

Planting Sustainability Prediction Using Random Forest Algorithm

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ABSTRACT

This study aimed to utilize smart space technologies in determining planting sustainability and soil moisture stress that will optimize IoT and data mining technique to help in achieving the government's goal of empowering and strengthening the nation's agricultural sector. The study employed the combined experimental, developmental, and quantitative research approach towards achieving the objectives of the study. In order to gather abiotic and edaphic data, including soil moisture, light, temperature, humidity, pH, and NPK level, the study constructed an IoT prototype. The researcher employed LoRa technology in transmitting collected data into the IoT gateway before uploading it to Firebase Realtime Database. The study also involved the development of a mobile application using Blynk IoT Framework and web interface for remote monitoring and control of irrigation and UV lighting system. Comparative analysis was conducted between Random Forest, KNN, and Naïve Bayes Algorithm in predicting planting sustainability based on available data. Based on the calculated Kappa of 0.9901, Random Forest demonstrated the highest level of accuracy with a "Almost Perfect" strength of agreement. Random forest was implemented using the RubixML library to enable the web interface to perform predictions of Planting Sustainability on data stored in the database. In the user evaluation test based on ISO25010 conducted by the researcher, the overall weighted mean for all criteria is 4.19, with an "Agree (A)" interpretation. This indicates that the developed system is of excellent quality, excelling in functionality, dependability, usability, efficiency, maintainability, and portability.

Index Terms: IoT, Data Mining, Agriculture, Vertical Farming, Wireless Sensor Node, Arduino, Blynk

INTRODUCTION

The Philippines is recognized as an agricultural nation since agriculture contributes significantly to the country's economy and because 32% of its total geographical area is made up of rural areas. [1]. The agricultural sector's Gross Domestic Product (GDP) serves as a measure of the agricultural sector's growth, which is essential to the nation's economic situation[2][3]. According to the data from the World Bank, Philippines's average GDP is 21.36 percent from 1960 to 2016. Based on records, the highest percentage was 31.06 percent in 1974, while the lowest was 9.65 percent in 2016. This demonstrates the unfortunate reality that agriculture's contribution to GDP (value added) is declining[4][5].

In order to increase and improve the productivity of the agriculture sector, the Philippine Department of Agriculture (DA) is increasingly embracing numerous technology innovations. Additionally, DA is exploring the use of "smart space" technologies to enhance farmers' access to crucial information about plants, soil conditions, and climate state, thereby enhancing their competitiveness in high-value agro-products[6][7]. This is also done to address the challenges of the future, such as tripling the amount of food produced and maintaining food security, commercial margins, and climate change mitigation[8][9]. To meet this demand, stakeholders are currently embracing the concept of internet of things (IoT) for analytics and increased production capacity [10][6]. IoT refers to interconnected objects, tools, vehicles, structures, sensors, and computer applications that are used to establish communication and exchange data. IoT enables users to track and regulate the environment remotely using an existing network architecture. The physical environment can

be linked with computer technology and online virtual resources to provide end users with both valuable information and functionalities[11][12]. The IoT is going to advance farming's future. Smart farming is already becoming more popular in the agricultural industry as a result of technological advances, and smart farming is rapidly becoming a norm[2].

The basic concept is to boost lettuce growth while maintaining high quality in a controlled environment [7] or residential area by employing vertical farming to maximize the use of available land. Vertical farming is an agricultural technique where crops are cultivated by stacking them vertically.

Successful agricultural production depends on the availability of the proper amounts of soil moisture, which is also important for evaluating the sustainability of planting. Lack of moisture may harm plants and reduce production. Root disease and wasted water are the results of excess[13]. Water serves as a delivery system for any nutrients that are not strongly linked to the soil, which is equally crucial. Therefore, it is essential to ensure that crops receive the optimum amount of water supply at the correct point of time, where understanding the level of soil moisture is crucial [14][15].

In view of this study, a data mining technique using a classification algorithm will be employed to determine planting sustainability. This is to make predictions on planting sustainability based on climatic variables so that proper intervention can take place to ensure the high quantity and quality of the harvest yield.

This study suggested a solution that will make use of the IoT concept by developing an Arduino-based system that can track essential parameters in real time and use a classification algorithm to predict the planting sustainability. The system will also activates the irrigation system if the level of soil moisture falls below a predetermined threshold to avoid water scarcity.

Related Studies

According to the author, the goal of experimental research is to draw conclusions from the application of theories in the real world and to test the validity of those conclusions. This CS technique is employed in a variety of disciplines, including artificial neural networks, theorem-proving automation, natural language processing, performance and behavior analysis, etc. It is crucial to reiterate that all experiments and findings must be able to be replicated. If we apply the experimental approach in the field of IS, we could also need to use other techniques or instruments. These techniques or instruments are utilized to back up and demonstrate the validity of the developed project. The technical issue is the first area of the project that can be evaluated using success criteria for the established project, such as availability, dependability, scalability, and stability. The second area of testing that requires input from system users is the project's usability; findings for this area can be achieved by the statistical analysis of a questionnaire, a tool that is utilized in conjunction with the experimental approach[16].

A published study by S. Dutta et al., proposed a way to technologically manage the entire procedure of assessing requirements to maintain plant development and sustainability such as soil moisture, temperature, relative humidity, and light without requiring the presence of growers[17].

In their article [24], Vimal and Shivaprakasha defined greenhouses as a regulated environment where plants can grow. The constant monitoring and management of ecological parameters are crucial for a greenhouse system to achieve the most extreme plant development. The researchers also provided formulae, which are illustrated below, for computing various climate variables based on voltage values obtained from DHT11 using an Arduino microcontroller.

Harshani et al. identified soil properties and factors such as texture, structure, porosity, and color in their research. The ratio of soil particles to organic matter is referred to as texture, structure is the aggregation of primary soil particles, porosity is the number of pores in the soil, and color is determined by its organic content and oxidation degree. Temperature, humidity, soil moisture, and pH level are all important soil parameters for farming. Temperature is an important component in plant growth, while humidity refers to the amount of water vapor in the soil. Soil moisture is required for plant nutrient uptake, and pH levels should be between 5.5 and 7.5 [18].

Researchers from India presented their findings in 2023 along with a solution they think will deal with the scarcity of arable land and water availability. The researchers introduce the idea of vertical farming. In order to grow plants vertically, layers of plants are typically stacked indoors. Vertical farming does not depend on the weather, utilizes less land, and produces more yield per square meter[19].

