

A Study of Cloud-Enabled Deep Learning for Monitoring and Predicting Soil Health in Agriculture

Ritik Sahu¹, Vinay Lowanshi^{2,*}, Nitya Khare²

Abstract

Soil health is a critical factor in ensuring sustainable agricultural practices and food security. Traditional methods for soil health assessment are often time-consuming, localized, and lack scalability. This study explores the integration of cloud-enabled deep learning techniques to monitor and predict soil health efficiently. Leveraging data from IoT sensors, satellite imagery, and lab-based analyses, a cloud-based framework is proposed to process and analyze soil health parameters such as pH, moisture content, and nutrient levels. Two advanced deep learning models, convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are used to predict soil conditions and identify trends that impact crop yield. The use of cloud computing platforms ensures real-time data processing, scalability, and cost-effective deployment. The framework is a useful tool for precision agriculture because of its excellent accuracy and dependability in forecasting soil health, as shown by experimental findings. This study highlights the potential of combining cloud technologies and artificial intelligence to address the challenges in sustainable farming and paves the way for future research in this domain.

Keywords: Soil health, convolutional neural networks, recurrent neural networks

INTRODUCTION

Crop productivity, environmental sustainability, and human fitness are intricately connected to the intrinsic homes of soil, necessitating the complete series and evaluation of a huge variety of numerous bodily, chemical, and organic soil characteristics. However, this method involves great temporal and monetary commitments. Consequently, researchers and practitioners within the fields of agriculture, ecology, and environmental technology are actively in search of specific and powerful methodologies for correct soil first-rate prediction. Deep learning, an exceptionally successful paradigm in domain names including speech recognition, photograph classification, and natural language processing, emerges as a promising road to this study's endeavor [1, 2]. The study offers a cutting-edge method for soil first-rate prediction leveraging present day deep learning techniques. A large and significant information-set encompassing a complete array of soil parameters, spanning tricky bodily, chemical, and organic attributes, is harnessed. The proposed

*Author for Correspondence

Vinay Lowanshi
E-mail: vinayggicse@gmail.com

¹Research Scholar, Department of Computer Science and Engineering, Sagar Institute of Research and Technology-Excellence (SIRTE), Bhopal, Madhya Pradesh, India

²Assistant Professor, Department of Computer Science and Engineering, Sagar Institute of Research and Technology-Excellence (SIRTE), Bhopal, Madhya Pradesh, India

Received Date: March 25, 2025

Accepted Date: May 08, 2025

Published Date: May 15, 2025

Citation: Ritik Sahu, Vinay Lowanshi, Nitya Khare. A Study of Cloud-Enabled Deep Learning for Monitoring and Predicting Soil Health in Agriculture. Journal of Remote Sensing & GIS. 2025; 16(2): 8–16p.

version synergistically integrates long-short-term-memory (LSTM) networks to adeptly seize the temporal dynamics and relationships amongst variables, and convolutional neural networks (CNNs) to extract exceptionally discriminative functions from soil samples [3]. Rigorous and meticulous experimentation substantiates the version's clear superiority over traditional machine learning models, yielding tremendous accuracy in soil prediction.

The implications of this study reverberate throughout the nation: states of sustainable land management, environmental monitoring, and

precision agriculture. A salient benefit of deploying deep learning in soil first-rate prediction lies in its inherent potential to assimilate and combine a plethora of heterogeneous information sources, encompassing intricate soil chemical and bodily parameters, detailed climatic information, and complex remote sensing information [4, 5]. This complete and holistic method fosters exceptionally specific and complete estimation of soil quality, thereby empowering knowledgeable and enlightened decision-making in the domains of soil management, precision farming, and land-use planning strategies.

Deep learning models have exhibited awesome prowess in tackling a myriad of complicated soil first-rate prediction challenges, spanning the correct prognostication of essential soil attributes including soil organic matter content, soil water retention characteristics, and soil nutrient availability. Diverging from conventional statistical models, deep learning models excel in capturing the complex nonlinear interactions among diverse soil features and a wide array of environmental elements influencing them [6, 7]. However, challenges, including acquisition and curation of significant, notable data-sets, in addition to the inherent risks related to over-fitting, necessitate diligent interest and concerted efforts from researchers a good way to foster the improvement of exceptionally dependable and accurate deep learning models for soil first-rate prediction. The research network on this area is actively engaged in surmounting those hurdles, with the overarching intention of improving the dependability, robustness, and precision of deep learning models in the context of soil first-rate prediction.

