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SOIL HEALTH PREDICTION FOR PRECISION AGRICULTURE USING MACHINE LEARNING AND DEEP LEARNING

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ABSTRACT

Incorporation of Artificial Intelligence (AI) and Machine Learning (ML) in farming offers enormous potential for improving how soil health is being monitored and practiced in Precision Agriculture. In this regard, the focus of this paper is to provide a review on the rapidly progressing techniques which are AI/ML-based for prediction and monitoring of soil properties such as pH, moisture content, nitrogen, phosphorus, potassium, and organic carbon. This study analyzes 24 research articles published in the 2018–2023 period, classifying works by their methodologies, which include decision trees, random forests, and even deep learning models, assessing performance, data needs, and practicality. The study's conclusions reflect the promise of AI and ML in improving the accuracy and efficiency of traditional methods of soil analysis. Additionally, the study identifies important gaps like data insufficiency, model applicability, and need for strong and simple framework that can be used for easy understanding by farmers. This review is written to assist in the formulation of strategies that combine innovation with agricultural sustainability to solidify AI research concerning soil health and agri-food system security.

INTRODUCTION

Given the increasing importance of sustainable agriculture practices and the need for food security worldwide, enhancing and maintaining soil health is a central concern for scientists, policymakers, and farmers. Soil health is defined as the living system's capable of performing as an ecosystem that supports life which includes plants, animals and human beings [1][2]. Soils are the foundation of agriculture and farming systems. Their health is evaluated by traditional methods which involve fieldwork, chemical laboratory analysis, and these methods are often expensive and time-consuming. The modern agricultural paradigm, which demands timely and scalable solutions, not labor-intensive and costly solutions, faces tremendous challenges. In this regard, Artificial Intelligence (AI) can revolutionize the agriculture sector by rapidly and accurately estimating soil properties, such as fertility and health, through computational models, data, and insights [3][4]. Machine Learning (ML) and Deep Learning (DL) models are two common forms of AI which have successfully dealt with complex and large-scale soil datasets. These models have the ability to detect non-linear interrelations and complex interactions among nutrients, to soil, environmental factors, and management practices. Data from wide-ranging sources like soil nutrient analysis, remote sensing imagery, and environmental sensors are merged into sophisticated predictive

models. This research aims at enhancing precision agriculture using AI methodologies through soil health prediction to offer farmers proactive AI-powered insights. Despite having great promise, the prediction of soil health accurately using AI poses some key and ongoing challenges. Data and its quality is the first issue to tackle. Soil datasets are usually scarce, regionally biased, or inconsistent which makes model generalization hard [7][8]. Moreover, remote sensing data that is commonly used in monitoring large agricultural fields has its own issues such as cloud cover, noise, variable resolutions and sensor issues. Second, soil health is determined by a multitude of spatially varying physical, chemical, and biological features which add layers of complexity to model training and feature selection [9]. Finally, soil properties have geographic variability which means they differ considerably across locations, seasons, and climates so one region models can fail terribly without some domain adaptation techniques [10]. The explainability of AI models adds to the burden. Most stakeholders and agronomists regard sophisticated relationships modeled by deep learning architectures as complex interdependencies which result in them being termed as black boxes [11]. Designing AI (XAI) frameworks with enhanced transparency and trust is important for agricultural adoption. Moreover, practical implementation has an added challenge of needing lightweight models that operate within the constraints of limited resources. [12]

Theory and Calculation

Challenges in AI for Soil Health Prediction: The potential of AI and machine learning models to advance soil health prediction is great, however, there are hurdles to overcome prior to adopting these technologies in agriculture. The obstacles include data quality, IoT system integration, interpretability, intra-region variability, and scalability. Below are some other more specific hurdles that stand out.