Embedded systems are used to enhance a set of smart applications running in a physical environment known as a "smart space." The study highlighted adaptability, interoperability, openness, expandability, and self-management as qualities of a smart space. [20].

A study was carried out in Porto, Portugal, with the goal of employing smart cities to enhance sustainability and quality of life. The UrbanSense project was used by the researchers to gather information on weather patterns, quality of life, and air quality. Additionally, researchers created an ontology for describing data from smart cities, which UrbanSense researchers then validated. All data were then published in internal data repositories for big data and research purposes. [21].

The authors used the Smart Space application to tackle the problems of meaningful event recognition, context information gathering, and visualization in an event recording system. This enables the system to visualize events using a timeline based on readings from standalone sensors or sensor networks and actions done by the smart space application[22].

The authors used the smart space idea to assist in managing equipment, decrease repetitive behavior, and provide convenience by acknowledging and implementing the recognized user's configuration automatically. The system was intended to recognize and monitor users in the smart room by remembering their usual activities such as switching on the light and TV and automatically saving it in the configuration of the user[23].

Similar research was conducted by the authors to utilize the concept of smart space technology to turn a conventional home into "smart homes" to aid and give comfort to physically disabled people. The proposed project is eyeing the idea of integrating digital assistants with the available smart devices in the markets today. This makes it possible for people with disabilities to manage their homes by controlling appliances with voice commands through a variety of readily available voice assistants [24].

The Internet of Things (IoT) is a network of connected objects connected to a cloud server. Embedded technology significantly impacts IoT by enabling the development of smaller, energy-efficient, and high-performance controllers that offer effective data storage, receiving, and control in their actuators [25].

DESIGN AND METHODOLOGY

Research Design

A research design includes the structure of a study and the strategies for conducting the studies. The study utilizes the combined experimental, developmental and quantitative research approach towards achieving the objectives of the study. This research approach is suitable for this study since it involves the development of the proposed prototype; develop a model; and evaluate the system's compliance in software development standards.

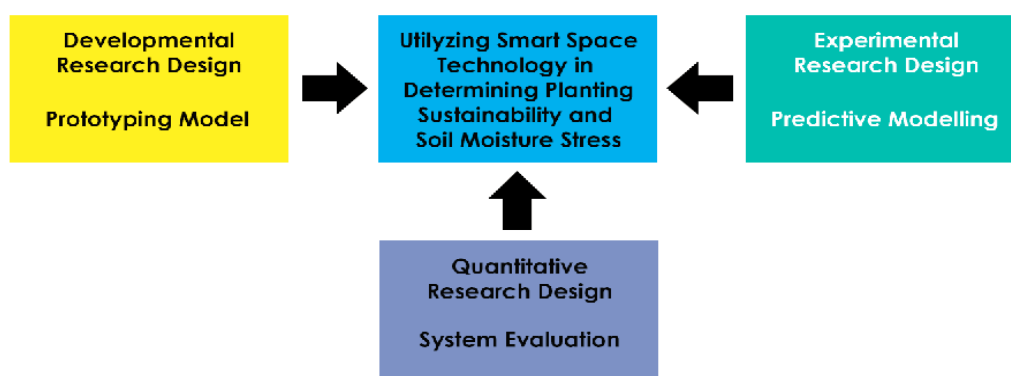


Fig. 1 Research Design of the Study

Figure 1 shows the research design of the study. The study's research design includes prototyping for developmental research, data mining for experimental research to predict planting sustainability, and quantitative research for determining compliance with ISO25010 standard.

Developmental Research Design

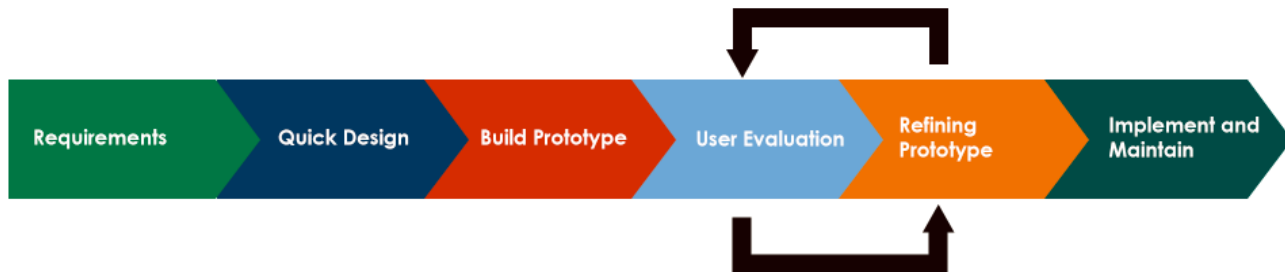


Fig. 2 Prototyping Model [26]

This study employs a prototyping model in the developmental research design. The Figure below illustrates the process and the expected outputs in every phase of the prototyping model.

1)Requirements:

In this stage, the researcher carefully analyzed the requirements and specifications needed in the development of the prototype that will help satisfy the research objectives. Different system functionalities as well as hardware components were identified. Abiotic and edaphic elements including temperature, soil moisture, light intensity, humidity, pH, and NPK level are among the abiotic and edaphic variables that the prototype is designed to collect data on. Data collected will be uploaded to a cloud server and later be used for identifying an algorithm that will determine planting sustainability.

2)Quick Design:

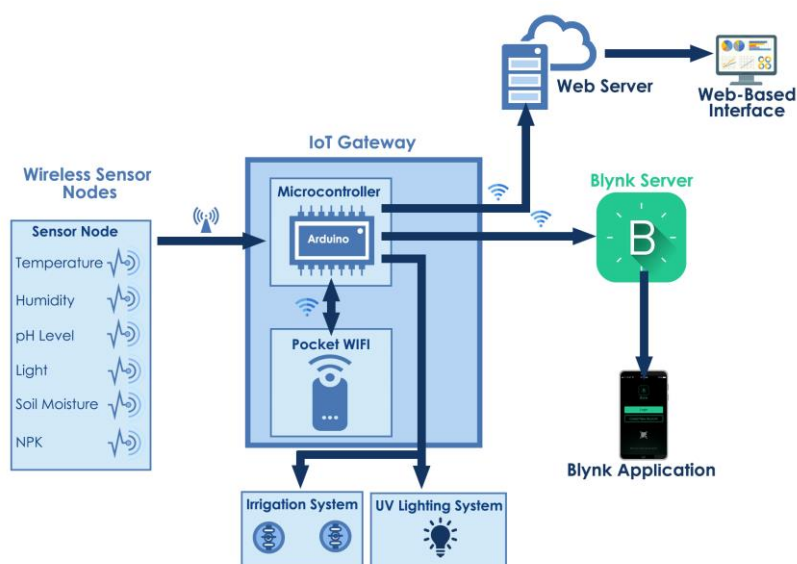


Fig. 3 Block Diagram of the Prototype

During this phase, an initial design was created. Fig. 3 illustrates how each component will interact and how data will flow from one component to another. The Wireless Sensor Node (WSN), IOT Gateway, Irrigation and UV Lighting System, Web Interface, and Mobile Application that displays the reading of various sensors are some of the components that make up the prototype. The mobile application also allows end-users to gain control of the irrigation and UV lighting system remotely.

