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Real-time Soil Nutrient Mapping Using Deep Learning and Sensor Fusion in Precision Farming

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Abstract

Precision farming is gaining much popularity as it increases crop yields and, at the same time, reduces input costs. Soil is a major factor in precision agriculture, particularly in terms of nutrient management, where we analyze and determine the quantity of nutrients in the soil that need to be supplemented with fertilizers to improve crop yield. Traditional soil nutrient detection methods were time-consuming and labor-intensive, making them unsuitable for large-scale agricultural planting. In this work, we leverage automatic, real-time soil nutrient mapping in precision agriculture through deep learning and sensor fusion. The approach is based on deep learning and utilizes both soil sensors and remote sensing. They have been used to relate sensor data to soil properties through deep learning. By sensor fusion, better prediction ability and precision are achieved. The procedure begins by capturing field and environmental data using sensors and drones and collecting thousands of data samples. The data is preprocessed and then processed through a deep learning model, which was trained to map soil nutrients. In-plant nutrient level prediction model: In this situation, plants with known nutrient levels will be selected only for model calibration. This farm nutrient level prediction model achieves optimal farm nutrient levels using remote sensing information. The model improves its ability to predict soil conditions over time as it learns and iterates. The method of the

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invention offers several benefits compared to traditional methods of soil nutrient mapping. It Saves You Time with Soil Sampling and Precise Measurements.

Keywords: Large-Scale, Labor-Intensive, Soil Nutrient, Real-Time, Soil Conditions.

1 Introduction

Real-time Soil Nutrient Content Map Conventional soil samples App – Using the latest technology, data and processing to create and access for the farmer a real-time map of the nutrient content in their soil. It enables the rapid and accurate assessment of soil fertility and the nutrient management required for sustainable agriculture and land use (Senapaty et al., 2023). It begins with one of the data acquisitions steps in real-time soil nutrient mapping using the perspective tool. The sources can be anything, such as aerial or satellite images, ground sensors, or soil sampling (Lachgar et al., 2024). Such data will be further processed to estimate and create a typical nutrient level distribution map for the soil. This information will then be processed by high-end software and algorithms to obtain a comprehensible set of data on the nutrient concentration in the soil (Reyana et al., 2023). Real time soil nutrient mapping has an enormous advantage in producing higher resolution and accurate maps with a short turn-around time. New equipment permitting a more detailed description of soil are responsible for this development (Ahmad et al., 2022). Real time soil nutrient mapping will help you determine where the field is lacking/has an excess of nutrients down to areas of a field. This is an effective means to decrease the potential of environmental damage, while avoiding fertilizer costs (Sivakumar et al., 2022). For instance, through real-time soil nutrient maps (CDs), farmers and land managers can make them to develop a plan for nutrient management during the growing season (Aadiwal et al., 2025). In-situ monitoring and control of soil nutrient levels, decreasing corrections from deficit to increase on the fertilizing amount and increasing production; would be much healthier for the soil and a higher quality gain (Mehedi et al., 2024). Not only can you learn something about the ecology of a site, but you can also track how levels of soil nutrients fluctuate (or don’t) over time with this technology. Conclusions Overall, the information from this study may provide a platform for formulating long-term soil management strategies and help maximize the application of nutrients, which can aid in developing sustainable agricultural action plans (Bisht, 2023). Contemporary, real-time soil nutrient mapping technologies (which are typically sensor- and data manipulation-based) facilitate the identification of high-resolution nutrient maps of targeted land areas as fast and accurately as possible. This information is of great importance to farmers, agronomists, and other professionals in the agricultural sector, enabling them to make informed decisions, such as whether to fertilize, irrigate, and manage crops, among others (Mustapha et al., 2017). These studies suggest that numerous practical problems need to be solved for real-time soil nutrient mapping to be successful. The sensors used for detecting soil nutrient levels need to be reliable and robust (Barrile et al., 2022). They need to detect minute alterations in those amounts and yield a reliable, soil-type-independent result (Paul et al., 2022). This aggregated data, when complete, is transferred to farmers or agronomists, as a result of which mistaken decision-making can occur if the data collection is incorrect. Maps from data processing must be precise and economical. It often means sifting through and making sense of large amounts of data in a short amount of time. Mapping must be quick and accurate, and any lag in data processing can result in outdated or even inaccurate maps, which could have significant implications for farm decisions. The integration and interoperability of various technologies and equipment are also another technical challenge (Monica Nandini, 2024). Several other manufacturers' sensors, data processing software, and toolsets are also being utilized for real-time soil nutrient mapping (Nambiar & Varma, 2023; Dosjanova, 2025). This technology wasn't designed to communicate with one another, but they must — if a working soil mineral fertility map is going to be a thing. The main contribution of the research has the following:

Fact sheets on yield by crop type assist farmers in knowing what practices may lead to yield increases or changes in grain quality: Type of crop Tillage Pest control Rotations Time of planting Previous crop Rainfall. It provides them with passenger information to help farmers and scientists manage the amount of fertilization (including nitrogen, phosphorus, potash, and phosphoric acid). The number of crops to grow, where to grow them, and how to treat them can be used by farmers to accurately add fertile matter, increasing the effectiveness of manure and meeting the nutritional needs of crops, resulting in better growth and yield. This enables the rapid identification of soil dietary deficiencies. More productive labor, cheaper farms.

Real-time Soil Nutrient Mapping and its Implication for Sustainable Agriculture and Environment-Dissemination to Precision Agriculture This approach prevents the redundant application of inputs such as fertilizers, water and pesticides over others', including quantity of input or their position, which is critical to sustainable agriculture and high crop productivity. It also has relatively minor negative environmental impacts (e.g., nutrient leaching, soil erosion, greenhouse gas emissions) and, as a result, is a critical component of environmental stewardship.

The remaining part of the research has the following chapters. Chapter 2 describes the recent works related to the research. Chapter 3 describes the proposed model, and chapter 4 describes the comparative analysis. Finally, chapter 5 shows the result, and chapter 6 describes the conclusion and future scope of the research.

