A ADVANCED JOURNAL IN ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TRENDS IN BIOLOGICAL SCIENCES
Open Journal

Review

Machine Learning Techniques for Accurate Agriculture through Wireless Sensor Networks: A Comprehensive Review

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Article information
Received: November 20th, 2023; **Revised:** December 22nd, 2023; **Accepted:** January 20th, 2024; **Published:** February 15th, 2024

Cite this article
Mekonnen Y, Namuduri S, Bhansali S. Machine learning techniques for accurate agriculture through wireless sensor networks: A comprehensive review. 2024; 3(1). doi: https://doi.org/10.70705/ppp.bioai.2024.v03.i01.pp5-10

ABSTRACT

Improving agricultural output while decreasing environmental impact requires widespread use of sensor technology and the IoT. New developments in the Internet of Things (IoT), Wireless Sensor Networks (WSN), and ICT may help solve some of the sector's technological, economic, and environmental problems. Big data with many modalities and geographical and temporal changes is increasing due to the proliferation of linked devices. For improved decision-making, more accurate forecasting, and dependable sensor management, intelligent processing and analysis of this massive data is essential. This article provides a thorough analysis of how various machine learning algorithms have been used for agricultural ecosystem sensor data analytics. In addition, the article delves into a case study of a prototype smart farm that integrates food, energy, and water (FEW) systems via the use of the Internet of Things (IoT).

Keywords
Internet of things (IoT); Mprecision agriculture (PA); Wireless sensor networks (WSN).

INTRODUCTION

The increasing demands of consumers, along with the scarcity of arable land, potable water, and reliable energy sources, are putting a strain on the agricultural sector. To alleviate some of this pressure, technology has emerged as a key player. Accompanying other machine-to-machine (M2M) based implementations like smart metering and smart cities, precision agriculture (PA) is another name for smart farming. The entire market value for PA solutions is projected to reach $4.7 billion in 2021, about twice the amount in 2016, according to Libelium, a key player in the IoT solution business.1 The agricultural sector has lagged behind other sectors when it comes to embracing the new M2M and IoT technology, despite an increasing amount of fascinating research and new smart farming initiatives.2 In order to implement smart farming practices, it is necessary to use sensor technologies that gather information on the soil, crops, climate, animals, and tractors. Farmers may get significant insights into weather predictions, crop monitoring and yield prediction, plant and animal disease diagnosis, and more with the use of edge IoT computing and analytics applied to sensor data.3

Depending on the specific agricultural method, smart agriculture may be used in many ways. Currently, data visualization technologies are available in large-scale agricultural settings that can send real-time data, and these tools make use of farm vehicles such as smart tractors that include GPS and several embedded sensors.4 With their integrated sensors, drones play a significant role in this context, allowing for a variety of aerial photography, field surveying, and location mapping tasks.5. Spatially enabled mobile sensing technologies are being used in small to medium-sized arable farms to analyze field conditions in depth, taking into account various soil layers, nutrient levels, and overall environmental factors.6,7 Smart irrigation, which optimizes the watering cycle by taking into account plants' evapotranspiration parameters, is also in its early stages of adoption. When planning when to water, many people utilize sensors that measure soil temperature and moisture.Connected devices are also used to track the whereabouts and well-being of cattle via the use of embedded sensors that wirelessly send data.13 Vertical farming that incorporates the new technologies of aquaponics, aeroponics, and hydroponics is another commonplace usage of the internet of things (IoT).14, 15 There has been extensive usage of WSN for environmental monitoring with a variety of intended uses.16

This article aims to provide a thorough overview of sensor and IoT data analytics utilizing machine learning (ML) methods for agricultural applications, while also highlighting the utilization of WSN and IoT in this sector. Yield prediction, irrigation decision assistance, and crop quality are three areas where a variety of relevant articles highlight the important and distinctive characteristics of ML models. Included in the presentation is a case study of an experimental testbed that delves into the FEEW system's dependency via the use of an end-to-end IoT platform. This paper's literature evaluation only incorporates articles published during the last three years. The following is the outline of the paper: The most current developments in the use of artificial intelligence (AI) in farming are detailed in the AI in Agriculture section. Learn about the most popular machine learning approaches used by WSN-based PA in this section on machine learning techniques. This section provides a concise overview of the literature on WSN-based PA applications that have made use of the ML approach in recent years. In the section titled "Case study on IoT based smart agriculture solution," a smart agriculture system based on the internet of things is detailed.