3)Build Prototype:

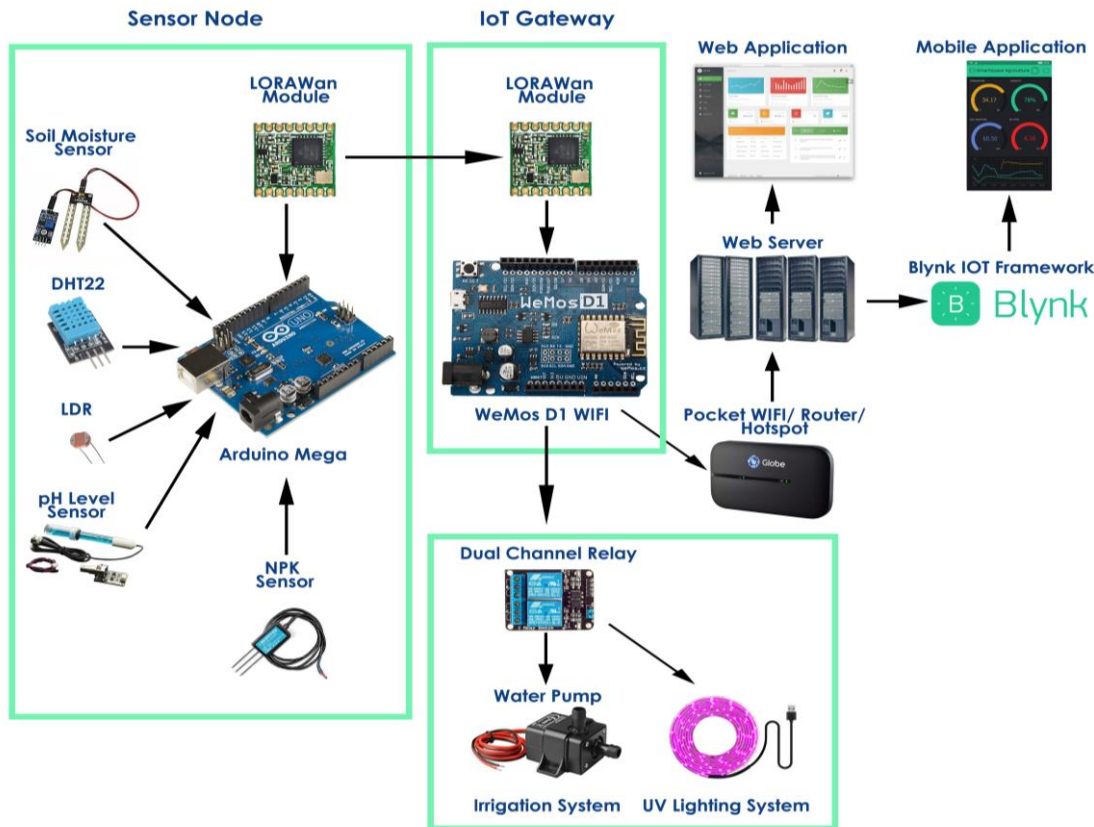


Fig. 4 System Architecture Design

Fig. 4 illustrates the architecture design that guides the researcher in building the prototype.

4)User Evaluation:

In this stage, the IT experts and agriculturists were invited to evaluate and to assist with discovering the strengths and weaknesses of the prototype. Comments and ideas were gathered from all the participants to further enhance and fix the errors discovered. The researcher adopted ISO25010 to evaluate the prototype. The prototype was evaluated based on characteristics stipulated in ISO25010 such as functionality, performance efficiency, compatibility, usability, reliability, security, maintainability, and portability [27]. Weighted mean responses from respondents were used to determine the prototype's conformity with the ISO standard. The researcher applied weighted mean as a statistical tool for interpreting the data gathered from the responses given by the respondents to evaluate the prototype. The formulas presented assessed the performance of the system.

$$W = \frac{\sum_{i=1}^n (w_i * X_i)}{\sum_{i=1}^n w_i} \quad \text{Equation 1}$$

Where:

- W - Weighted Mean
- n - number of terms to be averaged
- wi - weight applied to x values
- Xi - data values to be averaged

Table I Five-Point Likert Scale

Numerical Value	Range	Interpretation
5	4.51 – 5.00	Strongly Agree (SA)
4	3.51 – 4.50	Agree (A)
3	2.51 – 3.50	Moderately Agree (MA)
2	1.51 – 2.50	Disagree (D)
1	1.00 – 1.50	Strongly Disagree (SD)

Table I shows the Likert scale used in evaluating the prototype. The numerical value of 5 with a scale of 4.51 to 5.00 is interpreted as Strongly Agree (SA). The numerical value of 4 with a scale of 3.51 to 4.50 is interpreted as Agree (A). The numerical value of 3 with a scale of 2.51 to 3.50 is interpreted as Moderately Agree (MA). The numerical value of 2 with a scale of 1.51 to 2.50 is interpreted as Disagree (D). Lastly, the numerical value of 1 with a scale of 1.00 to 1.50 is interpreted as Strongly Disagree (SD).

5)Refining Prototype:

Tests such as unit testing and integration testing were regularly conducted during the construction of the prototype. All bugs found during tests need to be corrected to enable the prototype to read and generate accurate results. The researcher conducted a user evaluation to improve the prototype and identify errors impacting accuracy and efficiency. IT experts are being consulted to assess and provide suggestions for the project's improvement. This evaluation will help identify areas for improvement and enhance the project's overall performance. During this stage, all ideas and comments from the stakeholders were collected and addressed. Different alternatives were tested to meet the requirements and implement the changes.

6)Implement and Maintain:

The researcher built a wall-mounted platform to deploy the created prototype because there are no areas for performing conventional horizontal farming. This platform embraces the idea of vertical farming and may be utilized by residents interested in urban farming.



