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DEVELOPMENT OF A HANDHELD SOIL ANALYSIS SYSTEM FOR NPK NUTRIENT PROFILING UTILIZING NIR SENSOR TECHNOLOGY

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ABSTRACT

This paper demonstrates a portable soil tester that utilizes an Arduino microcontroller and Near-Infrared (NIR) sensors for rapid and effective soil quality evaluation. Soil quality plays a critical role in agriculture, influencing crop yield and ecosystem health. Traditional soil testing methods are often time-consuming and require specialized equipment. The proposed portable soil tester aims to provide an affordable, user-friendly, and swift solution for farmers and researchers to assess key soil properties directly in the field. This study explores how NIR sensors can detect essential nutrients-Nitrogen (N), Phosphorus (P), and Potassium (K), collectively known as NPK nutrients-in soils. The research applies linear regression techniques to develop models that predict nutrient levels based on NIR sensor readings. The system displays soil NPK content results in high, medium, and low categories.

INTRODUCTION

Agriculture is greatly influenced by soil quality as it impacts plant growth, nutrient availability, and overall crop productivity [1-3]. Traditional soil testing methods require the samples to be sent to laboratories, which can be time-consuming and not feasible for urgent decision-making. This problem can be solved by using portable soil testing devices for real-time assessment of soil health. This paper presents a portable soil tester based on Arduino with NIR sensors for the rapid and efficient analysis of soils. Precision agriculture has become a revolutionizing farming approach that uses cutting-edge technology to optimize resource utilization while increasing crop yields [4,5]. The use of Near-Infrared (NIR) sensors in agriculture has contributed to fast and non-destructive evaluation of various aspects of soils, such as nutrients, among others [6-10]. Nitrogen (N), Phosphorous (P), and Potassium (K) are the key nutrients for proper plant growth, commonly referred to as NPK fertilizers [11]. The accurate determination and management of these nutrients are vital for sustainable agricultural practices. In this paper, we try to explore the application of NIR sensors for NPK nutrient detection, focusing on the development of linear regression models to predict nutrient levels based on sensor readings.

1. SYSTEM ARCHITECTURE

The portable soil tester utilizes three core elements: an Arduino microcontroller, NIR sensors, and an OLED display. The Arduino microcontroller acts as the system's brain, aggregating information from the NIR sensors and then breaking it down to furnish applicable soil metrics. Accountable for quantifying the reflection of near-infrared radiance, the NIR sensors correlate to soil qualities. The OLED display permits patrons to attain immediate feedback concerning soil grade. Each segment plays a critical role in the device's performance and operation, collaborating to collect, analyze, and display soil parameter evidence.

