DOI: https://doi.org/10.52756/ijerr.2024.v45spl.015 *Int. J. Exp. Res. Rev.*, Vol. 45: 197-202 (2024)

Original Article | Peer Reviewed | Open Access

International Journal of Experimental Research and Review (IJERR)

ISSN: 2455-4855 (Online)
www.iaph.in

Real-Time Soil Nutrient Monitoring Using NPK Sensors: Enhancing Precision Agriculture

Rahul Adhikary[1], Suvra Jyoti Choudhury[2] and Tanmoy Shankar[3]*

[1]Department of Soil Science, M. S. Swaminathan School of Agriculture, Centurion University of Technology and Management, Paralakhemundi, 761 211, Odisha, India; [2]Department of Computer Science and Engineering IIIT Nagpur, India;[3]Department of Agronomy and Agroforestry, M. S. Swaminathan School of Agriculture, Centurion University of Technology and Management, Paralakhemundi, 761211, Odisha, India

E-mail/Orcid Id:

RA, rahul.adhikary@cutm.ac.in, https://orcid.org/0000-0003-0020-4161; *SC,* cshuvrajyoti@gmail.com, https://orcid.org/0000-0002-5441-1150; *TS,* tanmoy.shankar125@gmail.com, https://orcid.org/0000-0003-1888-9912

Article History:

Received: 04th Jul., 2024
Accepted: 12th Nov., 2024
Published: 30th Nov., 2024

Keywords:

Prediction, Neural network, Precision agriculture, NPK sensor

How to cite this Article:
Rahul Adhikary, Suvra Jyoti Choudhury and Tanmoy Shankar (2024). Real-Time Soil Nutrient Monitoring Using NPK Sensors: Enhancing Precision Agriculture. *International Journal of Experimental Research and Review*, *45*, 197-202.
DOI: https://doi.org/10.52756/ijerr.2024.v45spl.015

Abstract: Prediction of various parameters in the agriculture field using sensors is a significant topic nowadays. However, in many scenarios, the sensor data does not accurately detect the real parameter(/s) in the agriculture field. The sensor data may vary due to various external factors, whereas the real parameters don't vary too much for a particular agriculture field. The present work introduces a modified neural network approach to predict real agricultural parameters from sensor data with accuracy caused by several external factors and demonstrates enhanced predictive accuracy and adaptability. The neural network takes the sensor data as input in various weather conditions and tries to find out the original real parameters of that sensor data. The real-time sensor data was collected from multiple agricultural sites. The results demonstrated high predictive accuracy, with the neural network outperforming traditional statistical methods in forecasting soil moisture and other vital variables. Additionally, the model's ability to generalize across different environmental conditions enhances its applicability in various crop management scenarios. The study concludes that neural networks hold significant potential for improving the efficiency of smart agriculture systems by providing timely, data driven insights for farmers and agronomists. Further research will explore the integration of deep learning models and edge computing to enhance scalability and realtime responsiveness in field applications. The aforementioned research highlights the significance of NPK sensors in sustainable farming methods, namely in enabling accurate nutrient management via real-time data.

Introduction

In the last few decades, sensors have been used to manage and sense different parameters in agriculture. For example, a prototype portal was designed for integrated data visualization, applying context-based cartographic methods to agricultural and meteorological data gathered from Wireless Sensor Networks (WSN) (Kubicek et al., 2013). Each sensor was assigned a specific location within a wider spatial context. The geospatial data, sourced both locally and via Web Map Services (WMS), was merged with sensor readings—such as soil and air temperature, moisture levels, and humidity—automatically tracked at regular intervals. Built on an open-source and interoperable platform, the prototype acts as an experimental gateway, facilitating geospatial and sensor data integration and visualization. Agricultural applications, modern technology is becoming more and more crucial, especially when it comes to controlling vital nutrients like potassium (K), phosphorus (P), and nitrogen (N), which directly improve crop productivity and resource efficiency (Al-Mamun et al., 2021; Potdar et al., 2021; Yohannes et al., 2024). Nonetheless, over use