Fig. 5 Wall-Mounted Platform for Vertical Farming

To prevent water waste, the platform was built with irrigation and a water drainage system. The extra water will be collected and sent to the water storage using the water drain system. Additionally, a UV lighting system was built to aid plant growth in the lack of direct sunshine.

A. Experimental Design

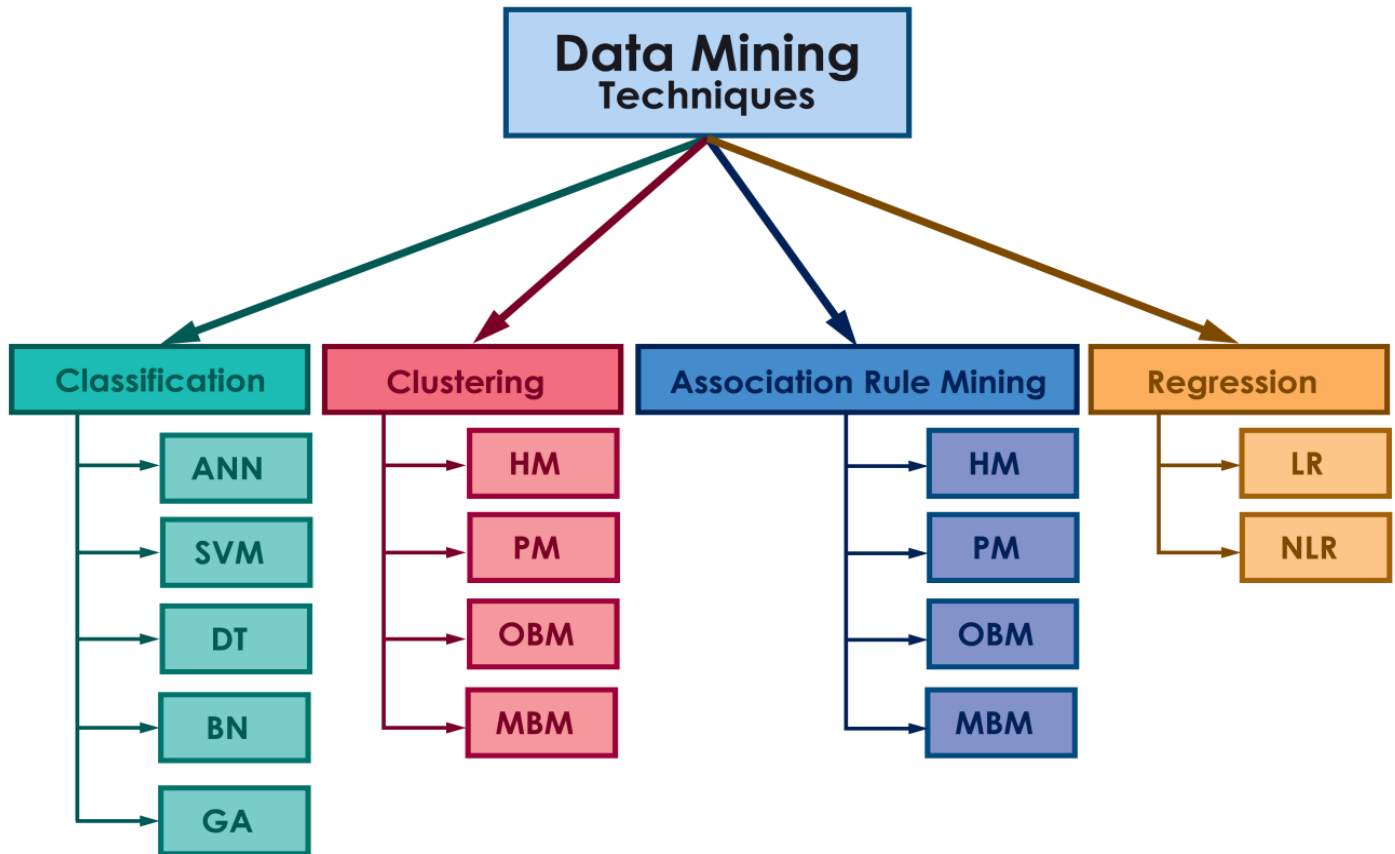


Fig. 6 Different Data Mining Techniques

This study uses data mining to classify planting sustainability using abiotic and edaphic data gathered from the indoor or greenhouse facility. Hidden information from databases is transformed into comprehensible structures using a computational process called data mining. To find patterns in massive amounts of data, it uses artificial intelligence, machine learning, statistics, and database systems. Predictive data mining is the most popular type with direct business applications because prediction is the end goal[28].

There are several data mining techniques, but the primary techniques are the Classification, the Clustering, the Association rule mining and Regression analysis. Fig. 6 displays the various data mining methods now in use.

This study focused on the Classification Techniques since the study is about predicting the planting sustainability based on data collected from the prototype. To determine which algorithm would provide the best fit and the highest accuracy, classification algorithms including Random Forest, Naive Bayes, and KNN were tested.

1)Study Area:

The study was conducted in Novaliches, District 5, Quezon City where the improvised vertical farming platform will be implemented. This is to support the Urban Farming Project of District 5, Quezon City, Philippines. Barangay Kaligayahan, Quezon City is the project's beneficiary and recipient of the developed prototype. The prototype was tested in Bagong Silang, Caloocan City under the assistance of Mr. Eduardo Torrest Jr., an entrepreneur and a lettuce grower.

Quezon City District 5



BARANGAY	ACTUAL POPULATION (NO)	GROWTH RATE (POP/N DENSITY)	(2010)	(2015)
Baclaran	38,799	37,909	0.232	183
Calatagan	11,314	12,596	0.751	5409
Ermita	29,332	47,553	4.562	324
Greater Lungsod	19,632	21,161	0.753	50
Guadalupe	46,706	53,788	1.412	419
Kalayaan	29,388	48,433	5.052	193
Magdalena	38,098	46,092	2.522	185
North Fairview	16,127	38,385	8.886	195
Northwest Proper	12,019	14,748	2.037	225
Pinoy Proper	20,804	31,031	4.377	133
San Agustin	20,850	21,305	0.240	209
San Bartolome	37,138	44,739	3.879	125
Santa Lucia	18,194	24,393	2.602	381
Santa Monica	27,054	44,325	4.963	289
Summit	-	-	-	-
TOTAL	361,644	488,172	2.868	174