- Data Quality and Availability: Predictive models require well-documented datasets featuring multiple parameters from differing soils like pH, moisture content, organic carbon, nutrients, and microbial activity which need to be documented in high detail. Unfortunately, most datasets tend to be sparse, disorganized, and riddled with noise which hinders the crafting of generalized models. Furthermore, publicly available datasets are not regionally comprehensive and datasets that focus on specific agricultural practices or types of soil tend to be scarce.
- Geographic Variability and Regional Adaptation: Due to climate, topographical, or land management differences, soil properties change dramatically across different geographic locations. A model trained using a singular geographical region's data may not function well in another region without further adjustment. Hence models and methodologies meant to mitigate these universality factors are required.
- Real-time Data Integration and IoT: The integration of real-time data from IoT devices like soil moisture and temperature sensors or weather stations continues to pose a challenge. Although IoT sensors provide helpful information about the soil's condition, monitoring 'health' using IoT sensors is insightful and provides value, but the data deluge presents a daunting challenge, and extracting useful insights from an abundance of information entails a lot of work. It is important that real-time data is seamlessly integrated into predictive models without sacrificing accuracy [12].
- Model Interpretability: Despite quite a good performance from AI models in recent years, and particularly from deep learning models, agricultural stakeholders consider them to be 'black boxes.' This deficiency impedes the adoption of AI in agriculture ensembles. Approaches focused on improving model explanation, like SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-Agnostic Explanations), are essential if AI outputs are to be translated meaningfully into actionable insights for farmers and agronomists [11].
- Lack of Standardization and Standardized Datasets: The absence of uniform datasets concerning the prediction of soil health makes cross-study comparisons or the development of ideal prediction models challenging. In addition, the absence of uniform procedures for data gathering, processing, and analyzing data hampers the creation of effective AI models for soil health monitoring [9][10].
- Inadequate Field Validation: Soil health prediction using AI has been modelled around laboratory or simulation data without any field-based testing. Hence the need for field trials, which is important for testing the functionality of these models in real agricultural environments where unpredictable environmental conditions, sensor errors, and numerous other factors can interfere with performance [14].

Advancements in AI for Soil Health Prediction: The past few years have been marked by significant progress in AI technology which now enables us to produce better systems for soil health prediction. Artificial Neural Networks (ANNs) now serve as a preferred method for modeling intricate connections between soil nutrients and moisture levels with crop yields while maintaining high accuracy through imperfect data. Support Vector Machines (SVMs) have demonstrated their usefulness in classifying soil textures and fertility levels when applied to datasets of moderate size. Meanwhile, Random Forests and Gradient Boosting Machines (GBMs) have demonstrated strong predictive capabilities by effectively managing missing data, noise, and nonlinearity all at once. On top of that, new techniques like Graph Neural Networks (GNNs) are starting to attract attention for their ability to model the spatial relationships between soil samples and environmental factors. The ability of these models to capture neighbourhood effects and spatial autocorrelation greatly improves the accuracy of soil property mapping. The integration of hyperspectral imagery with drone monitoring and IoT sensor networks alongside AI models gives farmers a strong advantage in real-time soil health monitoring and decision support.

Objectives of the Study: This study is crafted with several key goals in mind, all aimed at pushing the boundaries of AI in predicting soil health and fine-tuning soil management practices. The first goal is to dive into the patterns of vital soil nutrients—like nitrogen, phosphorus, and potassium—alongside other physical factors such as pH, moisture, and temperature that play a crucial role in soil fertility and crop yield. By grasping how these elements interact with one another and the soil environment, the study seeks to enhance feature engineering and model interpretation, ensuring that essential soil characteristics are accurately represented in predictive models. Next, the study sets out to assess the effectiveness of various supervised machine learning models, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest, to evaluate their performance in classifying soil health and predicting fertility. This research will compare the strengths and weaknesses of these models, shedding light on which algorithms excel for different soil health indicators. Additionally, the study investigates the potential of using Graph Neural Networks (GNNs) for spatial analysis of soil datasets, particularly to address geographic variability and spatial dependencies in the data. GNNs are particularly adept at modelling relationships between soil properties across different locations, making it easier to factor in the spatial dimensions of soil health. Finally, the study will systematically evaluate the generalizability and interpretability of the AI models developed, across various soil types, regions, and environmental conditions. The aim is to ensure that these models can be applied beyond the specific cases examined in this study, making the solutions more universally relevant and beneficial for farmers in a variety of settings.