2 Related Words

Zhao et al., (2021) have discussed Land analytics for precision agriculture encompasses the collection and analysis of data from automated vehicle sensors, including GPS, soil sensors, and weather sensors, to develop detailed maps and models of farm fields. This data integration is instrumental for making accurate and automated decisions for tasks such as planting, irrigation, and nutrient application. Radočaj et al. (Radočaj et al., 2022) have discussed How Remote sensing, including satellite images and aerial photographs, can be used to monitor the health and soil condition of crops. When used in conjunction with cutting-edge machine learning and data analytics methodologies, precision agriculture and the development of efficient fertilization strategies in specific areas will enable optimized crop production. Munnaf et al., (2023) have discussed Exact nitrogen application on the rate for opium poppy. It includes the gathering of measurements on soil and plant status using 'proximal' and 'remote' sensors. This information is then combined to construct an accurate nitrogen prescription map, allowing fertilizer to be placed where it is needed most. It will achieve the best growth and production of opium poppy and minimize environmental harm due to excessive fertilizer. Inoue et al., (2024) have discussed Hyperspectral sensing is a remote sensing technology that utilizes a range of wavelengths to determine the spectral signature of individual soil constituents, such as carbon. Mapping the amount of carbon in the soil by the acre enables farmers to identify areas that are less fertile and apply soil amendments to spread the crop more uniformly, thereby increasing carbon levels in the soil overall for sustainable agriculture. Munaganuri et al., (2024) have discussed PAMICRM is a system for precision agriculture that utilizes technologies such as image analysis and remote sensing data to calculate crop water requirements. Monica Nandini (Monica Nandini, 2024) have discussed that can combine various kinds of data from different sources to provide farmers with accurate and timely information to manage water resources effectively and increase crop yields. Karunathilake et al., (2023) has discussed Precision agriculture, also known as smart farming, combines technology, data analytics, and agronomy to maximize agricultural output through information-driven approaches. Crop monitoring with drones According to DW, "a variety of technologies, such as drones, sensors, and satellite imagery, now make it possible for farmers to know exactly when they need to sow, fertilize and harvest. Li et al., (2022) have discussed Soil and crop sensing utilizes technology to monitor and report on soil conditions and crop health for precision farming. It empowers farmers better to manage irrigation, fertilization, and other management operations, enabling them to achieve higher crop yields with a lower environmental impact. Kakarla et al., (2022) have discussed new sensing technologies in precision agriculture are the latest implementation that relies on high-tech sensors and data analytics to generate instantaneous data on soil, plants, and other environmental conditions. These technologies enable farmers to use data-driven logic for careful planning, optimize crop yield, conserve resources, and promote sustainability. Wang et al., (2022) has discussed the bidirectional GRU and RNN-based embedding of the fusion condition mechanism model for predicting soil nutrient concentration. It leverages data from various sources and integrates attention to emphasize the most important information, thereby enhancing prediction performance. It can be used in agriculture and on soils to improve crop yields. Shaikh et al., (2022) have discussed Digital farming, including precision agriculture and smart farming, utilizes cutting-edge technology to enhance farming practices and increase crop production. Machine learning and AI can provide a key hand by informing data-driven decision-making, predicting better planting and harvesting times, and identifying potential trouble spots ahead of time through real-time monitoring. Belal et al., (2021) have discussed Smart farming technologies include the use of modern techniques, such as GPS mapping, remote sensing, and data analytics, to enhance agricultural production and improve Soil and crop quality. These technologies enable farmers to make informed decisions about crop inputs and management, leading to higher yields, more efficient resource utilization, and improved overall farming efficiency. Abioye et al., (2022) and Gupta & Joshi, (2025) have discussed Drone Deploy utilizes machine learning and digital farming solutions for precision irrigation management, optimizing irrigation and minimizing water wastage. These solutions gather data from a soil moisture sensor and other variables, such as the weather forecast, to determine exactly when and how much to irrigate different Crops, making water more efficient and increasing productivity. Kganyago et al., (2024) have discussed Optical remote sensing is a new technology in agriculture that utilizes sensors installed on satellites, drones, or ground-based platforms to collect data on the health status and growth of crops. This information is then combined with sophisticated machine learning methods to predict biophysical and biochemical parameters, allowing farmers to optimize precision agriculture measures. Babu et al., (2025) have discussed Farming productivity soil mapping is a method of gathering information about the Soil system and analyzing it using the Internet of Things (IoT). It enables growers to make data-driven decisions regarding what to plant, how to irrigate, and when and how to fertilize, leading to more sustainable and productive agricultural practices and a better environmental impact. Saddik et al., (2022) have discussed This project designs an autonomous, low-cost robot with accurate sensors for monitoring soil in agricultural greenhouses. It will gather soil data and develop a detailed map to help farmers enhance their soil management. It will also contribute to improved harvest quantity, reduced soil mapping time, and lower manual labor and costs.

A major challenge for real-time soil nutrient mapping is the limitation of the sensors from the data acquisition side. These sensors focus only on a few physical soil properties (such as pH, moisture, and temperature) and are unreliable for measuring nutrients such as nitrogen or phosphorus (Table 1).

Table 1: Comprehensive Analysis

Author	Year	Advantage	Limitation
Zhao et al., 2021	2021	Increased efficiency in farming operations by providing real-time analytics and insights for improved decision making and resource allocation.	High cost of equipment and sensors can be a limitation for small-scale or low-income farmers to adopt precision agriculture technology.
Radočaj et al., 2022	2022	Increased efficiency and accuracy in assessing plant health and nutrient needs, leading to more targeted and effective fertilization practices.	Incomplete or low-resolution data may lead to imprecise fertilizer application, resulting in inefficient use of resources and potential negative impacts on the environment.
Munnaf et al., 2023	2023	Increasing crop yield and quality by accurately targeting nitrogen fertilizer application to specific areas of the field.	One limitation could be the accuracy of the remote sensor data and its ability to accurately determine nitrogen levels in the opium poppy plants.
Inoue et al., 2024	2024	One advantage is the ability to accurately assess and target areas for carbon amendment, leading to more effective soil carbon sequestration.	Hyperspectral sensing may not accurately capture soil carbon content in areas with high levels of soil moisture or vegetation cover.
Munaganuri et al., 2024	2024	Improved accuracy in estimating crop water requirements through utilizing multiple remote sensing data sources and multimodal image analysis techniques.	One limitation is that the accuracy of the estimation may be affected by weather and environmental conditions.
Karunathilake et al., 2023	2023	Increased efficiency and productivity by using advanced technologies to optimize crop management, leading to higher yields and cost savings.	Limitation: Reliance on technology may lead to higher costs, making it less accessible to small-scale and resource-poor farmers.
Li et al., 2021	2022	Accurate and timely monitoring of crops, allowing for more efficient use of resources and improved crop management decisions.	One limitation of soil and crop sensing is the potential for inaccuracies or errors in the data collected, leading to incorrect management decisions.
Kakarla et al., 2022	2022	Increased efficiency and accuracy in crop management and resource allocation, leading to improved yields and cost-saving opportunities for farmers.	High initial cost and need for complex infrastructure may limit adoption and accessibility for small-scale or resource-constrained farmers.
Wang et al., 2023	2023	Improved accuracy in soil nutrient content estimation.	Limited by the amount and quality of available training data, which can affect the accuracy of the model.
Shaikh et al., 2022	2022	Increased efficiency and productivity in farming operations by reducing human labor and improving crop yields through data-driven decision making.	Dependency on accurate and sufficient data inputs for optimal performance and decision-making.
Belal et al., 2021	2021	Increased efficiency and accuracy in managing and applying resources, leading to optimized soil conditions and improved crop yields.	Expensive initial investment and technical knowledge required may limit access for small-scale or resource-poor farmers.
Abioye et al., 2022	2022	Increased efficiency in water usage, leading to improved crop yield and reduced costs for farmers.	One limitation is that it relies heavily on accurate data collection and modelling, which may be difficult to achieve in certain environments.
Kganyago et al., 2024	2024	Improved precision and accuracy in monitoring crop health and growth, leading to more targeted and efficient management practices and higher crop yields.	One limitation of optical remote sensing for crop parameters is its inability to accurately measure below-canopy biomasses and soil characteristics.
Babu et al., 2025	2024	Improved monitoring and management of soil conditions can lead to optimized crop growth and higher yields, promoting sustainable and efficient farming practices.	Reliance on technology for data collection may not accurately reflect real-world conditions and can be expensive for small-scale farmers.
Saddik et al., 2022	2022	Improved efficiency and accuracy in identifying soil characteristics and nutrient needs, leading to more effective and sustainable farming practices.	Limitation: The accuracy and efficiency of the mapping process may be affected by adverse weather conditions or uneven terrain.