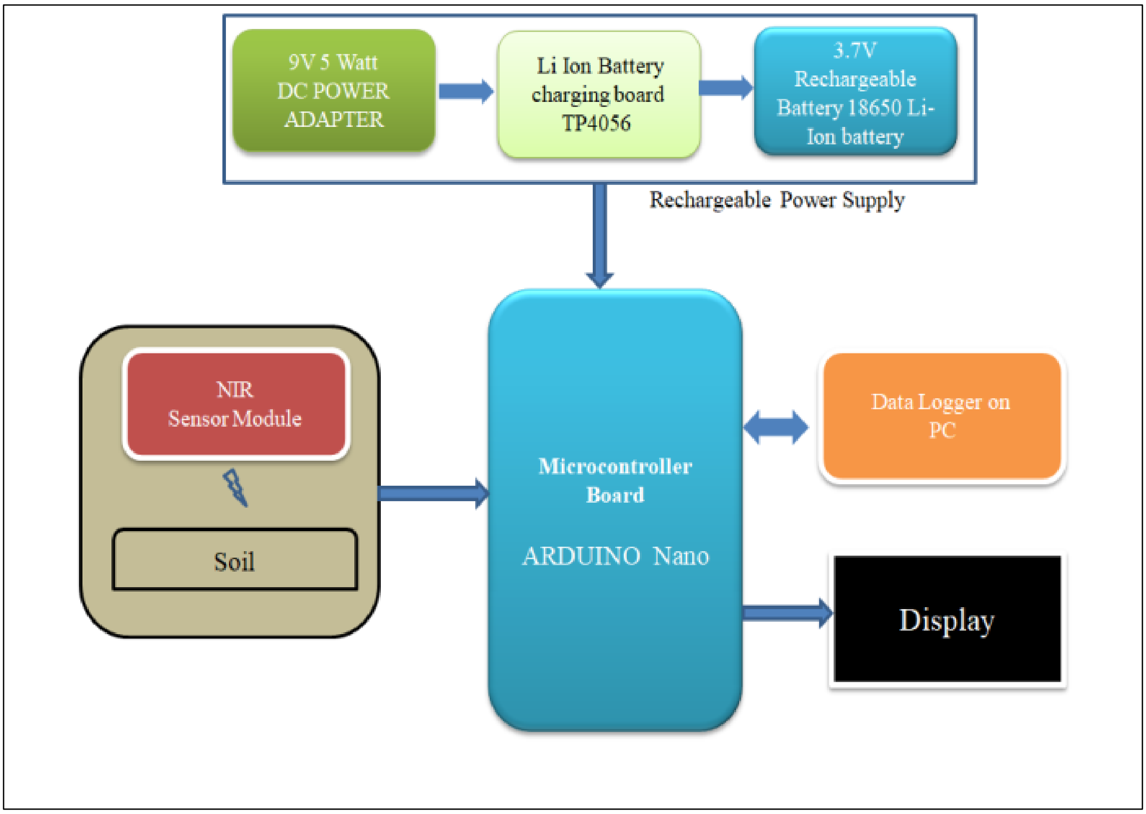


Fig.1: Architecture of NPK nutrients measurement device

2.1. MICROCONTROLLER

The Arduino Nano microcontroller is the mainstay of the system, similar to its brain that controls everything. It coordinates the working of all other components to achieve efficient operation. For instance, it communicates with NIR sensors for data acquisition, time management, and statistics analysis by calculation. Additionally, it also carries out communication between the NIR sensor and OLED display. In addition, the interface links with a computer by means of a unique type of connection for future reference concerning data or settings [12]. Near-infrared spectroscopy is a technique to measure soil without disturbing it; this method works because various parts of soil react differently to near-infrared light.

2.2. NEAR-INFRARED SPECTROSCOPY

Near-infrared spectroscopy is a non-destructive technique widely used for soil analysis. This is based on the fact that different soil components absorb and reflect light in the near-infrared region differently. By analyzing the spectrum of reflected light, it is possible to determine soil properties such as organic matter concentration, moisture level, and nutrient concentration [13,14]. NIR sensors are compact, lightweight, and suitable for field work.

The NIR sensor is the main sensor element of the NPK nutrient measuring device, it measures the reflection of near-infrared light from the soil sample. The NPK nutrient measurement device uses the AS7265x sensor module to monitor soil reflectance [15,16]. The reason for selecting the AS7265x sensor is its integration of six independent spectral channels, each with a dedicated photodiode array. These channels cover wavelengths ranging from approximately 410 nm to 940 nm, providing comprehensive coverage of the visible and NIR spectrum. This enables the sensor to capture detailed spectral information with high resolution and accuracy.

2.3 USER INTERFACE - OLED DISPLAY

A simplified grading system of “high,” “medium,” and “low” makes it possible to represent soil NPK content that is measured by the device on an OLED display. The intuitive representation of fertility through this method makes it easy for users to have a quick overview of their soil’s fertility levels without any need for complicated data interpretation. Moreover, the system simultaneously transmits real-time data and settings via serial communication, thus allowing users to save this important information for later use or analysis on their preferred computers.