LITERATURE REVIEW

Malashin et al. [1]: A study optimizing agricultural productivity and promoting sustainability requires accurate crop yield forecasts to ensure food security. Numerous agronomic and climatic factors, including crop type, year, season, and particular meteorological conditions of Indian states during the crop-growing season, were included in the analysis. One-hot encoding was used to represent features such as harvest and season. Using a Deep Neural Network (DNN) with hyperparameters optimized by a Genetic Algorithm (GA) to maximize the R^2 score was the main goal in order to predict the yield. By adjusting the hyperparameters, the best-performing model was able to reach an R^2 value of 0.92, which indicates good prediction accuracy and accounts for 92% of the variation in crop output [1].

Babu et al. [2]: The optimized DNN model was further analyzed using Explainable AI (XAI) techniques, specifically Locally Interpretable Model-Agnostic Explanations (LIME), to reveal feature importance and improve the interpretability of the model. In order to categorize the best crops based on more precise soil and climate data, the study incorporated extra information and emphasized the significance of characteristics like crop type, soil texture, temperature, and precipitation patterns. To increase accuracy, a GA-optimized DNN was also used for this classification task. The outcomes show how well this method works to categorize ideal crops and forecast crop productivity. Improving the quality of the soil is the most crucial stage. The system is made to use a variety of IoT-based technologies to gather all the necessary data. An extensive summary of national and international research is given in this study. Machine learning algorithms are used to train and process the gathered data in order to forecast areas where quality can be improved. Additionally shown is the state of the soil at the moment.

Babu et al. [3]: wastewater treatment is a complex process with many uncertainties, leading to variations in wastewater quality and costs, as well as environmental risks. Artificial intelligence (AI) has emerged as a potent instrument for wastewater treatment system research and management, and it can solve complicated nonlinear issues. Based on published papers and patents, this report provides an overview of the state and developments of AI research in wastewater treatment.

According to our findings, At the moment, AI is primarily utilized to regulate membrane fouling, optimize models and process parameters, and assess the removal of contaminants (both conventional and emergent). The elimination of phosphorus, organic pollutants, and new contaminants will remain the main topics of future research. Promising research avenues also include multi-objective optimization and the analysis of microbial community dynamics.

Koul et al. [4]: Wastewater treatment is a complex and unpredictable process that can lead to fluctuations in water quality, treatment costs, and potential environmental risks. Artificial Intelligence (AI) has emerged as a powerful tool for the analysis and management of wastewater treatment systems due to its ability to address complex nonlinear problems. This paper reviews the current state and future prospects of AI applications in wastewater treatment, based on existing literature and patents. Our findings indicate that AI is primarily used for controlling membrane fouling, optimizing process models and parameters, and evaluating the removal efficiency of various pollutants -- including conventional, emerging, and priority contaminants. Future research is expected to continue focusing on the removal of organic pollutants, emerging contaminants, and phosphorus. Additionally, promising directions include studying microbial community dynamics and implementing multi-objective optimization strategies. According to the knowledge map, future developments could involve the use of image-based AI and other algorithms in wastewater treatment, the prediction of water quality under circumstances, and the integration of AI with other information technologies. We also examine the development route of artificial intelligence (AI) in wastewater treatment and give a quick outline of the evolution of ANNs. Our results offer insightful information about the possible advantages and difficulties for researchers using AI to clean wastewater.

Zhang et al. [5]: A subfield of artificial intelligence (AI) called machine learning (ML) has proven useful in a few remote sensing applications, including the acquisition of geophysical data like soil moisture content (SMC). Deep Learning (DL) is a branch of machine learning that outperforms classical machine learning in solving prediction problems by using models with intricate structures. A DL-based framework for SMC inquiries was created for this study. A Bayesian optimization strategy was used to fine-tune the hyperparameters of the ML models to improve their predictive performance. Our study's findings demonstrated how five ML prediction models performed better when using the enriched data. On a 10% independent test subset, Gaussian Process Regression (GPR) had the greatest predictive accuracy with 4.05% RMSE and 0.81 R^2 .