Real-time soil nutrient mapping is based on the high-precision. The resolution offered by the data is impacted by soil type, terrain, planting vegetation, and a variety of other elements that may serve to reduce the resolution. Relatedly, obtaining high-resolution data at cost is challenging, especially at large scales.

Seamless soil nutrient maps are developed using advanced algorithms and data interpretation and extraction techniques for nutrient mapping. These processes may be influenced by multiple factors, including the quality of the data, sensor errors, and calibration issues, which can result in errors and uncertainties in the nutrient maps. Also critical are experienced, knowledgeable people to interpret and analyze the data (amazingly enough).

A hot topic in machine learning (ML), which is believed to disrupt precision agriculture, is deep learning. It involves training and utilizing numerous deep neural networks on extensive datasets. It has greatly enhanced the precision and efficiency of techniques used in small-scale farming (precision farming) when combined with other technology, such as sensor fusion. Sensor fusion - Sense camera, GPS, and weather sensors and fuse them to provide a bigger and better picture of the farm premises. This makes it a device for observing crop and row quality and conditions, which will assist in making decisions promptly based on data for crop management, irrigation, pest control, and other purposes. I correlate deep learning with sensor fusion to enable accurate and timely decision-making. By continuously learning from data, our deep learning algorithms can respond to dynamic conditions and provide tailored, local advice to farmers, enabling them to achieve optimal sustainable production and resource conservation. Deep learning and sensor fusion, when combined, have the potential to bring new life to the area of precision farming, which may also influence the future of agriculture.

3 Proposed System

A. Construction Diagram

- **Soil Health Connotation**

The word 'health' is derived from this form and thereafter sounds 'The ability of Soils to function as a living system, capable of supporting plants, animals and humans'. Soil health refers to the physical, chemical, and biological properties of soil that influence life processes. Critical Soil Health Operations: Soil Management Practices, Nutrient Recycling, and Soil Biodiversity. Land management practices, such as crop rotation, reduced tillage, and growing cover crops, can aid in maintaining high levels of organic matter, healthy soil structure, and minimizing soil erosion. The cycling of the necessary nutrients for plant growth (nutrient cycling) is a function of the organic matter and microbial activity in the range. Soil biodiversity— the variability among living organisms that exist within and contribute to the functioning of soil ecosystems—is crucial to maintaining soil quality and fertility through a variety of ecosystem processes, including nutrient cycling. These practices work in concert with one another to encourage the soil to remain healthy and fertile for generations to come.

- **Farmland Utilization and Management**

Farmland use and management refer to the procedures and methods employed to maintain and enhance the productivity, sustainability, and economic returns of the land and its resources related to agricultural activities, as well as to optimize the utilization of natural resources involved in agricultural production. The 'is the crop ready to cultivate its own insurgency' stages of the work — what to plant, how to irrigate best and fertilize for productivity, how to hedge against pests and diseases, and perhaps even how to preserve trampled soil — all are practical works. These businesses must be aware of soil quality, climate, and the market to make informed decisions.

Where s is the power per unit length, the latter y can be calibrated against the soil-water content.

$$\Delta V = \frac{-s}{4\pi y} ln\left(\Delta v\right) \tag{1}$$

An alternative multi-probe heat pulse sensor, equipped with a heater probe surrounded by multiple temperature sensors, has also been described.

$$\frac{dT\left(r,t\right)}{dt} = \frac{s}{4\pi yt} \exp\left(\frac{-r^2}{4\alpha t}\right) \tag{2}$$

With these assumptions, the EM wave velocity of propagation (v) in soil can be expressed as follows:

$$v \approx \frac{1}{\sqrt{\mu_q \varepsilon_q}} \approx \frac{d}{\sqrt{\varepsilon_q'}} \tag{3}$$

Where $d = \frac{1}{\sqrt{\mu_0 \varepsilon_0}}$

Another aspect of proper management is not just monitoring and evaluation but also the pseudo-skills that one possesses to manage the land, ensuring its soil health and productive capacity can be achieved through necessary adjustments. This can be as simple as rotating crops to maintain healthy soil, adopting farming practices that are sustainable for the environment, and managing resources and labor effectively. Farmland utilization and management is a holistic approach that balances short-term profits with long-term sustainability.

- **Functional Soil Management**

Functional management of soil enhances the health and fertility of the soil while maintaining optimal plant growth and productivity. This usually involves practices such as soil testing, crop rotation, cover cropping, and an organic supply of fertility. Soil tests can reveal the level of nutrients in your soil and its pH, helping you devise an effective fertilization schedule. It refers to a system of planting a variety of crops in the same plot, which is what makes crop rotation perfect for soil health management as well as keeping pests and diseases at bay. Other grains are planted to further contribute to the microflora and fauna of the soil, to protect it from erosion, to replenish it, and to provide food, structure, and other products we enjoy. Organic fertilizers are those that provide nutrients for plants, bringing about improved soil structure and water retention. When we integrate these practices, we help build healthy soil, resulting in better yields and healthier land overall.

- **Water Purification and Regulation**

Water purification and regulation are the aspects through which we can clean and control water resources to provide clean drinking water for humans. This includes various process steps, such as screening, Coagulation, and filtration, as well as Disinfection, to remove impurities and harmful substances from the water. Screening filters out large debris and particles, then Coagulation clumps tiny particles together to make them easier to remove. Figure 1: Shows the construction diagram.