Legend	
Barangay Hall	Road
Day Care Center	Waterways
Elementary School	Barangay Boundary
High School	District 1
Health Center	District 2
Hospital	District 3
Police Station	District 4
Fire Station	District 5
Catholic Church	District 6
Non-Catholic Church	

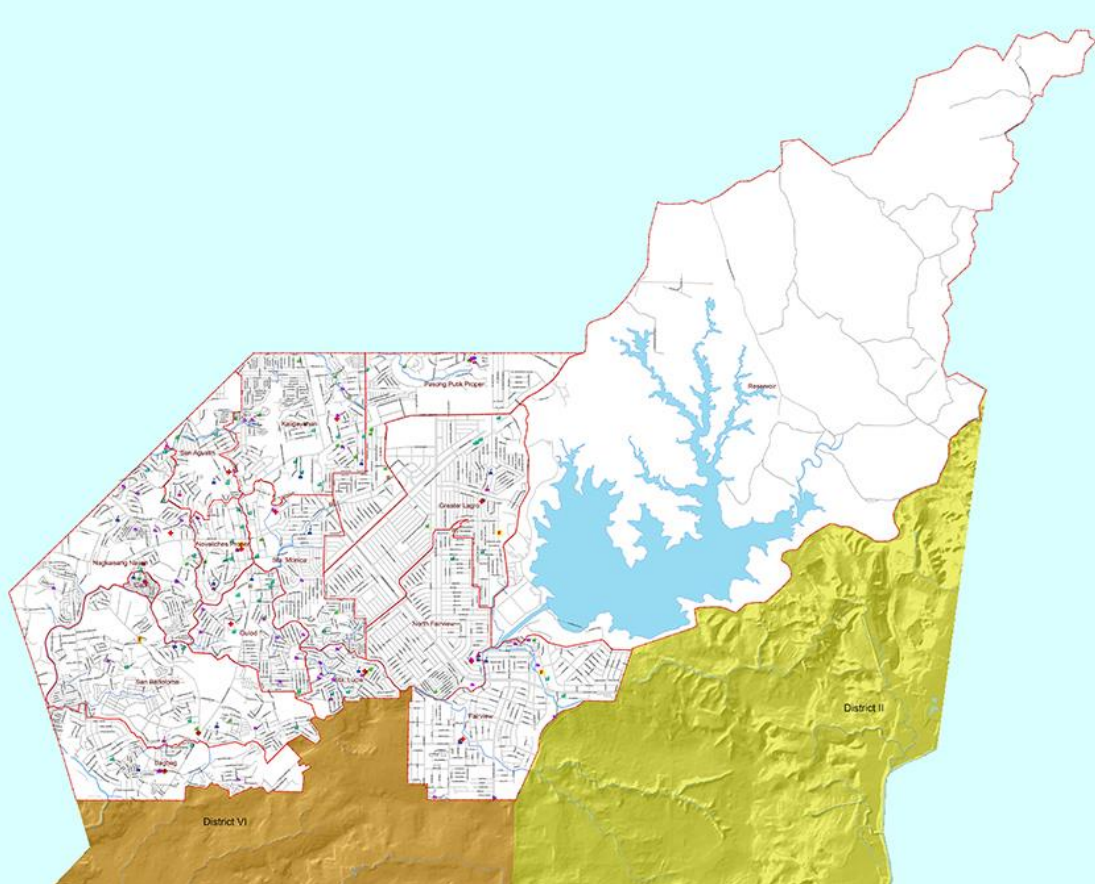


Fig. 7 District 5, Quezon City[29]

2)Collect:

The study's primary data was taken from the prototype's collected data. Data collected are presented to agriculturists and experts to be given proper assessment and to identify the planting sustainability based on values of different parameters. All data uploaded to the web server that was evaluated by experts were used as datasets and were utilized in designing a predictive model.

3)Prepare Data:

During this phase, all data collected from the database were processed in order to transform raw data into a useful and efficient format. The process involves removing missing, inconsistent, or irrelevant data, including duplicate records, missing values, and outliers. The data in .csv format will be used data mining, with 70% being training data and 30% being test data, ensuring a suitable format for the task.

4)Train Model:

The training instruments and provided training data are described in this section. In order to visualize data, this study uses Orange Visual programming. The 70% of the data was utilized as training data in creating a model that will give the highest accuracy in classifying the planting sustainability.

5)Test Data:

After the model was created, 30% of the dataset was used to test the model. Different models were tested to determine which of these models employs different classification algorithms. The dataset is converted to a.csv file and used machine learning models including KNN, Random Forest, and Naive Bayes. Evaluation results are provided by the confusion matrix.

6)Classification and Validation:

The researcher assessed the performance, efficacy, and accuracy of the classifier model's predictions using various measures. The reliability and validity of the data were determined through tests with known planting sustainability parameter values. The accuracy of the generated sample was evaluated by comparing the observed accuracy with an expected accuracy rate based on the Confusion Matrix[30]. Precision, Recall, and F-1 Score are taken into account and determined as performance indicators. Table II displays Cohen's Kappa, which is needed to properly interpret the performance of each classifier.

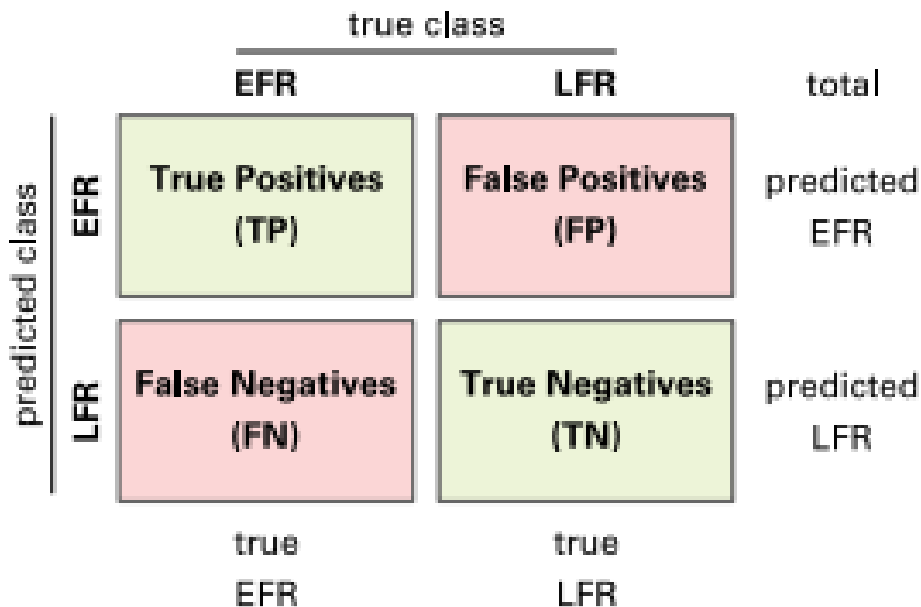


Fig. 8 Confusion Matrix [30]

Table II Magnitude of Kappa as Illustrated by Landis and Koch[31]

Kappa (K)	Strength of Agreement
< 0.00	Poor
0.00 – 0.20	Slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Almost Perfect

RESULT AND DISCUSSION

B. The Developed Prototype

The developed prototype is thoroughly discussed in this section. The prototype was created by integrating various pieces of hardware, software, and data mining theory to make it function in accordance with its design and specifications.

