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Leveraging IoT and Machine Learning for Data-Driven Farming Through the Use of Smart Irrigation

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ABSTRACT

Conventional irrigation techniques face obstacles pertaining to water loss and scheduling, which hinder the capacity to meet the growing demands for food production while preserving vital water supplies. In order to overcome these obstacles, this study presents an innovative smart irrigation system that improves water application efficiency and scheduling by combining machine learning, data analysis, and the Internet of Things (IoT). The foundation of this creative method is the collection of historical Environmental data from the West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL), Federal University of Technology, Akure and Soil profile Dataset form Nigeria National Legacy data and IITA Project sites making it the foundational dataset needed for accurate irrigation management. The smooth functioning of the system is ensured by using Internet of Things (IoT) sensors for real-time field data collection. Preprocessing techniques are then used to guarantee the quality and consistency of the data. This carefully selected dataset provides real-time intelligent irrigation decisions by acting as the training set for a machine learning algorithm. The irrigation process's control mechanisms work in perfect harmony with the model's predictions. Additionally, the system makes it easier for agricultural professionals to monitor and modify irrigation tactics. The system's effectiveness is validated by the experimental findings, which highlight the decision tree model in particular because of its superior balance of accuracy, precision, recall, and F1 score. Through the optimization of agricultural yield and the reduction of water loss, this method enhances productivity and sustainability.

1.0 INTRODUCTION

Water is one of the most critical resources on our planet, vital for sustaining life and fueling the growth of crops that feed billions of people [1]. Agriculture is the largest consumer of freshwater, accounting for approximately 70% of global water withdrawals [2]. In a world facing mounting challenges related to water scarcity, climate change, and the need to feed a growing population, the development of sustainable and efficient agricultural practices is of paramount importance. Smart Irrigation Systems represent a technological solution that holds the potential to address these pressing concerns by optimizing water use in agriculture [3].

Agriculture stands as a pivotal industry and forms the cornerstone of economies worldwide. The burgeoning concept of agricultural automation is of significant global importance. With the world's population expanding at a rapid pace, the demand for food is on an upward trajectory. The increasing need for food, coupled with evolving consumer preferences, has presented formidable challenges to the agriculture sector, making it imperative for the industry to devise techniques and methods that can effectively cater to the growing demands and shifting requirements [4].

Agriculture, being one of the most fundamental sectors in society, drives progress and advancements. Consequently, it is crucial to institute upgrades within this industry to enhance its overall performance and outcomes. Technological innovations in food production are essential to keep pace with the evolving preferences of consumers. Given that a substantial number of countries heavily depend on the agricultural sector, it becomes all the more critical to optimize the utilization of agricultural resources such as irrigation [5].

Traditional irrigation methods, often relying on static schedules or manual interventions, can be inefficient and lead to the overuse of water resources. This not only results in increased operational costs for farmers but can also contribute to environmental issues, such as the depletion of aquifers and water pollution due to runoff of excess fertilizers and pesticides.

The concept of Smart Irrigation Systems encompasses a range of technologies, including Internet of Things (IoT) sensors, data analytics, and automation, that together enable precise, data-driven irrigation strategies [6]. These systems gather real-time data on environmental conditions, soil moisture levels, and plant health. They then use this information to adjust irrigation schedules, ensuring that crops receive the right amount of water when and where it is needed. Such systems hold the promise of conserving water, reducing operational expenses for farmers, and improving crop yields.

The emerging SMART irrigation system significantly improves performance by automating irrigation processes and promoting water conservation. This innovative approach adapts irrigation practices in real-time based on soil and weather conditions, empowering farmers to efficiently meet their water needs with this newly adopted method that minimizes water wastage [7]. Technologies such as Internet of Things (IoT), smartphone applications, and sensors play a pivotal role in enabling farmers to access precise information about their fields, including soil temperature, water requirements, weather conditions, and more. IoT can be seen as an expansion of the current internet, encompassing all devices capable of connecting to the web and facilitating user-friendly device management. Consequently, IoT integration enhances the automation of various aspects of agriculture and farming, making the entire process more productive and streamlined. Additionally, the utilization of sensors proves invaluable for farmers in gaining a deeper understanding of their crops, mitigating environmental impacts, and conserving valuable resources [7]. By embracing SMART agriculture, farmers are presented with the opportunity to increase yields while simultaneously reducing their reliance on resources such as fertilizers, water, and seeds.