2. PROTOTYPING WITH 3D PRINTER

Fig. 2. 3D Printed Prototype of NPK Nutrient Detection System

An open-source TinkerCAD software was used in designing a 3D-printed custom case for the NPK meter so as to offer an appropriate solution for securing the fragile parts of the instrument. Through employing TinkerCAD's user-friendly interface and comprehensive features, we cautiously crafted this enclosure in order to suit the specific needs of NPK meter with ease of assembly and best operational conditions. We start here by considering how big or small is the soil nutrient measurement gadgets particularly where sensors, circuitry among other components are located on them. Next, precise measurements/adjustments; using Tinkercad's powerful design tools are done in order to develop an enclosure model that could virtually accommodate all fittings perfectly fitting well throughout, therefore enabling seamless integration process.
Autodesk Tinker CAD was used to create a 3D printed custom design of the equipment container (Figure 2) [17]. The NPK measurement device is housed in a practical and cost-effective manner through this 3D-printed custom enclosure designed with TinkerCAD software.

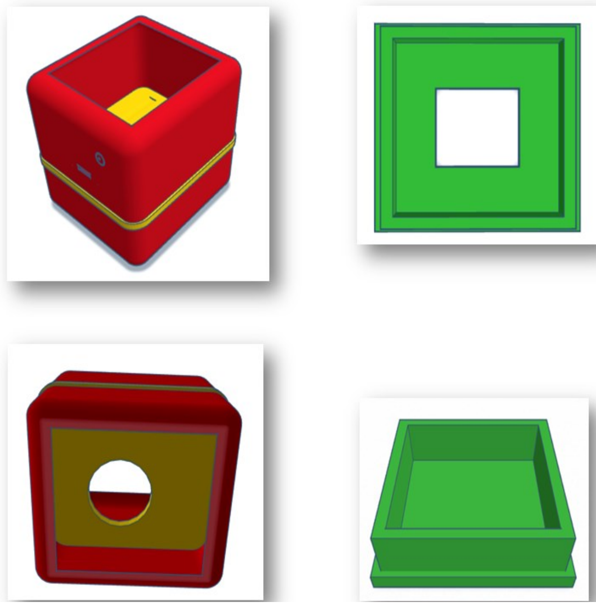


Fig. 2. Different views of a 3D printed customized design of device container using Autodesk Tinker CAD

3. DATA INTERPRETATION AND CALIBRATION

A soil sample of known origin is collected from fields and its composition checked in the laboratory, this confirms medium levels of nitrogen, phosphorus and potassium (NPK) as seen from Figure 4 in the laboratory report. The system requires calibration using several different soils having pre-determined characteristics for accurate soil analysis. In the first batch of samples, there are variations in nutrient compositions: one sample has high nitrogen (N) and medium phosphorous (P) and potassium (K), one sample has high phosphorous (P) and medium nitrogen (N) and potassium (K), another has high potassium (K) and medium nitrogen(N) and phosphorus(P). Precise chemical compounds are chosen to manipulate N, P, K compositions. Nitrogen levels are regulated by urea CO(NH2)2 while superphosphate Ca(H2PO4)2 increases phosphorus concentration.

Urea (CO(NH2)2) for regulating nitrogen levels: $CO(NH_2)_2 + 2H_2O \rightarrow 2NH_4^+ + CO_3^{2-}$

Yashawantrao Chavan Institute of Science, Satara

Soil and Water Testing Laboratory

Soil Testing Report

Details: **Date:** 25/08/2023

Name: Dr.Santosh Kamble **Mo.No.**9823524565

Department: Chemistry

Sample: Soil

Collection: Unknown

Collection Date: 18/08/2023

Sr. No	Parameter	Result Sample	Limit in Land Min. Conc	Suggestion
1.	PH	7.4	-	**Medium**
2.	EC	0.75	0.00-1.00	**High**
3.	Temperature	26	20-36	**Medium**
4.	N (kg/ha)	324.2	280-560	**Medium**
5.	P (kg/ha)	167.6	10-25	**Medium**
6.	K (kg/ha)	16.04	10-100	**Medium**
7.	Sodium (mg /kg)	16.7	0.00-15	**High**
8.	Calcium (mg/kg)	15.53	10-100	**Medium**
-	-	-	-	-