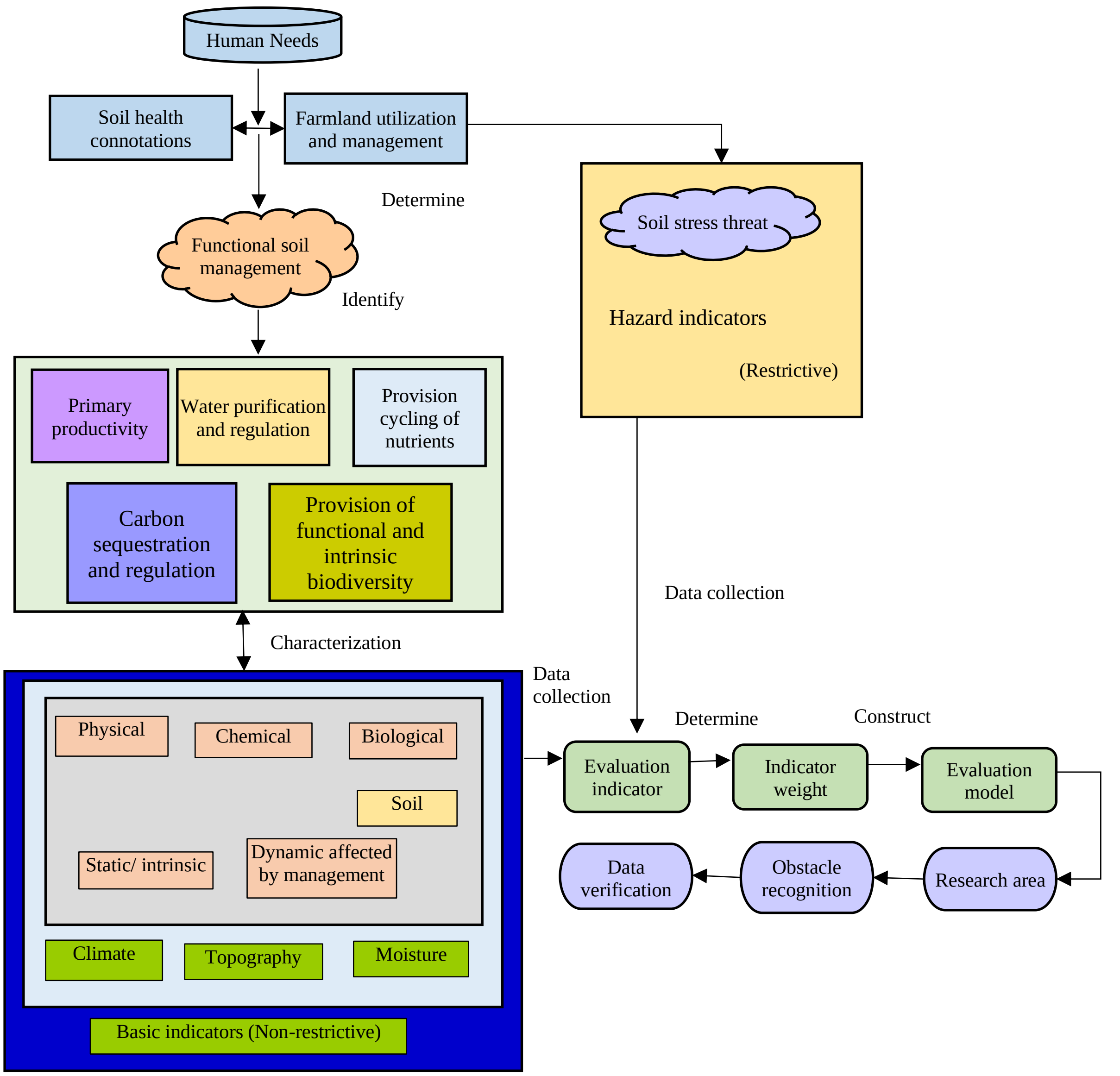

Figure 1: Construction Diagram

The latter will allow the particles to fall to the bottom through sedimentation, and the impurities are removed by filtration. Disinfection refers to the killing of pathogen organisms using chemical or physical agents. This process requires ongoing water quality testing and monitoring to maintain a clean, potable, and pure water supply. Their enforcement is the responsibility of Government bodies and water treatment authorities to ensure that regulations are adhered to for public health reasons.

- **Carbon Sequestration and Regulation**

Carbon Sequestration and Storage is the process of storing and capturing atmospheric carbon dioxide (CO2) to mitigate climate change effects. Primarily, these are the types of transactions that occur with all, or at least most, listed businesses, resulting in a net outcome – planting trees and investing in carbon capture and storage (CCS) technologies, which in practice amounts to a negative (or net zero) investment. This decreases the amount of CO2 in the air (CO2 is eliminated through vegetation as well as vegetation draws in through photosynthesis, and for this reason, is grabbed through CCD vegetation, ultimately in the treatment from industrial plants to help under times).

$$v = \frac{2R}{t} \tag{4}$$

The soil's dielectric permittivity can be estimated from equations (3) and (4).

$$\varepsilon_q' = \left(\frac{dt}{2R}\right)^2 \tag{5}$$

The dielectric permittivity of soil can be computed using (3) and (4).

$$\Gamma_{soil} = \frac{T_l}{T_b} = \frac{W_{soil} - W_0}{W_{soil} + W_0} \tag{6}$$

$$V = \frac{I \times t}{C} \tag{7}$$

This is part of what ultimately reduces the risk that CO2 contributes to the greenhouse effect and the warming of the Earth’s atmosphere. Furthermore, requirements such as carbon taxes and emission caps incentivize industries to reduce their carbon footprint and achieve more sustainable operations. Collectively, these steps are crucial for mitigating the damage caused by excessive carbon in our atmosphere.

- **Dynamic/ Affected by Management**

Dynamic outcomes affected by management databases are a business management practice in which the operations and performance of a company influence its management decisions. It is about constantly monitoring and fixing the things an organization is doing, how it is doing them, and with what, as the market, technology, and world of work change. That will make management nimble and agile, enabling them to adapt to the business's needs and compete effectively and quickly. Top management also needs to be proactive and make decisions by consulting with the teams and reviewing the data of the growing company. But, the effectiveness of dynamic or contingent management is crucial to the company's future sustainability and long-term growth.

- **Evaluation Indicator**

The "Assessment index" is an analytical tool used to assess performance or measure the effectiveness of specific processes or activities. It does this by defining specific yardsticks or criteria that should be achieved and then by gathering information or evidence to assess whether these have been completed. The primary step is to be clear on the purpose and goals of the evaluation.