Implementing Smart Irrigation Systems presents a promising solution to optimize water usage in agriculture, yet several challenges and limitations must be addressed for successful deployment. One significant hurdle is the initial investment required. Integrating sensors, controllers, and software systems entails substantial upfront costs, which can be prohibitive for small-scale farmers or regions with limited financial resources. Additionally, ensuring the accuracy and reliability of data collected by these systems is crucial. Malfunctioning sensors or inaccurate data interpretation could lead to inefficient irrigation practices, potentially causing crop damage or water waste.

Compatibility issues between various components of Smart Irrigation Systems pose another challenge. Achieving seamless integration between sensors, controllers, and existing irrigation infrastructure may require specialized expertise and technological adjustments. Moreover, maintaining a reliable power supply for continuous system operation is essential, especially in remote agricultural areas where access to electricity may be unreliable or nonexistent. Addressing this challenge may involve deploying alternative energy sources or developing energy-efficient components.

Machine learning (ML) techniques find applications in various domains, encompassing retail, where they are used to assess customer behavior and forecast customers' phone usage [8]. The utilization of machine learning in agriculture has also been ongoing for many years. Predicting crop yields poses a considerable challenge in precision agriculture, and numerous models have been proposed and validated to address this issue. Given the multitude of factors influencing crop yield, including climate, weather, soil conditions, fertilizer usage, and seed varieties, it is evident that crop yield prediction is a complex, multistep process. While contemporary crop yield prediction models can reasonably estimate actual yields, there is still room for improvement.

Machine learning, a subset of Artificial Intelligence (AI) that emphasizes learning from data, offers a practical approach to enhance yield prediction by leveraging multiple features. ML can identify patterns, correlations, and extract insights from datasets. These models must undergo training with datasets that contain outcomes based on past experiences. During the training phase, parameters of the models are established using historical data. The testing phase involves the use of historical data that was not part of the training set for evaluating model performance [9].

ML models can either be descriptive or predictive, contingent on the research problem and questions being addressed. Descriptive models serve to extract knowledge from the data and explain past events, whereas predictive models are employed to make future projections. The realm of ML research encompasses various challenges when striving to construct high-performance predictive models. The selection of appropriate algorithms tailored to the specific problem is of paramount importance, and the algorithms and underlying platforms must be capable of handling large volumes of data [10].

This aims of this research is to design a model for smart irrigation system that utilizes IoT data to precisely schedule and control irrigation. The research explore the various components and technologies that comprise these systems, the impact they can have on water conservation, and their role in enhancing agricultural productivity.

2.0 METHODOLOGY

2.1 Data Collection

Several parts make up the smart irrigation system, which allows for effective data collection. In the field, sensors are used to measure air temperature and humidity, such as DH11 sensors and soil moisture sensors. An Arduino Uno microcontroller functions as the primary control unit and is coupled to these sensors. The microcontroller facilitates data processing and communication with other system components by gathering data from the sensors in real-time[11]. In order to facilitate data transmission to the cloud, an internet connection is also established via a Node MCU. A database server stores the gathered sensor data, which includes temperature, humidity, and soil moisture levels. This offers a dependable and expandable approach to data management. .

2.1 Materials

The primary embedded system components used in this study are the environmental sensors and the Wi-Fi unit, which gathers data from the cloud and transmits it to the Arduino UNO, which regulates the DC motors' opening and closing. Sensors on the Arduino UNO were programmed using the Arduino IDE. The user could access an electronic cloud and see data. The artificial neural network was modeled to get the necessary values for the trained neural weights.

