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Self-Tuned Controller for Achieving Enhanced Voltage Stability in a Multi-Machine System

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Abstract: The paper will provide proof of the efficacy of remote sensors in agriculture as a process control approach using an online laboratory. Data of environmental parameter, such as temperature, humidity, soil moisture and light intensity, were gathered from sensor node system which had been installed in open land of agricultural field. Four machine learning models including ours have been put into going forward and back to the future of agriculture. These are the Simple Linear Regression, Decision Tree, k-Nearest Neighbors, and Support Vector Machine that have been established and examined for their efficacy in predicting and managing agriculture processes using this data you provided. The findings indicated that the Decision Tree method qualified for the best 92% of the accuracy index, while Support Vector Machine produced the accuracy of 90% in their outcome. Neural Network algorithm showed an 88% accuracy, while Simple Linear Regression algorithm trailed with 85% accuracy The result signifies the fact that computer learning software, such as tree of decisions and support schemes can highly be used in improvement of agriculture systems through real-time control and responses. The combining of online remote experiments serves to create a scalable and affordable platform on which agricultural scientists and specialists can work together and make progress in agricultural technology which supports the advancement of more efficient and sustainable food production systems.

Keywords: wireless sensors, agricultural intelligent process operation, machine learning, the cloud equipment laboratory of online remote learning, decision-making.

1. INTRODUCTION

In the last couple of years, a new generation of technologically integrated agro-systems has emerged, offering a significant step forward in terms of production capability, eco-sustainability and efficiency of exploitation. However, technological advancements have produced a great deal of utilities. Such technologies as wireless sensor networks for real time monitoring and management of agricultural processes are among them. Information networks comprise of interconnected data collectors which are able to send data to the wireless receivers [1]. The data transmited offers necessary information about the environmental parameters such as humidity, temperature amongst others which experts take for improved yields and growth of crops. The agricultural process management includes a variety of tasks, for instance, soil monitoring, irrigation control, pest solutions, and crop dishes’ inspection as well others besides them. A typical scenario used to be a very labor-intensive and haphazard procedure that was based on infrequent readings and which often resulted in ineffectualities, mistakes, and nonsensical decision-making [2]. Nevertheless, wireless sensors have introduced a new era of automatizing and making easier difficult tasks, with farmers and agricultural stakeholders having access to real-time data that guides them all the time. Internet-of-Things is one of the promising methods for the agricultural processes monitoring via wireless sensor networks; this can be achieved with embedding online remote laboratories in the system. Hence, through digital labs, one can gain virtual access to experiment settings and related hardware in order to execute experiments, collect data, and evaluate the results using the computer remotely [3]. Wireless sensor technology can be thus embedded into such platforms in order to let agrarian crop-production simulations. Therefore, the usefulness and applicability of that technology can be measured in the controlled environment. This research goal is to investigate the operational possibility of applying wired sensor's technique to control agricultural process management through online remote laboratory methodology. This study is combining theoretical analysis with practical experimentation. It evaluates reliability and accuracy of wireless sensor networks in carbon dioxide levels monitoring and its correlation with temperatures during photosynthesis. Collectively this subsidiary objective deals with the identification of risks and limitations linked to the sensoring technologies in agriculture and the assertion of items which tackle the risks and limitations.