The prototype's IoT gateway is shown in Fig. 9. The Internet of Things gateway, sometimes called an IoT gateway, acts as a link between WSN's and the cloud infrastructure. IoT gateway serves as a primary hub for sending to the cloud of abiotic and edaphic measurements. Arduino Wemos D1, relays, RFM95 LoRa Transceiver, casing, and antenna are the critical parts to build the IoT gateway.



Fig. 9 The Developed IoT Gateway

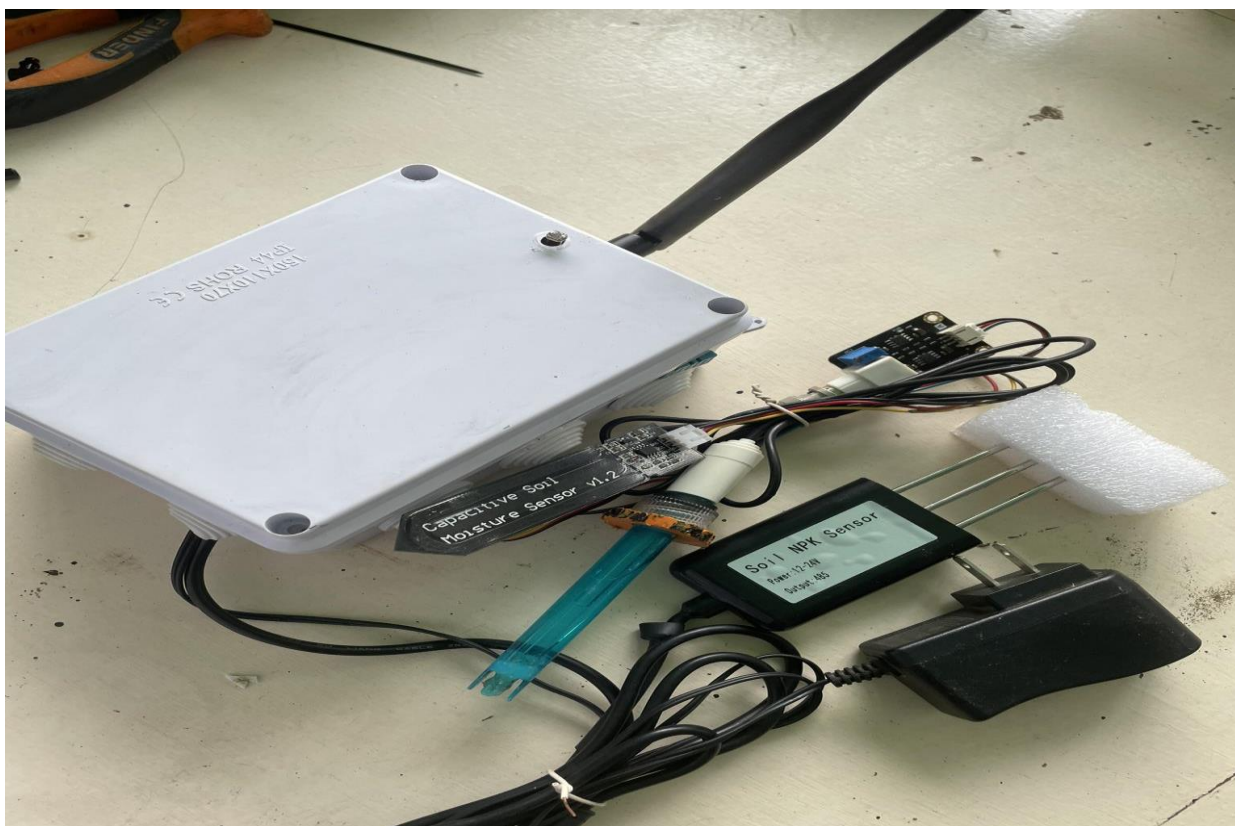


Fig. 10 The Wireless Sensor Node

Figure 10, on the other hand, shows a WSN's prototype that has been built and is in charge of reading greenhouse climatic and soil parameters and transmitting all of the collected data to the IoT gateway via radio frequency. The primary parts of the WSN are the Arduino Mega, RFM95 LoRa Transceiver, DHT11, NPK sensor, LDR, soil moisture sensor, pH sensor, and TTL to RS485 module.