Fig.4. Laboratory report for soil samples

Superphosphate ($Ca(H_2PO_4)_2$) for modifying phosphorus content: $Ca(H_2PO_4)_2 \rightarrow Ca^{2+} + 2H_2PO_4^{-}$ Additionally, potassium chloride (KCl) is utilized to adjust potassium levels in the soil samples.
Potassium Chloride (KCl) for adjusting potassium levels: $KCl \rightarrow K^{+} + Cl^{-}$.
These specific compounds are meticulously measured and added to the soil samples to ensure accurate variations in nutrient concentrations.
These samples are used to validate the AS7265x NIR sensor. Figure 5 illustrates the difference between the NIR sensor readings for the original soil sample and the first set of soil samples. These graphs reveal a substantial difference between the NIR sensor readings for the original soil sample and the first set of samples.

4. RESULT AND DISCUSSION

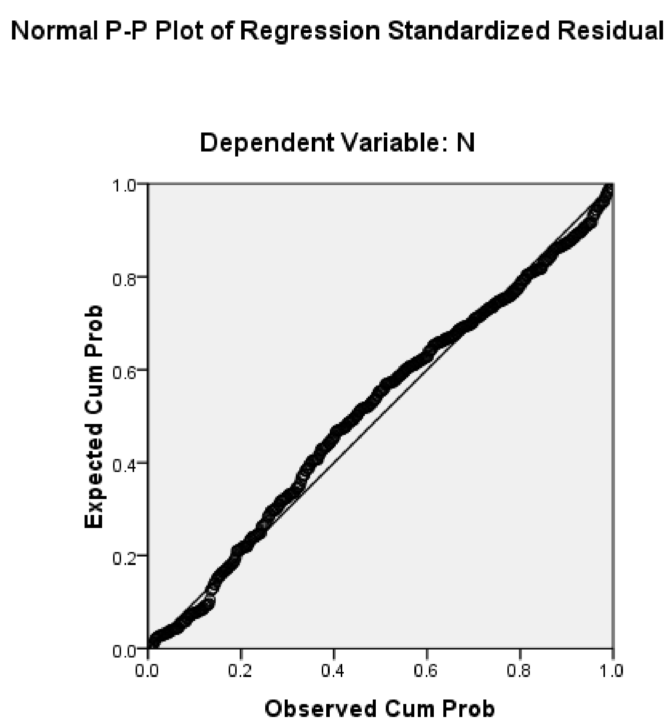
A consequent batch of soil samples, each characterized by specific concentrations of nitrogen (N), phosphorus (P), and potassium (K), is meticulously prepared and categorized into NPK-MED, N-HIGH PK-MED, P-HIGH NK-MED, K-HIGH NP-MED, NP-HIGH K-MED, PK-HIGH N-MED, and NK-HIGH P-MED. The NIR sensor readings obtained from observing this set of soil samples play an important role in the calibration, as exemplified in Table 1. The present system uses the multiple input linear regression method for mapping models to forecast nutrient levels based on the NIR sensor readings as illustrated in Model (1) to Model (3). This methodological approach provide the exact prediction of nutrient concentrations within the soil samples, enhancing the precision and reliability of the analysis process.