AI in Agriculture

Farmers may make better use of their land and its resources with the aid of artificial intelligence (AI). Big data is the massive amount of information gathered from many sources, such as sensors, the internet of things (IoT), global positioning systems (GPS), aerial images, and more.17 The Internet of Things (IoT) is a network of interconnected physical devices, software, sensors, and communications devices that can gather and transmit data over wireless and wired networks.18 Modern farms generate millions of data points per day using developing technologies like the Internet of Things (IoT) and unmanned aerial vehicles (UAVs). Farmers may now use AI to examine data received from their farms, including weather, temperature, water consumption, energy usage, and soil conditions, to make better choices. In addition to using sensor data for crop prediction, farmers may now better prepare for climate change and natural disasters by using intelligent data processing methods like machine learning. The Internet of Things (IoT) and artificial intelligence (AI) are starting to be recognized as potential tools to boost agricultural output and efficiency.19 From keeping tabs on when to harvest to identifying plant diseases20,21 The potential uses of AI in agricultural technology are vast and underexplored. The application of artificial intelligence was shown in Ref. 20 to train a dataset of cassava leaves to identify insect and disease damage; the program achieved a detection accuracy of 98%. Training robots to effectively manage, harvest, and preserve agriculture is another application of AI that can save a lot of time, energy, and human resources. Robotics, soil and crop monitoring, and predictive analytics are the three new frontiers of artificial intelligence (AI) in the agricultural sector.22,23

Planting, weeding, and harvesting are all crucial agricultural activities that autonomous robots can easily do in lieu of human workers.22 In recent years, new businesses such as Blue River Technology bought by John Deer use computer vision into its precision spray to keep an eye on cotton plants and spray them as they start to grow weeds.24 One new technology that might help alleviate the strain on harvesting crews is robotics and automation. Harvest CROO Robotics has created a robot to assist strawberry growers in harvesting and packaging the fruit.25

Some notable applications of ML methods include crop disease diagnosis and soil health monitoring. One example is Plantix, a picture recognition app that employs ML methods in its algorithm to identify agricultural plant illnesses and soil deficiencies from patterns in the soil.26 Through the camera on their smartphone, farmers may examine the data, as well as methods and answers to the issue. The same holds true for the identification of three agricultural illnesses and two pest dam-ages affecting cassava plants in Tanzania using deep conventional neural networks.20 The agricultural sector is the most prominent user of unmanned aerial vehicles (UAVs), with a predicted market value of $480 million by 2027.23 Large arable farms benefit greatly from the data collection capabilities of drones because of how quickly and efficiently they can cover enormous areas. Drone data may increase crop health, production, and decrease costs using artificial intelligence.27

Common applications of predictive analytics include identifying pests and diseases, developing remote PA systems, and using satellite data for weather and agricultural sustainability predictions.6,7 To build decision-making and prediction models for the future, data from sensors is processed, manipulated, and analyzed using predictive analytics. Also, ML methods are often used as decision-support tools in IoT WSN-based irrigation systems.10

Machine Learning Techniques

One branch of artificial intelligence, machine learning allows computers to mimic human learning processes. With the use of computational methods, its algorithms may learn from datasets directly, rather than relying on pre-mined equations. As the amount of training samples grows, the algorithms learn to improve their performance.pages 28–30 Machine learning (ML) methods are robust resources for addressing large, complex, non-linear problems using data from sensors and other networks. In real-world situations, it allows for better decision-making and more informed decisions with less human involvement. ML methods are always evolving and have a broad range of applications in almost every industry. Having said that, their uses are severely limited. Data quality, accurate model representation, and interdependencies between input and output variables all impact prediction accuracy.31

