Original Article
ISSN (Online): 2350-0530
ISSN (Print): 2394-3629

International Journal of Research - GRANTHAALAYAH
June 2024 12(6), 64–74

MAXIMIZING AGRICULTURAL WATER EFFICIENCY: INTEGRATING IOT AND SUPERVISED LEARNING FOR SMART IRRIGATION OPTIMIZATION

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Received 02 May 2024
Accepted 04 June 2024
Published 05 July 2024

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DOI
10.29121/granthaalayah.v12.i6.2024.5663

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

Optimum utilization of clean water around the globe is essential in order to avoid scarcity. In agriculture, due to the lack of intelligent irrigation systems, consumes more amount of fresh water. Smart irrigation using IoT technologies can solve the problem by achieving effective utilization of water. By examining ground parameters such soil temperature, air moisture, soil moisture, humidity, and weather data (precipitation) from the website, this research project forecasts the irrigation schedule. When designing intelligent irrigation, soil moisture is a key consideration. It is suggested that a hybrid machine learning algorithm be used to estimate the soil moisture for the next days using field, environmental, and weather data in order to accomplish smart irrigation. The field data are gathered by sensors and are transmitted via wifi to the server and the web-based interface is developed to visualize the current field data, weather data, and schedule of the next irrigation. The system is fully autonomous which starts and stops the irrigation based on the result of the algorithm. This work depicts the architecture of the system and describes the information processing of the results for a month. The accuracy of the propsed algorithm is good and has a minimum error rate of predicted soil moisture.

Keywords: Irrigation, IoT, Machine Learning, Precipitation

1. INTRODUCTION

Agricultural development depends on water as it is necessary for the development of plants. Therefore, a sufficient amount of water should be provided at the right moment to boost agricultural productivity. Authorities also worry about water shortages in numerous nations where fast and significant overall water usage has grown Fraiture & Wichelns (2010).

Conventional irrigation methods are not enough to solve water shortage Nikzad et al. (2019), Singh (2019) and Zhang et al. (2019). Though only if agricultural water is properly managed, land and water resources are enough to feed the globe for the next fifty years Molden (2007). This sector has to employ present technological developments and investigate new ideas in order to enhance water management and consequently reduce water usage.

Precision farming is meant to solve a lot of different farming problems. It minimizes water usage and might help output to be improved and expanded Zhang et al. (2002). Using creative technology, precision agriculture's main goals are to increase irrigation management and raise crop yields while using fewer energy and inputs. After gathering data using satellites, drones, and sensors among other observation techniques, precision agriculture links it to decision support tools via online and mobile apps. These information are collected and examined to improve and ease farmers' everyday life Khanna & Kaur (2019).

Technological developments in recent years have helped agriculture to become more industrialized and technologically accessible. Using several intelligent farming tools, which have raised their predictability and efficiency, farmers have gained control of agricultural and animal production operations.

Climate warming and extreme storms aggravate the hazards to important infrastructure Kumar et al. (2018). For many countries, one of the main agricultural issues is reduced water and energy use during irrigation. About 70% of water is used globally for agriculture; most of these countries suffer with water shortage therefore they have to employ smart irrigation methods and rational water resource management Johansson et al. (2016), Doungmanee (2016) and Munoz et al. (2018).

Data centers, sensors and software-equipped devices, machines, and data centers form part of the IoT and interact via the Internet Ray (2018). The main objectives of the Internet of Things are to enhance machine-to----communication and enable the optimal decision free from human involvement Popkova et al. (2019). The Internet of Things' development and application helped many procedures to change in spanning home security, equipment manufacture, health monitoring, automated transportation, and—most famously—agriculture Asghari et al. (2019).

Acknowledging the advantages of precision farming, this paper suggests a clever irrigation system using a supervised learning approach for crops. The suggested approach considers land and data from agricultural crops to make irrigation recommendations. This form of smart irrigation guarantees the required water supply to the crops without waste of resources and helps to save water resources. The section following details the intended work.