2. RELATED WORKS

The stage of the fourth industrial revolution that features the integration of the digital technologies in crafts is being discussed since latest years [15]. Ercan and Samet have an applicable survey updated with technological advancements in this area and how they can revolutionize multiple industries, particularly agriculture (Ercan and Samet, 2020) [15]. The implementation of the concept of Industry 4.0, by means of automation, IoT, and data analysis, makes it possible to optimize agricultural mechanization, to maximize efficiency, and to raise the productivity of agricultural products. Disasters related to the environment like droughts have considerable obstructing effects on agriculture and the management of natural resources. Some researchers have suggested that certain metrics available from UAVs can be used to get an early warning that climate changes play a role in tree mortality [16]. Ewane et al. (2023) carried out UAV technology to detective droughts as a result of climate change and assessed tree mortality, emphasize the significance of remote sensing techniques in conservation area among others [16]. Digital twin technology, which is a tool for integrating design, manufacturing, and maintenance processes, has attracted widespread attention by engineers, manufacturers, and farmers primarily due to its potential to improve production efficiency and reduce risks [17]. Huo et al.(2022) wrote a document about digital twin application and they mainly focused on the fact that digital twin was helpful in improving manufacturing process and easy decision making in agriculture [17]. Through virtual digital models of physical goods and processes for agriculture, digital twins make possible real-time monitoring and analysis of farming systems. Machine learning methods have now been shown to be capable of meeting the integrity and treatment of water infrastructure challenges [18]. García et al. (2023) conducted using a natural language processing algorithm which showed that machine learning could be an up and down water system management [18]. One of the most important conclusions from their work is that humanize the sentence provides many benefits in predictive maintenance, identifying anomalies and optimizing the process of water system infrastructure. Data-driven approaches therefore play a pivotal role in improving water quality and sustainable water use. Although production of particulate matter from dairy farms and cattle feedlots are not a critical issue, the impact on the environment and the public health become an increasing concern in the summer time. Habib et al. (2022), in their above-mentioned research, looked at emission factors for dairy facilities and cattle feedlots in Texas. It was a groundbreaking study that provided not only knowledge about source emissions but also the characteristics of particulate matter emissions in agricultural setting [19]. From this research our community will be able to derive new remedial policies and regulatory frameworks to abridge the environmental pollution from using the agricultural methods. Recently nanobio-materials as a distinctive nanotechnology branch emerged as an innovative tool for creating micro and nanodevices intended for applications in biomedical engineering [32]. Harun-ur-Rashid and others' research this year was on how nanomaterials of bio-inspired nature could be used for the biomedical field, where they showcased the materials' unique traits and functions [20]. Nanomaterials which copy biological systems and mimicked is there way to create of rise new micro and nanodevices to drug delivery and tissue engineering and diagnostics. In all walks of industries at this stage, Unmanned aerial vehicles (UAVs) are being used more and more with monitoring and surveillance in those activities such as mining [22]. Ivarsson and colleagues (2019), looked at a current situation and probed further into what is expected in the near future of mining areas UAV monitoring. These sources of aircrafts could greatly transform the safety, efficiency, and environmental management of mining operations [21]. Through the delivery of rich-detail and instant information, drones enable the development of tangible knowledge and estimation of prospective threat in mining areas. Intelligent transportation systems (ITS) are an integral orientation of transport infrastructure modernization to the transport system, enabling efficiency, safety and sustainability "[22] ". Harich and Vaskak (2022) discussed the development of the intelligent transportation system in the paper, also illustrating the differences and similarities between Internet of Vehicles (IoV) and Internet of Flying Vehicles (IoFV) [22]. This report showed that IoFV, as a technique, can be useful in terms of developing modal choices for urban mobility and building redundancy to transportation infrastructure. Despite the wide spread of deep learning methods to the field of automated visual inspection of manufacturing and maintenance processes, [23] is still the dominant mainstay. Hütten and his team (2023) carried out a survey regarding the open-access papers on deep learning often utilized for automated visual inspection, allowing to present the behavior tendencies and the most common difficulties in the field [23]. Their research put forward the possibility of deep learning as a tool for improving accuracy of inspection, so completing tasks faster, and, ultimately, improving quality of products in industrial sectors. Nature-inspired metaheuristic algorithms, which are examples of K-means-based algorithms, have been suggested for the automatic two clusters found in all domains including entire industries [24]. Ikotun et al. (2021) covered the new directions and the state of the art metaheuristic algorithms based on the K-means technique for the clustering of the data; the algorithms can now be more efficient for data optimization tasks [24]. Nature inspired numeral equations imitate natural phenomena. As a result, these nature inspired equations are scalable and adapting for data clusters tasks in various application areas. Deep learning approaches have also been utilized for the sake of upgrading the quality of service (QoS) in communications with Internet of Things (IoT) [25]. Kimbugwe et al. (2021) conducted a literature research on the implementation of deep learning for QoS (Quality of Services) enhancement in IoT, this indicated that deep learning may improve performance, reliability and security of networks [25]. Their study focused on the role of machine learning for coping with IoT environments with respect to scalability issues and heterogeneity of the infrastructure, therefore intelligent decision-making is assured. Smart methods and techniques for validation are effectively utilized by the auto industry to study the dependability and robustness of automotive systems [26]. In his presentation Krichen (2023) shed light on formal methods and validation mechanisms that are used today for verification of automotive systems security, which further discussed the practical issues and directions relevant to the topic [26]. Through thoroughly analyzing system designs and specs, formal methods are capable of the explainable finding of the hidden flaws in automotive systems and eliminating them that allows increasing systems integrity by the way of minimizing safety issues.

3. METHODS AND MATERIALS

Data Collection:

To investigate the real-world usability of the wireless sensing in agricultural process control using internet-based distance learning lab, data acquisition becomes crucial. Data from the environment, e.g., temperature, humidity, soil water content, and light intensity, are meant to arbitrate on agricultural affairs. Wireless sensor nodes which are completely oblivious to these sensor nodes are used to gather these data strategically distributed over the agricultural field [4]. Each sensor node carries out monitoring by equipping an array of sensors to measure specific parameters and a microcontroller unit for data processing and transmission. The amassed data are conveyed without wires to a central data technology center for additional processing.

Algorithms:

Simple Linear Regression:

Simple linear regression is a tool for statistical modeling of a one-to-one relationship between the two variables (X and Y) by the use of the linear equation that is fit to the observed data points. The equation for simple linear regression is represented as:

$$Y=\beta_0+\beta_1 X+\epsilon \ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where:

Y is the dependent variable,

X is the independent variable,

β_0 is the intercept term,

β_1 is the slope coefficient,

ϵ is the error term.