Supervised learning and unsupervised learning are the two main types of machine learning algorithms. To predict the target variable from out-of-sample data, supervised learning trains a model using a known set of labelled data.28 Supervised learning is often used in classification and regression procedures. In Figure 1 we can see the various approaches together with a list of typical algorithms that belong to them. To make inferences from unlabeled data, unsupervised learning searches for underlying structures or patterns in the data. In exploratory applications, when the data is unclear or there is no predetermined objective, it might be helpful. In addition, it works well as a dimensionality reduction strategy for multi-feature data. Exploratory data analysis uses clustering, the most popular learning model in this category, and it finds use in gene sequencing and object identification, among other areas.29 Data size, kind, and anticipated insight all play a role in algorithm selection. Most algorithm selections, however, are the result of trial and error rather than a universal prescription. Internet of Things (IoT) smart data analysis makes heavy use of supervised and unsupervised learning approaches in a wide range of applications.32 A new area where ML approaches are being used to quantify and comprehend the massive data is smart farming, which is made possible by WSN and the internet of things. Crop management, livestock management, water management, and soil management are among of the many ML applications in PA.ML is used in crop management for a variety of purposes, including yield prediction, disease identification, weed detection, phenotypic categorization, and a number of others.27 Applications of WSN-driven AI in agriculture will be the next topic covered in this study.

Regression.—Regression is supervised ML techniques that predict continuous responses such as stock prices, fluctuations in electricity demand, and time-series sensor data. Mainly, there are two types of regression algorithms: linear and nonlinear. Linear models rely on the assumption of a linear relationship between independent and de- pendent variables. As presented in Fig. 1, the common regression algorithms are linear, nonlinear, Gaussian process regression model (GPRM), support vector machine (SVM) regression, generalized linear model (GLM), decision tree (DT), ensemble methods, and neural networks. Four of these techniques were selected to be discussed in detail as they have been relevant to the application of crop yield pre- diction.

Application.—Extending the data infrastructure to cloud, part of the goal for this project is to live-stream sensor data using a mobile application. The mobile application platform enables intended users to understand what their farm is doing in real-time and additionally track critical information on energy consumption, irrigation events, and weather variables. The sensor data stored on the local database of the IoT gateway are constantly synchronized to an external MySQL database located in a virtual machine and Google Firebase cloud. It has been successfully implemented to be pushed to Microsoft Azure cloud services, as well. However, due to storage limit and cost, Google Fire- base is selected for this application. The mobile application, Green- Link Farming, is currently developed for Android OS and will be extended to iOS in the future. The functionality of the GreenLink Farming app is summarized as follows:

1. A dashboard menu with soil moisture content, leaf wetness, and soil temperature, critical to the feedback response of irrigation events, as shown on the right side of Fig. 8.
2. Insight into previously collected and real-time sensor data. These data are divided into five tracks: weather data, soil data, yield data, energy data, and water data, as shown in Fig. 7.

3. Data visualization capability: sensor data can be viewed as a list view or are plotted to get insight on trends and patterns into the data.
4. Data analytics: predictive modeling of crop yield, weather, en- ergy, and water using different ML techniques. The end objective for this is to eventually maximize food production through multi-objective optimization of the aforementioned variables. Additionally, it will explore the interdependent networks of food produc- tion on energy and water.

Data analysis.—Part of the goal for this project is to use high- resolution sensor data for the prediction of crop yield, weather, and crop quality from sensor data. This IoT solution manages variations in the field to increase crop yield, raise productivity, and reduce the consumption of agricultural inputs. The data-driven physical model enables farmers on how much energy is being produced and consumed by their farm, how much water is being consumed and recycled, and the quality of the yields. Monitoring weather data long-term will give better leverage in building a time-series forecast model that can accurately predict the weather a day ahead, equipping the farmer with decision making capability on when to irrigate. The mobile application platform provides just this, giving the intended user when to schedule irrigation on the dashboard. The number of measurements that sensors can take make the data storage and management process overwhelm- ing, but will help narrow down potential predictor attributes in crop data sets. As this project is ongoing, the data analysis level is in the prelim nary phase, where more data processing and mapping needs to be completed. The research task for the data analysis track, as shown in the left diagram of Fig. 8 are listed as follows:
1. Tracking and gathering data from food, energy, water infrastruc- ture
2. Data pre-processing to organize, clean, and prepare the data. This step is critical since the nature of this project has different tem- poral, spatial scale
3. Modeling of different machine learning algorithms
• Use classification and regression trees (CART) model to identify potential predictors for crop yield, FEW interactions, and yield quality
• Use autoregressive integrated moving average (ARIMA) model for all time-series based sensor data
• Use of deep neural network in remote sensing data to supplement the WSN data
• Evaluation of the models
4. Upgrading and modifying mobile and web-based application to display predicted values