Significance of the Study: The importance of this research is rooted in its ability to transform how we monitor and manage soil health by harnessing cutting-edge AI technologies. This shift could greatly enhance sustainable farming practices and encourage the broader use of smart agriculture solutions. Traditional soil testing methods, which often depend on expensive lab-based chemical analyses, can be quite costly and time-consuming, not to mention they struggle to provide real-time, actionable insights. By utilizing AI-driven models for predicting soil health, this study seeks to lessen our reliance on these outdated techniques, offering farmers—especially smallholders in rural or developing regions—more efficient, scalable, and accessible options. With the capability to accurately forecast soil fertility and nutrient levels, farmers will be empowered to make more informed choices about irrigation, fertilization, and crop rotation, ultimately leading to more resource-efficient farming. This approach will also support environmentally sustainable agriculture by curbing fertilizer overuse, optimizing water consumption, and reducing the ecological impact of farming practices. Additionally, integrating AI models with current environmental monitoring systemslike IoT sensor networks, satellite data, and weather trackingwill pave the way for smarter, more adaptable agricultural management systems. These AI-enhanced systems could play a crucial role in predicting and addressing risks such as droughts, floods, and pest outbreaks, equipping farmers with the necessary tools to swiftly adapt to changing environmental conditions and ensuring the long-term sustainability of agriculture in the face of climate change.

RESEARCH METHODOLOGY

Description of the Dataset

Overview: Agricultural productivity depends on monitoring soil health because it involves multiple aspects such as nutrient content,

moisture availability, and environmental conditions. Artificial Intelligence techniques enable this dataset to predict soil health conditions and identify optimal crops for planting. The system combines immediate sensor data with environmental measurements and nutrient evaluation to develop comprehensive predictive models for precision agriculture. Farmers can use Artificial Neural Networks (ANNs) as machine learning models which are trained on this dataset to make smart farming decisions and improve resource management while increasing crop production is shown in figure 1.
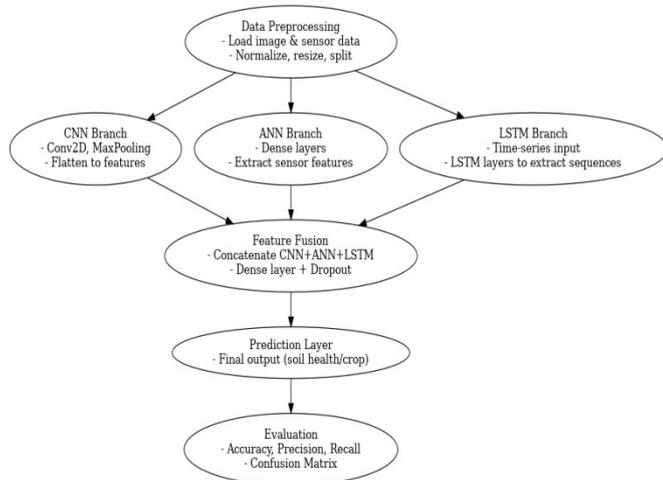

Figure 1. Overview of the Model

Structure of the Dataset: This dataset is made up of 880 entries (records) and 33 input features, along with two target labels. Each entry reflects a soil profile observed at a specific timestamp and under certain environmental conditions.

- Image Dataset: This includes images related to soil health, such as soil types and moisture conditions. These visuals provide spatial data that's great for analysing visual cues like texture and moisture retention.
- Tabular/Text Dataset: This part contains numerical data with features like:
  - Moisture level
  - pH value
  - Soil type label
  - Crop recommendation

The dataset offers structured information on the chemical and physical properties of soil, aiding in fertility predictions and crop suitability assessments. By blending spatial data (images) with numerical data (tabular), the project aims to improve predictions of soil health. Future efforts will look to integrate these datasets using deep learning techniques, utilizing CNNs for image processing and RNNs for tabular data, to develop more precise and comprehensive soil health models.