Model 1. Predication of N

a. **Predictors: (Constant), W, I, A, S, L, G, U, F, R, M, J, T, D, V, B, H, C, E**
b. **Dependent Variable: N**

Model 1	Coefficients
(Constant)	126.577
A	-29.626
B	20.153
C	-2.081
D	1.88
E	-10.269
F	30.977
G	57.235
H	-51.483
I	32.673
J	-45.151
M	36.178
L	7.806
R	-3.062
S	1.092
T	-47.261
U	32.705
V	-22.761
W	11.622

Model 1		
R		.759[a]
R Square		0.576
Adjusted R Square		0.558
Std. Error of the Estimate		75.45246
Change Statistics	R Square Change	0.576
	F Change	32.374
	df1	18
	df2	429
	Sig. F Change	0

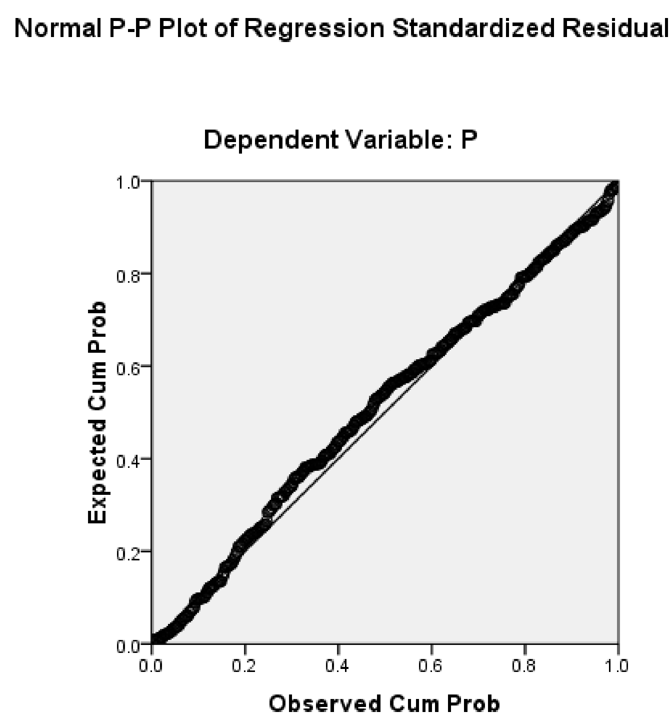


Model 2. Predication of P

a. Predictors: (Constant), D, G, S, W, I, L, C, U, R, M, J, T, A, V, H, F, B
b. Dependent Variable: P

Model 2	Coefficients
(Constant)	83.06
A	1.489
B	-0.745
C	0.182
F	0.032
G	-1.587
H	-1.059
I	3.904
J	4.39
M	-3.632
L	-3.425
R	0.795
S	0.006
T	2.137
U	-7.316
V	0.266
W	-1.191

Model		2
R		.675[a]
R Square		0.455
Adjusted R Square		0.433
Std. Error of the Estimate		5.41766
Change Statistics	R Square Change	0.455
	F Change	21.116
	df1	17
	df2	430
	Sig. F Change	0

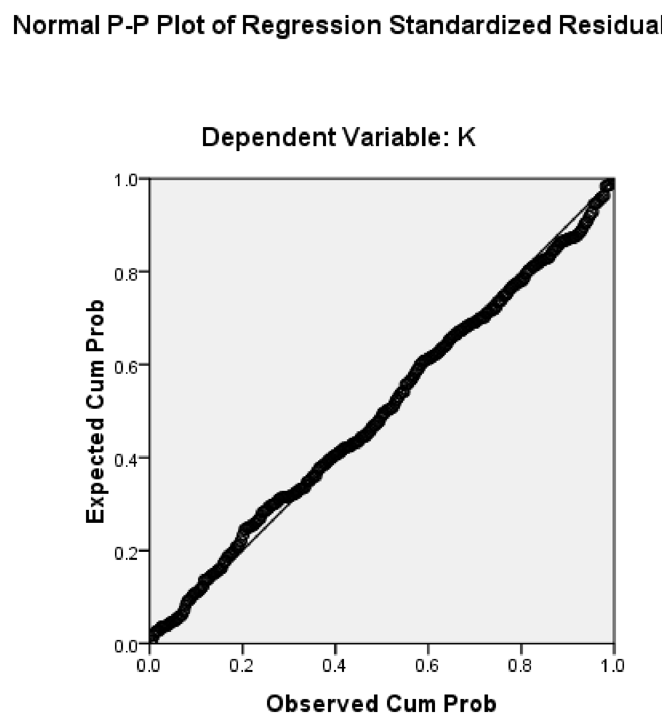


Model 3. Predication of K

a. Predictors: (Constant), D, G, S, W, I, L, C, U, R, M, J, T, A, V, H, F, B
b. Dependent Variable: K

