. Agric. 2016, 124, 150-160. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2016.03.025

[34] Naresh, M., & Munaswamy, P. (2019). Smart agriculture system using IoT technology. International Journal of Recent Technology and Engineering, 7(5), 98-102.

[35] Nayyar, A., & Puri, V. (2016). Smart farming: IoT based smart sensors agriculture stick for live temperature and moisture monitoring using Arduino, cloud computing & solar technology (pp.

673-680). https://doi.org/10.1201/9781315364094-121

[36] Pantazi, X.-E.; Moshou, D.; Alexandridis, T.K.; Whetton, R.L.; Mouazen, A.M. Wheat yield prediction using machine learning and advanced sensing techniques. Comput. Electron. Agric. 2016, 121, 57-65. https://doi.org/10.1016/j.compag.2015.11.018

[37] Pantazi, X.-E.; Moshou, D.; Bravo, C. Active learning system for weed species recognition based on hyperspectral sensing. Biosyst. Eng. 2016, 146, 193-202. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.biosystemseng.2016.01.014

[38] Pantazi, X.E.; Tamouridou, A.A.; Alexandridis, T.K.; Lagopodi, A.L.; Kashefi, J.; Moshou, D. Evaluation of hierarchical self-organising maps for weed mapping using UAS multispectral imagery. Comput. Electron. Agric. 2017, 139, 224-230. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2017.05.026

[39] Patil, A.P.; Deka, P.C. An extreme learning machine approach for modeling evapotranspiration using extrinsic inputs. Comput. Electron. Agric. 2016, 121, 385-392. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2016.01.016

[40] Pavithra, D.S.; Srinath, M.S. GSM based automatic irrigation control system for efficient use of resources and crop planning by using an Android mobile. IOSR J. Mech. Civ. Eng. 2014, 11, 49-55. https://doi.org/10.9790/1684-11414955

[41] Rajesh, D. Application of spatial data mining for agriculture. Int. J. Comput. Appl. 2011, 15, 7-9. https://doi.org/10.5120/1922-2566

[42] Raju, K. Lova & Veeramani, Vijayaraghavan. (2020). IoT Technologies in Agricultural Environment: A Survey. Wireless Personal Communications. 113. https://doi.org/10.1007/s11277-020-07334-x

[43] Ramos, P.J.; Prieto, F.A.; Montoya, E.C.; Oliveros, C.E. Automatic fruit count on coffee branches using computer vision. Comput. Electron. Agric. 2017, 137, 9-22. https://doi.org/10.1016/j.compag.2017.03.010

[44] Raut, R., Varma, H., Mulla, C., & Pawar, V. R. (2018). Soil monitoring, fertigation, and irrigation system using IoT for agricultural application. In Y. C. Hu, S. Tiwari, & K. Mishra (Eds.), Trivedi intelligent communication and computational technologies. Lecture notes in networks and systems (Vol. 19). Singapore: Springer. https://doi.org/10.1007/978-981-10-5523-2_7

[45] Ravindranath, K., Sai Bhargavi, Ch., Samaikya Reddy, K., & Sai Chandana, M. (2019). Cloud of things for smart agriculture. International Journal of Innovative Technology and Exploring Engineering, 8(6), 30-33.

[46] Sai Prasanna, G. V., & Vijay Kumar, G. (2019). Controlling and monitoring the plant growth conditions using embedded systems. International Journal of Innovative Technology and Exploring Engineering, 8(6), 1552-1555.

[47] Sakthipriya, N. An effective method for crop monitoring using wireless sensor network. Middle-East J. Sci. Res. 2014, 20, 1127-1132.

[48] Satyanarayana, G.V.; Mazaruddin, S.D. Wireless sensor based remote monitoring system for agriculture using ZigBee and GPS. In Proceedings of the Conference on Advances in Communication and Control Systems-2013, Makka Wala, India, 6-8 April 2013.

[49] Sengupta, S.; Lee, W.S. Identification and determination of the number of immature green citrus fruit in a canopy under different ambient light conditions. Biosyst. Eng. 2014, 117, 51-61. https://doi.org/10.1016/j.biosystemseng.2013.07.007

[50] Senthilnath, J.; Dokania, A.; Kandukuri, M.; Ramesh, K.N.; Anand, G.; Omkar, S.N. Detection of tomatoes using spectral-spatial methods in remotely sensed RGB images captured by UAV. Biosyst. Eng. 2016, 146, 16-32. https://doi.org/10.1016/j.biosystemseng.2015.12.003

[51] Shaobo, Y.; Zhenjianng, C.; Xuesong, S.; Qingjia, M.; Jiejing, L.; Tingjiao, L.; Kezheng, W. The appliacation of bluetooth module on the agriculture expert System. In Proceedings of the 2010 2nd International Conference on Industrial and Information Systems, Dalian, China, 10-11 July 2010; Volume 1, pp. 109-112.

[52] Song, Y.; Ma, J.; Zhang, X.; Feng, Y. Design of wireless sensor network-based greenhouse environment monitoring and automatic control system. J. Netw. 2012, 7, 838. https://doi.org/10.4304/jnw.7.5.838-844

[53] Statista. https://www.statista.com/statistics/471264/iot-number-of-connected-devices-worldwide/. Accessed by January 26th, 2023.

[54] Su, Y.; Xu, H.; Yan, L. Support vector machine-based open crop model (SBOCM): Case of rice production in China. Saudi J. Biol. Sci. 2017, 24, 537-547. https://doi.org/10.1016/j.sjbs.2017.01.024

[55] Torres-Ruiz, M.; Juárez-Hipólito, J.H.; Lytras, M.D.; Moreno-Ibarra, M. Environmental noise sensing approach based on volunteered geographic information and spatio-temporal analysis with machine learning. In Proceedings of the International Conference on Computational Science and Its Applications, Beijing, China, 4-7 July 2016; pp. 95-110. https://doi.org/10.1007/978-3-319-42089-9_7

[56] Udhaya N., Manjuparkavi R., Ramya R., (2018). International Journal of Advanced Research in Computer and Communication Engineering. 7(3), 84-86.

[57] Zhang, M.; Li, C.; Yang, F. Classification of foreign matter embedded inside cotton lint using short wave infrared (SWIR) hyperspectral transmittance imaging. Comput. Electron. Agric. 2017, 139, 75-90. [Google Scholar] [CrossRef] https://doi.org/10.1016/j.compag.2017.05.005

[58] Zheng, R.; Zhang, T.; Liu, Z.; Wang, H. An EIoT system designed for ecological and environmental management of the Xianghe Segment of China's Grand Canal. Int. J. Sustain. Dev. World Ecol. 2016, 23, 372-380. https://doi.org/10.1080/13504509.2015.1124470

[59] Johansson Anna, Maria Jansen, Anna Wagner, Anna Fischer, Maria Esposito. Machine Learning Techniques to Improve Learning Analytics. Kuwait Journal of Machine Learning, 2(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/189

[60] Kuna, S. L. ., & Prasad, A. K. . (2023). Deep Learning Empowered Diabetic Retinopathy Detection and Classification using Retinal Fundus Images. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1), 117–127. https://doi.org/10.17762/ijritcc.v11i1.6058

[61] Maruthamuthu, R., Dhabliya, D., Priyadarshini, G.K., Abbas, A.H.R., Barno, A., Kumar, V. V. Advancements in Compiler Design and Optimization Techniques (2023) E3S Web of Conferences, 399, art. no. 04047