2. PROPOSEDENERGY-EFFICIENTSMARTIRRIGATION SYSTEM

Field sensors, sink nodes, IoT-enabled valves, and user terminals are among the many components of the proposed energy-efficient smarter irrigation system. Once the matter calls for response, the user is alerted. While guaranteeing improved output, the smart irrigation system helps to water the crops as required and reduces water waste. This part contains a quick overview of all the elements. Figure 1 shows the general flow diagram of the intended task.

Gathering data from the agricultural field, the field sensor analyzes and sends the data to the sink node. The "field sensors" in this paper denote sensors of soil moisture, water level, and temperature. The watering for the crop is decided upon by the inputs of all these sensors. Gathering and distributing data from every sensor node to the "Cloud Server" (CS) falls to the sink node.

Figure 1

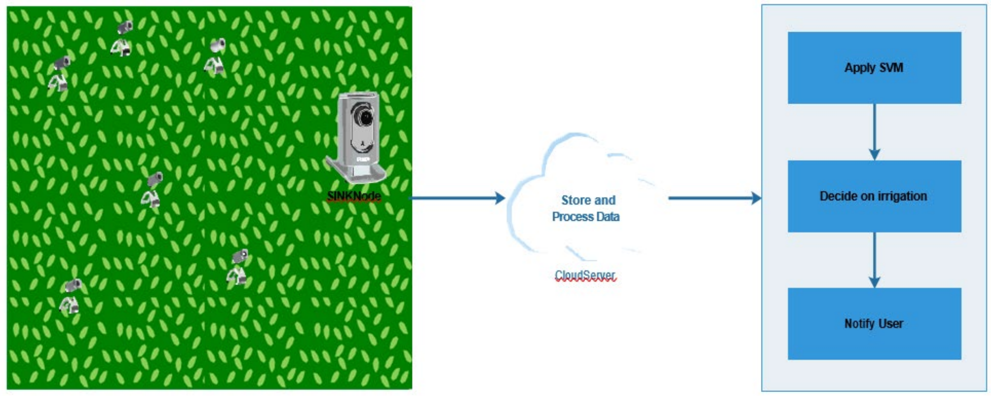

Figure 1 The Overall Flow of the Proposed Work

To make wise judgments, the CS cleans the duplicates and analyzes the data. Furthermore, this project controls water flow by means of IoT connected valve controllers. Current updates are then and there sent to the users.

The field sensors cover a hundred meters of ground. From all the field sensors, the sink node accumulates and sends data to the Control System (CS), which evaluates and verifies the data to ascertain when to water. A Support Vector Machine (SVM) makes the decision; so, the detected data guides the water flow. One may understand decision-making as follows.

3. DECISION MAKING BY SVM

Teaching the SVM classifier the desired feature set helps the classifier to decide on irrigation. Training the classifier on the training cases helps one to achieve this. This study uses $n(n - 1)/2$ SVM classifiers and derives the conclusion by determining the most commonly occurring choice. A traditional SVM uses a hyperplane as a dividing line and indicates two different classes for items.

$$w.tsi + bias \geq +1 for pi = +1 \tag{1.1}$$

$$w.tsi + bias \leq -1 for pi = -1 \tag{1.2}$$

In the above equations, $tsi$is a sample for training, and w seems to be a linear hyperplane. Because linear separation of data is never achievable, slack variables are used$\{sv\}q$ are introduced as shown in the following equation.

$$p(w.tsi) + bias > 1 - svi \tag{1.3}$$

Every pair of classes generates $n(n- 1)/2$ classifiers. This approach aggregates the classifier assessments to get an ultimate decision. This kind of classification guarantees more accurate results and saves time. With an IoT-enabled water valve controller, the suggested smart irrigation system preserves the soil moisture with 60% while the practical moisture of soil in the agricultural area is 60%. The valve is regulated according on the detected temperature (tmp) reading by the temperature sensor displayed in the following situation.

$$\begin{cases} if\, tmp<15°C; open valve by 3\ mm \\ if\, 15°C<tmp<25°C; open valve by 5mm \\ if\, tmp<25°C; open valve by 8\ mm \end{cases} \quad (1.4)$$

The primary flow of this work is shown by the following method.