Since water has an enormous specific heat capacity, the SMC is an important term of the total soil thermal inertia (P) and can be expressed by the following equation:

$$F = \sqrt{\lambda_q \rho_{soil} D_{soil}} \tag{8}$$

The bulk density and soil heat capacity are also factors that influence the thermal conductivity of the soil. SMC and LST are linearly inversely related and can be represented as:

$$SMC = \frac{RQV_{dry} - RQV}{RQV_{dry} - RQV_{wet}} \tag{9}$$

$$L_m = X + RG + E \tag{10}$$

This will clarify which criteria need to be assessed and what data should be collected. After the needs are defined, data collection takes several forms, including polling, surveillance, and performance reporting. The data is subsequently analyzed and compared with the preset conditions to determine the utility or effectiveness of the procedure. The assessment criterion outcome can then be used to facilitate the necessary enhancements or adjustments, allowing for improved performance in the future.

- **Evaluation Mode**

The E-valuation model can be useful as a means to learn from both failures and successes in any program, project, or process. This process has several phases: Planning, Data Capture, Analysis, and Reporting. Terms of Reference Design: The Terms of Reference should be established during the planning phase, which includes setting objectives, scope, and evaluation criteria. Data are collected through surveys, interviews, and observations. The data are then analyzed to determine how effective the program is and where good and bad teaching are occurring. The outcome of these evaluations is reflected in a report, which naturally contributes to further decisions on whether to proceed with the program or not. This tool helps ensure that programs are being followed and continually improved to achieve their desired outcomes.

- **Obstacle Recognition**

Obstacle recognition is a term used in vehicles, particularly in transportation, to describe a technology that identifies obstacles and responds appropriately, such as taking action to avoid them or preventing a collision that threatens safe driving. It contains means (e.g., sensors, such as cameras or lasers) for sensing the vehicle's environment. Computers analyze the data of obstacles (vehicles and pedestrians) and generate the distance of how far the car is from them. It is equipped with sensors and acquires information in real time. With this information, the system can, if necessary, alert or take control to sense the obstacle before it happens, allowing the vehicle and its occupants to avoid the collision. It's an important safety feature in 21st-century automobiles, utilizing proprietary algorithms and image processing techniques to detect, classify, and semantically understand and monitor objects.

- **Data Verification**

Testing the correctness of the data residing in the database to see if the data is accurately stored, retrieved and maintained in the database. Checking the data is called Data Validation and making sure (the quality, accuracy, consistency etc.) of the data to see if data is correct &right and then further identify the error and try to correct it. The good and reliable robust data must continue to be cared for, without which incorrect conclusions, decisions, and actions would surely follow. Data validation – you can do it manually, using automated tools, with data validation rules, and with algorithms. This is an ongoing activity, rather than an occasional one, which maintains high data quality and dependability in a system. Trusted, reliable data. Through best-in-class data authentication, in which information is verified, organizations can trust that their data is accurate and can aid them in making informed decisions.

B. Functional Working Model

- **Input**

The “input” procedure is a basic operation performed by a computer in which the user enters data and gives commands to the computer. It is inputting the data into the computer, which is then processed, stored, and finally displayed in some manner or used in some way. The input operation begins with interacting with an input device, such as a keyboard, mouse, or touchpad. These devices are attached to the computer via a variety of interfaces to create digital signals that the computer can comprehend and translate into performance signals.

$$T_I = \tau\left(rT_{sky} - eT_{surf}\right) + T_{atm} \tag{11}$$

There were two major steps in the data processing: Based on [55], (i) Radar modeling involved modeling the VNA, the antenna, and the multi-layer medium (soil) as linear systems in series and parallel in the frequency domain. This led to the overall transfer function:

$$Q_{11}(\omega) = L_b(\omega) + \frac{X_v(\omega)E_{hh}(\omega)X_l(\omega)}{1 - X_p(\omega)E_{hh}(\omega)} \tag{12}$$

When the user presses a button, the input device transmits signals to the computer's central processing unit (CPU). The brain, or CPU (central processing unit), is responsible for all game-related instructions, including those for input.

- **Output**

In computer programming, output refers to the process that generates specific information, data forms, and results through output devices. It is critical to the developmental process, as it provides the user with an indication of what their code is outputting and how their requests are being implemented. Output: Extracting data from a program and sending it to an external device (e.g., a monitor or file). Now, however, we need to instruct the program to output something. This can be accomplished by printing text, displaying graphics, or writing data to a file. When you write and save a Python script, the program executes your script and performs the necessary actions to produce the desired output. Formatting is a major concern of the production.

- **Max pooling**

Max Pooling is one of the popular operations used in neural networks, especially in CNNs, which are commonly employed in Image recognition tasks. The idea is to down sample the input by decreasing the spatial dimensions of the feature maps and retaining the most important features. Max pooling begins with a convolutional layer, and some features are extracted from the input image.

Full wave inversion for parameter recovery: A weight least square inverse problem was set up, and the objective function (8b) was minimized:

$$\Phi(i) = \left(e_{hh}^*(v) - e_{hh}(i,v)\right)^V \left(e_{hh}^*(v) - e_{hh}(i,v)\right) \tag{13}$$

The following model was described for SNR

$$SNR = J\cos\left(\frac{4\pi x}{\lambda}\sin G + \phi\right) \tag{14}$$

$$Abs = \alpha \times r \times D_0 \tag{15}$$

The layer has a feature map, which is a 3D table of numbers, where each number in the table indicates the level of activity at the associated spatial location. This feature map is partitioned into smaller non-overlapping regions known as pooling windows. For each window, apply max pooling, which retains the highest value within the window and ignores the rest. The outputs are down sampled feature maps with reduced spatial dimensions.

- **Up-conv**

Up sampling is an operation that appears in computer vision and image processing, most notably in the context of CNNs. This operation is often referred to as "transposed convolution" or "deconvolution" and is a popular technique for image upscaling, also known as "super-resolution" problems. To comprehend the role of "up-conv," you first need to understand what convolution is in CNNs. Figure 2: Shows the functional block diagram.