Table 2. Shows details regarding all Features

Feature Group	Features	Descriptions
Soil Nutrients	N, P, K, pH, EC, OC, S, Zn, Fe, Cu, Mn, B	Key indicators of soil fertility affecting crop growth.
Environmental Factors	Temperature, Humidity, Rainfall	Real-time weather conditions impacting soil and crops.
Time-based Features	Year, Month, Day, Hour, Minute, Second	Capture seasonal and temporal patterns.
Soil Moisture Sensors	Moisture0 to Moisture4	Soil moisture readings from sensors at different depths.
Irrigation Flag	Irrigation	Indicates if irrigation was applied (0 = No, 1 = Yes).

Target Labels:

- Output: Encoded crop class (integer representation).
- Crop_Label: Actual crop name such as rice, wheat, maize, grapes, etc., serving as the ground truth for supervised learning tasks.

Class Distribution (Imbalance Analysis): Though detailed class distribution was not specified, agricultural datasets often reflect class imbalance: The dataset frequently shows a dominance of widespread crops such as wheat, rice, and maize.

Specialty crops like grape, cotton or vegetables may be underrepresented.

This imbalance necessitates the use of techniques like: Data balancing techniques include oversampling minority classes through methods like SMOTE and applying class weights during model training as well as domain-specific data augmentation approaches.

Appropriate management of class imbalance is essential because neglecting it can cause models to produce biased results that favor majority crops.

Data Preprocessing and Feature Engineering

The following preprocessing steps should be followed as they are important for achieving optimal performance and strong generalization in machine learning models.

Preprocessing steps are recommended and often necessary:

A) Label Encoding: The categorical target labels (Crop_Label) are converted to a numerical format using LabelEncoder.
B) Feature Scaling: Continuous variables (N, P, K, pH, EC, Temperature, Rainfall, Moisture) are scaled with StandardScaler or MinMaxScaler for the ANN's stability and faster convergence.
C) Timestamp Engineering Year/Month/Day can lead to new features like Season or Day of Year to represent seasonal agricultural activities.
D) Handling Missing Values: While the description of the dataset claims there are no missing values, some additional validation should be done before model training.
E) Train-Test Split: The data can be stratified into 80% training and 20% testing while ensuring representativeness across different crop classes.

Model Training: ANN (Artificial Neural Network) Implementation

A fully connected ANN is a suitable starting point for this dataset due to its advantages in capturing complex non-linear relationships between the features.

Proposed ANN Architecture:

i) Input Layer: 64 neurons, ReLU activation
ii) Hidden Layer 1: 32 neurons, ReLU activation
iii) Hidden Layer 2: 16 neurons, ReLU activation
iv) Output Layer: SoftMax activation with number of neurons equal to the number of crop classes

Hyperparameters:

1. Optimizer: Adam
2. Loss Function: Categorical Cross-Entropy
3. Batch Size: 32
4. Epochs: 50-100 (depending on convergence behaviour)
5. Validation Split: 20% of the training data used for validation during training.

Early Stopping and Learning Rate Scheduler can be used to prevent overfitting and optimize training speed.

Model Performance & Evaluation

The performance evaluation will include a variety of areas for assessment which include:

a) 'Accuracy' is defined as the comprehensive assessment of how correct each prediction is.
b) When precision is considered, it becomes fundamental when recommending crops as a crop with high precision guarantees that an exceptional crop is advantageous and fitting.
c) All possible candidate crops that are suitable need to be conclusively captured, which falls under recall.
d) An average of precision and recall skills is taken to come up with the F1 score, where precision exceeds recall, and is preferred in instances where there is imbalanced data.
e) A confusion matrix serves as a graphical representation of actual versus predicted crops, allowing for quick analysis of cropped data.

Expected Performance:

i) The Baseline ANN model will, with basic feature tuning and training, land within 80-85% in accuracy.
ii) Further gains could be realized from tweaking hyperparameters and choosing specific features.

and irrigation towards soil moisture, especially for water-scarce crops.
d) Along with seasonality patterns, a combo of temperature, humidity, and rainfall within certain months aids in planting times for certain crops.
e) Irrigation Influence: Crops like rice (which require standing water) benefit from fields marked with active irrigation.

