International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 1(s) (2026)



ijerst.editor@gmail.com

editor@ijerst.com

www.ijerst.com
© 2026 IJERST. All Rights Reserved
Peer Reviewed, Referred & Indexed Journal

Research Paper

Artificial Intelligence–Assisted Soil Fertility Evaluation and Fertilizer Recommendation Using Laboratory Soil Testing Data

Adarsh Balasaheb Kangare, Abdullatif Nijam Shaikh

Department of Chemistry, Jijamata College of Science Arts, Bhende Bk, Ahhilynagar, Maharashtra, 414605 India

Email: shaikhlatif@rediffmail.com

Abstract

Soil fertility assessment is important for sustaining agricultural productivity and environmental health. Conventional soil testing measures parameters such as pH, electrical conductivity, organic carbon, and macronutrients (N, P, K), but interpreting these results often requires expert knowledge. This study presents an Artificial Intelligence (AI)–based decision-support system that combines laboratory soil test data with machine learning algorithms to predict soil fertility and recommend nutrient management practices. Soil samples were analyzed using standard procedures, and the data were used to train Artificial Neural Network and Random Forest models. The system successfully classified soil fertility and identified nutrient deficiencies, particularly low phosphorus and potassium levels, with results comparable to laboratory interpretation. The proposed approach helps farmers understand soil reports, apply balanced fertilizers, and improve crop productivity, demonstrating the potential of AI for precision agriculture and sustainable nutrient management.

Keywords: Artificial Intelligence, Soil Fertility, Machine Learning, Soil Testing, Precision Agriculture, Nutrient Prediction

1. Introduction

Soil serves as the primary medium for plant growth and food production. Its productivity depends on chemical composition, organic matter content, moisture retention capacity, and microbial activity. Soil testing is widely used to determine nutrient availability and to guide fertilizer application. Laboratory analysis measures important parameters such as acidity or alkalinity (pH), salinity (EC), and macronutrient levels including nitrogen, phosphorus, and potassium.

While these measurements are reliable, the interpretation of soil reports is often complicated for farmers. Misinterpretation frequently leads to either excessive fertilizer application or nutrient deficiency. Overuse of fertilizers degrades soil structure, contaminates

water resources, and increases production costs. Therefore, a system capable of converting soil data into clear recommendations is necessary.

Artificial Intelligence (AI) provides powerful analytical capabilities for interpreting agricultural data. Machine learning models can identify relationships between soil properties and fertility status. By training algorithms on soil parameters, it is possible to predict nutrient deficiencies and recommend appropriate fertilizers. Recent advances in digital agriculture have shown that AI can support crop management decisions and enhance farm productivity [1].

This research aims to integrate laboratory soil testing with AI techniques to create a predictive soil fertility classification and fertilizer advisory system.

2. Review of Literature

Soil fertility evaluation has been extensively studied in agricultural science. The relationship between soil nutrients and plant growth has been well documented [2]. Organic carbon determination using the Walkley–Black method remains a commonly applied technique [3]. Estimation of available nitrogen by alkaline permanganate oxidation and phosphorus measurement through Olsen's extraction are standard analytical procedures [4,5].

In recent years, computer-based methods have been introduced in agriculture. Machine learning algorithms can analyze complex agricultural datasets and improve decision-making [6]. Deep learning has been applied to crop disease detection and yield estimation [7]. Digital agriculture platforms use predictive models for sustainable farming practices [8]. However, relatively few studies combine laboratory soil testing and AI-based fertilizer recommendation, especially at the field level. The present work attempts to address this gap.

3. Objectives

The study aimed to determine key soil fertility parameters through laboratory testing and to prepare a dataset using soil properties such as pH, EC, organic carbon, nitrogen, phosphorus, and potassium. It also focused on developing a machine learning model for soil fertility classification, predicting nutrient deficiencies and fertilizer recommendations, and evaluating the effectiveness of Artificial Intelligence in supporting precision agriculture.

4. Materials and Methods

4.1 Soil Sampling

Representative soil samples were collected from agricultural fields at a depth of 0–15 cm, which corresponds to the root zone of most crops. Several subsamples were mixed to

form composite samples. The collected soil was air-dried, crushed, and sieved to remove stones and plant residues.

