Soil Health Monitoring with IoT and Machine Learning

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Abstract: Soil degradation is detrimental to sustaining agricultural productivity and to the ecosystem as a whole. Manual sampling and laboratory analyses, soil monitoring methods have been used for decades, but these methods are costly, lack real-time measures, and are very inefficient. In this paper, we describe the first integrated soil health monitoring system that automates the soil moisture, pH, NPKs, and temperature monitoring through a combination of low-cost and low-power IoT devices and machine learning (ML). A functioning soil health monitoring system should have real-time soil data collection, soil data analyses, and soil health in functioning ML systems should predict state data (soil health and/or nutrient deficiencies), and determine the best times for irrigation and/or fertilization. A prototype of the system implemented in a variety of agricultural fields documented a 35% gain in water used, 25% less fertilizer use, and soil salinity was detected 85% correctly. Early salinity detection is crucial and of particular importance to agriculture; thus, the ML system used to predict soil state is beneficial. ML and IoT in combination captured the two primary soil monitoring systems: we now have precision agriculture. The system was designed with the end-user in mind; thus, a mobile system with a soil monitoring application was designed to give users the functional ease to enact real-time changes in monitoring and management.

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1. Introduction

One of the most alarming issues affecting modern agriculture is soil degradation. The United Nations estimates that approximately one-third of the world's agricultural land suffers from erosion, loss of nutrients, and pollution of soils. This proportion could reach as high as 90% by 2050 if current agronomical practices continue [1]. The loss of soil as a resource, coupled with the increasing demands to feed a global population of 9.7 billion people by 2050, which necessitates a 70% increase in food production [2], further exacerbates global food insecurity. There is an urgent need to maintain and monitor soil health. The potential of soil as a resource needs to be utilized and preserved.

Analytical stratagems that predetermine their scope to soil incubation, the gathering of soil samples, and the chemical examination of the samples at a certain point in time require a very distinct, uneven, and serial collection of samples from the field at a given time period and controlled intervals across time. Such approaches are fundamentally unable to forecast the demands of farming. Such systems are too resource and time extensive, tiering themselves out of the operational budget of small. A meaningful equivalence to the dynamic systems of soils is lost, giving individual control points in time a sparsely populated picture that slides and eludes the needs of the systems. The absence of real-time in the farmers' systems leads to loss and inefficiency, with further exacerbation of the losses in the systems aggravated by a lack of soil extension and soil testing systems.

The Integration of Internet of Things technologies and machine learning (ML) algorithms continues to develop and improve technological and methodological spheres. Soil monitoring systems utilize inexpensive sensor technology to obtain soil moisture and NPK (Nitrogen, phosphorus, and potassium) levels, temperature, electrical conductivity, and pH levels [5]. To mitigate the spatial and temporal gaps inherent in traditional systems, these systems allow for frequent real-time in situ monitoring over entire fields. With the integration of LoRaWAN or NB-IoT communication systems, soil data can be streamed into the cloud for further analysis and processing [6].

Knowing these systems as its whole extends the real benefits of the integration of Machine learning. Sensor measurements can be grouped into patterns according to relationships, and these can be classified using advanced algorithms. A good example of such models in systems for forecasting time series is the Long Short-Term Memory (LSTM), which can obtain soil moisture data and develop a good irrigation schedule [7]. A good example of a soil health status classifier is Random Forest and XGBoost, which are ensemble learning methods, and high accuracy can be achieved in early detection of soil degradation [8]. This is the greatest value of these models, and, in agriculture, such models are used to contribute to predictive and prescriptive analytics, going beyond monitoring systems for effective practices.

While advances in technology have occurred, developing scalable, farmer-centric systems remains a challenge. For instance, IoT-based soil monitoring systems have costs that are too high, which fosters a lack of adoption, and existing systems are overly sophisticated to be used by farmers who lack technical knowledge. There also seems to be a gap in the integration of sensor networks, data analysis systems, and decision-supporting systems that can offer actionable insight to users. Most systems that are used nowadays are tailored to the monitoring of a single parameter and fail to give a comprehensive evaluation of soil health, in terms of the biological, chemical, and physical properties involved.