C. Mobile Application

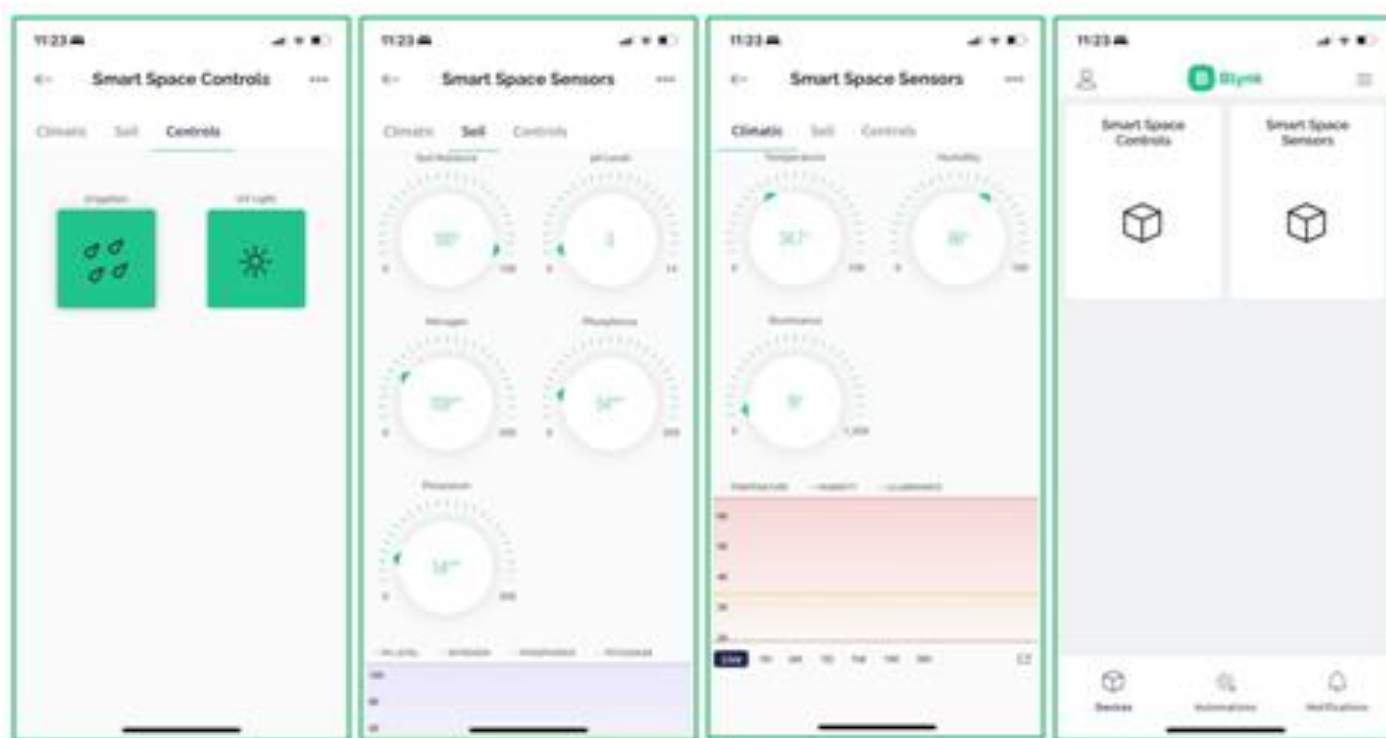


Fig. 11 Smart Space Argi Mobile Application

The IoT gateway pushes data to the Blynk IoT Platform enabling the Android Application to display all the collected data in addition to delivering the data into the cloud. By providing the most recent readings of climatic and edaphic parameters, the mobile application keeps the end-user or farmer informed about the state of his or her greenhouse facilities. The mobile application also enables remote control of the ventilation and irrigation system for the user. The researcher employs widgets, including pushbuttons for remote controls and gauges and graphs to display data. The programs use tabs titled Climatic, Soil, and Controls to organize the presentation of data and controls.

D. Web Interface

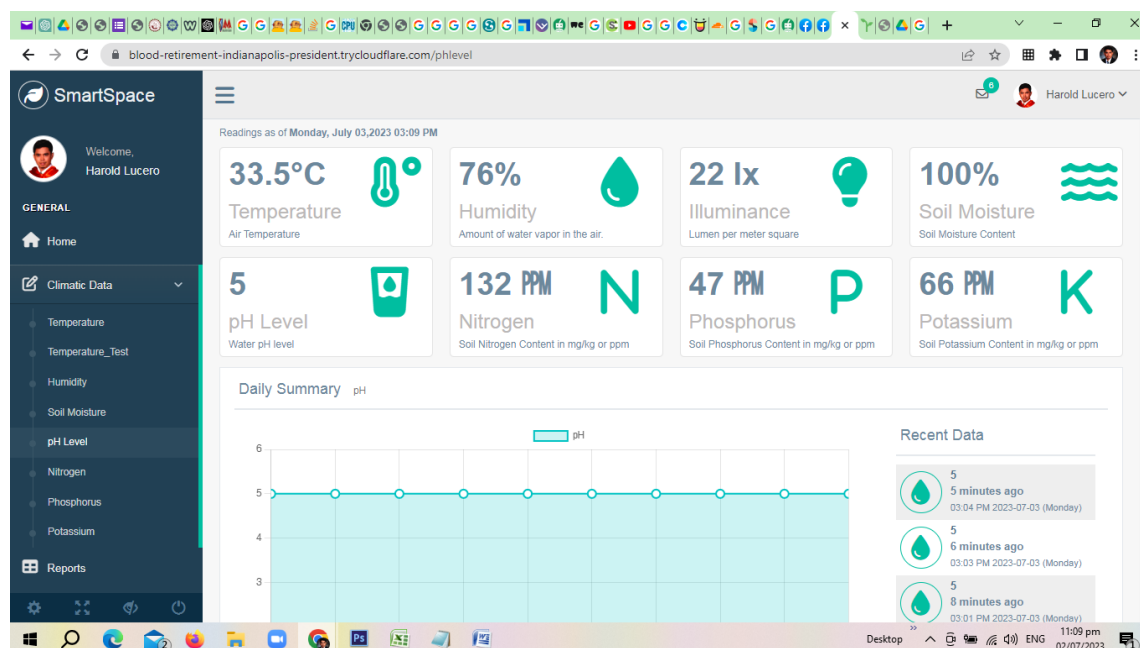


Fig. 12 Smart Space Web Interface

The end user can view all of this information through the system's web interface once the IoT gateway uploads the greenhouse data that has been collected. A web interface was developed to enable end-users gain access to green house's edaphic and climatic condition remotely using any browsers and internet connection. The web interface was hosted by CloudFare.com. Fig. 12 shows the screen shot of the web interface.

E. Comparative Analysis of Algorithm

Three Classification Algorithms were used in the comparative analysis, the KNN, Random Forest, and Naïve Bayes. The researcher employs Orange Visual Programming to perform the trade-off.

The dataset has 4,438 occurrences and was divided into training and testing subsets. The isSustainable column in the dataset comprises categorical data with the role feature "target." The training set is used to train the classification algorithm, while the testing set is used to evaluate its effectiveness. 70% of the dataset goes toward testing, and 30% goes toward training.

TABLE III Evaluation Results of the Algorithm

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.995	0.995	0.995	0.995	0.995
Naïve Bayes	0.996	0.894	0.894	0.898	0.894
KNN	0.478	0.495	0.493	0.491	0.495

Table III shows the result of the comparative analysis in which Random Forest registers the highest AUC, CA, F1, Precision and Recall with 0.995, 0. 995, 0. 995, 0. 995, and 0. 995 respectively. Second is Naïve Bayes with 0.956 AUC, CA of 0.894, F1 of 0.894, Precision of 0.898, and Recall of 0.894. The last among the four algorithms is the KNN with CA of 0.478, AUC of 0.495, F1 of 0.493, Precision of 0.491, and Recall of 0.495. To avoid over fitting, the evaluation of the algorithms was performed using 10-fold cross validation.