***Corresponding Author:** tanmoy.shankar125@gmail.com

of fertilizers in conventional farming frequently results in financial inefficiency and environmental harm (Hafsi et al., 2014; Leghari et al., 2016). One potential solution is the use of NPK sensors, which allow farmers to make accurate, data-driven decisions by giving them real-time information on soil nutrient levels (Zhang et al., 2021). According to Pooniya et al. (2018) and Eli et al. (2019), this method helps match fertilizer application with crop needs, lowering environmental concerns, including phosphorus runoff and nitrogen leaching. Further enhancing resource efficiency is automated nutrition management made possible by NPK sensors coupled with Internet of Things (IoT) devices (Ahmed et al., 2020; Sangwan et al., 2022). According to Mohanty et al. (2020) and Park et al. (2017), these sensors also improve fertilizer recommendations by making sure nutrients are only supplied when necessary, increasing productivity and sustainability. According to Lee et al. (2021) and Islam et al. (2022), NPK sensors are crucial for sustainable agriculture in the context of climate change due to their exceptional precision and flexibility in response to shifting environmental conditions (Al-Mamun et al., 2021; Ahmed et al., 2020; Ada˜o et al., 2020). To develop a more efficient four-layer, twelve-level (FLTL) remote sensing data management framework for handling and utilizing agricultural remote sensing big data in precision agriculture where sensors are typically deployed on high-resolution satellites, manned aircraft, unmanned aerial vehicles, and ground-based platforms-a five-layer, fifteen-level (FLFL) satellite remote sensing data management structure was outlined and adopted. This study presents a survey that includes hyperspectral sensors, inbuilt data processing and applications focusing on forestry and agriculture, where the use of UAVs in conjunction with hyperspectral sensors plays a key role (Ada˜o et al., 2017). First, the benefits of hyperspectral data over multispectral and RGB imaging are emphasized. Subsequently, hyperspectral acquisition devices are discussed, encompassing sensor varieties, modalities of acquisition, and UAV-compatible sensors suitable for both commercial and research applications. It is indicated that pre-flight procedures and post-flight pre-processing are required to guarantee that hyperspectral data may be processed further to obtain definitive information. Many toolboxes that provide direct access to level-one hyperspectral data are offered to simplify the processing of hyperspectral data by removing the common user from the mathematical complexity of the procedures. Machine learning (ML), in conjunction with data analysis, generates possibilities to understand and reconnoiter in the field of agriculture more effectively (Jhajharia and Mathur, 2022; Jain et al., 2023). When a sensor collects data from the environment, censor-collected data sheets are trained using different ML algorithms and models. After the performance of training, a trained model can be used to predict new inputs. Keeping this in mind, a modified neural network is used here. Now, in many cases, the ground sensor data do not accurately detect the original parameters of an agriculture field. To resolve this issue, in the proposed method, we create a neural network so that, if sensor data are inputted into the neural network, the real lab test data is the neural network's output.

Materials and Methods

The samples of soil were taken from different parts of the Gajapati district, Odisha. Five different places are Tikamala, Podasing, Ramapur, Anukumpa and Kankadaguda of Mohana and Gosani block of Odisha. We go over the experimentation process in this part. A modified neural network (NN) is employed to compute every operation. Let us first describe the NN that we employed in this experiment. Next, we go through how to train NN and how to test it using the trained NN.

Neural Network Architecture

The input layer, hidden layers, and output layer are the three components that make up a neural network (NN). Let our suggested NN model have a single hidden layer. The first layer has p input characteristics, also known as the input layer. There are q nodes in the second layer, or the hidden layer and each node's activation function is δ(.). The intended output of the j_{th} node of the k_{th} datum is in the final layer or the output layer; the overall number of datums is n, and r indicates the output node's number. In the literature, NN comes in a variety of forms. The model which uses the NN, as explained by Choudhury and Pal (2021). A fan-out layer is the first layer in an NN, also known as the input layer. This indicates that the first layer's input and output are identical in terms of mathematical equation express below.

