Development of an IoT-Based Soil Macronutrient Analysis System Utilizing Electrochemical Sensors and Machine Learning Algorithms

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***Abstract*— Efficient administration of principal soil nutrients is essential for achieving rational agriculture and minimizing economic losses. To improve on-site observing techniques and soil management, the utilization of advanced sensors capable of quantifying soil properties is crucial. In this study, three sensors were employed: an Ion Sensitive Field Effect Transistor (ISFET) pH sensor, a soil moisture sensor, and an RGB color sensor with an IR filter and white LED (TCS34725). The ISFET pH sensor, functioning as a Metal Oxide Semiconductor Field Effect Transistor (MOSFET), provided pH measurements ranging from 1 to 14 and exhibited temperature resistance between 0 to 100 degrees Celsius. The soil moisture sensor was designed to determine soil moisture content within a range of 0 to 1023. The RGB color sensor, by reducing the infrared spectral component of incoming light, enabled precise color measurements. These sensors were integrated into the Arduino MEGA 2560 microcontroller board to facilitate simultaneous operation of complex schemes. The acquired sensor data were correlated to the concentrations of soil macronutrients, specifically Nitrogen (N), Phosphorus (P), and Potassium (K). Through the implementation of machine learning algorithms, the levels of macronutrients can be determined, and for the training set of these algorithms, data collection was conducted using over 300 soil samples.**

Keywords*— *agriculture, soil macronutrients, sensors, machine learning algorithms

I. Introduction

Crop administration plays a crucial role in achieving good crop production and rational agriculture. Maintaining the physical, biological, and chemical compositions of the soil is essential for optimal quantitative and qualitative crop yields, which is vital in today's economy [1]. The study emphasizes the significance of nitrogen (N), phosphorus (P), and potassium (K) as macronutrients for crop growth. While commercial fertilizers containing these macronutrients have improved agricultural productivity, their excessive use can contribute to groundwater and surface contamination [1].

Electrochemical sensors have gained attention for soil nutrient detection, offering automated and efficient detection of multiple soil nutrients in a rapid manner. Integration of machine learning with sensor data enables real-time farm management systems empowered by artificial intelligence, providing valuable recommendations and insights for farmers to make informed decisions and take appropriate actions [2],[3].This study focuses to develop a soil macronutrient analysis system that will predict soil macronutrient levels through a machine learning algorithm. These predicted data and its corresponding soil parameters will be stored in the cloud database for monitoring or later retrieval for analysis [4].

II. Related Works

Innovative approaches for soil analysis and nutrient detection have been employed, including the use of a soil-testing device with color processing and elimination of lighting and distance effects [5]. Fiber optics have been utilized to detect NPK nutrients, enabling control over fertilizer dispensing [6]. Near infrared spectroscopy has been applied to identify soil nutrients and develop prediction models for organic matter, nitrogen, phosphorus, and potassium [7]. UV Spectroscopy has been used to construct a multi-parametric analytical device for on-field nutrient detection and fertilizer control [8]. The SoilMATTic prototype integrates automation, digital image processing, and artificial intelligence for accurate soil analysis and fertilizer recommendations [9]. Digital image processing and artificial neural networks have been employed for precise determination of soil macronutrients, pH levels, and fertilizer recommendations [10].

III. Implementation

A. Hardware Development

The development of hardware is composed of four sections namely: calibration and testing of sensors, designing of the analog readout circuit, integration of sensors and analog readout circuit in Arduino Mega 2560, and designing of acrylic box.

1) Calibration and Testing of Sensors

a. Calibration of ISFET pH Sensor

In practice, it is required to calibrate the ISFET pH sensor before use. The readings of an ISFET pH sensor change over time thus it is recommended to be recalibrated for its accuracy [11]-[13]. Three buffer solutions mainly pH 4, pH 7, and pH 10 are being used in this study. The voltages that will be generated upon measuring the buffer solutions will be shown in the Arduino IDE. The resulting voltages are needed to establish a linear line equation showing the relationship between voltage output and the pH level of the ISFET pH sensor. Fig. 1 shows an example of a linear trend line.