Proposed Algorithm for SmartIrrigation System

BEGIN
//Field Sensors
Acquire soil moisture, temperature and water level readings; Forward the sensed readings to the sink node;

//Sinknode
Receive readings from the field sensors;
Locally process it by removing duplicates;
Forward the data to the cloud server;
//Cloud server
Receive data from sink node; Apply SVM classifier;

Check for the temperature
If tmp<15°C
openvalveby3mm;
if 15°C<tmp< 25°C
open valve by 5 mm;
if tmp<25°C openvalveby8mm;
Stopwhensoilmoisturereaches60%;
Notify user by email;
END

This circumstance drives the suggested smarter method to provide water to the agricultural fields. The ideal temperature is set as the threshold; a constant learning process grounded on a trial-and-error technique fixes the threshold. The outcomes of the suggested activities are covered in the next part.

4. RESULTS AND DISCUSSION

This part runs and displays the suggested work using Matlab (2019B). The performance of the work is assessed in respect to past published works. The suggested method is evaluated using conventional performance criteria including accuracy, sensitivity, and specificity; its performance is then compared with that of present classifiers like k-NN, Relevant Vector Machine (RVM), and Support Vector Machine (SVM). The results of experiments show SVM beats RVM. The accuracy, sensitivity, and specificity metrics are computed using the following formulae:

$$Ac=\frac{T_p+T_n}{T_p+T_n+F_p+F_n}\times 100 \quad (1.5)$$

$$Sen=\frac{T_p}{T_p+F_n}\times 100 \quad (1.6)$$

$$Spc = \frac{T_n}{F_p + T_n} \times 100 \quad (1.7)$$

Where frates are respectively *Sp*, *Sn*, Fp, Fn. Different classifiers including k-NN, RVM, and SVM are shown in the graphs below.

Figure 2

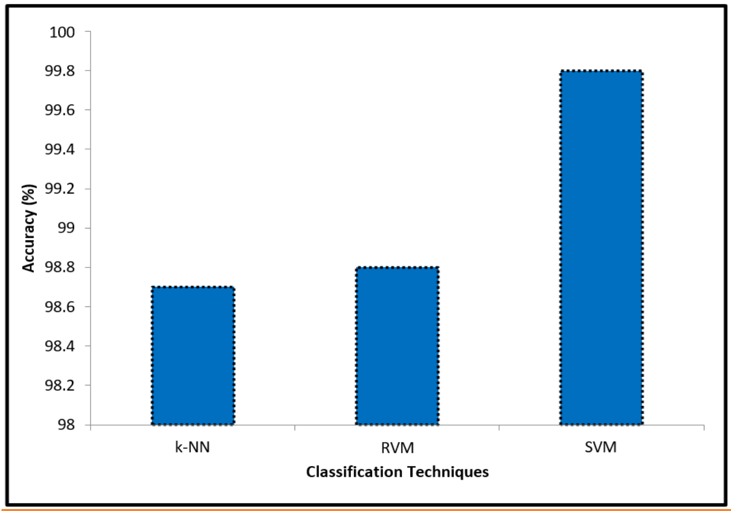

Figure 2 Accuracy Rate Analysis

Evaluated and contrasted with different classification methods including k-NN and RVM is the accuracy rate of the SVM classification strategy. SVM performs more effectively than the related methods.

Closely followed by the RVM classifier, which has a rate of 98.8 percent accuracy, the SVM classifier gets a rate of 99.8 percent accuracy. The sensitivity rate of the recommended method is shown graphically below.