2.2 Artificial Neural Network (ANN)

Deep learning concepts are based on artificial neurons (ANNs), which are collections of nodes or units that perform duties like to those of a human brain [12]. Neural networks process information through a non-linear mapping mechanism. Receiving a signal from an artificial neuron, processing it, and forwarding it to other neurons is the function of the neurons [13]. Initially, the movement was linked by edges, which are neurons, using real values; the output was then calculated using a non-linear function of the total of its inputs. These connections enable to solve complex equation problems, avoid some of the difficulties faced by non-linear approaches, and alter weight continuously to produce accurate results [14].

The weight can be computed using the threshold value, or it can be changed in response to the strength signal. Layers of neurons exist, and each type of neuron has a unique way of reacting to stimuli. The output layer comes last, whereas the input layer comes first. From the input to the output layers, the signal moves. The input node's information is numerical, and each piece of data corresponds to an activation value; each node is represented by a number. Both the number and the level of activation have grown. The subsequent node receives the activation values. Every node updates the activation function's value and determines its weight [15].

The neuron's activation function value determined whether or not to forward the signal based on that output. Until it reaches the output node, this process continues [16]. To determine the difference between the computed and estimated values, the network makes use of the cost function. Artificial neural networks (ANNs) find application in multiple domains such as fault tolerance, adaptive learning, parallel processing, data storage distribution, text classification and categorization, and paraphrasing. projection and image processing [17][18]. ANN techniques focus on biological instincts and assist in resolving any bodily issue that arises in daily life. The power system's issues with energy distribution, generation, and transmission are resolved by ANN approaches. The precise values of parameters can be ascertained, provided that the transmission and distribution system has certain limitations [19].

Artificial Neural Networks Architecture

1. The ANN Architecture as shown in Figure 1, has the

   Three levels make up the network architecture: the input layer, the output layer, and any hidden layers that may be present. Because of their numerous levels, these layers are sometimes referred to as the MLP (Multi-Layer Perceptron) [20].

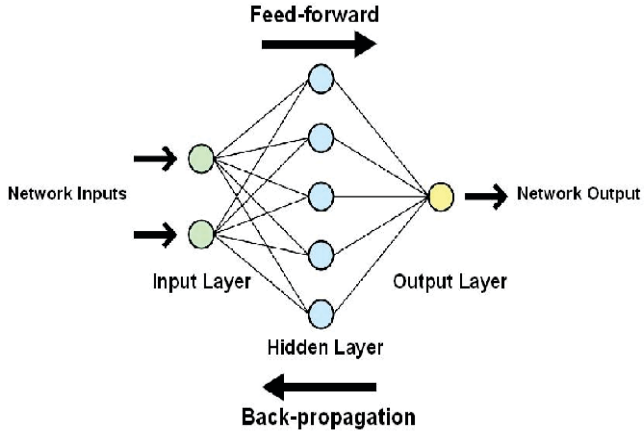

Figure 1: Artificial Neural Networks Architecture

2. The hidden layer serves as a "distillation layer," extracting key patterns from the inputs and forwarding them to the next layer for further analysis [21]. This process of selecting essential information while discarding unnecessary data enhances the network's efficiency and accelerates its performance.
3. Two things make the activation function (Figure 2) crucial: first, it makes it possible for you to power on your computer[22]. The existence of non-linear interactions between the inputs is captured by this model. It helps transform the input into an output that is easier to use.

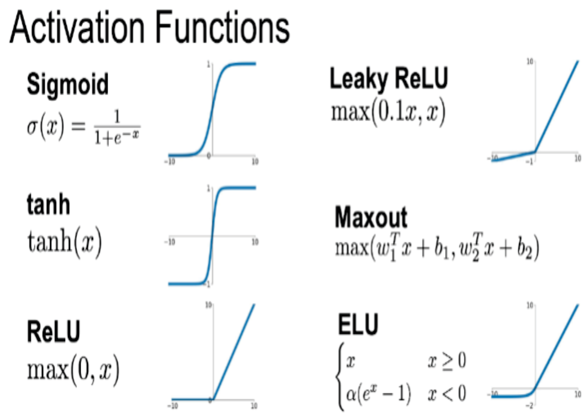

Figure 2: Activation Functions

4. To create a prediction error-reducing model, one must determine the "optimal values of W—weights." Error-tolerant learning is used to transform an artificial neural network (ANN) into a learning algorithm in order to accomplish this goal [23].
5. The optimization method quantifies prediction errors using a "gradient descent" technique [24]. Little changes