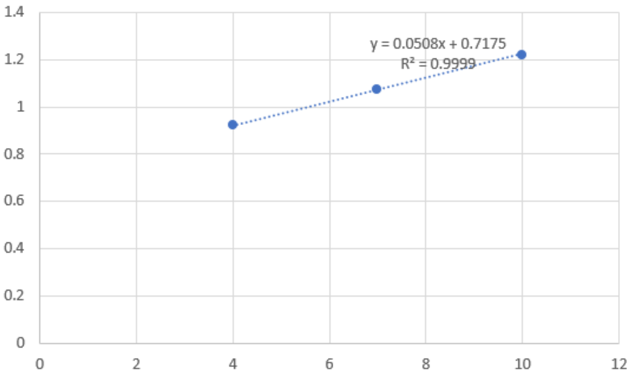


Fig. 1. Relationship between output voltage and the pH level of the ISFET pH sensor

b. Calibration of Soil Moisture Sensor

Soil moisture sensors are used to determine the moisture content in the soil. It is advised to calibrate the soil moisture sensor to produce useful data. The minimum and maximum moisture values of the soil are needed to properly calibrate the sensor. The calibration is done using the map() function in Arduino IDE.

c. Calibration of TCS34725

TCS34725 can sense RGB and clear light elements. The calibration is done by sensing the primary and secondary colors.

2) Designing of the Analog Readout Circuit

An alternative analog readout circuit is cheaper and easier to reproduce compared to the commercially available readout circuit while still being able to maintain its quality. The factors considered in choosing the components used were its characteristics concerning dc offset voltage, offset drift and biasing current factors on the precision of the device, and its accuracy, availability of the components on local stores, and the prices for being cost-efficient.

3) Integration of Sensors and Analog Readout Circuit in Arduino Mega 2560

The sensors and the alternative analog readout circuit were integrated into the Arduino MEGA 2560. The Arduino MEGA 2560 is a microcontroller board built for projects that require more random-access memory, sketch memory, and input and output ports.

4) Designing of Acrylic Box

The dimensions of the acrylic box in Fig. 2 are 300 millimeters long, 195 millimeters wide, and 10 millimeters high. For sufficient results, at least 30 soil samples were tested.

Measurements were based on the dimensions of the sensors, analog readout circuits, Arduino MEGA 2560, tablet PC, and buffer solutions that need to be inside the acrylic box.

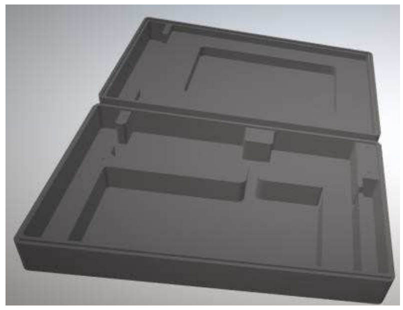


Fig. 2. Design of acrylic box

B. Software Development

The development of software is composed of three sections namely: the collection of the dataset for the machine learning algorithms, development of soil macronutrient prediction system, and designing of web application and website.

1) The Collection of the Dataset for the Machine Learning Algorithms

To develop an effective and accurate predictive model, multiple samples for the dataset was gathered. Soil samples from the soil tank of Bureau of Soil and Water Management were gathered and tested. The soil tank consists of 10 compartments with dimensions of 10m x 20m x 0.50m representing seven (7) soil orders – seven soil types collected from a various location in Luzon. The soil samples were tested for soil macronutrient (NPK) level by traditional colorimetry while also getting its corresponding soil pH level, moisture and RGB color using the sensors. ISFET pH meter tested water samples to acquire the pH level. These samples can be collected by installing tube wells or using suction lysimeter as shown in Fig. 3. Tube wells are used by farmers for irrigation monitoring while lysimeter allows extraction of soil water samples from various depths. Both tools were installed 20 cm deep from the topsoil. For sufficient results, at least 30 soil samples were tested.