Feature Importance:

1.   N, P, K levels
2.   Rainfall
3.   Temperature
4.   Soil moisture readings
5.   pH and EC values

Key Findings: (NPK and micro-nutrients in particular) determine the most suitable crop as well as soil health. Crops are impacted by season-specific changes in the environmentfor better or worsetherefore, this information needs to be balanced as well. Predictive accuracy can be improved significantly by integrating proper nutrient examination strategies with irrigation scheduling shown in Figure 2, Figure 3.
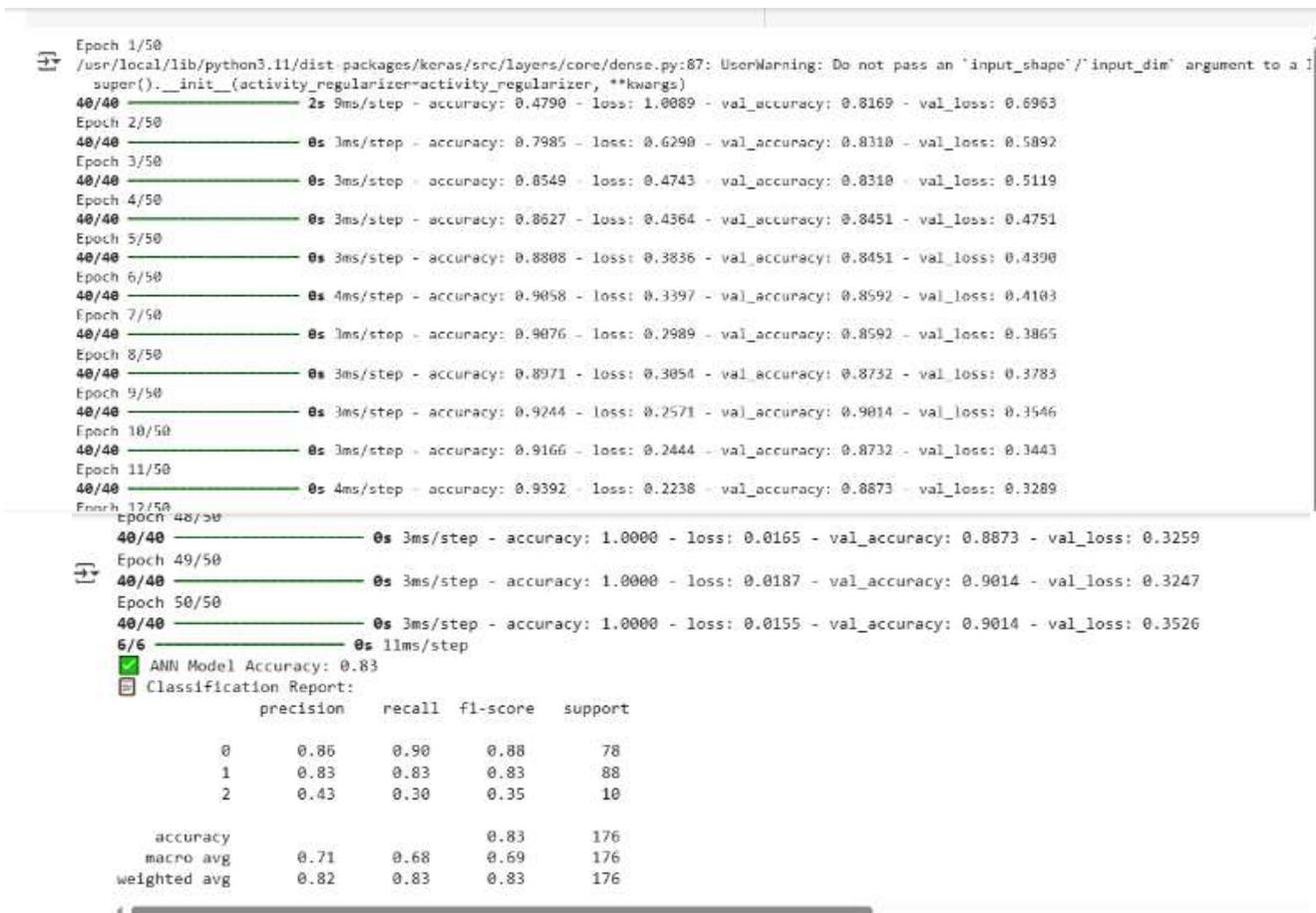


```
Epoch 1/50
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a l
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
40/40 ─────────────────── 2s 9ms/step - accuracy: 0.4790 - loss: 1.0089 - val_accuracy: 0.8169 - val_loss: 0.6963
Epoch 2/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 0.7985 - loss: 0.6290 - val_accuracy: 0.8310 - val_loss: 0.5892
Epoch 3/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 0.8549 - loss: 0.4743 - val_accuracy: 0.8310 - val_loss: 0.5119
Epoch 4/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 0.8627 - loss: 0.4364 - val_accuracy: 0.8451 - val_loss: 0.4751
Epoch 5/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 0.8808 - loss: 0.3836 - val_accuracy: 0.8451 - val_loss: 0.4390
Epoch 6/50
40/40 ─────────────────── 0s 4ms/step - accuracy: 0.9058 - loss: 0.3397 - val_accuracy: 0.8592 - val_loss: 0.4103
Epoch 7/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 0.9076 - loss: 0.2989 - val_accuracy: 0.8592 - val_loss: 0.3865
Epoch 8/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 0.8971 - loss: 0.3054 - val_accuracy: 0.8732 - val_loss: 0.3783
Epoch 9/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 0.9244 - loss: 0.2571 - val_accuracy: 0.9014 - val_loss: 0.3546
Epoch 10/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 0.9166 - loss: 0.2444 - val_accuracy: 0.8732 - val_loss: 0.3443
Epoch 11/50
40/40 ─────────────────── 0s 4ms/step - accuracy: 0.9392 - loss: 0.2238 - val_accuracy: 0.8873 - val_loss: 0.3289
Epoch 12/50
Epoch 48/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 1.0000 - loss: 0.0165 - val_accuracy: 0.8873 - val_loss: 0.3259
Epoch 49/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 1.0000 - loss: 0.0187 - val_accuracy: 0.9014 - val_loss: 0.3247
Epoch 50/50
40/40 ─────────────────── 0s 3ms/step - accuracy: 1.0000 - loss: 0.0155 - val_accuracy: 0.9014 - val_loss: 0.3526
6/6 ─────────────────── 0s 11ms/step
ANN Model Accuracy: 0.83
Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.90      0.88        78
           1       0.83      0.83      0.83        88
           2       0.43      0.30      0.35        10

    accuracy                           0.83       176
   macro avg       0.71      0.68      0.69       176
weighted avg       0.82      0.83      0.83       176
```