Kumar et al. [6]: Today, agriculture faces great challenges to increase productivity and quality while reducing its environmental impact. Addressing these challenges through scientific and technological advances has been the goal of many research teams around the world. Sustainable crop production relies on innovations in many fields, including agronomy, sensing, data science, robotics and biotechnology. Over the last two decades, there has been a growing trend towards the application of remote sensing techniques in the agricultural sector. Indeed, modern remote sensing offers unprecedented opportunities to easily, flexibly and quickly capture images of the land, thereby providing interesting information about the condition of the plants. An important topic that has dominated the field of remote sensing for many years concerns automated data processing, modeling, and analysis. Meanwhile, deep learning approaches continue to show remarkable performance in several areas, and existing studies recognize that this approach plays a key role in solving many challenging problems related to data modeling, interpretation, classification, etc. Accurate estimation of soil ion composition is crucial for preventing soil salinization and controlling crop irrigation. Traditional laboratory composition measurements, although accurate for calculating soil salinity parameters, often limit their application due to high costs and difficulties in long-term field measurements.

Liu et al. [7]: In this work, the authors examined the effectiveness of three machine learning models: Total dissolved ion content (TDI), potential salinity concentration (PS), sodium adsorption ratio (SAR), sodium exchangeable fraction (ESP), residual sodium carbonate (RSC), and magnesium adsorption ratio (MAR) in soil can all be predicted using Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGB). The model's input variables included soil temperature (T), electrical conductivity (EC), soil water content (SWC), and hydrogen concentration (pH). To train, test, and validate the model, 467 soil samples from the Shihezi region in northwest China were employed. The results showed that when EC, T, and pH were used as input variables, the RF and SVM models functioned well; however, when EC, SWC, and T were used, the XGB model performed better. Machine

learning is an essential decision support tool for predicting agricultural yields and helping with decisions about which crops to sow and what to do throughout the growing season.

Klombenburg et al. [8]: Numerous machine learning techniques have been used to aid in crop production prediction studies. To extract and compile the features and methods utilized in agricultural production forecasting research, we carried out a systematic literature review (SLR) in this work. 50 papers were chosen for additional analysis based on the inclusion and exclusion criteria after we extracted 567 pertinent studies from six electronic databases using the search parameters. We thoroughly examined these chosen papers, examined the aspects and methodologies employed, and offered recommendations for more study. Our data shows that temperature, precipitation, and soil type are the most frequently utilized features, while artificial neural networks are the most often employed technique in these models.

Zhou et al. [9]: Instead of storing data on your own hard drive (local server or PC), cloud computing refers to the availability of computer resources via the Internet (a network of distant servers). Since cloud computing is a relatively new idea, most poor nations are not yet prepared to embrace and use it. The manner that individuals acquire agricultural information will be altered by cloud computing. In the future, cloud computing infrastructure will play a crucial role in farmers' life. Cloud-based agricultural applications are becoming popular in several nations, including the US, Japan, Bhutan, and South Africa. The Internet of Things (IoT) has the potential to revolutionize the agriculture sector by providing real-time data on the condition of crops and livestock. This study aims to assess the scalability and performance of Wireless Sensor Networks (WSNs) in agriculture in two scenarios: monitoring a stable for horse training and an olive plantation. This paper presents performance evaluation metrics for stationary and mobile scenarios of 6LowPAN networks and suggests a novel classification method for IoT in agriculture based on several parameters. The performance of the 6LowPAN and low power loss network (RPL) routing protocols in the two agricultural situations is modeled and simulated in this study using the realistic WSN simulator COOJA. The primary distinction between the simulation setups for mobile and stationary nodes is the nodes' mobility.

Gupta et al. [10]: The study compares the average power consumption, radio duty cycle, and connection level of the sensor network graph in order to define various aspects of the power requirements in the two agricultural settings. The Random Waypoint (RWP) model is used to depict the motions of the horse in this innovative method for modeling and simulating moving animals in the COOJA simulator. The benefits of employing the RPL protocol for routing in both stationary and mobile sensor networks are demonstrated by the results, which enhance network performance and support dynamic topologies. Simulations and experimental verification of the suggested framework show that it is appropriate for both stationary and mobile applications, with minimal latency and effective communication performance [11]. The findings offer farms and livestock operations an effective monitoring and management solution, which has various real-world applications in precision agriculture. All things considered, this study offers a thorough review of the scalability and performance of WSNs in the agriculture industry, along with a novel classification scheme and performance evaluation criteria for both fixed and mobile situations for networks with 6LowPAN. The findings demonstrate that the suggested framework provides low latency and effective communication performance, making it appropriate for precision agriculture.