in W are explored, and the effect on prediction errors is evaluated, in order to get the ideal value for W. Ultimately, those W values are selected as optimal as additional W adjustments do not decrease errors.

The ANN make use of the three layers as shown in figure 3: input layer, hidden layer and output layer. Input layer have one neuron for each predictor variable. The output layer will have only one neuron, since prediction is based on one event only to pump the water.

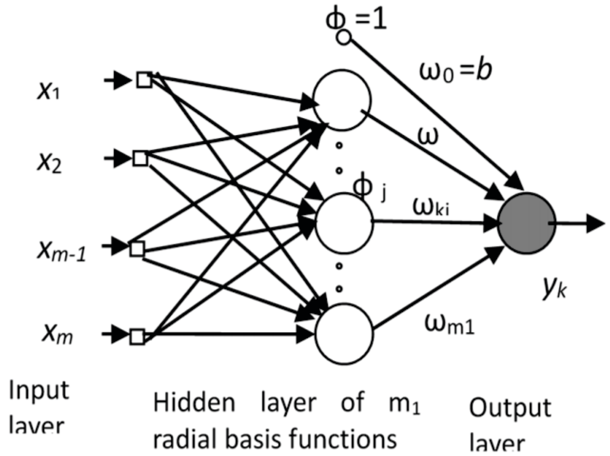

Figure 3: Neural Network for Smart Irrigation Model

The model make use of a single hidden layer feed-forward neural network. The transfer functions in the hidden nodes is defined by the multivariate Gaussian density function as in equation 1

$$\varphi_j(x) = e^{\left(-\frac{\|x-\mu_j\|^2}{2\sigma_j^2}\right)} \qquad (1)$$

The input vector in this case is x, and the Gaussian variables' mean and deviation are μ_j and ρ_j, respectively. Linear summation is carried out via the output nodes. Equation 2 defines the value of the k-th output node, y_k.

$$y_k(x) = \sum_{j=1}^{h} w_{kj}\varphi_j(x) + w_{k0} \qquad (2)$$

where w_{k0} is the bias term and w_{kj} is the weight of the connection between the k-th output node and the j-th hidden node.

2.3 Smart Irrigation System

The smart irrigation system consists of several layers. The Internet of Things (IoT) layer, the cloud layer, the application layer, data collection, data modeling and prediction layer. The Internet of Things (IoT) layer will consist of software and hardware components that work together to represent this layer. Temperature, humidity, and soil moisture are the three inputs from the sensor data that are included in the first layer, known as the input layer. Five nodes make up the second, hidden layer, which supports the irrigation system's final choice. The output layer, which makes up the final layer, has three settings for managing the irrigation system's water pumping. Hardware used include:

2.3.1 NodeMcu ESP8266

NodeMCU comprises open-source firmware with available open-source prototyping board designs. "Node" and "MCU" (microcontroller unit) are combined in its name. "NodeMCU" actually refers to the firmware, not the development kits that go along with it. This 32-bit microcontroller enables two-way communication between devices linked to Wi-Fi. The NodeMCU helps in transmitting data to cloud services via HTTP/HTTPS protocol, thereby making developers harness the scalability and reliability of cloud infrastructure for storing and processing vast amounts of data stored in MySQL database. It's a cheap semiconductor that comes pre-installed with TCP/IP networking software. This board has seventeen GPIO pins. It has a low-power consumption Tensilica L 106 RISC CPU inside. Power amplifiers, ADCs, and some power management modules are all compatible with it. It has 4KB of RAM available. The most basic version of NodeMcu is shown in Figure 4.