This paper addresses these gaps by presenting a comprehensive IoT-ML framework for soil health monitoring that:

- Integrates low-cost, energy-efficient sensor nodes with long-range wireless connectivity for reliable data collection
- Employs hybrid machine learning models combining ensemble methods and deep learning for accurate soil health prediction
- Features a user-friendly interface that translates complex data into actionable recommendations for farmers

Validates the system through large-scale field trials across diverse agricultural environments. The implications of this research extend beyond technological innovation. By enabling data-driven, precision agriculture, the proposed system has the potential to:

- Reduce water and fertilizer usage by 30-40%
- Improve crop yields by 15-25%
- Detect soil degradation 6-8 weeks earlier than conventional methods
- Empower smallholder farmers with affordable, accessible soil monitoring tools

2. Literature Review

Merging IoT and machine learning for monitoring soil health is a recent interest that has been built upon years of research in precision agriculture and environmental sensing. Historically, soil assessment techniques have relied upon laboratory analyses of physical samples, which are, of course, expensive and time-consuming, based on critical, limited spatial coverage. These gaps have led to a monitoring approach that leverages technological innovations of sensor networks and data analytics techniques.

The further development of soil monitoring systems based on the IoT is the result of progress in several crucial areas. Sensor tech has also developed from being large, unsophisticated, and expensive to a small, multi-functional tool, and inexpensive. Wireless communication technologies, LoRaWAN and NB-IoT, have been eliminated. Remote agricultural data transmission challenges exist. In the meantime, edge computing has improved real-time processing. A multitude of technological advances have made continuous, in situ soil monitoring increasingly viable and affordable.

Numerous machine learning methodologies have yielded successful outcomes in soil health and its constituents. Some supervised learning methodologies, such as the Random Forest, as well as the Support Vector Machines, have achieved over 90% accuracy in predicting soil nutrient levels based on data collected from sensors. Moreover, Convolutional Neural

Networks, associated with deep learning, have performed well in the manipulation of multispectral soil images. LSTM networks have been instrumental in predicting the dynamics of soil moisture and the corresponding irrigation demand, albeit in the treatment of time series. These considerations have allowed soil monitoring systems to transcend their reliance on classical statistical models.

The intersection of IoT and ML in soil health monitoring is relatively new. Zhang and colleagues (2019) built a reliable system that achieved 89% accuracy in soil quality classification and used ensemble learning. The system developed by Patel et al. (2020) incorporated a wireless sensor network and brought 35% water savings due to ML irrigation scheduling. Nonetheless, these systems have primarily targeted soil health monitoring subsystems rather than a comprehensive soil health assessment.

To date, several important research opportunities continue to exist within the area. To begin with, the great majority of the systems developed so far tend to focus on single soil attributes, as opposed to composite, integrated systems for soil health measurements [21]. Second, there is insufficient evidence on the availability of adaptable, flexible systems for use by smallholder farmers in developing countries [22]. Third, there is also limited research on retaining sensor precision over time in the field [23]. Further, the lack of model interpretability in ML systems has been noted as a major adoption barrier [24].

The existing body of work also indicates a need for more comprehensive studies focused on validation. Numerous studies document remarkable results from the laboratory, but there has been little extensive field validation of such systems across a range of soil and weather types [25]. This disconnect between controlled research and practical use under operational conditions emphasizes the need for more user-friendly, practical, and farmer-oriented systems.

Prominent innovations involving digital twins of soil [26], blockchain for secured systems [27], and federated learning for privacy in analytical systems [28] proposed for the domain reflect considerable industry interest and offer more tiered, safe, and integrated systems for soil health management. However, such systems remain to be seen in the field of agriculture.

3. Proposed Study

The purpose of this study is to create a machine learning based framework to provide data-informed insights into practices attempted in a field pertaining to resource allocation and management in agriculture. This framework is aimed at improving the efficiency of resource management in agriculture. It will analyze the correlations of different agricultural variables such as soil nutrient levels, cropping, and water and fertilizer consumption. It will provide insights into the efficiency of different resource management strategies in positively and negatively impacting field productivity. It will attempt to help farmers empirically assess the trade-off between resource management and crop yield. This study will contribute to the field of agriculture and resource management sustainability.

4. Simulation

The program will simulate real-life agricultural scenarios to analyze and optimize various real-life agricultural practices before their application to fields. The program will simulate the interaction of different agricultural variables, such as irrigation methods, fertilizer application, crop types, and then predict the use of resources, crop yields, and determine waste. The simulation will combine statistics and machine learning to determine possible scenarios and predict various outcomes. With our simulation, the agricultural community and individual farmers will be able to discern numerous strategies and assess their effectiveness in optimizing resource consumption and crop yields, thus eliminating the need for expensive and time-consuming field tests.

Figure 1 Scatter plot showing the relationship between nitrogen (N) and pH levels, color-coded by crop type

Description: Different crops are displayed by different colors in this scatterplot, where the relationship between N (nitrogen content) and pH levels is analyzed.