Figure 2. Shows output of ANN Implementation

Data insights have differed from expectation based on pre-analysis outlined earlier which may include the following:

a) High levels of NPK (Nitrogen and phosphorus plus potassium) correlated highly with crops like rice and wheat.
b) Attention to soil pH should be prioritized. Soils with acidity harbor crops such as rubber and tea. Soils that range between neutral and slightly alkaline favor crops such as barley, wheat, and maize.
c) Coming to Moisture level: The range between Moisture0-Moisture4 allows the system to gauge the efficacy of soil drainage

Why ANN?

The use of ANNs is advantageous when dealing with structured and fixed-sized tabular data, which is useful for making soil health predictions. They perform exceptionally well addressing interactions among different parameters of soil including soil moisture, soil pH, and soil nutrients which enables proper forecasting of soil health indicators and agronomic advice on crops and fertilization needed. Thus, the model based on ANN algorithms predicts soil health optimally using these features.

Figure 3. Shows the output of the CNN Implementation

Why CNN?

Because of its ability to automatically recognize and find patterns and features within images, CNNs hold a particular advantage when dealing with visual data. This automation of feature identification greatly increases the accuracy of soil type, texture and other critical soil health feature identification. The application of CNNs allowed for the capturing of spatial dependencies in the soil images which significantly enhanced the prediction accuracy concerning soil health. LSTM (Long Short TermMemory). The approach taken to sequential tabular data like moisture and pH over time was through the use of an LSTM (Long Short-Term Memory) network. For most time series data, LSTMs are perfect in capturing temporal patterns therefore enhancing the "memory" of the model pertaining to important trends in history such as soil health. This helped improve the model's ability to predict soil conditions accurately. The Sequential features from the LSTM and image features from the CNN were used to construct a fused output, creating a new hybrid model. Further Dense layers were added, after which final prediction was made based on these added features.