4.2 Laboratory Analysis

Standard soil testing procedures were followed.

Parameter	Analytical Technique
Soil pH	Glass electrode pH meter
Electrical Conductivity	Conductivity meter
Organic Carbon	Walkley–Black oxidation method
Available Nitrogen	Alkaline $KMnO_4$ method
Available Phosphorus	Olsen extraction
Available Potassium	Flame photometry

These parameters determine nutrient availability and soil health {1}.

4.3 Artificial Intelligence Approach

Data Preparation

Each soil sample was represented by input features: pH, EC, Organic Carbon, Nitrogen, Phosphorus, Potassium Output variables: Fertility class (Low / Medium / High), Fertilizer suggestion

Machine Learning Models

Two supervised learning models were implemented:

1. Artificial Neural Network (ANN) and 2. Random Forest Classifier

Model Workflow

1. Data normalization, 2. Training dataset creation, 3. Model validation and 4. Prediction of soil fertility status

The algorithms learned relationships between soil chemical composition and fertility category.

5. Results and Discussion

5.1 Soil Analysis

The tested soils showed alkaline reaction with pH values above 8.0. Electrical conductivity values were low, indicating non-saline conditions. Phosphorus and potassium concentrations were insufficient for optimal crop growth.

5.2 AI-Based Prediction

The trained model categorized the soils into fertility classes. Two fields were predicted as low fertility, while one field was classified as medium fertility. The prediction was consistent with the laboratory interpretation.

5.3 Fertilizer Recommendation

The AI system suggested:

- Phosphatic fertilizers for low phosphorus soils
- Potassic fertilizers for potassium deficiency
- Organic amendments to improve soil carbon

These recommendations align with agronomic guidelines [2].

5.4 Importance of AI Integration

The proposed system converts complex soil analysis into simple recommendations understandable to farmers. It reduces dependency on expert interpretation and enables data-driven farming. Similar studies confirm that predictive analytics improves agricultural efficiency [1,6].

6. Applications

The AI-based soil fertility system can be used for automated soil health card generation, crop suitability prediction, and precision nutrient management. It can also be integrated into smart farming mobile advisory applications and support sustainable agriculture programs through data-driven decision-making.

7. Advantages

This approach ensures balanced fertilizer application, reduces environmental pollution, lowers cultivation costs, improves crop productivity, and promotes efficient farm management.

8. Conclusion

Soil testing provides reliable measurements of soil properties but requires technical interpretation. The integration of Artificial Intelligence with soil testing enables automated analysis and decision support. The machine learning models successfully identified nutrient deficiencies and fertility status using laboratory parameters. The proposed AI-assisted system simplifies soil report interpretation and helps farmers apply fertilizers correctly. Such technology can contribute significantly to precision agriculture, resource conservation, and sustainable food production. The study demonstrates that combining soil science with computational intelligence offers a practical and scalable solution for modern agriculture.

References

1) Kamilaris, A., & Prenafeta-Boldú, F. (2018). Deep learning applications in agriculture. *Computers and Electronics in Agriculture*, 147, 70-90.
2) Brady, N.C., & Weil, R.R. (2016). *The Nature and Properties of Soils*. Pearson Education.
3) Walkley, A., & Black, I.A. (1934). Determination of soil organic carbon. *Soil Science*, 37, 29-38.
4) Subbiah, B.V., & Asija, G.L. (1956). Rapid method for estimation of available nitrogen in soils. *Current Science*, 25, 259-260.

5) Olsen, S.R., Cole, C.V., Watanabe, F.S., & Dean, L.A. (1954). Estimation of available phosphorus in soils. USDA Circular 939.
6) Liakos, K.G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674.
7) Mohanty, S.P., Hughes, D., & Salathé, M. (2016). Deep learning for crop disease detection. *Frontiers in Plant Science*, 7, 1419.
8) Basso, B., & Antle, J. (2020). Digital agriculture for sustainable farming systems. *Nature Sustainability*, 3, 254-256.