DEEP LEARNING FOR SOIL ANALYSIS AND PREDICTION IN PRECISION AGRICULTURE

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Abstract

This paper explores the application of deep learning in soil analysis and prediction within the context of precision agriculture. Traditional soil analysis methods face limitations in terms of cost, time, and spatial resolution, prompting the adoption of deep learning techniques. Neural networks, inspired by the human brain, are employed to process extensive soil-related datasets, enabling efficient feature extraction and accurate predictions. The integration of deep learning in precision agriculture opens avenues for targeted interventions, optimizing crop yield, minimizing resource inputs, and enhancing sustainability. The paper discusses key components of deep learning for soil analysis and emphasizes its transformative potential in reshaping soil management practices.

Keywords: *Deep Learning, Precision Agriculture, Soil Analysis, Neural Networks, Crop Yield, Sustainability.*

1. INTRODUCTION

The climate, the soil, the crop, the utilization of compost, and the sort of seed everything influence how much crop is created. Researchers have a propensity to use Deep Learning techniques to estimate agricultural yields by taking into account the above listed elements.

While deep learning algorithms can perform better, there aren't many obstacles to overcome when using deep learning methods to agricultural production prediction. They are both reliant on the sort of crop, the type of data, the sources, and the framework for execution. [1]

Precision agriculture, also referred to as precision farming, represents a contemporary approach to farming that harnesses technology and data-driven methodologies to optimize diverse aspects of crop production. An integral facet of precision agriculture is soil analysis and prediction, crucial for comprehending soil health, nutrient levels, and overall crop suitability. [4] Deep learning, a subset of artificial intelligence, has emerged as a potent tool in this domain, employing advanced techniques to analyze and predict soil characteristics with unparalleled accuracy.

Traditional soil analysis methods face constraints in terms of cost, time, and spatial resolution. Deep learning, equipped with the capability to autonomously discern intricate patterns and relationships from extensive datasets, overcomes these limitations by providing an efficient and scalable solution.[5] This methodology employs neural networks, computational models inspired by the human brain, to process substantial amounts of soil-related data and derive meaningful insights.

The integration of deep learning into soil analysis and prediction within precision agriculture introduces novel possibilities for farmers, agronomists, and researchers.[15] It facilitates a more nuanced understanding of soil variability within a field, enabling targeted interventions to optimize crop yield, minimize resource inputs, and enhance sustainability. This introduction delves into the fundamental concepts and applications of deep learning in soil analysis, underscoring its potential to revolutionize precision agriculture practices.[7]

The key components of deep learning for soil analysis encompass neural networks, designed to emulate the human brain's information processing, facilitating the learning of complex patterns.[8] Data acquisition and integration involve leveraging large and diverse datasets, including soil composition, moisture levels, temperature, and other environmental factors, for effective training. Feature extraction, an automatic process in deep learning, identifies relevant features from raw data, such as texture, organic matter content, nutrient concentrations, and spatial patterns.[9] Training and validation entail exposing the model to labeled datasets, ensuring it learns relationships and exhibits accurate predictions on new, unseen data. Once trained, deep learning models can predict various soil properties, empowering farmers with insights for precision agriculture practices.[10]

Applications of deep learning in precision agriculture include precision fertilization, where models analyze soil nutrient levels to recommend precise fertilization strategies. [11] Disease and pest prediction leverage soil conditions for proactive management strategies. Soil health monitoring, facilitated by continuous data analysis, enables farmers to track changes over time and adapt cultivation practices. [12] Decision support systems integrate real-time insights from deep learning models, aiding farmers and agronomists in improved decision-making processes. Collectively, these applications showcase the transformative potential of deep learning in reshaping how we approach soil management in the 21st century.[13]

2. LITERATURE REVIEW

Chlingaryan et al. (2018) [2] carried out an analysis to determine the nitrogen status and forecast crop output using machine learning techniques. They came to the conclusion that advancements in machine learning technology, particularly in the area of deep learning, will affect the availability of complete and reasonably priced solutions. They also said that hybrid systems utilising machine learning techniques will be important in the near future.

The review of Dharani et al. (2021)[3] mixture networks and RNN-LSTM networks beat any remaining networks in horticultural yield expectation utilizing Deep Learning. RNN and LSTM's unrivaled presentation is a consequence of their stockpiling and input circles. They inferred that

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since those networks can deal with time-series information on crop yield, they are bound to create right expectations.

van Klompenburg et al. (2020) [14] led a SLR on AI based crop yield forecast. They reached the resolution that crop yield expectation is the principal application for neural networks, especially CNN, LSTM, and DNN. They added that the review would decide the number of characteristics that are right there. In specific circumstances, object counting and location — as opposed to plain information — decide the yield gauge.