(a) (b)

Fig. 3. (a) Tube well and (b) Lysimeter

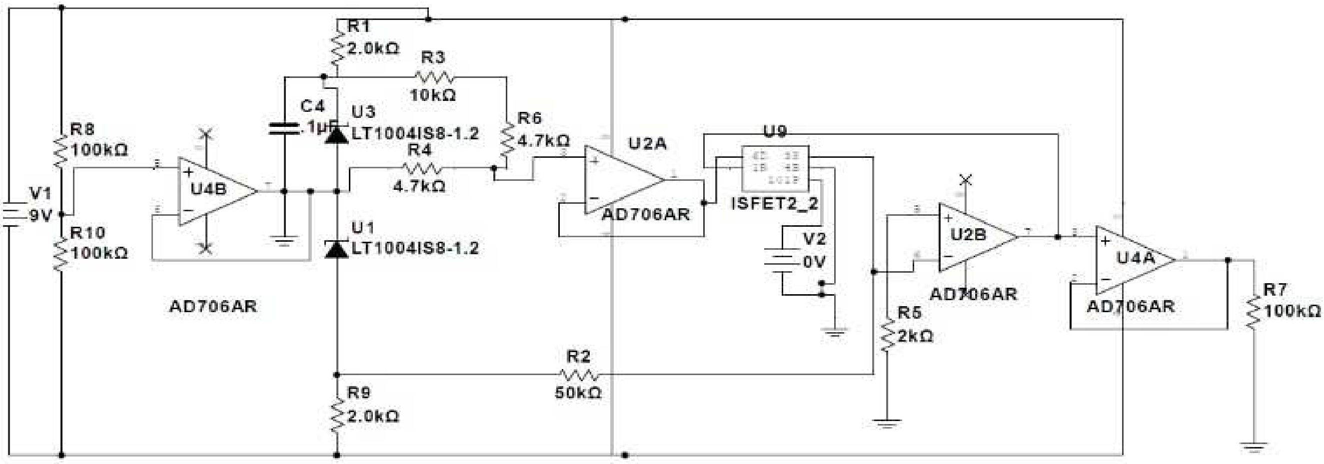


Fig. 4. Designed ARC

2) Development of Soil Macronutrient Prediction System

A predictive model for the macronutrient content using pH level, moisture level, and colors (RGB) of the soil as predictors or features was developed. After gathering the dataset, correlation tests were done between the variables. The next step is writing the codes in Python programming language for the four (4) machine learning algorithms namely Random Forest Classifier, K-Nearest Neighbor (KNN) classifier, Support Vector Machine, and Naive Bayes Classifier. The data gathered was used as dataset then split into two – test set and training set. Hyperparameter optimization was done to maximize the accuracy of the models to be used. After scaling and fitting, the four algorithms underwent cross-validation for the assessment of model performance. The best performing model will be the final machine learning model.

3) Designing of Web Application and Website

The designing of the web application is composed of two subprocesses: the back-end coding and the front-end coding. Flask, a Python web framework, is used to establish the functions and tools to be implemented on the application. The layout of the user interface, however, is done with HTML, CSS, and Bootstrap.

The website intended for the data presentation to remote users was designed on a free website builder, Wordpress. The synchronization of the local database to the Wordpress site is done with the help of Google Spreadsheet.

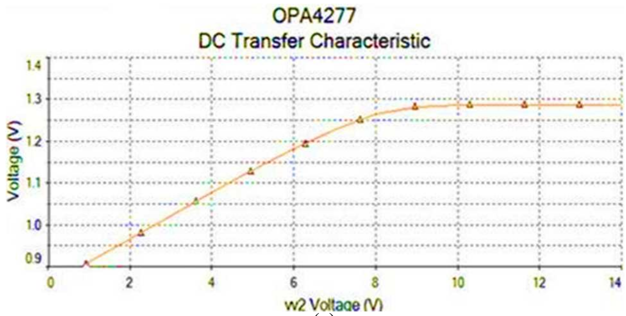
C. Evaluation

The prediction system is composed of 80% testing data and 20% training data. The dataset was gathered through the sensors. Over 300 samples were collected in this study. The actual validation is verified by the Agriculturist II of the BSWM by using their soil test kit.