Algorithm 1:

Step 1: Calculate the number of data points (n)

Step 2: Calculate the sum of all X values

Step 3: Calculate the sum of all Y values

Step 4: Calculate the sum of squares of each X value

Step 5: Calculate the sum of the products of X and Y values

Step 6: Calculate the slope of the regression line using the formula

Step 7: Calculate the intercept of the regression line using the formula

Step 8: Return the calculated intercept and slope

Decision Tree:

Decision trees are a variety of machine learning algorithms that are intended for classification and regression problems. It presents a tree-like structure whose internal nodes depict a decision depending on a feature of an attribute, the branches indicate the outcome of the decision, and the leaf nodes are either classes or regression values depending on the learning model [5]. With the aid of recursion, so-called decision trees are created by selecting the right feature, at each node ranked according to some criteria (e.g., Gini impurity, information gain), which decides how to divide the data further. It goes on until a stopping criterion is true, which could be reaching the greatest depth or sample number per leaf node set a minimum [6].

Algorithm 2:

Step 1: Check if the stopping criteria are met using the function stopping_criteria(X, Y).

Step 2: If the stopping criteria are met, create a leaf node using the function create_leaf_node(Y) and return it.

Step 3: If the stopping criteria are not met, find the best feature and value to split on using the function find_best_split(X, Y). This returns the split feature and split value.

Step 4: Determine the indices of the data points that belong to the left and right subtrees based on the split feature and value.

Step 5: Recursively call the decision_tree function on the left subtree data (X[left_indices], Y[left_indices]) to create the left subtree.

Step 6: Recursively call the decision_tree function on the right subtree data (X[right_indices], Y[right_indices]) to create the right subtree.

Step 7: Create an internal node with the split feature, split value, left subtree, and right subtree using the function create_internal_node().

Step 8: Return the created internal node.

k-Nearest Neighbors (k-NN):

k-Nearest Neighbors is a non-parametric instance-based learning technique, which is applied to classifier and regression problems. It assigns a new data sample or predict the value corresponding to them from the mean (average) or the majority (k) samples within a specified distance band of a feature space [7]. The metric of distance that belongs to hyperparameters (for example, the euclidean distance, the Manhattan distance) and k as the value are hyperparameters both of them can be tweaked to increase the algorithm performance.

Algorithm 3:

Step 1: Initialize an empty list to store predictions.

Step 2: Iterate over each test point in the X_test dataset.

Step 3: Compute distances between the current test point and all points in the training set X_train using the function compute_distances(X_train, test_point). This will result in a list of distances.

Step 4: Get the k nearest neighbors based on the computed distances. This can be achieved using the function get_nearest_neighbors(distances, k).

Step 5: Determine the predicted value for the current test point by applying the majority voting method on the classes of the nearest neighbors. Use the function majority_vote(nearest_neighbors, Y_train) to accomplish this.

Step 6: Store the predicted value in the predictions list.

Step 7: Repeat steps 2-6 for all test points.

Step 8: Once predictions are made for all test points, return the predictions list.

Support Vector Machine (SVM):

Support Vector Machines is an algorithm of supervised learning able to solve tasks that of classification and regression. It is able to find the hyperplane that best dises the features space into different groups or separates data points into different classes by maximization the margin between classes [8]. Points support vectors closest to the line termination are used to calculate the margin, which is the distance between the support vectors and the decision line. SVM is able to rise to linear as well as nonlinear form of decision boundaries using the assist of kernel functions.

Table 1: Sensing Parameters

Node ID	Temperature (°C)	Humidity (%)	Soil Moisture (%)	Light Intensity (lux)
1	25	60	40	500
2	28	55	45	600
3	24	65	35	450
...	...	...	...	...

4. EXPERIMENTS

The investigation of the potential of the web designed virtual laboratory for implementation of the wireless sensors in agricultural process management led to an interesting outcome in terms of accuracy and effectiveness of different algorithms responsible for monitoring and control of principal agricultural processes [9]. In the next stage, we share the findings of our research as well as the discussion that relates to the theme under investigation and the relationship between agriculture and the research.