$\delta\,(x_{ki}) = x_{ki}$, $i = 1, \cdot\cdot\cdot, p$;

$\delta\,(x_{k0}) = 1, \forall k$; ……………………………(1)

In this case, X_{ki} is the i_{th} feature of the input vector x_k, and $\delta\,(X_{k0})$ is the bias of the input layer. Regarding the second layer, or the layer that is hidden:

$z_{kh} = \sum_{i=0}^{p} w\,ih\,\delta\,(x_{ki})$, $h = 1, \cdot\cdot\cdot, q$

$\delta\,(z_{kh}) = \max(0, z_{kh})$, $h = 1, \cdot\cdot\cdot, q$;

$\delta\,(z_{k0}) = 1, \forall k$;……………………………….(2)

where the bias of the hidden layer is δ (z0), the bias connection of the h^{th} hidden neuron is w0h, and the connection between the i_{th} input node and the h^{th} hidden node is w_{ih}. Regarding the final layer and the output layer

$y_{kj} = \sum_{h=0}^{q} wih\ \delta\ (z_{kh})$

$o_{kj} = \delta\ (y_{kj}) = \max(0, y_{kj}),\ j = 1, \cdot\cdot\cdot,$ r…………………(3)

Here, the bias of j^{th} node is w_{0j} , the weight between the j^{th} output node and the h^{th} hidden node is w_{hj} . Thus, the instantaneous system error for the k^{th} training pattern *is as*

$$E^k = \sum_{J=1}^{r} \left(tk_j^{-0}kj\right)^2$$

One can utilize different loss functions, like cross-entropy, in place of square loss. Likewise, alternative options, such as the sigmoidal function, can be used as an activation function. The back-propagation approach is one of several learning techniques (Choudhury and Pal, 2021). The proposed neural network architecture pictorially described in (Figure 1).

Algorithm 1 : Training and testing of the proposed method for prediction of sensor data INPUT: $X_{T\ R}$: Training data set; $X_{T\ E}$: Training data set; p: Number of features of training data set; r: Number of features of target; N_1: Number of epochs for training; LR: Learning rate; $T_{T\ R}$: Target data set for training; $T_{T\ E}$: Target data set for Testing.

BEGIN

1: Set N_1, LR.

2: Trained a NN by $X_{T\ R}$ for N_1 epochs where the error function is defined by Eq. 4.

The target vector is the same as the corresponding field target $t \in T_{T\ R}$.

3: Pass $X_{T\ E}$ through the trained neural network and find out the error using $T_{T\ E}$.

END

Analysis of nutrient availability and nutrient uptake used the Kelplus Nitrogen auto-analyzer (Kelplus: Model classic DX) to estimate nitrogen following the Kjeldahl method. To find the phosphorus content vanado-molybdo-phosphate method was used. The flame photometric method was used to determine the potassium concentration in the laboratory.

NPK Sensor for Soil

The soil NPK sensor (Figure 2) is made to monitor potassium, phosphorus, and nitrogen levels precisely and accurately. This sensor offers real-time data with a precision of ±2%FS and a response time of ≤1 second, and it runs on a 5V power source. The sensor has a robust 316 stainless steel probe for long-lasting field use and employs the RS485 communication standard for output. In this work, we use ground sensors to collect the data

Specifications:

Range: 0 mg/kg to 1999 mg/L

1 mg/kg (mg/L) is the resolution.

Range of operation: -40 to 80°C

IP68 is the protection grade.

With its easy insertion design and ability to accurately monitor nutrient levels, the sensor is perfect for usage in various soil situations.

Data Transfer

A Max485 RS485 (Figure 3) to TTL converter module is utilized to enable communication between the Nano V3.0 board and the soil NPK sensor. This module translates the sensor's RS485 output into TTL signals that are compatible with the Nano V3.0 and enables half-duplex communication over long distances. The module enables the system to scale for larger applications and guarantees stable data transmission even in noisy situations.