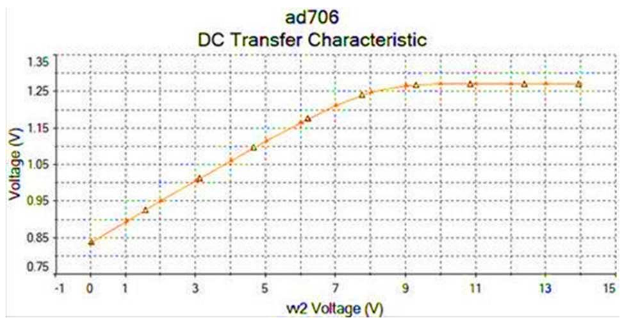
IV. RESULTS AND DISCUSSION

A. Final Design of the Analog Readout Circuit for ISFET

Fig. 4 shows the final design of the ARC using AD706 as an alternative operational amplifier for OPA4277 that the commercially available ARC used (WINSENSE). Fig. 5 (a) and (b) shows the linearity of the voltage vs pH of the two (2) operational amplifiers used by WINSENSE and the proponents for the design. This proves that AD706 can be an alternative operational amplifier for OPA4277.



(a)



(b)

Fig. 5. OPA4277 DC transfer characteristics (b) AD706 DC transfer characteristics

B. Actual Device

Fig. 6 shows the following components of the device: tablet PC, ISFET and RE Probe, a soil moisture sensor, soil probe with the RGB sensor, and buffer solutions. The buffer solutions provided is for the calibration of the ISFET pH meter.

C. Comparison of Machine Learning Algorithms

Fig. 7 presents the differences in accuracy with different ratios between the four (4) machine learning algorithms. Among the four algorithms, Random Forest classifier and KNN classifier show to have the highest accuracy.

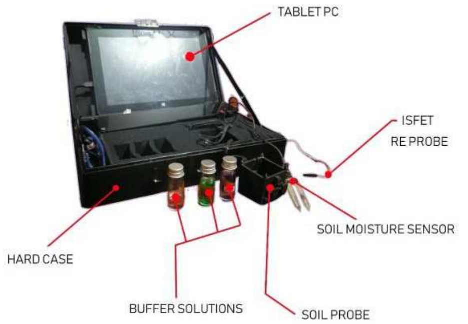


Fig. 6. SenSoil device

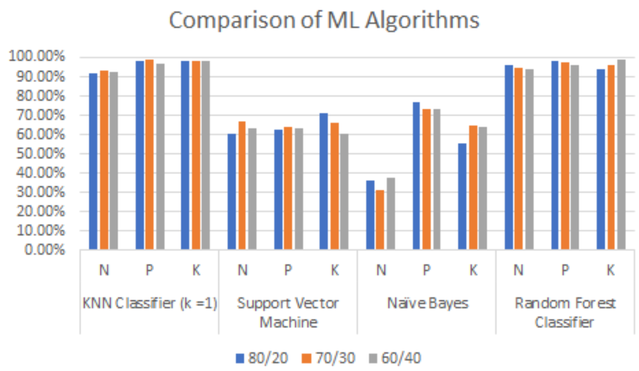


Fig. 7. Comparison of the four (4) machine learning algorithms

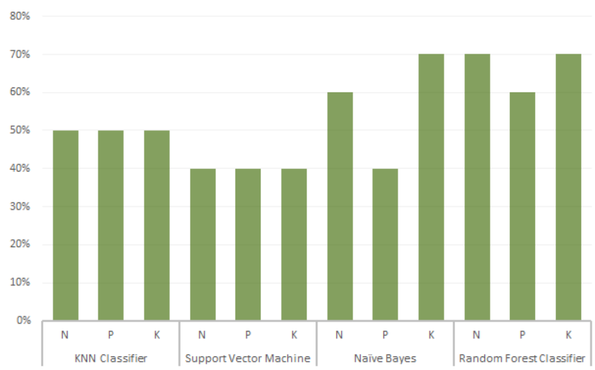


Fig. 8. Accuracy comparison of the four (4) models

Based on the graph in Fig. 8, Random Forest Classifier has the highest accuracy per level among other three (3) algorithms. In contrast to Fig. 7, this graph utilizes the Arduino data (including pH, soil moisture level, and R, G, and B colors) collected during the actual test as the initial dataset for testing each model's capability to predict new data. This approach aims to identify issues such as overfitting or selection bias by evaluating the model's performance on unseen data that was not utilized during its estimation.