HEALTH OF SOIL

“Soil health” refers to the soil's continuous capacity to sustain plants, animals, and people as a living ecosystem. It includes soil's physical, chemical, and biological characteristics, all of which work together to improve agricultural productivity, preserve environmental quality, and promote the health of plants and animals. The structure, organic matter content, nutrient availability, pH balance, and microbial activity of soil are important markers of its health. Healthy soil efficiently retains water, resists erosion, supports root development, and acts as a natural filter for contaminants. Factors such as overuse of chemical fertilizers, intensive farming practices, deforestation, and climate change can degrade soil health, leading to reduced fertility, loss of biodiversity, and increased greenhouse gas emissions.

Promoting soil health is critical for sustainable agriculture and requires practices like crop rotation, reduced tillage, organic farming, and the integration of advanced technologies for monitoring and management.

Image Acquisition

The images are vital and essential to monitoring the plant leaf condition. The image acquisition involves diverse apparatus. Appropriate assessment of RGB color within image is a necessary phase toward image capturing. Sensitivity of light in photo sensors, spatial resolution, as well as digital processing has enhanced considerably. Nowadays, each person, cultivator, or plant grower uses modern technology such as digital cameras integrated with mobile phone or tablet.

Image Pre-Processing

It follows the acquisition of image. Image acquisition and making images-database, as well as pre-processing are completed in this process. Database pre-processing is used for removing image undesired misrepresentation and offers feature augmentation. When considering a plant leaf, a variety of colors is attained. To differentiate diseased leaf color from leaf's original color, the RGB values are transformed during pre-processing to enhance perception. Thus, improvement in color accuracy for disease detection, and the pre-processing independency is fundamentally needed.

Image Segmentation

The diseased spot is segmented from the leaf in the image segmentation procedure. The dissimilar segmentation is obtainable such as clustering, thresholding, identification of edge, and segmentation techniques. The segmentation system accuracy depends on the quality of the data sets. As well it precisely segments the diseased as well as healthy parts of leaf. After segmentation, the diseased area of the leaf is extracted.

Feature Extraction

It is used for extracting the segmented image features. In a mathematical as well as texture analysis, texture features are considered based on geometric distribution of pixel recognized in the image matrix. Texture as well as statistical attribute removal are used to analyze the picture as a textured entity.

DEEP LEARNING

Deep learning is a branch of machine learning that focuses on evolutionary algorithms and classification problems [11]. Learning may be classified into three categories: unsupervised, semi-supervised, and supervised. The domains that have used deep-learning architectures include deep learning models, fully connected networks, recurrent neural networks, and artificial neural networks which include machine learning, artificial intelligence, computer vision, data analysis, social media site filtering, computational linguistics, computational biology, drug design, information retrieval, and clear overview [12–15]. Artificial neural networks (ANNs) were influenced by biological systems' decentralized organizational structure and knowledge acquisition. There are various ways in which ANNs differ from the human brain. Specifically, the organic brains of the majority of functioning things are dynamic and analog, but neural networks are steady and symbolic.

The usage of several network layers is referred to as “deep learning” in this context. According to early research, a network with one unconstrained width hidden layer and a non-polynomial input layer can be used as a universal classifier, but a linear perception cannot [9]. A more modern variation that has several layers of bounded size is called deep learning, which, in moderate circumstances, preserves theoretical subjectivity while enabling functional application and optimization. For the sake of performance, trainability, and intelligibility, deep learning structures are allowed to vary and deviate greatly from scientifically informed connectionist models, which accounts for the “organized” aspect [16].

Convolutional neural networks (CNNs), in particular, are at the center of most emerging deep learning methods. They may also include propositional formulation or layer-wise ordered latent variables in deep generative models, including deep belief networks and deep Boltzmann machines. The capacity to

convert the input data into a somewhat more abstract and composite representation increases with each deep learning level. An image identification method may use a matrix of pixels as its raw input. Then, while the second layer might design and encode edge configurations, the first representative layer could encode edges and abstract the pixels. The fourth layer might identify that a face is present in the image, while the third layer could encode a nose and eyes. Crucially, a deep learning algorithm may automatically determine which features are part of whatever level [17].