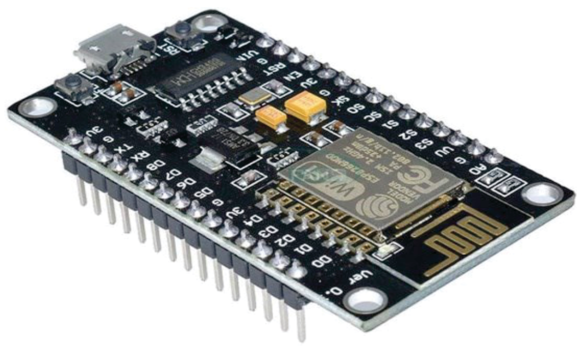

Figure 4: NodeMcu ESP8266

2.3.2 SOIL MOISTURE SENSOR MODULE

Soil Moisture Sensor Module: The amount of water in the soil is measured using a soil moisture meter as shown in figure 5. It is primarily made up of two conducting probes. The moisture content is determined by varying the resistance between these probes. Resistance is directly inversely correlated with soil moisture content. Analog data is transmitted by it. The result of feeding this into ADC will range in value from 0 to 1023. Consequently, the value drops if the soil is devoid of water. This will be number 1023. Therefore, we need to map (0,1023) to (1,100) in order to convert this value to a percent, and we can accomplish this by using the map function

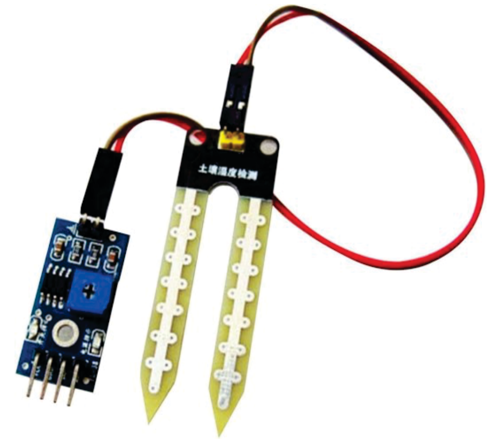

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Figure 5: Soil Moisture Sensor Module

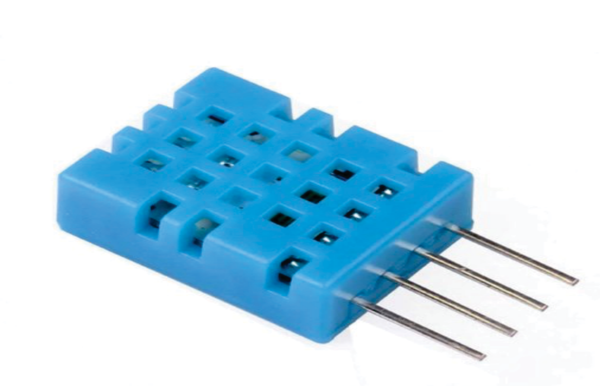
2.3.3 Dth11 Sensor

The DTH11 sensor as shown in Figure 6 is a multifunctional sensor that gauges the surrounding air temperature and humidity. It is composed of a temperature-sensing thermistor and material that detects humidity. A capacitor that has humidity acting as a dielectric material between them can be used to detect changes in humidity by changing the capacitance. The operation of thermistors is understood. The temperature has an effect on the resistance value fluctuations. We can obtain the 3-5 volts needed for it to function from the NodeMcu.

Figure 6: DTH11 sensor

2.3.4 Relay Module

Relay Module: This kind of switch operates on the principle of magnetism. The main job of the relay module is to regulate the motor. The highest output voltage of the NodeMcu (Figure 7) is 5 volts, which is not enough to run the motor. Therefore, we will connect the relay module to the NodeMCU and power it with a 9v battery in order to run the motor. When we wish to turn on the motor, we may send a high-to-low pulse to the relay module at any moment. This will cause the switch to close and send 9V to the motor. Fig. 6 illustrates the 1-channel Relay module as an example.