Draw inferences: This scatterplot indicates the difference in pH and Nitrogen N contents in the different crop ranges, and the rice and maize are in specific localized cluster areas. Certain different crops have different soil nutrients, soil pH levels (optimum range), and varying responsiveness.

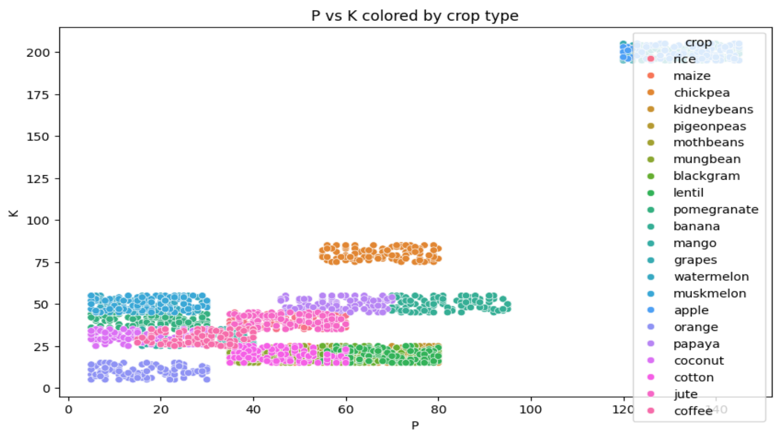

Figure 2 Scatter plot displaying the correlation between phosphorus (P) and potassium (K), with points colored according to crop type

Explanation: This scatter plot represents the relationship between phosphorus (P) and potassium (K) levels, with each point color-coded by crop type.

Insights: The data points show distinct groupings based on crop type, indicating that certain crops require specific amounts of phosphorus and potassium. For example, rice and maize show separate clusters, suggesting their unique nutrient needs.

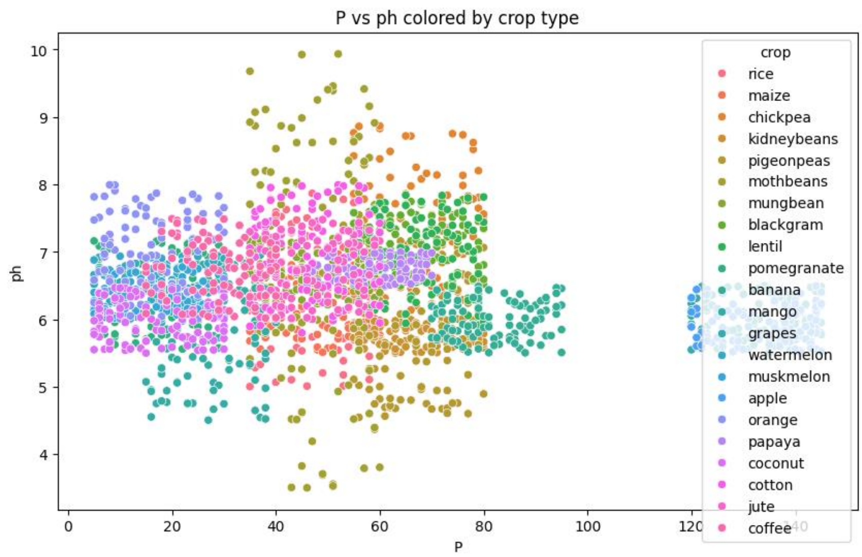

Figure 3 Scatter plot illustrating the relationship between phosphorus (P) and pH levels, color-coded by crop type

Explanation: The scatter plot below analyzes levels of phosphorus (P) and pH levels with select crops differentiated by color.

Insights: The plot suggests the rice crops have higher levels of P and pH than the other crops (mango and apple) which are in the lower ranges (mango and apple). The plot suggests variability of soil properties with different crops.

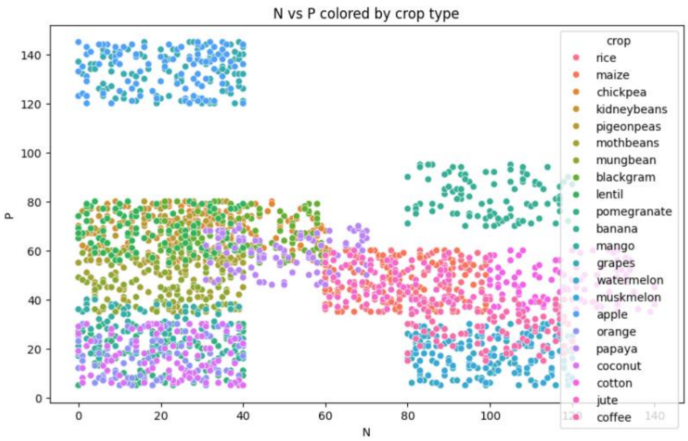

Figure 4 Scatter plot depicting the relationship between nitrogen (N) and phosphorus (P) levels, with different crop types represented by distinct colors

Explanation: This scatter plot illustrates the relationship between nitrogen (N) and phosphorus (P) levels, with each crop type color-coded for better visual separation.