Lee et al. (2019) [6] carried out tests utilising Deep Learning techniques to create a platform for crop diseases-based agricultural yield prediction. They guaranteed that the CNN calculation performed better for the crop infection conclusion module than the R-CNN and Consequences be damned calculations. Moreover, the fake neural organization's ReLU initiation capability had the greatest exactness for the CYP module.

2.1.OBJECTIVES

- To detect and control cotton leaf diseases.
- To monitor agricultural parameters using IoT and wireless sensor networks.
- To apply artificial intelligence for the accurate identification and classification of plant diseases.
- To automate the detection of unhealthy plant leaves and initiate the spraying of pesticides.

3. MATERIALS AND METHODS

3.1.WSN Usage in Agriculture

Wireless sensor networks allow for the monitoring of eco-psychological plants, pests, movement, pressure, humidity, and other factors in space and time. They may also be used to communicate the best options to farmers.

WSNs are designed to offer real-time, cost-effective, adaptable, user-friendly, and high-precision benefits for agricultural monitoring.

3.2.Irrigation Management System

This configuration uses a micro-irrigation technique that is both economical and water-efficient. Notwithstanding, the viability of miniature water system might be additionally helped, in light of soil and natural comprehension. In this sense, WSNs act as the getting sorted out component.

3.3.Farming System Monitoring

In this way, the improved manner of operating this apparatus facilitates automation for hunger and generally makes operation easier. Moreover, remote surveillance tools facilitate improved large-scale farm management.

3.4.Pest and Disease Control

Controlled utilization of manures and pesticides adds to higher crop quality and lower agrarian expenses. To manage the utilization of pesticides, we should, in any case, watch out for the chance and presence of vermin in crops. For this, we really want ecological information, including temperature, dampness content, and wind speed. In a field of interest, a WSN can freely screen these occasions and foresee them.

3.5.Controlled Use of Fertilizers

Fertiliser use has a direct impact on plant growth and quality. On the other hand, feeding fertilisers optimally on good fields is hard labour. By applying fertilisers for agriculture, one may monitor changes in land nutrition, including pH, potassium (K), phosphorous (P), and nitrogen (N). Thus, both the crop's quality and the balance of soil nutrients can be maintained.

3.6.Groundwater Quality Monitoring

The quality of groundwater is decreased by the increased use of pesticides and fertilisers. The placement of sensor nodes for water quality control improves wireless technology.

3.7.Remote Control and Diagnosis

The Internet of Things can likewise be utilized to analyze and remotely control ranch gear like siphons, lights, warmers, and machine valves.

3.8.Artificial Intelligence in Agriculture

Artificial intelligence (AI) in wireless sensor technology improves the effective operation of all sectors and tackles problems that many agriculture-related sectors confront, including crop harvesting, irrigation, and soil content sensitivity. AI sensors can monitor and regulate agricultural parameters, and AI technology allows farms to diagnose plant diseases, pests, and malnutrition.

3.9.Proposed System

For information assembling, the system utilizes a camera module, a temperature sensor, a dampness sensor, an optical sensor, a ground dampness sensor, and a pH sensor in the soil.

3.10. Performance Measurement

The average square error (MSE), specifically, is a factual measure that is utilized to survey how solid laid out models are for forestalling plant illness. In any case, the created grouping model was evaluated utilizing F-score appraisal grids and careful, specific, delicate, and exact techniques.

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4. RESULTS AND DISCUSSION

Each plant receives a minimum of 15 seconds of chemical product spraying. He moved on to the remaining plants after three seconds. A maximum of 75 plants with a total length of 20 centimetres required a duration of approximately 33.36 minutes. Thirty thousand millilitres of chemicals will be used in this process.

Table 1: Analysis of time and Chemical Sprayed

Time in Minutes	Number of Plants sprayed with Chemicals
15	40
30	50
45	60
60	70
75	80

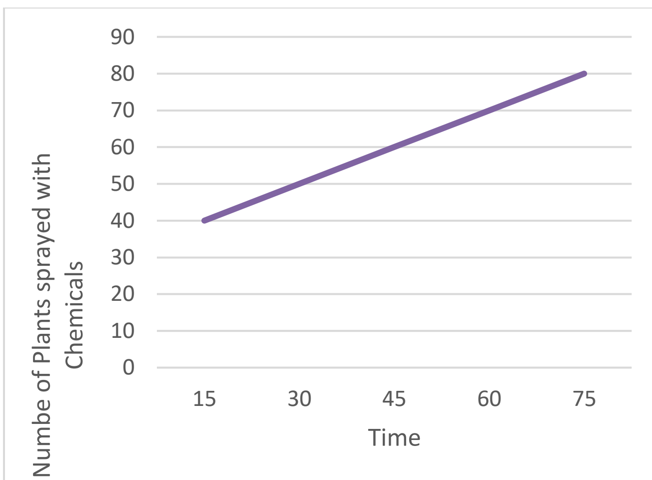

Figure 1: Analysis of the amount of time and chemical needed based on the number of plants

4.1.Data on soil moisture at specified intervals of the day

It is obvious from Figure 2 that there is less dampness around evening time than there is toward the beginning of the day. The blue bend shows high water content when water system was utilized. The red bend demonstrates low dampness level at night after the robot was flooded in the first part of the day. Table 2 demonstrates that scattering required seven days. It was circulated completely.