2.3.5 Pump for Water

Pump for Water: This submersible water pump is small in size and does not have self-prime. Compared to a non-brushless water pump, it operates more silently and smoothly thanks to its brushless motor construction.

3.0 IMPLEMENTATION AND RESULT

As shown in the Figure 8, the user effortlessly system monitors and manages the farming field's watering thanks to the integration of the Smart watering System with the mobile application system. With the aid of technologies that builds a connection between hardware and cloud databases, there is an interface on the mobile application system to examine data that has been immediately collected from the sensors. The primary menu of the mobile application, which shows the system login page, serves as its main interface. This will secure each user's login and keep third parties from accessing data that belongs to another client. Following a successful login, the user is presented with an additional menu where they can control the irrigation system.

To navigate the system, the user must choose one of the available alternatives. The control option allows the user to compel the water pump to turn "ON" or "OFF," or to leave it in AUTO mode, which automatically adjusts the pump's control based on the value of the sensor that is established in the system.

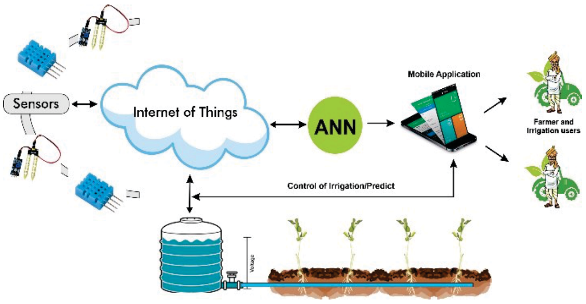


Figure 8.: The innovative Smart Irrigation System that demonstrates Cloud technologies, ANN, and IoT

Figure 7: Relay module

Table1: Performance metrics for the research.

No	Metrics	Description
1	Accuracy	The % of correct classification
2	F1 Score	The F-measure yields a single score that takes into account recall and precision in equal measure.
3	R^2	coefficient of determination
4	MSE	Used to compare the performance of the algorithms
5	RMSE (Root Mean Square Error)	Standard deviation of the errors that occur when a dataset is used to make a prediction

3.1 Performance Metrics Used in Results

The performances of the ML models as shown in Table 1 will be evaluated using certain percentage of the data. Error metrics to measure the accuracy, sensitivity and specificity of a predictive model can be formalized as follows: Mean Squared Error (MSE) and coefficient of determination (R^2) will be used as evaluation metrics to compare the performance of the algorithms.

4.0 CONCLUSION

This project showcase an innovative water pump control design for the creation of an intelligent irrigation system connected to a smartphone app. The irrigation method that has been designed helps farmers enhance crop output by saving water, time, and effort that would otherwise be squandered. The user interface of the smartphone app for the Smart Irrigation System offers a seamless and intuitive experience for end users. Its usability is enhanced through features such as customizable irrigation schedules, real-time moisture monitoring, weather integration, and alerts/notification system. . Future work on this project will make use of case studies of various crops in addition crop yield prediction to notify farmers using secure Application Programming Interface (API).

REFERENCES

[1] Foley, J. A. (2011). Can we feed the world sustain the planet?. *Scientific American,* 305(5), 60-65.

[2] D'Odorico, P., Chiarelli, D. D., Rosa, L., Bini, A., Zilberman, D., & Rulli, M. C. (2020). The global value of water in agriculture. *Proceedings of the national academy of sciences,* 117(36), 21985-21993.

[3] Jiménez, A. F., Cárdenas, P. F., & Jiménez, F. (2022). Intelligent IoT-multiagent precision irrigation approach for improving water use efficiency in irrigation systems at farm and district scales. *Computers and Electronics in Agriculture,* 192, 106635.

[4] Allioui, H., & Mourdi, Y. (2023). Exploring the Full Potentials of IoT for Better Financial Growth and Stability: *A Comprehensive Survey. Sensors,* 23(19), 8015.

[5] De Fraiture, C., & Wichelns, D. (2010). Satisfying future water demands for agriculture. *Agricultural water management*, 97(4), 502-511.