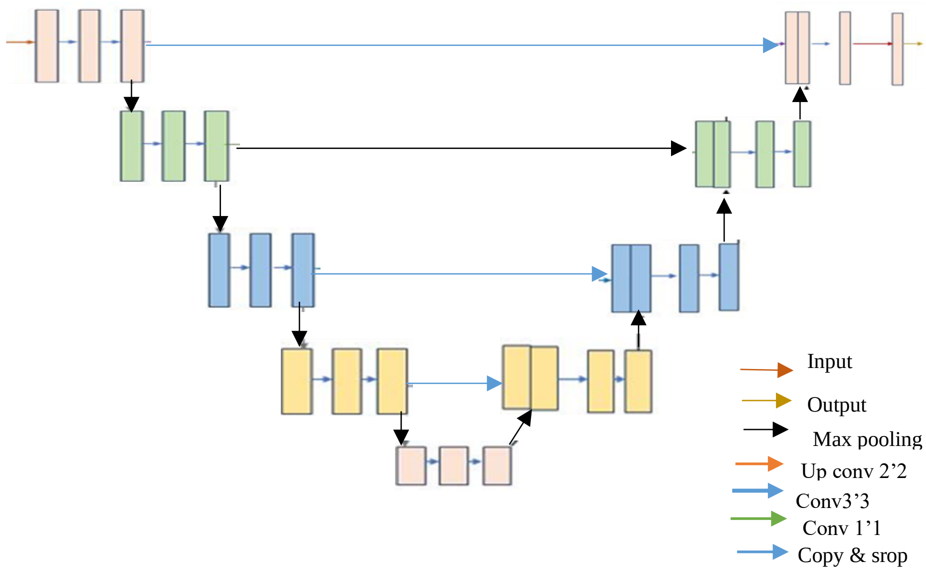

Figure 2: Functional Block Diagram

Convolution is a type of mathematical operation in which you attempt to extract features from a given image by multiplying it with a filter or kernel. These filters are typically smaller in spatial size than the input image and convolve over the entire picture to generate feature maps. These feature maps are subsequently fed through non-linear activation functions to encode complex patterns and features.

➢ **Copy and Crop**

The above is an image-editing method that utilizes the "Copy and Crop" technique. It allows users to copy a part of an image and paste the crop in the desired location. It comes in handy if you want to extract a part of an image and then resize it without distorting the rest of the image. In this section, we will describe how this operation works and its technical details. The part of the image that you want to copy is the first part of "Copy and Crop."

$$3Ag^{+} + PO_4^{-} \rightarrow Ag_3PO_4 \tag{16}$$

The sensing mechanism was confirmed by X-ray photoelectron spectroscopy (XPS) analysis of the Ag/rGO ISFET. The equations corresponding to the signals illustrated in the figure are:

$$b_v = \sigma\left(h_v O^b + x_{v-1} Z^b\right) \tag{17}$$

$$p_v = \sigma\left(h_v O^p + x_{v-1} Z^p\right) \tag{18}$$

$$x_v = \sigma_v \times \sigma_x\left(d_v\right) \tag{19}$$

$$NF_b = \frac{P_b - \overline{P}}{q_P} \tag{20}$$

$$E\left(S\right) = \sum_{b=1}^{M}\left(-f_b \log_2 f_b\right) \tag{21}$$

Where the inspection probability is the probability, the instance falls in class k given all its attributes are inspected, M is the number of unique class values, and S is the set of all the cases.

Typically, this is done with a selection tool, such as the marquee or lasso tool. After the desired area is selected, the software copies the designated area and places it in the clipboard or a temporary holding area. The following operation is the "crop" operation on the image, which involves resizing the image to a fixed size. In other words, the sponsor's first full-page image would either need to be resized or have its full-page design scaled up or down to reset the image dimensions or adjusted manually by grasping the edges of the image.

C. Operating System

➢ **Encoder**

An encoder is an electronic device or circuit that performs the inverse operation of a decoder. It encodes data and generates a code for it, allowing for easy processing and retrieval. A converter is simply a device that translates data from one form to another, allowing other devices to receive it in a more user-friendly format. There are three basic states an encoder is in: Input, Processing, and Output. Input Stage: This is the stage at which the device receives input from digital signals from various other sensors or devices. This input/output data is normally represented as binary digits (bits) in serial or parallel form.

The purity of the branch of the tree is estimated based on the Gini impurity (22) as well as this parameter.

$$B_E = 1 - \sum_{a=1}^{M} \left(f_b^2 \right) \tag{22}$$

$$RMSE = \sqrt{\frac{\sum_{b=1}^{M} \left(\hat{k}_b - k_b \right)^2}{M}} \tag{23}$$

For the true value, for the estimated value, M is the number of the samples analyzed.

$$Q(v) = F\left(\{V > v\}\right) = \int_v^{\infty} p(o) co = 1 - P(v) \tag{24}$$

The actual encoding occurs at the processing stage. The incoming data is analyzed by the encoder circuitry's logic path and transformed into a coded signal. It is achieved by assigning a unique code to each input signal, given the encoding scheme employed. The most typical voice encodings used are Binary, Gray, and BCD (Binary-Coded Decimal).

➢ **Decoder**

A decoder is a combinational digital circuit that decodes an n-coded input signal to produce a predefined set of m output codes where m is less than 2 to the power n. The task of a decoder is to transform the encoded input into some other shape or style. It can be thought of as a decoder or the inverse operation of encoding, which transforms encoded inputs into outputs. Such decoders are widely used in digital electronics, for example, in microprocessors, memory, and digital communication systems.

If the correlation is greater than the equation below between the variable and the large N number of input data, the variable is significant.

$$Absolute\,correlation \geq \frac{2}{\sqrt{M}} \tag{25}$$

$$h = h_d + h_v \tag{26}$$

$$MSE = \frac{1}{B \times A} \sum_{b,a} \left(k_{b,a} - \hat{k}_{b,a} \right)^2 \tag{27}$$

$$MAE = \frac{1}{B \times A} \sum_{b,a} \left| k_{b,a} - \hat{k}_{b,a} \right| \tag{28}$$

The basic operation of a decoder can be described by examining a 2-to-4 decoder, as shown below. It receives two inputs, A and B, and has four outputs, Y0 to Y3. The inputs could take any of four possible configurations: 00, 01, 10, or 11—only one of these inputs' maps to an output. In particular, with the inputs set to 00, a first output, Y0, will be enabled, while the others will remain in their disabled state. It can also be seen that when the inputs are 01, the output Y1 will be enabled. We can look at the circuitry of a decoder to understand this.

➢ **Encoder Vector**

The encoding vector is a mathematical concept used in various contexts, such as data compression, error correction, and neural networks. It's simply an arbitrary bunch of numbers representing information, probably in binary form. This is useful for succinctly representing large datasets or merely storing or transmitting the original data in a reduced dimension of the original one, which is of a large and complicated volume. This process is designed for Encoder Vector, and it can be divided into three principal steps: data preprocessing, encoding, and decoding. Preprocessing: In the first stage of CED, the input data are processed to ensure they are properly encoded. Figure 3: Shows the operational flow diagram.