This project implements an IoT based data-driven prototype for an integrated food, water, and energy system. The main goal is to monitor and measure the three interdependent resources using wireless sensor networks and IoT platform across the whole system. To easily navigate the data acquisition and integration, GreenLink Farming mobile application is designed and implemented with Google Firebase cloud storage as a back-end. The implication of such a system is many: it advances the current research challenge on the lack of data-driven integrated FEW systems, and it explores the application of AI in agriculture, and it facilitates the slowly adopt IoT technology into the agriculture sector. It revolutionizes the way farmers cultivate by giving them a direct insight into what their farm is doing through a mobile application capable of data integration, visualization, and analytics. With a cost feasibility analysis, the prototype can also be ideally implemented in regions of the world where access to electricity is a challenge through the use of off-grid solar panels with energy storage.71–73 There is no doubt data-driven techniques can tremendously help boost agricultural productivity. This case study presents an end-to-end IoT platform for agriculture to collect, monitor various sensors with a data analysis framework to be easily accessed via smartphone and internet.

Conclusions

A digital transformation is taking place in agriculture, as it has in other sectors. There has been an exponential growth in the quantity of data acquired from farms. The Internet of Things (IoT), robots, drones, artificial intelligence (AI), and wireless sensor networks are all seeing increased use. With the help of machine learning algorithms, it is possible to sift through the mountain of data and find patterns and insights. Researchers have relied on ML techniques in combination with WSNs more often during the last two years, and this publication has summarized such strategies. increasingly sophisticated methods, such as distributed (or edge) deep learning, may become increasingly popular in the next years. The application of AI may greatly enhance the automation of agricultural processes, leading to higher yields and more efficient use of natural resources. Within the precision agricultural ecosystem, this work has shown many ML models used for weed and disease detection, yield prediction, and other purposes. The work that was evaluated solely been focused specifically on WSN based PA application where ML algorithms were implemented for data mining, forecasting, and au- tomation purpose. By applying ML to sensor data, farm management systems are evolving into real AI systems, providing optimal insights for decisions and actions to be made. This remark is further proved and showcased through an experimental smart farm prototype case study. An environment to help anyone to deploy a PA monitoring application has been described and successfully evaluated in this case study. The architecture, hardware, communication protocol, and data acquisition infrastructure is detailed. The implementation of smartphone appli- cations and the back-end data analysis framework for prediction of weather, crop yield, and crop quality is presented.

REFERENCES

1. Folium. Important takeaways and characteristics sought for by the Smart Agriculture IoT industry. Libelium IoT Solutions technical report.

2. In their 2018 article titled "An overview of internet of things (iot) and data analytics in agriculture: Benefits and challenges," Olakunle Elijah, Tharek Abdul Rahman, Igbafe Orikumhi, Chee Yen Leow, and MHD Nour Hindia discuss the pros and cons of using IoT in the agricultural sector.

3. Sergio Romeo, "The state of smart farming made possible by the internet of things: current trends and developments," At the Bangor University Sensing Technologies for Effective Land Management Workshop, Principal Analyst-Beecham Research was present. Access the paper at: http://www.nrnlcee. ac.uk/documents/5.SaverioRomeoSmartFarming.pdf 2016.

4. "Internet of things in agriculture, recent advances and future challenges," published in Biosystems Engineering, volume 164, issue 31, by Antonis Tzounis, Nikolaos Katsoulas, Thomas Bartzanas, and Constantinos Kittas in 2017.

Fifthly, Beecham Research. The Internet of Things as a Tool for the Smart Agriculture Revolution: Looking Ahead to the Future of Farming. Report on technical aspects of Libelium IoT, 2016.

"IoT sensor network approach for smart farming: An application in food, energy and water system," by Yemeserach Mekonnen, Lamar Burton, Arif Sarwat, and Shekhar Bhansali, 6. Presented at the 2018 IEEE Global Humanitarian Technology Conference (GHTC), pages 1–5. 2018, IEEE.