“Deep learning” describes the number of layers that are used to change the data. Credit assignment path (CAP) depth is particularly high in deep learning systems [5]. The input-to-output transition chain is known as the CAP. CAPs are used to define possible causal relationships between input and output. In a feedforward neural network, the depth of the CAPs is equal to the network's depth plus one hidden layer. In recurrent neural networks, where a signal can pass through a layer more than once, the CAP depth is essentially infinite. The majority of studies concur that deep learning requires a CAP depth larger than 2, despite the fact that there is no universally accepted depth level that distinguishes shallow from deep learning. CAP of depth two is a universal approximation in that it may mimic any function [7].

METHODOLOGY

The proposed framework integrates cloud computing and deep learning technologies to provide an efficient and scalable solution for monitoring and predicting soil health. The framework consists of the following key components:

1. *Acquisition and integration of data*
 - i. *Sources of data:* Compile information on the moisture content, pH, and nutritional levels of the soil. Describe the vegetation and land use in both space and time. To combine data from several sources into a single dataset for analysis, use cloud infrastructure.
2. *Cloud infrastructure*
 - i. Employ cloud-based storage is (e.g., AWS S3, Google Cloud Storage) to handle large-scale soil data. Use scalable computing resources for data pre-processing and model training. Automatically scale storage and computation based on data volume and complexity.
3. *Data preprocessing*
 - i. Remove noisy, inconsistent, or incomplete records. Derive key features from raw data, such as normalized difference vegetation index (NDVI) from satellite imagery or texture and structure from soil data.
4. *Deep learning model*
 - i. To find temporal trends in soil health data, use Long Short-Term Memory (LSTM) networks.
 - ii. *LSTM:* One of the various varieties of Recurrent Neural Networks (RNNs), LSTM may also capture data from previous phases and utilize it to make predictions for the future.

An Artificial Neural Network (ANN) usually consists of three layers: (1) input layer, (2) hidden layers, and (3) output layer. The number of nodes in the input layer of a neural network (NN) with a single hidden layer is always determined by the data's dimension. These nodes are connected to the hidden layer by linkages known as “synapses”. Weight is a coefficient that determines the decision-maker for signals in the relationship between each pair of nodes from the input to the hidden layer. Naturally, learning involves constant weight adjustments; after learning is complete, the Artificial Neural Network will have the ideal weights for every synaptic connection.

The cell state is the main element of LSTM (Figure 1). Using the sigmoid function, gates are used to secure the cell state when information is added or removed (one implies allowing the alteration, whereas a value of zero signifies denying the modification). Their distinct gates can be distinguished: Using a sigmoid function, the forget gate layer determines which information LSTM will remove from the cell state based on the input data and the data received from the previously buried layer (one indicates keep it, 0 signifies delete it). It is computed as follows:

$$f_t = \sigma(w_f \{h_{t-1}, x_t\} + b_f) \quad (1)$$

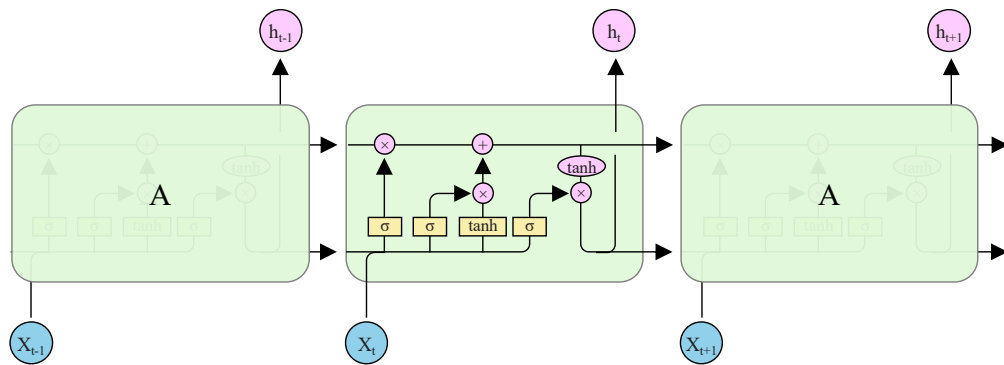


Figure 1. An LSTM's internal structure.