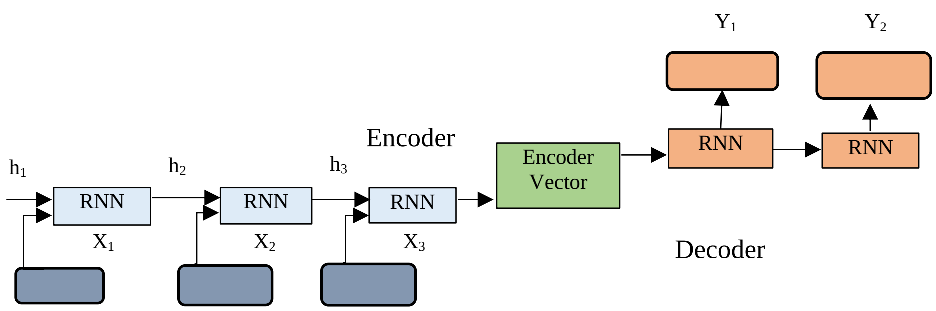

Figure 3: Operational Flow Diagram

The culprit could be encoding text into numbers, shrinking images, or transforming the raw data into feature vectors. After the data is preprocessed, it can be encoded. It's the site of most of the pressurizing or shaping. The EncAV Algorithm: EncAV receives the preprocessed data and performs a mathematical transformation on it, resulting in information compression.

➢ **RNN**

An RNN is an artificial neural network that processes sequenced data, i.e., time series, speech, or text. It is one of the most popular models for sequential data. It has been widely used in various domains, including speech recognition, natural language processing, and handwriting recognition. Fundamentally, RNNs function by iteratively feeding previously computed outputs back into the network, thereby enabling them to learn and process data sequences in a time-based manner.

The first-order spectral derivative can be estimated as follows:

$$\frac{\partial Q}{\partial \lambda_y} = \frac{Q(\lambda_y) - Q(\lambda_r)}{\lambda_r - \lambda_y} \tag{29}$$

Where Q is the SRC and λ_r λ_y are the wavelength regions of bands y and r.

This recursive property in RNNs enables them to learn sequential and long-range dependencies in the data, which is why they are superior to traditional feed-forward neural networks. An RNN has a simple architecture consisting of three layers: an input layer, a hidden layer, and an output layer.

$$Q_n(\lambda) = \sum_{y=1}^{f} p_y g q_y(\lambda) \tag{30}$$

$$\sum_{y=1}^{f} p_y = 1.0, \quad 0 \le p_y \le 1.0 \tag{31}$$

The linear mixture model can be written as

The input sequence of data is fed into the input layer and passed on to the hidden layer. The hidden layer then calculates a state representation from the current input and the secret state from the previous time step.

4 Result and Discussion

PFNL-SNM has been compared with the available real-time deep Learning and Sensor Fusion Nutrient Mapping (RTDL-SNM), Deep Learning and Sensor Fusion Soil Nutrient Mapping (DFNL-SNM) and Deep Learning and Sensor Fusion Mapping for Precision Agriculture (DLF-PA).

4.1. Accuracy of Nutrient Level Prediction

It is a measure of how well deep learning and sensor technology, in addition, can predict nutrient concentration in soil. Greater precision means better farmer decision-making. Table.2 shows the comparison of Accuracy between existing and proposed models. Figure 4: Shows the Computation of Accuracy of nutrient level prediction (Table 2).

Table 2: Comparison of Accuracy (in %)

No. of Inputs	DFNL-SNM	RTDL-SNM	DLF-PA	PFNL-SNM
100	78.14	79.35	78.70	80.28
200	76.51	77.61	77.12	78.86
300	76.03	75.27	74.92	77.60
400	74.74	74.46	73.29	75.61
500	72.63	72.17	72.15	73.14

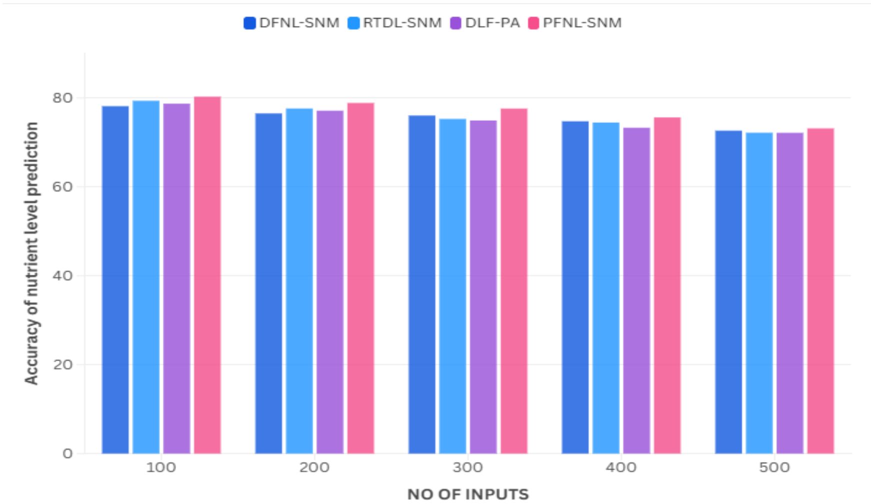

Figure 4: Computation of Accuracy of Nutrient Level Prediction

4.2. Real-time Processing Speed

Nutrient mapping technology should process data quickly, as farmers want instant knowledge of their soil's state, enabling informed decision-making. Real-time results require high processing speed. Table.3 shows the comparison of processing speed between existing and proposed models. Figure 5: Shows the Computation of Real-time processing speed (Table 3).

Table 3: Comparison of Processing Speed (in %)

No. of Inputs	DFNL-SNM	RTDL-SNM	DLF-PA	PFNL-SNM
100	89.14	90.35	87.70	94.28
200	87.51	88.61	86.12	92.86
300	87.03	86.27	83.92	91.60
400	85.74	85.46	82.29	89.61
500	83.63	83.17	81.15	87.14