Model 3	Coefficients
(Constant)	-470.59
A	-13.192
B	19.226
C	-22.234
F	17.148
G	4.227
H	31.101
I	-39.947
J	-112.654
M	55.069
L	79.422
R	-11.398
S	1.705
T	11.305
U	133.07
V	-12.938
W	5.066
D	-3.505

Model		3
R		.776[a]
R Square		0.602
Adjusted R Square		0.586
Std. Error of the Estimate		76.90369
Change Statistics	R Square Change	0.602
	F Change	38.291
	df1	17
	df2	430
	Sig. F Change	0



Model Summary
For dependent variable **N**:

- **R = 0.759** → Strong correlation between predictors and N.
- **R^2 = 0.576** → The model explains **57.6%** of the variance in N.
- **Adjusted R^2 = 0.558** → Adjusted for the number of predictors, indicating a strong model fit.
- **F-statistic (32.374, p < 0.001)** → The model is statistically significant.

For dependent variable **P**:

- **R = 0.675**, **R^2 = 0.455**, **Adjusted R^2 = 0.433** → The model explains 45.5% of the variance.
- **F-statistic (21.116, p < 0.001)** → The model is statistically significant.

For dependent variable **K**:

- **R = 0.776**, **R^2 = 0.602**, **Adjusted R^2 = 0.586** → The model explains 60.2% of the variance.
- **F-statistic (38.291, p < 0.001)** → Strong statistical significance.

Interpretation of Coefficients

- Variables **A, F, G, H, I, M, U, W** had statistically significant coefficients (**p < 0.05**) for **N**, suggesting they strongly impact the dependent variable.
- For **P**, **A, G, I, M, L, R, U, W, D** were significant.
- For **K, A, C, F, H, I, J, M, L, R, U** showed strong effects.

Negative coefficients (e.g., A, J, R for K, P, and N) indicate inverse relationships.

3. Interpretation of models

- The regression model successfully explains a significant portion of the variation in **N, P, and K** based on the predictor variables.
- **G, H, I, M, and R are the most critical factors** affecting nutrient levels.
- **E, S, and W do not have a meaningful impact** and could be excluded from future models for optimization.
- The model can be further refined by focusing on significant variables and performing residual analysis to confirm its predictive accuracy.

The normal probability plots of residuals is shown in provide numerical proof which supporting the validity of the mapping models developed for predicting soil nutrient levels. The plots have a linear pattern, indicating that the residuals closely follow a normal distribution. In this research context, the mapping models are mathematical equations which are derived from the regression analysis. The independent variables are the NIR sensor readings, and the dependent variable is the predicted nutrient level. This alignment validates the assumption of normality in the residuals; this confirms that the mapping models are reliable and accurate in predicting soil nutrient levels using data from NIR sensors. Once calibrated, the portable soil tester provides real-time data on key soil parameters. The system shows results in a user-friendly format, allowing farmers to interpret the data easily.

CONCLUSION

The results of this study highlight the potential of NIR sensors to revolutionize agricultural practices by providing rapid, non-destructive analysis of soil properties. The results of this study showed a strong correlation between spectral data obtained from NIR sensors and actual NPK nutrient levels in soil samples. The prepared linear regression models provided specific predictions of NPK concentrations, showing the potential of near-infrared reflectance spectroscopy as a reliable method for soil nutrient detection. Present work can be extended by integrating offline AI models. These models can help improve accuracy on different soil types. To achieve this, data collection activities focus on collecting samples from more soil types. The data generated is then used to improve the calibration process, ensuring that the system maintains accuracy and reliability across a wide range of soil compositions and conditions.

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