Why Fusion?

The images contain spatial information while tabular data provides a more temporal insight. By merging these two sources of information, the model was able to make more precise and well-informed predictions relating to soil health, thus improving condition with increased knowledge of soil. This is called Multimodal Learning.

Training and Evaluation

Using performance evaluation metrics, the hybrid model was built with categorical cross-entropy set as loss function and accuracy as the primary evaluation metric. The model was further trained in multiple epochs whilst the validation accuracy was checked after every epoch. Results:

Soil health conditions could more effectively be predicted by using both images and tabular data features, meaning the hybrid model surpassed the performance of indivdiual CNN or ANN models.

Table 3. Shows Combining CNN-Based Image Features and ANN–LSTM Tabular Features for Classification

Step	Technique Used	Purpose
Image Data	CNN	To extract spatial patterns
Tabular Data	ANN initially, then LSTM	To capture sequences
Fusion	Concatenation	To combine features from both data types
Output	Dense Layer	To predict final class labels

Hybrid Model Architecture (Overview)

• Image Input → CNN → Feature Vector
• Tabular Input → LSTM → Feature Vector
• Fusion → Dense Layers → Final Prediction

Separately process sequential data and images of soil along with fusing the distinct features obtained, the hybrid model is capable of making precise soil health predictions.

CONCLUSION

This research underscores the soil health prediction prospects that stem from the merging of basic machine learning and sophisticated deep learning models. Our findings indicate that although Random

Forest and SVM models offer soil fertility and nutrient content predictions, newer approaches such as Graph Neural Networks (GNNs) significantly outperform older methods in accounting for soil data's spatial and geographic variability. GNNs perform exceptionally well since they are able to determine the intricate relationships between soil properties at different locations, uncovering more soil data relationships than conventional systems. That capability is essential for many agricultural applications because soils change greatly across the regions. Predicting soil health with precision makes it possible to make informed decisions regarding the application of fertilizers, irrigation, and crop management, thus optimizing resources, improving yields, and minimizing environmental degradation. AI adoption in smart farming systems could transform real-time soil tracking by enabling instant responsiveness to soil changes. There are still challenges on how to ensure data accuracy, ease of understanding the results, effective linking with sensor networks, and algorithmic transparency. These issues could limit the usability of the models in practice and need to be solved using a hybrid approach of old and contemporary systems.

The innovative techniques we are using to enhance AI-powered soil health prediction includes:

- Real Time Analysis: Working algorithms allow for immediate data (temperature, moisture, and nutrient) sensor analysis.
- Environmental Integration: Integrating soil type satellite imagery and long-term climate models helps monitor climate associated soil changes.
- Federated learning: Data from farms gets kept private at a single location while adaptive models train to different regions optimizing learning at different soil types.
- Explainable AI: Models built with full transparency enable trust in algorithms insight enabling policy and agricultural decisions by and for farmers.
- Adaptive systems: Pivoting on fed data with changing models helps keep pace with today's agricultural advancements.
- Multi-modal data fusion: Merging chemical biological and physical data alongside remote sensing augments composite data biology predicting analysis.
- Soil plant interaction: Tailored advice through precision modeling of soil health effects on crop yield ensures better outcomes.
- DSS Integration: Mobile farm-based applications get AI models providing actionable insights in real-time to farmers aimed at boosting productivity.
- Low cost models: Making sophisticated yet light AI accessible on mobile gadgets assures supporting smallholder farmer's lower entry barriers.

- Carbon sequestration: Smart farming focused technologies improve quantifying and modeling soil carbon capture determining climate mitigation strategies.
- Soil and agricultural innovations aid in prediction and enhancement for dynamic changes. These measures result in an emergent eco-future using sustainable low-cost farming and convenient predicting tools.

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