Result and Discussion

Numerous sites utilized the Arduino Nano microcontroller for field experiments after it was built with a variety of sensors. An evaluation of the NPK sensor's performance for precise nutrition control involved a comparison of sensor and laboratory data. Samples of soil were taken from Tikamala, Podasing, Ramapur, Anukumpa and Kankadaguda, five different places in the Indian state of Odisha. The nitrogen (NPK) and potassium (PPK) levels determined using the two methods are displayed in table 1. The sensor recorded somewhat lower NPK levels than the lab results; there was an 11% variation in nitrogen, a 12% difference in phosphorus, and a 9% variation in potassium. Despite these variations, the sensor results are sufficiently stable for real-world field applications. The sensor recorded lower values for all nutrients, with nitrogen displaying a 10% fluctuation, phosphorus 12%, and potassium 9%, similar to the findings from Tikamala. The near alignment points to the sensor's dependability in determining nutrient concentrations. The nitrogen, phosphorus, and potassium sensor data displayed differences of roughly 10%, 12%, and 9%, respectively, indicating a trend of continuous sensor underestimating in comparison to laboratory values. Nonetheless, the disparities stay within reasonable bounds for pragmatic agricultural choices. Sensor readings in Anukumpa revealed reduced levels of potassium (9%), phosphorus (12%), and nitrogen (10%). This is consistent with the general pattern seen in other places. With an approximate variance of 10%, the nitrogen levels at Kankadaguda showed the most significant fluctuation. Additionally,

DOI: https://doi.org/10.52756/ijerr.2024.v45spl.015

Table 1. Soil test data from Laboratory and from sensor.

Location	Latitude	Longitude	Data Type	Nitrogen (kg/ha)	Phosphorus (kg/ha)	Potassium (kg/ha)
Tikamala	19.178418°	84.157859°	Laboratory	125.4	50.4	492.8
			Sensor	112.86	44.3	448.4
Podasing	19.173651°	84.149551°	Laboratory	137.9	51.52	392.0
			Sensor	124.11	45.33	356.7
Ramapur	19.176435°	84.164624°	Laboratory	139.9	42.56	347.2
			Sensor	125.9	37.45	315.9
Anukumpa	19.184965°	84.186024°	Laboratory	150.5	31.36	436.8
			Sensor	135.4	27.59	397.4
Kankadaguda	19.166454°	84.170097°	Laboratory	200.7	26.88	302.4
			Sensor	180.6	23.6	275.1

there was a 9% and 12% variation in the potassium and phosphorus readings, respectively (Hua et al., 2020; Thompson et al., 2015).

Experimental set up

The specifications that were utilized to train our NN model are provided in this section. Here, we outline the hidden layer nodes (q), the number of epochs (N_1), and the learning rate used to train the network. Every outcome presented here is the mean of twenty-five random runs. In our experiment, we utilize $N_1 = 1000$ in all circumstances. Our NN model employs the 1 hidden layer in every scenario. However, depending on the input features, different nodes exist in the hidden layer. The total number of nodes in the second layer i.e., in the hidden layer is 10p. We set the learning rate for the proposed method as (LR) = 0.001. Here, we take 7 sensor data as input and 4 real lab test data as output in the neural network. Four of the seven sensor input data are moisture sensor data of different time frames, and the three are sensor data of soil N-P-K. The lab test data are soil N, P and K for a particular field. Here, the input data is Sensor data and the target data is Soil data (Table 2 and 3).

Discuss the MSE loss of the proposed neural network using different parameters. As far as we know, this type of network has not yet been proposed, and we haven't compared our proposed method with any other methods. Using LR = 0.001, the training loss is 0.5748, and, the testing loss is 0.6523. Now, using LR = 0.001, we always don't get optimal results. To check which LR is good, we perform various experiments. Using Table I, we illustrate the variation in training loss with variable learning rates. Table I shows that when LR = 0.004, the training loss is minimum within the seven instances.

Now, in Tables 2 and 3, we use 1000 epochs and various LR to do the experiments. Now, using 1000 epochs and LR =0.001 always we don't get optimal results. So, using Table II, we perform different LR with different epochs to check the proposed method's performance. Here, we take two sets of LR (0.004, 0.005) and two sets of epochs (1000, 10000) to do the experiments. In total, here, we take total (2 x 2 =4) types of experiments to check the performance. From Table II we can find that when LR= 0.004 and the number of epochs = 10000, then the training loss is minimum.

Table 2. Loss variation with variable learning rates.

LR	Loss
0.08	0.8836
0.07	1.1278
0.09	0.8722
0.001	0.5748
0.004	0.5539
0.005	0.6108
0.008	0.6620

Table 3. Loss variation with variable learning rates and EPOCHS.