Figure 3

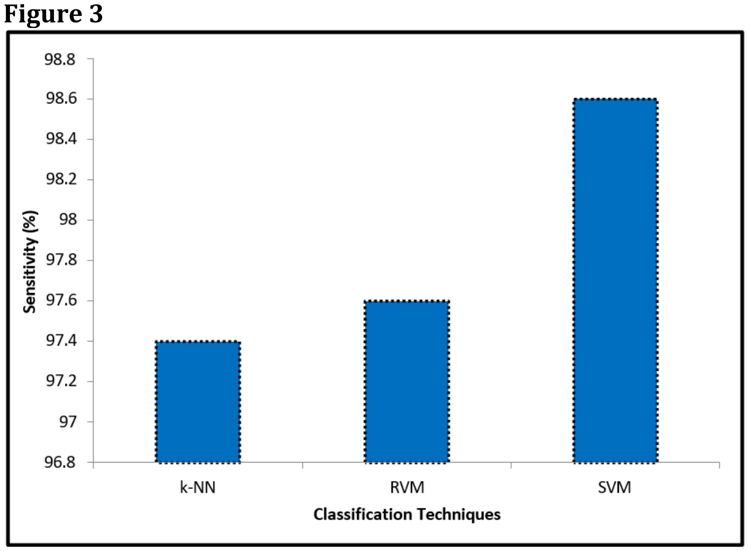

Figure 3 Sensitivity Rate Analysis

The sensitivity of the proposed method is assessed and found to be appropriate with respectable rates. The RVM classifier shows 97.4% while the SVM displays

98.6% as the sensitivity. The sensitivity rates indicate some variations even if the SVM and RVM classifier accuracy rates are more near to one another.

The low number of false negatives provides the justification for the greater sensitivity rates of ensemble classification. Figure 4 shows the specificity rate analysis of the recommended strategy.

Figure 4

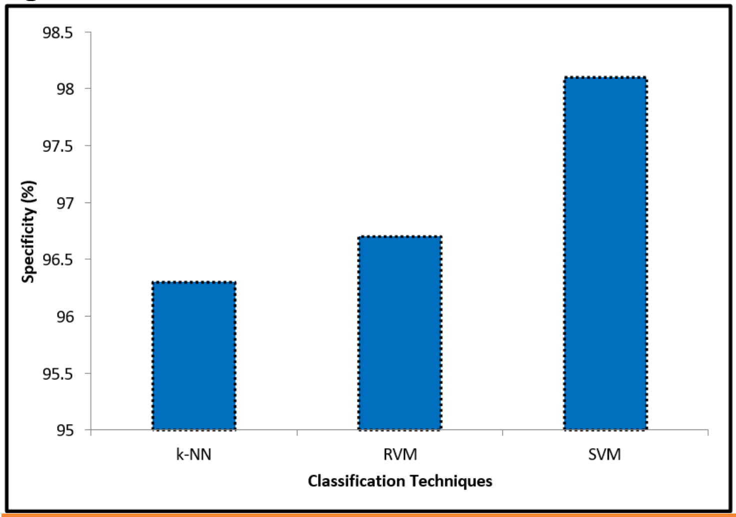

Figure 4 Specificity Rate Analysis

The SVM works better with the highest specificity rate according the specificity rate study. Following the SVM with 98.1 percent as the specificity rate comes the RVM classifier with 96.7 percent.

Higher accuracy, sensitivity, and specificity rates abound from the SVM classifier. The time needed for the many categorizing techniques is compiled in the following table.

Figure 5

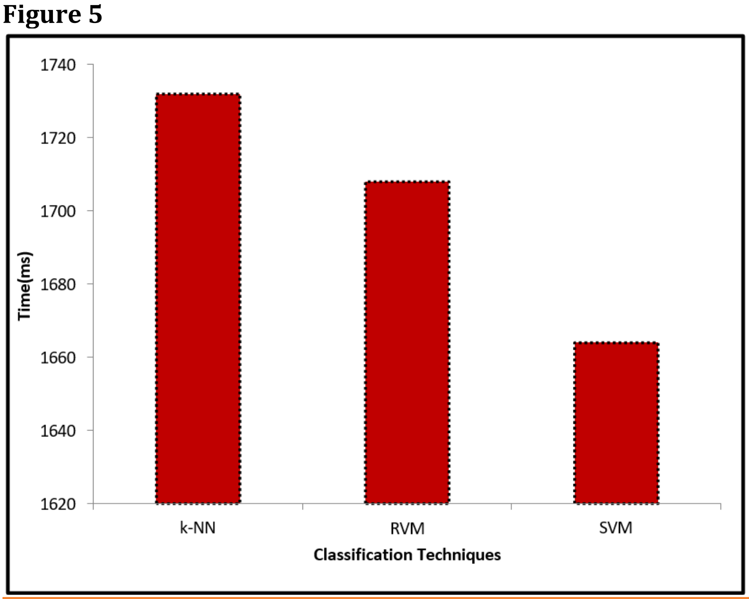

Figure 5 Time Consumption Analysis

Thus, the performance of the work is investigated and it is discovered that the SVM beats the related classifiers. The following shows the projected work's energy usage analysis.