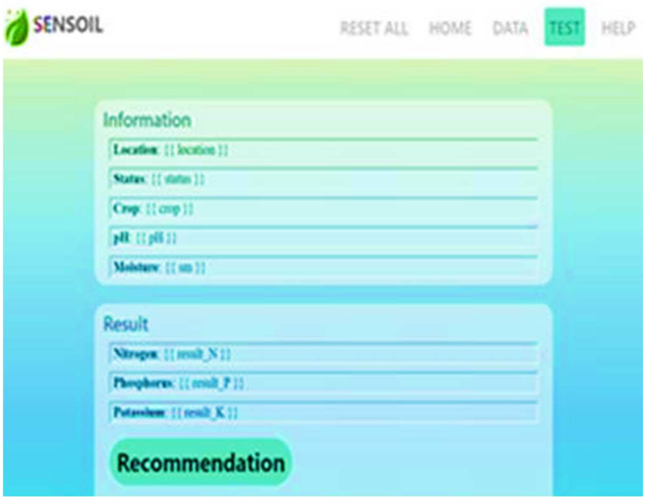
D. Web Application and Website Interface

A fertilizer recommendation is provided through a web application as shown in Fig. 9 and10 after the results are known. The computation is dependent on the chosen crops and the combination of nutrients per sack of fertilizer.

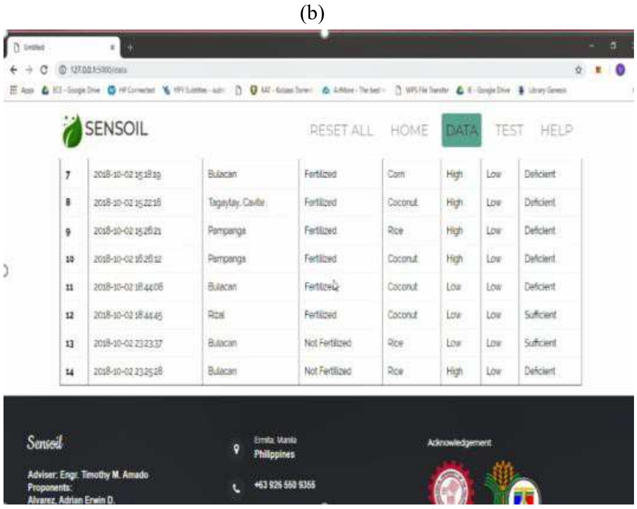
E. Validation of Device Output

Table 1 shows the predicted and actual results of pH, Nitrogen, Phosphorus, and Potassium gathered in Atimonan, Cabanatuan, Tagaytay, and Lysimeter area of BSWM's soil tank. The actual results were analyzed by an Agriculturist. The wrong predicted values for Phosphorus indicated that there is a need for more data to train to increase its accuracy. Thirty (30) trials were also conducted for each soil to test the device reliability. The results tell that there is a good reliability percentage (93.33%) for Nitrogen and Phosphorus while excellent reliability percentage (100%) for Potassium.