LR	Epochs	Loss
0.004	1000	0.5539
0.005	1000	0.6108
0.004	10000	0.5426
0.005	10000	0.5514

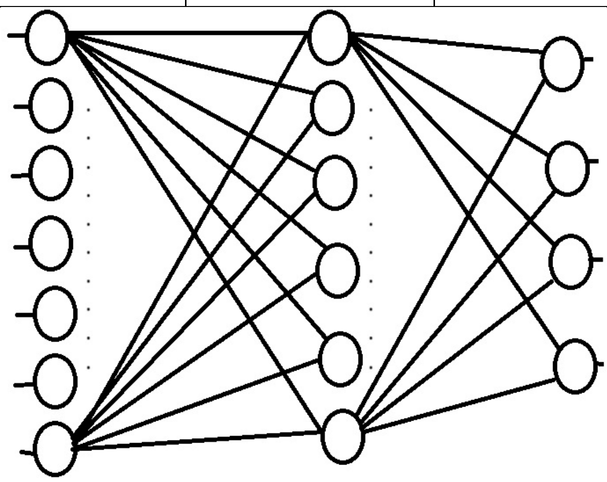

Figure 1. Proposed neural network architecture.

DOI: https://doi.org/10.52756/ijerr.2024.v45spl.015

Figure 2. Ground N-P-K sensors with display.

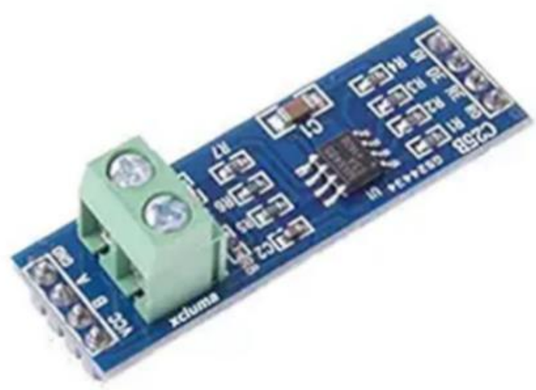

Figure 3. MAX485 TTL to RS485 Converter Module.

Conclusion

Here, we suggested a novel approach to training a neural network (NN) that can forecast a soil's actual parameters based on the ground sensor placed there. As far as we know, this is the first study using modified NN, in which we attempt to forecast the actual parameters of an agricultural field using a ground sensor placed there. We do not compare our work with any current methods because this kind of work has not been done previously. To verify how the suggested method's result varies, The results from our study indicate that neural networks provide superior accuracy in sensor data prediction compared to traditional methods, demonstrating their robustness in diverse agricultural environments. Furthermore, the scalability of neural networks makes them suitable for integration into various crop management systems, enabling farmers to adapt to changing conditions in real time. Neural network-based sensor data prediction holds great promise for revolutionizing decision-making processes in smart soil sensors, contributing to more sustainable, efficient, and productive farming practices.

Acknowledgment

The authors acknowledge the M. S. Swaminathan School of Agriculture, Centurion University of Technology and Management, Odisha, India, for providing all the facilities necessary to carry out this study.

Conflict of Interest

The authors declare no conflict of interest.

References

Ada˜o, T., Hrusˇka, J., Pa´dua, L., Bessa, J., Peres, E. , Morais, R., Ahmed, N., Ullah, S., & Saleem, S. (2020). IoT-based NPK monitoring system for optimized fertilizer application. *Computers and Electronics in Agriculture*, *174*, 105465.

Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., & Sousa, J.J. (2017). Hyperspectral imaging: A review on uav-based sensors, data processing and applications for agriculture and forestry, *Remote Sensing, 9*(11), 1110. https://doi.org/10.3390/rs9111110

Al-Mamun, M. R., Hasan, M. R., Ahommed, M. S., Bacchu, M. S., Ali, M. R., & Khan, M. Z. H. (2021). Nano fertilizers towards sustainable agriculture. *Environmental Technology & Innovation, 23*, 101658.