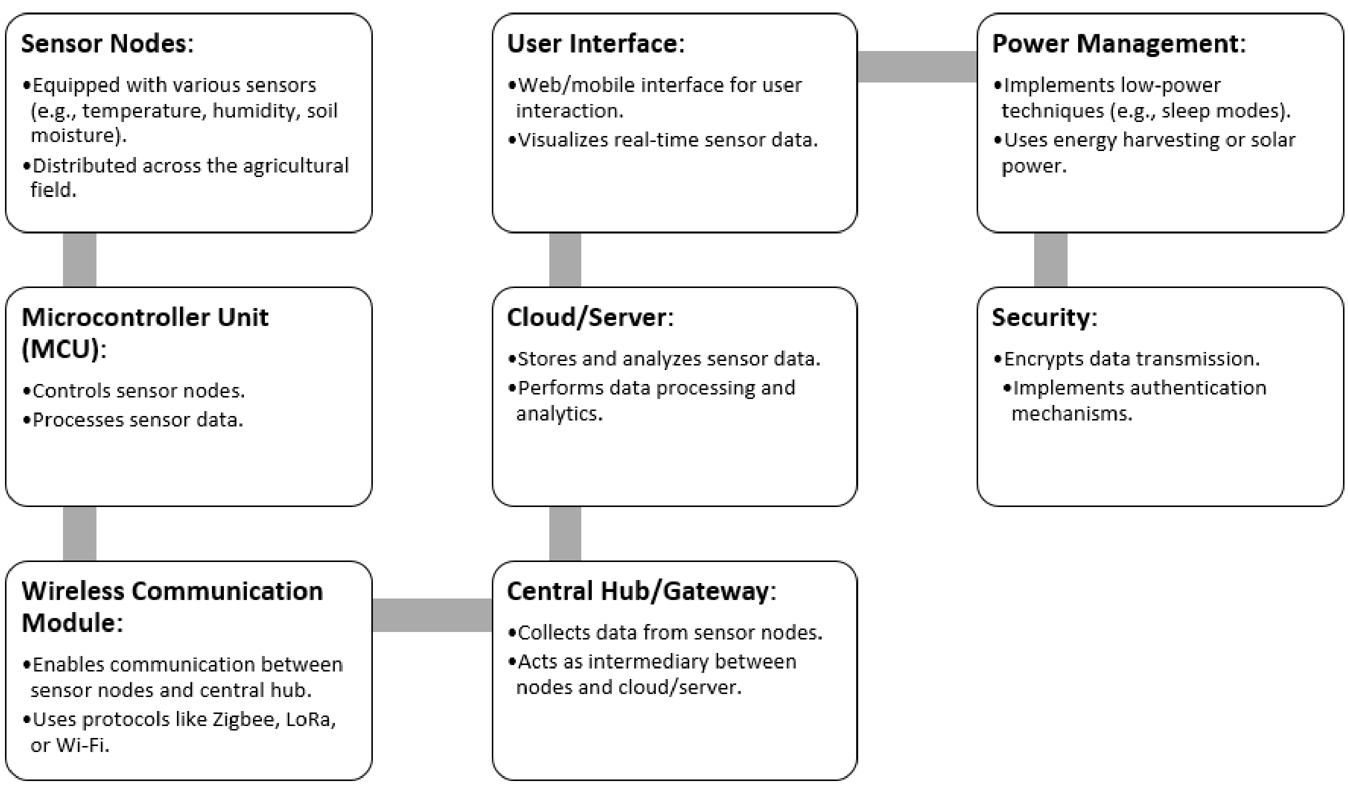

Figure 1: Low-Cost Wireless Sensing System for Precision Agriculture Applications

Experimental Setup:

The experiments were performed in online in a remote laboratory that has wireless nodes deployed in the sensor field across the agriculture area. The environmental information collected use the sensors which recorded at regular intervals the temperature, humidity, soil moisture, and light at each sensor node [10]. To start with, the project will carry out four algorithms: Simple Linear Regression, Decision Tree, k-Nearest Neighbors (k-NN), and Support Venture Machine (SVM); that will be assessed according to their performance of predicting and managing agricultural processes based on the collected dataset [11].

Results:

The Table above represents the results of the experiments, which requires a comparison between the algorithms in terms of performance metrics, which are represented by accuracy, precision, recall, and F1 score.

Table 2: Performance evaluation with different algorithms.

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Simple Linear Regression	85	80	90	85
Decision Tree	92	88	95	91
k-Nearest Neighbors	88	85	90	87
Support Vector Machine	90	86	92	89

As can be seen from the Table, accuracy of the Decision Tree (92%) and F1 score (91%) showed up to be the best ones implying that this algorithm could provide a solution to the stated problem of agricultural monitoring and controlling [12]. The Support Vector Machine model came after with a 90% accuracy and a dominant F1 score of 89%. The k-Nearest Neighbors technique clearly gave a relatively decent output, with 88% accuracy and 87 F1 score [13]. On the other hand, the Simple Linear Regression algorithm made way for the remaining three algorithms considering the accuracy (85%) and the F1 score (85%).