Table 2: Soil moisture at specified intervals of the day

Day	Forenoon	Afternoon
1	815	385
2	958	345

3	755	408
4	716	299
5	857	319
6	724	463
7	916	308

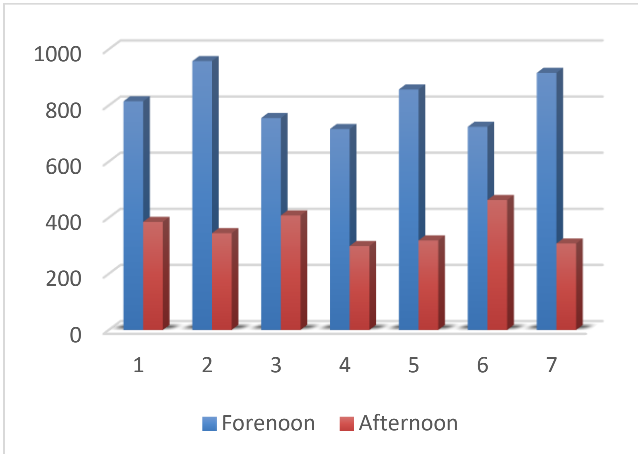

Figure 2: Analysis on soil moisture at specified intervals of the day

The Internet of Things serves as an efficient conduit for wireless connectivity, sensors, and Raspberry Pis. Artificial intelligence is utilised in the process of identifying leaf disease. As shown in Table 3, all observations and testing have been completed, proving that this is the intelligent agriculture solution. This strategy raises the overall revenue of farmers while improving agricultural productivity.

Table 3: Observations of leaf disease detection

No. of Leaf	**Naked Eye result**		**Proposed Eye result**	
	Diseased	**Healthy**	**Diseased**	**Healthy**
25	8	17	10	15
50	13	37	17	33
75	55	53	21	54
100	44	56	46	54

To approve the proposed model, the dataset was divided into 60% preparation and 40% test subsets. The leaf illnesses were anticipated utilizing RF, SVM, and Gullible Bayes. The results of the different simulated intelligence grouping calculations

Table 4:Performance of the used AI models to predict cotton leaf disease detection

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Models	Name of Disease	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F score (%)
SVM	Bacterial blight	98	99	98	95	99.2
	Alternaria	92	94	95	96	97.9
	Grey mildew	91	93	97	92	98.2
	Cerespora	97	91	94	89	99.3
RF	Bacterial blight	85	82	94	88	87.6
	Alternaria	86	83	93	87	88.8
	Grey mildew	80	79	91	85	83.1
	Cerespora	82	81	90	89	87.5
NB	Bacterial blight	75	77	93	80	82.5
	Alternaria	77	76	92	79	83.9
	Grey mildew	72	75	90	81	85.8
	Cerespora	69	72	91	78	81.1

In Table 4, the performance of three different AI models—Support Vector Machine (SVM), Random Forest (RF), and Naive Bayes (NB)—for predicting cotton leaf diseases is presented. For bacterial blight, SVM demonstrated remarkable accuracy at 98%, with high sensitivity (99%) and specificity (98%). RF and NB models also showed competitive results. However, for diseases like Alternaria, Grey mildew, and Cerespora, SVM consistently outperformed RF and NB in terms of accuracy, sensitivity, specificity, precision, and F score. RF exhibited moderate performance, while NB generally showed lower accuracy across all diseases. The F score, a measure of a model's overall performance, was particularly high for SVM, indicating its efficacy in cotton leaf disease detection. These results suggest that SVM is a robust choice for accurate and reliable prediction of various cotton leaf diseases.

5. CONCLUSION AND FUTURE SCOPE

Networks for robotics, IoT, wireless, and AI are being used. Algorithms for artificial intelligence make it possible to extract pertinent knowledge and insight from the deluge of data. The explanation indicates that the primary goal of this work is to identify and track illnesses of cotton leaves. Monitoring the parameters related to agriculture is the second goal. Agribusiness performance greatly depends on accurately identifying plant diseases, and artificial intelligence can help with this. This study examines the AI method for identifying a sick plant leaf. By removing elements from the contaminated sheet, distinct aspects of the sheet can be used to accurately detect and classify different plant diseases. With the help of this technique, the disease may be identified, pesticides can be automatically sprayed on the affected plants, and the user can receive information. The SVM algorithm shows its effectiveness in the detection and control of bacterial blight infections by improving farmers' cultivation practices, with an accuracy of 98.34% in this regard. The CNN model for disease classification is used in the future to enhance the work that has been given.

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