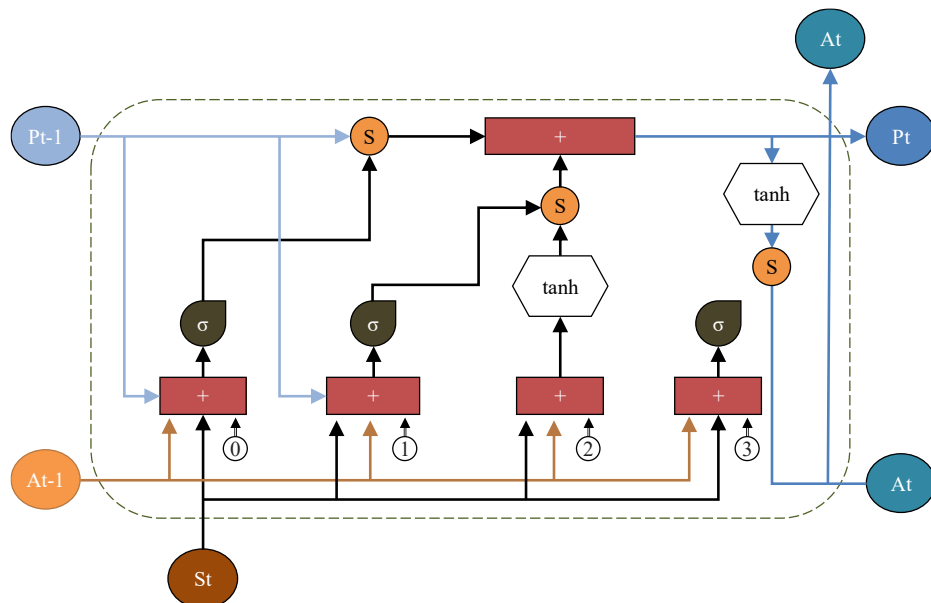


Figure 2. Working of LSTM.

The input/update gate layer selects the data that the LSTM will keep in the cell state. After the input gate layer determines which information will be updated first using a sigmoid function, a Tanh layer proposes a new vector to be added to the cell state.

The LSTM then updates the cell state with the new vector values after forgetting the information we chose to ignore. Figure 2 shows the working of LSTM model further it is computed as follows:

$$it = \sigma(wi \{ht-1, xt\} + bi) \quad (2)$$

and

$$C^t = \tanh(wc \{ht-1, xt\} + bc) \quad (3)$$

By using a sigmoid function to choose which part of the cell LSTM will output, the output layer determines what will be our output, and the layers are shown in Figure 3. The result is then sent through a Tanh layer (value between -1 and 1) to output only the information we have chosen to send to the following neuron. It is computed as follows:

$$Ot = \sigma(wo \{ht-1, xt\} + bo) \quad (4)$$

and

$$ht = Ot \times \tanh(Ct) \quad (5)$$

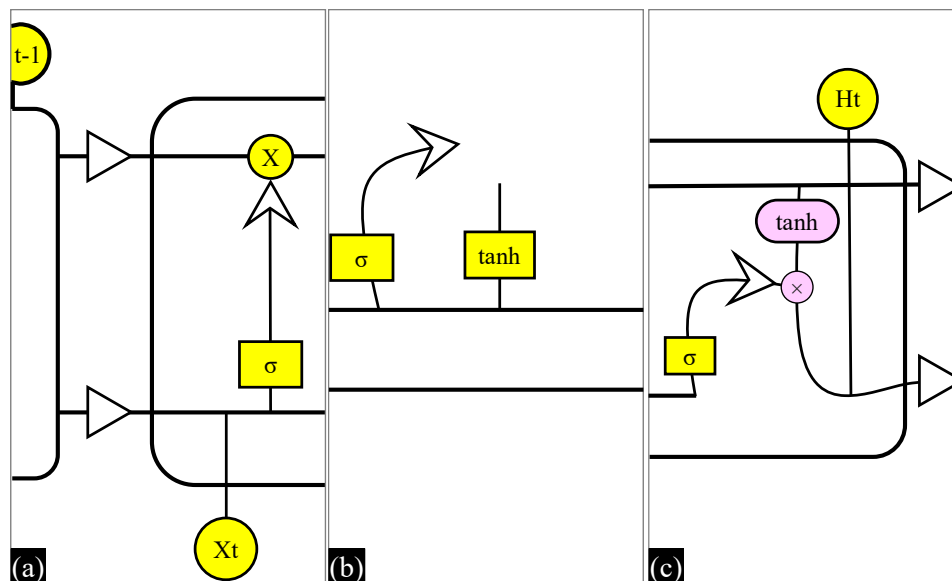


Figure 3. LSTM layer. (a) Forget gate layer, (b) input/update gate layer, (c) output gate layer.