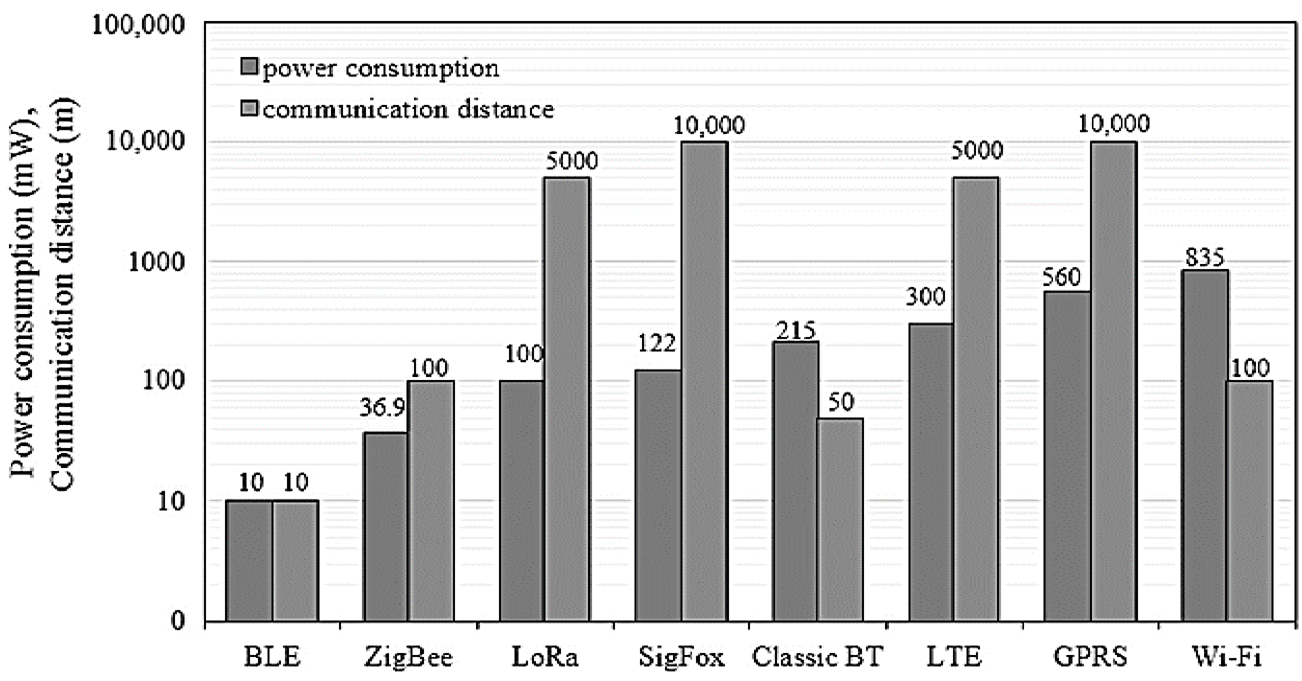

Figure 2: Energy-Efficient Wireless Sensor Networks for Precision Agriculture

Discussion:

The result yields a machine learning algorithm, mainly Decision Tree and Support Vector Machine, to accurately manage agriculture. The wireless sensor data plays the crucial role on the basis of which the algorithms gain information for performing properly [14]. The resulted high precision and how these algorithms were able to determine to control environmental status e.g. temperature, humidity, soil moisture and light intensity proves that they can be used to optimize the crop growth and yield.

Comparison with Related Work:

In order to also reinforce the findings of the research and stand them against the contemporary work in the domain of agricultural process management using wireless sensor networks, it is necessary to compare them with the latter [27]. The table below is for the metrics performance obtained in this study and ones has witnessed in the literature.