Figure 6

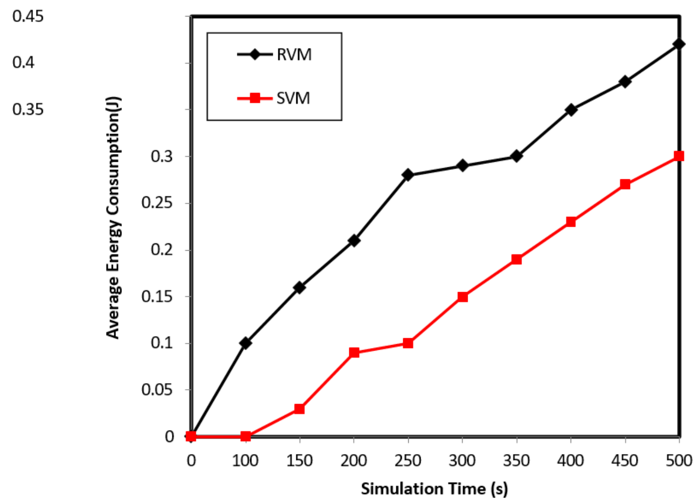

Figure 6 Energy Consumption Analysis

On accepted performance criteria, the experimental results show that the suggested strategy beats similar solutions. The crop output may be improved as the soil moisture is kept constant all through. Besides water waste is also avoided as the water supply is started upon demand. The chapter is summed up in the next part.

5. CONCLUSION

This paper proposes a smart irrigation system using IoT and a supervised learning algorithm for contemporary agriculture. The sink node gathers the data while the suggested work uses numerous field sensors. Supervised learning algorithm controls the IoT-enabled water valve. The performance of the task is assessed with respect to numerous benchmark criteria. For precision agriculture, a hybrid ML system is put forth to forecast soil moisture. Different climatic factors, such as air temperature, moisture content, soil temperature, and soil humidity, all affect how moist the soil is. For the purpose of predicting soil moisture in this suggested work, weather data is used. In order to forecast soil moisture for the upcoming days for optimal irrigation, this work takes into account both field sensor data and precipitation information. The suggested technique predicts soil moisture with a reasonable degree of accuracy and a low rate of error. The deep learning technique will be used in the future to forecast soil moisture for intelligent irrigation.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

REFERENCES

Abdullah, A., Enazi, S. A., & Damaj, I. (2016). AgriSys: A Smart and Ubiquitous Controlled-Environment Agriculture System, 2016 3rd MEC International Conference on Big Data and Smart City (ICBDSC), Muscat, 1-6. https://doi.org/10.1109/ICBDSC.2016.7460386

Asha Paul, M., & Jansi Rani, P. A., Sheela, E.D. (2021). Coral Reef Classification using Improved WLD Feature Extraction with Convolution Neural Network Classification. Recent Advances in Computer Science and Communications, 14(8). https://doi.org/10.2174/2666255813999200511101830

Asha Paul, M., & Jansi Rani, P. A. (2021). Statistical Modeling Based Directional Pattern Design (SMDPD) Feature Extraction for Coral Reef Classification. Environmental Monitoring and Assessment, 193, 583. https://doi.org/10.1007/s10661-021-09314-5

Asha Paul, M., Jansi Rani, P. A., & Liba Manopriya, L. (2020). Gradient Based Aura Feature Extraction for Coral Reef Classification. Wireless Personal Communications, 114(1), 149-166. https://doi.org/10.1007/s11277-020-07355-6

Banđur, D., Jakšić, B., Banđur, M., & Jović, S. (2019). An Analysis of Energy Efficiency in Wireless Sensor Networks (WSNs) Applied in Smart Agriculture. Comput. Electron. Agric, 156, 500-507. https://doi.org/10.1016/j.compag.2018.12.016