CONCLUSION

This study highlights the transformative potential of integrating cloud-enabled deep learning techniques for monitoring and predicting soil health in agriculture. By leveraging real-time data from IoT sensors, satellite imagery, and soil analysis, the proposed framework demonstrates significant improvements in the accuracy and scalability of soil health assessment. Deep learning models such as CNNs and RNNs effectively analyze and predict soil parameters, while cloud computing platforms ensure seamless data storage, processing, and accessibility.

The findings underscore the practical advantages of this approach, including enhanced precision in soil health management, real-time monitoring capabilities, and cost-efficiency for large-scale agricultural operations. For wider implementation, however, issues including data accessibility, model interpretability, and cloud infrastructure expenses need to be resolved.

Future research can explore integrating federated learning to enhance data privacy and collaboration among stakeholders, as well as incorporating advanced AI techniques like transformers for improved predictive accuracy. By advancing these technologies, this work contributes to the development of sustainable and data-driven solutions for modern agriculture.

REFERENCES

1. Malashin I, Tynchenko V, Gantimurov A, Nelyub V, Borodulin A, Tynchenko Y. Predicting sustainable crop yields: Deep learning and explainable AI tools. (MDPI) Sustainability. 2024; 16(21): 9437.
2. Suresh Babu CV, Mahalashmi J, Vidhya A, Nila Devagi S, Bowshith G. Save soil through machine learning. In: Habib M, editor. Global Perspectives on Robotics and Autonomous Systems: Development and Applications. Pennsylvania, USA: IGI Global; 2023. p. 345–62.
3. Suresh Babu CV, Yadavamuthiah K, Abirami S, Kowsika S. Artificial intelligence in wastewater management. In: Shikuku V, editor. Artificial Intelligence Applications in Water Treatment and Water Resource Management. Pennsylvania, USA: IGI Global; 2023. p. 31–45.
4. Koul B, Yakoob M, Shah MP. Agricultural waste management strategies for environmental sustainability. Environ Res. 2022; 206: 112285.
5. Zhang Z, Chen J, Li D. A deep learning framework for soil moisture prediction using sensor and remote sensing data. Agric For Meteorol. 2021; 308: 108568.
6. Kumar V, Nehra M. Machine learning and deep learning approaches in remote sensing for agriculture. J Photogramm Remote Sens. 2021; 174: 16–29.

7. Liu X, Zhang J, Chen Y, Sun S, Wu L. Soil nutrient prediction using machine learning models in a highly variable arid environment. *Sci Total Environ.* 2021; 772: 144773.
8. Van Klompenburg T, Kassahun A, Catal C. Crop yield prediction using machine learning: A systematic literature review. *Comput Electron Agric.* 2020; 177:105709.
9. Zhou L, Pan S, Wang J, et al. Cloud computing and agriculture: A literature review. *Comput Electron Agric.* 2020; 179: 105840.
10. Gupta S, Gupta C, Khanna A. A cloud-integrated IoT-enabled framework for precision agriculture. *Comput Electron Agric.* 2020; 172: 105338.
11. Behzad M, Kiani-Harchegani M, Karimi M, Mousavi S. Machine learning-based prediction of soil cation exchange capacity using soil spectral data. *Catena.* 2020; 188: 104444.
12. Pham TV, Jeon CH, Han D. A comparative study of machine learning techniques for predicting soil water content. *J Hydrol (Amst).* 2019; 575: 22–33.
13. Wang Q, Zhou L, Zhou Y, Ma J. Machine learning algorithms for soil organic carbon prediction using visible and near-infrared spectra. *Soil Tillage Res.* 2019; 195: 104384.
14. Duan Y, Zhang L, Lu S, Chen X, Zhou X. Soil nutrient prediction using visible and near-infrared spectroscopy: A comparison of models and wavelengths. *Soil Sci Soc Am J.* 2018; 82(4): 1029–40.
15. Mishra A, Sharma SK, Pandey A. Predicting soil organic carbon stock using geostatistical techniques and remote sensing indices. *Ecol Indic.* 2017; 78: 400–12.
16. Gholizadeh A, Ayoubi S. Predicting soil organic carbon and total nitrogen using soil spectral data and machine learning algorithms. *Catena.* 2017; 156: 35–45.
17. Ananthi N, Divya J, Divya M, Janani V. IoT based smart soil monitoring system for agricultural production. In: 2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR). 2017; 209–214.