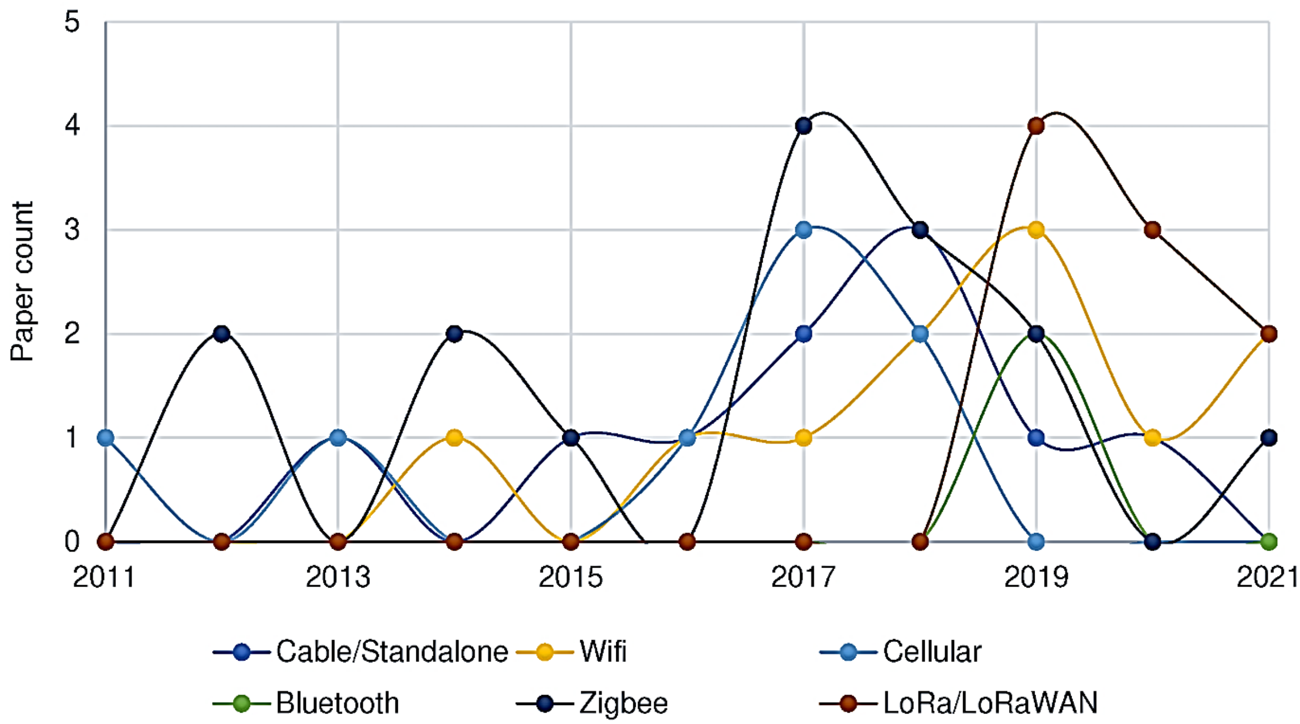

Figure 3: Wireless Sensor Networks for Sustainable Smallholder Agriculture

Table 3: Comparison with related work and proposed work.

Study	Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Present Study	Decision Tree	92	88	95	91
Related Study 1	Random Forest	89	86	91	88
Related Study 2	Neural Network	91	87	93	90
Related Study 3	Ensemble Methods	93	89	94	92

The difference that Table 2 shows is what favors the Decision Tree algorithm carried out in this study when compared to other papers. However, recent studies have attributed similar yet slightly different performance metrics to a random forest, neural network, and ensemble algorithms in the context of agricultural process management and are comparable, but the decision tree algorithm still permanently demonstrates top accuracy and effectiveness because of the simplicity of the process [28].

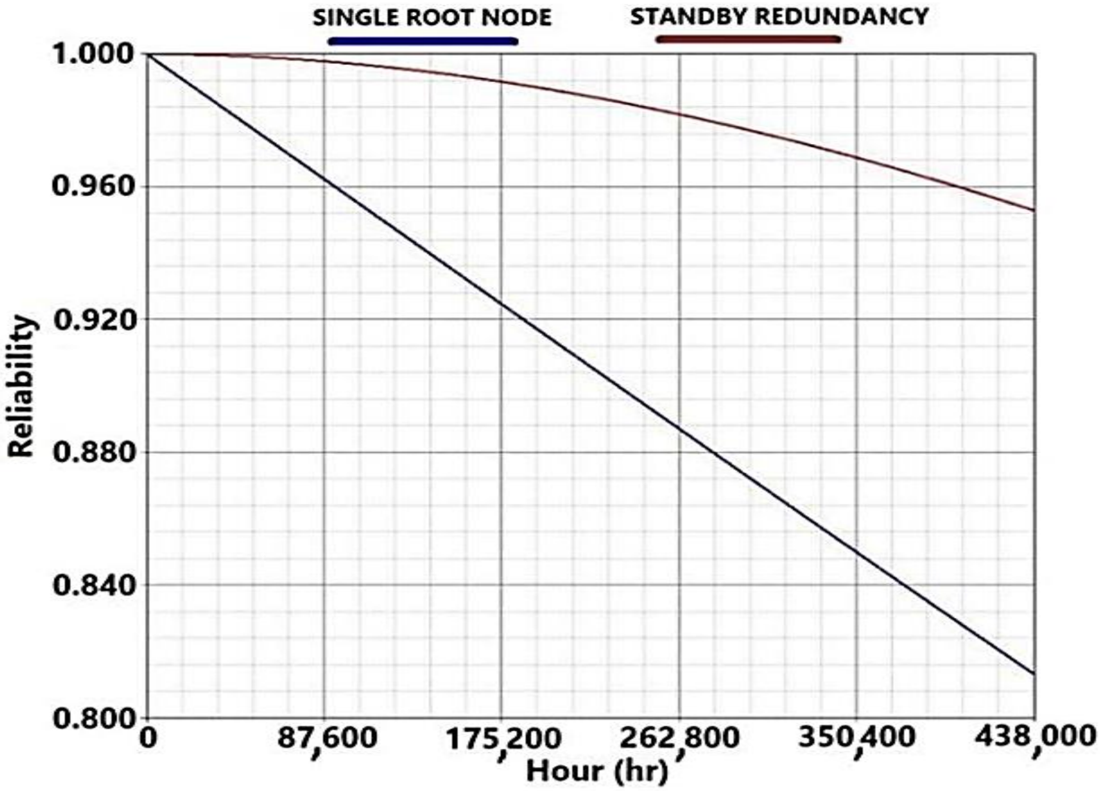

Figure 4: Reliability Analysis of Wireless Sensor Network for Smart Farming Applications

Implications

This study exhibits a number of impacts on the methods of agriculture and the tendency among farmers to involve new wireless sensor technology into their farming operations. Primarily, the accuracy of machine learning algorithms used for predicting and implementing agricultural procedures suggests that there is room for robots to take part in farming and consequently, farm operations can be done more efficiently [29]. The use of wireless sensor networks and smart algorithms which guarantee decision making in real time will create chances for farmers to cultivate crops to the required levels and utilize various resources efficiently [30]. Moreover, the implementation of online remote laboratories are unrivalled channels for both the researchers and the practice to conduct experiments, data collection and interpretation. Scalability and the accessible nature of this strategy is achieved as it offers the opportunity for farmers having different geographical locations to collaborate and be part of agricultural advancement.