Bhoi, A., Nayak, R.P., Bhoi, S.K., Sethi, S., Panda, S.K., Sahoo, K.S., & Nayyar, A. (2021). IoT-IIRS: Internet of Things Based Intelligent-Irrigation Recommendation System Using Machine Learning Approach for Efficient Water Usage. PeerJ Computer Science, 7. https://doi.org/10.7717/peerj-cs.578

Castañeda-Miranda, A., & Castaño-Meneses, V.M. (2020). Internet of Things for Smart Farming and Frost Intelligent Control in Greenhouses. Computers and Electronics in Agriculture, 176. https://doi.org/10.1016/j.compag.2020.105614

Chen, Q., & Chen, T.Y. (1993). Estimation of River Basin Evapotranspi- Ration Over Complex Terrain Using NOAA AVHRR Data. Acta Geogr. Sin. 48(1), 61-69. https://doi.org/10.11821/xb199301008

Clean Water Crisis Facts and Information-National Geographic (2022). Accessed: Aug. 16, 2022.[Online].

Cruz, M.A.A., Rodrigues, J.J.P.C., Al-Muhtadi, J., Korotaev, V., & Albuquerque, V.H.C. (2018). A Reference Model for Internet of Things Middleware. 1 1. IEEE Internet ThingsJ. 5. https://doi.org/10.1109/JIOT.2018.2796561

Difallah, W., Benahmed, K., Draoui, B., & Bounaama, F. (2017). Linear Optimization Model for Efficient Use of Irrigation Water. Int. J. Agron. https://doi.org/10.1155/2017/5353648

Dutta, R., Morshed, A., Aryal, J., D'Este, C., & Das, A. (2014). Development of an Intelligent Environmental Knowledge System for Sustainable Agricultural Decision Support. Environ. Model. Softw., 52, 264-272. https://doi.org/10.1016/j.envsoft.2013.10.004

Elavarasan, D., Vincent, D.R., Sharma, V., Zomaya, A.Y., & Srinivasan, K. (2018). Srinivasan Forecasting Yield by Integrating Agrarian Factors and Machine Learning Models: A Survey Comput. Electron. Agric., 155, 257-282. https://doi.org/10.1016/j.compag.2018.10.024

Goap, A., Sharma, D., Shukla, A. K, & Krishna, C. R. (2018). An IoT Based Smart Irrigation Management System using Machine Learning and Open Source

Technologies. Computers and Electronics in Agriculture, 155, 41-49. https://doi.org/10.1016/j.compag.2018.09.040

Goldstein, A., Fink, L., Meitin, A., Bohadana, S., Lutenberg, O., & Ravid, G. (2017). Applying Machine Learning on Sensor Data for Irrigation Recommendations: Revealing Theagronomist's Tacit Knowledge. Precis. Agric. 19, 421-444. https://doi.org/10.1007/s11119-017-9527-4

Gu, Z., Qi, Z., Burghate, R., Yuan, S., Jiao, X., & Xu, J. (2020). Irrigation Scheduling Approaches and Applications: A Review. J. Irrig. Drain.Eng, 146. https://doi.org/10.1061/(ASCE)IR.1943-4774.0001464

Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A Vision, Architectural Elements, and Future Directions. Futur. Gener. Comput. Syst. 29, 1645-1660. https://doi.org/10.1016/j.future.2013.01.010

Gutierrez, J., Villa-medina, J.F., Nieto-Garibay, A., & Porta-gandara, M. A. (2014). Automated Irrigationsystem Using a Wireless Sensor Network and GPRS module. IEEE Trans. Instrum. Meas. 63, 166-176. https://doi.org/10.1109/TIM.2013.2276487

Hargreaves, G. H., & Samani, Z. A. (1985). Reference Crop Evapotranspiration from Temperature. Appl. Eng. Agric. 1, 96-99. https://doi.org/10.13031/2013.26773

Hedley, C. B., Roudier, P., Yule, I. J., Ekanayake, J., & Bradbury, S. (2013). Soil Water Status and Watertable Depth Modelling using Electromagnetic Surveys for Precision Irrigation Scheduling. Geoderma, 199, 22-29. https://doi.org/10.1016/j.geoderma.2012.07.018