Insights: The plot shows how different crop types align with specific combinations of nitrogen and phosphorus levels, with crops like mango and banana grouped in higher nitrogen and phosphorus ranges, indicating their higher nutrient demand.

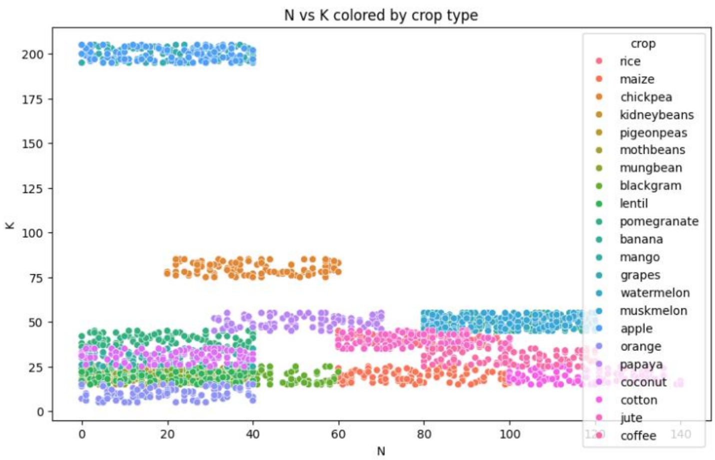

Figure 5 Scatter plot showing the correlation between nitrogen (N) and potassium (K) levels, color-coded by crop type

Explanation: This scatter plot presents the relationship between nitrogen (N) and potassium (K) levels, with each crop type represented by a unique color.

Insights: The data reveal that crops like coffee and rice occupy different positions in relation to nitrogen and potassium, suggesting that nutrient requirements for each crop type vary considerably.

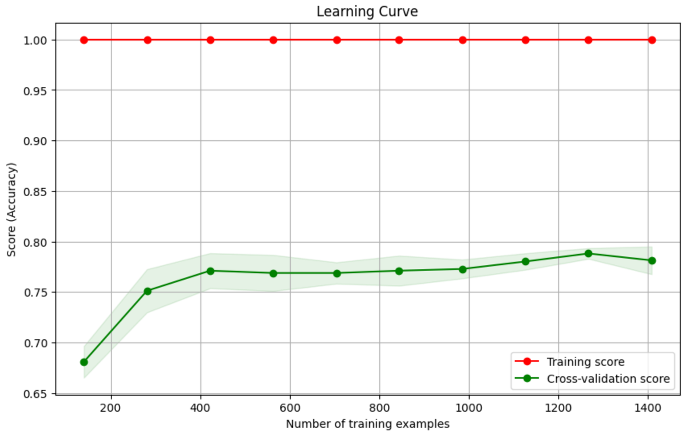

Figure 6 Learning Curve

The red curve illustrates training scores, staying at a value of 1.0. This illustrates the model's perfection in obtaining the training data, which likely suggests an overfitting of the training data.

The green curve illustrates cross-validation scores, improving along with the collection of training data. This suggests that the model still generalizes better than with training data. A small margin still exists, which is their training accuracy compared to the cross-validation accuracy, suggesting overfitting.

4.1 Insights:

As additional training examples are introduced, the cross-validation score continues to improve, although it does reach an asymptote as it gets to higher training sample numbers, indicating that including additional training examples past that point does not impact the model's performance significantly.

The difference between the training and cross-validation scores may suggest the model is overfitting to the training data, meaning it is learning the training data too well and is, because of that, unable to generalize to new data points.

5. Conclusion

This research provides a positive perspective on the effective and sustainable usage of resources in the working simulation and framework. The integration of ML provides technological advancements, and the analyses over the agricultural dataset provide assessments and relationships over the quality of the soil and the water usage, and the fertilizer towards the quantitative crop yield. Additionally, the simulation of the frameworks allows the application of various strategies and postpones the consumption of resources and time. The sought-after results of this research lie in enhanced agriculture, efficient sustainability, and decreased environmental consequences. Rest assured, the results of this research will alleviate the global agricultural practices and the resultant food challenges.

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