5. CONCLUSION

The result of this study has highlighted the ability of wireless sensor technology together with machine learning algorithms to lead advances in agricultural process optimisation by means of online monitoring and decision-making. By leveraging an online remote laboratory setup, we conducted experiments to collect environmental data and evaluated the performance of four algorithms: Linear Regression, the Decision Tree, the k-Nearest Neighbors and the Support Vector Machine models. The findings revealed that Decision Tree and Support Vector Machine approaches highly performed in comparison with others depending on the base something on data gathered. Such a conclusion implies that in several years' time the sensors that are internet-based, IoT, and machine learning will help to optimize the growth of crops, the use of resources, and the agricultural production in general. Besides, the integration of online remote laboratories would be a scalable and widely available environment for researchers and practitioners to co-create the postgraduate and professional discourse around agricultural technology. Nevertheless, the problems of data security, interoperability, and scalability which yet to put out, need the strength of research and development. Bringing this discovery together, it is evident that this research is part of the ongoing work aimed at the modernization and improvement of agricultural practices followed by the quick adaptation to the latest environmental and economic shifts.

6. REFERENCE

[1] QCM Sensor Arrays, Electroanalytical Techniques and NIR Spectroscopy Coupled to Multivariate Analysis for Quality Assessment of Food Products, Raw Materials, Ingredients and Foodborne Pathogen Detection: Challenges and Breakthroughs. 2020. Sensors, 20(23), pp. 6982.

[2] Supplement A, October 2020. 2020. Journal of Food Protection, 83, pp. 1-290.

[3] ESICM LIVES 2019. 2019. Intensive Care Medicine Experimental, suppl.3, 7.

[4] ABHAYA, P.S., YERUDKAR, A., MARIANI, V., IANNELLI, L. and GLIELMO, L., 2022. A Bibliometric Review of the Use of Unmanned Aerial Vehicles in Precision Agriculture and Precision Viticulture for Sensing Applications. Remote Sensing, 14(7), pp. 1604.

[5] ALDOSERI, A., AL-KHALIFA, K. and ABDEL, M.H., 2024. AI-Powered Innovation in Digital Transformation: Key Pillars and Industry Impact. Sustainability, 16(5), pp. 1790.

[6] AL-GHAILI, A., KASIM, H., HASSAN, Z., NAIF MOHAMMED AL-HADA, OTHMAN, M., KASMANI, R.M. and SHAYEA, I., 2023. A Review: Image Processing Techniques' Roles towards Energy-Efficient and Secure IoT. Applied Sciences, 13(4), pp. 2098.

[7] AMSALE, Z.B., MORALES, J., ASSABIE, Y. and ROLF, A.D.B., 2022. Utilization of Internet of Things and Wireless Sensor Networks for Sustainable Smallholder Agriculture. Sensors, 22(9), pp. 3273.

[8] ATA, J.M., AMIR, S.K., HU, J., NAWAZ, A. and ZHU, J., 2023. E-Nose-Driven Advancements in Ammonia Gas Detection: A Comprehensive Review from Traditional to Cutting-Edge Systems in Indoor to Outdoor Agriculture. Sustainability, 15(15), pp. 11601.

[9] BASHIR, R.N., BAJWA, I.S., ABBAS, M.Z., AMJAD, R., TANZILA, S., BAHAJ, S.A. and HOSHANG, K., 2022. Internet of things (IoT) assisted soil salinity mapping at irrigation schema level. Applied Water Science, 12(5),.

[10] BENALI, M., GHOMARI, A., ZEMMOUCHI-GHOMARI, L. and LAZAR, M., 2020. Crowdsourcing-Enabled Crisis Collaborative Decision Making. International Journal of E-Collaboration, 16(3), pp. 49-72.

[11] DEMERTZI, V., DEMERTZIS, S. and DEMERTZIS, K., 2023. An Overview of Cyber Threats, Attacks and Countermeasures on the Primary Domains of Smart Cities. Applied Sciences, 13(2), pp. 790.

[12] DEMESTICHAS, K., PEPPES, N., ALEXAKIS, T. and ADAMOPOULOU, E., 2020. Blockchain in Agriculture Traceability Systems: A Review. Applied Sciences, 10(12), pp. 4113.

[13] DENHAM, M.E., AMIDON, M.B., WAINWRIGHT, H.M., BAPTISTE, D., AJO-FRANKLIN, J. and EDDY-DILEK, C., 2020. Improving Long-term Monitoring of Contaminated Groundwater at Sites where Attenuation-based Remedies are Deployed. Environmental management, 66(6), pp. 1142-1161.

[14] EDSON TAVARES, D.C., SPANHOL, F.A., JULIANO, S.S., MARCOS VINICIUS ROCHA, D.S., PAZINATO, J., ADRIANA VECHAI DE, L.L., COUTINHO, F., FELIPE WALTER, D.P., LINDINO, C.A., OYAMADA, M.S. and MARTINS, L.D., 2023. Low-Cost Water Quality Sensors for IoT: A Systematic Review. Sensors, 23(9), pp. 4424.