Choudhury S.J., & Pal, N. R. (2021). Deep and structure-preserving autoencoders for clustering data with missing information. *IEEE Transactions on Emerging Topics in Computational Intelligence*, *5*(4), 639 – 650. https://doi.org/10.1109/TETCI.2019.2949264

Jain, N., Awasthi, Y., & Jain, R. (2023). An IoT-based soil analysis system using optical sensors and multivariate regression. *Int. J. Exp. Res. Rev.*, *31*(Spl Volume), 23-32. https://doi.org/10.52756/10.52756/ijerr.2023.v31spl.003

Hafsi, C., Debez, A., & Abdelly, C. (2014). Potassium deficiency in plants: Effects and signaling cascades. *Acta Physiologiae Plantarum*, *36*(5), 1055–1070.

Hua, W., Luo, P., An, N., Cai, F., Zhang, S., Chen, K., Yang, J., & Han, X. (2020). Manure application increased crop yields by promoting nitrogen use efficiency in the soils of 40-year soybean-maize rotation. *Scientific Reports*, *10*(1). https://doi.org/10.1038/s41598-020-71932-9

Jhajharia, K., & Mathur, P. (2022). A comprehensive review on machine learning in agriculture domain. *IAES International Journal of Artificial Intelligence*, *11*(2), 753.

Eli-Chukwu, N.C. 2019. Applications of Artificial Intelligence in Agriculture: A Review. *Engineering, Technology & Applied Science Research*, *9*(4). 4377–4383. http:// https://doi.org/10.48084/etasr.2756.

Kubicek, P., Kozel, J., Stampach, R., & Lukas, V. (2013). Prototyping the visualization of geographic and sensor data for agriculture. *Computers and Electronics in Agriculture*, *97*, 83–91.

Lee, S., Choi, J., & Kim, Y. (2021). Soil fertility management through real-time data. *Precision Agriculture*, *22*(1), 113–129.

Leghari, S. J., Wahocho, N. A., Laghari, G. M. (2016). Role of nitrogen for plant growth and development: A review. *Advances in Environmental Biology*, *10*, 209.

Mohanty, S.R., Pal, A.R., & Das, M. (2020). Application of sensors in precision agriculture: Impact on productivity. *Agronomy Journal*, *112*(4), 2338–2350.

Park, S. Y., Oh, J. K., & Kim, S. H. (2017). Sensor-based nutrient management in paddy fields. *Journal of Environmental Management*, *204*, 456–465.

Pooniya, V., Bhatia, R., Rana, K. S., & Kumawat, N. (2018). Optimizing nitrogen and water use efficiency. *Agricultural Water Management*, *207*, 38–45.

Potdar, R. P., Shirolkar, M. M., Verma, A. J., More, P.S., & Kulkarni, A. (2021). Determination of soil nutrients (NPK) using optical methods. *Journal of Plant Nutrition*, *44*(12), 1826-1839. https://doi.org/10.1080/01904167.2021.1884702

Sangwan, S., Singh, J., & Malhotra, R. (2022). IoT-driven soil nutrient monitoring. *Smart Agriculture Technologies*, *12*, 203–212.

Thompson, L.J., Ferguson, R.B., Kitchen, N., Frazen, D.W., Mamo, M., Yang, H., & Schepers, J.S. (2015). Model and sensor-based nitrogen management. *Agronomy Journal*, *107*, 2020–2030. https://doi.org/10.2134/agronj15.0116

Yohannes, Z., Yoseph, T., Kiflu, A., Ayalew, T., & Haile, A. (2024). Liquid bio-slurry enhances the productivity of N-fertilized maize under field conditions in Ethiopia. *International Journal of Experimental Research and Review*, *43*(Spl Vol), 13–31. https://doi.org/10.52756/ijerr.2024.v43spl.002

Zhang, Z., Liu, D., Wu, M., Xia, Y., Zhang, F., & Fan, X. (2021). Long-term straw returning improves soil K balance and potassium-supplying ability. *Scientific Reports*, *11*(1), 1–15. https://doi.org/10.1038/s41598-021-01594-8

How to cite this Article:

Rahul Adhikary, Suvra Jyoti Choudhury and Tanmoy Shankar (2024). Real-Time Soil Nutrient Monitoring Using NPK Sensors: Enhancing Precision Agriculture. *International Journal of Experimental Research and Review*, *45*, 197-202.

DOI : https://doi.org/10.52756/ijerr.2024.v45spl.015