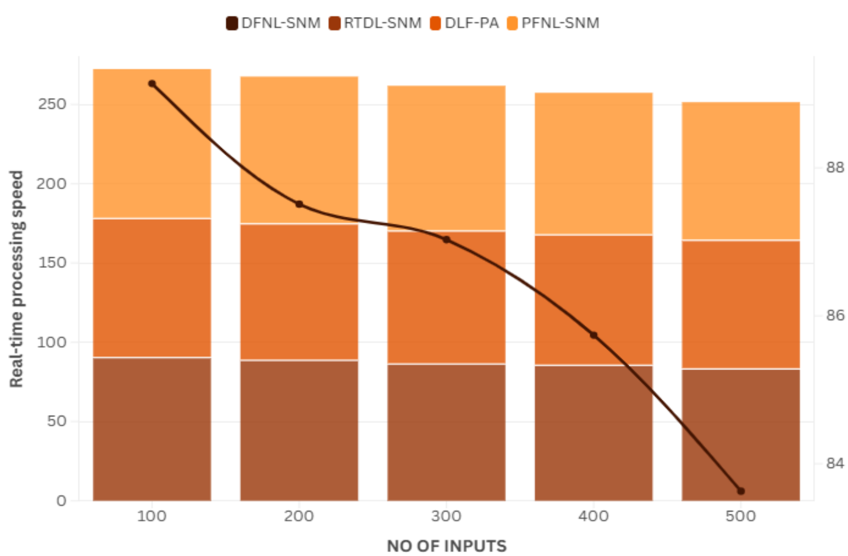

Figure 5: Computation of Real-Time Processing Speed

4.3. Sensitivity and Specificity

These parameters represent the system's capability to discriminate between the presence and/or absence of various nutrients in the soil. High sensitivity ensures that no nutrient deficiency is overlooked, whereas high specificity guarantees that the identified nutrients are truly present in the soil. Table.4 shows the comparison of Sensitivity between existing and proposed models. Figure 6: Shows the Computation of Sensitivity and specificity (Table 4).

Table 4: Comparison of Sensitivity (in %)

No. of Inputs	DFNL-SNM	RTDL-SNM	DLF-PA	PFNL-SNM
100	84.14	85.35	83.70	86.28
200	82.51	83.61	82.12	84.86
300	82.03	81.27	79.92	83.60
400	80.74	80.46	78.29	81.61
500	78.63	78.17	77.15	79.14

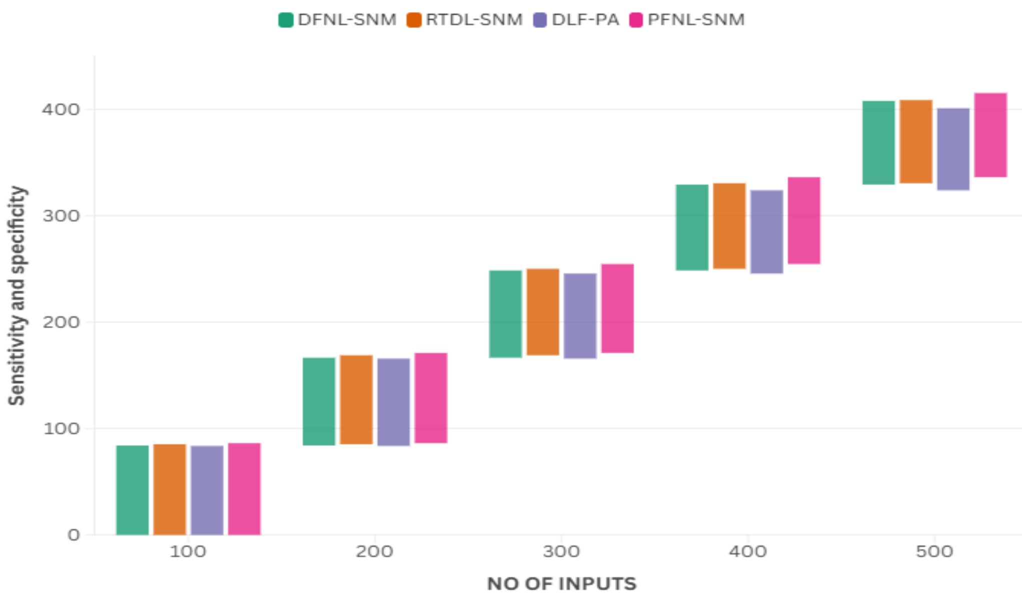

Figure 6: Computation of Sensitivity and Specificity

4.4. Robustness and Adaptability

The nutrient mapping platform is designed to function effectively under a wide range of soil and climate conditions. It should also be adjustable to multiple farming styles (i.e., conventional or organic systems) to deliver consistent results. Table 5 shows the comparison of Robustness between existing and proposed models. Figure 7: Shows the Computation of Robustness and adaptability.

Table 5: Comparison of Robustness (in %)

No. of Inputs	DFNL-SNM	RTDL-SNM	DLF-PA	PFNL-SNM
100	81.14	82.35	80.70	83.28
200	79.51	80.61	79.12	81.86
300	79.03	78.27	76.92	80.60
400	77.74	77.46	75.29	78.61
500	75.63	75.17	74.15	76.14

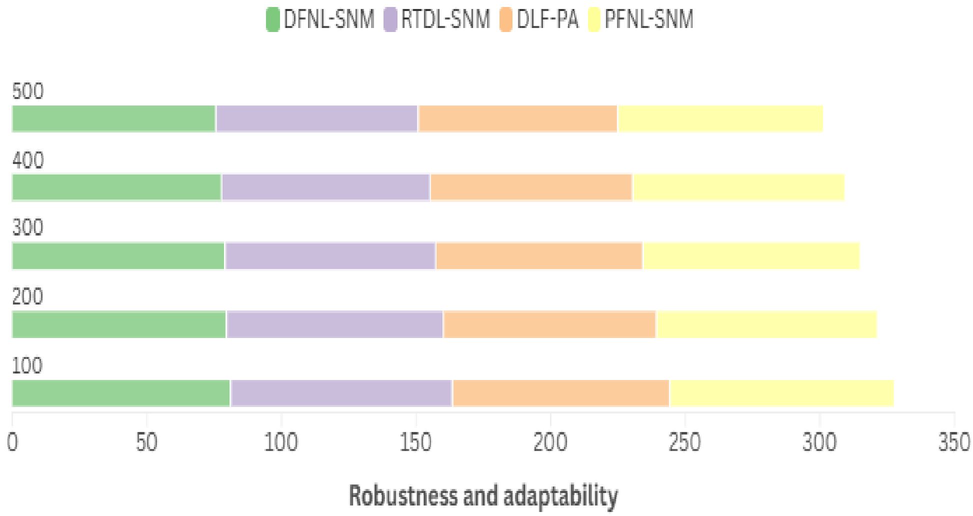

Figure 7: Computation of Robustness and Adaptability

5 Conclusion

In summary, the research developed time-stream-processed soil nutrient maps in real time, demonstrating that deep learning and sensor fusion can be applied to precision farming. The soil nutrient content was estimated locally in real-time with high resolution, utilizing a system that integrates several sensors and deep learning models. This is a change that will improve farm management and potentially generate significantly higher crop yields. The work also demonstrated that the system was considerably more accurate than conventional soil tests, highlighting the tool's potential application in precision farming. In this way, with deep learning, the system continues to learn and becomes the perfect one, suitable for the changing soil conditions throughout the years and seasons. If further developed and implemented, this technology can revolutionize precision agriculture and contribute to sustainable farming practices.

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