7. "Smart gar-dening iot soil sheets for real-time nutrient analysis" by L. Burton, N. Dave, R. E. Fernandez, K. Jayachandran, and S. Bhansali was published in the Journal of The Electrochemical Society (2018).

"Wireless soil monitoring sensor for sprinkler irrigation automation system," published in Wireless Personal Communications, volume 98, issue 2, pages 1835, was written by G. Nagarajan and R. I. Minu in 2018.

9. "Automated irrigation system using a wireless sensor network and gprs module" ("Joaquín Gutiérrez, Juan Francisco Villa-Medina, Alejandra Nieto-Garibay, and Miguel Ángel Porta-Gándara," IEEE transactions on instrumentation and measurement, 63(1), 166 (2013)).

Agricultural Water Management, 151, 64 (2015), by Honorio Navarro-Hellín, Roque Torres-Sánchez, Fulgencio Soto-Valles, Cristina Albaladejo-Pérez, Juan Antonio López-Riquelme, and Rafael Domingo-Miguel.

11. In their 2017 article "Proposed fuzzy-nn algorithm with loracommunication protocol for clustered irrigation systems," Sotirios Kontogiannis, George Kokkonis, Soultana Ellinidou, and Stavros Valsamidis discuss the use of loracommunication in this kind of system.

12. "Thoreau: A subterranean wireless sensing network for agricul-ture and the environment," in 2017 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), pages 78-84, by Xufeng Zhang, Arseniy Andreyev, Colleen Zumpf, M. Cristina Negri, Supratik Guha, and Monisha Ghosh. 2017 IEEE.

Using the Internet of Things (IoT), V. Gokul and Sitaram Tadepalli developed a system to monitor cattle in real-time and detect illnesses early on. Pages 469–476 of the 2017 International Conference on I-SMAC (Internet of Things in Social, Mobile, Analytics, and the Cloud). 2017 IEEE.

14. In their 2017 article "Future food-production systems: vertical farming and controlled-environment agriculture," Kurt Benke and Bruce Tomkins discuss potential methods for creating food in the future.

The Vertical Farm: How to Feed the Planet in the Twenty-First Century by Dickson Despommier, Macmillan, 2010.

Using a wireless sensor network, Moses Oluwafemi Onibonoje and Temitayo Olayemi Olowu "Real-time remote monitoring and automated control of granary environmental factors," The citation is from the 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), volume 11, pages113-218. 2017 IEEE.

In their 2017 article "Big data in smart farming-a review," Sjaak Wolfert, Lan Ge, Cor Verdouw, and Marc-Jeroen Bogaardt discuss the use of big data in more efficient agricultural practices.

18. "Internet of things (iot): A vision, architectural elements and future directions" by Jayavardhana Gubbi, Rajkumar Buyya, Slaven Marusic, and Marimuthu Palaniswami, published in Future Generation Computer Systems, 29(7), 1645 (2013).

19. „Machine learning in agriculture: A review," Sensors, 18(8), 2674 (2018), by Konstantinos Liakos, Patrizia Busato, Dimitrios Moshou, Simon Pearson, and Dionysis Bochtis.

20. "Deep learning for image-based cassava disease detection," published in Frontiers in Plant Science, 8, 1852 (2017) by Amanda Ramcharan, Kelsee Baranowski, Peter McCloskey, Babuali Ahmed, James Legg, and David P. Hughes.

"On precisely relating the growth of phalaenopsis leaves to greenhouse environmental factors by using an iot-based monitoring system," published in Computers and Electronics in Agriculture, volume 136, issue 125 (2017), was written by Min-Sheng Liao, Shih-Fang Chen, Cheng-Ying Chou, Hsun-Yi Chen, Shih-Hao Yeh, Yu-Chi Chang, and Joe-Air Jiang.

23. "A thorough evaluation of AI-based agricultural automation," Artificial Intelligence in Agriculture, 2019, Kirtan Jha, Aalap Doshi, Poojan Patel, and Manan Shah.

23.1 "The future of agriculture," Anthony King et al., Nature, 544(7651), S21 (2017).