[6] Keswani, B., Mohapatra, A. G., Keswani, P., Khanna, A., Gupta, D., & Rodrigues, J. (2020). Improving weather dependent zone specific irrigation control scheme in IoT and big data enabled self driven precision agriculture mechanism. *Enterprise Information Systems*, 14(9-10), 1494-1515.

[7] Bwambale, E., Abagale, F. K., & Anornu, G. K. (2022). Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: A review. *Agricultural Water Management*, 260, 107324.

[8] Amiri, Z., Heidari, A., Darbandi, M., Yazdani, Y., Jafari Navimipour, N., Esmaeilpour, M., & Unal, M. (2023). The Personal Health Applications of Machine Learning Techniques in the Internet of Behaviors. *Sustainability,* 15(16), 12406.

[9] Ahmed, A. N., Othman, F. B., Afan, H. A., Ibrahim, R. K., Fai, C. M., Hossain, M. S., ... & Elshafie, A. (2019). Machine learning methods for better water quality prediction. *Journal of Hydrology*, 578, 124084.

[10] Kerschke, P., Hoos, H. H., Neumann, F., & Trautmann, H. (2019). Automated algorithm selection: Survey and perspectives. *Evolutionary computation*, 27(1), 3-45.

{11] Ali, A. S., Zanzinger, Z., Debose, D., & Stephens, B. (2016). Open Source Building Science Sensors (OSBSS): A low-cost Arduino-based platform for long-term indoor environmental data collection. *Building and Environment,* 100, 114-126.

[12] Kim, H. (2022). Deep learning. In Artificial Intelligence for 6G (pp. 247-303). Cham: Springer International Publishing.

[13] Krenker, A., Bešter, J., & Kos, A. (2011). Introduction to the artificial neural networks. Artificial Neural Networks: Methodological Advances and Biomedical Applications. InTech, 1-18.

[14] Kan, M. S., Tan, A. C., & Mathew, J. (2015). A review on prognostic techniques for non-stationary and non-linear rotating systems. Mechanical Systems and Signal Processing, 62, 1-20.

[15] Szandała, T. (2021). Review and comparison of

commonly used activation functions for deep neural networks. Bio-inspired neurocomputing, 203-224.
[16] Alaloul, W. S., & Qureshi, A. H. (2020). Data processing using artificial neural networks. Dynamic data assimilation-beating the uncertainties.
[17] Thakur, A., & Konde, A. (2021). Fundamentals of neural networks. International Journal for Research in Applied Science and Engineering Technology, 9(VIII), 407-426.
[18] Pavithra, V., & Jayalakshmi, V. (2023). Smart energy and electric power system: current trends and new intelligent perspectives and introduction to AI and power system. In Smart Energy and Electric Power Systems (pp. 19-36). Elsevier.
[19] Elsheikh, A. H., Sharshir, S. W., Abd Elaziz, M., Kabeel, A. E., Guilan, W., & Haiou, Z. (2019). Modeling of solar energy systems using artificial neural network: A comprehensive review. Solar Energy, 180, 622-639.
[20] Naskath, J., Sivakamasundari, G., & Begum, A. A. S. (2023). A study on different deep learning algorithms used in deep neural nets: MLP SOM and DBN. Wireless personal communications, 128(4), 2913-2936.
[21] Metawea, M., Metawa, S., & Metawa, N. (2022). An Overview of Neural Network in Financial Risk Management. Artificial Intelligence and Big Data for Financial Risk Management, 214-226.
[22] Szandała, T. (2021). Review and comparison of commonly used activation functions for deep neural networks. Bio-inspired neurocomputing, 203-224.
[23] Reddy, M. D. (2023). Mitigation of Grid Current Harmonics by ABC-ANN based Shunt Active Power Filter. Journal of Advanced Research in Applied Sciences and Engineering Technology, 33(1), 285-298.
[24] Zhang, G., Martens, J., & Grosse, R. B. (2019). Fast convergence of natural gradient descent for over-parameterized neural networks. Advances in Neural Information Processing Systems, 32.