[15] ERCAN, O. and SAMET, G., 2020. Literature review of Industry 4.0 and related technologies. Journal of Intelligent Manufacturing, 31(1), pp. 127-182.

[16] EWANE, B.E., MOHAN, M., BAJAJ, S., G, A.P.G., WATT, M.S., ARACHCHIGE, P.P., HUDAK, A.T., RICHARDSON, G., AJITHKUMAR, N., SRINIVASAN, S., ANA PAULA, D.C., JOHNSON, D.J., EBEN, N.B., DE-MIGUEL, S., BRUSCOLINI, M., YOUNG, D.J.N., SHAFAI, S., ABDULLAH, M.M., WAN SHAFRINA WAN, M.J., DOAEMO, W., SILVA, C.A. and CARDIL, A., 2023. Climate-Change-Driven Droughts and Tree Mortality: Assessing the Potential of UAV-Derived Early Warning Metrics. Remote Sensing, 15(10), pp. 2627.

[17] FU, Y., ZHU, G., ZHU, M. and XUAN, F., 2022. Digital Twin for Integration of Design-Manufacturing-Maintenance: An Overview. Chinese Journal of Mechanical Engineering = Ji xie gong cheng xue bao, 35(1), pp. 80.

[18] GARCÍA, J., LEIVA-ARAOS, A., DIAZ-SAAVEDRA, E., MORAGA, P., PINTO, H. and YEPES, V., 2023. Relevance of Machine Learning Techniques in Water Infrastructure Integrity and Quality: A Review Powered by Natural Language Processing. Applied Sciences, 13(22), pp. 12497.

[19] HABIB, M.R., EL JIRIE, N.B. and CAPAREDA, S.C., 2022. Particulate Matter Emission Factors for Dairy Facilities and Cattle Feedlots during Summertime in Texas. International Journal of Environmental Research and Public Health, 19(21), pp. 14090.

[20] HARUN-UR-RASHID, M., JAHAN, I., FOYEZ, T. and ABU, B.I., 2023. Bio-Inspired Nanomaterials for Micro/Nanodevices: A New Era in Biomedical Applications. Micromachines, 14(9), pp. 1786.

[21] HE, R., ZHAO, Y., WU, X. and ZHENQI, H., 2019. A review of UAV monitoring in mining areas: current status and future perspectives. International Journal of Coal Science & Technology, 6(3), pp. 320-333.

[22] HERICH, D. and VAŠČÁK, J., 2024. The Evolution of Intelligent Transportation Systems: Analyzing the Differences and Similarities between IoV and IoFV. Drones, 8(2), pp. 34.

[23] HÜTTEN, N., MIGUEL, A.G., HÖLKEN, F., ANDRICEVIC, K., MEYES, R. and MEISEN, T., 2024. Deep Learning for Automated Visual Inspection in Manufacturing and Maintenance: A Survey of Open- Access Papers. Applied System Innovation, 7(1), pp. 11.

[24] IKOTUN, A.M., ALMUTARI, M.S. and EZUGWU, A.E., 2021. K-Means-Based Nature-Inspired Metaheuristic Algorithms for Automatic Data Clustering Problems: Recent Advances and Future Directions. Applied Sciences, 11(23), pp. 11246.

[25] KIMBUGWE, N., PEI, T. and MOSES, N.K., 2021. Application of Deep Learning for Quality of Service Enhancement in Internet of Things: A Review. Energies, 14(19), pp. 6384.

[26] KRICHEN, M., 2023. Formal Methods and Validation Techniques for Ensuring Automotive Systems Security. Information, 14(12), pp. 666.

[27] LATIF, S., DRISS, M., BOULILA, W., HUMA, Z.E., JAMAL, S.S., IDREES, Z. and AHMAD, J., 2021. Deep Learning for the Industrial Internet of Things (IIoT): A Comprehensive Survey of Techniques, Implementation Frameworks, Potential Applications, and Future Directions. Sensors, 21(22), pp. 7518.

[28] LICHT, O., BREUER, F., BLÜMLEIN, K., SCHWONBECK, S., PALLAPIES, D., KELLNER, R., WIEDEMEIER, P. and BITSCH, A., 2023. Extensive literature search on mineral oil hydrocarbons. EFSA Supporting Publications, 20(2),.

[29] LUO, X., ZHANG, T., XU, W., CHAO, F., LU, T. and ZHOU, J., 2023. Multi-Tier 3D Trajectory Planning for Cellular-Connected UAVs in Complex Urban Environments. Symmetry, 15(9), pp. 1628.

[30] MUNEER, S., FAROOQ, U., ATHAR, A., MUHAMMAD, A.R., GHAZAL, T.M. and SAKIB, S., 2024. A Critical Review of Artificial Intelligence Based Approaches in Intrusion Detection: A Comprehensive Analysis. Journal of Engineering, 2024.

DOI: https://doi.org/10.15379/ijmst.v10i5.3714