Table IV Observed Accuracy, Expected Accuracy, and Kappa Values of Classifiers

Model	Observed Accuracy	Expected Accuracy	Kappa	Strength of Agreement
Random Forest	0.99512	0.50608	0.9901	Almost Perfect
Naïve Bayes	0.89410	0.50081	0.7879	Substantial
KNN	0.49531	0.50929	-0.0285	Poor

Table IV presented the Observed Accuracy, Expected Accuracy, Kappa Values and the Strength of Agreement of the three classifiers used by the researcher. Random Forest registers the highest value of Observed Accuracy of 0.99512, Expected Accuracy of 0.50608, Kappa of 0.9901, and "Almost Perfect" in terms of Strength of Agreement. Naïve Bayes has 0.89410 for Observed Accuracy, 0.50081 for Expected Accuracy, 0.7879 for Kappa, and Substantial for the Strength of Agreement. KNN has 0.49531 for Observed Accuracy, 0.50929 for Expected Accuracy, -0.0285 for Kappa, and Poor for the Strength of Agreement.

The result presented in Table IV illustrates that Random Forest registers the highest Kappa with an interpretation of "Almost Perfect" in the strength of agreement.

F. System Evaluation

The user, agriculturist, and information technology experts evaluated the constructed prototype using the ISO25010 standard as part of the prototyping methodology. The system was evaluated based on Functional Suitability, Performance Efficiency, Compatibility, Usability, Reliability, Security, Maintainability, and Portability. Three (3) IT industry specialists, one (1) agriculturalist, and one (1) lettuce farmer all took part in the test. The evaluation's findings are shown in Table V.

Table V User Evaluation Results

Factor	Weighted Mean	Interpretation	Rank
Functional Suitability	4.35	Agree(A)	2
Performance Efficiency	4.33	Agree(A)	3
Compatibility	4.07	Agree(A)	6
Usability	4.36	Agree(A)	1
Reliability	4.25	Agree(A)	4
Security	4.10	Agree(A)	5
Maintainability	3.93	Agree(A)	7
Portability	4.10	Agree(A)	5
Over-all Mean	4.19	Agree(A)	

Table V presents the result of the user evaluation for each criterion. The constructed system displays a high level of usability as it received the highest ranking among criteria based on the computed weighted mean of 4.35, with verbal interpretation of "Agree (A)." Next came Functional Suitability, which received a weighted mean of 4.25 and verbal interpretation of "Agree (A)," followed by Performance Efficiency, which received a computed weighted mean of 4.33 and was verbally interpreted as "Agree (A)." Reliability has 4.25 weighted mean and a verbal interpretation of "Agree (A)." Security and Portability shares the same rank with 4.10 weighted mean and a verbal interpretation of "Agree (A)." The Compatibility is ranked sixth with a computed weighted mean of 4.07 and a verbal interpretation of "Agree (A)." Lastly, the Maintainability has the lowest weighted mean of 3.93 and verbal interpretation of "Agree (A)". The developed prototype has done well in terms of a number of quality parameters, as evidenced by the overall weighted mean of 4.19, with a verbal interpretation of "Agree (A)". The outcome indicates that the system is of excellent quality, excelling in a number of areas including functionality, dependability, usefulness, efficiency, maintainability, and portability. It shows strong performance across several metrics, proving that it satisfies or even exceeds the standards outlined in the ISO 25010 quality model.

CONCLUSION

An IoT gateway and a wireless sensor node (WSN) comprise the project's two components. An Arduino Mega connects to the sensors and peripherals that the WSN is equipped with to collect data from the surroundings. For long-distance, high-data-rate, error-prone communication, the WSN makes use of components such the RFM95 LoRa Transceiver, DHT11, RS485 Soil NPK Integrated Sensor, Light Dependent Resistor, Soil Moisture Sensor, pH Sensor, and Max485 TTL to RS-485 module. The IoT gateway offers connectivity, protocol translation, data filtering, and local processing capabilities as it transmits the collected data to the cloud platform. The IoT gateway utilizes the WeMos- D1 R2 WiFi ESP8266 Development Board and contains a LoRa transmitter for data reception. Before being sent to the cloud platform, which requires internet connectivity, all data received from the WSN is organized in JSON format.

The wireless sensor node, IoT gateway, web interface, and mobile application are the four parts that make up the overall system. Utilizing LoRa technology, all captured data is transmitted over radio frequency into the IoT gateway, enabling the system to consume less internet. Once data has been received by the IoT gateway over the internet, it will be uploaded and stored in Firebase, a backend cloud computing service. The constructed web interface allows the end-user to view and access all of these records. Only authorized users can use the web interface, which is password and username protected. The web component can provide the most recent data gathered from the greenhouse along with a projection of how long the planting will last. Additionally, graphs are used to provide end users with a simple way to see the historical values of various abiotic elements as well as the soil moisture level and nutrients from the wireless sensor nodes. Along with the web components, a mobile application was developed to improve the system's usability and accessibility and allow end users more access to the greenhouse. The mobile application shows the most recent sensor readings from the gadget. The irrigation system and air-cooling system can also be managed by the farmer or end user using the application.

Random Forest, Nave Bayes, and KNN are the three classification methods that the researcher compares using Orange Visual Programming. Based on the result, Random Forest Algorithm exhibits the highest level of accuracy based on the computed Kappa of 0.9901, with an “Almost Perfect” strength of agreement. Random Forest algorithm was implemented into the system’s web interface using a machine learning PHP library, Rubix ML. All collected data is uploaded to the cloud and kept in the Firebase database using the constructed wireless sensor node and IoT gateway. Based on the abiotic variables and soil nutrients found in the greenhouse or indoor farm, the results have been classified and marked as "Sustainable" or "Not Sustainable" in the database. The system can also measure soil moisture using a soil moisture sensor integrated into Arduino Mega that triggers the sprinkler system when the water level drops at the threshold point or as the crop needs.

The overall weighted mean of 4.19, with a verbal interpretation of "Agree (A)", shows that the developed prototype performed well in terms of quality characteristics stipulated in ISO25010. The result shows the system demonstrated high quality, excelling in a variety of factors such as functionality, dependability, usefulness, efficiency, maintainability, and portability. The results show that the system meets or exceeds the requirements specified in the ISO 25010 quality model.

ACKNOWLEDGEMENT

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