(a)



(b)



(c)

Fig 9. Web application (a) User interface (b) Result section (c) Offline database

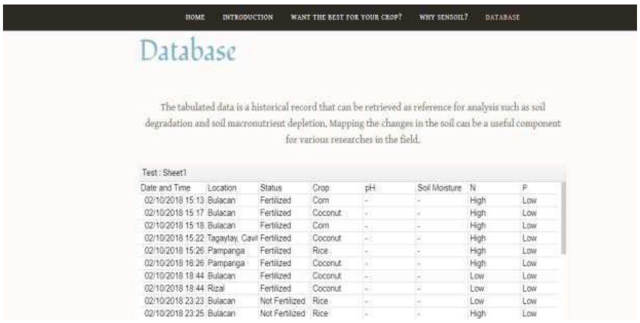


Fig 10. Online database

TABLE I. PREDICTED VS ACTUAL DATA OF PH, NITROGEN, PHOSPHORUS, AND POTASSIUM

Soil	pH		Nitrogen		Phosphorus		Potassium	
	Predicted	*Actual*	*Predicted*	*Actual*	*Predicted*	*Actual*	*Predicted*	*Actual*
Atimonan	6.89	6.8	Low	Low	High	High	Sufficient	Sufficient
Cabanatuan	6.4	6	Low	Low	Low	Medium	Sufficient	Sufficient
Tagaytay	6.78	6	Medium	Medium	Low	Medium	Sufficient	Sufficient
San Ildefonso	5.85	5.8	Low	Low	Low	Low	Sufficient	Sufficient

The information regarding the comparison between this study and previous research conducted in soil analysis, both within the country and internationally, is condensed in Table II. The methods reported in [10]-[11], [13], and [15] reported the high accuracies since they used images of soil mixed with typical test chemicals used in the conventional soil testing. Our proposed work utilized the ISFET which not only used in pH measurement but is proven to be utilized in NPK analysis, exhibiting higher accuracy results.

V. CONCLUSION

The development of an IoT device which predicts the macronutrient level of the soil for specific crops utilizing machine learning algorithms and electrochemical sensors was successfully implemented. The Random Forest Classifier provides the highest accuracy among the predictive models. The model for predicting Nitrogen has an accuracy of 95.83%, for Phosphorus is 98.10% and lastly for Potassium is 93.75%. This is made possible by using the ISFET pH sensor, a soil moisture sensor, and RGB sensor. An alternative readout circuit for ISFET which is cheaper and easier to reproduce compared to the commercially available readout circuit while still being able to maintain its quality was also designed. An offline and online database system was also developed to have a historical record that can be retrieved as a reference for analysis such as soil degradation and soil macronutrient depletion and nutrient mapping.

TABLE II. PERFORMANCE COMPARISON OF THE PROPOSED WORK VERSUS PRIOR WORKS

	This work Sensoil	**Soilmac.pH [14]**	**15]**	**[16], [17]**	**Automated Soil Nutrient Monitoring [18]**	**SoilMATTic [9]**	**Crop Prediction [19]**	**SoilMATe [10]**
Year	2023	2023	2023	2021	2018	2018	2017	2017
Sensors	ISFET pH sensor, Soil moisture, RGB color sensor	TCD1304AP Linear CCD sensor (one at a time)	-	digital single-lens reflex (DSLR) camera	Carbon, pH, NPK sensor	1080p Full-HD Webcam	NPK sensor	1080p Full-HD Webcam
Parameters	NPKpH	NPKpH	NPK	NPKpH	NPKpH and moisture	NPKpH	NPK	NPKpH
Recommendation	Fertilizer	Fertilizer	-	Fertilizer	Fertilizer	Fertilizer	Crop and Fertilizer	Fertilizer
Software / Algorithm	Random Forest, NB, KNN, SVM	VIS-NIR Spectroscopy	Sample Datasets, Enhanced Genetic Algorithm	Image Processing, OpenCV	SVM	Image Processing, ANN	Agro Algorithm	Image Processing, ANN
Microcontroller	Arduino Mega	Arduino Mega	-	-	Arduino Uno	-	Raspberry Pi	-
Data Display	Web Application	Printed result	-	Mobile application	Website interface	Printed result	-	Printed result
Database	Yes	None	None	None	Yes (SQLlite)	None	Yes	None
Accuracy	**93.33%**	**95%**	**20 - ~90%**	**88-98%**	**90%**	**96.67%**	**-**	**98.33%**

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