In the 2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU), pages 1-6. IEEE, 2019, the authors "An experimental set up for utilizing convolutional neural network in automated weed detection" are included.

Twenty-five. CROO. http://harvestcroo.com.

URL: https://plantix.net/en. 26. Pantix.

27. Sungchan and Akash Ashapure "Unmanned aerial system based tomato yield es-timation using machine learning," in Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping IV, volume 11008, page 110080O, by Oh, Thiago G. Marconi, Anjin Chang, Jinha Jung, Juan Landivar, and Juan Enciso. Optics and Photonics Society International, 2019.

Book 28: Bayesian reasoning and machine learning by David Barber, published in 2012 by Cambridge University Press.

Page 29 of Christopher M. Bishop's 2006 Springer book Pattern Recognition and Machine Learning.

30. Kevin P. Murphy, (2012, MIT Press) Machine learning: a probabilistic viewpoint.

31. "Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review" (Anna Chlingaryan, Salah Sukkarieh, and Brett Whelan, 2018).

In their 2018 survey, Mohammad Saeid Mahdavinejad, Mohammadreza Rezvan, Mohammadamin Barekatain, Peyman Adibi, Payam Barnaghi, and Amit P. Sheth discussed the use of machine learning in the interpretation of data from the internet of things (IoT).

33. "Predicting high-magnitude, low-frequency crop losses using machine learning: an application to cereal crops in Ethiopia," Climatic Change, 154(1-2), 211 (2019), by Michael L. Mann, James M. Warner, and Arun S. Malik.

34. "Wheat yield prediction using machine learning and advanced sensing techniques," Computers and Electronics in Agriculture, 121, 57 (2016), by Xanthoula Eirini Pantazi, Dimitrios Moshou, Thomas Alexandridis, Rebecca L. Whetton, and Abdul Mounem Mouazen.

35. "Artificial neural network model as a data analysis tool in precision farming," Transactions of the ASABE, 49(6), 2027 (2006), by A. Irmak, J. W. Jones, W. D. Batchelor, S. Irmak, K. J. Boote, and J. O. Paz.

36. In a 2018 article published in Computers and Electronics in Agriculture, Xianming Dou and Yongguo Yang examine the use of four distinct machine learning methods to estimate evapotranspiration in various terrestrial ecosystems.

In a 2017 article published in Computers and Electronics in Agriculture, Yu Feng, Yong Peng, Ningbo Cui, Daozhi Gong, and Kuandi Zhang discuss the use of temperature data to model reference evapotranspiration using an extreme learning machine and a generalized regression neural network.

The article "Using deep learning to pre-dict soil properties from regional spectral data" was published in 2019 by J. Padarian, B. Minasny, and A. B. McBratney in Geoderma Regional, volume 16, issue e00198.

The article "Machine learning in wireless sensor networks: Algorithms, strategies and applications" was published in the fourth quarter of 2014 by IEEE Communications Surveys Tutorials and was written by M. A. Alsheikh, S. Lin, D. Niyato, and H. Tan.

40. “Types of machine learning algorithms” by Taiwo Oladipupo Ayodele, presented in IntechOpen’s 2010 volume on new developments in machine learning.

41. “An introduction to computing with neural nets” by Richard P. Lippmann, on pages 36–54 of Artificial Neural Networks: Theoretical Concepts. in 1988 by the IEEE Computer Society Press.

Gary James, Daniela Witten, Trevor Hastie, and Robert Tibshirani are the 42nd person on the list. Volume 112. An Introduction to Statistical Learning. Cambridge University Press, 2013.

Section 43 of Machine Learning, Volume 24, Issue 2, pages 123, was written by Leo Breiman in 1996.

Leo Breiman’s “Random forests” from 2001’s Machine Learning, volume 45, issue 1, page 5.

45. Springer, 2012, Cha Zhang and Yunqian Ma, Ensemble machine learning: techniques and applications.

Chapter 40 of Bayesian inference in statistical analysis by George E. P. Box and George C. Tiao (Volume 46). November 2011, John Wiley & Sons.

47. AI: a contemporary perspective, Stuart J. Russell and Peter Norvig. Pearson Education Limited, Malaysia, 2016. M.