Jesi, V. E., Kumar, A., Hosen, B., & David D, S. (2022). IoT Enabled Smart Irrigation and Cultivation Recommendation System for Precision Agriculture. ECS Transactions 107, 1. https://doi.org/10.1149/10701.5953ecst

Jha, K., Doshi, A., Patel, P., & Shah, M. (2019). A Comprehensive Review on Automation in Agriculture Using Artificial Intelligence, Artificial Intelligence in Agriculture. https://doi.org/10.1016/j.aiia.2019.05.004

Jing, W., Yaseen, Z.M., Shahid, S., Saggi, M.K., Tao, H., Kisi, O., Salih, S.Q., Al-Ansari, N., & Chau, K.-W. (2019). Implementation of Evolutionary Computing Models for Reference Evapotranspiration Modeling: Short Review, Assessment and Possible Future Research Directions. Eng. Appl. Comput. Fluid Mech, 13, 811-823. https://doi.org/10.1080/19942060.2019.1645045

Khattab, A., Abdelgawad, A., & Yelmarthi, K. (2016). Design and Implementation of a Cloud-Based Iot Scheme for Precision Agriculture. 28th International Conference on Microelectronics (ICM), IEEE, Giza, Egypt, 201-204.

King, B. A., & Shellie, K. C. (2016). Evaluation of Neural Network Modelingto Predict Non-Water-Stressed Leaf Temperature in Wine Grape for Calculation of Crop Water Stress Index, Agricult. Water Manage., 167, 38-52. https://doi.org/10.1016/j.agwat.2015.12.009

Kumar, G.R., Gopal, T.V., Sridhar, V., & Nagendra, G. (2018). Smart Irrigation System. International Journal of Pure and Applied Mathematics, 119(15), 1155-1168.

Liu, Y., Ren, Z.-h, Li, D.-M, Tian, X.-K, & Lu, Z.-N. (2006). The Research of Precision Irrigation Decision Support System Based on Genetic Algorithm. International Conference on Machine Learning and Cybernetics. https://doi.org/10.1109/ICMLC.2006.258403

Lukas, Tanumihardja, W.A., & Gunawan, E. (2015). On the Application of IoT: Monitoring of Troughs Water Level Using WSN. In: Conference on Wireless Sensors (ICS). IEEE, 58-62. https://doi.org/10.1109/ICWISE.2015.7380354

Morillo, J. G., Martín, M., Camacho, E., Díaz, J. A. R., & Montesinos, P. (2015). Toward Precision Irrigation for Intensive Strawberry Cultivation, Agricult. Water Manage, 151, 43-51. https://doi.org/10.1016/j.agwat.2014.09.021

Mulenga, R., Kalezhi, J., Musonda, S. K., & Silavwe, S. (2018). Applying Internet of Things in Monitoring and Control of an Irrigation System for Sustainable Agriculture for Small-Scale Farmers in Rural Communities, inProc. IEEE PES/IAS Power Africa, 841-845. https://doi.org/10.1109/PowerAfrica.2018.8521025

Moller, A., Mulder, V., Heuvelink, G., Jacobsen, N., & Greve, M. (2021). Can We Use Machine Learning for Agricultural Land Suitability Assessment? Agronomy, 11, 703. https://doi.org/10.3390/agronomy11040703

Parr, J. F., Reganold, J. P., & Papendick, R. I. (1990). Sustainable Agriculture, Sci. Amer., 262(6), 112-121. https://doi.org/10.1038/scientificamerican0690-112

Pavithra, D.S. (2014). GSM Based Automatic Irrigation Control System for Efficient Use of Resources and Crop Planning by using an Android Mobile. IOSR Journal of Mechanical and Civil Engineering, 1(4), 49-55. http://dx.doi.org/10.9790/1684-11414955

Phillips-Wren, G., & Ichalkaranje, N. (2008). Intelligent Decision Making: An AI-Based Approach; Springer Science & Business Media: Berlin, Germany, 97. https://doi.org/10.1007/978-3-540-76829-6

Pour, O.M.R., Piri, J., & Kisi, O. (2018). Comparison of SVM, ANFIS and GEP in Modeling Monthly Potential Evapotranspiration in an Arid Region (Case Study: Sistan and Baluchestan Province, Iran). Water Supply, 19, 392-403. https://doi.org/10.2166/ws.2018.084

Roopaei, M., Rad, P., Choo, K.R., & Choo, R. (2017). Cloud of Things in Smart Agriculture: Intelligent Irrigation Monitoring by Thermal Imaging. IEEE Cloud Comput, 4, 10-15. https://doi.org/10.1109/MCC.2017.5

Sami, M., Khan, S.Q., Khurram, M., Farooq, M.U., Anjum, R., Aziz, S., Qureshi, R., & Sadak, F. (2022). A Deep Learning-Based Sensor Modeling for Smart Irrigation System. Agronomy, 12, 212. https://doi.org/10.3390/agronomy12010212

Smith, D., & Peng, W. (2009). Machine Learning Approaches for Soil Classification in a Multi-Agent Deficitirrigation Control System. IEEE International Conference on Industrial Technology-- (ICIT), Churchill, Victoria, Australia. https://doi.org/10.1109/ICIT.2009.4939641

Sun, Y., Song, H., Jara, A. J., & Bie, R. (2016). Internet of Things and Big Data Analytics for Smart and Connected Communities, IEEE Access, 4, 766-773. https://doi.org/10.1109/ACCESS.2016.2529723

Torres-Sanchez, R., Navarro-Hellin, H., Guillamon-Frutos, A., San-Segundo, R., Ruiz-Abellón, M.C., & Domingo-Miguel, R. (2020). A Decision Support System for Irrigation Management: Analysis and Implementation of Different Learning Techniques. Water, 12, 548. https://doi.org/10.3390/w12020548

Tripathy, A.K., Adinarayana, J., Vijayalakshmi, K., Merchant, S.N., Desai, U.B., Ninomiya, S., & Kimura, T., (2014). Knowledge Discovery and Leaf Spot Dynamics of Groundnut Crop Through Wireless Sensor Network and Data Mining Techniques. Comput. Electron. Agric. 107, 104-114. https://doi.org/10.1016/j.compag.2014.05.009

Viani, F., Bertolli, M., Salucci, M., & Polo, A. (2017). Low-Cost Wireless Monitoring and Decision Support for Water Saving in Agriculture. IEEE Sens. J. 17, 4299-4309. https://doi.org/10.1109/JSEN.2017.2705043

Vij, A., Singh, V., Jain, A., Bajaj, S., Bassi, A., & Sharma, A. (2020). IoT and Machine Learning Approaches for Automation of Farm Irrigation System. Procedia Computer Science, 167, 1250-1257. https://doi.org/10.1016/j.procs.2020.03.440

Yamaç, S.S., & Todorovic, M. (2020). Estimation of Daily Potato Crop Evapotranspiration using Three Different Machine Learning Algorithms and Four Scenarios of Available Meteorological Data. Agric. Water Manag, 228. https://doi.org/10.1016/j.agwat.2019.105875

Yu, S., & Lu, H. (2018). An Integrated Model of Water Resources Optimization Allocation Based on Projection Pursuit Model-Grey Wolf Optimization Method in a Transboundary River Basin. J. Hydrol., 559, 156-165. https://doi.org/10.1016/j.jhydrol.2018.02.033

Zamora-Izquierdo, M.A., Santa, J., Martínez, J.A., Martínez, V., & Skarmeta, A.F. (2019). Smart Farming IoT Platform Based on Edge and Cloud Computing. Biosyst. Eng., 177, 4-17. https://doi.org/10.1016/j.biosystemseng.2018.10.014

Zhang, H., Xiong, Y., Huang, G., Xu, X., & Huang, Q. (2017). Effects of Water Stress on Processing Tomatoes Yield, Quality and Water Use Efficiency with Plastic Mulched Drip Irrigation in Sandy Soil of the Hetao Irrigation District. Agric. Water Manag, 179, 205-214. https://doi.org/10.1016/j.agwat.2016.07.022

Zhang, N., Wang, M., & Wang, N. (2002). Precision Agriculture-A World Wide Overview," Comput. Electron. Agricult., 36(2-3), 113-132. https://doi.org/10.1016/S0168-1699(02)00096-0